FIRAT UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
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INTERNET OF THINGS BASED INTELLIGENT FACIAL EXPRESSION MONITORING USING EMG SIGNALS

Masood Abdulrahman OTHMAN

Master's Thesis

DEPARTMENT OF COMPUTER ENGINEERING

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THESIS APPROVAL

This thesis, which was prepared according to the thesis writing rules of the Graduate School of Natural and Applied Sciences, Fırat University, was evaluated by the committee members who have signed the following signatures and was unanimously approved after the defense exam made open to the academic audience.

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This thesis was approved by the Administrative Board of the Graduate School on

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Signature

Assoc. Prof. Dr. Kürşat Esat ALYAMAÇ
Director of the Graduate School

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Masood Abdulrahman OTHMAN
ELAZIG - 2021

DECLARATION

I hereby declare that I wrote this Master's Thesis titled “Internet of Things Based Intelligent Facial Expression Monitoring using EMG Signals” in consistent with the thesis writing guide of the Graduate School of Natural and Applied Sciences, Firat University. I also declare that all information in it is correct, that I acted according to scientific ethics in producing and presenting the findings, cited all the references I used, express all institutions or organizations or persons who supported the thesis financially. I have never used the data and information I provide here in order to get a degree in any way.

29 January 2021

Masood Abdulrahman OTHMAN

PREFACE

The purpose of this thesis is to propose a bio-sensing wearable mask device to monitor the intensity of the human status of a patient using facial surface electromyography (sEMG). Many intensive care units lack effective continuous real monitoring system for patients. Moreover, integrated remote health monitoring has still not been investigated elaborately. An effective understanding of this problem is important to enhance scalable real-time monitoring. This helps to understand embedded surface sensors integrated into the wearable devices to monitor the activities of facial muscles and remotely through the surveillance system. Thus, the final purpose of this thesis is to demonstrate facial electromyograms techniques for clinical purposes. A relationship between Internet of Things and patients are studied to solve the research problem. Machine learning and Arduino based system are used to develop facial expression monitoring using sEMG Signals.

There is a pain intensity in the facial expressions in the video or physiological signal fusion that monitors different expressions such as surprise, fear, anger, or smile. Nevertheless, limited studies are carried out on an integrated remote health monitoring system for the pain assessment. Some studies use sEMG sensors for validation of IoT to collect geospatial location data and improve employees working conditions as IoT is critical to identify the best training pathways in the healthcare environment. Solving the problems will assist in IoT system bio-potential monitoring for automatic sick situation assessment. The facial action coding system, EMG application, IoT application, machine learning, smartphone, and Arduino software are the materials and methods used for pain facial expressions and measure the facial activity of muscles.

The results show that Person 3 records the highest signal in Smile, Fear, Angry, and Surprise when compared to its Mean to that of Person 1 and Person 2. EMG measurement is critical for clinical purposes to detect facial expressions. The findings of this study contribute immensely to humanity and science for understanding of facial surface electromyography (sEMG) for remote monitoring of patients.

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Facial expressions are important aspects of human behaviors used to develop automated tools to assess anger, smile, fear, or surprise. These tools are effective to replace self-reporting methods, suitable for patients who are incapable to report their health status, especially patients in critical situation or under intensive care unit (ICU) and minors**.**

In this thesis, we propose a wearable device with a bio-sensing mask to monitor the intensity of the human status of a patient using facial surface electromyography (sEMG). Wearable devices are the wireless sensor nodes, integrated into the Internet of Things (IoT) systems for remote monitoring of patients. At 1000 Hz sampling frequency, approximately nine sEMG channels are sampled for transmission to the cloud server and cover the entire frequency range through the gateway.

We also consider low energy consumption wearing devices in the design process to carry out long-term monitoring. We develop a mobile web application to transmit large amounts of real-time sEMG data. We also perform digital signal processing, visualization, and interpretation to explain real-time sick situations such as angry, fear, surprise or smile data to caregivers.

The cloud platform is a bridge between the web browser and sensor nodes. It helps to manage the wireless intercommunication between the web application and server. This study proposes a real-time scalable IoT system for bio-potential monitoring, a solution that is wearable to automatically assess situation using classification and facial expressions to assess fear, surprise, anger, or smile.

Keywords: Bio potentials, sEMG, IoT, Facial Expression Recognition, Internet of Things.

ÖZET

EMG Sinyalleri Kullanarak Nesnelerin İnterneti Tabanlı Akıllı Yüz İfadesi İzleme

Masood Abdulrahman OTHMAN

Yüksek Lisans Tezi

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Yüz ifadeleri, kızgın, gülümseme, korku veya sürprizleri değerlendirmek için otomatik araçlar geliştirmek için kullanılan insan davranışlarının önemli yönleridir. Bu araçlar, özellikle yoğun bakım ünitesinde (YBÜ) ve reşit olmayanlarda olmak üzere sağlık durumlarını bildiremeyen hastalar için uygun olan kendini raporlama yöntemlerinin yerini almak için etkilidir.

Bu çalışmada, yüz yüzey elektromiyografisi (sEMG) kullanan bir hastanın insan durumunun yoğunluğunu izlemek için biyosensing maskeli giyilebilir bir cihaz öneriyoruz. Giyilebilir cihazlar, hastaların uzaktan izlenmesi için Nesnelerin İnterneti (IoT) sistemlerine entegre edilen kablosuz sensör düğümleridir. 1000 Hz'de bulut sunucusuna iletim için yaklaşık dokuz sEMG kanalı örneklenir ve ağ geçidi boyunca tüm frekans aralığını kapsar.

Ayrıca, uzun vadeli izleme yapmak için tasarım sürecinde düşük enerji tüketen cihazların kullanılmasını da düşünüyoruz. Büyük miktarlarda gerçek zamanlı sEMG verilerini iletmek için bir mobil web uygulaması geliştirdik. Ayrıca, kızgın, korku korkusu veya gülümseme verisi gibi gerçek zamanlı hasta durumları bakıcılara açıklamak için dijital sinyal işleme, görselleştirme ve yorumlama da yapıyoruz.

Bulut platformu, web tarayıcısı ve sensör düğümleri arasında bir köprüdür. Web uygulaması ve sunucu arasındaki kablosuz iletişimi yönetmeye yardımcı olur. Bu çalışma, gerçek zamanlı ölçeklenebilir IoT sistemi biyopotansiyel izleme, korku, sürpriz, kızgın veya gülümsemeyi değerlendirmek için sınıflandırma ve yüz ifadeleri kullanarak otomatik hasta durum değerlendirmesi için giyilebilir bir çözüm önermektedir.

Anahtar Kelimeler: Biyo potansiyel, SEMG, IoT, Yüz İfadesi Tanıma, Nesnelerin İnterneti.

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SYMBOLS AND ABBREVIATIONS

ABBREVIATIONS

AU	:	Action units
BSF	:	Band Stop Filter
ECG	:	Electrocardiography
EEG	:	Electroencephalography
EMG	:	Electromyography
EOG	:	Electrooculography
ESP	:	Extra Sensory Perception
FACS	:	Facial Action Coding System
FEMG	:	Facial electromyography
GPS	:	Global Positioning System
GSM	:	Global System for Mobile communication
Hz	:	Hertz
ICU	:	Intensive Care Unit
IDE	:	Integrated development environment
IoT	:	Internet of Things
KNN	:	K-Nearest Neighbor
LAB	:	View: Laboratory Virtual Instrument Engineering Workbench
ML	:	Machine learning
MUAP	:	Motor unit action potential
NI	:	National Instrument
SEMG	:	Surface Electromyography
SVM	:	Support Vector Machine
TCP	:	Transmission Control Protocol
ICUs	:	Intensive Care Units
MUAPs	:	Motor Unit Action Potentials
LDA	:	Linear Discriminant Analysis
RMS	:	Root Mean Square
ROC	:	Receiver operating characteristic

1. INTRODUCTION

In the healthcare system, the facial expression monitoring system (FEMS) is critical for optimizing the health process [1], and this facilitates the workflows and reduces medical costs. The FEMS is a pivotal tool for remote sensing, patients' diagnosis, and for relieving patients' discomfort. Previous studies have used many tools such as telemedicine, survey methods, and focus groups to collect data on patients' health and suitable medication [1-2]. Their outcomes reveal that angry, surprise, or smile monitoring systems and feedback systems are the pivotal tools to monitor daily habits. However, many constraints have been recorded to meet this self-reporting approach. For example, people face challenges to enter and monitor daily information manually. Moreover, this method is unsuitable for people with limited cognitive and expression skills, such as children with limited intelligent, newborn babies, sedated patients, and older adults' patients subjected to intensive care units (ICU). Lack of effective real monitoring system for patient continuous is the third shortcoming, leading to persistence and severe delay in patient's long-time intensive care.

Recent studies are explored to evaluate the facial expressions in the video [2] or physiological signal fusion [1], regarding pain intensity monitoring that involves surprise, fear, angry, or smile. Nevertheless, limited studies are carried out on an integrated remote health monitoring system for pain assessment.

To identify facial expressions, extracted features must be categorized into unique different classes. Different factors lead to misclassification and EMG pattern variations which are electrode positions, muscles tiredness, sweating, and different causes. A proficient and fast classifier can address these shortcomings, which involves novel patterns that are required to implement effective online training to achieve real-time constraints. Different classification algorithms that uses machine learning is used for the facial expression's classifications [1-2].

Fright, annoyance, happiness, unhappiness, anxiety, and profound disapproval are remarked daily through specific facial expressions. However, studies that explore the context of facial expression in pain are scanty, essentially for the academic, psychological, medical research. Pain is a pivotal symptom experience by chronic-ill patients. However, measurement of pain in an unbiased manner is still challenging [2].

In clinical settings, common bioelectrical signals to measure mental and physical activities, such as heart, eyes, brain, and muscle are "Electrocardiography (ECG), Electrooculography (EOG), Electroencephalography (EEG), and Electromyography (EMG)" signals, respectively. These applications perform the pivotal roles in monitoring bio-signal activities that include analysis of muscle activation and diagnosis of heart disease.

1.1. Literature review

Numerous studies have discussed different functions of facial expression monitoring systems. Moreover, EMG sensors are effective for the validation of IoT, used to collect geospatial location data and improve employees working conditions. Undergraduate and master's students can use IoT to collect research information and improve their academic learning. IoT is critical to identify the best training pathways in the healthcare environment.

Facial expression monitoring systems had attracted the attention of several studies in the previous decades. The face is an object of major importance as it identifies people. Facial expressions are evaluated through pain in facial muscles because they communicate emotions [3]. Facial expressions are observed through conversation and interactions with other persons, neighborhood, and environment. Facial expressions play an active role in human feeling and enhancing verbal communication [4]. According to Ekman [11] emotions such as fear, sadness, surprise, anger, and happiness are types of facial expressions. Non-verbal communication is another example of facial expression as this displays nervousness [6]. Eyes are also significant features of facial expressions; eyes as organs of vision can be used to evaluate an individual nervousness. Eyes contact is also an important aspect of interpersonal communication. For further clarifications, facial expression analysis will be discussed in discussion and analysis section.

The Facial Action Coding System (FACS) that is developed by Ekman and Friesen [7] is the most used technique to code facial expressions in the behavioral sciences [15], and it is a research tool to measure facial expression [9]. To apply this method, 46 components corresponding to the movements of individual facial muscles will be described [8]. The method provides a comprehensive technique to investigate the elementary component of expressions, assisting in decomposing a complete speech into phonemes, proven to discover facial movements that reveal emotional and cognitive states [13]. FACS has some of the shortcoming such as manual coding is considered the major one as it is time inefficient. Moreover, it is cost-ineffective as it consumes more than 100 hours of training to master and proficient FACS tasks. The manual coding of video takes also nearly two hours. FACS can assist in describing the facial expressions and Action units (AU). This represents a small fraction of the method to build facial expression. The action of facial muscles is the focal point of FACS AU [10]. AU is a small fraction that cannot be interpreted as originated from the action [11].

The EMG application is carried out with an electromyogram to record electrodes and translate an electrical signal into a graph. The EMG can detect the potential signal when myocytes are activated by electricity or nerves. Signals help to detect medical abnormalities. Moreover, the activation level help to evaluate the "biomechanics of human or animal movement" [12].

Facial EMG is more effective and precise for recording and measurement of facial expression than depending on visual observation. EMG is effective in measuring muscle activity, which helps to amplify and detect small electrical pulses emitted through the contraction of muscle fibers. Through the electrical activity, EMG can be used to measure small changes in the facial muscles, thereby reflecting small muscle movements. Moreover, EMG plays a leading role in biomedical applications and clinical diagnosis [17].

1.2. Facial Expressions

The face is an object of major importance as it identifies people. Facial expressions are evaluated through pain in facial muscles because they communicate emotions [6]. Facial expressions are observed through conversation and interactions with other persons, neighborhood, and environment. Facial expressions play an active role in human feeling and assist in enhancing verbal communication [3]. Based on Ekman [10], the major types of facial expression are fear, surprise, sadness, anger and happiness. Non-verbal communication is another example of facial expression as this displays nervousness [9]. Eyes are also significant features of facial expressions; eyes as organs of vision can be used to evaluate an individual nervousness. Eyes contact is also an important aspect of interpersonal communication.

1.2.1. Facial Action Coding System

Ekman and Friesen [11] have developed a unique method to code facial expression and it is also considered the most common in the fields of behavioral sciences. 46 gestures relating to facial muscle movements is included in the elements. As shown in Figure 1.1 [4], the method provides a comprehensive technique to investigate the elementary component of expressions, assisting in decomposing a complete speech into phonemes, proven to discover facial movements that reveal emotional and cognitive states [5]. Time inefficiency in manual coding is regarded as one of the major shortcoming of this method. Moreover, it is cost-ineffective as it consumes more than 100 hours of training to master and proficient FACS tasks. The manual coding of video takes also nearly two hours. FACS can assist in describing the facial expressions and Action units (AU). This represents a small fraction of the method to build facial expression. The core of this method entirely depends on the action of the facial muscles [13]. AU is a small fraction that cannot be interpreted as originated from the action [6]. Appendix A [7][8] provides an overview of AU and FACS with their corresponding facial muscles.

In this thesis, we investigate a branch of behavioral science and time required to code FACS automatically and manually train by a human expert. The system will be accessible to the thesis community, and it will an important tool for human-computer interaction.

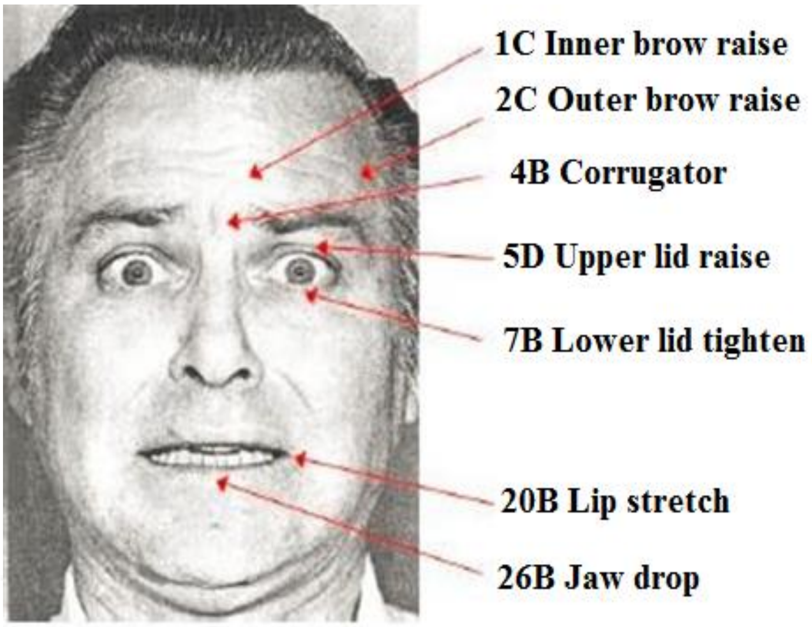


Figure 1.1. Example of facial action from the FACS [15].

1.3. Electromyography

The EMG application is carried out with an electromyogram to record electrodes and translate an electrical signal into a graph. The EMG can detect the potential signal when myocytes are activated by electricity or nerves. Signals help to detect medical abnormalities. Moreover, the activation level help to evaluate the "biomechanics of human or animal movement [9].

For recording and measuring facial expressions, EMG is more accurate than visual observation. EMG is effective in measuring muscle activity, which helps to amplify and detect small electrical pulses emitted through the contraction of muscle fibers. Through the electrical activity, EMG can be used to measure small changes in the facial muscles, thereby reflecting small muscle movements. In this way, EMG can measure both facial activities and produce weak emotional stimuli shown in Figure 1.2.

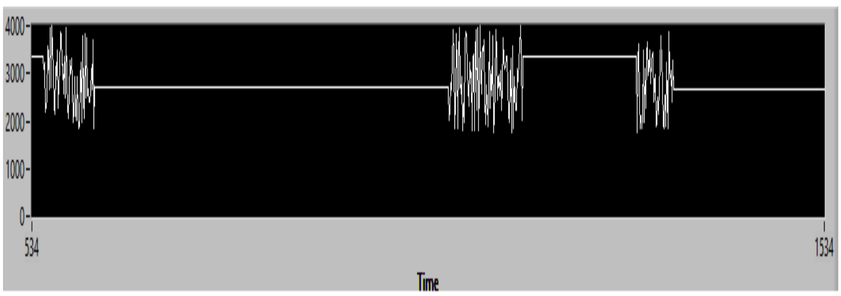


Figure 1.2. Electromyography signals

1.3.1. Usage and Benefits of Facial EMG

Human facial activity serves as a source of a wealth of information [10]. Measuring facial electromyogram is a critical tool to obtain useful information. The potential facial EMG application comprises of brain information that includes emotions, pain, mental disorders, fatigue, etc., which may be observed from the face. Many paralyzed people owing to illness and accident may fail to carry out the physical exercise and facial muscle exercise. Thus, EMG plays a leading role in biomedical applications and clinical diagnosis [18]. The major benefits of facial EMG are as follows [19]:

1. It is an accurate and sensitive process for measuring emotional expression.
2. It helps to measure or detect weak facial muscle signals [11].
3. EMG is not as disturbing as other physiological indicators such as electroencephalogram (EEG) and f MRI [12].
4. Facial EMG measurement is the only useful method when no movement is visible to the naked eye.
5. EMG is a language-independent and does not require memory.

1.3.2. Analysis of EMG Signal & Recording

An EMG signal processing is subdivided into three parts:

- Electrode selection and placement
- EMG Recording
- Signal Processing

In facial EMG activity, every step is carefully handled to eliminate noise and reduce measurement error.

Electrode selection and placement: - Potential bio-activities human body can be picked by the electrode between the human body and measurement instrument. A transducer can convert one form of energy into another form, taking the bio-potential signals from the human body and convert it into the electrical signal. Two types of electrodes are used to detect EMG signals: surface electrode and needle electrode. The surface electrode is mostly used because it is non-invasive. Table 1.1 provides a comparison between the electrodes [22].

Table 1.1. Comparative analysis between surface and needle Electrode [22]

	Surface Electrode	Needle Electrode
Advantages	• Easy to use • Non- invasive • Large recording region • Safer electrodes • No hider movement.	• **Capable of identifying and detecting MUAP** • **Better selectivity of the needle electrodes** • **High signal to noise ratio**
Disadvantages	• Measuring exclusively the surface muscle EMG • Artifact • Low signal to noise ratio • Poor selectivity	• **Difficult to use** • **Movement obstructing** • **Hazardous** • **Invasive**
Applications	• **Recorded large muscles** • **Violent exercise**	• **Ability to record single motor units or small muscles.** • **Ability to record deep into the muscle**

Using a conductive gel or paste, surface electrodes can detect the EMG signal for double-sided adhesive collars to attach surface. This is often applied in paired electrode configuration. The amplitude and spectrum of the signal will depend on the location/position of the electrode. Thus, it is critical to insert an electrode on the best facial EMG position, and the best suitable electro deposition is inserted in the muscle stomach [23]. The amplitude of facial EMG signals is low because finding the correct right position of the electrode is not an easy task [22]. Figure 1.3 reveals the electrode location used to measure facial activity.

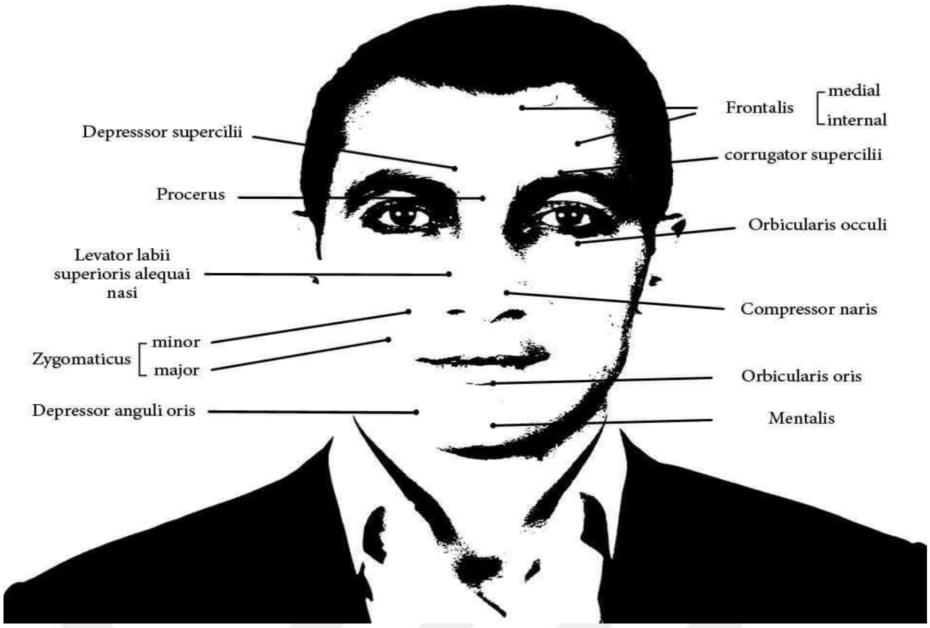


Figure 1.3. Electrode locations for measuring Facial EMG activity

In Figure 1.3, data are available when evaluating the facial muscles. The reference electrode is referred to as ground electrodes, inserted at a 3-4 cm midline app, superior to the upper borders of the inner eyebrows. The human frontalis muscle offers the function of facial expressions that covers part of the human skull. At 1cm lateral to the vertical line, the electrode is placed on the imaginary vertical line in the frontalis of the vertical line, which traverses the pupil of the eye [25]. In facial expression, Zygomatic major is the muscle, drawing the angle of the mouth that helps to smile.

To evaluate the electrical activity in Zygomatic major, we place an electrode in the midway and the imaginary line to join the preauricular and cheilion depression. In the second electrode, it is placed at 1 cm inferior to the first electrode toward the same imaginary toward the mouth [13].

Signal processing stage is the second stage. The EMG is significant as it serves as the first information for the facial muscle innervations. Before measuring facial EMG signal, EMG signals contain the noise and error, generated by other muscles in the face, electrode contact or by power line interface [14]. In this case, signal processing is critical for this analysis. On facial muscle, we insert the electrode on the patient skin. The EMG signal delivers the preamplifier, which provides two functions:

Signal EMG intensity is too small, which the computer could unable to read.The loading effects are minimized by the high input impedance amplifier [15]. An analog-to-digital converter, subsequent pre-amplification, and the predominated frequency range of facial EMG signals pass filtered (Butterworth filter) within the 20-550 Hz frequency range [3].

The 50 Hz power line interference is removed by applying a 50 Hz notch filter. In signal processing, we use a rectifier to convert all negative amplitudes into positive amplitudes. Then, we move the negative spikes to positive, reflected by the baseline. In this way, we collect the absolute signal value, referred to as full-wave rectification, critical to obtain the EMG signals shape or "envelope" [16].

We record the EMG using the facial muscle electrode. We measure the bio-electrical activity using the facial muscle electrode. Then, we sent the ground electrode to an amplifier. Using electrical activity, the amplifier is used to eliminate random voltages. To produce a raw EMG signal, this is achieved by removing the signal from the muscle electrode and the ground electrode [17].

1.4. Facial electromyogram

Facial muscles and skeletal muscles are equal in characteristics. They are striated muscle contracted owing to potential action in the muscle cell base. Facial muscles comprise of motor units that can generate a potential action when the motor unit catches fire.

Motor unit action potential (MUAP) is used to monitor the sum of the motor 1 unit. MUAP and motor unit can be seen from the surface electrodes when there is a distribution of the cells of motor 1 unit through a larger part of muscle as opposed to its concentration at one point. We processed EMG montages similar to EEG montages. Cacioppo and Fridlund [18] enhance understanding of EMG research.

Target muscles determine facial expressions using FACS. This reduces the influence of non-target muscles on motor units. However, EMG placement should be carried out carefully. As revealed by Hayes, primary energy on the EMG signal is between 10 and 200 Hz [21]. Between 10 and 30 Hz, this power is based on the motor unit firing rates. Whereas, the motor unit action potential (MUAPs) shape play a bigger role at higher frequencies [18]. According to Van Boxtel [5], a 15- 25 Hz high-pass filter frequency for facial EMG, which depends on the muscle, is effective to eliminate low-frequency contamination. However, EMG signals are kept and used for further measures.

EMG is used to record an electrode on the facial muscles**.** We measure the bio-electrical activity using the ground electrode and facial muscle electrode, sent to an amplifier. This erodes the amplifier random voltages. The signal is subtracted from the ground electrode using electrical noise.

1.5. The aim of thesis

In this thesis, we introduce cloud technology to achieve scalability and the IoT as an evaluation tool to carry out systems that monitor remote patients. The proposed systems for inpatients and ICU patients are the pain intensity testing tools, which is an alternative for facial video detecting tool, referred to as sEMG.

Embedded surface sensors integrated into the wearable devices are the effective systems to monitor the activities of facial muscles and remotely monitored through the surveillance system.

Besides, embedded surface sensors offer a remote facial expression monitoring system and effective for the assessment of sick situations. Our system offers multi-functional purposes that include "wireless network transmission, signal preprocessing, visualization of remote data, and bio-potential data acquisition."

With the assistance of the Wi-Fi hotspot technology, we can access the system devices using a backend cloud to support patients. Computer systems and smart devices using network systems offer effective care to the patient.

The purpose of this thesis is to demonstrate EMG techniques for clinical purposes. The human face is a rich source of information and offers an emotional state, such as pain, anger, sadness, etc. [1]. In this thesis, we investigate the possibilities of acquiring and processing the facial EMG signals to extract the time-domain signal intensity using various filtering, rectification, and similar techniques to measure the effect of pain and its signal sensitivity.

Zygomatic muscle activity of facial EMG that controls smiling and frontalis muscles were recorded, processed and analyzed. Facial EMG offers the following main benefits: It helps ICU patients, children, and neonates to experience no pain or hurt verbally. Although, pains suffered by new born babies are often unidentified because babies are unable to communicate with us [18]. Moreover, we are unable to observe the ICU patients for a long period [19]. Thus, it offers the major hurdle to analyze pain young children and infants are undergoing [20].

Facial expression is the assessment tool to describe emotional intensity in neonates and patients in ICU. Thus, facial EMG is an effective tool to measure people's emotional responses. These signals are measured during human-computer interaction and when playing video games. However, this thesis is mainly for clinical purposes.

2. INTERNET OF THINGS AND MACHINE LEARNING

2.1. Internet of Things (IoT)

The IoT is rapidly developing in the present Information Technology (IT) environment. IoT is a fusion of wireless networks and computing. Presently, IoT has become one of the most rapidly developing technologies in many countries. The IoT connects physical infrastructures such as vehicles, buildings, and various gadgets to embedded smart sensors. This helps in exchanging and collecting information from different environment [18].

The IoT has become popular in all aspects of life, which include online business, smart cities, healthcare, smart security, and smart grid [18]. The IoT shares knowledge and information globally. To improve daily life, IoT helps to share food, personal computers, and to automate various programs [21]. The IoT is a dynamic network globally connected to the Internet, interconnected with the virtual and physical objects. The IoT connects data to the physical or virtual world [2]. Moreover, IoT is a smart world that connects the wireless network between physical and virtual objects. IoT facilitates smart cities and smart homes integration [22]. The wireless sensor network is critical to the IoT as this facilitates sensors' interconnection to obtain information from servers or automated systems [23]. The IoT is defined as interconnected computing devices, objects, and machines with the ability to transfer network devices through IT. The IoT automates and facilitates human daily life and interconnect the entire human race [24].

2.1.1. Top IoT Applications

IoT has become a part of human lives, and the new most important areas to apply IoT are given as follows:

- Health care: With the IoT, people's health can be monitored through sensor devices to track their daily activities remotely. Health care systems and smart medical devices can be used in companies and people's health [25].
- Smart city: IoT can be used to solve traffic congestion using smart city applications, thereby make cities safer and reduce noise and pollution. Through smart cities, people will illuminate the streets more effectively [26][19].
- Smart grid: A smart grid is one of the specific IoT applications, implemented through the behavior of electricity suppliers and buyers in an automated way to improve reliability, availability, and economics of electricity [18].

- Wearable: Wearable in IoT continues to be a hot topic. Wearable's creator, Jawbone, is probably the one with the greatest funding to date for all IoT startups. Many wearable objects are available, such as a smartwatch and a Sony smart trainer [34].
- Transportation and logistics: Transportation and logistics are the first business units interested in IoT applications using the GPS, GSM and light sensors to track items [27].
- Home automation: Monthly utility bills will be reduced if people can connect homes. Many companies are more dynamic in using IoT for home automation [28].

IoT application areas are shown in Figure 2.1

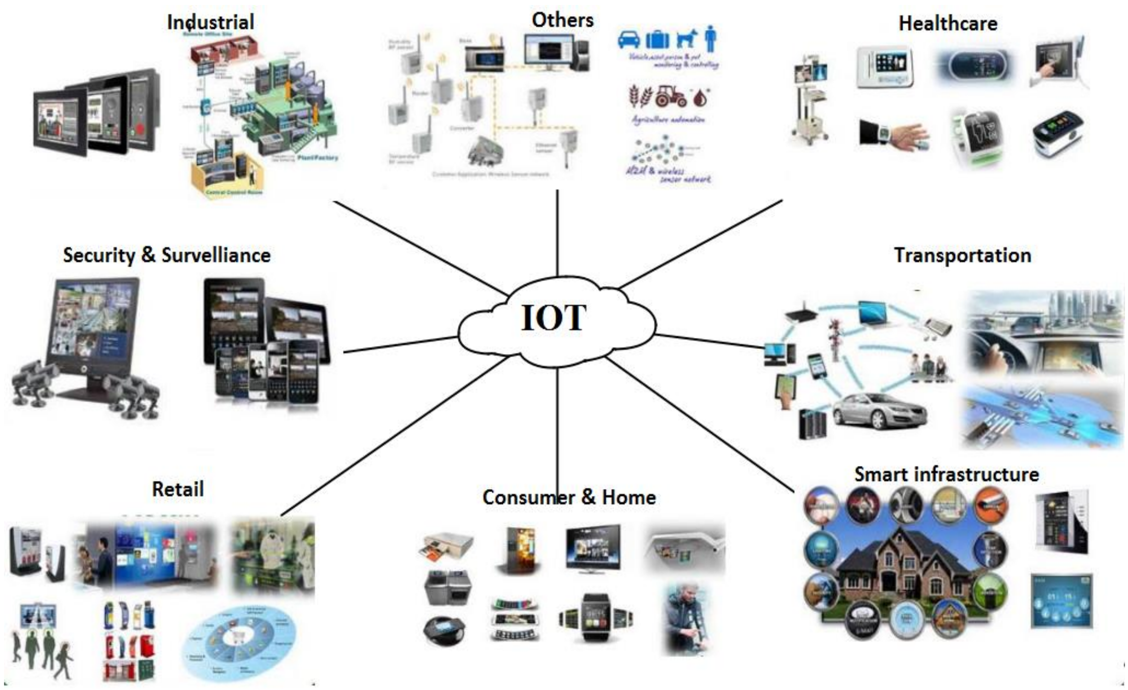


Figure 2.1. The areas of IoT application

In Figure 2.1, the IoT has been used in many applications. Some applications are attributed to IoT platforms while others are not. Nonetheless, none of the applications has a computer vision module that allows images to be used as sensors [29].

2.1.2. IoT Platform

As discussed previously, we must connect these applications to achieve full IoT potential. IoT platforms must be used to manage these applications [30][42].

A camera, as a connected device, is also an engine that can be used to capture images under specific conditions and the goal is to use the camera's image through the sensor. For example, when certain conditions are reached, the camera may connect and send images. The proposed system is a solution for using a camera with a computer vision and sensor to detect objects in the image [31].

The IoT architecture consists of a variety of technologies, such as cloud services, sensors, communication layers to understand how different technologies are linked and set-up through IoT arrangement [32]. Figure 2.2 shows layers of an IoT system.

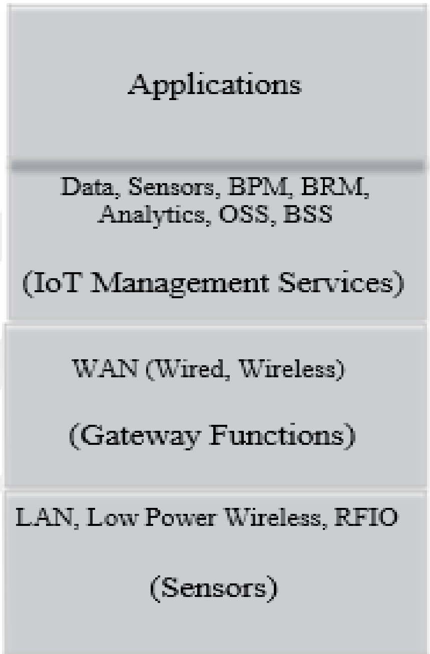


Figure 2.2. The IoT architecture

All layers of IoT are depicted as follows:

- ✓ **Application layer:** The application provides a user experience.
- ✓ **Management service layer:** In this layer, certain information processes will be completed through security control, analysis, management of the equipment, and process modeling.
- ✓ **Gateway layer:** This layer helps in applying powerful and high-performance wired or wireless network infrastructure such as vehicle media.
- ✓ **Sensor connection and network:** This layer can interconnect the digital and physical world to collect and process real-time data.

2.2. Machine learning

Machine Learning (ML) is the statistical and algorithmic models used to carry out specific tasks without implementing explicit instructions. ML is a subset of artificial intelligence that relies on reasoning and patterns [28]. Applying mathematical model, ML algorithms used sample data (referred to as the "training data") to predict specific tasks without carrying out explicitly programming [33].

Computational statistics are closely interrelated with ML as both use computer systems to make predictions. Using unsupervised learning, ML uses mathematical optimization that uses theory, methods, and application to focus on exploratory data analysis. [34]. ML is also a predictive analysis of cross-business problems. ML is a pivotal tool to predict the future; it helps classify information to assist people to make valid decisions. In ML, we develop algorithms to analyze and train historical data to identify patterns to predict future events shown in Figure 2.3.

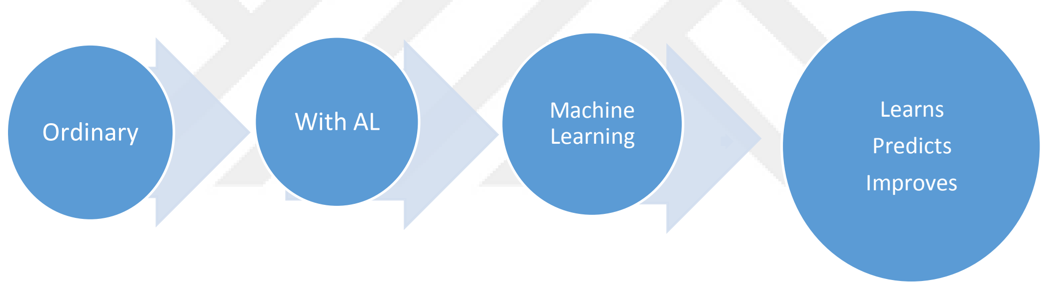


Figure 2.3. Machine Learning

There are three learning methods for machine learning which are supervised learning, unsupervised learning, and reinforcement learning. Regarding supervised learning, the trained dataset is labeled as a mapping between input and output. The input model is trained using different examples. With the trained dataset using the ML algorithm, the spam data can easily be detected as shown in Figure 2.4.

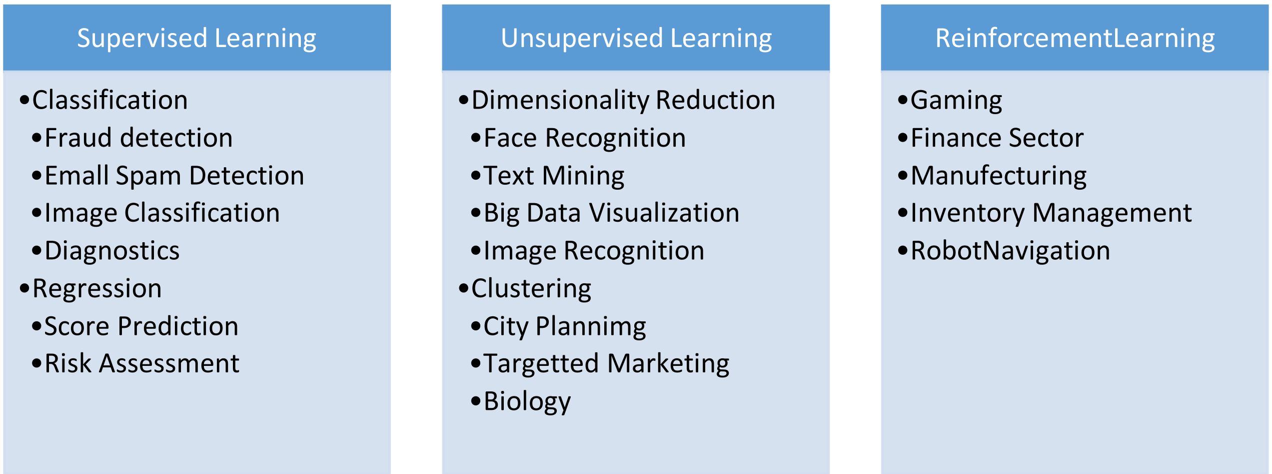


Figure 2.4. Types of Machine Learning

Classification is the division of data into several groups that are predefined. This entails assigning old data forecasts to previously unseen data records based on a trained construct model. [35]. Examples of the use of classification algorithms include: determining if a credit card transaction is fraudulent or not, judging whether the mortgage default probability is fair or bad, diagnosing whether a patient has a certain condition, a simple picture that should or should not be branded as a cat [36]. The most well-known algorithms used in the literature and chosen for use in this research are as follows. There are several distinct algorithms for classification.

2.2.1. Naïve Bayes Classifier

The algorithm for the Naïve Bayes classifier is named after the classification algorithm for Thomas Bayes. The Naïve Bayes classification is intended to determine the class (i.e. the form of data given to the system) with a set of calculations defined in accordance with the probability principles [37]. The 'Naïve' part of the algorithm comes from the fact that it is presumed that the attributes (features) are independent of each other in the dataset. This implies that all of the other attributes are not contingent on the presence of an attribute in the dataset. The framework includes a certain amount of training data under the Naïve Bayes classification. There must be a class category for the data provided for learning [38]. The new test data submitted to the system are run according to the pre-obtained probability values with the probability processes carried out on the training data and the test data submitted are used to assess the category [39][40].The Bayes Theorem is defined as follows:

$$P(C|X) = \frac{P(X|C)*P(C)}{P(X)} \quad (2.1)$$

In (2.1), P(C) is the posterior probability of attribute X given to class C. P(X) is the probability that class C attributes are given. The previous probability of class C is P(C), and the prior probability of the attributes is P(X).

The Naïve Bayes classification can be summarized as follows:

• The dataset is translated into a frequency table.

• The most probable class would be considered as the class estimate [38][39].

• The likelihood of each variable is determined for probability classification.

In calculating the likelihood of each class, the Naïve Bayes equation is used.

It is usually assumed that a continuous-valued attribute has a Gaussian distribution with a mean μ and standard deviation σ, defined by

$$g(x, \mu, \sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{2.2}$$

For those classifiers that do not use Bayes' theorem, a theoretical rationale is given by Bayesian classifiers by using filing. For example, under some conditions, it can be seen that, like the naive Bayesian classifier, several neural network and curve-fitting algorithms yield the maximum posteriori hypothesis.

With predictors continuous and not in discrete values, it is assumed that a Gaussian distribution give samples as values. The training of multiple classifiers for expression classification. Based on the training data, the Gaussian distribution parameters of each expression is estimated by the feature matrix. In the test data, we calculate the posterior probability of the category c for pattern recognition [40].

The Gaussian of the Bayes' theorem is clarified in the following equation. It is obvious that variable X of the probability density is continuous and functions as a category c which is Gaussian [39].

2.2.2. Decision Trees

Decision Tree algorithms for supervised learning are among the most common algorithms. It can be used in order to solve problems of classification and regression. However it is often used in classification, since planning and tests are easy and the results are easier to explain and more effective [41]. Decision-tree classification is conducted in two stages. For a tree to be built, the first move is. In the second step, classification rules are obtained from this tree structure. According to the algorithm used, the tree structure can differ. Different tree structures may offer various outcomes for classification. There are a number of algorithms based on decision trees that are developed. According to root, node, and branching parameters, these algorithms are divided into different categories. ID3, C4.5, CART, and C5 [42] are widely recognized algorithms.

The C4.5 algorithm was used in this thesis. It is one of the algorithms with the most simple decision tree. To calculate how far apart the teaching samples are [43], it uses the principles of entropy and information gain. Here are the formulas of these two principles summarized.

$$info(D) = Entropy(D) = -\sum_{i=1}^{m} p_i \, log2(p_i) \tag{2.3}$$

Where D is the training dataset, the probability of class observation is determined by p_i and the number of samples is m. In Equation 2.3, the measurement of the expected information to identify the observation in D is given. The quantity of information is still needed after the separation process in order to establish a good classification, and this is given in Equation 2.4.

$$Info_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} * Info\left(D_j\right) \tag{2.4}$$

Where A is a vector of {a1, a2 ... av} attributes. It will break the D attribute A into {D1, D2 ... Dv}. Then, as shown in Equation 2.4, the information gain is derived from the difference between Equations 2.5.

$$Gain(D) = -info(D) - Info_A(D) \tag{2.5}$$

Thus, the attribute provides high knowledge gain when the decision tree is generated using data gain, and the distinction will be made [43].

2.2.3. Logistic Regression

Logistic Regression is another well-known supervised learning algorithm used for classification. Logistic Regression predicts the probability of an outcome which can only have two values (binary 0 or 1). The calculation is based on the use of one or two predictors (numerical and categorical) [44]. Logistic Regression gives the relationship between the predictive attributes (independent variables) and the goal attribute (dependent variable). A logistic curve that is restricted to values between 0 and 1[45] The logistic regression model is developed by. The Model Formula of Logistic Regression is given by:

$$P(Y = 1|X = x) = \frac{1}{1+e^{-(b_0+b_{1x})}} \tag{2.6}$$

Only two values are used for the goal attribute, such as Y = 0 and Y = 1, and b is a coefficient that can be calculated from the maximum probability equation. T The linear and logistic regression model formula is shown in Figure 2.5.

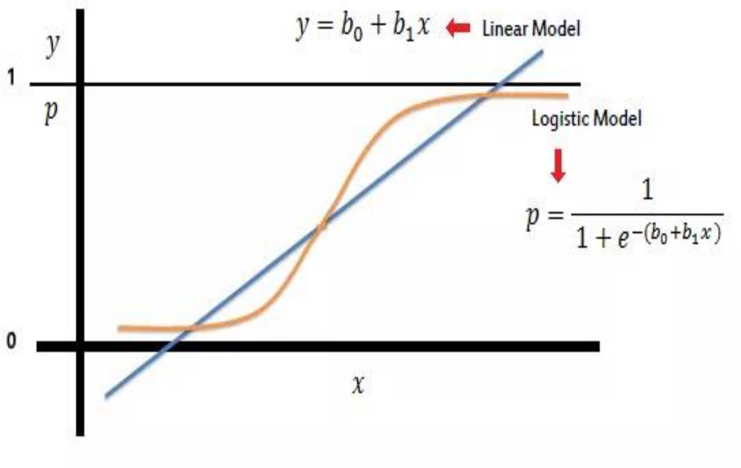


Figure 2.5. Linear and Logistic Regression Model

2.2.4. Support Vector Machine (SVM)

SVM is a supervised learning algorithm based on supervised learning theory which is used to classify and regress. The SVM is a linearly divisible two-class learning operation, [46]. The goal of the SVM is to find a hyper plane with a maximum margin capable of separating the two groups. In the training data of a classifier, an excellent classification performance and high precision of estimation for data from the same distribution as the training data can be generalized. In two classes, support vector machines are broken down into linear and nonlinear vector support machines. The ideal representation of the linear separable hyper plane shown in the Figure 2.6 [47].

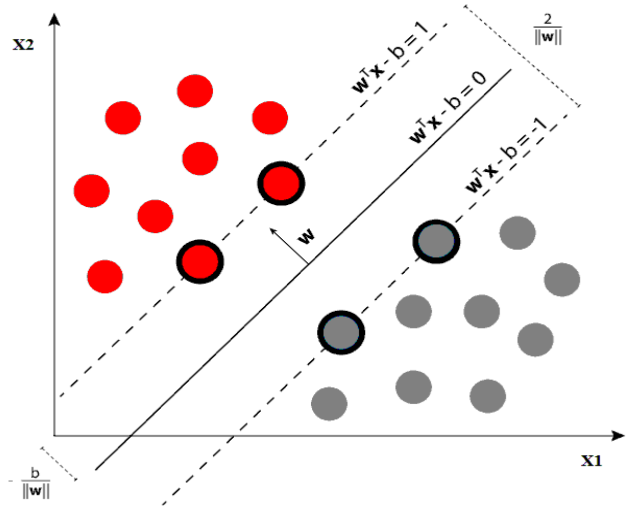


Figure 2.6. SVM for Classification Problem

The difference between two planes of equal distance is called a margin, seen in the dotted lines in Figure 2.6 and drawn parallel to the separator plane. Linear SVM uses a high-dimensional input vector; the plane which best separates a training set of (xi, yi) pairs is defined as in Equation 2.7. [13].

$$\boldsymbol{w}^T x_i + b \geq +1 \qquad for\, y_i = +1$$
$$\boldsymbol{w}^T x_i + b \leq -1 \qquad for\;\; y_i = -1$$

(2.7)

$$m = \frac{2}{\|\boldsymbol{w}\|} \qquad to\ maximiz$$
$$m = \frac{\|\boldsymbol{w}\|}{2} \qquad to\ minimize$$

$$W^{T\, X_i} + b = 0 \tag{2.8}$$

In Equation 2.8, where xi is any point, yi is a class label, yi {+1,-1}, w is a normal hyperplane, weight variable, m is the distance margin of the boundary plane, and b is a fixed bias. In classification problems, we aim to raise the margin or decrease the 'w'.

2.2.5. K-Nearest Neighbor (K-NN) Algorithm

K-NN is one of the simplest and most widely used classification algorithms. It is used to solve both classification problems and regression problems. [48]. K-NN is an algorithm for non-parametric learning, also called lazy'. The notion of "lazy" means that schooling should not have a preparation period. It does not benefit from the outcomes of testing, but instead it "memorizes" the training dataset. In the entire dataset, it finds the closest neighbors [49] When it is used for a forecast to be made. The distance of the latest data to be included in the sample dataset shall be calculated on the basis of the available data and the area of K in the vicinity shall be investigated. Three kinds of distance functions are widely used for distance measurements; Euclidean distance, distance from Manhattan, and distance from Minkowski. In this thesis, we use Minkowski distance to [16] [17], A standard measure used for measuring the distances between the characteristics of the input. The formula is shown below. [50] for this distance.

$$d(i,j) = [\textstyle\sum_{k=1}^{n} |x_k - y_k|^{\wedge q}]^{\wedge 1/q} \tag{2.9}$$

Where the value of q is normally between 1 and 2, it can also be infinity. As seen in the Figure 2.7, Two observation points are x and y, and d is the difference between two points and the number of samples is n..

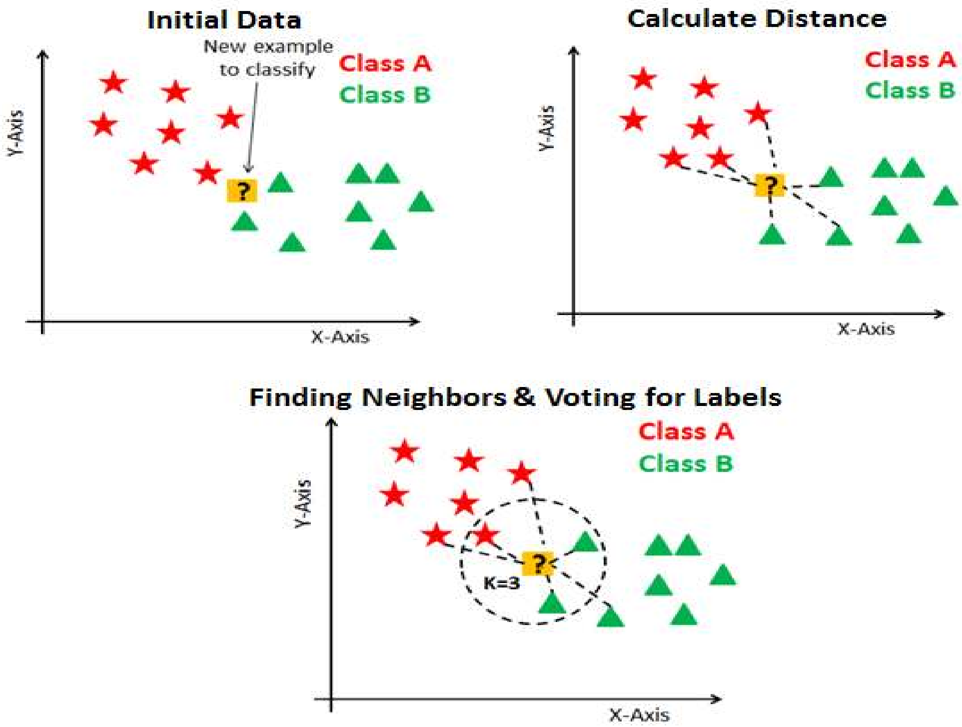


Figure 2.7. K-NN Algorithm

The Minkowski distance measure is a general distance measure, and special cases of Minkowski distance measure are Euclidean and Manhattan distance measurements. The distance from Minkowski will be the distance from Manhattan for q=1 and the distance from Euclidean for q=2.

3. MATERIAL AND METHOD

3.1. Hardware Implementation

3.1.1. Arduino

Arduino is easy to use open-source tools that consists of hardware and software. The Arduino board can read input indicators through sensors. The buttons or messages can be converted to outputs-activate motors. With the LEDs, the content is posted online. With Arduino, we can send a set of instructions to the microcontroller board, using the Arduino software and the Arduino programming language.

For many decades, developers have used Arduino to develop thousands of projects, from ordinary objects to complex scientific projects. Students, artists, hobbyists, professionals, and programmers use the Arduino to accumulate incredible knowledge through newbies and experts [51].

It is useful for students who have no electronics and programming background knowledge. In the software community, the Arduino board can accommodate new challenges, from simple 8-bit boards to IoT applications. It is also applied in wearables, 3D printing, as well as embedded environments. The entire Arduino development boards are open source, assisting users to build applications specific to their needs. The software is an open-source, constantly evolving through global contributions. Figure 3.1 represents the prototype of the Arduino.

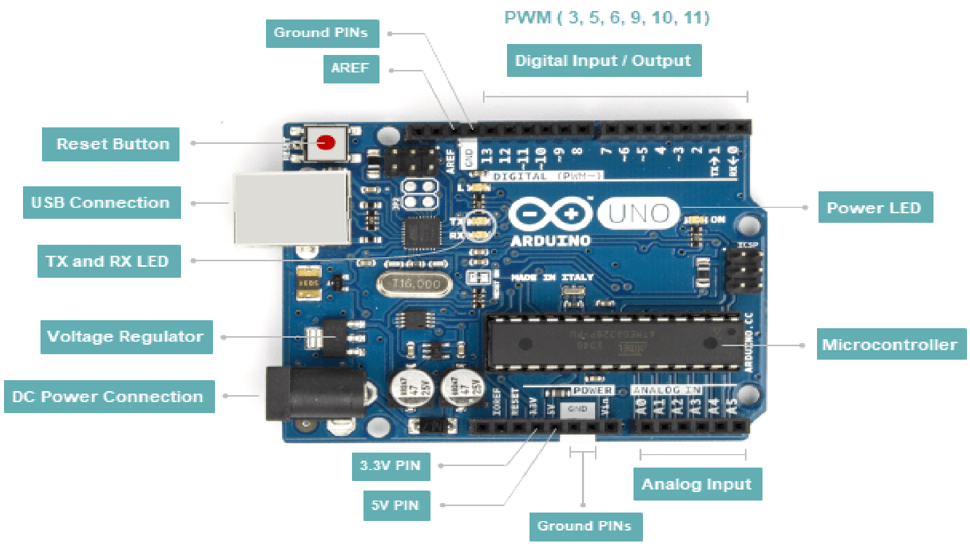


Figure 3.1. Arduino UNO

A microcontroller board based on the ATmega328 is the Arduino Uno. It has 20 digital input/output pins, a 16 MHz resonator, a USB connection , a power jack, an in-circuit system programming (ICSP) header, and a reset button (of which 6 can be used as PWM outputs and 6 can be used as analog inputs). It contains all the microcontroller needs to support; just connect it to a computer with a USB cable or power it to get started with an AC-to-DC adapter or battery.

The Uno differs from all previous boards in that the FTDI USB-to -serial driver chip is not included. Instead, an ATmega16U2 programmed as a USB-to-serial converter is featured. This auxiliary microcontroller has its own USB bootloader, allowing it to be reprogrammed by experienced users.

It takes about 100 microseconds (0.0001 s) to read an analog input on ATmega based boards (UNO, Nano, Mini, Mega), so the maximum reading rate is about 10,000 samples in a second.

3.1.2. Wi-Fi microchip (ESP8266)

The ESP8266 is an effective and low-cost Wi-Fi microchip. The Wi-Fi comprises of a complete TCP/IP stack and offers microcontroller functions. The ESP8266 is developed by Espressif Systems [1]. Ai-Thinker, the third-party manufacturer, used the ESP-01 modules made by a third-party manufacturer to attract Western manufacturers. One of the characteristics of this module is that it connects Wi-Fi with the microcontroller. It further connects Wi-Fi with TCP/IP through using Hayes' command. This module is affordable and does not require external components. These features attract many hackers to the chip, module, and software [3].

The ESP8266 can be controlled from your local Wi-Fi network or from the internet (after port forwarding). The ESP-01 module has GPIO pins that can be programmed to turn an LED or a relay ON/OFF through the internet. The module can be programmed using an Arduino/USB-to-TTL converter through the serial pins (RX, TX).

ESP8285 is similar to ESP8266 with 1 MiB in-built flash memory. The ESP8285 chips is given in Figure 3.2.

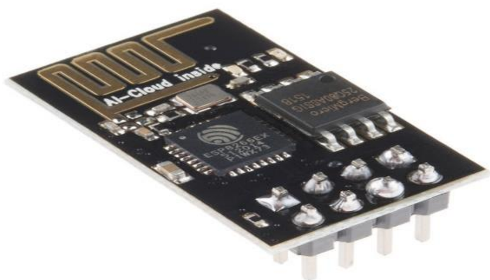


Figure 3.2. ESP8285

3.1.3. Three EMG Muscle Sensor

Traditionally, EMG is the muscle activity measured by detecting myoelectric potentials. The sensor will measure the electrical activity of the filtered and corrected muscle. **0**-Vs volts are output according to the muscle activity whereas Vs represents the power supply voltage. To attach electrodes, it is essential to go through the voltage and flex muscles. The kit comprises everything to use muscle activity with a controller and Arduino. We can use muscle activity to control the muscle sensor kit [32] as shown in Figure 3.3.

Figure 3.3. EMG Sensor

3.1.4. Smartphone

A smartphone is a mobile communication device that performs many functions similar to a computer. A smartphone is protected with a touch screen interface capable of allowing users to download applications and have access to the Internet. A smartphone can perform many functions. It also has a pleasing visual screen size with higher resolutions [52].A smartphone allows an interaction between the system and the user. Smartphones have powerful computing capabilities to perform different operations, such as wireless Internet access or surveillance cameras via a Wi-Fi. The system is getting smarter with the help of powerful smartphone applications [34].

Besides IoT is a part of Internet development, through which people communicate, send and retrieve data. To perform the activity and get notified, IoT-based applications are leveraged remotely [11]. To obtain images and notifications, a ThingView application can be installed on a smartphone. In the proposed system, a smartphone is used to view data from a remote location. Besides, it can be used to send notification and receive messages.

3.1.5. Power Supply

A very simple power supply is observed on the Arduino UNO, using a Micro USB connection. The gadget uses a 5200 MAh external battery.

3.2. Software Implementation

3.2.1. Arduino 1.8.10

Developers can easily write the code with the Arduino software and upload the code on the development board. Arduino runs on Linux, Windows, and Mac OS X. It is written in the Java environment as shown in Figure 3.4.

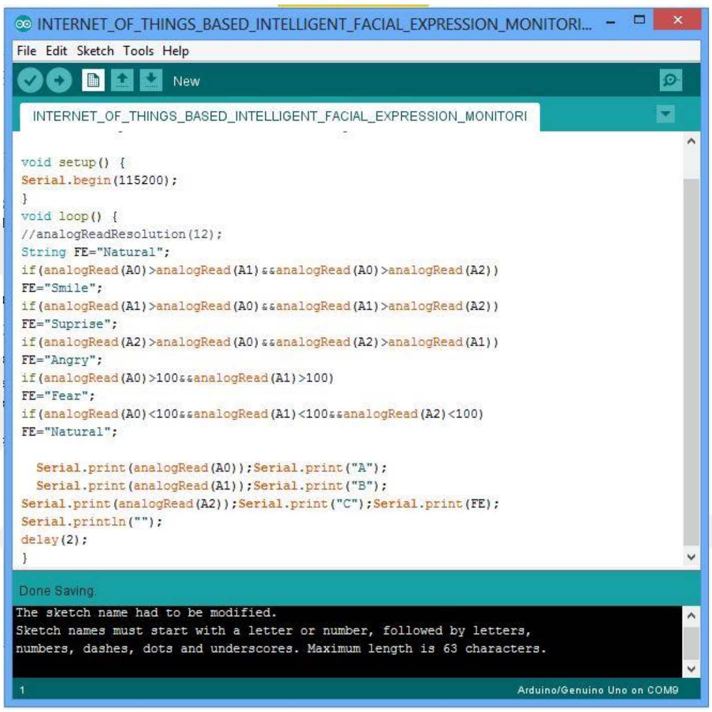


Figure 3.4. Arduino software

3.2.2. LAB View

Laboratory Virtual Instrument Engineering Workbench (LabVIEW) is a system and design platform and development that uses the visual programming language [1].

The "G" as in G code is different from "G" the graphic language. Apple Macintosh released LabVIEW in 1986 and was run on various operating systems (OS) that include Linux, Microsoft Windows, UNIX, and Mac OS. LabVIEW is used for industrial automation instrument control and data acquisition.

LabVIEW is a system engineering software to test, measure, and control application to connect a hardware and data insights.

"The LabVIEW Advanced Signal Processing Toolkit" is a software tool to perform time-series, time-frequency, and wavelet analysis. These LabVIEW accessories are available separately

[18]. We choose the appropriate analysis tool to extract the signal basic information. Moreover, we use time-frequency analysis that changes spectral content for an evolutionary signal. For short-term events, the time-series analysis is used for fixed signals. The wavelet analysis offers transient and evolutionary signals.

3.2.3. ThingSpeak

ThingSpeak is an IoT analytics platform service that visualizes, aggregates and analyzes real-time data in the cloud. It is possible to send data to ThingSpeak from a device, create instant visualizations of real-time data, and send alerts as shown in Figure 3.5.

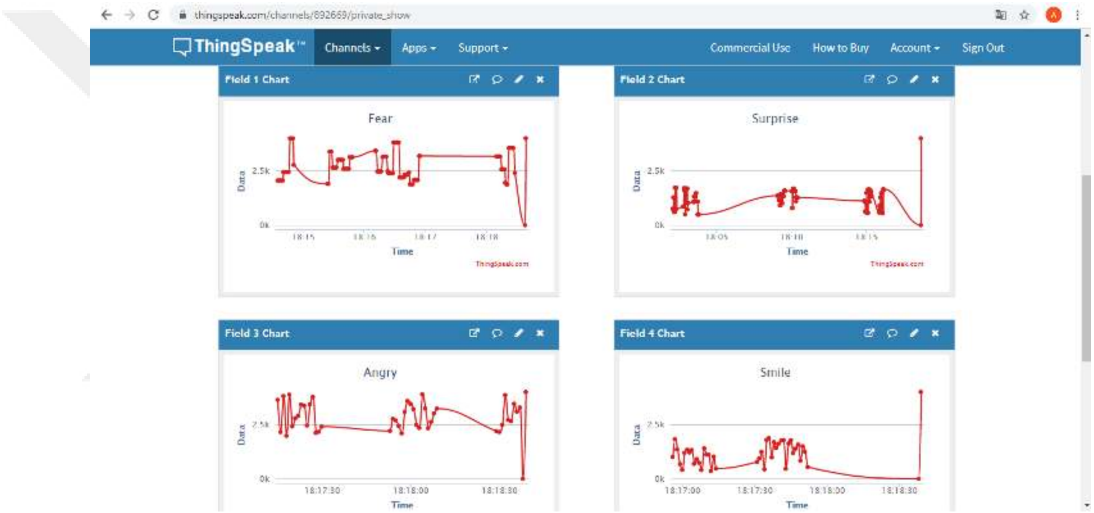


Figure 3.5. IoT platform ThingSpeak cloud

ThingSpeak is an open source IoT web application built using the Ruby on Rails framework and serves as a platform for creating IoT applications. It was originally launched in 2010 by a company called ioBridge [30] as an open data platform for the Internet of Things. The whole application is deployed online on its dedicated website and it is also available on GitHub [31] under the General Public License (GNU) for local deployment with customizable parameters.

The primary element of ThingSpeak platform is a channel. Channels store all the data that a ThingSpeak application collects. Each channel includes eight fields that can hold any type of data in either numeric or alphanumeric format, plus three fields for location data (elevation, latitude and longitude) and one for status data [32].

There is a technical collaboration between ThingSpeak and the MathWorks Company. It also gets integrated support from MATLAB which is a high-level programming language for numerical computing. Close relationship with MathWorks allows users to utilize MATLAB's capabilities for visualization and analysis on uploaded data without requiring the purchase of a MATLAB license. The ThingSpeak documentation site is a part of MathWorks' website and MathWorks user accounts can be used as a valid login to the ThingSpeak website. The ThingSpeak support toolbox is available for desktop MATLAB to analyze and visualize data stored on the ThingSpeak platform either web version or private installation.

3.2.4. ThingView

ThingView facilitates visualization of ThingSpeak channels. We connect to ThinkSpeak after input channel ID and password. The application will follow the Windows settings for public channels. This includes chart type, color, time scale, and results. The current version supports the line and column, which display charts and splines as line charts.

The data is displayed in the default settings in dedicated channels. Only the API key is not enough to read the dedicated window settings as shown in Figure 3.6.

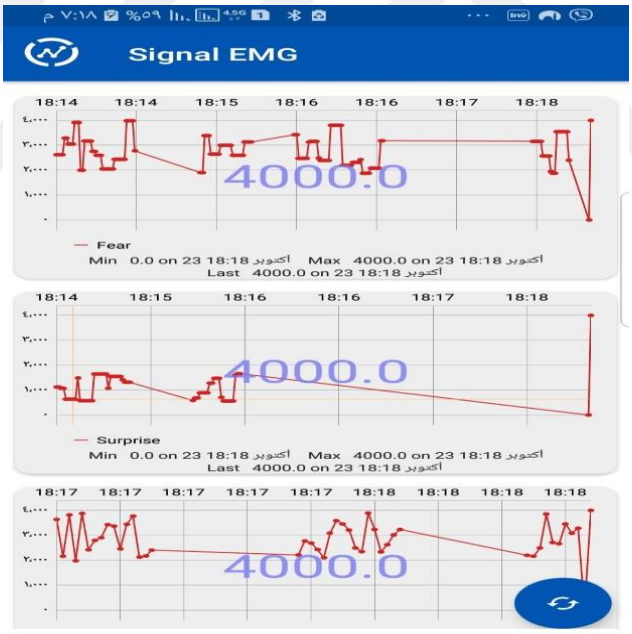


Figure 3.6. ThingView mobile application

3.3. Proposed Method

Naive Bayes is a powerful ML algorithm for classification. This is an extension Bayes' theorem independent of each feature for various tasks, which include text classification and spam filtering. To perform facial expression recognition in an ML, smile, surprise, anger, and fear expressions were selected for the case study. The four expressions related to the expression muscle were the inputs of sEMG. Lists the dominant muscles and facial movement units among adults. The number of electrodes is reduced when using a unipolar configuration in the amplifier to reduce its attractiveness to the face. To capture the facial muscle activity, a pregelatinized Ag / Ag Cl sensor was placed on the left side four muscles of the face based on the human EMG guidelines [10].

Behind the left ear, the reference electrode is placed in the bone area. When a person maintains a neutral expression and four expressions, a facial sEMG signal is collected: a smile will make the person angry and scared. Figure 3.7 shows the steps to process sEMG data to train a classifier.

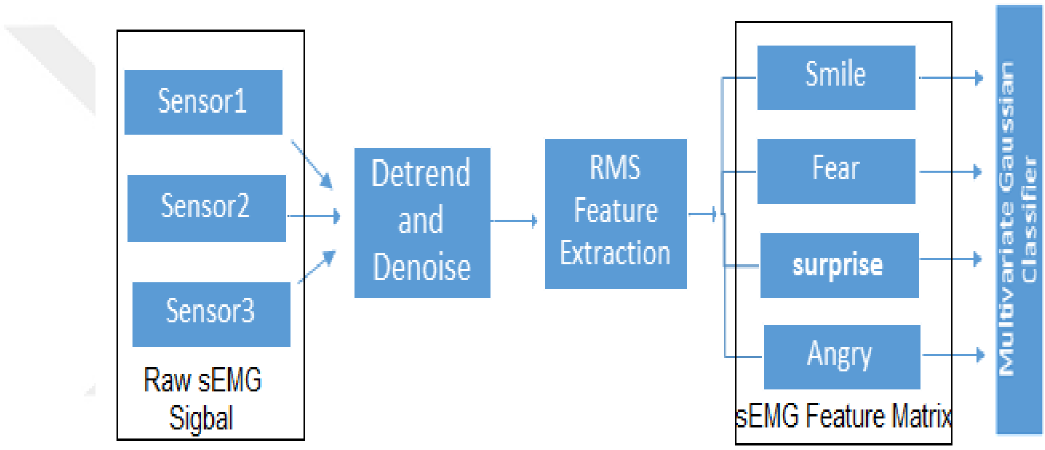


Figure 3.7. sEMG signal processing and pattern training flow chart

From three EMG sensors, the sEMG signal is sampled. After sampling, we apply a 50Hz notch Butterworth filter and 20Hz high-pass Butterworth filter to each signal to reduce the effects of artifacts coupled to the wires and power line interference. Before the RMS feature extraction and construction of the feature matrix, the data is segmented into 200-millisecond slices. We extract the RMS features using the following formula [39].

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{3.1}$$

IoT identifies an emerging pattern where a vast number of handheld systems are connected to the Internet (ThingSeak). These connected devices connect with individuals and other objects and also provide sensor data for cloud storage and cloud computing applications where the data is stored and analyzed to obtain valuable insights. Cheap cloud storage ability and increased computer networking enable this trend.

You can explain Facial Expression IoT structures at a high level the show the Figure 3.8.

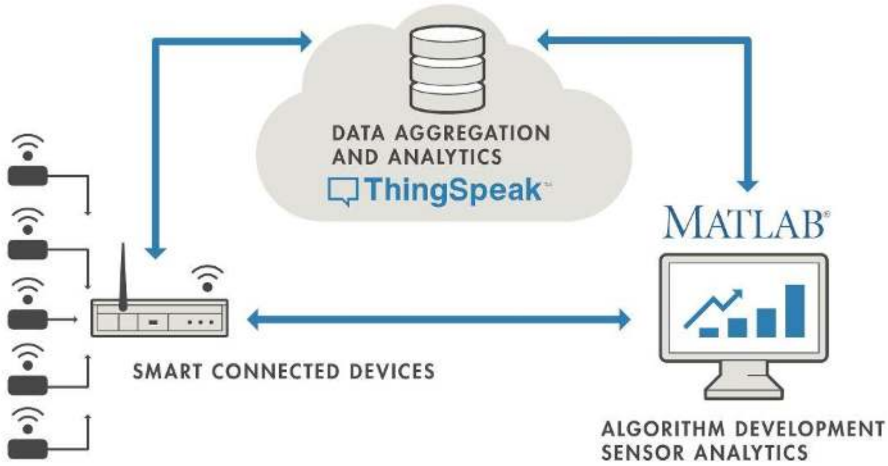


Figure 3.8. IOT structure

Finally, send the data to ThingSpeak. From this, the data can be displayed using a computer or a smartphone, in a way that you can share your link wherever changes can be seen.

3.4. Experimental Method

At the beginning of this thesis, we provided three EMG Sensors, Arduino, and Board, two batteries, one box, and a wire. These provided EMG sensors each one of them comprised of 3 Surface EMG which sums to 9 surface EMG. After that, we assembled all of our provided hardware as it is shown in Figure 3.9. Then, we connected all of our three sensors to the board which is inside the box and after that we attached both batteries to both sensors as it is shown Table 3.1.

Table 3.1. Power and EMG Sensor connection

Battery	EMG Sensor
+	+VS
-	-VS
(- and +)	Grand

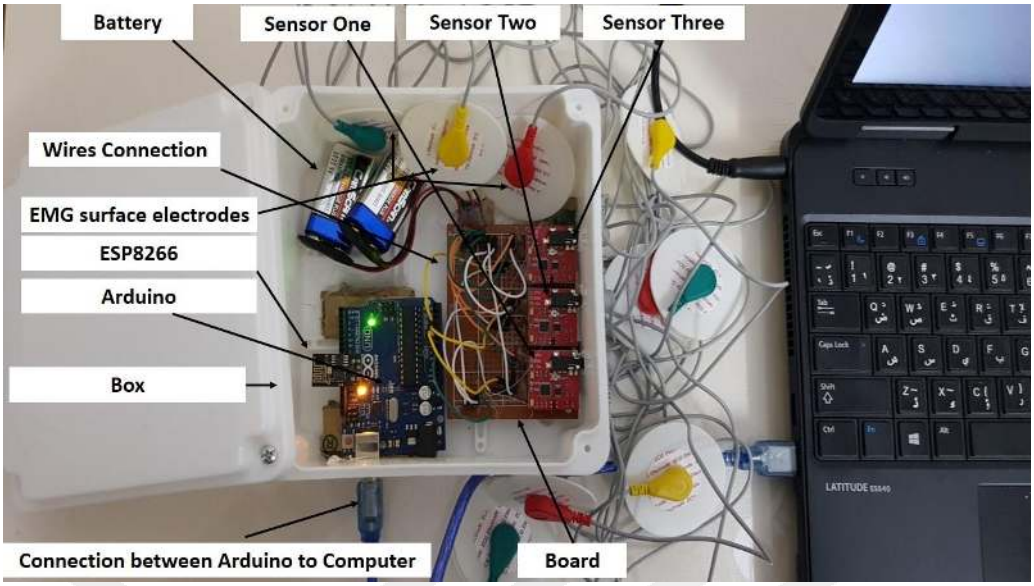


Figure 3.9. Hardware Facial Expression System

A very useful function that converts an analog voltage on a pin to a digital number is an Analog to Digital Converter (ADC). We will begin using electronics to communicate with the analog world around us by transitioning from the analog world to the digital world.

It is not possible for any pin on a microcontroller to do analog to digital conversions. These pins have a 'A' in front of their mark (A0 through A5) on the Arduino board to signify that analog voltages can be read by these pins.

In this manner, we connected all three sensors with the batteries. Furthermore, we connected our sensors with Arduino which in this way our first sensor SIG is connected with A0pin of Arduino, second sensors with A1 pin of Arduino and the third sensor with A2 pin of Arduino. Afterwards, we linked all three Grand to one wire and we attached it to Grand ort of Arduino. All of our hardware were assembled in one box which enabled us to connect it to a computer. By the means of Arduino, we attached our sensors with the facial muscles. After we got the signals from the face, by the visual system we made, we were able to analyze and classify the signal to some categories such as Natural, Smile, Angry, Fear, Surprise.

We took a moment to determine the placement of the sensors on the face because the location of the sensors are important for obtaining the required signal from the face. We researched and experimented thoroughly to reach this conclusion of attaching the sensors to the facial muscles. Consequently, the first EMG Sensor is attached to the Zygomaticus Muscle, also the second sensor is attached to the Depressor Muscle and the third one is attached to the Frontals muscles.

After that, we were able to categorize (classify) them to signal from the first sensor, signal from the second sensor, and signal from the third sensor classification to facial expressions fear, surprise, anger, or smile. In this way, we can understand and reach all of the conditions of facial expressions. During receiving signal from sensors, there were a signal peak around 75 without any activity or reaction from facial expression, in this case the system ignored all peak signals as shown in Figure 3.10.

Figure 3.10. Software System

Considering that we only used IOT we need a place to store and save all of our data. These data are shared so any person who is in need for these kinds of data can benefit from it, we observed and concluded that Cloud storage is the best for this case and will benefit our work greatly. We created a ThingSpeak account. Thus, we could show and send our data to anyone we want and they can see it from anywhere they want also be aware of it. Later, all of our hardware is assembled and programed using useful and simple software. In the analysis section, we will talk about how we gathered the data and also where did we get the data from. Furthermore, we will talk about how we saved the data and used it, and the role of machine learning. We will discuss how it received the signals and how and in which way it categorized these data in the program; all of this issues will be discussed and revealed shown in Figure 3.11.

Figure 3.11. Thingspeak cloud

In the process of collecting the data, we asked people consent to collect data from their face and they agreed to our request. We collected data in a healthy and hygienic way, for example, we cleansed their face with sterilized wet tissue paper. Then, for each person we used 9 surfaces EMG which we not used before in other words they were new. At last, we collected data from 20 individuals, which 7 of them were females and 13 of them were males. We attached our sensors to their face and gathered our data as a result. Next, we saved our collected data. In the end, we used machine learning to categorize and classify our collected data.

Machine learning techniques can be applied using different sets of information such as data trends, patterns, and outlines. Data visualization tools can be used for data exploration, key traits identification, and findings communications. It cannot be decided which algorithm in machine learning is best to solve a particular problem. There is a wide variety of algorithm in the Statistics Toolbox that can be used for similar syntax.

Different approaches of machine learning can be tested through using these algorithms such as applying decision tree to the dataset. Computationally speaking, some of the algorithms are intensive. Thus, these algorithms can be speeded up by using built-up support for parallel computing.

Based on applying different trained models, their performance can be compared and tested to come up with authentic results. It can be seen that different algorithms classify the test data very accurately. Sometimes, models need further modifications and refinements to run faster in the application. The reduction and refinement of the model in tools authorize one to analyze how effective the algorithm parameters are. They also help to identify a subset of features that can help to produce identical results.

Enterprise systems use machine learning algorithms through using MATLAB compiler with add-on builder products. This can be done by integrating the MATLAB models directly into applications written in java. On the other hand, .NET models are deployable like Excel add-ins or executable standalone.

3.5. Experimental Setup

The motivation for this thesis is to meet the growing demand for automatic sick assessment in the healthcare environment to improve patient care and streamline workflow for medical staff. Facial expressions are behavioral signs and assessment tools. Self-reported is an indicator of a sick situation in distant populations. We propose the wearable sensor node concept for sick patients to meet the requirements of multichannel bio-potential acquisition and IoT transmission framework [9]. An IoT architecture and mobile web application are customized for bio-potential processing and remote sick monitoring. Hybrid applications are interoperable on a single platform across multiple mobile platforms.

The purpose of the experiment was to collect facial muscle data. Figure 3.12 represent the process and hardware or environment for recording facial EMG signals. Physiological EMG recordings were performed in university laboratories.

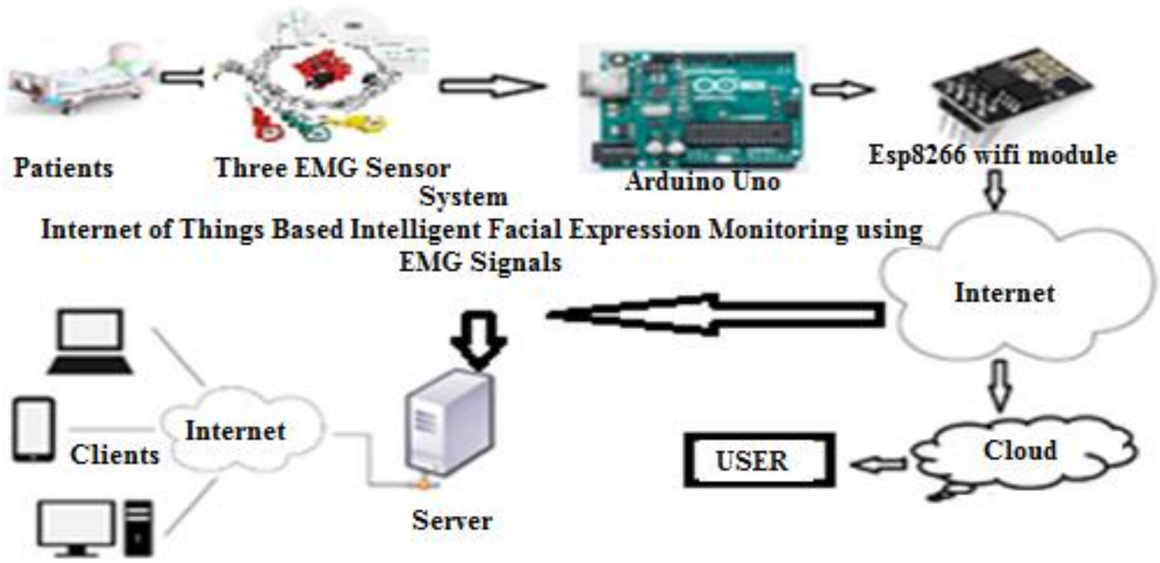


Figure 3.12. System design

3.6. Facial muscles

In the subcutaneous, facial expression muscle tissue or facial muscles are responsible for the skin folds' movement. This offers different facial expressions. Inserted in the skin, facial muscles originate from the visceral skulls (facial bones) [19]. Facial muscles are at the natural holes of the face (eyes, nose, and mouth in the closure or at the whole's expansion as revealed in Table 3.2.

Table 3.2. Facial actions during the expression of elementary emotions

Type	Sensor1 Value
Happiness	• Orbicularis oculi • Zygomaticus ajor
Surprise	• Frontalis • Levator Palpebrace superioris
Fear	• Frontalis • Levator Palpebrace superioris • Corrugator supercilii
Anger	• Levator Palpebrace superioris • Corrugator supercilii • Orbicularis oculi
Sadness	• Corrugator supercilii • Frontalis • Depressor supercilii
Disgust	• Alaeque nasi • Lavator labii superioris

3.7. Raw EMG Signal

EMG is an experimental technique to develop, record, and analyze myoelectric signals, formed from physiological variations in the muscle fiber membranes [14]. Unprocessed and unfiltered signals are to detect the superimposed MUAPs called as a raw EMG Signal. Figure 3.13

represents the raw surface EMG recording (SEMG) using static contractions of the biceps brachia muscle.

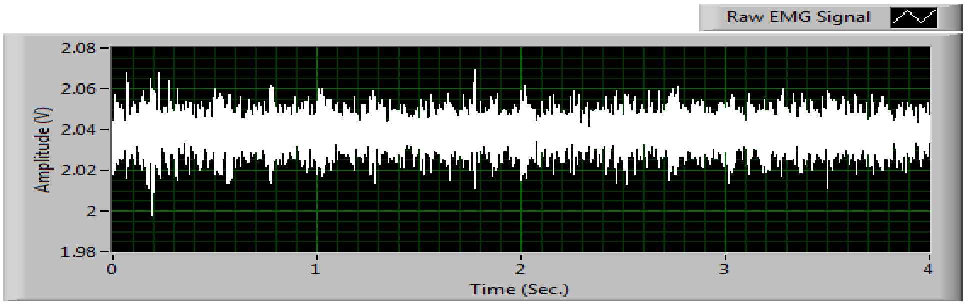


Figure 3.13. Raw EMG signal

In the relaxed state of muscle, we observed a noise-free EMG baseline in the EMG plot. Many factors are responsible for the raw EMG baseline noise. These include the EMG amplifier quality, subject under investigation, and the environmental noise. In case the art amplifier is available, the skin is prepared, the averaged baseline noise is between 3 and 5 microvolts, 1 to 2 achievable. The EMG baseline is an important checkpoint for EMG measurement. When the noise in interfered in the detection mechanism, the apparatus increases base or muscle activity.

In healthy and relaxed muscles, no significant EMG activity can be detected due to the depolarization or inactivity. The spikes of the raw EMG are random in shape, which reveals that it may not reproduce the exact one raw in terms of shape.

We carried out rectification and all negative amplitudes are converted to positive amplitudes. The negative spikes rise to positive values, reflected by the baseline [41]. The standard amplitude parameters are the main effect, which includes peak/max, average, and area), applied to the curve. The original value of EMG is zero which denotes the full-wave of the rectified EMG signal. In the LabVIEW environment, the signal value is called full-wave rectification. The rectification step can obtain the EMG signal shape or envelope. The envelope is captured with unrectified signal in low-passed show in Figure 3.14 [19, 41].

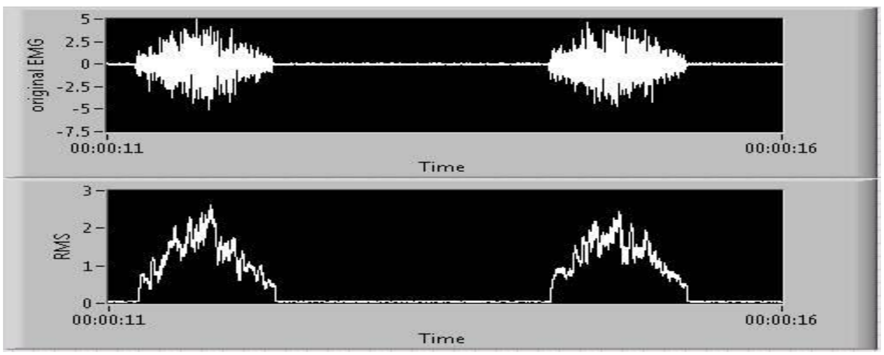


Figure 3.14. Rectified EMG Signal

3.8. Output Filtering

In this part, a digital filter is used that systematically performs some mathematical operations on a signal that is sampled and discrete-time to modify some aspect of the signal. It separates the signals from those signals that have been collected from distorted signals. Following equation represents the model that uses a low pass filter and it also shows the result of the given filer.

$$Voltage\ Gain, (AV) = \frac{Vout}{Vin} = \frac{A_F}{\sqrt{1+(\frac{f}{fc})^2}} \tag{3.2}$$

Where:

AF = the pass band gain of the filter, (1 + R2/R1)

f = the frequency of the input signal in Hertz, (Hz)

fc = the cut-off frequency in Hertz, (Hz)

3.9. Application

3.9.1. Application using Naïve Bayes

The training data this table 3.3 Facial Expression data.

Table 3.3. Training Dataset

Type	Sensor1 Value		Sensor2 Value		Sensor3 Value	
	Min	Max	Min	Max	Min	Max
Smile	98	1024	0	98	25	98
Angry	27	90	125	1024	17	107
Fear	122	969	100	980	10	98
Surprise	23	96	18	96	95	1017

In the following tables, the training data can be aggregated though counting the numbers; these numbers are based on computing and probabilities.

The classifier is used to predict whether a given facial expression is "smile", "angry", "surprised" or "fear" when only three features (Sensor1, Sensor2, and Sensor3) are known.

We can predict facial expression assuming your facial expressions RMS: 1085,215, and 170. Using Naive Bayes, it is similar to predicting Y when the variable X is known. We solve this manually using Naive Bayes to calculate four probabilities, namely the probability of expressing "smile" or "angry" or "surprised" or "fear" to reveal the highest probability of winning. The above table's lists all the information used to calculate these probabilities.

Table 3.3 Computing the Probabilities

Type	Sensor1 >1085	Sensor1 !>1085	Sensor2 >215	Sensor2 !>215	Sensor3 >140	Sensor3 !>140	Total
Smile	170	3	12	161	4	169	173
Angry	0	161	161	0	4	157	161
Fear	126	0	126	0	0	126	126
Surprise	9	131	9	131	131	9	160
Total	305	295	308	292	139	461	600

Step 1: For each class of Facial Expression, we compute the 'Prior' probabilities. With the proportion of each facial expression, the 'Priors' is provided from the information that is related population. Otherwise, the training data can compute it. From the training data, out of 600 records, we have is 164 smile, 0 angry, 132 surprised, and 9 fear. The priors are 0.2733, 0.26833, 0.22, and 0.23833.

P(Y=Smile) = 164/600 = 0.2733

P(Y=Angry) = 161/600 = 0.26833

P(Y=Fear) = 132/600 = 0.22

P(Y= Surprised) = 143/600= 0.23833

Step 2: Compute the evidence probability in the denominator. For the Expression P of Xs for X. Since the denominator is similar in classes; thus, it is optional. The probabilities will not be affected by it.

P(x1=1085) = 305/ 600= 0.5083333

P(x2=215) = 292/ 600= 0.486667

P(x3=170) = 466/ 600= 0.776667

Step 3: In the numerator, we compute the likelihood probability of evidence. This is the conditional probabilities. From the formula, P(X1 |Y=k). X1 is 'sensor1=1085', whereas k is 'Smile.' This shows that the Sensor 2 probability is '215', referred to as a Smile. From the table, we record 164 Smile active. Thus, P (Long | Smile) = 164/164=1. Here, likelihood of probability of banana as follows:

P (x1 = 1085 | Y = Smile) = 164/ 164= 1

P (x1 = 215 | Y = Smile) = 158/ 164=0.9634

P (x1 = 170 | Y = Smile) = 164/ 164= 1

Overall Likelihood of Smile= 1 * 0.9634 * 1 = 0.9634

Step 4: 3 equations are substituted with the aid of the Naïve Bayes formula to get the smile probability.

Step 5: if a Facial Expression '1085', '215' and '170', what is the Expression?

$$\mathrm{P(Smile|S1, S2\ and\ S3)} = \frac{P(S3|Smile)*P(S2|Smile)*P(S3|Smile)*P(Smile)}{P(S1)*P(S2)*P(S3)} \tag{3.2}$$

$$\mathrm{P(Smile|1085{,}215\ and\ 170)} = \frac{P(1085|Smile)*P(215|Smile)*P(170|Smile)*P(Smile)}{P(1385)*P(215)*P(170)}$$

$$= \frac{1 * 0.9634 * 1*0.2733}{0.508333*0.48666*0.77666}$$

$$= \frac{0.263352}{0.19213} = 1.3705$$

$$\mathrm{P(Angry|1085{,}215\ and\ 170)} = \frac{P(1085|Smile)*P(215|Smile)*P(170|Smile)*P(Angry)}{P(1385)*P(215)*P(170)}$$

$$= \frac{1 * 0.9634 * 1*0.26833}{0.508333*0.48666*0.77666}$$

$$= \frac{0.263352}{0.19213} = 1.3455$$

$$\mathrm{P(Fear|1085{,}215\ and\ 170)} = \frac{P(1085|Smile)*P(215|Smile)*P(170|Smile)*P(Fear)}{P(1385)*P(215)*P(170)}$$

$$= \frac{1 * 0.9634 * 1*0.22}{0.508333*0.48666*0.77666}$$

$$= \frac{0.263352}{0.19213} = 1.1031$$

$$\mathrm{P(Surprised|1085{,}215\ and\ 170)} = \frac{P(1085|Smile)*P(215|Smile)*P(170|Smile)*P(\mathrm{Surprised})}{P(1385)*P(215)*P(170)}$$

$$= \frac{1 * 0.9634 * 1*0.2383}{0.508333*0.48666*0.77666}$$

$$= \frac{0.263352}{0.19213} = 1.1950$$

Answer: Smile- Since it has the highest probability amongst the classes

Similarly, we calculate the probabilities of "anger", "surprised" and "fear". The denominators in all four cases are the same, so the calculation is optional. Smiling is most likely; so, this will be our prediction.

- ✓ In its application, Naive Bayes is an effective way to make multiple predictions.
- ✓ Naive Bayes required lesser training time and is more effective than other algorithms such as logistic regression.

3.9.2. Application using decision tree

Assume whether the dataset can determine which algorithm is related to facial expression to Facial Expression.

Table 3.4. Computing the Probabilities

Type	Sensor1	Sensor2	Sensor3
Smile	>1085= 170	>215= 12	>140= 4
Angry	>1085= 0	>215= 161	>140= 4
Fear	>1085= 126	>215= 126	>140= 0
Surprise	>1085= 9	>215= 9	>140= 131
Smile	!>1085= 3	!>215= 161	!>140= 169
Angry	!>1085= 161	!>215= 0	!>140= 157
Fear	!>1085= 0	!>215= 0	!>140= 126
Surprise	!>1085= 131	!>215= 131	!>140= 9
Total	600	600	600

Here, the dependent variable is determined by some independent variables. The independent variables are active and non-active Sensor One. The dependent variable is whether to Facial Expression.

Firstly, the parent node must be found for the decision tree as in the following steps:

$$y = -\sum_{i=1}^{k} pi \log k(pi) \tag{3.3}$$

$$y = -\left(\frac{173}{600}\right) log4 \left(\frac{173}{600}\right) - \left(\frac{161}{600}\right) log4 \left(\frac{161}{600}\right) - \left(\frac{126}{600}\right) log4 \left(\frac{126}{600}\right) - \left(\frac{140}{600}\right) log4 \left(\frac{140}{600}\right) = 0.994$$

From the table 3.4 data for outlook can be reached at the table 3.5 easily.

Table 3.5. Sensor One Expression

	Facial Expression				
Sensor One	**Smile**	**Angry**	**Fear**	**Surprise**	**Total**
>1085	170	0	126	9	305
!>1085	3	161	0	131	295
Total	173	161	126	140	600

At this point, the average weighted entropy must be calculated. For example, it has been found that the probabilities are multiplied by the total weight of each feature.

$$E(S, \text{active}\ ) = -\left(\frac{170}{305}\right) log4\left(\frac{170}{305}\right) - \left(\frac{0}{305}\right) log4\left(\frac{0}{305}\right) - \left(\frac{126}{305}\right) log4\left(\frac{126}{305}\right) - -$$

$$\left(\frac{9}{305}\right) log4\left(\frac{9}{305}\right) = 0.573$$

$$E(S, Not\ active\ ) = -\left(\frac{3}{295}\right) log4\left(\frac{3}{295}\right) - \left(\frac{161}{295}\right) log4\left(\frac{161}{295}\right) - \left(\frac{0}{295}\right) log4\left(\frac{0}{295}\right) - -$$

$$\left(\frac{131}{295}\right) log4\left(\frac{131}{295}\right) = 0.446$$

$$E(S, \text{Sensor One}) = \left(\frac{305}{600}\right) * 0.573 + \left(\frac{295}{600}\right) * 0.446 = 0.511$$

From the Table 3.4, data for outlook can easily be derived from Table 3.5.

Table 3.6. Sensor Two Expression

	Facial Expression				
Sensor Two	**Smile**	**Angry**	**Fear**	Surprise	**Total**
>215	12	161	126	9	308
!>215	161	0	0	131	292
Total	173	161	126	140	600

$$E(S, active\ ) = -\left(\frac{12}{308}\right) log4\left(\frac{12}{308}\right) - \left(\frac{161}{308}\right) log4\left(\frac{161}{308}\right) - \left(\frac{126}{308}\right) log4\left(\frac{126}{308}\right) - -$$

$$\left(\frac{9}{308}\right) log4\left(\frac{9}{308}\right) = 0.674$$

$$E(S, Not\ active\ ) = -\left(\frac{161}{292}\right) log4\left(\frac{161}{292}\right) - \left(\frac{0}{292}\right) log4\left(\frac{0}{292}\right) - \left(\frac{0}{292}\right) log4\left(\frac{0}{292}\right) - -$$

$$\left(\frac{131}{292}\right) log4\left(\frac{131}{292}\right) = 0.496$$

$$E(S, \text{Sensor Tow}) = \left(\frac{308}{600}\right) * 0.674 + \left(\frac{292}{600}\right) * 0.496 = 0.588$$

From the Table 3.4 data for outlook can be seen at the table 3.6 easily and from the Table 3.4, data for outlook can easily be derived from Table 3.7.

Table 3.7. Sensor Tree Expression

	Facial Expression				
Sensor Three	**Smile**	**Angry**	**Fear**	**Surprise**	**Total**
>140	4	4	0	131	139
!>140	169	157	126	9	461
Total	173	161	126	140	600

$E(S, active) = -\left(\frac{4}{139}\right) log4\left(\frac{4}{139}\right) - \left(\frac{4}{139}\right) log4\left(\frac{4}{139}\right) - \left(\frac{0}{139}\right) log4\left(\frac{0}{139}\right) - -$

$\left(\frac{131}{139}\right) log4\left(\frac{131}{139}\right) = 0.188$

$E(S, Not\ active) = -\left(\frac{169}{461}\right) log4\left(\frac{169}{461}\right) - \left(\frac{157}{461}\right) log4\left(\frac{157}{461}\right) - \left(\frac{126}{461}\right) log4\left(\frac{126}{461}\right) - -$

$\left(\frac{9}{461}\right) log4\left(\frac{9}{461}\right) = 0.841$

$E(S, \text{Sensor Three}) = \left(\frac{139}{600}\right) * 0.188 + \left(\frac{461}{600}\right) * 0.841 = 0.689$

Next, this step is to find the information gain. It is found that the difference is between the parent entropy and average weighted entropy. $IG(S, \text{Sensor One}) = 0.994 - 0.511 = 0.483$

$IG(S, \text{Sensor Two}) = 0.994 - 0.588 = 0.406$

$IG(S, \text{Sensor Three}) = 0.994 - 0.689 = 0.304$

Now the feature that has the highest entropy gain must be selected which is Sensor One and it forms the first node of the decision tree. Now our data look as table 3.7 and table 3.8.

Table 3.8. Computing the Probabilities

Type	**Sensor1 >1085**	**Sensor2 >215**	**Sensor3 >140**
Smile	170	12	4
Angry	0	161	4
Fear	126	126	0
Surprise	9	9	131
Total	600	600	600

Table 3.8. Computing the Probabilities

Type	**Sensor1 !>1085**	**Sensor2 !>215**	**Sensor3 !>140**
Smile	3	161	169
Angry	161	0	157
Fear	0	0	126
Surprise	131	131	9
Total	600	600	600

Next, the next node must be found in the decision tree. Now we will find one Sensor One active. It has to be determined which sensors (Two or Three) has higher information gain.

Calculate parent entropy E (active)

$E(S, active\ ) = -\left(\frac{170}{305}\right) log4 \left(\frac{170}{305}\right) - \left(\frac{0}{305}\right) log4 \left(\frac{0}{305}\right) - \left(\frac{126}{305}\right) log4 \left(\frac{126}{305}\right) - -$ $\left(\frac{9}{305}\right) log4 \left(\frac{9}{305}\right) = 0.573$

Now calculate the information gain of Temperature. IG (active, Sensor Two)

$E(active\ , Sesnor\ Two) = -\left(\frac{12}{308}\right) log4 \left(\frac{12}{308}\right) - \left(\frac{161}{308}\right) log4 \left(\frac{161}{308}\right) - \left(\frac{126}{308}\right) log4 \left(\frac{126}{308}\right) - -$ $\left(\frac{9}{308}\right) log4 \left(\frac{9}{308}\right) = 0.674$

$E(active\ , Three) = -\left(\frac{4}{139}\right) log4 \left(\frac{4}{139}\right) - \left(\frac{4}{139}\right) log4 \left(\frac{4}{139}\right) - \left(\frac{0}{139}\right) log4 \left(\frac{0}{139}\right) - -$ $\left(\frac{131}{139}\right) log4 \left(\frac{131}{139}\right) = 0.188$

Now calculate information gain.

$IG(S, \text{Sensor Two}) = 0.573 - 0.674 = -0.101$

$IG(S, \text{Sensor Three}) = 0.573 - 0.188 = 0.385$

Here, the value of IG (Sensor one, Sensor Tow) is the highest. So, the node that is under Sensor One is Sensor Three. .

Note: Any branch that has an entropy of more than 0 must be further splatted.

Finally, our decision tree will look as Show in Figure 3.15.

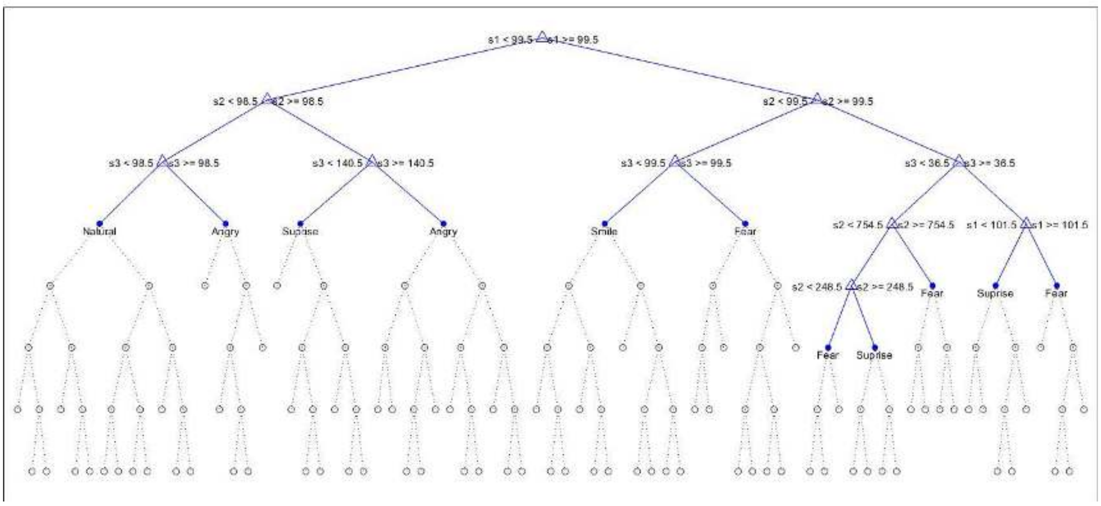


Figure 3.15. Facial Expression decision tree

4. RESULTS

4.1. Classification of the Signals

In classification, we did extract features in facial expressions as shown in Figure 4.1. Different factors lead to misclassification. These factors are sweat, electrode position, and muscle fatigue. This factors cause variation in the EMG pattern and misclassification. A classifier can address these flaws. However, the classifier must be proficient to address real-time restraints and classify the new patterns in online training. We apply different classification algorithms based on pattern recognition. These are applied to classify facial expressions.

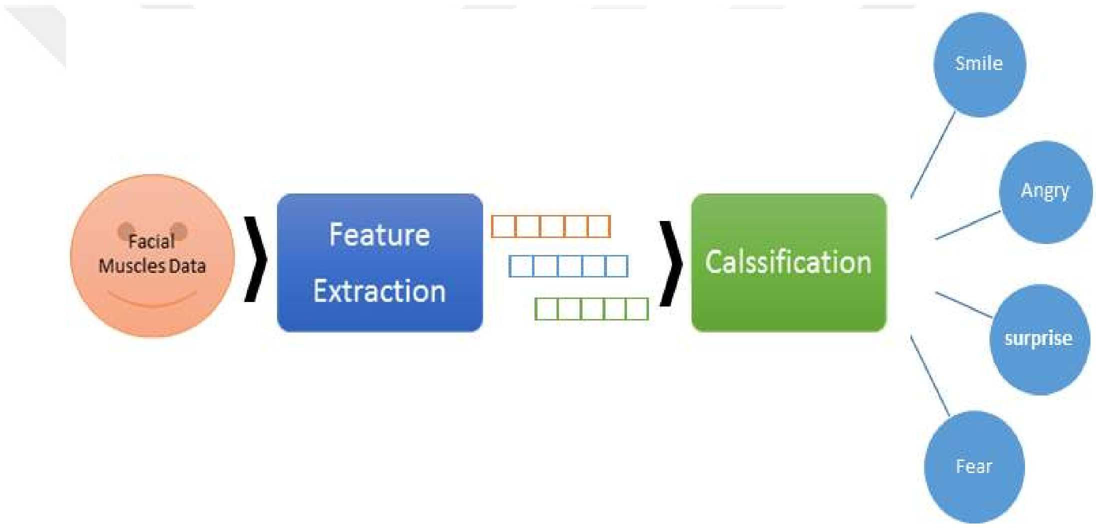


Figure 4.1. Facial Expression Analysis and Classification

4.2. EMG Analysis Result

Using supervised machine learning, a remote multi-channel bio-potential monitoring system is implemented based on IoT. Bio-potential measurement equipment carries wireless data streaming. We measure three EMG sensor bio-potential according to application requirements. However, the current system supports full eight channels of wireless data transmission and online processing, where bytes are transmitted at a 24KB / s data rate. Moreover, the system in other multi-channel bio-potential applications requires remote monitoring and online data as shown in Figure 4.2.

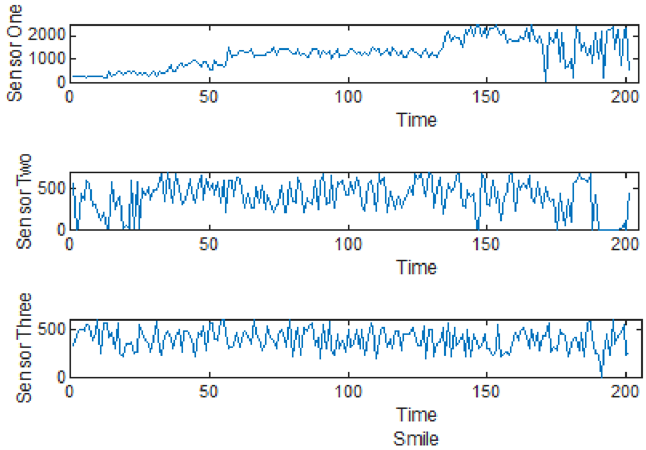
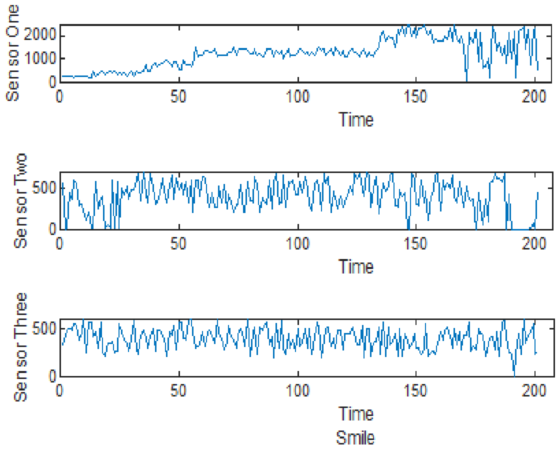


Figure 4.2. EMG data stream processing in MATLAB

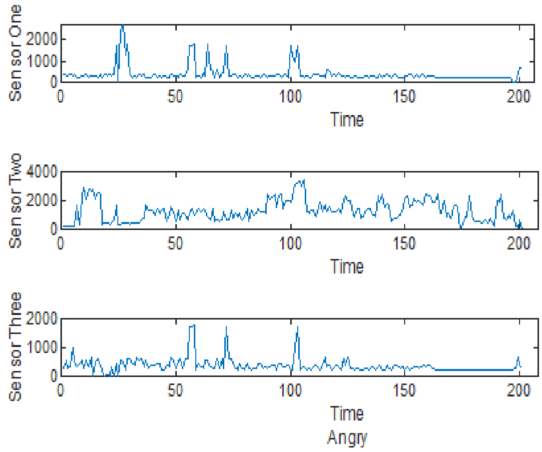
Time series analysis plot analyze whether the components of the time series exhibit the additive or multiplicative attributes of behavior in the ability to recognize patterns such as sensor one, sensor two and sensor three. This is the idea behind the decomposition time series. The goal of time series decomposition is to separate the original signal into three main patterns.

The general behavior of the time series can be indicated by trend. It represents a period pattern of 200 data - its trend. The facial expression component displays the differences related to the events of the three sensors. Finally, the face change illustrates Smile, fear, anger, and surprise. Facial change is defined as the distinction between the combination of expressions and the original data. Thus, if we were to combine all three components, we get the background of the original data shown in Figure 4.3. Usually, all the information can be displayed in a decomposition plot using methods of decomposition.

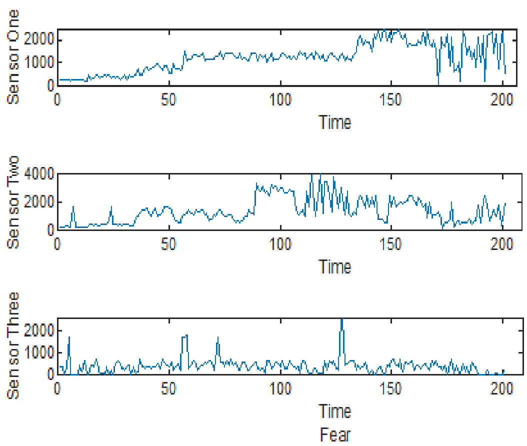
A prominent method to recognize the application of time series components in a face change model is to analyze a time series. In this thesis, we provide the results of facial EMG signals experiments performed in the laboratory. We used the offline Facial EMG raw data signal, related to signal processing to remove unwanted signals and noise from the original EMG signal. Signal processing converts an original signal into a signal, which represents the intensity of facial movement. In the signal processing, each step is carefully analyzed. We extracted two raw facial EMG signals from the facial muscles. Appendix B shows the MATLAB code for Z muscle. The results signal processing of the zygosity. In our experiments, we placed electrodes on the required facial muscles and used other electrodes as common reference electrodes (at the hairline).



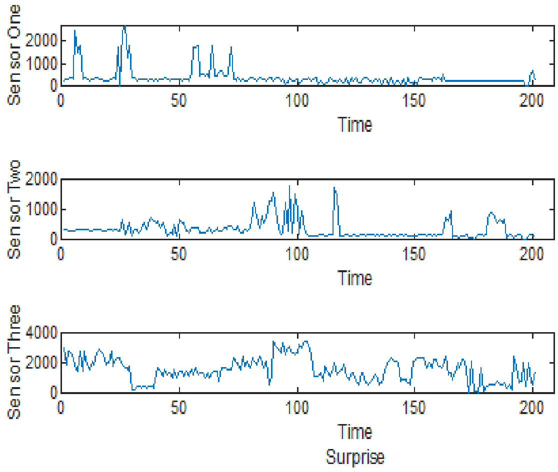
a- Time series for Smile



c- Time series for Angry



b- Time series for Fear



d- Time series for Surprise

Figure 4.3. Time series

4.3. Experimental Results

The facial expressions dataset the data were collected from 20 person facial in Zakho city from the family and friends. This data has not been used in any application for machine learning, and this is the first study of such data known as facial expressions. There are three distinct characteristics of the new facial expression dataset. Table 4.1 outlines the general features of the facial expressions dataset.

The results of the facial expressions of the data, which included sensor 1, sensor 3, and sensor 3, are given in Mean, Min, and Max time series. The results show that sensor 2 records the highest signal when compared its max to that of sensor 1 and sensor 2 as revealed in Figure 4.4 and Table 4.1. Moreover, sensor 1 records the highest Mean compared to the other two. The time series of entire sensor 1, sensor, 2, and sensor 3 are provided in Figure 4.5.

Table 4.1. Shows the correlation coefficient among the three features of facial expressions dataset

Attribute Name	Attribute Description	Attribute Type	Min	Max	Mean
Sensor One	Zygomaticus ajor	Numerical	98	1013	209
Sensor Two	Depressor Muscle	Numerical	53	1019	251
Sensor Three	Frontals muscles	Numerical	73	986	186
Class	Natural,Smile , Angry, Fear, and Surprise				

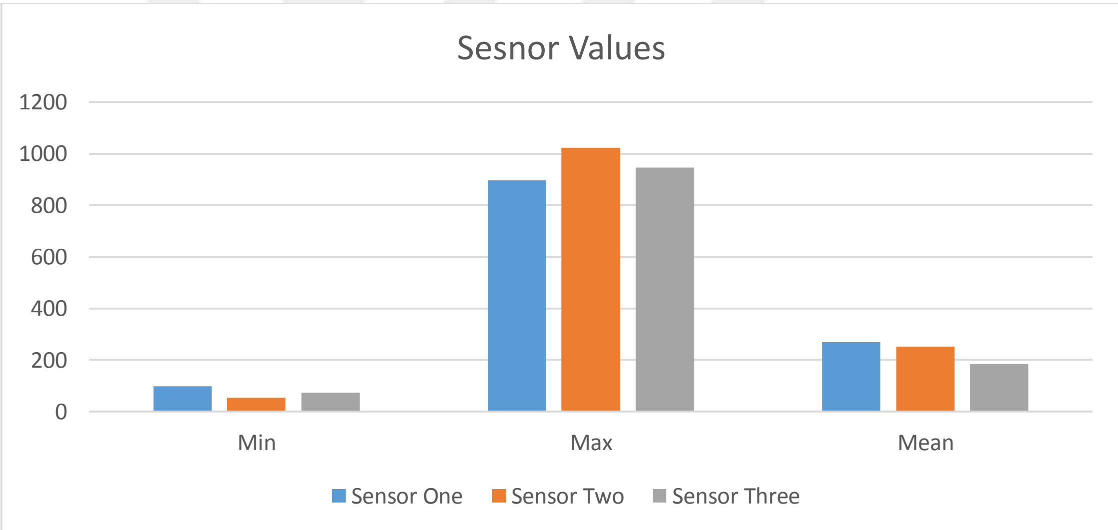


Figure 4.4. Average of Sensor 1, 2, and 3

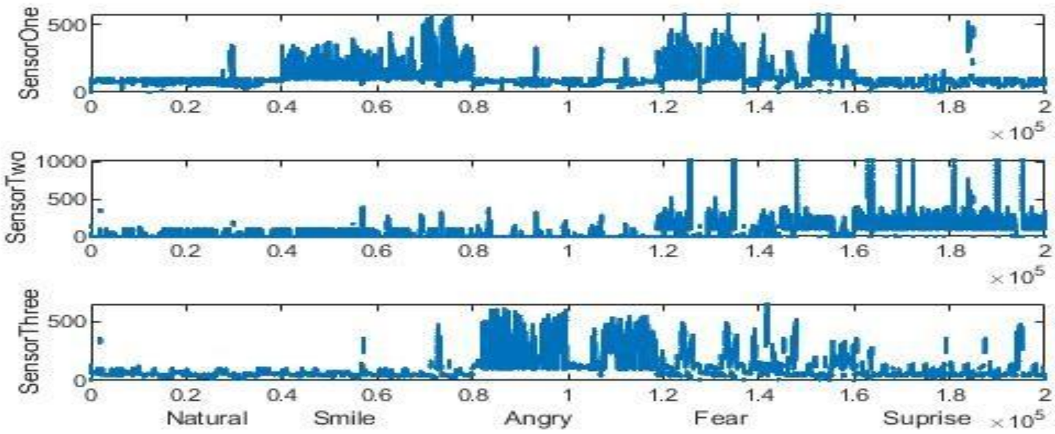


Figure 4.5. EMG RMS values of 20 People

The next step is the classification of different facial expressions with features obtained from EMG signals. Certain measurements are obtained from the confusion matrix to evaluate the effectiveness of the classification methods. The confusion matrix is the most important tool used to evaluate the performance of a classifier. Table 4.2 shows the representation of the complexity matrix for multi-class classification.

Table 4.2. Confusion Matrix for multi-class classification problem

		Actual class				
		1	2	3	4	Sum
Predicted class	1	TP_{11}	FP_{12}	FP_{13}	FP_{14}	RT_1
	2	FP_{21}	TP_{22}	FP_{23}	FP_{24}	RT_2
	3	FP_{31}	FP_{32}	TP_{33}	FP_{34}	RT_3
	4	FP_{41}	FP_{42}	FP_{43}	TP_{44}	RT_4
	Sum	CT_1	CT_2	CT_3	CT_4	total

In Table 4.2, the TP (True positive) value in the confusion matrix is the number of samples in which the predicted class and the real class are the same. FP (False positive) shows the number of instances where the predicted class and the real class are not the same. Precision, recall, F1 and accuracy metrics are measured from the confusion matrix. Precision shows the relationship between the results and shows the ratio of correct class to estimation. Precision calculation is given in Equation (4.1).

$$Precision = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_{ii}}{RT_i} \quad (4.1)$$

In (4.1), C is the number of classes, TP_{ii} is the number of correctly classified samples. RTi value is the sum of TP and FPs in the related row. The second measurement is Recall, which is predicted as class-i correctly classified samples for the class i. For the class is the division of the number of samples tagged as. Calculation of Recall value is given in Equation (4.2).

$$Recall = \frac{1}{C}\sum_{i=1}^{C}\frac{TP_{ii}}{CT_i} \tag{4.2}$$

CT_i in equation (4.2) represent the sum of TP and FP in the related column. Another measurement is F1 and it is the geometric average of Recall and Precision. If these values are close to one, it indicates that it is a good classification. F1 measure is given in (4.3).

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4.3}$$

The last parameter is accuracy and it is the number of samples correctly classified among all samples. Accuracy rate is calculated according to Equation (4.4).

$$Accuracy = \frac{\sum_{i=1}^{C} TP_{ii}}{total} \tag{4.4}$$

When a multivariate Decision tree classifier is used for the EMG sensor, training data and leave-one-out cross-validation are used in the classifier to improve the prediction accuracy. The correct classification 91%. The incorrect classification 9%. Matlab was used to classify the specific machine learning algorithms and to compare them. Table 4.3 displays the findings with consideration of 3 feature as well as parameters. The RMS features scatter plot of four expressions from a three channels training data with three channels sEMG. Each test data consists of four expressions: smile, surprise, anger, and fear. Figure 4.6 lists the classification results of a test data set.

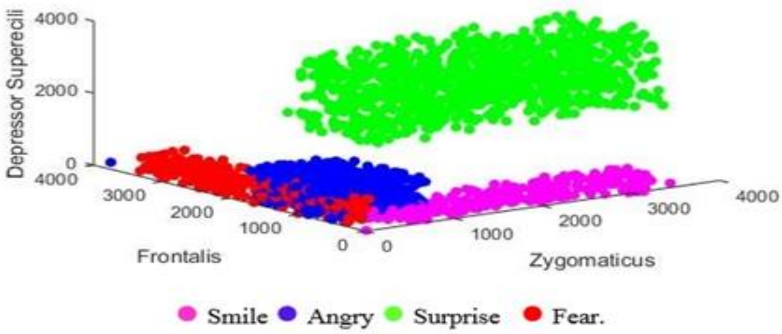
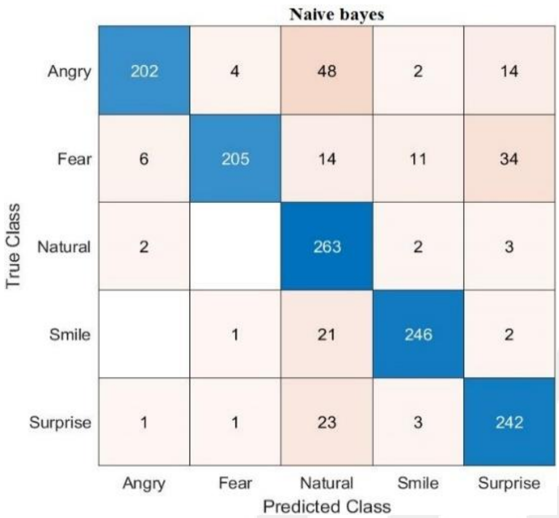
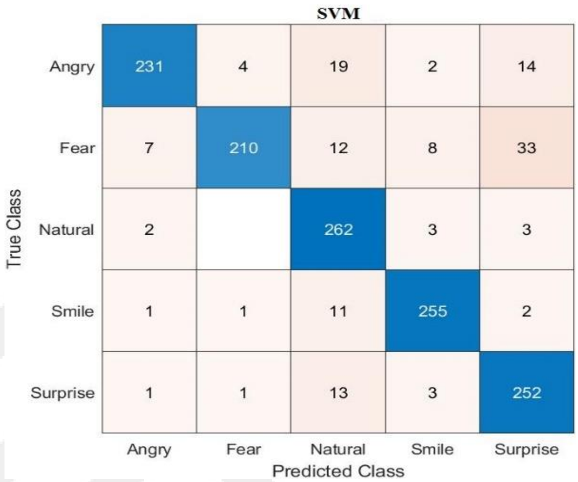


Figure 4.6. Four expressions of RMS feature training data.

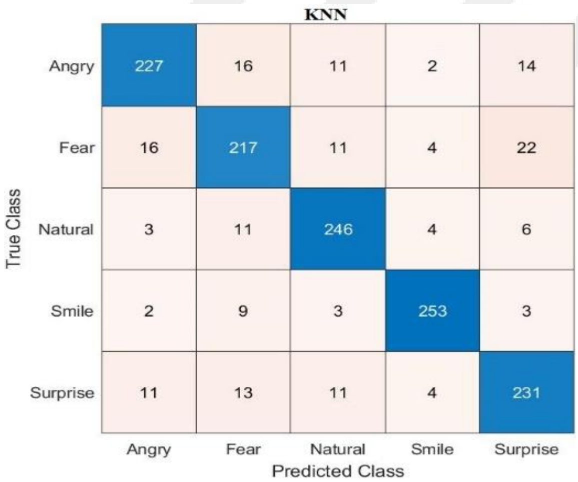
The numbers on the y-axis in Figure 4.6 indicate the classification results. From a to d, the numbers represent a smile, surprise, anger, and fear, respectively. This indicates a misclassified data point and misclassified as an expression is the frown expression. The complexity matrices of the highest-performing classifiers are shown in Figure 4.7.



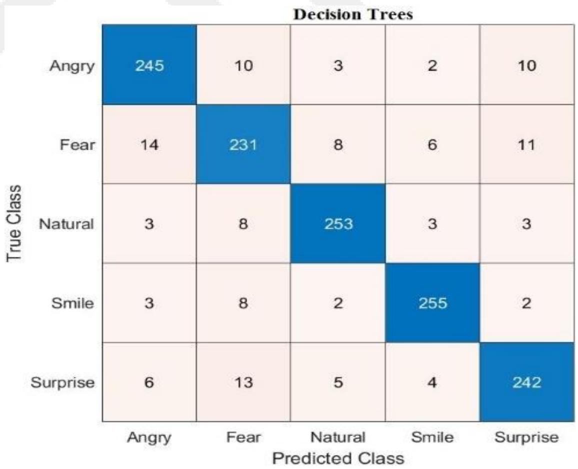
(a) Confusion matrix of Naïve Bayes



(b) Confusion matrix of SVM



(c) Confusion matrix of KNN



(d) Confusion matrix of Decision tree

Figure 4.7. Confusion matrix of four classifiers for six facial expressions

The decision tree system, as seen in Figure 4.7, has a stronger confusion matrix than other methods. Table 4.3 displays the precision rates and other statistics of each form.

Table 4.3. Comparison of various classification algorithms

Algorithm	Performance measures (%)			
	Accuracy Rate	Precision	Recall	F1
Naive Bayes	85.8	85.8	87.8	85.8
SVM	89.6	89.6	90.4	89.4
KNN	87.0	87.0	87.2	87
Decision Tree	**90.8**	**91**	**90.6**	**90.9**

The results of ROC Curve using Decision tree of Smile, Fear, Anger and Surprise. The results show that angry it is greater than from all result show in Figure 4.8.

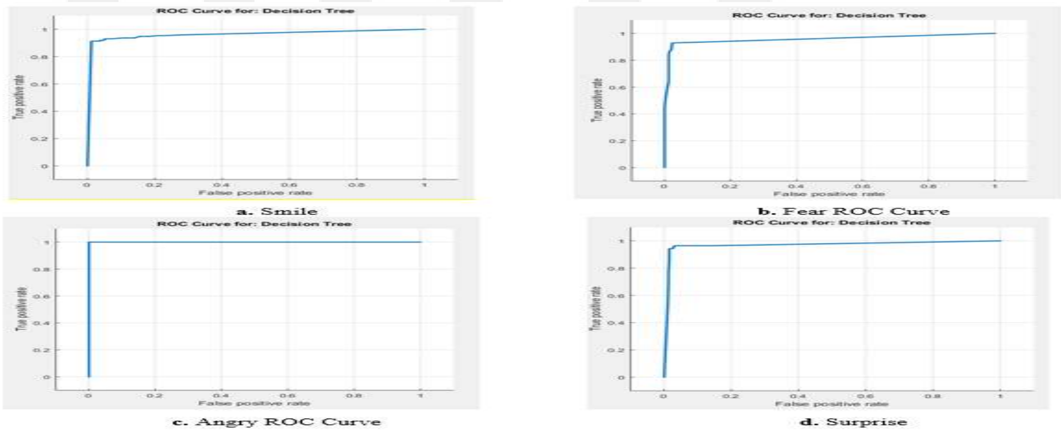


Figure 4.8. Facial Expression ROC Curve

The other datasets that are freely accessible were obtained It consists of four features is called Facial Surface EMG Dataset [53].

The data consists of EMG signals from 5 different muscles of the face. These muscles have been chosen as corrugator supercilii, zygomaticus major, orbicularis oris, orbicularis oculi and masseter. Experiments were carried out in two stages. In the first stage, signals were read from the right side of the participant's face using the zygomaticus major, orbicularis oris, orbicularis oculi and corrugator supercilii muscles. At this point, the participants were asked to grin, shrink their lips and frown while calculating EMG signals. The participants were supposed to perform the same acts in the second process while chewing gum. The data from the zygomaticus major, orbicularis oris, orbicularis oculi and masseter muscles on the right side of the face were measured this time. Acts require resting intervention in all stages. While resting was taken as neutral in the first phase, chewing gum was performed during rest in the other phase. The location of the sensors is shown in Figure 4.9.

(a) Electrode placement for first phase (b) Electrode placement for second phase

Figure 4.9. Two different sensor layouts for reading EMG signals [54]

The actions of the participants were repeated 10 times for each facial expression. The sampling rate of the data was chosen as 2048 Hz. E-Prime simulation software was used to collect experimental data [55]. 8 women and 7 men took part in the experiments. Participants are between 26 and 57 years of age, and all have normal vision and hearing. Measurements were taken using a gelled Ag-AgCl electrodes. These electrodes have two caps and there is also a ground electrode. The sensor measuring the Corrugator supercilii has been removed since the measuring device has only 4 channels when receiving data in the second phase. The display of the signals received for different situations is given in Figure 4.10.

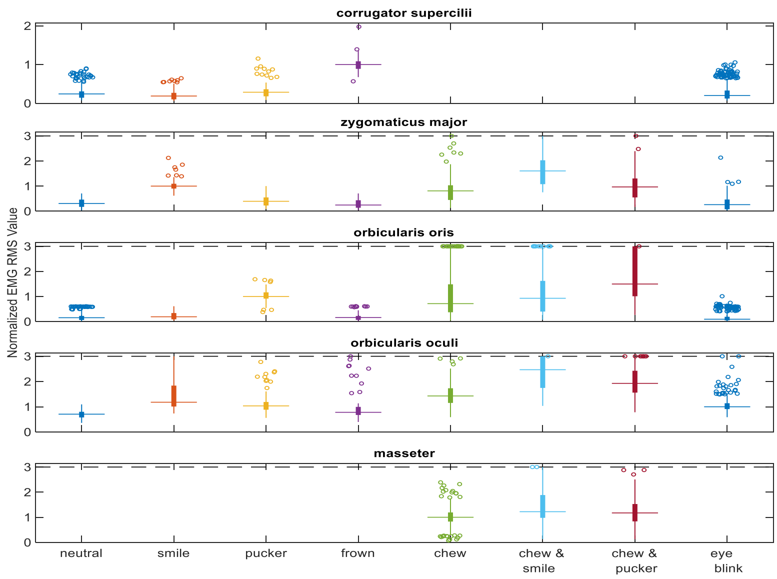
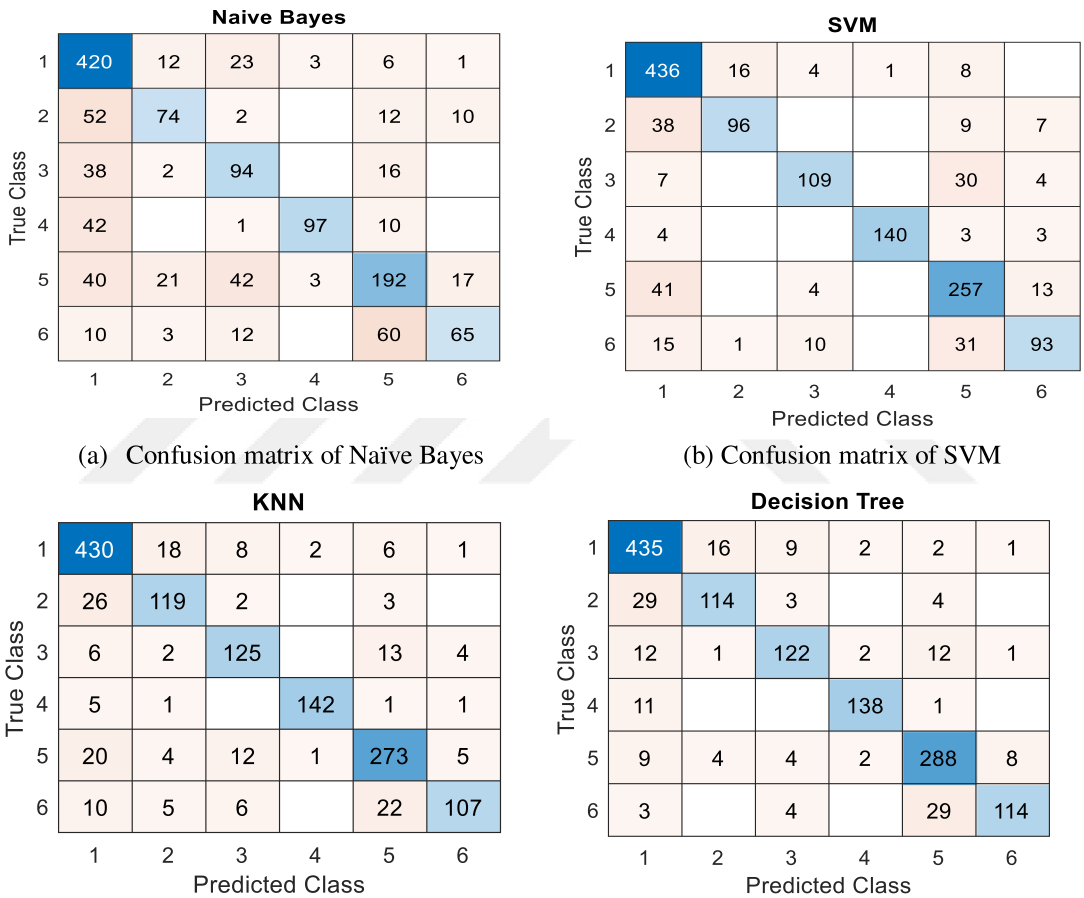


Figure 4.10. The normalized EMG RMS signals for different facial expressions [54]

For each muscle, the average values in Figure 4.10 are taken and standardized for each participant. Moreover by sending the signals via a band-pass filter, the sounds have been suppressed. In the diagram, the horizontal lines represent the median value. By separating the values obtained into the median, the properties for the form of movement are obtained. The purpose of the acquired characteristics was to identify facial expressions using the MATLAB Classifier Learner. It was omitted from the data collection because the wink response would not appear in all other actions. On the data collection, 5-point cross validation was applied for verification. The complexity matrices of the highest-performing classifiers are shown in Figure 4.11.



(a) Confusion matrix of Naïve Bayes (b) Confusion matrix of SVM

(c) Confusion matrix of KNN (d) Confusion matrix of Decision tree

Figure 4.11. Confusion matrix of four classifiers for six facial expressions

As shown in Figure 4.11, the decision tree method has a better confusion matrix than other methods. The accuracy rates and other statistics of each method are given in Table 4.4.

Table 4.4. Comparison of various classification algorithms

Algorithm	**Performance measures (%)**			
	Accuracy Rate	**Precision**	**Recall**	**F1**
Naive Bayes	68.26	61.68	69.83	64.33
SVM	81.94	78.00	84.17	80.50
KNN	86.67	84.50	87.33	85.67
Decision Tree	**87.75**	**85.00**	**88.50**	**86.50**

Based on the Table 4.4. Decision Tree classifier performance is better than Naïve Bayes, KNN and SVM because of the high recognition ratio owing to its flexibility.

5. CONCLUSIONS AND DISCUSSION

EMG measurement technology is a critical tool for clinical purposes to detect facial expressions because when someone has a facial expression, their facial muscles change, and this method can be used for detection and analysis. However, FACS is a time-consuming technology that requires expert knowledge or training. The current study can be improved by applying a method that for the recognition all the facial expressions base while they are on SEMG in bi-polar configuration. The study depended on the volunteers' facials to derive SEMG signals. It has been mentioned that two classification techniques were applied in this thesis.

Based on the tests, Decision Tree classifier's performance is better than Naïve Bayes because of the high recognition ratio owing to its flexibility. Researchers may have results that are better in the field of recognition of facial expression based on EMG in previous studies, but there are some reasons that are directly affective to these results. The most important reasons are different facial gestures and the number of facial gestures selected in different facial gesture-based systems applications. Just as expected, as the number of facial movements (classes) increases, the data overlap ratio becomes greater. Then the number of recognitions gets smaller. In addition, that the frequency spectrum ranges of each facial expression are very similar to each other and the implementation of frequency domain features makes it difficult to distinguish them. Nevertheless, such bandwidths help test muscle tiredness more reliably and predict improvements in the recruitment of motor units. Consequently, the identification of facial expression / gesture dependent on SEMG obviously has an accurate output. Furthermore, the most significant problem that separates this approach from others, such as picture or video dependent, is that peripheral constraints on the percentage of recognition are ineffectual. Finally, demonstrates and compares different algorithms and automated facial expression recognition methods based on EMG.

We develop methods that focus on pain facial expressions. We measure the facial activity of muscles, the electrical muscles and the activity intensity with EMG. We also measure facial activity with vision-based methods. The FACS is comprehensive that describes facial activities based on human anatomy [1-2]. Video sequences are another method based on the LDA classifier. In this thesis, we focus on Facial EMG Activity intensity [2].

The general scheme of the proposed method. It illustrates a general outline of the proposed operation. The preparation of objects and placement of electrodes is considered as the first two phases of the thesis. The system configuration and data collection are discussed. In the next step, the signaling processing is mentioned. Amplified and filtered before treatment is the EMG signal recorded by the surface electrode. Using a 48 Hz-52 Hz filter, we remove noise and artifacts from the original signal. For processing, the received signal distinguishes the correct signal. We extract the valid features from each window (256 ms), submitted them to the workbook. We obtained the features to study the bandwidth. Before classification, all RMS properties are sent from the threshold line to aggregate the active properties. Finally, active SMRs are compiled through Decision Tree and Naïve Bayes workbooks and grouped into five separate face modes [1].

5.1. Future work

This project can be applied to the patient. The signals show emotional excitement (fear, surprise, anger, or smile) / injury or false. Our main goal is to analyze the emotional facial expressions/injuries of the intensive care unit (ICU) and newborns. To distinguishing newborn pain from crying is a challenge. Another important issue is that newborns grow very fast; thus, we must change the size according to their age. It is also important to have a system to automatically detect pain to increase the efficiency and overhead associated with monitoring patient progress.

Besides, we must evaluate other patterns that detect the facial expressions of patients by using camera recordings. There is also a need to check the utilization of the patient bed system. The complexity is increased because the patient's face relative to the camera also partially obscures the face. Here, the facial motion coding system can help us to understand the facial expression/injury of patients. In this system, we will use an Active Appearance Model (AAM) based system for detection to track faces and extract visual appearance. Decision Tree can be used to classify AU and pain.

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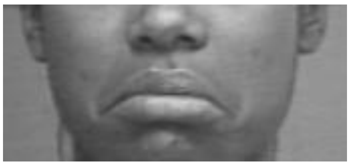
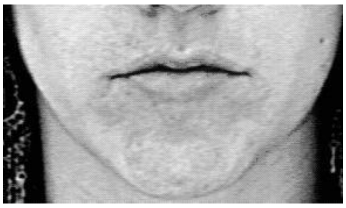
Appendix- 1: FACS – Facial Action Coding System

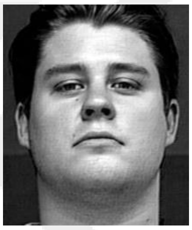
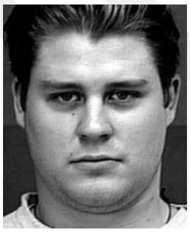
(Ekman and Friesen 1978)

AU	Description	Facial muscle	Example image
1	Inner Brow Raiser	Frontalis, pars medialis	
2	Outer Brow Raiser	Frontalis, pars lateralis	
4	Brow Lowerer	Corrugator supercilii, Depressor supercilii	
5	Upper Lid Raiser	Levator palpebrae superioris	
6	Cheek Raiser	Orbicularis oculi, pars orbitalis	
7	Lid Tightener	Orbicularis oculi, pars palpebralis	
9	Nose Wrinkler	Levator labii superioris alaquae nasi	

10	Upper Lip Raiser	Levator labii superioris	
11	Nasolabial Deepener	Zygomaticus minor	
12	Lip Corner Puller	Zygomaticus major	
13	Cheek Puffer	Levator anguli oris (a.k.a. Caninus)	
14	Dimpler	Buccinator	
15	Lip Corner Depressor	Depressor anguli oris (a.k.a. Triangularis)	
16	Lower Lip Depressor	Depressor labii inferioris	

17	Chin Raiser	Mentalis	
18	Lip Puckerer	Incisivii labii superioris and Incisivii labii inferioris	
20	Lip stretcher	Risorius w/ platysma	
22	Lip Funneler	Orbicularis oris	
23	Lip Tightener	Orbicularis oris	
24	Lip Pressor	Orbicularis oris	
25	Lips part**	Depressor labii inferioris or relaxation of Mentalis, or Orbicularis oris	
26	Jaw Drop	Masseter, relaxed Temporalis and internal Pterygoid	

27	Mouth Stretch	Pterygoids, Digastric	
28	Lip Suck	Orbicularis oris	
41	Lid droop**	Relaxation of Levator palpebrae superioris	
42	Slit	Orbicularis oculi	
43	Eyes Closed	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	
44	Squint	Orbicularis oculi, pars palpebralis	
45	Blink	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	
46	Wink	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	

51	Head turn left	
52	Head turn right	
53	Head up	
54	Head down	
55	Head tilt left	
56	Head tilt right	
57	Head forward	

58	Head back	
61	Eyes turn left	
62	Eyes turn right	
63	Eyes up	
64	**Eyes down**	

Currıculum Vıtae

[redacted]

PERSONAL INFORMATIONS

RESEARCHER INFORMATION

[redacted]

EDUCATION

Master Degree **:** Internet of Things Based Intelligent Facial Expression Monitoring using EMG Signals

Firat University, Natural and Applied Sciences Graduate School, Department of Computer Engineering, 2020

Supervisor: Assoc. Prof. Dr. Ilhan AYDIN

Bachelor **:** Zakho University, Science Faculty, Department of Computer Science, 2017

High School **:** Zakho High School Duhuk, Iraq

RESEARCH EXPERIENCES

Graphics: Adobe (Photoshop-primer-after effect), movies maker

Languages: C++, C#, Python, Visual Basic

Windows: Windows 10, Windows 8, Windows Seven, Windows XP, Linux

Others: Microsoft Office 2003,2007,2010,2013, Matlab ...etc.

E-marketing: Facebook, e-mail, YouTube, Google group, yahoo, Hotmail,

E-commerce: design website (word press, html, Css, php, java script, Dreamweaver) ,Gmail, twitter

Network: Wireless network, cisco packet tracer, configuration…etc.

Database: MySQL -Access-Sql server.

WORK EXPERIENCE

2015 – 2017: Company accountant manager

2013 – 2015: Company project manager

2010 – 2013: Teacher at Zakho Technical Institute

ACADEMIC ACTIVITIES

Proceedings:

Internet of Things Based Intelligent Facial Expression Monitoring using EMG Signals International Conference on Advanced Technologies, Computer Engineering and Science (ICATCES 2020), Jun 03-05, 2020 / Karabuk, Turkey, page 115 to 120.