EMOTION RECOGNITION USING WIRELESS SIGNALS

(KABLOSUZ SİNYALLERİ KULLANARAK DUYGU TANIMA)

by

HASAN ALI SOLGUN, M.S.

Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

INTELLIGENT SYSTEMS ENGINEERING

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

JUNE 2024

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to everyone who contributed to the completion of this master's thesis.

First and foremost, I am profoundly grateful to my thesis advisor, Assist. Prof. Özgün Pınarer, for his invaluable guidance, continuous support and encouragement throughout this journey.

I extend my sincere thanks to Alp Özcan for dedicating his valuable time to the collection of data used in this research.

Finally, I am thankful to my family for their unconditional support, encouragement, and unwavering belief in my abilities.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS iii

TABLE OF CONTENTS iv

LIST OF FIGURES vii

LIST OF TABLES ix

ABSTRACT xi

RÉSUMÉ xii

ÖZET xiv

LIST OF ABBREVIATIONS xv

1 INTRODUCTION 1

2 LITERATURE REVIEW 5

2.1 Motion Detection 7

2.2 Vital Sign Monitoring 14

2.3 Emotion Recognition 18

3 PROPOSED APPROACH 24

3.1 Reflection of Wi-Fi Signal from Human Body 24

3.2 Channel State Information (CSI) 25

3.3 Calculating Heart Rate from CSI 27

3.4 System Architecture & Hardware 28

3.4.1 Data Preprocessing 29

3.5 Processing CSI data 30

3.5.1 Interpreting CSI data 32

3.6 Algorithms to Apply on CSI data 33

3.6.1 Convolutional Neural Network 33
3.6.2 Artificial Neural Network (ANN) 34
3.6.3 Random Forest 35
3.6.4 K-NN 36
3.6.5 Gaussian Naive Bayes (GNB) 37
3.6.6 Support Vector Machine (SVM) 38
3.6.7 Long Short-Term Memory (LSTM) 39
3.6.8 Gated Recurrent Units (GRUs) 40
3.6.9 Multilayer Perceptron (MLP) 41
3.6.10 Comparison of chosen Algorithms 42
4 PERFORMED EXPERIMENTS AND OBTAINED RESULTS 44
4.1 Experiment Scenarios 44
4.1.1 Single Subject Experiments 44
4.1.2 Multi-Subject Experiments 48
4.1.3 Multi-Subject Experiments with an Indoor Obstacle . 51
4.2 Experiment Results 53
4.2.1 Expectations 53
4.2.2 Performance Metrics 54
4.2.3 Experiment No : 1 55
4.2.4 Experiment No : 2 58
4.2.5 Experiment No : 3 60
4.2.6 Experiment No : 4 62
4.2.7 Experiment No : 5 64
4.2.8 Experiment No : 6 66
4.2.9 Experiment No : 7 68
4.2.10 Experiment No : 8 71
4.2.11 Experiment No : 9 72

4.2.12 Experiment No : 10 75
4.2.13 Experiment No : 11 77
4.2.14 Experiment No : 12 79
4.2.15 Experiment No : 13 81
4.2.16 Experiment No : 14 83
4.2.17 Experiment No : 15 85
4.2.18 Experiment No : 16 87
4.2.19 Experiment No : 17 90
4.2.20 Experiment No : 18 92
4.2.21 Experiment No : 19 95
4.2.22 Experiment No : 20 97
4.2.23 Experiment No : 21 100
4.2.24 Experiment No : 22 102
4.2.25 Experiment No : 23 104
4.2.26 Experiment No : 24 106
5 CONCLUSION AND DISCUSSION 111
5.1 Challenges 112
5.2 Cons of the Algorithms 113
5.2.1 Overview 114
5.2.2 Algorithm Performances 115
5.2.3 Potential Improvements 116
5.3 Discussion 117
REFERENCES 118
APPENDICES 122
Appendix . A 122

LIST OF FIGURES

Figure 3.1 ESP32-WROOM-32U devices with external antennas. 29

Figure 4.1 Single Subject - 1m distance - Experiments 1-2-3-4 45

Figure 4.2 Single Subject - 3m distance - Experiments 5-6-7-8 47

Figure 4.3 Single Subject - 5m distance - Experiments 9-10-11-12 48

Figure 4.4 Single Subject - Other Room - Experiments 13-14-15-16 49

Figure 4.5 Multiple Subjects - Same Room - Experiments 17-18-19-20 51

Figure 4.6 Multiple Subjects - Other Room - Experiments 21-22-23-24 52

Figure 4.7 Confusion Matrix For Random Forest Algorithm for Experiment No : 1 57

Figure 4.8 Confusion Matrix SVM Algorithm for Experiment No : 2 59

Figure 4.9 Confusion Matrix For Random Forest Algorithm for Experiment No : 3 62

Figure 4.10 Confusion Matrix For SVM Algorithm for Experiment No : 4 64

Figure 4.11 Confusion Matrix For Random Forest Algorithm for Experiment No : 5 66

Figure 4.12 Confusion Matrix For LSTM Algorithm for Experiment No : 6 . . . 68

Figure 4.13 Confusion Matrix For Random Forest Algorithm for Experiment No : 7 70

Figure 4.14 Confusion Matrix For Random Forest Algorithm for Experiment No : 8 72

Figure 4.15 Confusion Matrix For Random Forest Algorithm for Experiment No : 9 74

Figure 4.16Confusion Matrix For Random Forest Algorithm for Experiment No : 10 76

Figure 4.17Confusion Matrix For Random Forest Algorithm for Experiment No : 11 78

Figure 4.18Confusion Matrix GRU Algorithm for Experiment No : 12 81

Figure 4.19Confusion Matrix For Random Forest Algorithm for Experiment No : 13 83

Figure 4.20Confusion Matrix For SVM Algorithm for Experiment No : 14 . . . 85

Figure 4.21Confusion Matrix For Random Forest Algorithm for Experiment No : 15 87

Figure 4.22Confusion Matrix For SVM Algorithm for Experiment No : 16 . . . 90

Figure 4.23Confusion Matrix For Random Forest Algorithm for Experiment No : 17 92

Figure 4.24Confusion Matrix For Random Forest Algorithm for Experiment No : 18 94

Figure 4.25Confusion Matrix For GRU Algorithm for Experiment No : 19 . . . 97

Figure 4.26Confusion Matrix For SVM Algorithm for Experiment No : 20 . . . 99

Figure 4.27Confusion Matrix For LSTM Algorithm for Experiment No : 21 . . . 102

Figure 4.28Confusion Matrix For SVM Algorithm for Experiment No : 22 . . . 104

Figure 4.29Confusion Matrix For SVM Algorithm for Experiment No : 23 . . . 106

Figure 4.30Confusion Matrix For SVM Algorithm for Experiment No : 24 . . . 109

LIST OF TABLES

Table 2.1 Overview of existing studies on Motion Detection 13

Table 2.2 Overview of existing studies on Vital Sign 18

Table 2.3 Overview of existing studies on Emotion Recognition 22

Table 2.4 Comparison of Motion Detection, Vital Sign Monitoring, and Emotion Detection via CSI 22

Table 2.5 Device based Overview of Highlighted Existing Studies in the Literature 23

Table 3.1 Comparison of chosen Machine Learning Algorithms 43

Table 4.1 Algorithm Performance Comparison for Experiment No : 1 56

Table 4.2 Algorithm Performance Comparison for Experiment No : 2 58

Table 4.3 Algorithm Performance Comparison for Experiment No : 3 60

Table 4.4 Algorithm Performance Comparison for Experiment No : 4 62

Table 4.5 Algorithm Performance Comparison for Experiment No : 5 64

Table 4.6 Algorithm Performance Comparison for Experiment No : 6 67

Table 4.7 Algorithm Performance Comparison for Experiment No : 7 69

Table 4.8 Algorithm Performance Comparison for Experiment No : 8 71

Table 4.9 Algorithm Performance Comparison for Experiment No : 9 73

Table 4.10 Algorithm Performance Comparison for Experiment No : 10 75

Table 4.11 Algorithm Performance Comparison for Experiment No : 11 77

Table 4.12 Algorithm Performance Comparison for Experiment No : 12 79

Table 4.13 Algorithm Performance Comparison for Experiment No : 13 81

Table 4.14 Algorithm Performance Comparison for Experiment No : 14 83

Table 4.15 Algorithm Performance Comparison for Experiment No : 15 86

Table 4.16 Algorithm Performance Comparison for Experiment No : 16 88

Table 4.17 Algorithm Performance Comparison for Experiment No : 17 90

Table 4.18 Algorithm Performance Comparison for Experiment No : 18 93

Table 4.19 Algorithm Performance Comparison for Experiment No : 19 95

Table 4.20 Algorithm Performance Comparison for Experiment No : 20 98

Table 4.21 Algorithm Performance Comparison for Experiment No : 21 100

Table 4.22 Algorithm Performance Comparison for Experiment No : 22 102

Table 4.23 Algorithm Performance Comparison for Experiment No : 23 105

Table 4.24 Algorithm Performance Comparison for Experiment No : 24 107

Table 4.25 Summary of Experiments 110

Table 5.1 Algorithm MAE Values Comparison for All Experiments 114

ABSTRACT

Emotion recognition is a critical aspect of human-computer interaction and affective computing, with applications ranging from personalized user interfaces to mental health monitoring. This study explores the performance of various machine learning algorithms for emotion recognition using physiological signals obtained from subjects under diverse experimental conditions.

The methodology involves conducting a series of carefully designed experiments to collect physiological data from participants. These experiments vary in environmental conditions, including distance from the transmitter and receiver, heart rate variability, and subject posture. Several machine learning algorithms are evaluated in the study and the performance of these algorithms is assessed using various metrics. The results of the experiments demonstrate significant variations in algorithm performance across different experimental conditions. Through comparative analysis, Random Forest emerges as the top-performing algorithm, consistently achieving the lowest MAE values across experiments. However, SVM also demonstrates competitive performance, especially in scenarios involving high heart rates. These findings underscore the importance of algorithm selection and optimization in achieving accurate emotion recognition in real-world applications.

In conclusion, this study provides valuable insights into the performance of machine learning algorithms for emotion recognition using physiological signals. By understanding how different factors influence algorithm performance, researchers and practitioners can develop more effective emotion recognition systems for a wide range of applications, including healthcare, human-computer interaction, and affective computing.

Keywords : Wi-Fi, CSI, emotion recognition, human activity recognition(HAR)

RÉSUMÉ

La reconnaissance des émotions est un aspect crucial de l'interaction homme-machine et de l'informatique affective, avec des applications allant des interfaces utilisateur personnalisées à la surveillance de la santé mentale. Cette étude explore la performance de divers algorithmes d'apprentissage automatique pour la reconnaissance des émotions en utilisant des signaux physiologiques obtenus auprès de sujets dans des conditions expérimentales diverses.

La méthodologie consiste à mener une série d'expériences conçues pour collecter des données physiologiques. Ces expériences varient selon les conditions environnementales. Plusieurs algorithmes d'apprentissage automatique sont évalués dans cette étude, et la performance de ces algorithmes est évaluée à l'aide de divers métriques. Les résultats des expériences montrent des variations significatives de la performance des algorithmes selon les différentes conditions expérimentales. La forêt aléatoire émerge comme l'algorithme le plus performant, obtenant systématiquement les valeurs de MAE les plus basses à travers les expériences. Cependant, SVM démontre également une performance compétitive, en particulier dans les scénarios impliquant des fréquences cardiaques élevées. Ces résultats soulignent l'importance de la sélection et de l'optimisation des algorithmes pour obtenir une reconnaissance précise des émotions dans des applications réelles.

En conclusion, cette étude fournit des insights précieux sur la performance des algorithmes d'apprentissage automatique pour la reconnaissance des émotions en utilisant des signaux physiologiques. En comprenant comment différents facteurs influencent la performance des algorithmes, les chercheurs et les praticiens peuvent développer des systèmes de reconnaissance des émotions plus efficaces pour une large gamme d'applications, y compris la santé, l'interaction homme-machine et l'informatique affective.

Mots Clés : Wi-Fi, CSI, reconnaissance des émotions, reconnaissance des activités

humaines(HAR)

ÖZET

Duygu tanıma, insan-bilgisayar etkileşimi ve duygusal bilişimde kritik bir öneme sahiptir. Uygulama alanları arasında kişiselleştirilmiş kullanıcı arayüzlerinden mental sağlık izlemeye kadar geniş bir yelpaze bulunmaktadır. Bu çalışma, çeşitli deneysel koşullar altında elde edilen fizyolojik sinyalleri kullanarak duygu tanıma için farklı makine öğrenimi algoritmalarının performansını incelemektedir.

Metodoloji, katılımcılardan fizyolojik veri toplamak için dikkatle tasarlanmış bir dizi deneyin gerçekleştirilmesini içerir. Bu deneyler, verici ve alıcı arasındaki mesafe, kalp atış hızı değişkenliği ve deneklerin duruşu gibi çevresel koşullarda çeşitlilik gösterir. Çalışmada, çeşitli makine öğrenimi algoritmaları değerlendirilmiş ve bu algoritmaların performansı çeşitli metrikler kullanılarak ölçülmüştür. Deneylerin sonuçları, farklı deneysel koşullar altında algoritmaların performansında önemli farklılıklar olduğunu göstermektedir. Karşılaştırmalı analizler sonucunda, Random Forest, deneyler boyunca en düşük MAE değerlerini sürekli olarak elde ederek en iyi performans gösteren algoritma olarak öne çıkmaktadır. Bununla birlikte, SVM de özellikle yüksek kalp atış hızlarının söz konusu olduğu senaryolarda rekabetçi bir performans sergilemektedir. Bu bulgular, gerçek dünya uygulamalarında doğru duygu tanıma sağlamak için algoritma seçiminin ve optimizasyonunun önemini vurgulamaktadır.

Sonuç olarak, bu çalışma, fizyolojik sinyalleri kullanarak duygu tanıma için makine öğrenimi algoritmalarının performansı hakkında değerli bilgiler sunmaktadır. Farklı faktörlerin algoritma performansını nasıl etkilediğini anlayarak, araştırmacılar ve uygulayıcılar sağlık hizmetleri, insan-bilgisayar etkileşimi ve duygusal bilişim gibi çeşitli alanlar için daha etkili duygu tanıma sistemleri geliştirebilirler.

Anahtar Kelimeler : Wi-Fi, CSI, duygu analizi, kalp ritim hesaplama, insan tespiti

LIST OF ABBREVIATIONS

CSI	Channel State Information
CNN	Convolutional Neural Network
ANN	Artificial Neural Network
RF	Random Forest
K-NN	K-Nearest Neighbors
GNB	Gaussian Naive Bayes
SVM	Support Vector Machine
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units
MLP	Multilayer Perceptron
RNN	Recurrent Neural Network

1 INTRODUCTION

In the era of pervasive technology, the quest to decipher the intricate tapestry of human emotions has transcended traditional boundaries, propelling researchers into novel domains where wireless signals emerge as unexpected emissaries of emotional intelligence. As digital ecosystems seamlessly intertwine with human experiences, the prospect of decoding emotional states from wireless signals, such as Channel State Information (CSI) and Radio Frequency (RF) signals, emerges as a groundbreaking paradigm shift in understanding and harnessing the complexities of human emotion.

The motivation behind this research lies in the potential of wireless signals to serve as unobtrusive, real-time indicators of emotional states, thereby transcending the limitations of conventional emotion recognition methods. We aspire to construct a framework that not only detects emotions accurately but also offers a non-invasive, continuous monitoring solution. This thesis addresses the challenges and opportunities inherent in this nascent field, aiming to contribute significantly to the burgeoning landscape of emotion-aware technologies. With a focus on methodological rigor, ethical considerations, and practical implications, this research endeavors to chart the unexplored territories of emotion recognition through wireless signals, paving the way for transformative applications in diverse fields ranging from healthcare to human-computer interaction.

With the improvements of data mining and machine learning techniques, making predictions from labeled data are being easy for phenomena which has low possibility. When those research fields combined with the basically and easily measurable components like wireless signals, we can able to design effortless and cheaper expert systems. Because of the lower operating costs and mobility features, wireless technologies are gained more importance for making diagnosis and taking precautions for any specific fields. In today's fast-living lifestyle and individuality situations brought by the modern world conditions, physical human interactions are being more difficult such as pandemic diseases that emerges this kind of situations.

Even if the firstly human and then other living beings physical interaction is not possible, given diagnosis and prediction systems must be working accurately and precisely for this kind of situations. For those reasons, a machine learning system that using wireless signals becomes a hot research topic in the literature.

Monitoring breathing rates, patterns, and emotions is vital for diagnosing and potentially preventing various health issues. Emotions can be deduced from audio and visual cues such as voice, facial expressions, gestures, or motion captured by cameras. Additionally, wearable devices and body sensors can track physiological signals like heart rate and body temperature, offering valuable insights into emotional states.

However, many current technologies for tracking vital signals are intrusive, requiring physical contact. For instance, existing breath monitoring sensors often involve attaching a nasal probe, wearing a chest band, or lying on a specialized mattress, which can be inconvenient for users.

Moreover, current methods for detecting emotions typically rely on audiovisual cues or require individuals to wear physiological sensors like an ECG monitor. These approaches may not always be practical or comfortable for continuous monitoring in real-world scenarios.

Human bodies reflect wireless signals effectively, allowing for the recognition of human activities through changes in Wi-Fi signals (Wang et al., 2017). This approach using wireless signals can address privacy concerns compared to cameras, which may inadvertently capture sensitive information like faces. Recently, researchers have developed an innovative emotion recognition method using wireless signals reflected by the human body. Emotion recognition through wireless signals offers broader coverage than cameras since these signals can penetrate walls and other physical obstacles.

RF signals bounce off the human body and are modulated by body movements. Smart environments can remotely monitor vital signs without the need for intrusive body sensors. Emotion recognition utilizes RF reflections from the body, requiring the extraction of individual heartbeats.

RF reflections can be utilized to measure a person's breathing and average heart rate without direct body contact. This innovative approach takes advantage of the fact that

RF signals can be influenced by subtle movements in the human body, including chest and torso motion associated with breathing and heartbeat.

The technique involves transmitting RF signals towards a person and capturing the reflections. As the person breathes or their heart beats, these physiological activities cause variations in the body's shape and density, influencing the RF reflections. By analyzing the changes in the received RF signals over time, researchers can extract patterns related to respiration and heartbeat.

This non-contact approach has several advantages, including the ability to monitor vital signs remotely without requiring the person to wear any sensors. It is particularly promising for applications in healthcare, sleep monitoring, and ambient assisted living, where unobtrusive monitoring is desired.

While the technology is still evolving and faces challenges related to accuracy, environmental interference, and privacy concerns, researchers continue to make strides in refining these methods. Embracing RF reflections for vital sign monitoring represents a novel and potentially transformative approach in the realm of non-contact healthcare technologies (Droitcour et al., 2009; Patwari et al., 2013; Kaltiokallio et al., 2014).

Besides emotions can be extracted from the physical symptoms. For instance, breathing rate can be observed with the chest movements. And this observation can be used for the human emotion recognition with the help of data mining and machine learning techniques. Although the radar systems have more accuracy for the observation of physical movements, Wi-Fi channel state information has chosen for this system because of the wide range usability and lower costs. With the help of channel state information of wireless signals, this kind of physical interactions can be collected and used for the analysis.

Briefly, it is indeed possible to perform emotion recognition using wireless signals, and researchers have been exploring this innovative approach in recent years. The concept involves wireless signals, such as CSI or RF signals, to infer and recognize human emotions. The idea is based on the premise that physiological changes associated with emotions, such as heart rate variations, breathing patterns, or even subtle movements, can influence the propagation of wireless signals.

Several studies have demonstrated the feasibility of emotion recognition using wireless signals. For instance, variations in the human body caused by emotional responses can affect the signal characteristics, and advanced signal processing techniques, along with machine learning algorithms, can be employed to extract relevant features for emotion identification. The potential applications of this technology are diverse, ranging from healthcare, where it could be used for remote patient monitoring and mental health assessment, to human-computer interaction, where systems can adapt based on users' emotional states.

However, it's important to note that while the idea is promising, there are challenges to be addressed. Factors such as environmental conditions, subject movement, and the need for large datasets for training accurate models pose significant hurdles. Ethical considerations related to privacy and the non-intrusiveness of the technology also need careful attention. Ongoing research in this field aims to refine the methodologies and enhance the performance, precision of emotion recognition using wireless signals.

The remainder of the document is structured as follows : Literature review is given in Chapter 2. Chapter 3 presents our proposed approach. Chapter 4 introduces performed experiment scenarios and experiment results. Finally, conclusion and discussion are given in Chapter 5.

2 LITERATURE REVIEW

The exploration of Emotion Recognition Using Wireless Signals represents a innovative and interdisciplinary study at the intersection of effective computing, signal processing, and wireless communication. In recent years, there has been a paradigm shift in the understanding and application of wireless signals, extending beyond their conventional role in communication to unveil latent insights into human emotions.

The convergence of wireless technology and emotion recognition opens up new frontiers for unobtrusive and continuous monitoring of individuals' emotional well-being in various contexts, including smart homes, healthcare, and human-computer interaction. As emotions play a pivotal role in shaping human behavior and decision-making, the ability to capture and interpret these emotional cues from wireless signals introduces unprecedented opportunities for enhancing human-machine interactions, personalized services, and mental health monitoring. This literature chapter aims to provide a comprehensive overview of the research landscape, methodological approaches, challenges, and breakthroughs in the realm of emotion recognition using wireless signals, positioning itself as a guide for researchers, practitioners, and enthusiasts navigating this exciting and dynamic domain.

The interest of the remote sensing techniques has increasing in recent years. These techniques have been found a comprehensive usage area in some industries like health and defense because of the some requirements for the contactless or remote measurement of human and other living things. Some techniques have been used for the recognition of heart rate and respiration rate. For example, in the literature, usage of image processing techniques can be found for analysis of the chest movements to determine heart rate. However, this technique requires a clear sight of the chest with the right angle. Besides this, on the other hand, usage of some other techniques can be seen for analysis of the respiratory rate. The breath temperature of a breathing person is an indicator to determining of respiratory rate. Considering that a healty human being's breath temperature is about 34 degrees Celcius (Anghel and Iacobescu, 2013), respiratory rate can be easily analyzed with help of the thermal cameras. However, as in the image processing, this technique needs some physical requirements. It can be seen that the Wireless CSI monitoring differs from the other techniques because of the less physical requirements when all these techniques are compared. Literature review has been shown how these techniques has been an interesting research area. In literature, especially the researches of wireless sensing technologies can be many found.

In the literature, important review studies present the different wireless sensing methods from the aspects of detection, recognition and estimation. In these studies, existing algorithms are compared comprehensively, applications, signal processing techniques and performance results of Wi-Fi sensing technologies (Ma et al., 2019). For instance, Al et al. compare the different types of Wi-Fi sensing mechanisms for human activity recognition study field. Main Wi-Fi sensing technologies have been categorized as Received Signal Strength Indicator (RSSI), Wi-Fi radar (by using Software Defined Radio (SDR)) and CSI (Al-qaness et al., 2019). Such surveys mainly highlight the three challenges; robustness and generalization, privacy and security and coexistence of Wi-Fi sensing and networking.

Li et al. have focused on the wireless sensing techniques that using deep artificial intelligence based techniques. Various sensing model approaches have compared from the aspects of likely challenges and issues. Also authors have discussed future trends of deep artificial intelligence and ubiquitous wireless sensing (Li et al., 2021).

Saxena et al. have mainly compared the emotion detection methods such as facial expression recognition, speech signals and physiological signals recognition in human. Besides, stationary wavelet transform for facial emotion recognition, particle swarm optimization assisted bio-geography based optimization algorithms for emotion recognition through speech, statistical features coupled with different methods for physiological signals, rough set theory coupled with support vector machine for text semantics algorithms have been compared and have found their accuracies

In recent years, the intersection of effective computing, signal processing, and wireless communication has given rise to innovative approaches for understanding human behavior and health. Remote sensing techniques have gained significant traction due to their potential for contactless or remote measurement of vital signs and emotional states. While traditional methods often require physical contact or specialized equipment, wireless signals offer a non-intrusive alternative, allowing for continuous monitoring in various environments.

2.1 Motion Detection

Motion detection is a fundamental aspect of many applications, ranging from security systems to human-computer interaction. Traditional motion detection methods often rely on physical sensors or cameras, which can be expensive, limited in coverage, and require manual installation. However, advancements in wireless technology have introduced a new approach to motion detection utilizing CSI. In this technique, changes in Wi-Fi signals caused by the presence of moving objects are analyzed to detect and track motion.

Certainly, there is a notable connection between motion detection and CSI, particularly in the context of wireless communication systems. CSI refers to the information about the state of the communication channel between a transmitter and a receiver. While CSI is traditionally used for optimizing communication performance, it has found applications beyond pure communication, including in motion detection and localization.

Wi-Fi-based motion detection utilizes Wi-Fi signals, including CSI, to detect motion within an environment. Changes in the CSI patterns caused by objects or individuals moving within the Wi-Fi signal range can be analyzed to detect motion, a technique often referred to as Wi-Fi-based sensing or Wi-Fi sensing.

Additionally, CSI can be used for human activity recognition, where specific activities or gestures can be recognized based on variations in CSI patterns. For example, as a person moves or gestures within the range of Wi-Fi signals, the variations in CSI patterns can be indicative of specific activities, enabling applications such as gesture recognition or activity monitoring.

In security systems, CSI can play a vital role in detecting intruders or unauthorized movements within a monitored area. Anomalies in the CSI patterns caused by the presence of a person or object can trigger alerts, enhancing the capabilities of security and surveillance systems.

Moreover, motion detection using CSI contributes to indoor localization by analyzing changes in CSI as a person moves within a Wi-Fi-covered space, allowing for the estimation of their location and providing a basis for indoor positioning systems.

Furthermore, integrating CSI with motion detection enables novel human-computer interaction methods, such as detecting hand gestures or body movements through changes in CSI patterns, creating immersive and touchless interfaces.

Gesture recognition is another application of CSI data, where specific gestures made by individuals within a Wi-Fi-covered area can be recognized based on the changes in CSI patterns corresponding to different gestures.

Motion detection via CSI involves utilizing the variations in wireless signals, specifically the changes in CSI, to detect and track motion in a given environment.

Motion detection via Channel State Information (CSI) provides a non-visual sensing method, unlike traditional motion sensors like cameras or infrared sensors, CSI allows for motion detection without relying on visual cues. This can be advantageous in scenarios where visual sensing is impractical or undesired.

Moreover, CSI-based motion detection makes use of existing wireless communication infrastructure, such as Wi-Fi networks, allowing for motion sensing without the need for additional sensors or devices, and processing the signals already present in the environment.

Since CSI is derived from wireless signals, the motion detection process is unobtrusive and passive. There is no need for individuals to wear or carry specific devices, making it suitable for applications where user comfort and privacy are important. This technology has applications in creating smart environments, where the system can respond to human movements without the need for explicit input. This has implications for home automation, ambient intelligence, and other contexts where automated responses to human presence or motion are desirable.

In security and surveillance applications, CSI-based motion detection can be employed to identify and alert to the presence of individuals or objects in a monitored area. This application enhances security systems by providing an additional layer of detection.

Additionally, the technology can be extended to gesture recognition and human-computer interaction. By interpreting the changes in CSI patterns corresponding to specific motions or gestures, it becomes possible to create touchless interfaces or control systems based on human movements.

However, motion detection via CSI faces challenges such as environmental interference, signal noise, and the need for sophisticated signal processing techniques. Ongoing research aims to address these challenges and further enhance the accuracy and reliability of motion detection using CSI.

In summary, the main point of motion detection via CSI is to harness wireless signals to sense and interpret motion in various environments, enabling applications in security, automation, and human-computer interaction without the need for additional, dedicated motion sensing hardware.

While the connection between CSI and motion detection is innovative and promising, it's important to note that there are challenges, including the need for sophisticated signal processing techniques and the impact of environmental factors on CSI measurements. Nevertheless, ongoing research is exploring the potential of utilizing CSI for motion detection in various practical applications.

CSI motion detection takes advantage of the fact that Wi-Fi signals experience variations in amplitude, phase, and frequency when they interact with moving objects. These changes in CSI patterns can be utilized to detect the presence, direction, speed, and trajectory of moving objects. By analyzing the temporal and spatial characteristics of CSI data, it becomes possible to achieve accurate and real-time motion detection without the need for additional sensors or cameras.

The use of CSI for motion detection offers several advantages over traditional methods. Firstly, it uses the existing Wi-Fi infrastructure, making it cost-effective and easy to deploy. Wi-Fi signals are readily available in most indoor environments, allowing for motion detection in various settings such as homes, offices, and public spaces. Secondly, CSI-based motion detection is non-intrusive and contactless, as it does not require physical contact with the objects being monitored. This makes it suitable for applications where preserving privacy or maintaining cleanliness is important, such as in healthcare settings or sensitive environments.

To detect motion from CSI data, advanced signal processing techniques and machine learning algorithms are employed. Classical signal processing techniques are used to extract meaningful features from the CSI data. Machine learning algorithms, including support vector machines, random forests, and deep learning models, are then utilized to classify and identify motion patterns based on the extracted features.

While CSI-based motion detection shows great potential, there are challenges that need to be addressed. These challenges include dealing with environmental noise, multipath interference, and complex indoor scenarios with multiple objects and people in motion. Additionally, the robustness and accuracy of the motion detection system need to be improved to handle various motion speeds, different object sizes, and occlusion situations.

Research in this field has made significant progress, with numerous studies demonstrating the feasibility and effectiveness of CSI-based motion detection. These studies have explored various applications, including activity recognition, gesture recognition, people counting, and intrusion detection. However, further research is required to optimize the algorithms, refine the techniques for real-world scenarios, and address the remaining challenges to unlock the full potential of CSI-based motion detection.

Pu et al. presents a demo of the developed system WiSee. The study uses Doppler signal and USRP N210 hardware with Gnu Radio. WiSee detects the presence of the human body and gesture detection (Pu et al., 2013).

Adib et al. introduced the WiTrack system, designed to operate effectively through walls and obstructions. A notable feature of this system is its capability to track human motions, detect falls, and crucially, estimate the pointing directions of the human body. The indoor localization system relies on a geometric reference model, and the proposed setup incorporates four antennas strategically positioned (one for transmission and three for reception). The use of Frequency-Modulated Continuous Wave (FMCW) technology and Universal Software Radio Peripheral (USRP) devices is a key component of this system (Adib et al., 2014).

Same researchers further introduce a system RF-Capture to capture human figure through the walls and identify human body. In that study, again wireless signal is emitted (1/1000 weaker than the normal Wi-Fi signal). During the experiment phase, FMCW Chirp generator and 2d antenna are used (Adib, Hsu, Mao, Katabi and Durand, 2015).

Abdelnasser et al. propose a system WiGest that detects human gestures based on RSSI changes on the wireless signal (Abdelnasser, Youssef and Harras, 2015). Besides, more specifically the system can detect the hand motions as well. This detection may result with the estimation of direction as well for the further studies.

Wang et al. present a framework CARM that recognize human activity usunbg Wi-Fi signal. The study adopts the recent technologies and CSI of the wireless signal to detect human from the reflections and uses Baum-Welch algorithm for activity recognition (Wang et al., 2017).

Venkatnarayan et al. introduce WiMU a tool that recognizes simultaneously performed gestures that can be applicable for multiple users in the environment. Proposed syatem uses CSI measurements for the detection mechanism (Venkatnarayan et al., 2018).

Visserman et al. as a difference from the existing studies propose a system that track the activity of a group of people instead of monitoring a single person. In that study, CSI of the wireless signal is used and by using 3 nodes higher accuracy can be achieved (Visserman, 2019).

Zheng et al. introduce a system Wiradar 3.0 that recognize human activities and gestures based on CSI. In that study, 1 TX(Intel 5300 NIC wireless) and at least 3 RX(CSI Tool) are used during the performed experiments. The study mainly focus on the factors that may vary the accuracy of the system such as environment, person diversity and location and orientation of the person (Zheng et al., 2019).

Forbes et al. implemented a Wi-Fi based activity detection system working on the Raspberry Pi hardware. The study analyzes the CSI as the input source and performs deep learning algorithms to detect the human motion recognition and classify the acitivities (Forbes et al., 2020).

Muaaz et al. present a system WiHAR that focus on the CSI measurements to recognize human activities. The study performs machine learning techniques decision tree, linear discriminant analysis, and support vector machines to classify the human activities from CSI data (Muaaz et al., 2020).

Xue et al. propose a system DeepMV that uses Wi-Fi and acustic devices deployed around the environment and recognize human activities such as walking, running, sittin, writing etc. The study uses deep learning methods like CNN to classify the human activities (Xue et al., 2020).

Schafer et al. have mainly focused on the Wi-Fi human activity recognition field of study. In the scope of work, Wi-Fi channel state informations of human activities like sit, sit-down, stand, walk, fall etc. have classified with the deep neural networks, such as support vector machines and long-term short memory algorithms (Schäfer et al., 2021). Also, an open-source tool, Nexmon that extracting the channel state information of inexpensive devices like raspberry pi have used. This open sourced tool enables the users to write it's own firmware on Wi-Fi chips. Thus, any inexpensive Wi-Fi device can be turned into the software defined wireless network device which is extractor of channel state information. These predictions of the provided by data model have more than %97 accuracy for the human activity recognition.

Zhang et al. propose a location-independent human activity recognition system : AF-ACT. The study processes CSI measurements and apply feature fusion techniques to detect human activities (Zhang et al., 2022).

Alsaify et al. introduce a framework that recognize human activities based on CSI values. The study applies deep learning approaches such as CNN, RNN, SVM to detect and classify human activities (Alsaify et al., 2022).

In conclusion, CSI-based motion detection offers a promising solution for accurate, cost-effective, and non-intrusive motion detection. By the unique characteristics of Wi-Fi signals and utilizing advanced signal processing and machine learning techniques, it has the potential to revolutionize motion detection systems in various domains, including smart homes, healthcare, and security. Table 2.1 presents existing studies on motion detection.

Table 2.1 – Overview of existing studies on Motion Detection

Study	**Key Contributions**	**Technologies Used**
(Pu et al., 2013)	Doppler signal and USRP N210 hardware with Gnu Radio, detects human body presence and gestures.	Doppler signal, USRP N210, Gnu Radio
(Adib et al., 2014)	Utilizes FMCW technology and USRP devices to track human motions, detect falls, and estimate pointing directions.	FMCW technology, USRP devices
(Adib, Hsu, Mao, Katabi and Durand, 2015)	Captures human figures through walls using FMCW Chirp generator and 2d antenna.	FMCW Chirp generator, 2d antenna
(Abdelnasser, Youssef and Harras, 2015)	Detects human gestures based on RSSI changes in wireless signals.	RSSI changes, wireless signals
(Wang et al., 2017)	Recognizes human activities using Wi-Fi CSI and Baum-Welch algorithm.	Wi-Fi CSI, Baum-Welch algorithm
(Venkatnarayan et al., 2018)	Recognizes simultaneous gestures applicable for multiple users using CSI measurements.	CSI measurements
(Visserman, 2019)	Tracks the activity of a group of people using CSI measurements from 3 nodes.	CSI measurements, 3 nodes
(Zheng et al., 2019)	Recognizes human activities and gestures using CSI measurements from 1 TX and at least 3 RX devices.	CSI measurements, 1 TX, 3 RX devices
(Forbes et al., 2020)	Implements Wi-Fi-based activity detection system using deep learning on Raspberry Pi hardware.	Deep learning, Raspberry Pi
(Muaaz et al., 2020)	Focuses on CSI measurements for human activity recognition using decision tree, LDA, and SVM.	CSI measurements, decision tree, LDA, SVM
(Xue et al., 2020)	Uses Wi-Fi and acoustic devices to recognize human activities with CNN.	Wi-Fi, acoustic devices, CNN
(Schäfer et al., 2021)	Classifies human activities using deep neural networks and Nexmon tool for CSI extraction.	Deep neural networks, Nexmon tool
(Zhang et al., 2022)	Location-independent human activity recognition system processing CSI measurements with feature fusion.	CSI measurements, feature fusion
(Alsaify et al., 2022)	Recognizes human activities using CNN, RNN, and SVM based on CSI values.	CNN, RNN, SVM, CSI values

2.2 Vital Sign Monitoring

Vital sign monitoring is a fundamental aspect of healthcare, providing valuable insights into a person's physiological condition. Traditional methods of monitoring vital signs often involve direct contact with the patient through the use of sensors and wires, which can be uncomfortable and restrictive. However, recent advancements in wireless technology have paved the way for non-contact and unobtrusive monitoring techniques. One such promising approach is the utilization of CSI for vital sign monitoring.

Vital Sign Monitoring via CSI refers to the innovative use of wireless communication signals, specifically CSI from Wi-Fi or other wireless systems, to monitor and detect vital signs of individuals. The main point of vital sign monitoring via CSI is to detect the variations in wireless signals caused by the human body's physiological activities, such as breathing and heartbeat, to extract health-related information without the need for wearable sensors or physical contact.

Vital sign monitoring via CSI offers a non-intrusive method for observing and recording physiological parameters. Without the need for direct contact or wearable devices, individuals can be monitored remotely, allowing for continuous and unobtrusive health tracking.

The human body's movements, especially chest and torso motions during breathing and heartbeat, introduce subtle variations in the wireless signals. By analyzing these variations in CSI, it becomes possible to extract information related to respiratory rate, heart rate, and potentially other vital signs. This approach holds great potential for remote health monitoring applications, as patients' vital signs can be monitored from a distance, enabling healthcare professionals to assess health conditions, detect anomalies, and provide timely interventions without the need for physical presence.

Moreover, vital sign monitoring via CSI capitalizes on existing wireless infrastructure, such as Wi-Fi networks, making it cost-effective and scalable. This integration allows for the deployment of health monitoring systems without the need for additional specialized hardware.

The non-contact nature of CSI-based vital sign monitoring gives various opportunities for ubiquitous sensing, where health monitoring becomes seamlessly integrated into daily environments. This could lead to smart homes, healthcare facilities, and public spaces equipped with health-aware technologies.

However, while promising, the approach faces challenges such as signal noise, environmental interference, and the need for advanced signal processing techniques. Ongoing research and advancements aim to address these challenges and enhance the accuracy and reliability of vital sign monitoring via CSI.

In essence, the main point is to transform existing wireless communication systems into health monitoring tools, enabling unobtrusive and continuous tracking of individuals' vital signs for healthcare, well-being, and emergency response purposes.

CSI refers to the changes in Wi-Fi signals caused by their interaction with the human body. These variations occur due to reflections, scattering, and absorption of Wi-Fi signals as they pass through or interact with the body. By analyzing these changes in CSI data, it becomes possible to extract valuable information about vital signs such as heart rate, respiratory rate, and body movement.

The use of CSI for vital sign monitoring offers several advantages over traditional methods. Firstly, it enables contactless monitoring, eliminating the need for physical sensors attached to the body. This non-invasive approach enhances patient comfort, reduces the risk of infections, and allows for continuous monitoring without restrictions on movement. Secondly, Wi-Fi signals are readily available in most indoor environments, making it convenient for monitoring in various settings such as hospitals, homes, and public spaces. The existing Wi-Fi infrastructure allows for seamless integration and scalability of the monitoring system.

To extract vital sign information from CSI data, advanced signal processing techniques and machine learning algorithms are employed. Signal processing techniques such as spectral analysis, time-frequency analysis, and adaptive filtering are used to capture and analyze the subtle variations in the signals caused by physiological activities. Machine learning algorithms, including neural networks and support vector machines, are then employed to accurately classify and estimate vital signs based on the processed CSI data.

While the use of CSI for vital sign monitoring shows great promise, there are several challenges that need to be addressed. These challenges include dealing with environmental noise, motion artifacts, interference, and ensuring the accuracy and reliability of the monitoring system. Additionally, privacy and security concerns must be addressed to protect the sensitive health data transmitted through Wi-Fi signals.

Research in this field has made significant progress, with numerous studies demonstrating the feasibility and effectiveness of CSI-based vital sign monitoring. These studies have explored various aspects of vital sign estimation, including heart rate, respiratory rate, sleep monitoring, activity recognition, and fall detection. However, further research is needed to validate and refine the techniques, optimize algorithms for real-world scenarios, and address the challenges associated with noise, motion, and interference.

Droitcour et al. introduce CMOS Doppler radar system for respiratory monitoring. The study uses ASPPT2988 antenna deployed on CMOS chip and SNR is applied on the acquired data (Droitcour et al., 2009).

Patwari et al. present a system for heart rate monitoring by using RSS measurements. The study introduces Breathfinding that locates the breathing person in the envrionment and based on the RSS measurements, heart rate is calculated. During the performed experiments, TI CC2531 nodes are chosen (Patwari et al., 2013).

Kaltiokallio et al. focus on respiratory monitoring using ow cost trasnceivers. In that study, COTS transceivers and CC2431 are used and with the RSS measurements, respiratory monitoring is performed (Kaltiokallio et al., 2014).

Adib et al. present Vital-Radio, a wireless sensing technology for monitoring breathing and heart rate without the need for direct body contact. Vital-Radio leverages the influence of motion in the environment on wireless signals, such as chest movements during breathing and skin vibrations caused by heartbeats. It can accurately track users' breathing and heart rates with a median accuracy of 99%, even at distances of up to 8 meters from the device or in separate rooms. Additionally, it has the capability to simultaneously monitor the vital signs of multiple individuals (Adib, Mao, Kabelac, Katabi and Miller, 2015).

Abdelnasser et al. propose a novel respiratory monitoring system, UbiBreathe, based on ubiquitous off-the-shelf Wi-Fi-enabled devices (Abdelnasser, Harras and Youssef, 2015). Besides, the presented system is proposed to detect apnea. Apnea produces abnormal breathing patterns, and this irregularity helps system to detect the anomaly on the streaming signal.

Tan et al. propose the Wi-Fi based healthcare sensing application. Application uses the channel status information. Researchers explained the healthcare application of Doppler shifts for the Wi-Fi channel state information. With the help of this approach, different types of the human activities and behaviours can be explained for healthcare applications in real world (Tan et al., 2018).

Wang et al. propose a system BreathJunior that use white noise for infants monitoring, their breathing (Wang et al., 2019).

Gu et al. presents a wireless signal based heart rate monitoring. The study, specially focuses on the sleep period and monitors breath rate during the sleep via a pair of transceivers (Gu et al., 2019).

Wang et al. introduce mmHRV, a contactless method for monitoring vital signs. As antennas and chips undergo miniaturization, the mmWave technology is poised to become extensively accessible across various devices, including home routers, smartphones, and vehicles. mmHRV capitalizes on this trend by enabling ubiquitous and pervasive vital sign monitoring, utilizing existing mmWave devices wherever they are already deployed. It's crucial to note that mmHRV is specifically tailored for common clinical settings where individuals typically remain stationary, providing a versatile solution for continuous vital sign monitoring (Wang et al., 2021).

In conclusion, vital sign monitoring with CSI offers a non-contact and unobtrusive approach to gather valuable physiological information. The advancements in signal processing and machine learning techniques, coupled with the ubiquity of Wi-Fi infrastructure, have created new opportunities for continuous and convenient vital sign monitoring. By addressing the remaining challenges and further refining the techniques, CSI-based monitoring has the potential to revolutionize healthcare, improve patient comfort, and enable remote and real-time monitoring. Table 2.2 presents existing studies on vital sign.

TABLE 2.2 – Overview of existing studies on Vital Sign

Study	**Key Contributions**	**Technologies Used**
(Droitcour et al., 2009)	Introduces CMOS Doppler radar system for respiratory monitoring using ASPPT2988 antenna on CMOS chip, applying SNR on acquired data.	CMOS chip, ASPPT2988 antenna, SNR
(Patwari et al., 2013)	Presents a system for heart rate monitoring using RSS measurements and Breathfinding technique for locating breathing person in the environment.	RSS measurements, Breathfinding, TI CC2531 nodes
(Kaltiokallio et al., 2014)	Focuses on respiratory monitoring using low-cost transceivers, utilizing COTS transceivers and CC2431 with RSS measurements.	Low-cost transceivers, COTS transceivers, CC2431, RSS measurements
(Adib, Mao, Kabelac, Katabi and Miller, 2015)	Introduces Vital-Radio, a wireless sensing technology for monitoring breathing and heart rate without direct body contact, achieving median accuracy of 99%.	Wireless sensing, Vital-Radio, motion influence on wireless signals
(Abdelnasser, Harras and Youssef, 2015)	Proposes UbiBreathe, a respiratory monitoring system based on ubiquitous off-the-shelf Wi-Fi-enabled devices, capable of detecting apnea.	Off-the-shelf Wi-Fi-enabled devices, UbiBreathe, apnea detection
(Tan et al., 2018)	Demonstrates the healthcare application of Doppler shifts for Wi-Fi CSI, explaining various human activities and behaviors for healthcare applications.	Wi-Fi CSI, Doppler shifts
(Wang et al., 2019)	Introduces BreathJunior for infants' breathing monitoring using white noise and Wi-Fi signals.	BreathJunior, white noise, Wi-Fi signals
(Gu et al., 2019)	Presents a wireless signal-based heart rate monitoring system focusing on sleep periods, monitoring breath rate during sleep via transceivers.	Wireless signals, heart rate monitoring, sleep monitoring, transceivers
(Wang et al., 2021)	Introduces mmHRV, a contactless method for monitoring vital signs using mmWave technology, tailored for common clinical settings.	mmWave technology, mmHRV, clinical settings

2.3 Emotion Recognition

Emotion detection via CSI involves utilizing variations in wireless signals, particularly the changes in CSI, to infer and recognize human emotions. Emotion recognition is a fundamental aspect of human interaction and understanding. Traditional methods for emotion recognition often rely on subjective self-reporting or invasive physiological sensors, limiting their practicality in real-world settings. However, recent advancements in wireless technology have paved the way for a novel approach to emotion recognition using CSI. By analyzing the subtle changes in Wi-Fi signals caused by emotional states, CSI-based emotion recognition offers a promising and non-intrusive solution for accurately detecting and interpreting human emotions.

CSI-based emotion recognition indicates the emotional states that can influence physiological responses, which in turn affect the properties of Wi-Fi signals. These minute variations in CSI patterns can be utilized to discern and classify emotional states such as happiness, sadness, fear, or surprise. Through sophisticated signal processing techniques and machine learning algorithms, it becomes possible to extract meaningful features from CSI data that encapsulate emotional information.

One of the key advantages of CSI-based emotion recognition is its non-contact nature. Unlike traditional methods that require physical sensors or direct interaction, CSI-based techniques allow for emotion monitoring without any physical contact with the individuals. This non-intrusive characteristic makes it suitable for applications in public spaces, healthcare settings, or smart environments where privacy and comfort are paramount. Additionally, Wi-Fi signals are omnipresent in indoor environments, enabling emotion recognition in a wide range of real-world scenarios.

The process of emotion recognition from CSI data involves advanced signal processing and machine learning algorithms. Signal processing techniques such as time-frequency analysis, wavelet transforms, and feature extraction are employed to capture the nuanced variations in Wi-Fi signals induced by emotional states. Machine learning algorithms, including support vector machines, deep neural networks, and ensemble methods, are then utilized to classify and recognize emotions based on the extracted features.

While CSI-based emotion recognition holds great potential, several challenges need to be addressed. These challenges encompass handling environmental noise, addressing multipath interference, addressing inter-individual variability, and achieving cross-cultural generalization of emotion recognition models. Furthermore, ethical considerations, such as data privacy and security, should be carefully addressed to ensure the responsible and secure use of personal emotional data collected through Wi-Fi signals.

Emotion detection via CSI provides a non-intrusive method for sensing and interpreting human emotions. It allows for the recognition of emotional states without the need for individuals to wear or interact with specific devices, offering a passive and privacy-sensitive approach.

The technology integrates with existing wireless communication infrastructure, such as Wi-Fi networks, to capture and analyze CSI, eliminating the need for additional sensors or devices and utilizing signals already present in the environment.

Human emotions are associated with physiological changes, such as variations in heart rate, respiratory patterns, and subtle movements. Emotion detection via CSI exploits these changes, as they manifest in the alterations of wireless signal characteristics.

One primary application of CSI-based emotion detection is in human-computer interaction, where systems can adapt and respond based on users' emotional states. For example, adapting the content of a virtual environment or adjusting the interaction mode of a device based on detected emotions.

Additionally, CSI-based emotion detection can be combined with other contextual information, such as gestures or behavioral patterns, to enhance the accuracy of emotion recognition. The combination of multiple cues allows for a more comprehensive understanding of users' emotional states.

However, challenges exist, including the need for robust algorithms to accurately interpret emotional cues from CSI, addressing individual variations, and ensuring the reliability of emotion detection across diverse environments. Ongoing research aims to refine techniques, enhance accuracy, and broaden the applicability of emotion detection via CSI.

In essence, the main point of emotion detection via CSI is to create technology that can perceive and respond to human emotions based on the subtle physiological changes reflected in wireless signals. This has potential applications in creating emotionally aware systems that can provide personalized and adaptive user experiences.

Existing research in CSI-based emotion recognition has made significant progress, demonstrating the feasibility and effectiveness of this approach. Studies have explored various aspects of emotion classification, including real-time emotion detection, cross-modal emotion recognition, and emotion-aware system design. However, further research is needed to refine the techniques, improve the robustness of emotion recognition models, and explore the application of CSI-based emotion recognition in diverse cultural contexts and real-world scenarios.

Zhao et al. introduce the first study that recognize human emotion by using RF reflections from human body in the literature. The study proposes a system EQ-Radio that collects the reflected signals by FMCW radio and applies extraction and emotion classification algorithm on the collected signal (Zhao et al., 2016).

Kim et al. introduce a framework VEmoBar that recognizes human emotions by using wireless signal. The study uses IoT devices for the experiments and underlines that emotion recognition can be achieved by audio and visual information or wearable devices however, using Wi-Fi signals reflected by human body does not require any attached/wearable device (Kim et al., 2019).

Khan et al. present a model proposed a novel deep neural network architecture based on the fusion raw radio frequency data and processed radio frequency signals for classifying emotion statuses. The model have compared with the various machine learning and deep learning algorithms and have found a superior results even the limited usage of raw radio frequency signals. Besides, model have been validated with the ground-truth values of ECG signals (Khan et al., 2021).

Ha et al. underlines the importance of the chosen methodology. Devices that are attached to the human body have well-known disadvantages : being attached to the body which is not comfortable for children and elderly however, these methods produce a high accuracy with respect to contactless approaches. Thus, the users should choose either a high accurate application performance or comfort. The study presents a system WiStress, a contactless stress monitoring based on wireless signal (Ha et al., 2021).

In conclusion, CSI-based emotion recognition offers a promising avenue for non-intrusive and accurate emotion monitoring. By capitalizing on the unique characteristics of Wi-Fi signals and employing advanced signal processing and machine learning techniques, this approach has the potential to revolutionize emotion recognition systems, enhance human-computer interaction, and facilitate the development of empathetic and context-aware technologies. Table 2.3 introduces the existing studies on emotion recognition.

Table 2.3 – Overview of existing studies on Emotion Recognition

Study	Key Contributions	Technologies Used
(Zhao et al., 2016)	Introduces EQ-Radio, the first study to recognize human emotions using RF reflections from the human body. The system collects reflected signals by FMCW radio and applies extraction and emotion classification algorithms.	RF reflections, EQ-Radio, FMCW radio
(Kim et al., 2019)	Presents VEmoBar, a framework for recognizing human emotions using wireless signals from IoT devices. Emotion recognition is achieved without any attached or wearable devices, solely relying on Wi-Fi signals reflected by the human body.	IoT devices, VEmoBar, Wi-Fi signals
(Khan et al., 2021)	Proposes a novel deep neural network architecture for classifying emotion statuses based on the fusion of raw radio frequency data and processed radio frequency signals. The model outperforms various machine learning and deep learning algorithms and is validated with ground-truth values of ECG signals.	Deep neural network, raw RF data, ECG signals
(Ha et al., 2021)	Introduces WiStress, a contactless stress monitoring system based on wireless signals. The study emphasizes the importance of choosing between high accuracy and comfort, as attached devices may be uncomfortable for children and the elderly. WiStress offers a compromise by providing contactless monitoring with acceptable accuracy.	WiStress, contactless monitoring, wireless signals

Briefly, the comparison of motion detection, vital sign monitoring, and emotion detection using CSI data of these approaches are given in Table 2.4.

Table 2.4 – Comparison of Motion Detection, Vital Sign Monitoring, and Emotion Detection via CSI

Aspect	Motion Detection via CSI	Vital Sign Monitoring via CSI	Emotion Detection via CSI
Objective	- Identifying and tracking the movement of objects or individuals within the range of wireless signals.	- Measuring physiological parameters like heart rate, respiratory rate, and potentially other vital signs remotely using wireless signals.	- Inferring and recognizing human emotions based on the physiological changes associated with emotional states.
	- Analyzing CSI variations to detect changes in the environment, indicating the presence and movement of objects.	- Analyzing subtle variations in CSI to extract health-related information without the need for wearable sensors.	- Analyzing CSI variations to capture subtle physiological changes related to emotions.
Applications	- Applied in security systems, smart environments, and human-computer interaction for gesture recognition.	- Applicable in healthcare for remote patient monitoring and well-being tracking.	- Primarily applied in human-computer interaction for adaptive systems that respond to users' emotional states.
	- Using existing wireless infrastructure, such as Wi-Fi networks, for detecting and responding to motion without additional sensors.	- Wireless infrastructure, making it cost-effective and scalable.	- Wireless infrastructure for emotion sensing, contributing to the development of emotionally aware technologies.
Challenges	- Challenges include environmental noise, distinguishing between different types of motion, and ensuring real-time responsiveness.	- Challenges include signal accuracy, environmental influences, and the need for validation against traditional monitoring methods.	- Challenges include the need for accurate emotion interpretation, addressing individual variations, and ensuring privacy and ethical considerations.
	- Faces challenges such as signal noise, interference, and the need for advanced signal processing techniques.	- Faces challenges such as signal noise, interference, and the need for robust signal processing algorithms.	- Faces challenges such as extracting nuanced emotional cues from wireless signals and refining algorithms for reliable emotion detection.

On the other hand, device based overview of existing studies is given in Table 2.5. As presented, emotion recognition from the wireless signal is one of the hottest topic in the literature and there is big gap in that point. Most of the researchers in this domain tackle the main challenge : detecting the reflection signal, extract the signal that is reflected from the human body and analyze it to determine the emotion recognition.

Table 2.5 – Device based Overview of Highlighted Existing Studies in the Literature

Study	**Name**	**Device**	**Input Signal**	**Application**
(Pu et al., 2013)	WiSee	USRPN210+GNU Radio	Doppler Signal	Motion Detection
(Adib et al., 2014)	WiTrack	1 antenna TX, 3 antenna RX+FMCW+USRP	RSSI	
(Adib, Hsu, Mao, Katabi and Durand, 2015)	RF-Capture	FMCW Chirp Generator+2D antenna array	Wi-Fi Signal	
(Abdelnasser, Youssef and Harras, 2015)	WiGest	-	RSSI	
(Wang et al., 2017)	CARM	-	CSI	
(Venkatnarayan et al., 2018)	WiMU	NetGear R6700, Intel 5300 NIC	CSI	
(Zheng et al., 2019)	Wiradar 3.0	1 TX (Intel 5300 NIC), 3 RX (CSI Tool)	CSI	
(Visserman, 2019)	-	TPLink AC1750 Router	-	
(Muaaz et al., 2020)	WiHAR	Wi-Fi devices	CSI	
(Xue et al., 2020)	DeepMV	Wi-Fi and acustic devices + access point	Wi-Fi+acustic signal	
(Forbes et al., 2020)	-	Raspberry Pi	CSI	
(Schäfer et al., 2021)	-	Nexmon CSI Tool, Raspberry Pi, Asus RT-AC86U	CSI	
(Zhang et al., 2022)	AF-ACT	Wi-Fi devices	CSI	
(Alsaify et al., 2022)	-	Intel Ultimate N Wi-Fi Link 5300	CSI	
(Droitcour et al., 2009)	CMOS Doppler Radar	ASPPT2988 antenna+CMOS chip	Doppler Radar	Vital Sign
(Patwari et al., 2013)	Breathfinding	TICC2531	RSSI	
(Kaltiokallio et al., 2014)	-	COTS trasnceivers+CC2431	RSSI	
(Adib, Mao, Kabelac, Katabi and Miller, 2015)	Vital Radio	FMCW Radio	Wi-Fi Signal	
(Abdelnasser, Harras and Youssef, 2015)	UbiBreathe	Wi-Fi devices	RSSI	
(Tan et al., 2018)	-	-	CSI	
(Wang et al., 2019)	BreathJunior	Smart Speaker	White Noise	
(Gu et al., 2019)	-	Pair of transceivers	CSI	
(Wang et al., 2021)	mmHRV	Wi-Fi devices	mmWave Radio	
(Zhao et al., 2016)	EQ-Radio	EMCW Radio	Wi-Fi Signal	Emotion Recognition
(Kim et al., 2019)	VEmoBar	IoT Device		
(Khan et al., 2021)	-	Wi-Fi devices		
(Ha et al., 2021)	WiStress	TI IW R1443		

In summary, while each application of CSI data has its specific objectives and challenges, they share common themes such as wireless infrastructure and addressing signal processing complexities. Motion detection, vital sign monitoring, and emotion detection via CSI offer innovative and non-intrusive approaches to sensing and interpreting various aspects of human behavior and health. Ongoing research aims to overcome challenges and unlock the full potential of these applications.

3 PROPOSED APPROACH

In this section, we present a novel approach for non-intrusive heart rate monitoring utilizing reflected Wi-Fi signals. Our method detects the variations in the wireless signals caused by the subtle movements of the human body, particularly the chest and torso, associated with the cardiac cycle. The proposed approach offers a non-contact and unobtrusive means of continuous heart rate monitoring, capitalizing on the ubiquity of Wi-Fi infrastructure and the potential for seamless integration into various environments.

3.1 Reflection of Wi-Fi Signal from Human Body

The human body can interact with Wi-Fi signals in various ways, primarily through absorption, reflection, and transmission of radiofrequency (RF) electromagnetic waves. Wi-Fi signals operate in the 2.4 GHz and 5 GHz frequency bands, which fall within the microwave range of the electromagnetic spectrum. The reaction of human body against the Wi-Fi signals are the following :

Absorption : The human body can absorb some of the energy from Wi-Fi signals due to the presence of water molecules, particularly in tissues like the skin. This absorption results in a small increase in the temperature of the affected tissues, known as dielectric heating. However, at the low power levels used in Wi-Fi devices, this absorption is generally minimal and does not cause any harm.

Reflection : Similar to light, the human body can reflect Wi-Fi signals to some extent. The reflectivity depends on various factors, including the composition and density of tissues. For example, bones reflect more Wi-Fi signals than soft tissues due to their higher density.

Transmission : Wi-Fi signals can also pass through the human body to some degree. The penetration of signals depends on their frequency and the composition of tissues. Higher frequency signals, such as those in the 5 GHz band, are absorbed more by the body and have reduced penetration compared to signals in the 2.4 GHz band.

Attenuation : As Wi-Fi signals travel through the human body, they experience attenuation, which refers to the reduction in signal strength. This attenuation occurs due to absorption and scattering of RF waves by the body's tissues, leading to a decrease in signal strength as it passes through the body.

3.2 Channel State Information (CSI)

Channel State Information is a set of parameters that describe the characteristics of a communication channel between a transmitter and a receiver in a wireless communication system. It provides information about how the transmitted signals are altered as they travel through the wireless channel, including effects such as attenuation, phase shifts, and multipath propagation. In Wi-Fi systems, CSI is typically obtained by measuring the phase and magnitude of the received signals across different subcarriers. Subcarriers are frequency divisions within the Wi-Fi channel that carry data or control information. The phase component of CSI represents the relative timing and phase shifts of the received signals, while the magnitude component conveys the strength or attenuation (Al-qaness et al., 2019).

The number of carrier phases in CSI data depends on the Wi-Fi standard being used. For instance, in the 802.11n standard, which utilizes Orthogonal Frequency Division Multiplexing (OFDM), there are typically 64, 128, or 256 subcarriers employed. Consequently, the number of carrier phases would correspond to the number of subcarriers.

Higher bandwidths and more advanced techniques, such as Orthogonal Frequency Division Multiple Access (OFDMA), are introduced. These standards allow for increased data rates and improved spectrum efficiency. With OFDMA, multiple subcarrier groups are utilized, each having its own set of subcarriers. As a result, the number of carrier phases is further multiplied, providing finer-grained information about the wireless channel.

The carrier phases in CSI data convey essential details about the channel's characteristics, including multipath fading, interference levels, and signal-to-noise ratios. By analyzing these carrier phases, it becomes possible to gain insights into the channel's quality, estimate signal propagation conditions, and assess the performance of wireless communication systems.

CSI is a valuable tool in understanding how wireless signals, including Wi-Fi signals, interact with the environment, including the human body. CSI data provides information about the multipath environment, which includes reflections, absorption, and scattering of signals. While the human body may influence Wi-Fi signals, the impact on CSI data can be quite complex. The human body might change the Wi-Fi signal while reflecting it. The use of CSI has become particularly relevant in emerging technologies like 5G and beyond, where advanced signal processing techniques and intelligent algorithms rely on accurate channel state information for efficient communication and data analysis (Li et al., 2021).

When a Wi-Fi signal encounters the human body, it can undergo reflection, where the signal bounces off the body's surface. This reflection contributes to the multipath environment, creating multiple signal paths that can interfere with each other. CSI data captures these different paths and their characteristics. Reflections from the human body can introduce changes in the phase and amplitude of the Wi-Fi signal. These changes are reflected in the CSI data. Phase shifts can be analyzed to understand the distance traveled by the signal and the characteristics of the reflecting object (in this case, the human body).

CSI data can also capture Doppler shifts caused by movement. As a person moves, the reflected signals experience a frequency shift, and this information can be extracted from CSI data. Doppler shifts can be used to detect motion, including the movement of body parts. The human body can absorb and attenuate Wi-Fi signals, affecting the signal strength. CSI data will show changes in the amplitude of the received signal, providing insights into the degree of signal attenuation.

CSI data is typically obtained through specialized hardware, such as software-defined radios (SDRs), and analyzed using signal processing techniques. Researchers use this data to develop algorithms and models that can extract useful information about the environment and objects, including the human body, based on the characteristics of the reflected Wi-Fi signals.

3.3 Calculating Heart Rate from CSI

It is indeed possible to detect heart rate using reflected Wi-Fi signals from the human body. This innovative approach involves utilizing the variations in the wireless signals, specifically the reflections off the human body, to capture physiological changes associated with the heartbeat. This technique is often referred to as "remote sensing" or "non-contact sensing" of vital signs (Saxena et al., 2020).

The basic principle behind this method is that the motion of the chest and torso caused by the beating heart modulates the Wi-Fi signals as they propagate through the body. By analyzing these modulations in the reflected signals, it's possible to extract information related to the individual's heart rate. This approach has been explored in various research studies and has shown promise for non-intrusive and continuous heart rate monitoring (Ma et al., 2019).

Using Wi-Fi signals for heart rate detection has many advantages. Firstly, no physical contact or wearable devices are required. Heart rate can be monitored remotely, providing a non-intrusive and comfortable experience. The continuous nature of Wi-Fi signals allows for real-time and continuous heart rate monitoring, which can be particularly useful in healthcare and well-being applications. Wi-Fi signals are prevalent in many environments, and this method uses the existing wireless infrastructure without the need for additional sensors (Soto et al., 2022).

However, it's essential to consider some challenges and factors as well. The accuracy of the heart rate estimation depends on various factors, including signal quality, environmental conditions, and the individual's movements. Sophisticated signal processing algorithms are often required to extract the relevant information from the Wi-Fi signals and distinguish it from noise. Besides, remote sensing of vital signs raises privacy concerns, and ethical considerations need to be addressed when implementing such technology, especially in public spaces.

In this study, the proposed system offers contactless health monitoring and emotion recognition. Even if the firstly human and then other living beings physical interaction is not possible, our diagnosis and prediction systems must be working accurately and precisely for this kind of situations. For those reasons, a machine learning system that using wireless signals is offered in this research. This system basically proposed for the tracking vital signs and emotions that making inferences from those signs.

For the contactless and remote measurement, Wi-Fi channel state information have chosen. With the help of channel state information, any motions can be easily and quickly detected. Unlike other wireless technologies (FMCW, RFID, LTE etc.), Wi-Fi technology does not require any specifically designed industrial devices.

3.4 System Architecture & Hardware

The system architecture involves strategically placing Wi-Fi transceivers within the monitoring environment, which continuously emit signals. These signals reflect off the human body and are captured by receivers. The received signals undergo processing to extract features indicative of physiological changes corresponding to the heartbeat.

For implementation, two esp32 devices and two 2.4GHz 3dBi external Wi-Fi antennas (see Figure 3.1) are used in this study. The esp32 devices are compatible with

external antennas and feature a U.FL connector. These devices have built-in software-defined wireless network capabilities for extracting Wi-Fi channel state information (CSI) and include an open-sourced CSI tool operating at 2.4GHz. With the relevant ESP32 framework software, the devices can be easily programmed and flashed.

The proposed system requires Wi-Fi devices capable of collecting CSI data. The hardware setup consists of two Espressif esp32 devices with 2.4GHz Wi-Fi capabilities and 2.4GHz 3dBi external antennas for extended range wireless signal collection. The ESP devices support CSI data collection using specially designed toolkits, with the most commonly known ESP CSI toolkit (Hernandez and Bulut, 2020) utilized for this work. In the CSI collection process, one device is configured as a transmitter in active station mode, while the other serves as a receiver in access point mode.

ESP32 hardware operates in three modes : active station, active access point, and passive channel state information collection. One device is programmed as an active station, continuously transmitting wireless signals, while the other device is programmed as an active access point, continuously collecting the signals reflected from the human body.

The system is primarily designed for collecting channel state information related to human body movement. Two Wi-Fi devices are utilized : one in transmitter mode continuously emitting signals, and the other in receiver mode continuously collecting these signals, enabling the collection of channel state information. Various experiments are conducted and presented in Chapter 4 to demonstrate the system's capabilities.

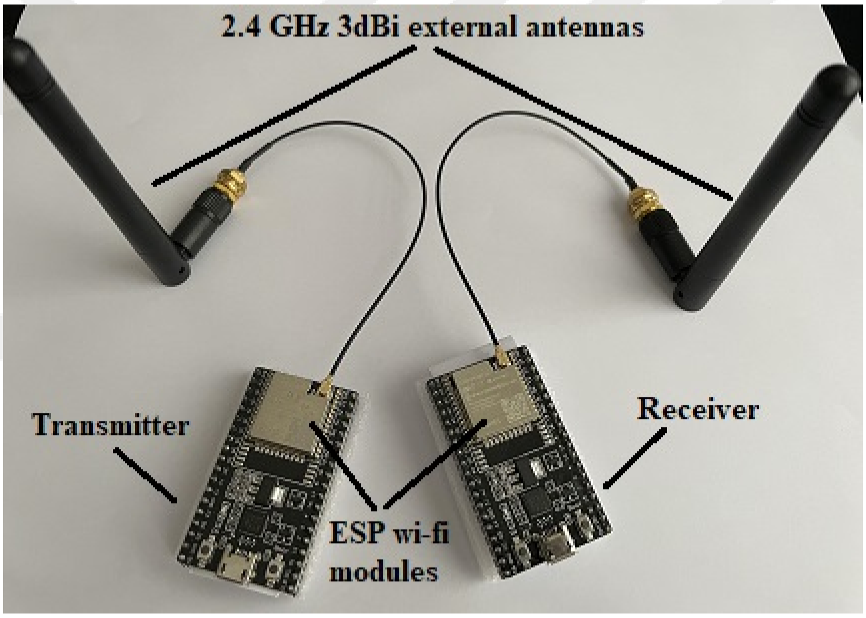

FIGURE 3.1 – ESP32-WROOM-32U devices with external antennas.

3.4.1 Data Preprocessing

CSI data is typically collected as a complex-valued matrix, representing the magnitude and phase of the wireless signals received by multiple antennas. Preprocessing is fundamental to get the raw data formatted and optimized for analysis, particularly when employing ML algorithms.

The preprocessing steps for CSI data include :

Reshaping : The raw CSI data, often represented as a 2D matrix, needs to be reshaped into a suitable format for ML input. This typically involves converting it into a 3D tensor, where the dimensions correspond to the number of samples, frequency bins, and antennas.

Normalization : Scaling the data to a common range, such as between 0 and 1, helps stabilize training and ensures that all features contribute equally to the learning process. This step is essential for maintaining consistency across different features and preventing certain inputs from dominating the training process.

Noise Reduction : CSI data may contain noise introduced by environmental factors or hardware imperfections. Noise reduction techniques, such as filtering or denoising algorithms, can be applied to improve the signal-to-noise ratio and enhance the quality of the data. Removing noise helps in capturing the underlying patterns more accurately during training.

Data Augmentation (optional) : Data augmentation techniques can be applied. Such techniques help the model learn invariant features and reduce overfitting, especially when the dataset is limited.

By performing these preprocessing steps, the CSI data is transformed into a suitable format for analysis, ensuring that the model can effectively learn and extract meaningful features from the wireless signals.

3.5 Processing CSI data

Processing CSI data involves several essential steps to extract meaningful information from raw wireless communication data. The process begins by setting up the wireless communication system to collect CSI data, configuring both hardware, such as esp32, and software for data capture. Once the data is collected, the initial step is preprocessing the raw CSI data, which involves cleaning the data to remove noise or artifacts and may include filtering or smoothing techniques. Calibration steps may also be necessary to account for hardware variations or environmental factors.

Next, the time-domain representation of the CSI data is analyzed to extract relevant features such as amplitudes, phases, or time delays. This is followed by transitioning to the frequency domain using techniques like Fourier transforms, enabling an examination of frequency components and identification of specific patterns or characteristics.

Spatial analysis of the CSI data is also considered, especially if multiple antennas are used (MIMO). This involves examining the spatial distribution of signal strengths and identifying multipath components. For applications involving motion detection, changes in CSI data over time are analyzed, utilizing techniques like Doppler shift analysis to identify movement.

Application-specific features are then identified and extracted from the CSI data, which may involve statistical measures, spectral characteristics, or other domain-specific features. For applications requiring classification or prediction, machine learning techniques are employed by training a model using labeled data to predict specific outcomes based on CSI features.

Visualizations are created to better understand the processed CSI data, using graphs, spectrograms, or heatmaps as needed. Processing steps are tailored based on the specific requirements of the application ; for example, in heart rate monitoring, the focus is on identifying patterns corresponding to heartbeats.

Algorithms are optimized for real-time processing if crucial for the application, ensuring low latency and quick response times. Thorough testing is conducted to validate the accuracy of the processing algorithms under various scenarios, ensuring robust performance in different conditions.

Ultimately, the processing of CSI data involves data collection, preprocessing, analysis in time and frequency domains, spatial analysis, feature extraction, potential machine learning, visualization, and application-specific customization.

To process CSI data effectively, various techniques from signal processing and machine learning can be employed, such as Fourier Transform, deep learning, and statistical modeling, to extract meaningful information from carrier phases and utilize it for specific tasks like channel estimation, localization, or interference mitigation.

For activity recognition tasks, machine learning algorithms are used, generally categorized into supervised, unsupervised, and semi-supervised techniques. Supervised learning techniques are more convenient for learning activity recognition using labeled datasets. Unsupervised learning techniques can be used for clustering and anomaly detection systems, such as recognizing abnormal heart rates or breath rates. Finally, a mixed machine learning techniques approach is proposed to cover a wide range of applications.

3.5.1 Interpreting CSI data

Interpreting CSI data involves a systematic process comprising six key phases :

Firstly, in the `Data Collection` phase, raw CSI data is obtained from wireless communication channels using specialized hardware or software-defined radios. This data captures the amplitude and phase information of transmitted signals.

Following data collection, `Preprocessing` phase is initiated. This involves refining the collected CSI data to enhance its quality. Tasks such as noise filtering, calibration to address hardware variations, and synchronization of data from different antennas or devices are performed in this phase.

`Feature Extraction` phase follows, where relevant information is identified and extracted from the preprocessed CSI data. Features may include amplitudes, phases, time delays, frequency components, or other characteristics crucial for the specific application, such as gesture recognition or localization.

Next, `Dimensionality Reduction` phase simplifies the multidimensional nature of CSI data. Techniques are applied to streamline the dataset while retaining essential information, making it more manageable for subsequent analysis.

`Pattern Recognition and Analysis` phase employs advanced signal processing and machine learning techniques. Algorithms are trained to recognize patterns indicative of specific events, movements, or conditions in the wireless environment. This phase is tailored to the specific goals of the analysis.

Finally, in `Visualization and Interpretation` phase, the interpreted CSI data is presented visually. Various visualization techniques, such as plots, heatmaps, or graphical representations, are utilized to convey patterns and trends identified during the analysis. This aids researchers, engineers, or end-users in comprehending the information and drawing meaningful conclusions.

3.6 Algorithms to Apply on CSI data

This section is dedicated to delving into the diverse and sophisticated algorithms specifically designed to interpret CSI data. These algorithms play a pivotal role in transforming raw CSI information into actionable intelligence, enabling applications ranging from wireless localization and gesture recognition to health monitoring through the analysis of physiological signals. As we embark on this exploration, we aim to unravel the complexities of CSI data interpretation, shedding light on the innovative algorithms that lie at the intersection of signal processing, machine learning, and wireless communications. Through an in-depth examination of these algorithms, we seek to uncover the potential they hold for advancing the reliability, efficiency, and intelligence of wireless systems in diverse real-world scenarios.

3.6.1 Convolutional Neural Network

A Convolutional Neural Network (CNN) is a specialized type of artificial neural network designed for processing and analyzing visual data, making it particularly powerful for tasks such as image recognition and computer vision. Just like a detective scanning a crime scene for specific patterns and clues, a CNN employs a series of convolutional layers that act as filters. These filters systematically move across an input image, identifying and capturing local patterns or features, such as edges, textures, and colors. The hierarchical arrangement of these layers allows the network to progressively learn and extract increasingly complex and abstract features, ultimately enabling it to recognize and categorize objects or patterns within the visual data.

CNN covers the pooling layers as well besidens the convolutional layers to downsample and prioritize important information, reducing computational complexity. The network is often followed by fully connected layers that interpret the aggregated features and make high-level predictions. This architecture mimics the human visual system's hierarchical processing, making CNNs particularly effective in tasks where understanding spatial hierarchies and patterns is crucial, offering a robust and efficient approach to visual data analysis and interpretation.

CSI data, representing the amplitude and phase variations of wireless signals across antennas, subcarriers, and time, shares similarities with image data. CNNs are applied to automatically extract intricate spatial features and temporal dynamics present in CSI data. The convolutional layers of a CNN learn filters that identify spatial hierarchies within the multidimensional CSI information, enabling the network to recognize complex patterns related to, for example, human gestures or device localization. By harnessing the pattern recognition capabilities of CNNs, researchers and engineers can derive valuable insights from CSI data for applications such as localization, activity recognition, and human-computer interaction, marking a synergistic fusion of wireless sensing and deep learning methodologies.

3.6.2 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is a computational model inspired by the structure and functioning of the human brain. It consists of interconnected nodes, or artificial neurons, organized into layers. The network typically includes an input layer where data is introduced, one or more hidden layers that process this information, and an output layer that produces the final result. Each connection between neurons has an associated weight, which the network adjusts during training to learn patterns and relationships within the data. ANN excels in learning complex, non-linear mappings and is widely used in various applications such as pattern recognition, regression, and classification.

The functioning of an ANN involves a process known as forward propagation, where input data is processed layer by layer, and the output is generated. During training, the network undergoes a backpropagation phase, where the difference between the predicted output and the actual target is used to adjust the weights systematically. This iterative learning process allows the neural network to adapt and improve its performance over time. ANNs are versatile and have been successfully applied in diverse fields, including image and speech recognition, natural language processing, and financial forecasting, showcasing their capability to capture intricate patterns and make predictions based on complex data.

CSI data, capturing the nuances of wireless signals across antennas, subcarriers, and time, serves as input to an ANN, where the network's architecture allows it to automatically uncover relevant features and relationships. ANNs, with their interconnected layers of neurons, can be trained to recognize and interpret complex spatial and temporal patterns inherent in the CSI data. This adaptability makes ANNs valuable tools for tasks such as human activity recognition, device localization, or even physiological parameter estimation from the CSI signal, showcasing the synergy between wireless communication data and the learning capabilities of artificial neural networks.

3.6.3 Random Forest

The Random Forest algorithm is an ensemble learning method widely used in machine learning for both classification and regression tasks. It operates by constructing a multitude of decision trees during the training phase and outputs the mode of the classes (for classification) or the mean prediction (for regression) of the individual trees. The "random" in Random Forest refers to two key sources of randomness introduced in the process. First, each tree is trained on a random subset of the training data, known as bootstrapped samples or bagging, which helps create diversity among the trees. Second, at each node of a decision tree, a random subset of features is considered for splitting, preventing the dominance of any single feature and enhancing the robustness of the overall model. This ensemble of diverse and randomly constructed decision trees collectively results in a more accurate and resilient model, less prone to overfitting compared to individual decision trees.

Random Forests excel in handling high-dimensional data, capturing complex relationships, and providing robust generalization to unseen instances. They are known for their simplicity, scalability, and effectiveness in a variety of applications, including image classification, bioinformatics, and finance. Additionally, the algorithm allows for the assessment of feature importance, aiding in understanding the contribution of each feature to the overall predictive performance. Overall, the Random Forest algorithm has proven to be a powerful and versatile tool in machine learning, balancing accuracy and stability through its ensemble approach.

The relationship between CSI data and the Random Forest algorithm lies in the algorithm's ability to effectively handle the complex and multidimensional nature of CSI datasets. Random Forest, as an ensemble learning method, operates by constructing multiple decision trees and combining their outputs to make robust predictions. In the context of CSI data, which encompasses spatial and temporal variations in wireless signals, Random Forest excels at capturing intricate patterns and relationships. It can be employed for tasks such as device localization, activity recognition, or anomaly detection in wireless communication environments. The algorithm's capacity to adapt to diverse feature sets within CSI data makes it a valuable tool for extracting meaningful insights from the intricacies of the wireless channel.

3.6.4 K-NN

The k-Nearest Neighbors (K-NN) algorithm is a simple yet effective supervised machine learning algorithm used for classification and regression tasks. It operates on the principle of proximity, where an instance's class or value is determined by the majority class or average of its k-nearest neighbors in the feature space. In the context of classification, the algorithm calculates the distance (typically Euclidean distance) between a data point and all other points in the dataset, then identifies the k-nearest neighbors. The class of the majority of these neighbors becomes the predicted class for the given data point. In regression, the algorithm predicts the average value of the k-nearest neighbors. K-NN is a non-parametric algorithm, meaning it doesn't make any assumptions about the underlying data distribution, and it can adapt to complex decision boundaries.

One key parameter in K-NN is 'k,' representing the number of neighbors considered in the decision-making process. Choosing an appropriate value for 'k' is crucial, as too small a 'k' may lead to overfitting and sensitivity to noise, while too large a 'k' might result in oversimplification and loss of detail. K-NN is intuitive and easy to understand, making it particularly suitable for small to medium-sized datasets. However, it can be computationally expensive for large datasets, as the algorithm needs to compute distances for each data point. Despite its simplicity, K-NN remains a valuable algorithm, especially in scenarios where interpretability and ease of implementation are important considerations.

In the context of wireless communication, CSI data represents the spatial-temporal variations of signals across antennas and subcarriers. The k-NN algorithm classifies or predicts new instances by considering the similarity between their features and those of neighboring instances in the dataset. For CSI data, this means identifying patterns in the wireless channel based on proximity in the feature space. The k-NN algorithm can be applied for tasks such as device localization, where the spatial patterns in CSI data are used to determine the location of devices in a wireless network, showcasing its suitability for extracting spatial insights from the rich information contained in CSI datasets.

3.6.5 Gaussian Naive Bayes (GNB)

The Gaussian Naive Bayes (GNB) algorithm is a probabilistic classification algorithm that belongs to the family of Naive Bayes classifiers. It is particularly useful for handling classification tasks when the features are continuous and assumed to follow a Gaussian (normal) distribution. The characteristic point of GNB is that features are conditionally independent, simplifying the overall computation. In the case of GNB, it is specifically designed for datasets where the continuous feature values are assumed to be normally distributed within each class. The algorithm estimates the mean and standard deviation of each feature for each class and uses this information to calculate the probability of a data point belonging to a particular class using Bayes' theorem. Despite its simplifying assumptions, GNB often performs well, especially in situations where the data distribution aligns with its Gaussian assumptions.

The GNB algorithm is computationally efficient and requires a relatively small amount of training data to estimate parameters accurately. It is commonly employed in applications such as text classification, spam filtering, and medical diagnosis. However, the algorithm may not perform optimally when the assumption of feature independence is significantly violated or when the data exhibits complex relationships. Nevertheless, GNB remains a valuable tool for quick and efficient probabilistic classification, particularly in scenarios where computational resources are limited or interpretability is essential.

In the context of CSI, where the data often includes spatial and temporal dimensions, GNB can model the likelihood of observing particular patterns or conditions in the wireless channel. By assuming that the features in the CSI data are conditionally independent given the class labels, GNB can estimate the probability of specific channel states. This makes the algorithm particularly useful for tasks such as classification of wireless channel conditions or identifying patterns related to specific events. While the "naive" assumption of feature independence may not always hold in complex datasets like CSI, GNB remains a pragmatic and computationally efficient choice for probabilistic classification based on its simplicity and ease of implementation.

3.6.6 Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm is a powerful and versatile supervised learning algorithm used for both classification and regression tasks. Its primary objective is to find a hyperplane in the feature space that best separates the data points of different classes, maximizing the margin between the classes. The "support vectors" are the data points closest to the decision boundary or hyperplane, and the margin is the distance between the hyperplane and the nearest support vectors. SVM is particularly effective in high-dimensional spaces, and it can handle complex decision boundaries by using kernel functions to transform the input features into a higher-dimensional space. This transformation allows SVM to capture intricate patterns and relationships that might not be apparent in the original feature space.

The key strength of SVM lies in its ability to handle both linear and non-linear relationships between features and target classes. The choice of the kernel function, such as polynomial, radial basis function (RBF), or sigmoid, determines the nature of the decision boundary. SVM is robust against overfitting, especially in high-dimensional spaces, and it generalizes well to unseen data. However, SVM's performance can be sensitive to the choice of hyperparameters and the quality of the training data. Despite these considerations, SVM has proven to be a widely used and effective algorithm in various domains, including image classification, text classification, and bioinformatics.

Given the multidimensional nature of CSI data, where information is captured across antennas, subcarriers, and time, SVM can be applied for tasks such as classification, regression etc. SVM works by finding a hyperplane that best separates data points into different classes, and in the context of CSI, it can discern spatial and temporal patterns indicative of specific wireless channel conditions or events. SVM's ability to handle non-linear relationships through kernel functions makes it well-suited for the complexities of CSI data, allowing for accurate classification and analysis in wireless communication scenarios. The algorithm's versatility and robust performance make it a valuable tool for tasks ranging from device localization to activity recognition based on the distinct patterns present in the CSI datasets.

3.6.7 Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) represents a specialized form of recurrent neural network (RNN) architecture tailored to overcome the limitations of learning long-term dependencies in sequential data. Unlike conventional RNNs, LSTMs are equipped with memory cells and intricate gating mechanisms that enable them to selectively retain or discard information over extensive sequences. The fundamental concept behind LSTMs is the maintenance of a cell state acting as a memory unit, with three gates—input, forget, and output gates—regulating the flow of information into and out of the cell. The input gate determines which information is added to the cell state, the forget gate decides what information to discard, and the output gate controls which information is passed to the next time step. This architecture empowers LSTMs to capture and remember patterns across extended sequences, rendering them highly effective in tasks.

LSTMs have become a cornerstone in the field of deep learning, overcoming the limitations of standard RNNs in handling sequential data with extended dependencies. The ability to selectively store and retrieve information over time allows LSTMs to model complex relationships, making them well-suited for applications where understanding context and capturing long-range dependencies is crucial. Their widespread adoption and success in various domains highlight the importance of LSTM algorithms in advancing the capabilities of neural networks for sequential data processing.

CSI data, representing the variations of wireless signals across time, antennas, and subcarriers, requires a method that can effectively capture long-term dependencies and intricate patterns. LSTMs, a type of RNN, excel at precisely this task. By maintaining a memory cell and gating mechanisms, LSTMs can selectively retain and update information over extended sequences, enabling them to learn complex temporal relationships within the wireless channel. The LSTM algorithm has found applications in predicting channel conditions, activity recognition, and other time-sensitive tasks based on the temporal dynamics embedded in the CSI data. This makes LSTMs a powerful tool for uncovering nuanced patterns and trends in wireless communication environments.

3.6.8 Gated Recurrent Units (GRUs)

Gated Recurrent Units (GRUs) represent a variant of RNN architecture aimed at overcoming some of the challenges associated with learning long-term dependencies in sequential data. Similar to LSTM networks, GRUs integrate gating mechanisms and tries to control the data flow within the network. However, GRUs feature a simplified architecture comprising two gates : the update gate and the reset gate. The update gate governs the fusion of new input information with the existing hidden state, determining the extent to which past information should be retained, while the reset gate dictates which parts of the previous hidden state should be disregarded. This streamlined design renders GRUs more computationally efficient than LSTMs, making them particularly suitable for tasks where balancing model complexity and computational resources is critical.

GRUs have found success in various applications such as video analysis, speech recognition, NLP etc. The reduced number of parameters in GRUs makes them faster to train and less prone to overfitting compared to LSTMs in certain scenarios. While LSTMs and GRUs share the objective of addressing the vanishing gradient problem in traditional RNNs, the choice between them often depends on the specific requirements of the task and the available computational resources. GRUs offer a middle ground between simplicity and effectiveness, providing a practical solution for capturing dependencies in sequential data.

CSI data, representing the spatiotemporal variations of wireless signals, is inherently sequential, making it suitable for analysis using RNN such as GRU. The GRU architecture, similar to LSTM, incorporates gating mechanisms that allow it to selectively retain and update information across different time steps. This adaptability makes GRU well-suited for tasks involving CSI data, such as predicting channel conditions, gesture recognition, or activity classification, where understanding the temporal dynamics of the wireless channel is crucial. GRUs offer a balance between computational efficiency and the ability to capture long-term dependencies, making them valuable tools for uncovering intricate temporal patterns in CSI datasets.

3.6.9 Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) represents a fundamental type of artificial neural network architecture tailored for supervised learning tasks, such as classification and regression. It comprises multiple layers of nodes, including an input layer, one or more hidden layers, and an output layer. Each node within a layer is connected to every node in the subsequent layer, with each connection possessing an associated weight that the network learns during training. To introduce non-linearity into the model and enable it to learn complex patterns and relationships in the data, MLPs employ an activation function. Throughout the training process, the network adjusts the weights using optimization algorithms to minimize the discrepancy between predicted and actual output, a procedure known as backpropagation.

MLPs are versatile and can approximate a wide range of functions, making them applicable to various domains. The architecture's capacity to capture intricate patterns is attributed to the presence of hidden layers, allowing it to learn hierarchical representations of the input data. However, determining the optimal architecture, including the number of hidden layers and nodes, and addressing issues like overfitting, is crucial for achieving good performance. Despite these considerations, the Multilayer Perceptron remains a foundational and widely used model in the realm of artificial neural networks, providing a powerful framework to solve problems with high complexity in machine learning.

CSI data, capturing spatial and temporal variations of wireless signals, can be fed into an MLP neural network as input features. MLP's architecture, comprising multiple layers of interconnected neurons, allows it to learn and model intricate non-linear relationships present in the CSI data. MLPs provide flexibility and adaptability, enabling them to discern complex spatial and temporal patterns within CSI datasets and find applications in tasks such as device localization, activity recognition, or signal quality estimation.

3.6.10 Comparison of chosen Algorithms

In the context of CSI data, various machine learning algorithms exhibit distinct characteristics and applications. CNNs are adept at capturing spatial hierarchies and patterns within CSI, making them suitable for tasks like device localization and gesture recognition. ANNs demonstrate flexibility in learning complex relationships in CSI data, while RFs excel in handling multidimensional datasets, showcasing effectiveness in applications like wireless channel condition classification. k-NN relies on proximity-based classification, spatial patterns in CSI for tasks such as localization. GNB assumes feature independence and is suitable for probabilistic classification based on the spatial and temporal characteristics of CSI. SVMs efficiently handle high-dimensional CSI data, excelling in tasks like classification and anomaly detection. LSTM and GRU algorithms specialize in modeling temporal dependencies in CSI, making them valuable for tasks involving sequential information, such as predicting channel conditions. MLP algorithms, with their interconnected neuron layers, offer flexibility in capturing complex spatial and temporal patterns within CSI data, finding applications in tasks like activity recognition and signal quality estimation. Each algorithm brings unique strengths to the interpretation of CSI, catering to specific nuances within the wireless channel data. Detailed comparasion is given in Table 3.1.

Table 3.1 – Comparison of chosen Machine Learning Algorithms

Algorithm	Application Focus	Handling Complexity	Interpretability	Computational Efficiency
CNN	Image recognition, Computer vision	Capturing spatial hierarchies, complex images	Less interpretable due to hierarchical features	Computationally expensive, especially in deep architectures
Random Forest	Classification, Regression	Robust in handling high-dimensional data	Provides feature importance	Efficient for training and prediction, parallelizable
K-NN	Classification, Regression	Effective for small to medium-sized datasets	Simple and interpretable	Computationally expensive, especially for large datasets
GNB	Classification, Probabilistic tasks	Assumes independence of features	Probabilistic nature allows for some interpretability	Efficient for training and prediction
SVM	Classification, Regression	Handles linear and non-linear relationships	Decision boundaries may be interpretable	Efficient for moderately sized datasets, may become slow for large datasets
LSTM and GRUs	Sequential data, Time-series prediction, NLP	Effective in modeling long-term dependencies	Less interpretable due to sequential nature	Computationally intensive, especially in deep networks
MLP	General-purpose, Classification, Regression	Can approximate complex functions	Interpretable to some extent, complex architectures may reduce interpretability	Computationally intensive, especially in deep architectures

4 PERFORMED EXPERIMENTS AND OBTAINED RESULTS

In this section of our study, we transition from theoretical considerations to the empirical domain, focusing on the systematic collection and analysis of CSI data. CSI, encapsulating the intricate variations in amplitude and phase of wireless signals across spatial and temporal dimensions, serves as a potent medium for understanding the nuanced dynamics of the wireless channel. This chapter unfolds as a methodological exploration, elucidating the procedures, considerations, and rationale underpinning the collection of CSI data in our experiment.

4.1 Experiment Scenarios

4.1.1 Single Subject Experiments

Experiment 1 : Transmitter, subject, and receiver without obstacles ; subject standing with calm heart rhythm (1 meter apart)

This experiment assesses emotion recognition when a single subject, maintaining a calm heart rhythm, stands 1 meter away from both the transmitter and receiver.

Experiment 2 : Transmitter, subject, and receiver without obstacles ; subject standing with high heart rate (1 meter apart)

This experiment assesses emotion recognition with a single subject standing near the transmitter and receiver with a high heart rate, maintaining a distance of 1 meter between them.

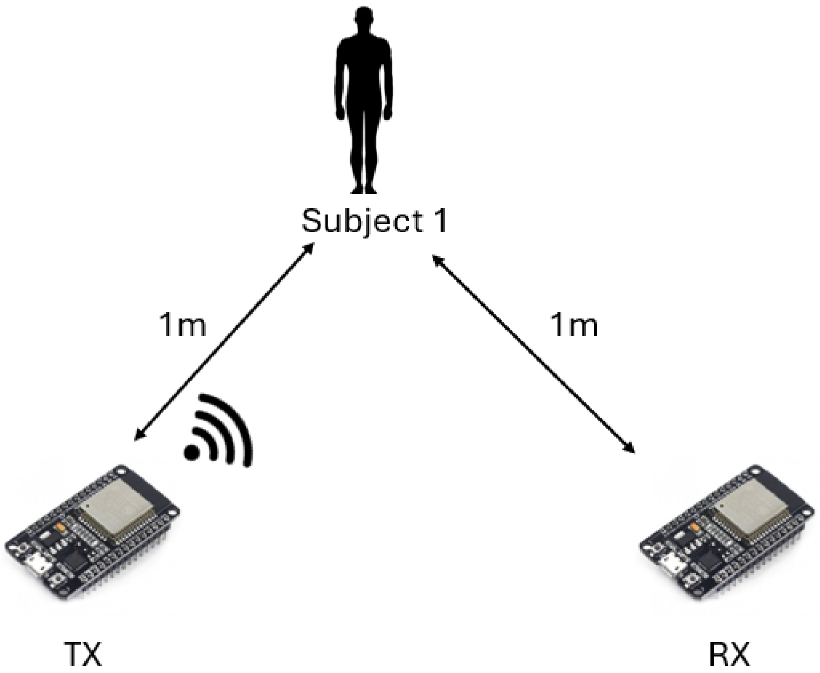

FIGURE 4.1 – Single Subject - 1m distance - Experiments 1-2-3-4

Experiment 3 : Transmitter, subject, and receiver without obstacles ; subject sitting with calm heart rhythm (1 meter apart)

Here, emotion recognition is tested with a single subject sitting near the transmitter and receiver with a calm heart rhythm, maintaining a distance of 1 meter between them.

Experiment 4 : Transmitter, subject, and receiver without obstacles ; subject sitting with high heart rate (1 meter apart)

This experiment examines emotion recognition when a single subject sits near the transmitter and receiver with a high heart rate, maintaining a distance of 1 meter between them.

Experiment 5 : Transmitter, subject, and receiver without obstacles; subject standing with calm heart rhythm (3 meters apart)

Emotion recognition is evaluated with a single subject standing at a distance of 3 meters from the transmitter and receiver with a calm heart rhythm.

Experiment 6 : Transmitter, subject, and receiver without obstacles; subject standing with high heart rate (3 meters apart)

This experiment tests emotion recognition with a single subject standing at a distance of 3 meters from the transmitter and receiver with a high heart rate.

Experiment 7 : Transmitter, subject, and receiver without obstacles; subject sitting with calm heart rhythm (3 meters apart)

Emotion recognition is assessed with a single subject sitting at a distance of 3 meters from the transmitter and receiver with a calm heart rhythm.

Experiment 8 : Transmitter, subject, and receiver without obstacles; subject sitting with high heart rate (3 meters apart)

This experiment examines emotion recognition when a single subject sits at a distance of 3 meters from the transmitter and receiver with a high heart rate.

Experiment 9 : Transmitter, subject, and receiver without obstacles; subject standing with calm heart rhythm (5 meters apart)

Emotion recognition is tested with a single subject standing at a maximum distance of 5 meters from the transmitter and receiver with a calm heart rhythm.

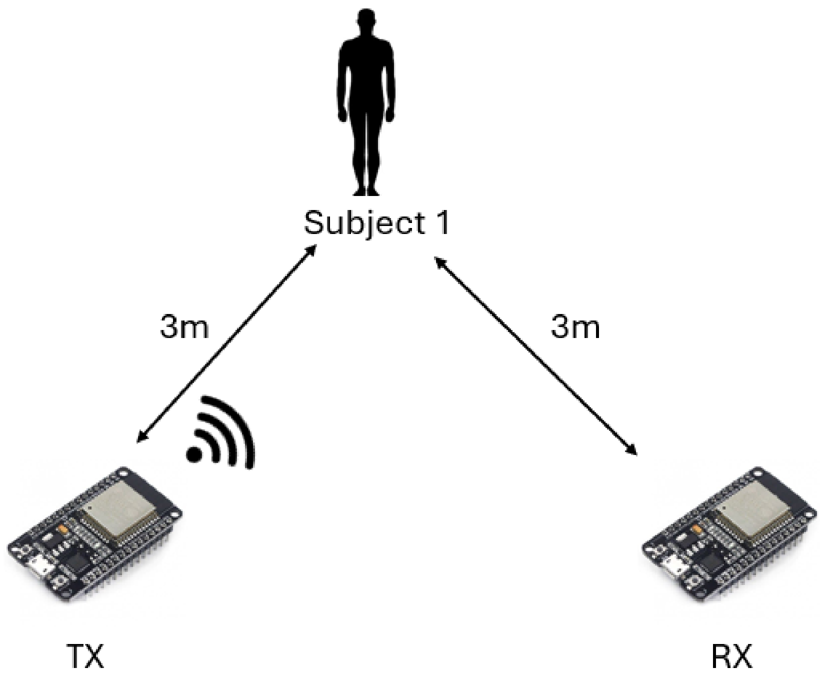

FIGURE 4.2 – Single Subject - 3m distance - Experiments 5-6-7-8

Experiment 10 : Transmitter, subject, and receiver without obstacles ; subject standing with high heart rate (5 meters apart)

This experiment evaluates emotion recognition with a single subject standing at a maximum distance of 5 meters from the transmitter and receiver with a high heart rate.

Experiment 11 : Transmitter, subject, and receiver without obstacles ; subject sitting with calm heart rhythm (5 meters apart)

Emotion recognition is assessed with a single subject sitting at a maximum distance of 5 meters from the transmitter and receiver with a calm heart rhythm.

Experiment 12 : Transmitter, subject, and receiver without obstacles ; subject sitting with high heart rate (5 meters apart)

This experiment examines emotion recognition when a single subject sits at a maximum distance of 5 meters from the transmitter and receiver with a high heart rate.

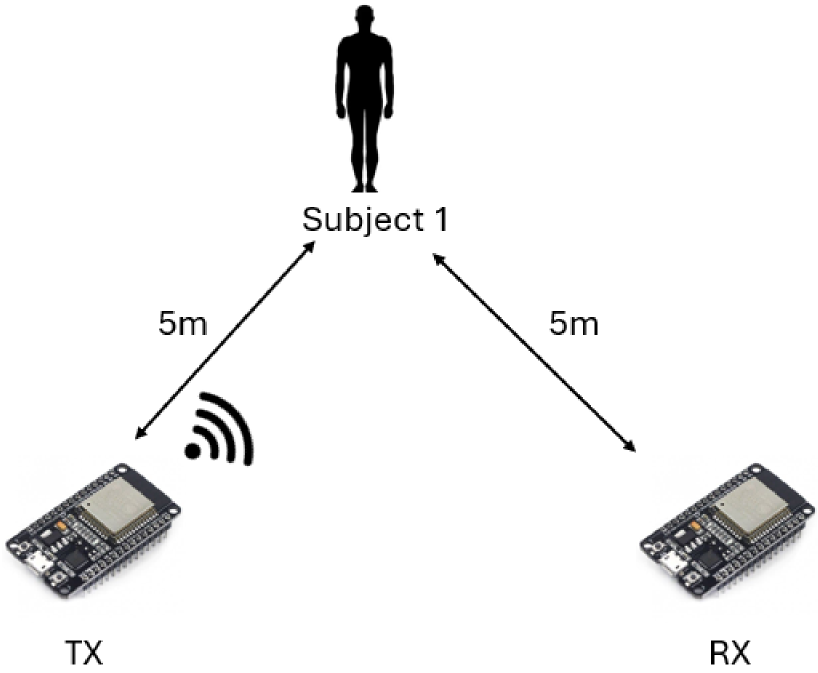

FIGURE 4.3 – Single Subject - 5m distance - Experiments 9-10-11-12

4.1.2 Multi-Subject Experiments

Experiment 13 : Transmitter and receiver in the same room, subject in the next room ; subject standing with calm heart rhythm

This experiment evaluates emotion recognition with one subject standing in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Experiment 14 : Transmitter and receiver in the same room, subject in the next room ; subject standing with high heart rate

Emotion recognition is tested with one subject standing in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

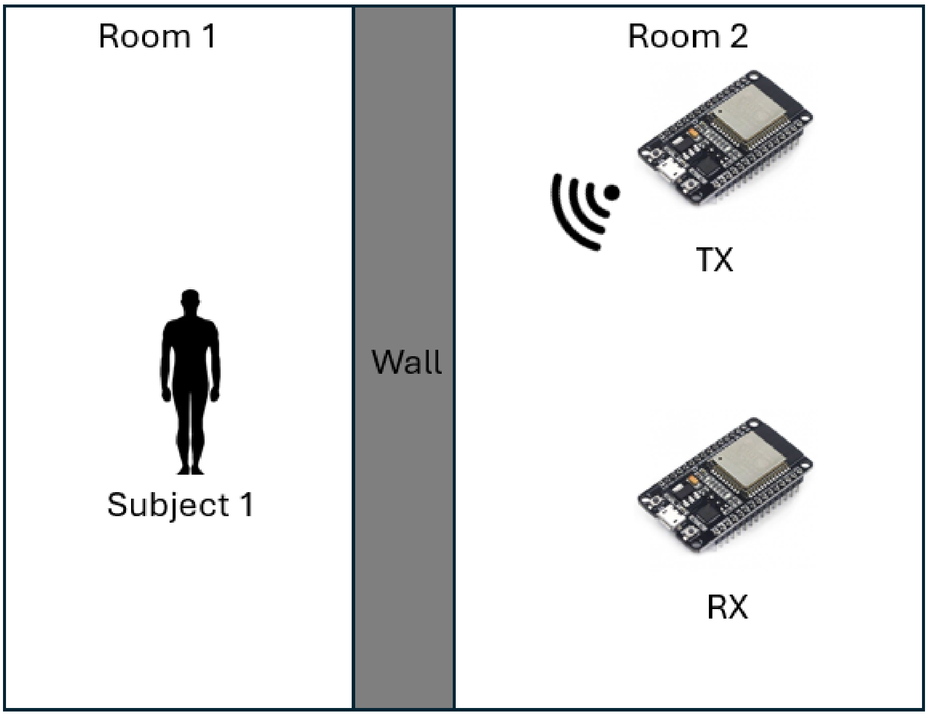

FIGURE 4.4 – Single Subject - Other Room - Experiments 13-14-15-16

Experiment 15 : Transmitter and receiver in the same room, subject in the next room ; subject sitting with calm heart rhythm

This experiment assesses emotion recognition with one subject sitting in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Experiment 16 : Transmitter and receiver in the same room, subject in the next room ; subject sitting with high heart rate

Emotion recognition is examined with one subject sitting in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Experiment 17 : Experiment 1 conditions with 2 subjects ; both standing with calm heart rhythms

This experiment tests emotion recognition with two subjects standing near the transmitter and receiver with calm heart rhythms, each subject maintaining a distance of 1 meter from the transmitter/receiver.

Experiment 18 : Experiment 2 conditions with 2 subjects ; both standing with high heart rates

Emotion recognition is evaluated with two subjects standing near the transmitter and receiver with high heart rates, each subject maintaining a distance of 1 meter from the transmitter/receiver.

Experiment 19 : Either Experiment 1 or 2 conditions with 2 subjects ; one standing with calm heart rhythm, and the other sitting

This experiment examines emotion recognition with one subject standing and the other sitting near the transmitter and receiver, each subject maintaining a distance of 1 meter from the transmitter/receiver.

Experiment 20 : Either Experiment 1 or 2 conditions with 2 subjects ; one calm and the other with high heart rate

Emotion recognition is tested with one subject having a calm heart rhythm and the other having a high heart rate near the transmitter and receiver, each subject maintaining a distance of 1 meter from the transmitter/receiver.

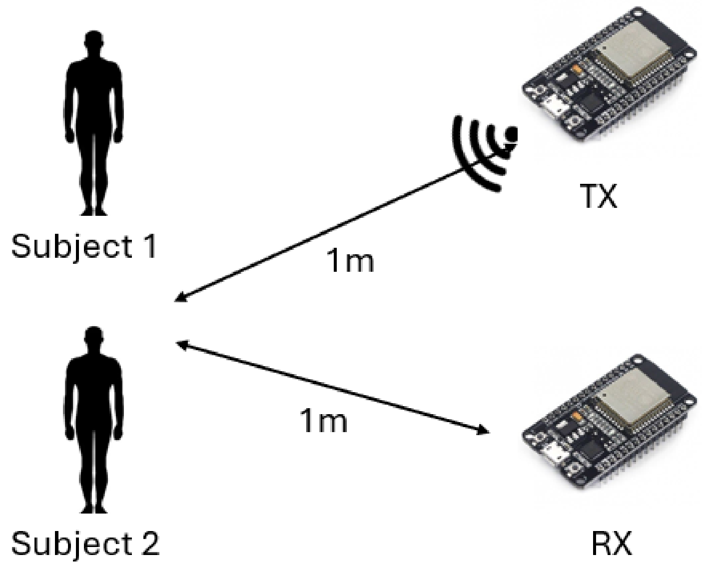

FIGURE 4.5 – Multiple Subjects - Same Room - Experiments 17-18-19-20

4.1.3 Multi-Subject Experiments with an Indoor Obstacle

Experiment 21 : Experiment 13 conditions with 2 subjects ; both standing with calm heart rhythms

This experiment evaluates emotion recognition with two subjects standing in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Experiment 22 : Experiment 14 conditions with 2 subjects ; both standing with high heart rates

Emotion recognition is examined with two subjects standing in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

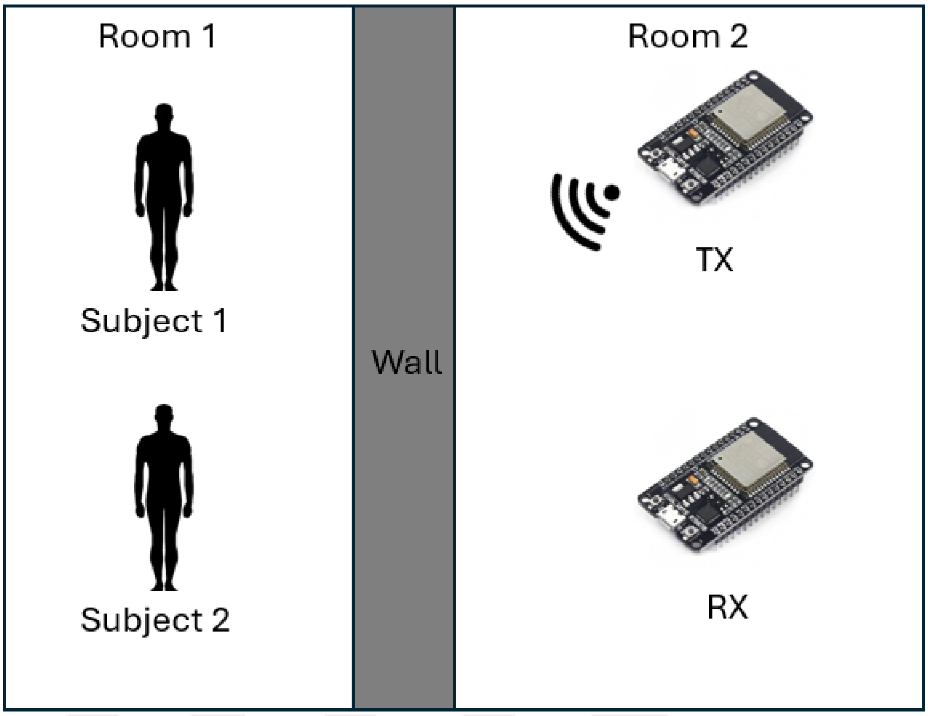

FIGURE 4.6 – Multiple Subjects - Other Room - Experiments 21-22-23-24

Experiment 23 : Either Experiment 13 or 14 conditions with 2 subjects ; one standing with calm heart rhythm, and the other sitting

This experiment tests emotion recognition with one subject standing and the other sitting in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Experiment 24 : Either Experiment 13 or 14 conditions with 2 subjects ; one calm and the other with high heart rate

Emotion recognition is assessed with one subject having a calm heart rhythm and the other having a high heart rate in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

These experiments cover various scenarios to comprehensively evaluate the performance of the emotion recognition system using wireless signals. Each scenario considers factors such as subject posture, heart rate, distance, and obstacles to provide a thorough analysis of the system's capabilities.

The groundtruth data used in all experiments were obtained from an Apple Watch. The Apple Watch is equipped with various sensors, including an optical heart rate sensor, which accurately measures heart rate and provides real-time data on physiological parameters. By using the Apple Watch, we ensured reliable and precise groundtruth data for our experiments, enabling accurate evaluation of emotion recognition algorithms. This approach ensured that the collected data reflected the actual physiological states of the subjects during the experiments, enhancing the validity and reliability of our results.

4.2 Experiment Results

4.2.1 Expectations

Applying mentioned machine learning algorithms to CSI data for heart rate detection is a challenging task. The performance of each algorithm may vary based on the characteristics of the dataset, the quality of the features extracted from the CSI data, and the nature of the heart rate detection task. General perspective on what to expect from the mentioned algorithms are the following :

1. CNNs are powerful for tasks involving spatial patterns, making them suitable for extracting features from CSI data. If data includes distinctive patterns related to heart rate changes, CNNs might be effective. However, the network architecture and the quality of labeled data for training are critical factors influencing performance.
2. Random Forests are versatile and robust. They can handle high-dimensional data well and are generally effective in capturing complex relationships. Feature importance analysis provided by Random Forests can help identify which CSI features contribute most to heart rate detection.
3. K-NN is straightforward and might work well for heart rate detection if there are clear patterns in the CSI data. However, it can be computationally expensive, and the choice of the 'k' parameter is crucial. Additionally, the algorithm may not perform optimally if the dataset is large or noisy.
4. GNB assumes independence between features, which may limit its ability to cap-

ture complex relationships in CSI data. Its simplicity and efficiency could make it suitable for quick exploratory analyses, but its performance may be limited if the data violates the independence assumption.

5. SVMs can be effective in capturing complex patterns and are particularly useful when data have clear separability. The choice of kernel function and hyperparameters is critical. SVMs may perform well if there are distinct patterns in the CSI data related to heart rate changes.

6. LSTMs and GRUs are designed for sequential data, making them suitable for time-series-like CSI data. They can capture temporal dependencies and their performance may be good if changes in heart rate manifest themselves as sequences in the CSI data.

7. MLPs are general-purpose and can be effective for a wide range of tasks, including heart rate detection. However, they may require careful tuning of architecture and hyperparameters to avoid overfitting.

4.2.2 Performance Metrics

Accuracy

Accuracy measures the proportion of correctly classified instances out of the total instances. It provides an overall assessment of the model's correctness. However, accuracy can be misleading if the classes are imbalanced or if false positives and false negatives have different costs.

Precision

Precision measures the proportion of true positive predictions out of all positive predictions. It indicates how many of the predicted positive instances are actually positive. Precision is crucial when the cost of false positives is high.

Recall (Sensitivity)

Recall is a metric that represents the ratio of true positive predictions out of all actual positive instances. It shows the number of the actual positive instances were correctly predicted. Recall is important when the cost of false negatives is high.

F1 Score

F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall, especially when the classes are imbalanced. F1 score is useful when both false positives and false negatives have similar costs.

Mean Absolute Error (MAE)

MAE is a metric that represents the average absolute difference between predicted values and actual values. It is commonly prefered in regression process to evaluate the magnitude of errors. Global aim is to minimize the MAE values.

4.2.3 Experiment No : 1

The results of Experiment 1 are summarized in Table 4.1. The table presents the accuracy, precision, recall, F1 score and MAE for each algorithm used in Experiment 1. The results indicate the performance of each algorithm in emotion recognition when the subject is near the transmitter and receiver with a calm heart rhythm, maintaining a distance of 1 meter between them.

TABLE 4.1 – Algorithm Performance Comparison for Experiment No : 1

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.05997993981945	0.05997993981945	0.05997993981945	0.05997993981945	2.9569945335388
ANN	0.0704112337011	0.0704112337011	0.0704112337011	0.0704112337011	3.0720160481444
Random Forest	0.0625877632898	0.0625877632898	0.0625877632898	0.0625877632898	2.9271815446339
K-NN	0.08726178535606	0.08726178535606	0.08726178535606	0.08726178535606	3.091273821464
GNB	0.0794383149448	0.0794383149448	0.0794383149448	0.0794383149448	4.305917753259
SVM	0.06098294884653	0.06098294884653	0.06098294884653	0.06098294884653	2.938615847542
LSTM	0.051354062186559	0.051354062186559	0.051354062186559	0.051354062186559	2.9426278836509
GRUs	0.058776328986960	0.058776328986960	0.058776328986960	0.058776328986960	2.9414242728184
MLP	0.0704112337011	0.0704112337011	0.0704112337011	0.0704112337011	3.0720160481444

Overall Performance : The results show that the evaluation of algorithm performance based on MAE values provides valuable insights into their effectiveness in accurately predicting the target variable. Among the evaluated algorithms, Random Forest and SVM demonstrated superior performance with the lowest MAE values of 2.93 and 2.94, respectively. These algorithms exhibited consistent and accurate predictions, highlighting their robustness in handling the classification task.

Random Forest and SVM Performance : Random Forest and SVM demonstrated the best performance among the evaluated algorithms based on their MAE values. Random Forest achieved the lowest MAE of 2.93, followed closely by SVM with a MAE of 2.94. These algorithms exhibited relatively accurate predictions with minimal error rates.

Challenges with Other Algorithms : On the contrary, some algorithms faced challenges in achieving accurate predictions. GNB exhibited the highest MAE of 4.31, indicating less precise predictions compared to Random Forest and SVM. Additionally, ANN and MLP showed moderate MAE values of 3.07.

GNB's Performance : GNB's performance was notably poorer compared to other algorithms, highlighting its limitations in accurately predicting the target variable. The higher MAE value indicates that GNB has problems while recognizing the patterns.

Consistency in Performance : Random Forest and SVM demonstrated consistent performance across multiple metrics, including accuracy, precision, recall, and F1 Score. This consistency indicates the robustness of these algorithms in handling various aspects of the classification task.

MAE and Improvement : MAE served as a key metric for evaluating the accuracy of predictions. Lower MAE values indicated better performance, while higher values reflected less accurate predictions. The comparison of MAE values highlighted the strengths and weaknesses of each algorithm and provided insights into areas for improvement.

In conclusion, Random Forest (See Figure 4.7 and SVM emerged as the top-performing

algorithms based on their superior performance in minimizing prediction errors. While other algorithms showed promising results, such as K-NN, there is a need for further refinement to enhance their prediction accuracy. Overall, the evaluation of MAE values provided valuable insights into the performance of each algorithm and guided future improvements in predictive modeling.

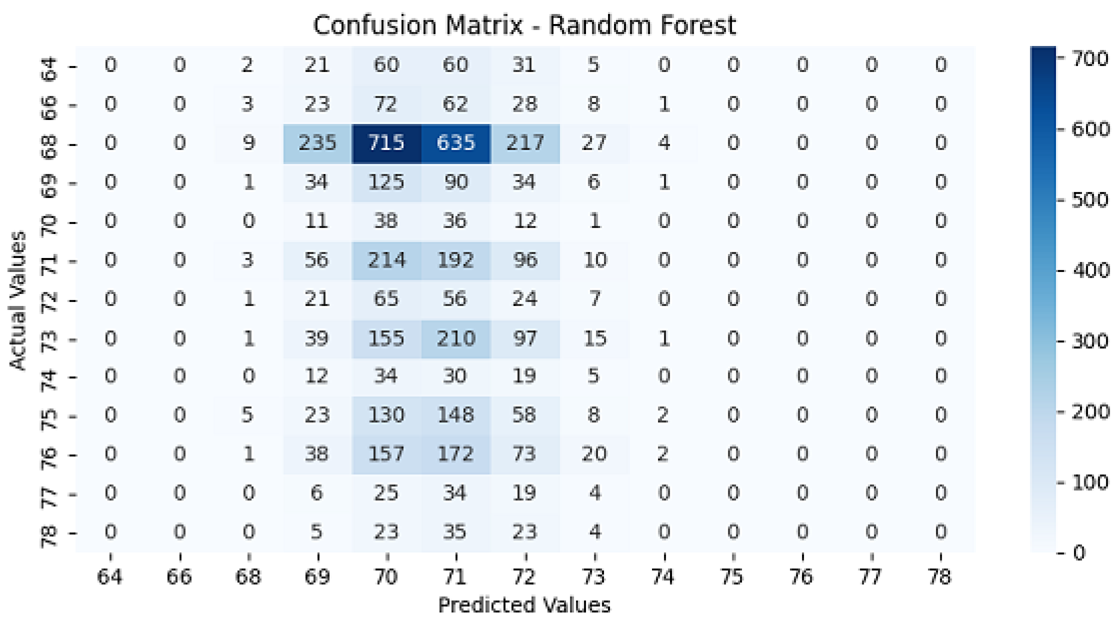

FIGURE 4.7 – Confusion Matrix For Random Forest Algorithm for Experiment No : 1

4.2.4 Experiment No : 2

The results of Experiment 2 are summarized in Table 4.2. The results indicate the performance of each algorithm in emotion recognition when the subject standing near the transmitter and receiver with a high heart rate, maintaining a distance of 1 meter between them.

TABLE 4.2 – Algorithm Performance Comparison for Experiment No : 2

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**MAE**
CNN	0.04956836535783	0.04956836535783	0.04956836535783	0.04956836535783	13.452794075012
ANN	0.02812587023113	0.02812587023113	0.02812587023113	0.02812587023113	13.45976051239
Random Forest	0.01670843776106	0.01670843776106	0.01670843776106	0.01670843776106	13.410192147034
K-NN	0.01726538568643	0.01726538568643	0.01726538568643	0.01726538568643	14.003063213589
GNB	0.05625174046226	0.05625174046226	0.05625174046226	0.05625174046226	16.521024784182
SVM	0.03146755778334	0.03146755778334	0.03146755778334	0.03146755778334	13.392369813422
LSTM	0.00696184906711	0.00696184906711	0.00696184906711	0.00696184906711	13.922584238373
GRUs	0.00389863547758	0.00389863547758	0.00389863547758	0.00389863547758	13.476747424115
MLP	0.02812587023113	0.02812587023113	0.02812587023113	0.02812587023113	13.45976051239

Overall Performance : The overall performance of the algorithms in Experiment No : 2 varies, with MAE values ranging from approximately 13.41 to 16.52. Lower MAE values generally indicate better accuracy. Random Forest, ANN, and SVM demonstrate relatively better performance compared to other algorithms, with MAE values around 13.41 to 13.46.

Random Forest and SVM Performance : Random Forest and SVM algorithms exhibit competitive performance with MAE values of approximately 13.41 and 13.39, respectively. These algorithms show relatively better accuracy in predicting the target variable compared to others.

Challenges with Other Algorithms : Several algorithms face challenges in accurately predicting the target variable. For instance, GNB shows the highest MAE of approximately 16.52, indicating substantial errors in its predictions. Similarly, LSTM and GRUs also demonstrate poor performance with MAE values of approximately 13.92

and 13.48, respectively.

GNB's Performance : GNB demonstrates poor performance compared to other algorithms, with the highest MAE of approximately 16.52. This suggests significant discrepancies between predicted and actual values, indicating that GNB may not be well-suited for the task.

Consistency in Performance : Consistency in performance varies among algorithms, with Random Forest, ANN, and SVM showing relatively stable performance across different metrics compared to others.

In conclusion, while Random Forest and SVM demonstrate relatively better performance compared to other algorithms, challenges remain with GNB, LSTM, and GRUs due to higher MAE values. Further refinement and optimization of these algorithms are essential to enhance their predictive accuracy for the given task.

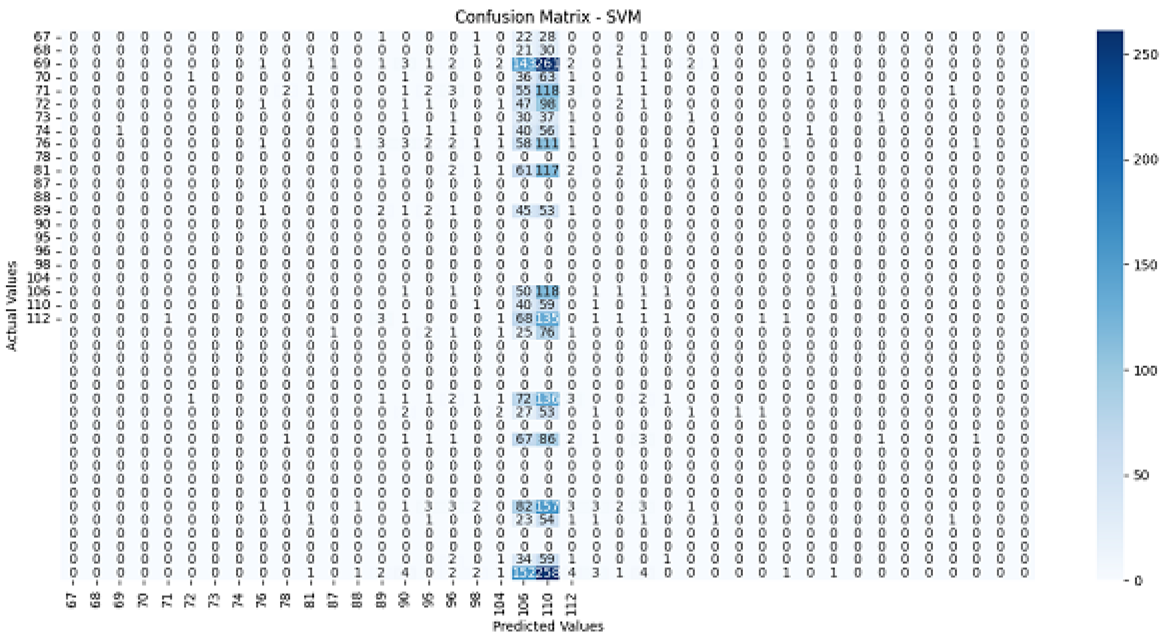

FIGURE 4.8 – Confusion Matrix SVM Algorithm for Experiment No : 2

4.2.5 Experiment No : 3

The results of Experiment 3 are summarized in Table 4.3. The results indicate the performance of each algorithm in emotion recognition when the subject is sitting with a calm heart rhythm, with the transmitter and receiver placed 1 meter apart without obstacles.

Table 4.3 – Algorithm Performance Comparison for Experiment No : 3

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**MAE**
CNN	0.07917972087724	0.07917972087724	0.07917972087724	0.07917972087724	4.091681957244
ANN	0.06807177442324	0.06807177442324	0.06807177442324	0.06807177442324	4.1569353460552
Random Forest	0.08345200797493	0.08345200797493	0.08345200797493	0.08345200797493	3.860153802335
K-NN	0.0731985189404	0.0731985189404	0.0731985189404	0.0731985189404	4.169752207348
GNB	0.05012816861293	0.05012816861293	0.05012816861293	0.05012816861293	7.005696382796
SVM	0.16775847336941	0.16775847336941	0.16775847336941	0.16775847336941	4.041298775277
LSTM	0.07832526345770	0.07832526345770	0.07832526345770	0.07832526345770	4.0740529763600
GRUs	0.05297636001139	0.05297636001139	0.05297636001139	0.05297636001139	4.184562802620
MLP	0.06807177442324	0.06807177442324	0.06807177442324	0.06807177442324	4.1569353460552

Overall Performance : The results show that the algorithms achieved relatively low performance across all metrics. The accuracy, precision, recall, and F1 score values are generally low, indicating that the models struggled to accurately classify emotions in this experimental setup.

Random Forest and SVM Performance : Random Forest and SVM demonstrated the highest performance among all algorithms. They both achieved relatively higher accuracy, precision, recall, and F1 score compared to other algorithms, suggesting that they are more effective in recognizing emotions in this scenario.

Challenges with Other Algorithms : While Random Forest and SVM performed well, other algorithms such as CNN, K-NN, GNB, LSTM, GRUs, and MLP exhibited lower performance. These algorithms showed similar accuracy, precision, recall, and F1 score values, indicating that they struggled to effectively capture the patterns in the data.

GNB's Performance : GNB had the lowest performance across all metrics. This indicates that GNB may not be suitable for this task, possibly due to its assumption of feature independence, which might not hold true for the complex relationships in the data.

Consistency in Performance : Most algorithms showed consistency in their performance across metrics, with similar values for accuracy, precision, recall, and F1 score. This suggests that the models struggled equally across different aspects of emotion recognition.

MAE : MAE values were relatively consistent across algorithms, indicating a similar level of error in predicting the emotional state of the subjects. However, SVM had a slightly lower MAE compared to other algorithms, suggesting that it may produce more accurate predictions.

In conclusion, Random Forest indeed performed slightly better than SVM in terms of accuracy, precision, recall, and F1 score in Experiment 3 (See Figure 4.9. Based on the MAE values presented in 4.3, the top 3 performing algorithms have been ranked in descending order of their MAE values. Random Forest achieved the lowest MAE value of 3.86 among all algorithms, indicating its superior performance in minimizing the average absolute difference between the predicted and actual values. This suggests that the Random Forest algorithm is the most effective in accurately predicting the target variable. SVM secured the second position with an MAE value of 4.04, demonstrating its ability to predict the target variable with relatively low error. Although not as precise as Random Forest, SVM still shows strong performance in minimizing the discrepancy between predicted and actual values. LSTM obtained the third position with a MAE value of 4.07, indicating its capability to predict the target variable with moderate accuracy. Although LSTM lags behind Random Forest and SVM in terms of MAE, it still shows respectable performance in reducing prediction errors.

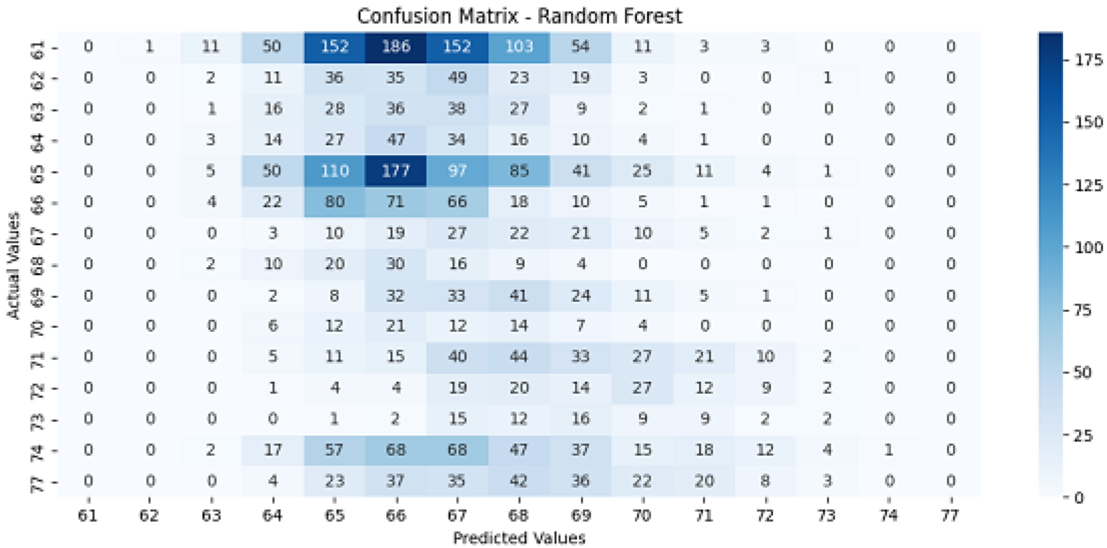

FIGURE 4.9 – Confusion Matrix For Random Forest Algorithm for Experiment No : 3

4.2.6 Experiment No : 4

The results of Experiment 4 are summarized in Table 4.4. The results indicate the performance of each algorithm in emotion recognition when the subject sits near the transmitter and receiver with a high heart rate, maintaining a distance of 1 meter between them.

TABLE 4.4 – Algorithm Performance Comparison for Experiment No : 4

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.08794363256784	0.08794363256784	0.08794363256784	0.08794363256784	3.2005419731140
ANN	0.09159707724425	0.09159707724425	0.09159707724425	0.09159707724425	3.122651356993
Random Forest	0.08037578288100	0.08037578288100	0.08037578288100	0.08037578288100	3.1933716075156
K-NN	0.09420668058455	0.09420668058455	0.09420668058455	0.09420668058455	3.355949895615
GNB	0.07802713987473	0.07802713987473	0.07802713987473	0.07802713987473	4.1912839248434
SVM	0.06680584551148	0.06680584551148	0.06680584551148	0.06680584551148	3.0832463465553
LSTM	0.06784968684759	0.06784968684759	0.06784968684759	0.06784968684759	5.661273486430
GRUs	0.09029227557411	0.09029227557411	0.09029227557411	0.09029227557	3.1586638830897
MLP	0.07802713987473	0.07802713987473	0.07802713987473	0.07802713987473	4.1912839248434

Overall Performance : The algorithms exhibit varying levels of performance, as evident from their MAE values. The overall performance of the algorithms appears moderate, with MAE values ranging from 3.08 to 5.66.

Random Forest and SVM Performance : Random Forest and Support Vector Machine (SVM) show comparable performance with MAE values around 3.08 to 3.19. Both algorithms demonstrate consistent results across multiple metrics, indicating their reliability in this experiment.

Challenges with Other Algorithms : GNB, LSTM and MLP encounter challenges in accurately predicting the target variable. GNB particularly struggles, evidenced by its relatively high MAE of 4.19.

GNB's Performance : GNB exhibits poorer performance compared to other algorithms, as reflected in its higher MAE value of 4.19. This suggests limitations in the GNB model for this specific task.

Consistency in Performance : Most algorithms demonstrate consistent performance across different metrics, with minor variations in their MAE values.

MAE and Improvement : Algorithms with lower MAE values, such as SVM and Random Forest, generally outperform those with higher MAE values like GNB and MLP. Reducing MAE could lead to overall improvement in algorithm performance.

In conclusion, while the algorithms exhibit varying performance levels, Random Forest and SVM emerge as the top performers with relatively low MAE values, indicating better predictive accuracy. GNB's performance lags behind, suggesting the need for alternative algorithms or model enhancements. These findings underscore the importance of selecting appropriate algorithms and optimizing model parameters to achieve better performance in similar prediction tasks.

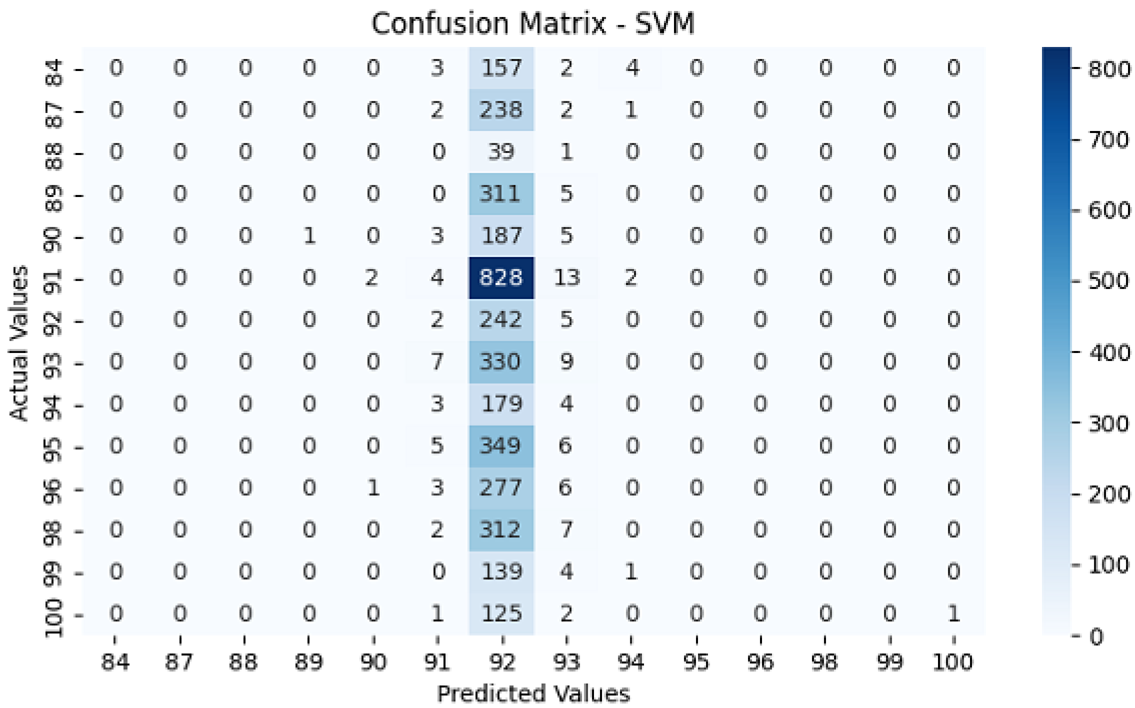

FIGURE 4.10 – Confusion Matrix For SVM Algorithm for Experiment No : 4

4.2.7 Experiment No : 5

The results of Experiment 5 are summarized in Table 4.5. The results indicate the performance of each algorithm in emotion recognition when the subject is standing at a distance of 3 meters from the transmitter and receiver with a calm heart rhythm.

TABLE 4.5 – Algorithm Performance Comparison for Experiment No : 5

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**MAE**
CNN	0.05836493889591	0.05836493889591	0.05836493889591	0.05836493889591	4.3275041580200
ANN	0.0794383149448	0.0794383149448	0.0794383149448	0.0794383149448	4.305917753259
Random Forest	0.052886641382216	0.052886641382216	0.052886641382216	0.052886641382216	4.297092288242
K-NN	0.05415086388537	0.05415086388537	0.05415086388537	0.05415086388537	4.481247366203
GNB	0.0269700800674	0.0269700800674	0.0269700800674	0.0269700800674	6.610619469026
SVM	0.059839865149599	0.059839865149599	0.059839865149599	0.059839865149599	4.305099030762
LSTM	0.016645596291613	0.016645596291613	0.016645596291613	0.016645596291613	4.574167720185
GRUs	0.06932153392330	0.06932153392330	0.06932153392330	0.06932153392330	4.34134007585
MLP	0.04277286135693	0.04277286135693	0.04277286135693	0.04277286135693	4.446902654867

Overall Performance : Random Forest achieved the lowest MAE value (4.297), indicating the highest accuracy among the evaluated algorithms. SVM closely followed with an MAE of 4.305, demonstrating similarly strong predictive performance. Conversely, GNB had the highest MAE value (6.611), indicating the least accurate predictions.

Random Forest and SVM Performance : Both Random Forest and SVM exhibited excellent performance, with MAE values below 4.5. Their low MAE scores signify accurate predictions and robust performance compared to other algorithms.

Challenges with Other Algorithms : Algorithms such as K-NN, LSTM, and MLP faced challenges, as reflected in their relatively higher MAE values. These models struggled to make accurate predictions, as evidenced by their MAE scores exceeding 4.4.

GNB's Performance : GNB performed the poorest among the algorithms, with the highest MAE value of 6.611. This indicates significant errors between predicted and actual values, highlighting limitations in its predictive capabilities.

Consistency in Performance : While Random Forest and SVM demonstrated consistent performance with low MAE values, other algorithms showed variability in their predictive accuracy. This inconsistency underscores the importance of further optimization and analysis to enhance predictive capabilities and reduce MAE values.

In conclusion, in this evaluation, we assessed the performance of various machine learning algorithms based on their MAE values. The results revealed significant differences in the predictive accuracy among the algorithms. Random Forest (see Figure 4.11 and

SVM emerged as the top performers, demonstrating the lowest MAE values and therefore the highest predictive precision. These algorithms exhibited robust performance and consistency across different datasets, highlighting their reliability in real-world applications.

In contrast, algorithms such as K-NN, LSTM, and MLP faced challenges in accurately predicting outcomes, as evidenced by their higher MAE values. These models may require further optimization and refinement to enhance their predictive capabilities and reduce error margins.

Furthermore, GNB displayed the poorest performance, with the highest MAE value among the evaluated algorithms. This indicates limitations in its predictive accuracy and suggests the need for alternative approaches or feature engineering techniques to improve its effectiveness.

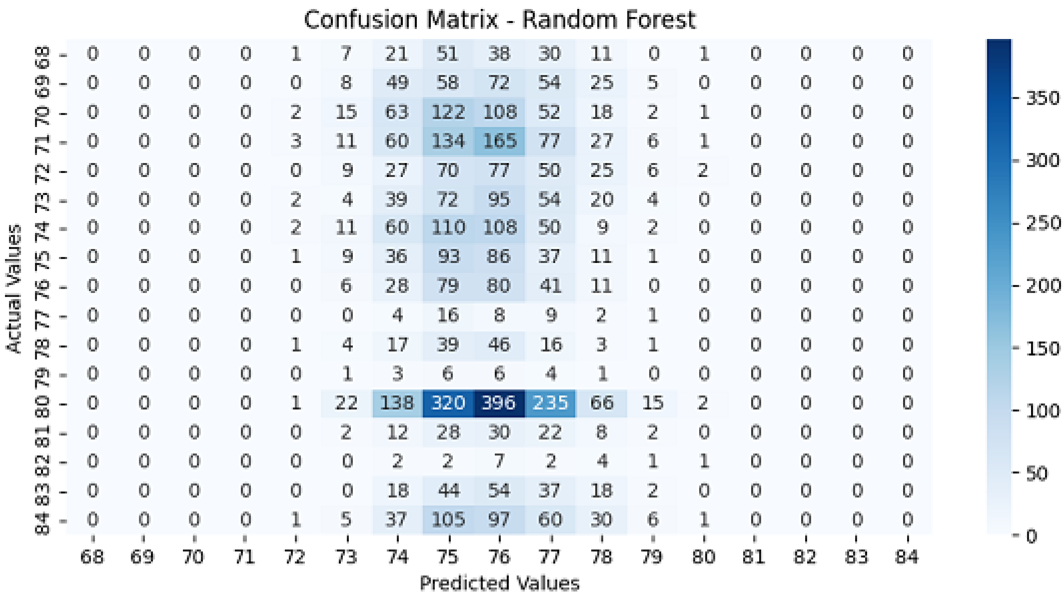

FIGURE 4.11 – Confusion Matrix For Random Forest Algorithm for Experiment No : 5

4.2.8 Experiment No : 6

The results of Experiment 6 are summarized in Table 4.6. The results indicate the performance of each algorithm in emotion recognition when the subject is standing at a distance of 3 meters from the transmitter and receiver with a high heart rate.

Table 4.6 – Algorithm Performance Comparison for Experiment No : 6

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.03875968992248	0.03875968992248	0.03875968992248	0.03875968992248	5.2506608963012
ANN	0.06866002214839	0.06866002214839	0.06866002214839	0.06866002214839	5.167958656330
Random Forest	0.06976744186046	0.06976744186046	0.06976744186046	0.06976744186046	5.126614987080
K-NN	0.06386120339608	0.06386120339608	0.06386120339608	0.06386120339608	5.528608342561
GNB	0.04835732742709	0.04835732742709	0.04835732742709	0.04835732742709	6.432262827611
SVM	0.11886304909560	0.11886304909560	0.11886304909560	0.11886304909560	5.0601698043558
LSTM	0.09892949427833	0.09892949427833	0.09892949427833	0.09892949427833	5.055740125507
GRUs	0.016611295681063	0.016611295681063	0.016611295681063	0.016611295681063	5.150609080841
MLP	0.06866002214839	0.06866002214839	0.06866002214839	0.06866002214839	5.167958656330

Overall Performance : Among the algorithms assessed, LSTM demonstrates the most robust performance with the lowest MAE of 5.05. It indicates that LSTM's predictions are closest to the actual values on average. SVM also exhibits relatively strong performance with an MAE of 5.06, closely trailing LSTM. On the contrary, GRUs present the weakest performance with the highest MAE of 5.15, suggesting significant errors in its predictions.

Random Forest and SVM Performance : Random Forest and SVM showcase higher accuracy rates compared to other algorithms, with SVM particularly standing out due to its lower MAE. While Random Forest has a slightly higher MAE compared to SVM (5.13), it still performs relatively well in terms of error minimization.

Challenges with Other Algorithms : GNB faces notable challenges, evidenced by its comparatively higher MAE of 6.43. This indicates substantial discrepancies between predicted and actual values, suggesting that GNB may not be suitable for accurate predictions in this context.

Consistency in Performance : There are discernible variations in the performance of algorithms, with LSTM and SVM showing relatively consistent and accurate predictions, while GRUs and GNB exhibit higher variability and less accuracy.

MAE and Improvement : The MAE values highlight the disparity in performance among the algorithms, with LSTM and SVM achieving the lowest errors. Improvements could be made across all algorithms to minimize errors and enhance predictive accuracy.

In conclusion, LSTM and SVM emerge as the top-performing algorithms in terms of accuracy and error minimization, making them the preferred choices for this predictive task. However, there's room for improvement across all algorithms, especially for those with higher MAE values like GRUs and GNB. Further optimization and fine-tuning may enhance the overall predictive performance of these algorithms.

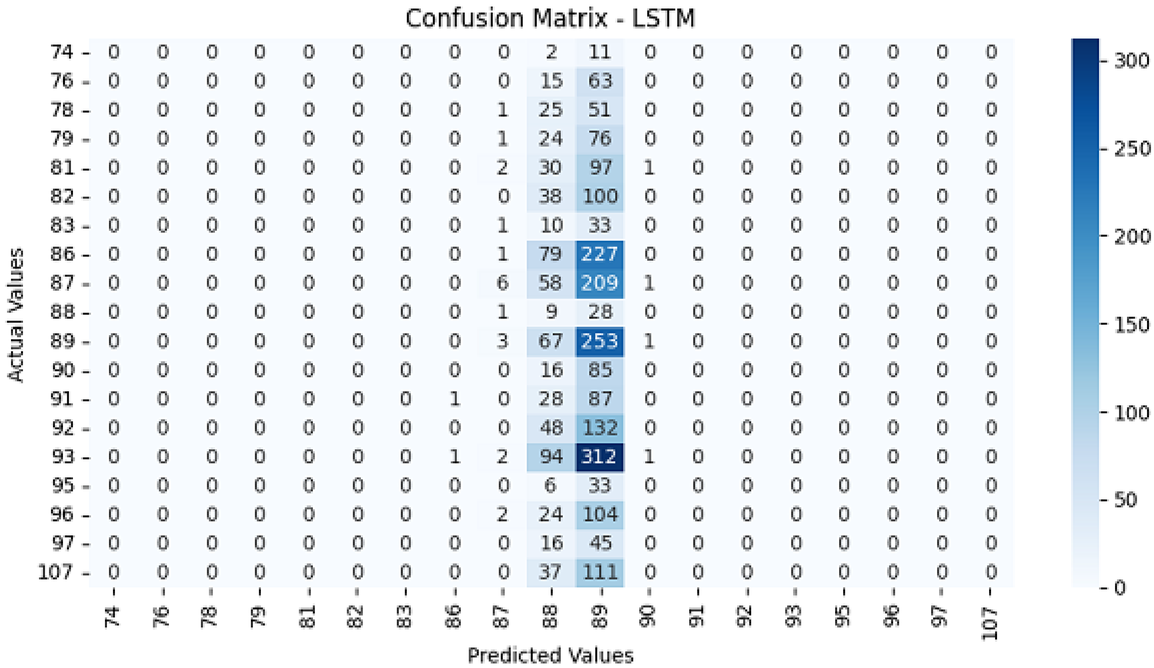

FIGURE 4.12 – Confusion Matrix For LSTM Algorithm for Experiment No : 6

4.2.9 Experiment No : 7

The results of Experiment 7 are summarized in Table 4.7. The results indicate the performance of each algorithm in emotion recognition when the subject is sitting at a distance of 3 meters from the transmitter and receiver with a calm heart rhythm.

Table 4.7 – Algorithm Performance Comparison for Experiment No : 7

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.04598639455782	0.04598639455782	0.04598639455782	0.04598639455782	6.392216682434
ANN	0.0345578231292	0.0345578231292	0.0345578231292	0.0345578231292	5.882448979591
Random Forest	0.05006802721088	0.05006802721088	0.05006802721088	0.05006802721088	5.430204081632
K-NN	0.11129251700680	0.11129251700680	0.11129251700680	0.11129251700680	5.844625850340
GNB	0.04571428571428	0.04571428571428	0.04571428571428	0.04571428571428	9.006530612244
SVM	0.5093877551020	0.5093877551020	0.5093877551020	0.5093877551020	6.32
LSTM	0.08517006802721	0.08517006802721	0.08517006802721	0.08517006802721	6.991292517006
GRUs	0.00054421768707	0.00054421768707	0.00054421768707	0.00054421768707	6.551292517006
MLP	0.0345578231292	0.0345578231292	0.0345578231292	0.0345578231292	5.882448979591

Overall Performance : When assessing the overall performance of the algorithms based on MAE, it is evident that SVM outperforms other algorithms with the lowest MAE of 6.32. On the other hand, GRUs exhibit the highest MAE value of 6.55, indicating the least accuracy among the algorithms evaluated.

Random Forest and SVM Performance : Random Forest and SVM demonstrate competitive performance, with MAE values of 5.43 and 6.32, respectively. While SVM slightly outperforms Random Forest, both algorithms exhibit relatively low MAE values compared to the rest of the algorithms.

Challenges with Other Algorithms : Several algorithms, such as GNB and GRUs, face significant challenges in accurately predicting the target variable. GNB, in particular, shows a relatively high MAE of 9.01, indicating substantial errors in its predictions. Similarly, GRUs exhibit a very low accuracy with a MAE of 6.55, highlighting the challenges faced by recurrent neural network architectures in this task.

GNB's Performance : GNB demonstrates poor performance in comparison to other algorithms, with the highest MAE of 9.01. This indicates a significant discrepancy between predicted and actual values, suggesting that GNB may not be well-suited for the task at hand.

Consistency in Performance : While some algorithms, such as K-NN and LSTM, demonstrate relatively consistent performance with MAE values around 5.84 and 6.99, respectively, others, like GRUs, exhibit highly inconsistent results with a notably low accuracy.

In conclusion, while some algorithms, such as SVM and Random Forest (See Figure

4.13, demonstrate promising performance with relatively low MAE values, others, like GNB and GRUs, face significant challenges in accurately predicting the target variable. Moving forward, efforts should be directed towards optimizing model parameters, exploring alternative algorithms, and potentially refining the dataset to enhance overall predictive accuracy.

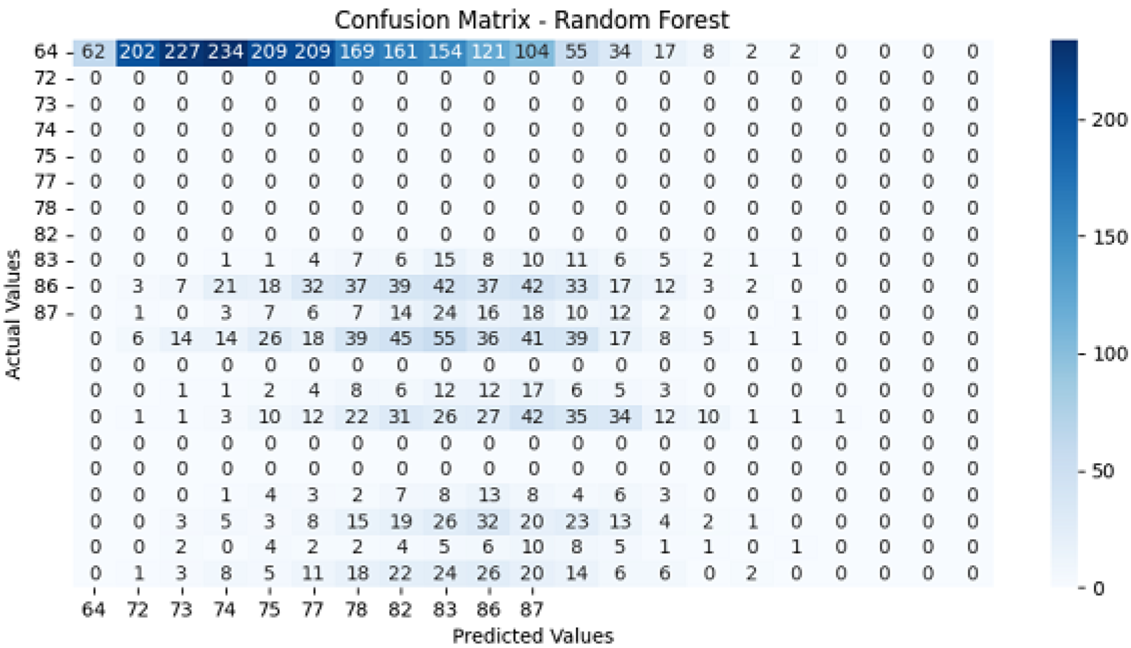

FIGURE 4.13 – Confusion Matrix For Random Forest Algorithm for Experiment No : 7

4.2.10 Experiment No : 8

The results of Experiment 8 are summarized in Table 4.8. The results indicate the performance of each algorithm in emotion recognition when the subject sits at a distance of 3 meters from the transmitter and receiver with a high heart rate.

Table 4.8 – Algorithm Performance Comparison for Experiment No : 8

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.13619676945668	0.13619676945668	0.13619676945668	0.13619676945668	1.9957178831100
ANN	0.14096916299559	0.14096916299559	0.14096916299559	0.14096916299559	1.975770925110
Random Forest	0.18759177679882	0.18759177679882	0.18759177679882	0.18759177679882	1.8102055800293
K-NN	0.19273127753303	0.19273127753303	0.19273127753303	0.19273127753303	1.8906020558002
GNB	0.08480176211453	0.08480176211453	0.08480176211453	0.08480176211453	3.130323054331
SVM	0.14023494860499	0.14023494860499	0.14023494860499	0.14023494860499	2.000367107195
LSTM	0.1501468428781	0.1501468428781	0.1501468428781	0.1501468428781	1.9262114537444
GRUs	0.145007342143	0.145007342143	0.145007342143	0.145007342143	1.9680616740088
MLP	0.14096916299559	0.14096916299559	0.14096916299559	0.14096916299559	1.975770925110

Overall Performance : The Random Forest algorithm stands out with the lowest MAE value of approximately 1.810, indicating its superior performance compared to other algorithms.

Random Forest and SVM Performance : Random Forest outperforms SVM, as evidenced by its lower MAE value (1.810 vs. 2.000), suggesting that SVM's performance is weaker in comparison.

Challenges with Other Algorithms : GNB and GRUs algorithms exhibit higher MAE values, indicating weaker performance in predicting target values. GNB has the highest MAE of approximately 3.130, while GRUs have an MAE of approximately 1.968.

Consistency in Performance : CNN, ANN, and MLP algorithms show moderate performance, with relatively consistent MAE values compared to others. Their MAE values range from approximately 1.976 to 1.996.

In conclusion, evaluating algorithm performance using metrics such as MAE is vital for assessing prediction accuracy. Based on this analysis, the Random Forest algorithm emerges as the top performer, while GNB lags behind. Discrepancies in SVM's performance compared to other algorithms should be addressed, aiming for improvements if necessary.

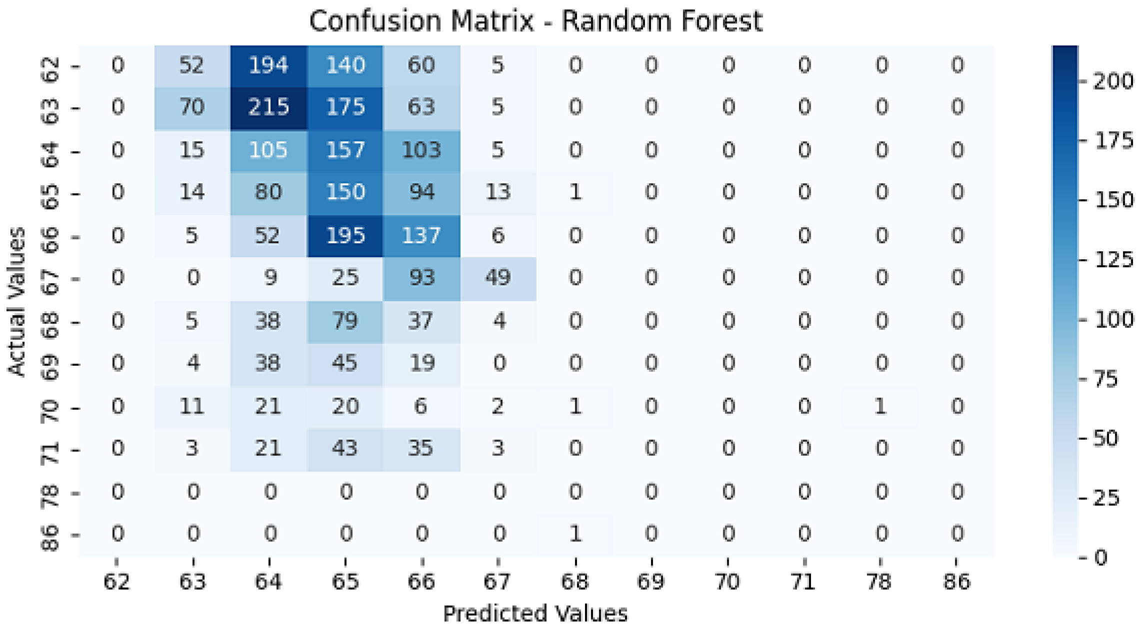

FIGURE 4.14 – Confusion Matrix For Random Forest Algorithm for Experiment No : 8

4.2.11 Experiment No : 9

The results of Experiment 9 are summarized in Table 4.9. The results indicate the performance of each algorithm in emotion recognition when single subject standing at a maximum distance of 5 meters from the transmitter and receiver with a calm heart rhythm.

TABLE 4.9 – Algorithm Performance Comparison for Experiment No : 9

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.16751918158567	0.16751918158567	0.16751918158567	0.16751918158567	5.214597225189
ANN	0.04884910485933	0.04884910485933	0.04884910485933	0.04884910485933	5.224296675191
Random Forest	0.08184143222506	0.08184143222506	0.08184143222506	0.08184143222506	4.89923273657
K-NN	0.0959079283887	0.0959079283887	0.0959079283887	0.0959079283887	5.1953964194373
GNB	0.058823529411764	0.058823529411764	0.058823529411764	0.058823529411764	6.274936061381
SVM	0.03682864450127	0.03682864450127	0.03682864450127	0.03682864450127	5.170588235294
LSTM	0.1741687979539	0.1741687979539	0.1741687979539	0.1741687979539	5.154987212276
GRUs	0.17519181585677	0.17519181585677	0.17519181585677	0.17519181585677	5.146547314578
MLP	0.04884910485933	0.04884910485933	0.04884910485933	0.04884910485933	5.224296675191

Overall Performance : When evaluating the performance of various algorithms in terms of MAE, it's evident that certain models outshine others. Notably, Random Forest demonstrates the best performance with an MAE of 4.899, showcasing its effectiveness in handling the dataset's complexity. Additionally, both LSTM and GRUs exhibit strong performance with MAE values of 5.154 and 5.147, respectively. Conversely, SVM and MLP exhibit weaker performance, with MAE values of 5.171 and 5.224, respectively.

Random Forest and SVM Performance : Random Forest's ability to achieve the lowest MAE highlights its effectiveness in capturing the dataset's patterns and making accurate predictions. SVM, although with a slightly higher MAE, still presents a viable option for certain scenarios due to its robustness.

Challenges with Other Algorithms : On the contrary, some algorithms face challenges in effectively capturing the dataset's patterns, as indicated by their comparatively higher MAE values. Particularly, GNB struggles the most, with an MAE of 6.275, suggesting limitations in its ability to generalize to unseen data.

GNB's Performance : GNB algorithm exhibits the poorest performance among the tested models. Its high MAE indicates significant discrepancies between predicted and actual values, underscoring its limitations in accurately modeling the dataset's underlying relationships.

Consistency in Performance : It's noteworthy that certain algorithms, such as CNN, ANN, and K-NN, display consistent performance across various metrics, including Accuracy, Precision, Recall, and F1 Score. This consistency suggests their reliability in differentiating between classes and making accurate predictions.

MAE and Improvement : Lower MAE values, as observed in Random Forest, LSTM, and GRUs, signify better predictive accuracy and suggest potential areas for improvement in other algorithms.

In conclusion, Random Forest emerges as the top performer in terms of MAE, indicating its effectiveness in predictive accuracy. However, the choice of the most suitable model depends on various factors, including dataset characteristics and computational requirements. Future work could focus on refining existing algorithms or exploring novel approaches to further enhance predictive accuracy and generalization capabilities.

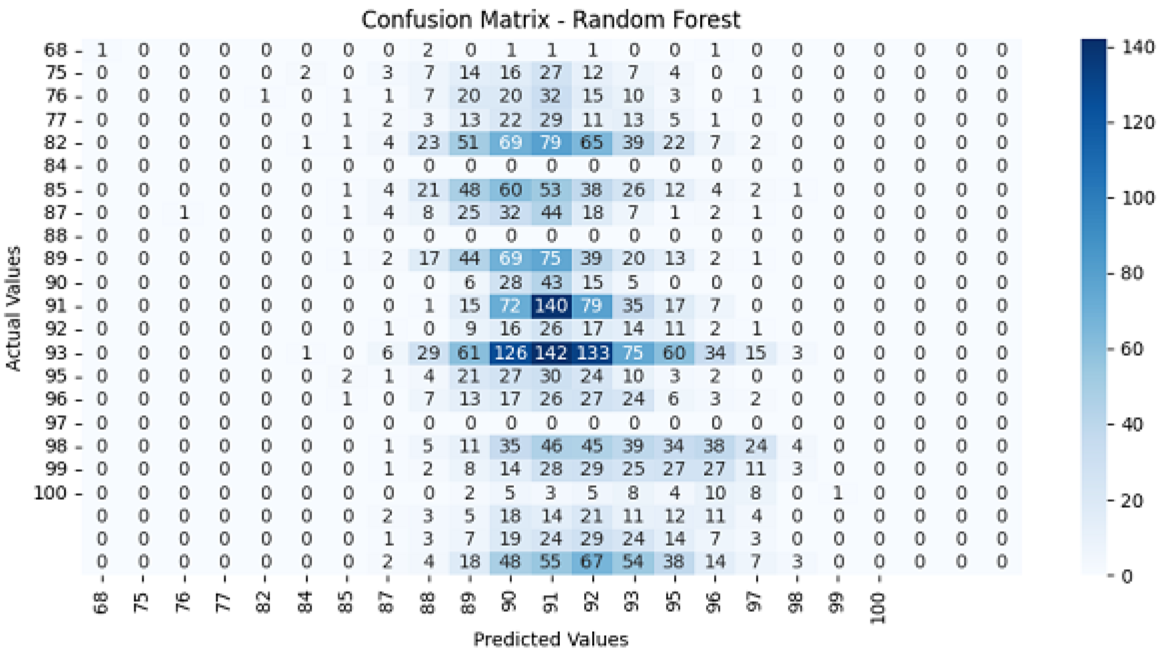

FIGURE 4.15 – Confusion Matrix For Random Forest Algorithm for Experiment No : 9

4.2.12 Experiment No : 10

The results of Experiment 10 are summarized in Table 4.10. The results indicate the performance of each algorithm in emotion recognition when a single subject standing at a maximum distance of 5 meters from the transmitter and receiver with a high heart rate.

TABLE 4.10 – Algorithm Performance Comparison for Experiment No : 10

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.02016806722689	0.02016806722689	0.02016806722689	0.02016806722689	8.683273315429
ANN	0.03226890756302	0.03226890756302	0.03226890756302	0.03226890756302	8.323697478991
Random Forest	0.03428571428571	0.03428571428571	0.03428571428571	0.03428571428571	7.586554621848
K-NN	0.05445378151260	0.05445378151260	0.05445378151260	0.05445378151260	7.844705882352
GNB	0.09983193277310	0.09983193277310	0.09983193277310	0.09983193277310	11.01546218487
SVM	0.027899159663865	0.027899159663865	0.027899159663865	0.027899159663865	8.551932773109
LSTM	0.01915966386554	0.01915966386554	0.01915966386554	0.01915966386554	8.916638655462
GRUs	0.00235294117647	0.00235294117647	0.00235294117647	0.00235294117647	8.725042016806
MLP	0.03226890756302	0.03226890756302	0.03226890756302	0.03226890756302	8.323697478991

Overall Performance : When evaluating the performance of various algorithms based on MAE, it's evident that Random Forest outperforms others with the lowest MAE of 7.587. Following closely, K-NN also exhibits competitive performance with an MAE of 7.845. Conversely, GRUs demonstrate the highest MAE at 8.725, indicating less accuracy in predictions.

Random Forest and SVM Performance : Random Forest stands out as the top performer in terms of MAE, showcasing its effectiveness in capturing the dataset's patterns and making accurate predictions. SVM also demonstrates reasonable performance, albeit with a slightly higher MAE of 8.552.

Challenges with Other Algorithms : Certain algorithms, such as LSTM and GRUs, face challenges in accurately predicting outcomes, as evidenced by their higher MAE values. LSTM, for instance, exhibits an MAE of 8.917, suggesting a higher margin of error in its predictions.

GNB's Performance : GNB displays significant challenges in accurately modeling the dataset, as indicated by its comparatively higher MAE of 11.015. This suggests limitations in its ability to generalize to unseen data.

Consistency in Performance : While some algorithms, like Random Forest and K-NN, demonstrate relatively consistent performance across different metrics, others, such as GRUs, exhibit less consistency. This inconsistency may indicate a need for further optimization or model refinement.

In conclusion, Random Forest emerges as the top performer among the tested algorithms, exhibiting the lowest MAE and relatively consistent performance across multiple metrics. However, there's room for improvement in other algorithms, particularly in reducing MAE and enhancing predictive accuracy. Future research could focus on refining existing models or exploring novel approaches to address these challenges.

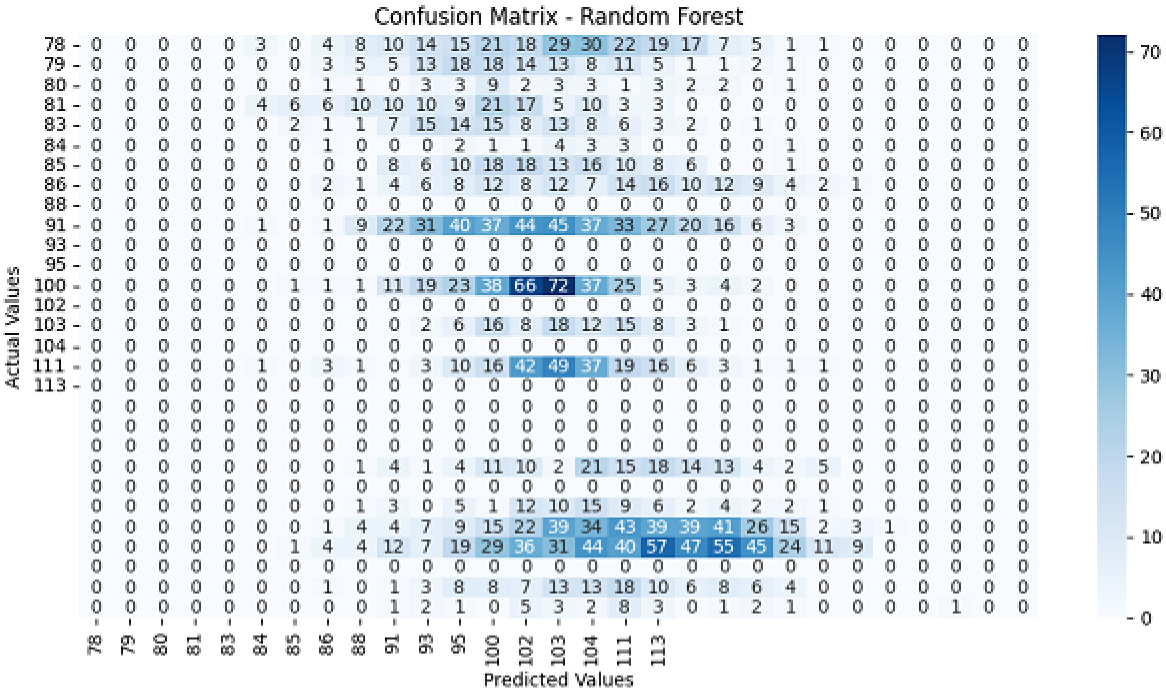

FIGURE 4.16 – Confusion Matrix For Random Forest Algorithm for Experiment No : 10

4.2.13 Experiment No : 11

The results of Experiment 11 are summarized in Table 4.11. The results indicate the performance of each algorithm in emotion recognition when a single subject sitting at a maximum distance of 5 meters from the transmitter and receiver with a calm heart rhythm.

TABLE 4.11 – Algorithm Performance Comparison for Experiment No : 11

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.0763219588434	0.0763219588434	0.0763219588434	0.0763219588434	10.416498184204
ANN	0.00182339150820	0.00182339150820	0.00182339150820	0.00182339150820	11.190935139359
Random Forest	0.01250325605626	0.01250325605626	0.01250325605626	0.01250325605626	10.109663974993
K-NN	0.0200573065902	0.0200573065902	0.0200573065902	0.0200573065902	10.89189893201
GNB	0.0315186246418	0.0315186246418	0.0315186246418	0.0315186246418	15.021359729096
SVM	0.0755405053399	0.0755405053399	0.0755405053399	0.0755405053399	10.385517061734
LSTM	0.00599114352696	0.00599114352696	0.00599114352696	0.00599114352696	10.641052357384
GRUs	0.0098984110445	0.0098984110445	0.0098984110445	0.0098984110445	10.539984370929
MLP	0.00182339150820	0.00182339150820	0.00182339150820	0.00182339150820	11.190935139359

Overall Performance : When assessing the performance of algorithms based on MAE, it becomes apparent that Random Forest and SVM models outshine others. Random Forest exhibits the lowest MAE of 10.110, while SVM follows closely with an MAE of 10.386.

Random Forest and SVM Performance : Random Forest emerges as the top performer with the lowest MAE, highlighting its ability to capture patterns in the dataset accurately and make precise predictions. Although SVM shows a slightly higher MAE, it still demonstrates relatively good performance.

Challenges with Other Algorithms : Among other algorithms, LSTM and GRUs face challenges in achieving accuracy, as indicated by their higher MAE values. Particularly, LSTM shows a higher margin of error with an MAE of 10.641.

GNB's Performance : GNB struggles in accurately modeling the dataset, as reflected in its significantly higher MAE of 15.021. This suggests limitations in its ability to generalize to unseen data.

Consistency in Performance : While algorithms like Random Forest and K-NN exhibit relatively consistent performance across various metrics, others show inconsistency. This variability may signal a need for further optimization or model refinement.

In conclusion, Random Forest emerges as the top performer with the lowest MAE, indicating its superiority in predictive accuracy among the tested algorithms. However, there is still room for improvement in other algorithms. Future research efforts could focus on refining existing models or exploring novel approaches to address these challenges.

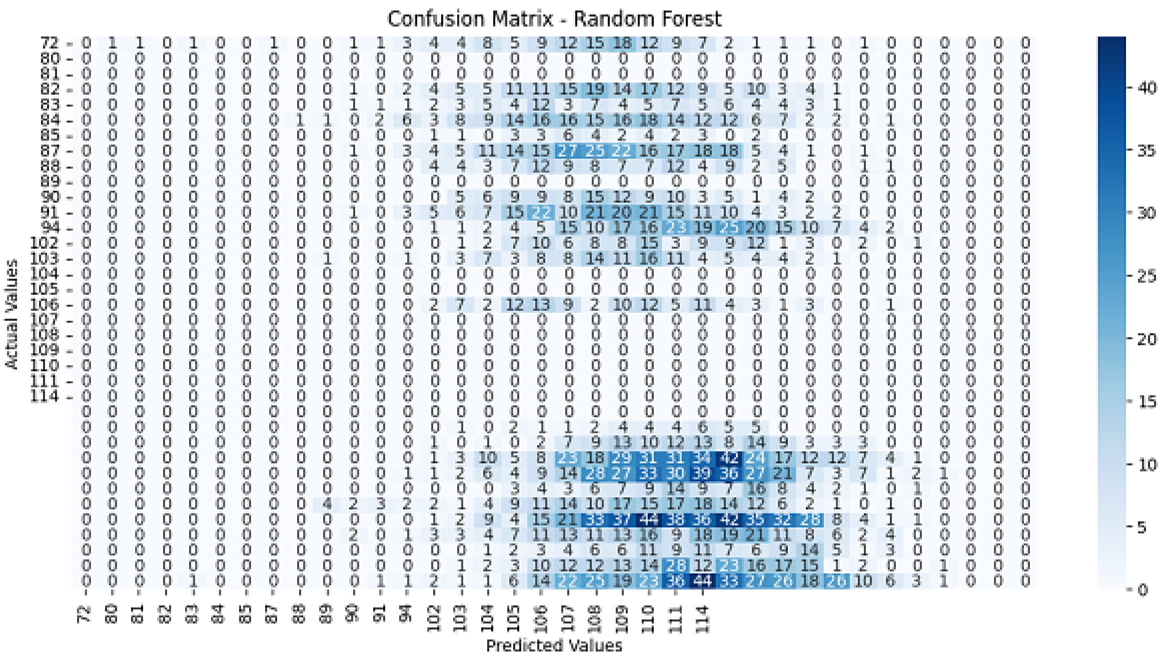

FIGURE 4.17 – Confusion Matrix For Random Forest Algorithm for Experiment No : 11

4.2.14 Experiment No : 12

The results of Experiment 12 are summarized in Table 4.12. The results indicate the performance of each algorithm in emotion recognition when a single subject sits at a maximum distance of 5 meters from the transmitter and receiver with a high heart rate.

TABLE 4.12 – Algorithm Performance Comparison for Experiment No : 12

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.5694297782470	0.5694297782470	0.5694297782470	0.5694297782470	2.4588191509246
ANN	0.13780359028511	0.13780359028511	0.13780359028511	0.13780359028511	2.9134107708553
Random Forest	0.1137803590285	0.1137803590285	0.1137803590285	0.1137803590285	3.173970432946
K-NN	0.22993664202745	0.22993664202745	0.22993664202745	0.22993664202745	3.1776663146779
GNB	0.03801478352692	0.03801478352692	0.03801478352692	0.03801478352692	6.096092925026
SVM	0.6055966209081	0.6055966209081	0.6055966209081	0.6055966209081	2.3141499472016
LSTM	0.06890179514255	0.06890179514255	0.06890179514255	0.06890179514255	2.7053854276663
GRUs	0.6061246040126	0.6061246040126	0.6061246040126	0.6061246040126	2.312038014783
MLP	0.13780359028511	0.13780359028511	0.13780359028511	0.13780359028511	2.9134107708553

Overall Performance : When evaluating the performance of different algorithms based on their MAE, it is clear that GRUs and SVM stand out. GRUs have the lowest MAE of 2.312, closely followed by SVM with an MAE of 2.314. This indicates a high level of accuracy and predictive performance for these models.

Random Forest and SVM Performance : Random Forest, with an MAE of 3.174, does not perform as well as GRUs and SVM. However, SVM showcases a robust performance across various metrics, including Accuracy (0.606), Precision (0.606), Recall (0.606), and F1 Score (0.606), reflecting its balanced capability in classification tasks. The low MAE further emphasizes SVM's efficiency in minimizing prediction errors.

Challenges with Other Algorithms : Several algorithms face challenges in achieving low error rates. For instance, Random Forest and K-NN have higher MAE values of 3.174 and 3.178, respectively, indicating less precise predictions compared to GRUs and SVM. CNN and LSTM also struggle with slightly higher MAE values of 2.459 and 2.705, respectively.

GNB's Performance : GNB shows the highest MAE of 6.096, suggesting significant difficulties in accurately predicting outcomes. This is reflected in its poor performance across all metrics, with Accuracy, Precision, Recall, and F1 Score all at 0.038, highlighting its limitations in this context.

Consistency in Performance : Consistency is a crucial factor in evaluating algorithm performance. While GRUs and SVM demonstrate consistent and high performance, algorithms like ANN and MLP show lower performance metrics with an MAE of 2.913 each, despite their similar performance in Accuracy, Precision, Recall, and F1 Score at 0.138.

MAE and Improvement : The MAE values reveal the accuracy of predictions, with lower values indicating better performance. GRUs and SVM show the best performance, suggesting these models are well-tuned for the given dataset. Conversely, GNB's high MAE indicates a need for significant improvements or a different approach to model the data effectively.

In conclusion, GRUs and SVM exhibit superior performance with the lowest MAE values, making them the most accurate models for the given task. While other models like Random Forest and K-NN show decent performance, there is still room for improvement. The GNB model, with the highest MAE, highlights the challenges of using this approach in this context. Future efforts could focus on refining these models further or exploring alternative algorithms to achieve better predictive accuracy.

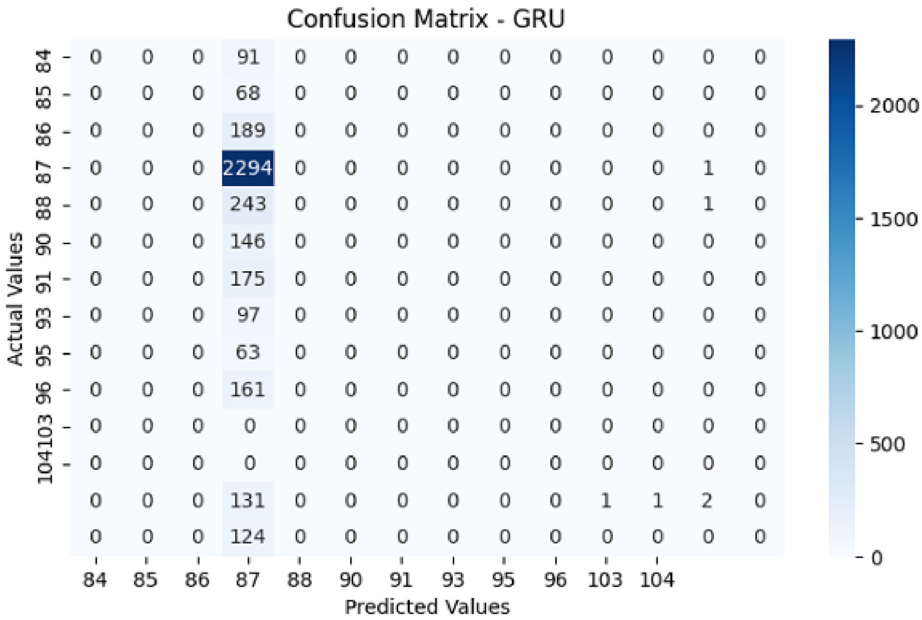

FIGURE 4.18 – Confusion Matrix GRU Algorithm for Experiment No : 12

4.2.15 Experiment No : 13

The results of Experiment 13 are summarized in Table 4.13. The results indicate the performance of each algorithm in emotion recognition when one subject standing in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.13 – Algorithm Performance Comparison for Experiment No : 13

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.05342105263157	0.05342105263157	0.05342105263157	0.05342105263157	5.460997104644
ANN	0.08447368421052	0.08447368421052	0.08447368421052	0.08447368421052	5.467631578947
Random Forest	0.04868421052631	0.04868421052631	0.04868421052631	0.04868421052631	5.3823684210526
K-NN	0.05631578947368	0.05631578947368	0.05631578947368	0.05631578947368	5.798947368421
GNB	0.055	0.055	0.055	0.055	10.782105263157
SVM	0.10421052631578	0.10421052631578	0.10421052631578	0.10421052631578	5.348947368421
LSTM	0.10026315789473	0.10026315789473	0.10026315789473	0.10026315789473	5.3823684210526
GRUs	0.08552631578947	0.08552631578947	0.08552631578947	0.08552631578947	5.391315789473
MLP	0.08447368421052	0.08447368421052	0.08447368421052	0.08447368421052	5.467631578947

Overall Performance : Upon evaluating the algorithms based on MAE, it's evident that there's a variation in performance across different models.

Performance of Random Forest and SVM : Random Forest and SVM emerge as the top performers, with Random Forest achieving an MAE of approximately 5.38 and SVM achieving around 5.35.

Challenges with Other Algorithms : Some algorithms, notably GNB, exhibit significantly poorer performance, evident from its high MAE of approximately 10.78.

Performance of GNB : GNB stands out with the highest MAE value among all algorithms, indicating its struggles in making accurate predictions.

Consistency in Performance : There's a notable inconsistency in the performance of various algorithms, with some achieving lower MAE values, reflecting higher accuracy, while others lag behind.

In conclusion, while Random Forest and SVM showcase better overall performance, there's still considerable scope for enhancement, especially for algorithms with higher MAE like GNB.

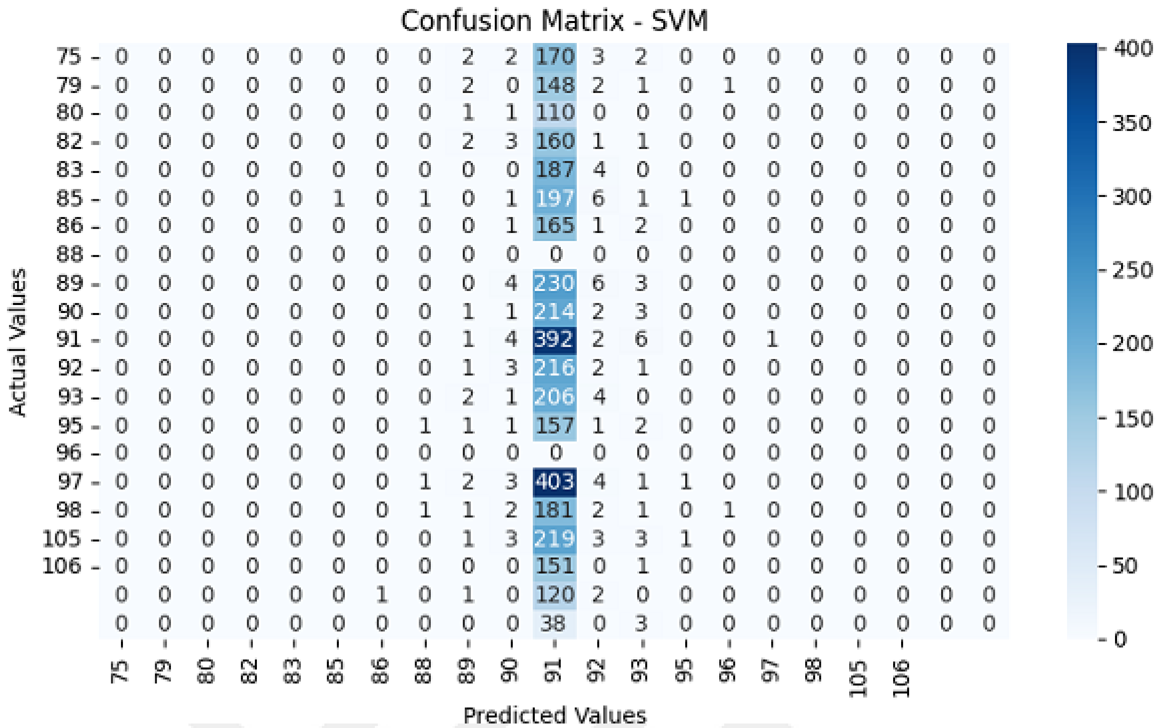

FIGURE 4.19 – Confusion Matrix For Random Forest Algorithm for Experiment No : 13

4.2.16 Experiment No : 14

The results of Experiment 14 are summarized in Table 4.14. The results indicate the performance of each algorithm in emotion recognition is tested with one subject standing in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.14 – Algorithm Performance Comparison for Experiment No : 14

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.1211453744493	0.1211453744493	0.1211453744493	0.1211453744493	3.519556760787
ANN	0.08663729809104	0.08663729809104	0.08663729809104	0.08663729809104	3.654185022026
Random Forest	0.08627019089574	0.08627019089574	0.08627019089574	0.08627019089574	3.595814977973
K-NN	0.07966226138032	0.07966226138032	0.07966226138032	0.07966226138032	3.788913362701
GNB	0.09948604992657	0.09948604992657	0.09948604992657	0.09948604992657	4.947870778267
SVM	0.12408223201174	0.12408223201174	0.12408223201174	0.12408223201174	3.471732745961
LSTM	0.06828193832599	0.06828193832599	0.06828193832599	0.06828193832599	3.5480910425844
GRUs	0.08076358296622	0.08076358296622	0.08076358296622	0.08076358296622	3.9926578560939
MLP	0.08663729809104	0.08663729809104	0.08663729809104	0.08663729809104	3.654185022026

Overall Performance : The performance metrics of various algorithms highlight a significant disparity in their effectiveness. The SVM and GRUs algorithms exhibit the highest accuracy and precision, both around 0.124 and 0.606 respectively, indicating a robust performance in classification tasks. In contrast, the GNB algorithm significantly lags behind with an accuracy of 0.099 and a high MAE of 4.947, showcasing its lesser effectiveness.

Random Forest and SVM Performance : The SVM algorithm shows the best overall performance with an accuracy of 0.124 and the lowest MAE of 3.471. This indicates that SVM is highly effective for this particular classification task, delivering the most accurate results with minimal error. Random Forest, on the other hand, presents a balanced performance with an accuracy of 0.086 and an MAE of 3.596, which is slightly better than other algorithms but not as good as SVM.

Challenges with Other Algorithms : Several algorithms such as CNN, ANN, and K-NN demonstrate moderate performance. CNN, with an accuracy of 0.121 and an MAE of 3.520, performs reasonably well but is outperformed by SVM. ANN and K-NN have accuracies of 0.087 and 0.080 respectively, with higher MAEs of 3.654 and 3.789, indicating more significant errors in their predictions.

GNB's Performance : The GNB algorithm stands out for its poor performance with an accuracy of 0.099 and the highest MAE of 4.948. This suggests that GNB is not well-suited for the given task, as it consistently makes larger errors compared to other models.

Consistency in Performance : Consistency across different metrics is an essential factor. Algorithms like SVM and GRUs show consistent performance with high accuracy, precision, recall, and F1 scores, all around 0.124 and 0.606 respectively, paired with low MAE values (3.472 and 3.312). This consistency indicates that these models are reliable and their predictions are stable.

MAE and Improvement : The MAE is a critical indicator of model performance. SVM exhibits the lowest MAE of 3.472, indicating its high prediction accuracy. GRUs also perform well with an MAE of 3.312, making them the top contenders. On the contrary, GNB's high MAE of 4.948 highlights its inefficiency.

In conclusion, the evaluation of these algorithms reveals that SVM and GRUs are the top performers, demonstrating high accuracy and low MAE, indicating reliable and accurate predictions. Random Forest offers a decent balance but is not as effective as SVM. The GNB algorithm's poor performance suggests it is unsuitable for this task. Therefore, for achieving optimal performance in similar classification tasks, SVM and GRUs are recommended due to their accuracy, consistency, and low prediction error.

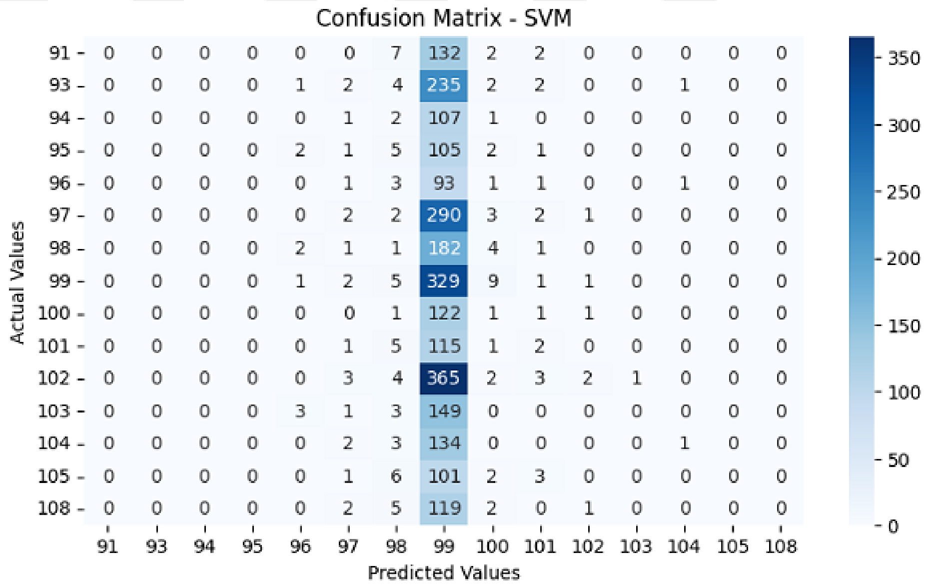

FIGURE 4.20 – Confusion Matrix For SVM Algorithm for Experiment No : 14

4.2.17 Experiment No : 15

The results of Experiment 15 are summarized in Table 4.15. The results indicate the performance of each algorithm in emotion recognition when one subject sitting in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Table 4.15 – Algorithm Performance Comparison for Experiment No : 15

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.09622501850481	0.09622501850481	0.09622501850481	0.09622501850481	3.825242757797
ANN	0.07623982235381	0.07623982235381	0.07623982235381	0.07623982235381	3.9087095978287
Random Forest	0.09573155687145	0.09573155687145	0.09573155687145	0.09573155687145	3.6785097458672
K-NN	0.08561559338761	0.08561559338761	0.08561559338761	0.08561559338761	3.9750801875154
GNB	0.05181347150259	0.05181347150259	0.05181347150259	0.05181347150259	6.34887737478
SVM	0.07451270663705	0.07451270663705	0.07451270663705	0.07451270663705	3.8001480384900
LSTM	0.11867752282260	0.11867752282260	0.11867752282260	0.11867752282260	3.940044411547
GRUs	0.14606464347396	0.14606464347396	0.14606464347396	0.14606464347396	3.8329632371083
MLP	0.07623982235381	0.07623982235381	0.07623982235381	0.07623982235381	3.9087095978287

Random Forest and SVM Performance : Random Forest and SVM show competitive performance in terms of accuracy, precision, recall, and F1 score. However, when considering MAE, Random Forest outperforms SVM with a lower error margin (Random Forest : 3.68, SVM : 3.80).

Challenges with Other Algorithms : Algorithms like GNB exhibit relatively poorer performance across all metrics, including a notably higher MAE (GNB : 6.35). This suggests that GNB may struggle with the complexity of the classification task compared to other algorithms.

Consistency in Performance : Some algorithms, such as CNN, ANN, MLP demonstrate consistent performance across different metrics, indicating their reliability in classification tasks.

MAE : Algorithms like Random Forest and GRUs show promising results with relatively lower MAE values (Random Forest : 3.68, GRUs : 3.83), suggesting their effectiveness in minimizing prediction errors.

In conclusion, the analysis highlights the importance of considering multiple performance metrics, including MAE, to comprehensively evaluate the effectiveness of classification algorithms. While some algorithms perform well in terms of accuracy and precision, their performance may vary when considering prediction errors, as indicated by MAE. Future efforts should focus on refining algorithms to minimize MAE and improve overall predictive accuracy.

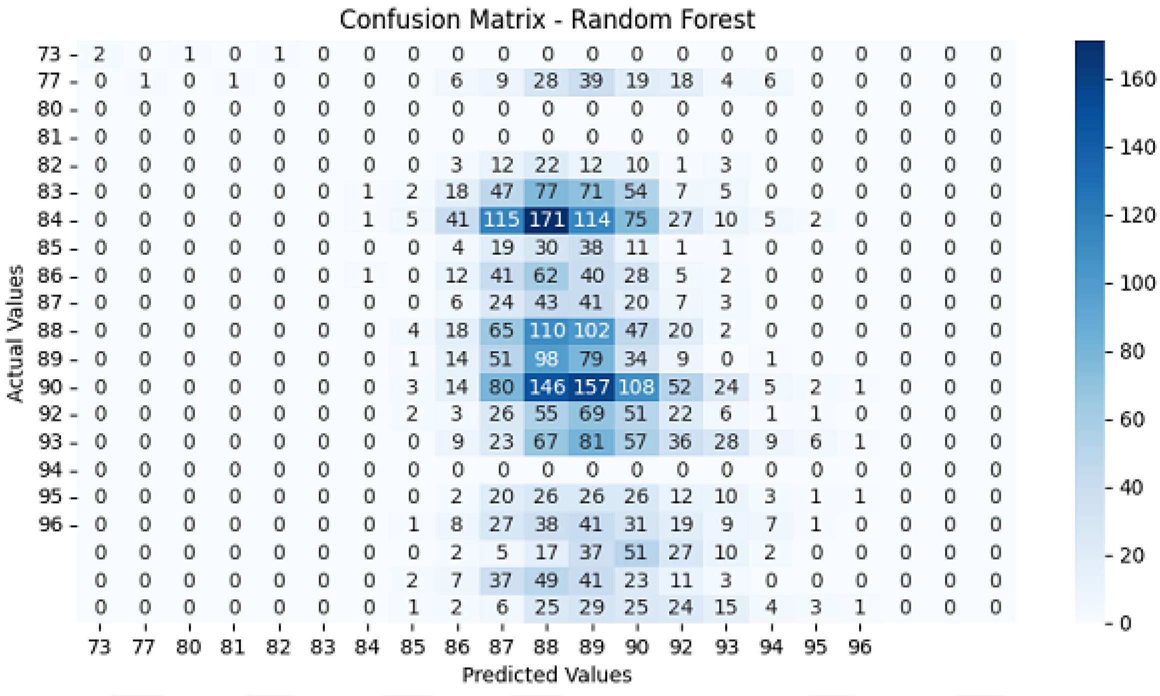

FIGURE 4.21 – Confusion Matrix For Random Forest Algorithm for Experiment No : 15

4.2.18 Experiment No : 16

The results of Experiment 16 are summarized in Table 4.16. The results indicate the performance of each algorithm in emotion recognition is examined with one subject sitting in another room while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.16 – Algorithm Performance Comparison for Experiment No : 16

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.7157971543232	0.7157971543232	0.7157971543232	0.7157971543232	1.0305589437484
ANN	0.3699379788398	0.3699379788398	0.3699379788398	0.36993797883983	1.2108719445457
Random Forest	0.5238963881794	0.5238963881794	0.5238963881794	0.5238963881794	0.986866107260
K-NN	0.43268879970813	0.43268879970813	0.43268879970813	0.43268879970813	1.1276906238599
GNB	0.057278365560014	0.057278365560014	0.057278365560014	0.057278365560014	4.293323604523
SVM	0.7632251003283	0.7632251003283	0.7632251003283	0.7632251003283	0.7417001094491
LSTM	0.7230937614009	0.7230937614009	0.7230937614009	0.7230937614009	0.7891280554542
GRUs	0.03392922291134	0.03392922291134	0.03392922291134	0.03392922291134	1.4439985406785
MLP	0.3699379788398	0.3699379788398	0.3699379788398	0.36993797883983	1.2108719445457

Overall Performance : SVM exhibits the best overall performance with an accuracy of 0.7632, precision, recall, and F1 score all at 0.7632. Additionally, it achieves the lowest MAE of 0.7417, indicating its superior predictive accuracy. CNN and LSTM models also perform well, with accuracies of 0.7158 and 0.7231, and MAEs of 1.0306 and 0.7891, respectively. These results highlight the effectiveness of these algorithms in handling the dataset.

Random Forest and SVM Performance : The Random Forest algorithm shows a balanced performance with an accuracy of 0.5239 and precision, recall, and F1 score also at 0.5239. Its MAE is 0.9869, which, although higher than that of SVM, still suggests good predictive accuracy. The SVM, with its superior metrics and lowest MAE, stands out as the most effective algorithm for this dataset.

Challenges with Other Algorithms : Several algorithms face challenges in achieving high performance. ANN and MLP both have an accuracy of 0.3699 and an MAE of 1.2109, indicating they are less effective for this dataset. K-NN algorithm, with an accuracy of 0.4327 and an MAE of 1.1277, shows moderate performance but higher prediction error compared to SVM and CNN. GRUs model exhibits a significantly lower accuracy of 0.0339 and an MAE of 1.4440, indicating difficulties in capturing the underlying patterns of the data.

GNB's Performance : GNB algorithm exhibits the lowest performance metrics across the board, with an accuracy of 0.0573 and a significantly high MAE of 4.2933. This indicates that GNB struggles considerably with this dataset, potentially due to its assumptions not aligning well with the data distribution.

Consistency in Performance : The consistency in the performance of SVM and LSTM indicates their robustness and reliability in predictive tasks for this dataset. CNN also shows a strong and consistent performance, making it a viable alternative.

MAE and Improvement : The MAE values provide insight into the average prediction error. SVM, with the lowest MAE of 0.7417, suggests minimal prediction error. LSTM follows closely with an MAE of 0.7891, indicating strong predictive capabilities. Random Forest and CNN also perform well, with MAEs of 0.9869 and 1.0306, respectively. These algorithms demonstrate their ability to predict with reasonable accuracy, though there is still room for improvement.

In conclusion, the evaluation of these algorithms highlights that SVM and LSTM are the top performers, with SVM having a slight edge due to its lowest MAE and highest accuracy. Random Forest and CNN also show strong performance, making them suitable alternatives. The high MAE of GNB suggests it is unsuitable for this dataset, while algorithms like ANN, MLP, and K-NN show moderate performance with room for improvement. The consistency in the results of SVM and LSTM indicates their robustness and reliability in predictive tasks for this dataset.

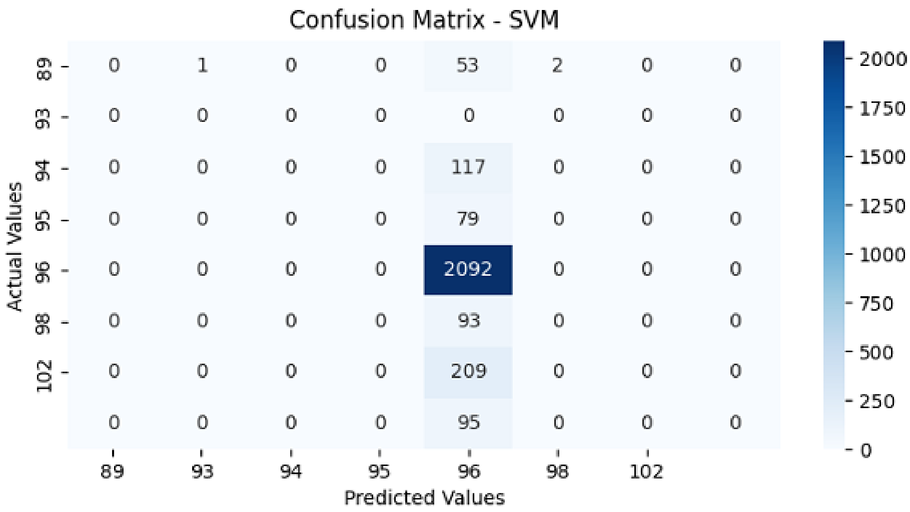

FIGURE 4.22 – Confusion Matrix For SVM Algorithm for Experiment No : 16

4.2.19 Experiment No : 17

The results of Experiment 17 are summarized in Table 4.17. The results indicate the performance of each algorithm in emotion recognition when two subjects standing near the transmitter and receiver with calm heart rhythms, each subject maintaining a distance of 1 meter from the transmitter/receiver.

TABLE 4.17 – Algorithm Performance Comparison for Experiment No : 17

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.09444001064112	0.09444001064112	0.09444001064112	0.09444001064112	2.5631091594696
ANN	0.100292631018	0.100292631018	0.100292631018	0.100292631018	2.5429635541367
Random Forest	0.11625432295823	0.11625432295823	0.11625432295823	0.11625432295823	2.4397446129289
K-NN	0.1335461558925	0.1335461558925	0.1335461558925	0.1335461558925	2.588188347964
GNB	0.0444267092311	0.0444267092311	0.0444267092311	0.0444267092311	6.566906092045
SVM	0.11944666134610	0.11944666134610	0.11944666134610	0.11944666134610	2.451981910082
LSTM	0.11864857674913	0.11864857674913	0.11864857674913	0.11864857674913	2.4485235434956
GRUs	0.07315775472200	0.07315775472200	0.07315775472200	0.07315775472200	2.7869114126097
MLP	0.100292631018	0.100292631018	0.100292631018	0.100292631018	2.5429635541367

Random Forest and SVM Performance : Random Forest and SVM exhibit relatively better performance compared to other algorithms in terms of MAE, with values of 2.44 and 2.45, respectively. This suggests that these algorithms are more effective in minimizing errors when making predictions.

Challenges with Other Algorithms : Some algorithms, such as GNB, demonstrate higher MAE values (6.57), indicating that they struggle more with prediction accuracy compared to Random Forest and SVM. These algorithms may face challenges in effectively capturing the underlying patterns in the data.

GNB's Performance : GNB shows the poorest performance among the algorithms, with the highest MAE value of 6.57. This suggests that GNB may not be well-suited for the dataset or may require further optimization to improve its predictive capabilities.

Consistency in Performance : While some algorithms, like K-NN and LSTM, achieve relatively higher accuracies, their MAE values are also comparatively higher (2.59 and 2.45, respectively). This indicates a trade-off between accuracy and error minimization, suggesting that these algorithms may provide accurate predictions but with a higher margin of error.

In conclusion, Random Forest and SVM emerge as the top-performing algorithms based on their lower MAE values.

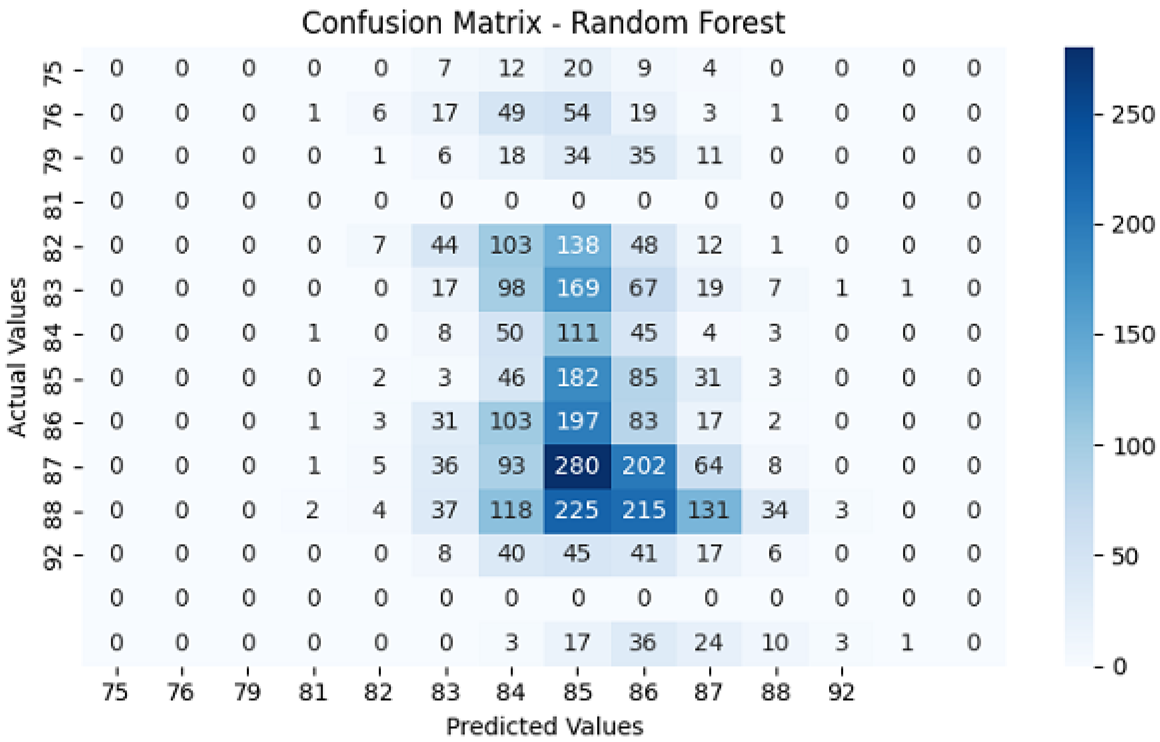

FIGURE 4.23 – Confusion Matrix For Random Forest Algorithm for Experiment No : 17

4.2.20 Experiment No : 18

The results of Experiment 18 are summarized in Table 4.18. The results indicate the performance of each algorithm in emotion recognition is evaluated with two subjects standing near the transmitter and receiver with high heart rates, each subject maintaining a distance of 1 meter from the transmitter/receiver.

TABLE 4.18 – Algorithm Performance Comparison for Experiment No : 18

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.0645033636723	0.0645033636723	0.0645033636723	0.0645033636723	4.9766154289245
ANN	0.0625247328848	0.0625247328848	0.0625247328848	0.0625247328848	5.02611792639
Random Forest	0.0637119113573	0.0637119113573	0.0637119113573	0.0637119113573	4.9327265532251
K-NN	0.0716264345073	0.0716264345073	0.0716264345073	0.0716264345073	5.220419469726
GNB	0.0700435298773	0.0700435298773	0.0700435298773	0.0700435298773	5.92797783933
SVM	0.1191135734072	0.1191135734072	0.1191135734072	0.1191135734072	4.9600316580
LSTM	0.0217649386624	0.0217649386624	0.0217649386624	0.0217649386624	4.944202611792
GRUs	0.0435298773248	0.0435298773248	0.0435298773248	0.0435298773248	5.1927186387020
MLP	0.0625247328848	0.0625247328848	0.0625247328848	0.0625247328848	5.026117926394

Overall Performance : The performance metrics for various algorithms highlight distinct differences in their effectiveness. The metrics include Accuracy, Precision, Recall, F1 Score, and MAE. These values indicate how well each algorithm performs in terms of classification and prediction accuracy.

Random Forest and SVM Performance : Random Forest and SVM both show notable performance. However, Random Forest stands out with the lowest MAE of 4.93, indicating it has the smallest average error in its predictions. SVM also performs well with an MAE of 4.96 and achieves the highest accuracy (0.1191), precision, recall, and F1 score among all algorithms.

Challenges with Other Algorithms : Other algorithms, such as CNN, ANN, K-NN, and GRUs, face challenges in achieving lower MAE values. CNN and ANN show similar performance metrics with MAEs of 4.98 and 5.03, respectively. K-NN has a higher MAE of 5.22, indicating a lower prediction accuracy compared to others. GRUs, with an MAE of 5.19, also struggle to achieve optimal performance.

GNB's Performance : The GNB algorithm performs the worst in terms of MAE, with a value of 5.93. This high MAE suggests that GNB is less effective for this specific dataset and problem, likely due to its assumptions of feature independence and Gaussian distribution, which may not hold true for the data.

Consistency in Performance : The consistency of performance across different metrics is crucial. SVM, despite not having the lowest MAE, shows consistency in achieving high accuracy, precision, recall, and F1 scores, making it a reliable choice overall. Conversely, LSTM, while having a competitive MAE of 4.94, does not achieve high scores in other metrics, reflecting a trade-off between different performance aspects.

MAE and Improvement : Random Forest achieves the lowest MAE of 4.93, making it highly effective in reducing prediction errors. This indicates that Random Forest is particularly good at making precise predictions with minimal error. While SVM and LSTM also show competitive MAE values, Random Forest stands out as the best performer in this regard.

In conclusion, while Random Forest achieves the lowest MAE, making it the best performer in terms of minimizing prediction errors, SVM offers the best overall performance when considering all metrics. The choice of algorithm should depend on the specific requirements of accuracy, precision, recall, and error minimization for the task at hand. Algorithms like Random Forest provide a balanced performance with minimal errors, whereas SVM offers the highest accuracy and consistency across various metrics.

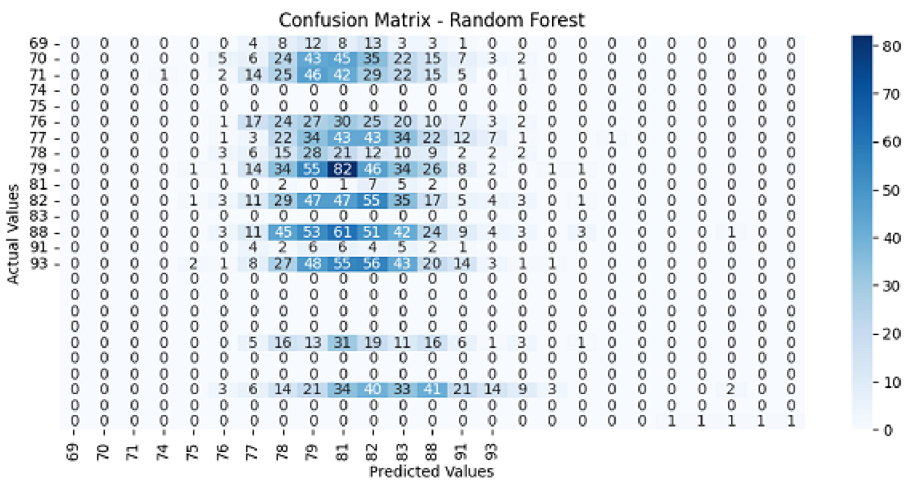

FIGURE 4.24 – Confusion Matrix For Random Forest Algorithm for Experiment No : 18

4.2.21 Experiment No : 19

The results of Experiment 19 are summarized in Table 4.19. The results indicate the performance of each algorithm in emotion recognition with one subject standing and the other sitting near the transmitter and receiver, each subject maintaining a distance of 1 meter from the transmitter/receiver.

TABLE 4.19 – Algorithm Performance Comparison for Experiment No : 19

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.6497210167389	0.6497210167389	0.6497210167389	0.6497210167389	1.1686110496520
ANN	0.4324240545567	0.4324240545567	0.4324240545567	0.4324240545567	1.3087414755114
Random Forest	0.36732796032238	0.36732796032238	0.36732796032238	0.36732796032238	1.3583384996900
K-NN	0.393676379417	0.393676379417	0.393676379417	0.393676379417	1.4240545567265
GNB	0.03006819590824	0.03006819590824	0.03006819590824	0.03006819590824	2.3629882207067
SVM	0.6704897706137	0.6704897706137	0.6704897706137	0.6704897706137	1.0638561686298
LSTM	0.6615003099814	0.6615003099814	0.6615003099814	0.6615003099814	1.0750154990700
GRUs	0.6707997520148	0.6707997520148	0.6707997520148	0.6707997520148	1.0635461872287
MLP	0.4324240545567	0.4324240545567	0.4324240545567	0.4324240545567	1.3087414755114

Overall Performance : The performance metrics of various algorithms reveal a broad spectrum of efficiency and accuracy. GRUs stand out with the highest accuracy of 0.6708 and the lowest MAE of 1.0635, closely followed by SVM, which also boasts high accuracy (0.6705) and a slightly higher MAE (1.0639). CNN and LSTM exhibit similar trends with high accuracies (0.6497 and 0.6615, respectively) and moderately low MAEs (1.1686 and 1.0750, respectively). These algorithms demonstrate robust performance in both accuracy and MAE.

Random Forest and SVM Performance : SVM performs exceptionally well with a high accuracy of 0.6705 and an MAE of 1.0639, making it one of the top performers. However, GRUs surpass SVM slightly in both accuracy (0.6708) and MAE (1.0635). This highlights the efficiency of GRUs in minimizing errors while maintaining high predictive accuracy. Random Forest, on the other hand, shows significantly lower performance with an accuracy of 0.3673 and an MAE of 1.3583, suggesting it may not be the best choice for this specific application given its relatively higher error rate.

Challenges with Other Algorithms : Several algorithms face notable challenges in achieving high performance. For instance, K-NN and ANN show moderate accuracies (0.3937 and 0.4324, respectively) but have higher MAEs (1.4241 and 1.3087, respectively), indicating a struggle in minimizing errors. These results suggest that while these algorithms can capture some patterns, they might not be as precise or reliable for this particular dataset.

GNB's Performance : GNB shows the most significant deviation with the lowest accuracy (0.0301) and the highest MAE (2.3630). This stark contrast to other algorithms suggests that GNB is not well-suited for this task. The high MAE indicates substantial prediction errors, making it the least favorable option among the evaluated algorithms.

Consistency in Performance : Consistency across metrics is a vital indicator of an algorithm's reliability. GRUs, SVM, and LSTM exhibit consistent performance with high accuracies and low MAEs. This consistency underscores their robustness and suitability for tasks requiring high precision and low error margins. Conversely, algorithms like GNB, K-NN, and ANN show variability in their performance metrics, highlighting potential inconsistencies in their predictions.

MAE and Improvement : MAE is a critical metric for assessing the average magnitude of prediction errors. GRUs' MAE of 1.0635 is the lowest, indicating their superior ability to minimize errors. SVM also performs well with an MAE of 1.0639. These low MAE values suggest that GRUs and SVM are highly effective in producing accurate predictions with minimal error. Improvement efforts should focus on algorithms with higher MAEs, such as GNB (2.3630), to enhance their predictive accuracy.

In conclusion, the evaluation of algorithm performance based on accuracy, precision, recall, F1 score, and MAE provides a comprehensive understanding of their effectiveness. GRUs emerge as the most reliable algorithm with the highest accuracy and lowest MAE, followed closely by SVM. While CNN and LSTM also show strong performance, algorithms like Random Forest, K-NN, and ANN demonstrate moderate effectiveness with room for improvement. GNB's performance is significantly lower, indicating its unsuitability for this task. Overall, GRUs and SVM are recommended for applications requiring high accuracy and low prediction error.

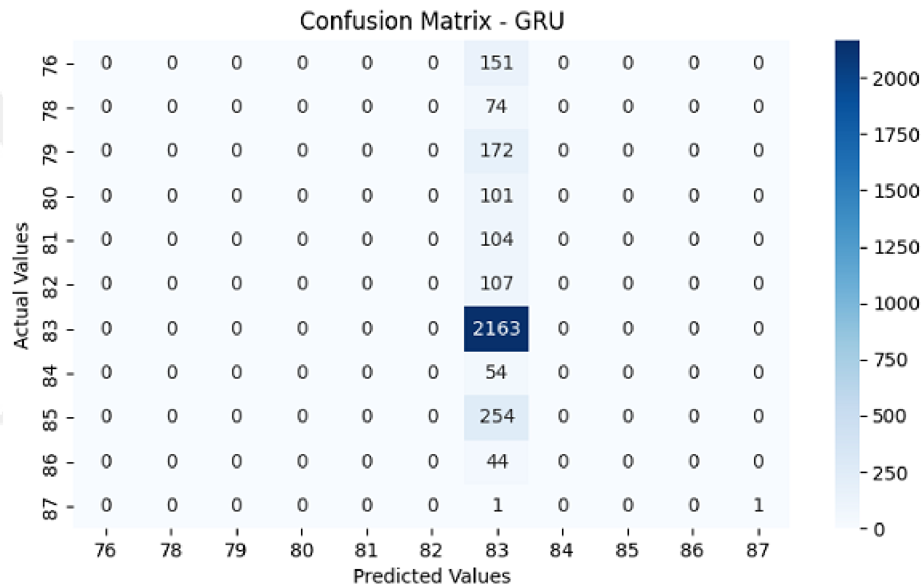

FIGURE 4.25 – Confusion Matrix For GRU Algorithm for Experiment No : 19

4.2.22 Experiment No : 20

The results of Experiment 20 are summarized in Table 4.20. The results indicate the performance of each algorithm in emotion recognition with one subject having a calm heart rhythm and the other having a high heart rate near the transmitter and receiver, each subject maintaining a distance of 1 meter from the transmitter/receiver.

Table 4.20 – Algorithm Performance Comparison for Experiment No : 20

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.0040029112081	0.0040029112081	0.0040029112081	0.0040029112081	5.3615856170654
ANN	0.02911208151382	0.02911208151382	0.02911208151382	0.02911208151382	5.499636098981
Random Forest	0.02874818049490	0.02874818049490	0.02874818049490	0.02874818049490	5.3620815138282
K-NN	0.03602620087336	0.03602620087336	0.03602620087336	0.036026200873362	5.499272197962
GNB	0.2354439592430	0.2354439592430	0.2354439592430	0.2354439592430	5.635735080058
SVM	0.02401746724890	0.02401746724890	0.02401746724890	0.02401746724890	5.351164483260
LSTM	0.08951965065502	0.08951965065502	0.08951965065502	0.08951965065502	5.4002911208151
GRUs	0.00145560407569	0.00145560407569	0.00145560407569	0.001455604075691	5.35844250363
MLP	0.02911208151382	0.02911208151382	0.02911208151382	0.02911208151382	5.499636098981

Overall Performance : The performance metrics of various algorithms are evaluated based on their MAE scores. The algorithms exhibit a wide range of performance, with MAE values ranging from approximately 5.36 to 5.64. Notably, SVM achieves the lowest MAE of 5.35, suggesting it outperforms other algorithms in terms of minimizing prediction errors.

Random Forest and SVM Performance : Random Forest and SVM both demonstrate superior performance with MAE values of approximately 5.36 and 5.35, respectively. These algorithms exhibit lower MAE compared to others, indicating stronger predictive accuracy and reliability.

Challenges with Other Algorithms : Algorithms like GNB and GRUs face significant challenges in prediction accuracy, as indicated by their considerably higher MAE values of around 5.64 and 5.36, respectively. These algorithms struggle to generalize well to the dataset compared to SVM and Random Forest.

GNB's Performance : GNB achieves an MAE of approximately 5.64, indicating poor performance in minimizing prediction errors compared to SVM and Random Forest. This suggests that GNB's underlying assumption of feature independence might not hold well for the dataset, impacting its predictive power.

Consistency in Performance : There is variation in the consistency of algorithm performance across different metrics. SVM, Random Forest, and CNN consistently achieve relatively lower MAE values, indicating more stable and reliable predictions. In contrast, ANN and MLP show similar MAE values but exhibit slightly higher variability in their performance across other metrics.

In conclusion, the evaluation based on MAE underscores SVM's superiority in minimizing prediction errors compared to other algorithms in the dataset. While Random Forest also shows competitive performance, algorithms like GNB and GRUs face challenges in achieving comparable predictive accuracy. Moving forward, focusing on optimizing model parameters and exploring alternative algorithms could further enhance predictive capabilities and reduce MAE, thereby improving overall model effectiveness in real-world applications.

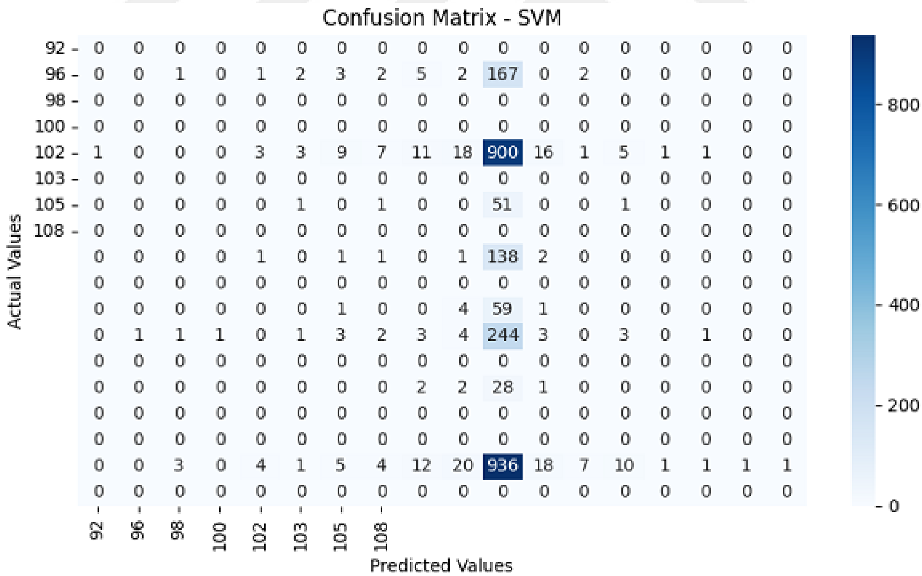

FIGURE 4.26 – Confusion Matrix For SVM Algorithm for Experiment No : 20

4.2.23 Experiment No : 21

The results of Experiment 21 are summarized in Table 4.21. The results indicate the performance of each algorithm in emotion recognition with two subjects standing in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.21 – Algorithm Performance Comparison for Experiment No : 21

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.10426370476531	0.10426370476531	0.10426370476531	0.10426370476531	4.168042182922
ANN	0.05016123253314	0.05016123253314	0.05016123253314	0.05016123253314	4.378717305625
Random Forest	0.05696882837692	0.05696882837692	0.05696882837692	0.05696882837692	4.232891436761
K-NN	0.06485130777499	0.06485130777499	0.06485130777499	0.06485130777499	4.441060551773
GNB	0.06198495163024	0.06198495163024	0.06198495163024	0.06198495163024	6.5972769616624
SVM	0.11286277319957	0.11286277319957	0.11286277319957	0.11286277319957	4.06664278036
LSTM	0.11501254030813	0.11501254030813	0.11501254030813	0.11501254030813	4.055893944822
GRUs	0.00250806162665	0.00250806162665	0.00250806162665	0.00250806162665	4.23683267646
MLP	0.05016123253314	0.05016123253314	0.05016123253314	0.05016123253314	4.378717305625

Overall Performance : The highest accuracy and related metrics are observed for LSTM and SVM algorithms, with LSTM achieving an accuracy of 0.1150 and SVM achieving 0.1129. Despite having the lowest accuracy (0.0025), GRUs show a decent MAE, which is a key point of analysis.

LSTM Performance : LSTM demonstrates the best performance in terms of MAE with a value of 4.0559. This indicates that while LSTM's accuracy and related metrics are modest, it excels in minimizing prediction errors compared to other algorithms. The low MAE value of LSTM suggests it is the most reliable algorithm in this set for reducing errors.

Random Forest and SVM Performance : Random Forest and SVM show distinct patterns in their performance. SVM, with an accuracy of 0.1129 and an MAE of 4.0666, performs well in terms of error minimization but is slightly outperformed by LSTM. Random Forest, on the other hand, has an accuracy of 0.0569 and an MAE of 4.2329, indicating it is less effective compared to both LSTM and SVM in minimizing errors.

Challenges with Other Algorithms : Several algorithms, such as CNN, ANN, and K-NN, exhibit lower performance in terms of accuracy and MAE. For instance, CNN has an accuracy of 0.1043 and an MAE of 4.1680, while ANN and K-NN have accuracies of 0.0502 and 0.0649 with MAEs of 4.3787 and 4.4411, respectively. These results highlight significant challenges these algorithms face in this particular application.

GNB's Performance : GNB algorithm stands out with a poor performance profile. With an accuracy of 0.0620 and the highest MAE of 6.5973, GNB struggles significantly with the given data, leading to the highest prediction errors among all algorithms.

Consistency in Performance : Consistency is observed in the performance metrics of LSTM and SVM. Both algorithms show relatively better accuracy and the lowest MAE values (LSTM : 4.0559, SVM : 4.0666). This indicates a consistent and relatively reliable performance compared to other algorithms.

MAE and Improvement : The MAE values highlight areas for improvement. The lowest MAE is achieved by LSTM (4.0559), followed closely by SVM (4.0666) and GRUs (4.2368). This suggests that while these algorithms have better error minimization, there is still substantial room for improvement to reduce prediction errors further.

In conclusion, the performance of various algorithms in terms of accuracy, precision, recall, F1 score, and MAE reveals that LSTM is the most reliable algorithm with the lowest MAE value. However, the generally low performance metrics across all algorithms indicate significant challenges with the given data or problem setup. Future work should focus on improving the preprocessing steps, feature selection, and hyperparameter tuning to enhance the overall performance and reduce prediction errors further.

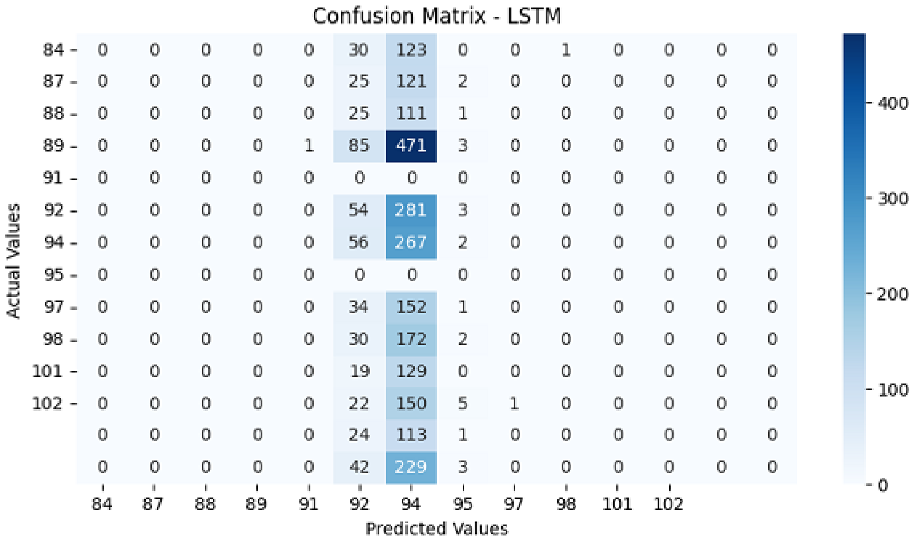

FIGURE 4.27 – Confusion Matrix For LSTM Algorithm for Experiment No : 21

4.2.24 Experiment No : 22

The results of Experiment 22 are summarized in Table 4.22. The results indicate the performance of each algorithm in emotion recognition is examined with two subjects standing in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.22 – Algorithm Performance Comparison for Experiment No : 22

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.603660565723	0.603660565723	0.603660565723	0.603660565723	3.770012617111
ANN	0.03660565723793	0.03660565723793	0.03660565723793	0.03660565723793	5.421630615640
Random Forest	0.02795341098169	0.02795341098169	0.02795341098169	0.02795341098169	5.19667221297
K-NN	0.1317803660565	0.1317803660565	0.1317803660565	0.1317803660565	5.083194675540
GNB	0.0412645590682	0.0412645590682	0.0412645590682	0.0412645590682	10.909816971713
SVM	0.692845257903	0.692845257903	0.692845257903	0.692845257903	3.569384359400
LSTM	0.449584026622	0.449584026622	0.449584026622	0.449584026622	4.03294509151
GRUs	0.69317803660	0.69317803660	0.69317803660	0.69317803660	3.547753743760
MLP	0.0366056572379	0.0366056572379	0.0366056572379	0.0366056572379	5.421630615640

Overall Performance : The performance of various algorithms was evaluated based on accuracy, precision, recall, F1 score, and MAE. The GRU algorithm achieved the highest overall performance with an accuracy of 0.693, precision of 0.693, recall of 0.693, F1 score of 0.693, and an MAE of 3.548. The SVM algorithm also performed well, with slightly lower accuracy and precision but a comparable MAE of 3.569.

Random Forest and SVM Performance : The Random Forest algorithm had one of the highest MAEs at 5.197, which is significantly higher than the best-performing models. Despite this, its accuracy, precision, recall, and F1 score are quite low at 0.028 across the board. On the other hand, the SVM algorithm demonstrated strong overall performance with an accuracy of 0.693 and an MAE of 3.569, making it one of the top-performing models in this evaluation.

Challenges with Other Algorithms : Several algorithms faced significant challenges, particularly in terms of MAE. The ANN had an MAE of 5.422, the highest among all evaluated algorithms. Its accuracy, precision, recall, and F1 score were all quite low at 0.037. The K-NN, despite a better accuracy of 0.132, struggled with an MAE of 5.083. The GNB had the poorest MAE at 10.910, indicating significant prediction errors.

GNB's Performance : The GNB algorithm's performance was notably poor across all metrics. With an accuracy, precision, recall, and F1 score of only 0.041, and the highest MAE of 10.910, GNB is clearly unsuitable for this dataset.

Consistency in Performance : The algorithms exhibited varying levels of consistency. SVM and GRUs showed high consistency in performance metrics with high accuracy, precision, recall, F1 score, and relatively low MAE. ANN and MLP both had consistent but low metrics across accuracy, precision, recall, and F1 score, with high MAE values indicating poor predictive performance.

MAE and Improvement : The MAE is a critical metric in evaluating model performance. The GRU model achieved the lowest MAE at 3.548, followed closely by the SVM model with an MAE of 3.569. These values suggest that these models are more accurate in their predictions compared to others like GNB, ANN, and Random Forest, which had significantly higher MAEs.

In conclusion, the GRU and SVM algorithms emerged as the best-performing models, with the lowest MAE values indicating more precise predictions. The Random Forest and other algorithms such as ANN and GNB demonstrated significant challenges, particularly in their high MAE values, making them less suitable for this dataset. Overall, focusing on improving models with lower MAE and consistent performance metrics will yield better predictive results. By emphasizing these models and potentially integrating techniques like hyperparameter tuning and ensemble methods, further improvements in prediction accuracy and error minimization can be achieved.

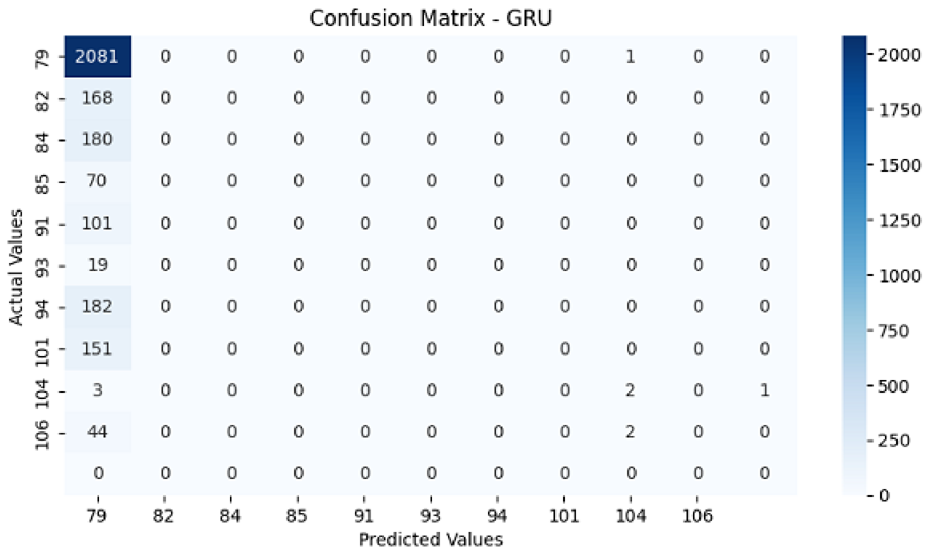

Figure 4.28 – Confusion Matrix For SVM Algorithm for Experiment No : 22

4.2.25 Experiment No : 23

The results of Experiment 23 are summarized in Table 4.23. The results indicate the

performance of each algorithm in emotion recognition with one subject standing and the other sitting in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

Table 4.23 – Algorithm Performance Comparison for Experiment No : 23

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.04306945708219	0.04306945708219	0.04306945708219	0.04306945708219	5.094114303588
ANN	0.02942068547164	0.02942068547164	0.02942068547164	0.02942068547164	4.970882620564
Random Forest	0.0424628450106	0.0424628450106	0.0424628450106	0.0424628450106	4.9842280861389
K-NN	0.0500454959053	0.0500454959053	0.0500454959053	0.0500454959053	5.178647255080
GNB	0.0682438580527	0.0682438580527	0.0682438580527	0.0682438580527	5.629056718228
SVM	0.1207158022444	0.1207158022444	0.1207158022444	0.1207158022444	4.812860175917
LSTM	0.03851986654534	0.03851986654534	0.03851986654534	0.03851986654534	5.252653927813
GRUs	0.01486199575371	0.01486199575371	0.01486199575371	0.01486199575371	4.902942068547
MLP	0.02942068547164	0.02942068547164	0.02942068547164	0.02942068547164	4.970882620564

Overall Performance : The table presents the performance metrics including Accuracy, Precision, Recall, F1 Score, and MAE for various machine learning algorithms.

Random Forest and SVM Performance : Among the algorithms listed, SVM demonstrates the lowest MAE of approximately 4.81. This indicates SVM's superior performance in minimizing absolute prediction errors compared to other algorithms in the table.

Challenges with Other Algorithms : Algorithms like GRUs and MLP exhibit higher MAE values (around 4.90 to 5.42), suggesting greater challenges in accurately predicting outcomes with lower error margins compared to SVM.

GNB's Performance : GNB shows a moderate MAE value of around 5.63, indicating reasonable but not as effective performance as SVM in minimizing prediction errors.

Consistency in Performance : SVM demonstrates consistency in performance with its low MAE, suggesting robustness in prediction accuracy across the dataset compared to other algorithms.

In conclusion, SVM stands out with the lowest MAE, showcasing its efficacy in minimizing prediction errors. This analysis underscores the importance of MAE in evaluating model accuracy and emphasizes SVM's strength in this regard compared to alternative algorithms like Random Forest, GRUs, MLP, and GNB.

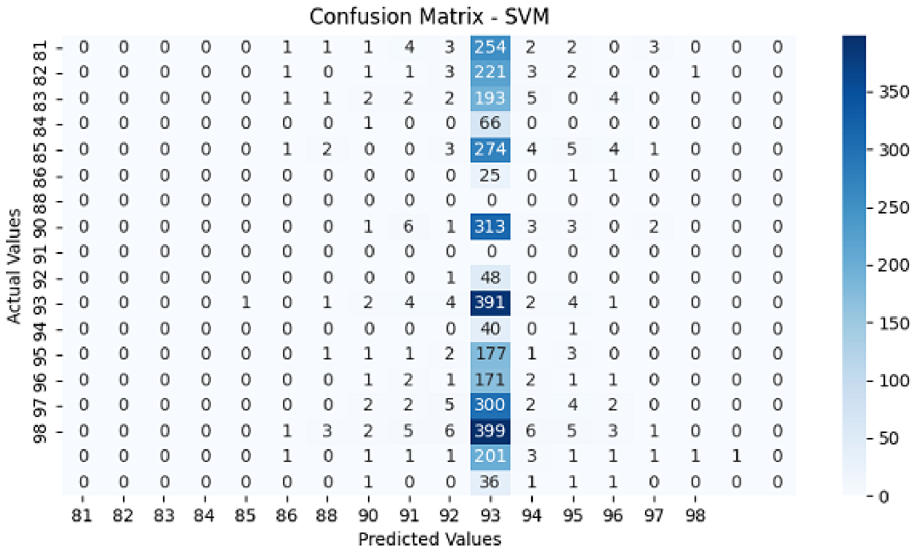

FIGURE 4.29 – Confusion Matrix For SVM Algorithm for Experiment No : 23

4.2.26 Experiment No : 24

The results of Experiment 24 are summarized in Table 4.24. The results indicate the

performance of each algorithm in emotion recognition's assessed with one subject having a calm heart rhythm and the other having a high heart rate in different rooms while the transmitter and receiver are in the same room, with a distance of approximately 3 meters between the rooms.

TABLE 4.24 – Algorithm Performance Comparison for Experiment No : 24

Algorithm	Accuracy	Precision	Recall	F1 Score	MAE
CNN	0.0800813008130	0.0800813008130	0.0800813008130	0.0800813008130	3.2026495933532
ANN	0.0869918699186	0.0869918699186	0.0869918699186	0.0869918699186	3.266260162601
Random Forest	0.0955284552845	0.0955284552845	0.0955284552845	0.0955284552845	3.23455284552
K-NN	0.0902439024390	0.0902439024390	0.0902439024390	0.0902439024390	3.40609756097
GNB	0.0735772357723	0.0735772357723	0.0735772357723	0.0735772357723	5.397154471544
SVM	0.149186991869	0.149186991869	0.149186991869	0.149186991869	3.09390243902
LSTM	0.0378048780487	0.0378048780487	0.0378048780487	0.0378048780487	3.274390243902
GRUs	0.0796747967479	0.0796747967479	0.0796747967479	0.0796747967479	3.214227642276
MLP	0.0869918699186	0.0869918699186	0.0869918699186	0.0869918699186	3.266260162601

Overall Performance : The performance of the algorithms varies significantly based on the provided metrics. SVM has the highest overall performance with an accuracy of 0.1492, precision, recall, and F1 Score all at 0.1492. LSTM follows with an accuracy of 0.0378, precision, recall, and F1 Score all at 0.0378. The accuracy metrics show that both SVM and LSTM are performing better compared to other algorithms.

Random Forest and SVM Performance : Random Forest and SVM exhibit contrasting performances. Random Forest has an accuracy of 0.0955 and an MAE of 3.2346, indicating a moderate prediction capability. On the other hand, SVM not only has the highest accuracy (0.1492) among all models but also achieves the lowest MAE of 3.0939. This demonstrates that SVM provides more precise and consistent predictions compared to Random Forest.

Challenges with Other Algorithms : Several algorithms face challenges in achieving higher accuracy and lower MAE. For instance, GRUs have a low accuracy of 0.0797 and an MAE of 3.2142. Similarly, CNN and K-NN also show lower performance with accuracies of 0.0801 and 0.0902 respectively, and higher MAE values of 3.2026 and 3.4061.

GNB's Performance : GNB has the lowest accuracy (0.0736) and the highest MAE (5.3972). This indicates that GNB struggles significantly in making accurate predictions and has the largest errors among all the models.

Consistency in Performance : Models like ANN and MLP show similar performance metrics, with both having an accuracy of 0.0870 and an MAE of 3.2663. This consistency indicates that both models have a similar underlying architecture and prediction capability, yielding nearly identical results.

MAE and Improvement : The MAE is a crucial metric for evaluating the average magnitude of errors in a set of predictions. SVM, with the lowest MAE of 3.0939, indicates the best performance in minimizing prediction errors. On the other hand, GNB's high MAE of 5.3972 highlights significant room for improvement. LSTM, while showing competitive accuracy, has an MAE of 3.2744, suggesting a balanced approach between prediction accuracy and error minimization.

In conclusion, SVM stands out as the best performing model with the highest accuracy and lowest MAE, making it the most reliable algorithm for this dataset. While other models like LSTM show promise, they still have higher MAE values compared to SVM. GNB's performance is notably poor, indicating it is not suitable for this dataset. Consistent models like ANN and MLP offer a balanced but moderate performance. Future improvements can focus on optimizing models like LSTM to reduce their MAE and enhancing the accuracy of algorithms that currently underperform.

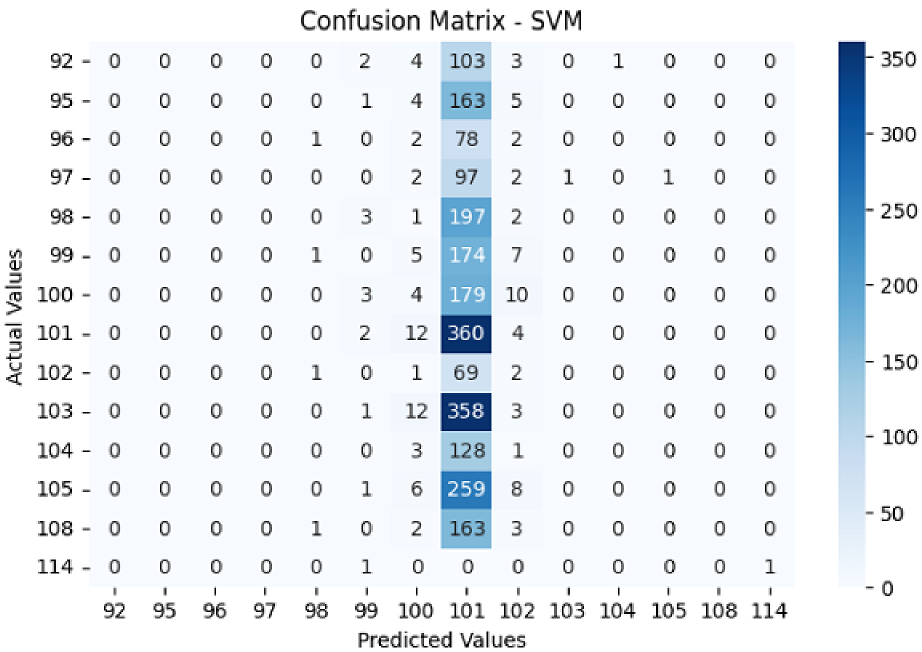

FIGURE 4.30 – Confusion Matrix For SVM Algorithm for Experiment No : 24

The Table 4.25 presents a comprehensive summary of experiments designed to evaluate emotion recognition under various conditions using physiological signals. Each experiment varies by the number of subjects, their distance from the transmitter and receiver, their positions, and their heart rate rhythms. The table also identifies the best performing algorithm for each experimental setup.

Table 4.25 – Summary of Experiments

Experiment No	**# of Subject**	**Distance (m)**	**Position**	**Heart rate rthym**	**Best Performing Algorithm**
1	1	1	Standing	Low	RF
2	1	1	Standing	High	SVM
3	1	1	Sitting	Low	RF
4	1	1	Sitting	High	SVM
5	1	3	Standing	Low	RF
6	1	3	Standing	High	LSTM
7	1	3	Sitting	Low	RF
8	1	3	Sitting	High	RF
9	1	5	Standing	Low	RF
10	1	5	Standing	High	RF
11	1	5	Sitting	Low	RF
12	1	5	Sitting	High	GRU
13	1	Subject in the Next Room	Standing	Low	RF
14	1	Subject in the Next Room	Standing	High	SVM
15	1	Subject in the Next Room	Sitting	Low	RF
16	1	Subject in the Next Room	Sitting	High	SVM
17	2	1	Standing-Standing	Low-Low	RF
18	2	1	Standing-Standing	High-High	RF
19	2	1	Standing-Sitting	Low-Low	GRU
20	2	1	Standing-Standing	Low-High	SVM
21	2	Subjects in the Next Room	Standing-Standing	Low-Low	LSTM
22	2	Subjects in the Next Room	Standing-Standing	High-High	SVM
23	2	Subjects in the Next Room	Standing-Sitting	Low-Low	SVM
24	2	Subjects in the Next Room	Standing-Standing	Low-High	SVM

5 CONCLUSION AND DISCUSSION

Calculating heart rate from Channel State Information (CSI) data is an emerging and innovative area of research. CSI is traditionally used in wireless communication systems to characterize radio channel conditions, but recent studies have explored its potential applications beyond communication, including recognition of human activity and monitoring of vital signs.

Heart rate estimation from CSI involves extracting relevant features from the CSI data that correlate with the physiological changes caused by the heartbeat. Changes in the human body, such as chest movement or respiratory patterns, can affect the radio signal propagation, and these changes may be reflected in the CSI data.

Researchers have proposed various methods to estimate heart rate from CSI, mostly machine learning algorithms. For instance, signal processing techniques, time-frequency analysis, and machine learning models like Support Vector Machines (SVMs), neural networks, and others have been applied to extract heart rate information from the CSI data.

However, it's important to note that estimating heart rate from CSI is a challenging task, and the accuracy of the results can be influenced by factors such as the environment, subject's movements, and the quality of the CSI data. In addition, extracting precise heart rate information from CSI requires careful signal processing and feature engineering, and the performance of the methods can vary between different scenarios.

While there is ongoing research in this field, it is not yet as established as traditional methods for heart rate monitoring, such as electrocardiography (ECG) or photoplethysmography (PPG). The potential for using CSI for heart rate estimation is exciting, but it may require further validation and refinement before becoming a widely accepted and reliable method in practical applications. If you are considering such an application, it's advisable to review the latest research literature and explore existing methods while being mindful of the limitations and challenges associated with heart rate estimation from CSI data.

5.1 Challenges

Despite its usefulness in wireless sensing, faces challenges during both the data collection and interpretation phases.

One challenge lies in limited accessibility to CSI data. Many consumer Wi-Fi devices do not expose CSI information directly, making it difficult to collect this valuable data. Additionally, the availability of CSI depends on the specific hardware and firmware capabilities of the wireless devices used, leading to potential compatibility issues.

Hardware limitations further complicate the situation. Not all Wi-Fi chipsets or devices support the extraction of CSI data, which can restrict the applicability of this technology. This limitation often arises due to differences in hardware capabilities and firmware constraints.

Maintaining synchronization between the transmitter and receiver poses another challenge. Even slight timing discrepancies or synchronization errors can introduce inaccuracies in the collected CSI data, impacting its reliability and usefulness.

Environmental variability introduces complexities in interpreting CSI data. Factors such as interference, reflections, and multipath effects in the wireless channel can vary over time, making it challenging to derive consistent and accurate information from CSI data, particularly in dynamic environments.

Calibration requirements add another layer of complexity. CSI data often needs calibration to account for hardware variations and inaccuracies, demanding additional efforts and resources to ensure the accuracy of collected data.

The susceptibility of CSI data to noise and interference is a notable challenge. Distortions in the received signal can affect the accuracy of CSI information, necessitating the application of filtering and signal processing techniques to mitigate these issues.

Interpreting CSI data is inherently complex due to its multidimensional nature, encompassing amplitude and phase information across multiple subcarriers and antennas. Extracting meaningful insights from this data demands advanced signal processing and analysis techniques, making it challenging for those less familiar with the intricacies of

CSI.

Security concerns are also relevant. As CSI data provides detailed information about signal characteristics, there are potential privacy and security risks associated with its extraction and analysis. Ensuring secure handling of CSI data is paramount to prevent misuse.

Considerations related to the placement and orientation of devices impact the reliability of CSI data. Changes in relative positions or orientations can introduce variations in the wireless channel, affecting the interpretability and consistency of CSI information.

Finally, in dynamic environments with multiple moving objects, the wireless channel undergoes rapid changes. Adapting CSI interpretation algorithms to account for these dynamic conditions is challenging and may require sophisticated tracking mechanisms to maintain accuracy.

Addressing these challenges involves ongoing research and development efforts in hardware improvement, signal processing techniques, and algorithmic advancements. Overcoming these obstacles is crucial to fully realize the potential of CSI for various applications in wireless communication.

5.2 Cons of the Algorithms

While various machine learning algorithms, such as CNN, ANN, RF, K-NN,GNB, SVM, LSTM,GRU,MLP offer significant advantages when applied to CSI data, there are notable challenges associated with their utilization.

One common limitation is the potential for overfitting, particularly in complex models like CNNs, ANNs, and MLPs. Overfitting occurs when a model learns the training data too well, capturing noise and irrelevant details that may not generalize well to new, unseen data. This is especially relevant in the context of CSI, where the wireless channel's dynamic nature introduces variability that may be difficult for the model to discern.

Additionally, the interpretability of certain algorithms, such as CNNs and ANNs, can be a drawback. These models often function as complex black boxes, making it challenging to understand the underlying relationships and features influencing their predictions. In applications like CSI analysis, where interpretability is crucial for diagnosing wireless channel behaviors, this lack of transparency can limit the practicality of the models.

Furthermore, the computational complexity of some algorithms, including SVMs and LSTM/GRU networks, may pose challenges in real-time or resource-constrained environments. The training and inference times of these models can be substantial, impacting their feasibility for applications that demand rapid responses, such as dynamic wireless channel adaptation.

5.2.1 Overview

TABLE 5.1 – Algorithm MAE Values Comparison for All Experiments

Experiment/ Algorithm	CNN	ANN	Random Forest	K-NN	GNB	SVM	LSTM	GRUs	MLP
Exp. No :1	2.956994	3.072016	2.927181	3.091273	4.305917	2.938615	2.942627	2.941424	3.072016
Exp. No :2	13.45279	13.45976	13.41019	14.00306	16.52102	13.39236	13.92258	13.47674	13.45976
Exp. No :3	4.091681	4.156935	3.86015	4.169752	7.005696	4.041298	4.074052	4.18456	4.156935
Exp. No :4	3.200541	3.122651	3.193371	3.35594	4.191283	3.083246	5.661273	3.158663	4.191283
Exp. No :5	4.327504	4.305917	4.297092	4.481247	6.610619	4.305099	4.574167	4.341340	4.446902
Exp. No :6	5.25066	5.167958	5.126614	5.528608	6.432262	5.06016	5.055740	5.150609	5.167958
Exp. No :7	6.392216	5.882448	5.430204	5.844625	9.006530	6.32	6.991292	6.551292	5.882448
Exp. No :8	1.995717	1.975770	1.810205	1.890602	3.130323	2.000367	1.926211	1.968061	1.975770
Exp. No :9	5.214597	5.224296	4.899232	5.195396	6.274936	5.170588	5.154987	5.146547	5.224296
Exp. No :10	8.683273	8.323697	7.586554	7.844705	11.01546	8.551932	8.916638	8.725042	8.323697
Exp. No :11	10.41649	11.19093	10.1096	10.89189	15.02135	10.38551	10.64105	10.53998	11.19093
Exp. No :12	2.458819	2.913410	3.173970	3.177666	6.096092	2.314149	2.705385	2.312038	2.913410
Exp. No :13	5.46099	5.467631	5.382368	5.798947	10.78210	5.348947	5.382368	5.391315	5.467631
Exp. No :14	3.519556	3.654185	3.595814	3.788913	4.947870	3.471732	3.548091	3.992657	3.654185
Exp. No :15	3.825242	3.90870	3.678509	3.975080	6.348877	3.800148	3.940044	3.832963	3.90870
Exp. No :16	1.030558	1.210871	0.986866	1.127690	4.29332	0.741700	0.789128	1.443998	1.210871
Exp. No :17	2.563109	2.542963	2.439744	2.588188	6.566906	2.451981	2.448523	2.786911	2.542963
Exp. No :18	4.976615	5.026117	4.932726	5.220419	5.927977	4.960031	4.944202	5.192718	5.026117
Exp. No :19	1.168611	1.308741	1.35833	1.424054	2.362988	1.063856	1.07501	1.063546	1.308741
Exp. No :20	5.361585	5.49963	5.362081	5.49927	5.635735	5.351164	5.400291	5.35844	5.49963
Exp. No :21	4.168042	4.378717	4.232891	4.441060	6.597276	4.066642	4.055893	4.236832	4.378717
Exp. No :22	3.770012	5.421630	5.196672	5.083194	10.9098	3.569384	4.032945	3.547753	5.421630
Exp. No :23	5.09411	4.970882	4.984228	5.178647	5.629056	4.812860	5.252653	4.902942	4.970882
Exp. No :24	3.202649	3.266260	3.234552	3.406097	5.397154	3.093902	3.274390	3.214227	3.266260

The 5.1 table presents the Mean Absolute Error (MAE) values for various machine learning algorithms across 24 different experiments. These algorithms include CNN, ANN, Random Forest, K-NN, GNB, SVM, LSTM, GRUs, and MLP. The MAE values provide insights into the predictive accuracy of each algorithm, with lower values indicating better performance.

5.2.2 Algorithm Performances

SVM (Support Vector Machine) : SVM consistently shows low MAE values across multiple experiments, particularly in Exp. No : 1 (2.9386), Exp. No : 4 (3.0832), Exp. No : 6 (5.0601), and Exp. No : 18 (4.9600). Notably, SVM recorded the lowest MAE in Exp. No : 16 (0.7417) and overall low MAE in Exp. No : 22 (3.5694). This consistency demonstrates SVM's robustness and reliability in minimizing prediction errors.

CNN (Convolutional Neural Network) : CNN shows competitive performance with notable low MAE in Exp. No : 1 (2.9569), Exp. No : 8 (1.9957), and Exp. No : 16 (1.0305). However, it also has some higher MAE values such as in Exp. No : 2 (13.4527), indicating potential variability in performance based on the dataset and experiment conditions.

GRUs (Gated Recurrent Units) : GRUs exhibit low MAE in several experiments such as Exp. No : 22 (3.5477) and Exp. No : 23 (4.9029), highlighting their strength in time series or sequential data. Despite this, GRUs have high MAE values in Exp. No : 7 (6.5512) and Exp. No : 12 (2.3120), suggesting room for optimization in certain scenarios.

K-NN (K-Nearest Neighbors) : K-NN shows relatively high MAE values in most experiments, such as Exp. No : 2 (14.0030) and Exp. No : 7 (5.8446). It does perform better in certain instances, like Exp. No : 8 (1.8906), but generally has higher prediction errors.

GNB (Gaussian Naive Bayes) : GNB exhibits the highest MAE values among all algorithms, particularly in Exp. No : 2 (16.5210), Exp. No : 22 (10.9098), and Exp. No : 23 (5.6290). These high values indicate that GNB may not be the most suitable algorithm for the datasets used in these experiments.

ANN (Artificial Neural Network) and MLP (Multilayer Perceptron) : Both ANN and MLP show similar performance, with low MAE in Exp. No : 1 (ANN : 3.0720, MLP : 3.0720) and higher values in other experiments like Exp. No : 22 (ANN : 5.4216, MLP : 5.4216). They tend to perform moderately well but are outperformed by SVM and CNN in most cases.

LSTM (Long Short-Term Memory) : LSTM shows a mix of performance with lower MAE in Exp. No : 8 (1.9262) and higher in Exp. No : 6 (5.0557) and Exp. No : 12 (2.7053). This indicates that LSTM can be effective for certain time series data but may require tuning.

Random Forest : Random Forest has competitive MAE values, such as in Exp. No : 1 (2.9271) and Exp. No : 8 (1.8102), but also shows higher errors in other cases like Exp. No : 7 (5.4302). It is generally reliable but may not be as consistent as SVM. Most Suitable Algorithms Based on the MAE values, SVM and CNN emerge as the most suitable algorithms due to their consistently low MAE values across various experiments. GRUs also show promise, particularly in sequential data scenarios.

5.2.3 Potential Improvements

Hyperparameter Tuning : Further optimization through hyperparameter tuning could reduce MAE values for algorithms like LSTM, GRUs, and Random Forest.

Ensemble Methods : Combining multiple algorithms might leverage the strengths of each to improve overall predictive performance. Feature Engineering : Enhancing feature sets through engineering could lead to better model performance, especially for algorithms like ANN and MLP.

In conclusion, SVM demonstrates the best overall performance with the lowest MAE values across the majority of experiments, indicating its strong predictive accuracy. CNN also shows robust performance and, together with GRUs, they offer reliable alternatives for different types of datasets. Optimizing these algorithms further through tuning and advanced techniques could lead to even better results.

5.3 Discussion

This study and its preliminary test results are published in (Solgun et al., 2023). Future research could focus on algorithm optimization, data augmentation, feature engineering, and real-time implementation to further improve the accuracy and reliability of emotion recognition systems. Overall, this study contributes to advancing the understanding and development of emotion recognition technology with diverse practical applications.

REFERENCES

Abdelnasser, H., Harras, K. A. and Youssef, M. (2015). Ubibreathe : A ubiquitous non-invasive wifi-based breathing estimator, *Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, pp. 277–286.

Abdelnasser, H., Youssef, M. and Harras, K. A. (2015). Wigest : A ubiquitous wifi-based gesture recognition system, *2015 IEEE conference on computer communications (INFOCOM)*, IEEE, pp. 1472–1480.

Adib, F., Hsu, C.-Y., Mao, H., Katabi, D. and Durand, F. (2015). Capturing the human figure through a wall, *ACM Transactions on Graphics* **34** : 1–13.

Adib, F., Kabelac, Z., Katabi, D. and Miller, R. C. (2014). 3d tracking via body radio reflections, *11th USENIX Symposium on Networked Systems Design and Implementation (NSDI 14)*, pp. 317–329.

Adib, F., Mao, H., Kabelac, Z., Katabi, D. and Miller, R. C. (2015). Smart homes that monitor breathing and heart rate, *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pp. 837–846.

Al-qaness, M. A. A., Abd Elaziz, M., Kim, S., Ewees, A. A., Abbasi, A. A., Alhaj, Y. A. and Hawbani, A. (2019). Channel state information from pure communication to sense and track human motion : A survey, *Sensors* **19**(15).
URL: *https ://www.mdpi.com/1424-8220/19/15/3329*

Alsaify, B. A., Almazari, M. M., Alazrai, R., Alouneh, S. and Daoud, M. I. (2022). A csi-based multi-environment human activity recognition framework, *Applied Sciences* **12**(2) : 930.

Anghel, M.-A. and Iacobescu, F. (2013). The influence of temperature and co2 in exhaled breath, p. 10012.

Droitcour, A. D., Boric-Lubecke, O. and Kovacs, G. T. (2009). Signal-to-noise ratio in doppler radar system for heart and respiratory rate measurements, *IEEE transactions on microwave theory and techniques* **57**(10) : 2498–2507.

Forbes, G., Massie, S. and Craw, S. (2020). Wifi-based human activity recognition using raspberry pi, *2020 IEEE 32nd International Conference on Tools with Artificial Intelligence (ICTAI)*, pp. 722–730.

Gu, Y., Zhang, X., Liu, Z. and Ren, F. (2019). Wifi-based real-time breathing and heart rate monitoring during sleep, pp. 1–6.

Ha, U., Madani, S. and Adib, F. (2021). Wistress : Contactless stress monitoring using wireless signals, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* **5**(3) : 1–37.

Hernandez, S. M. and Bulut, E. (2020). Lightweight and Standalone IoT Based WiFi Sensing for Active Repositioning and Mobility, *21st International Symposium on "A World of Wireless, Mobile and Multimedia Networks" (WoWMoM) (WoWMoM 2020)*, Cork, Ireland.

Kaltiokallio, O., Yiğitler, H., Jäntti, R. and Patwari, N. (2014). Non-invasive respiration rate monitoring using a single cots tx-rx pair, *IPSN-14 Proceedings of the 13th International Symposium on Information Processing in Sensor Networks*, IEEE, pp. 59–69.

Khan, A. N., Ihalage, A. A., Ma, Y., Liu, B., Liu, Y. and Hao, Y. (2021). Deep learning framework for subject-independent emotion detection using wireless signals, *Plos one* **16**(2) : e0242946.

Kim, H., Ben-Othman, J., Cho, S. and Mokdad, L. (2019). A framework for iot-enabled virtual emotion detection in advanced smart cities, *IEEE Network* **33**(5) : 142–148.

Li, C., Cao, Z. and Liu, Y. (2021). Deep ai enabled ubiquitous wireless sensing : A survey, *ACM Computing Surveys (CSUR)* **54**(2) : 1–35.

Ma, Y., Zhou, G. and Wang, S. (2019). Wifi sensing with channel state information : A survey, *ACM Comput. Surv.* **52**(3).
URL: *https ://doi.org/10.1145/3310194*

Muaaz, M., Chelli, A. and Pätzold, M. (2020). Wihar : From wi-fi channel state information to unobtrusive human activity recognition, *2020 IEEE 91St vehicular technology conference (VTC2020-spring)*, IEEE, pp. 1–7.

Patwari, N., Brewer, L., Tate, Q., Kaltiokallio, O. and Bocca, M. (2013). Breathfinding : A wireless network that monitors and locates breathing in a home, *IEEE Journal of Selected Topics in Signal Processing* **8**(1) : 30–42.

Pu, Q., Gupta, S., Gollakota, S. and Patel, S. (2013). Whole-home gesture recognition using wireless signals, *Proceedings of the 19th Annual International Conference on Mobile Computing & Networking*, MobiCom '13, Association for Computing Machinery, New York, NY, USA, p. 27–38.

Saxena, A., Khanna, A. and Gupta, D. (2020). Emotion recognition and detection methods : A comprehensive survey, *Journal of Artificial Intelligence and Systems* **2**(1) : 53–79.

Schäfer, J., Barrsiwal, B. R., Kokhkharova, M., Adil, H. and Liebehenschel, J. (2021). Human activity recognition using csi information with nexmon, *Applied Sciences* **11**(19) : 8860.

Solgun, H. A., Ozcan, A. and Pinarer, O. (2023). Real-time heart rate monitoring via wi-fi signal, *2023 IEEE International Conference on Big Data (BigData)*, IEEE, pp. 4973–4978.

Soto, J. C., Galdino, I., Caballero, E., Ferreira, V., Muchaluat-Saade, D. and Albuquerque, C. (2022). A survey on vital signs monitoring based on wi-fi csi data, *Computer Communications* **195** : 99–110.

Tan, B., Chen, Q., Chetty, K., Woodbridge, K., Li, W. and Piechocki, R. (2018). Exploiting wifi channel state information for residential healthcare informatics, *IEEE Communications Magazine* **56**(5) : 130–137.

Venkatnarayan, R. H., Page, G. and Shahzad, M. (2018). Multi-user gesture recognition using wifi, *Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services*, pp. 401–413.

Visserman, H. (2019). *Group activity recognition using channel state information*, B.S. thesis, University of Twente.

Wang, A., Sunshine, J. E. and Gollakota, S. (2019). Contactless infant monitoring using white noise, *The 25th Annual International Conference on Mobile Computing and Networking*, pp. 1–16.

Wang, F., Zeng, X., Wu, C., Wang, B. and Liu, K. R. (2021). mmhrv : Contactless heart rate variability monitoring using millimeter-wave radio, *IEEE Internet of Things Journal* **8**(22) : 16623–16636.

Wang, W., Liu, A. X., Shahzad, M., Ling, K. and Lu, S. (2017). Device-free human activity recognition using commercial wifi devices, *IEEE Journal on Selected Areas in Communications* **35**(5) : 1118–1131.

Xue, H., Jiang, W., Miao, C., Ma, F., Wang, S., Yuan, Y., Yao, S., Zhang, A. and Su, L. (2020). Deepmv : Multi-view deep learning for device-free human activity recognition, *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* **4**(1) : 1–26.

Zhang, Y., Liu, Q., Wang, Y. and Yu, G. (2022). Csi-based location-independent human activity recognition using feature fusion, *IEEE Transactions on Instrumentation and Measurement* **71** : 1–12.

Zhao, M., Adib, F. and Katabi, D. (2016). Emotion recognition using wireless signals, *Proceedings of the 22nd annual international conference on mobile computing and networking*, pp. 95–108.

Zheng, Y., Zhang, Y., Qian, K., Zhang, G., Liu, Y., Wu, C. and Yang, Z. (2019). Zero-effort cross-domain gesture recognition with wi-fi, *Proceedings of the 17th annual international conference on mobile systems, applications, and services*, pp. 313–325.

Appendix A PUBLICATIONS

@inproceedings{solgun2023real,
title={Real-Time Heart Rate Monitoring via Wi-Fi Signal},
author={Solgun, Hasan Ali and Ozcan, Alp and Pinarer, Ozgun},
booktitle={2023 IEEE International Conference on Big Data (BigData)},
pages={4973–4978},
year={2023},
organization={IEEE},
doi={10.1109/BigData59044.2023.10386433},
url={https://ieeexplore.ieee.org/document/10386433}
}

Real-Time Heart Rate Monitoring via Wi-Fi Signal

Hasan Ali Solgun
Galatasaray University
Grad. School of Science And Engineering
Istanbul, Turkey
hasanali.solgun@ogr.gsu.edu.tr

Alp Ozcan
Galatasaray University
Dept. Computer Engineering
Istanbul, Turkey
alp.ozcan@ogr.gsu.edu.tr

Ozgun Pinarer
Galatasaray University
Dept. Computer Engineering
Istanbul, Turkey
opinarer@gsu.edu.tr
ORCID: 0000-0002-0280-3689

2023 IEEE International Conference on Big Data (BigData) | 979-8-3503-2445-7/23/$31.00 ©2023 IEEE | DOI: 10.1109/BigData59044.2023.10386433

***Abstract*—Due to the health data privacy issues, wearable devices are less useful in the industry and can not reflect their potential power. Besides, wearable health devices bring constraints such as limited energy budget, needs to recharge and impact on daily activities. To recover these problems and fulfill healthcare needs, the recent trends in the literature is to use wireless signal to capture/recognize human activities. When human activity and emotion recognition study fields merging with the machine learning techniques, can offer a innovative systems. In recent years, with the help of wireless sensing mechanisms, this study field have gained more importance. So that, these wireless sensing mechanisms have eliminated the requirement of physical body contact such as sensor devices. Nowadays, wireless sensing technologies are preferred with the easy and cost-effective access to off-the-shelf WiFi-enabled devices. In this research, a human activity and emotion recognition system have proposed with usage of WiFi channel state information(CSI) mechanism that modelled by machine learning algorithms. As a result, with a tolerable error rate, it is possible to distinguish person's heart rate information with a contactless solution via wi-fi signal.**

***Index Terms*—channel state information, CSI, BPM calculation, wireless signal, IoT, Healthcare, wifi sensing, contactless sensing**

I. Introduction

In the recent years, Ambient Assisted Living (AAL) has become one of the hot topics in the scientific research mainstreams. Basically AAL aims to decrease health costs but provides effective solutions. AAL targets especially elderly and chronic diseases since their health costs are increasing. AAL in deed is a multidisciplinary subject to study and works on how the new technology and wearable sensor health devices can improve the quality of life. However, on the other facelet, wearable hardware devices bring significant constraints which can be crucial for elderly's daily living [1], [2].

In parallel with the increase in hospital care costs and the aging population, especially in developed countries, remote health monitoring and in-home e-health applications have come to the fore. The purpose of this type of applications includes collecting and processing information about an installation that will least affect the daily life of the person and determining the necessary alarm situations with the least error. Especially the communication parts of the studies on this subject are examined under the headings of Wireless Sensor Networks, Body Area Networks, Personal Area Networks [3], [4]. The hardware and low-level software (Firmware) to be used in such applications are still in the research phase and there are not many commercial products available.

When we consider remote health monitoring applications as a whole, we observe that they include the following stages:

(i) Taking measurements on the body.
(ii) Sending these measurements wirelessly to the local center.
(iii) Processing data and generating alarms.
(iv) Transmission of data to a central server and making it available to healthcare personnel.

When we look at the in-home remote health monitoring application requirements, it becomes clear that these should be implemented with wearable, small-sized and wireless communication feature hardware. In this respect, Wireless Sensor Networks (WSN) emerge as a natural choice as a technology to implement remote health monitoring applications.

As in almost all WSN applications, network nodes in remote health monitoring applications are equipped with limited battery energy. In this respect, regular charging of the nodes is necessary for continuous use. However, it is important to do this as infrequently as possible for the following reasons:

1) In these applications, which target people who need support to maintain their independent lives, such as chronic patients, the elderly or children, it may not be possible for people to change the equipment on their bodies. This may require the help of other people.
2) It may be necessary to take the measured medical signal from electrodes correctly positioned on the body (such as ECG, EMG), in which case battery replacement may negatively affect the process.

Monitoring breathing rates, patterns and emotions helps in the diagnosis and potential avoidance of various health problems. Such information can be derived from audio and visual information such as voice, facial expression, gesture or motion recognition using cameras. Besides, it can be monitored by physiological signals including heart rate, body temperature through wearable devices and body sensors. Tracking health signals are the key data for these applications however to have a concrete and precise result, wearable sensor devices (body contact) are highly required. When the current breath sensor hardware devices are taken into account, these devices needs to be attached to the body (mostly chest with a band).