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OPTIMAL FEATURE TUNING MODEL BY VARIANTS OF CONVOLUTIONAL NEURAL NETWORK WITH LSTM FOR DRIVER DISTRACT DETECTION IN IOT PLATFORM

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Doctor of Philosophy

Supervisor
Asst. Prof. Dr. Ayça KURNAZ TÜRKBEN

İstanbul, 2024

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The Dissertation titled OPTIMAL FEATURE TUNING MODEL BY VARIANTS OF CONVOLUTIONAL NEURAL NETWORK WITH LSTM FOR DRIVER DISTRACT DETECTION IN IOT PLATFORM , prepared by HAMEED MUTLAG FARHAN and submitted on 05/07/2024 has been **accepted unanimously** for the degree of PhD. in Electrical and Computer Engineering.

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I hereby declare that this thesis meets all format and submission requirements of a Ph.D. Dissertation.

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

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Hameed Mutlag Farhan FARHAN

DEDICATION

To Allah, the Most Merciful and Compassionate, who guided me through every step of this journey, I offer my sincerest gratitude. To all those who supported and encouraged me, whether through a kind word, a piece of advice, or a heartfelt prayer, your unwavering support has been my strength. This thesis is dedicated to each one of you,

My advisor, for their guidance, expertise, and unwavering support throughout this academic journey. Your mentorship has been invaluable in shaping my research and professional development.

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My family, especially my father and mother, whose boundless love, sacrifices, and belief in my abilities have been the cornerstone of my achievements. Your constant support has been my greatest strength.

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My friends, for their camaraderie, laughter, and unwavering support that have made this journey unforgettable. Your friendship has made the challenges more manageable xand the successes more joyful.

And to all those who have supported and encouraged me along the way, whether through a kind word, a listening ear, or a helping hand, I am deeply grateful for your belief in me.

This thesis stands as a tribute to the collective encouragement and support of all those who have uplifted me on this remarkable journey. Thank you for being my pillars of strength.

PREFACE

In presenting this doctoral Dissertation, I am filled with a profound sense of accomplishment and gratitude. This work represents the culmination of years of rigorous study, research, and exploration in Computer Engineering & AI Filed. As I reflect on this journey, I am reminded of the countless individuals and experiences that have shaped and enriched my academic pursuit.

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This Dissertation is dedicated to all those who have contributed, directly or indirectly, to its fruition. It is my hope that this work contributes to the body of knowledge in Computer Engineering and inspires future generations of scholars.

ABSTRACT

OPTIMAL FEATURE TUNING MODEL BY VARIANTS OF CONVOLUTIONAL NEURAL NETWORK WITH LSTM FOR DRIVER DISTRACT DETECTION IN IOT PLATFORM

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Nowadays, traffic accidents are caused due to the distracted behaviors of drivers that have been noticed with the emergence of smartphones. Due to distracted drivers, more accidents have been reported in recent years. Therefore, there is a need to recognize whether the driver is in a distracted driving state, so essential alerts can be given to the driver to avoid possible safety risks. For supporting safe driving, several approaches for identifying distraction have been suggested based on specific gaze behavior and driving contexts. Thus, in this paper, a new Internet of Things (IoT)-assisted driver distraction detection model is suggested. Initially, the images from IoT devices are gathered for feature tuning. The set of Convolutional Neural Network (CNN) methods like ResNet, LeNet, VGG 16, AlexNet GoogleNet, Inception-ResNet, DenseNet, Xception, and mobilenet are used, in which the best model is selected using Self Adaptive Grass Fibrous Root Optimization (SA-GFRO) algorithm. The optimal feature tuning CNN model processes the input images for obtaining the optimal features. These optimal features are fed into the Long Short-Term Memory (LSTM) for getting the classified distraction behaviors of the drivers. From the validation of the outcomes, the accuracy of the proposed technique is 95.89%. Accordingly, the accuracy of the existing techniques like SMO-LSTM, PSO-LSTM, JA-LSTM, and GFRO-LSTM is attained as 92.62%, 91.08%, 90.99%, and 89.87%, respectively for dataset 1. Thus, the suggested model achieves better classification accuracy while detecting distracted behaviors of drivers and this model can support the drivers to continue with safe driving habits.

Keywords: Driver Distract Detection in IoT , Optimal Feature Tuning Model, Convolutional Neural Networ, Long Short-Term Memory, Self Adaptive Grass Fibrous Root Optimization.

ÖZET

IOT PLATFORMUNDA SÜRÜCÜ DİKKAT DAĞILMASINI ALGILAMAK İÇİN LSTM İLE EVRIMSEL SİNİR AĞININ ÇEŞİTLERİYLE OPTİMUM ÖZELLİKLİ AYAR MODELİ

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Günümüzde akıllı telefonların ortaya çıkmasıyla birlikte fark edilen sürücülerin dikkat dağınıklığı nedeniyle trafik kazaları meydana geliyor. Dikkatsiz sürücüler nedeniyle son yıllarda daha fazla kaza rapor edildi. Bu nedenle, sürücünün dikkati dağılmış bir sürüş durumunda olup olmadığının anlaşılmasına ihtiyaç duyulmakta ve olası güvenlik risklerinden kaçınmak için sürücüye gerekli uyarılar verilebilmektedir. Güvenli sürüşü desteklemek için, belirli bakış davranışına ve sürüş bağlamlarına dayalı olarak dikkat dağınıklığını belirlemeye yönelik çeşitli yaklaşımlar önerilmiştir. Bu nedenle, bu makalede Nesnelerin İnterneti (IoT) destekli yeni bir sürücü dikkat dağınıklığını tespit etme modeli önerilmektedir. Başlangıçta, özellik ayarlama için IoT cihazlarından gelen görüntüler toplanır. ResNet, LeNet, VGG 16, AlexNet GoogleNet, Inception-ResNet, DenseNet, Xception ve mobilenet gibi Evrişimli Sinir Ağı (CNN) yöntemleri kümesi kullanılır ve burada En iyi model, Kendini Uyarlayan Çim Fibröz Kök Optimizasyonu (SA) kullanılarak seçilir. -GFRO) algoritması. Optimum özellik ayarlama CNN modeli, optimum özellikleri elde etmek için giriş görüntülerini işler. Bu optimum özellikler, sürücülerin sınıflandırılmış dikkat dağıtma davranışlarını elde etmek için Uzun Kısa Süreli Belleğe (LSTM) beslenir. Sonuçların doğrulanmasından önerilen tekniğin doğruluğu %95,89'dur. Buna göre mevcut tekniklerin doğruluğu SMO-LSTM, PSO-LSTM, JA-LSTM ve GFRO-LSTM gibi veri seti 1 için sırasıyla %92,62, %91,08, %90,99 ve %89,87 olarak elde edilmiştir. Model, sürücülerin dikkat dağıtıcı davranışlarını tespit ederken daha iyi sınıflandırma doğruluğu

elde etmekte ve bu model, sürücülerin güvenli sürüş alışkanlıklarına devam etmelerine destek olabilmektedir.

Anahtar Kelimeler: IoT'da Sürücü Dikkatinin Tespiti, Optimal Özellik Ayarlama Modeli, Evrişimsel Sinir Ağı, Uzun Kısa Süreli Bellek, Kendini Uyarlayan Çim Lifli Kök Optimizasyonu.

TABLE OF CONTENTS

Pages

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

CNN	:	Convolutional Neural Network;
DDD	:	Distract Driver Detection
GPS	:	Global Positioning System
HCF	:	Hybrid Cnn Framework
IOT	:	Internet Of Thing
ITS	:	Information Technology Service
JA	:	Jaya Optimization
LSTM	:	Long Short-Term Memory
PSO	:	Particle Swarm Optimization
RFID	:	Radio-Frequency Identification
RNN	:	Recurrent Neural Network
SAGFRO	:	Self Adaptive Grass Fibrous Root Optimization
SMO	:	Spider Monkey Optimization
SVM	:	Support Vector Machine
VANET	:	Vehicular Ad-Hoc Network

LIST OF SYMBOLS

E_{oc}	:	Standard Potential
I_L	:	Current Limitation Density
$I_{o,a}$	:	Anode
$I_{o,c}$	:	Cathode
R_{Ω}	:	Area-Specific Resistance
A	:	Tafel Line Slope
B	:	Constant
Ep_{lstm}^{ep}	:	Epochs
HN_{lstm}^{hn}	:	Hidden Neurons

1. INTRODUCTION

IoT [1] is rapidly recognized in the field of wireless communication. IoT communicates and transfers information to millions of people, objects, and devices all over the world. Desktop interactions with computers will be no longer in the next generation. The technologies all around the world are developing as the growth of objects and surroundings is increasing [2]. All these things will be in the form of a network in the future. These things include switches, tags, and Radio-Frequency Identification (RFID) devices [3]. The unique term "things" can exchange information and interact with one another to achieve a common goal. In this case, a cloud-based system is introduced to provide service to all users. This cloud-based device connects all dissimilar devices and offers services to the users [4]. Among them, the Information Technology Service (ITS)-cloud-based approach is implemented to enhance vehicle-to-vehicle security and communications [5]. ITS-cloud delivers various services such as business applications, cloud backup, research applications, and correspondence applications. The IoT devices have high security [6]. In this research work, the development of Artificial Intelligence (AI) is utilized for implementing smart technology into cars and gives new communication between cars and their drivers. AI has played an important role in the developed of smart vehicular network-based IoT for accident prevention methods. The main features of AI are that it has not only avoided the detection problem of diabetes drivers during driving times. Moreover, it has introduced an AI warning scheme which is utilized to minimize traffic accidents when the drivers come across to unavoidable distractions. Additionally, the recent advanced benefits of AI in this research work is helped to avoid the distraction of drivers and the other features for detecting the hand location, head location, and pupil diameter.

The people are always engaged in activities like texting, drinking, applying makeup, and talking on the phone while driving the vehicle. The drivers should be alert of these activities and need to focus on driving to prevent accidents [7]. The manufacturers of automobiles should provide advanced intelligence systems on vehicles to alert drivers and to detect distracted drivers [8]. Advanced devices are introduced to detect the inattention of drivers. Some models were built to observe, monitor, and detect distracted drivers effectively [9]. The microphones and other electronic devices within the vehicles help to alarm the signal to the drivers when get distracted and avoid the risk of accidents [10]. The main cause of the accidents was related to the improper behavior of drivers. The behavior of speeding, drunk driving, and not wearing seatbelts are also included in the bad behavior of drivers. Real-time problems can be tackled and prevented by adopting deep learning techniques [11].

Deep learning approaches are proposed to classify the behavior of drivers using 2D cameras and to extract the image features [12]. The video screening and classification method is introduced to detect the movements of the drives accurately. Support Vector Machine (SVM)-based deep learning approach is used to detect the task of distracted drivers [13]. Distracted drivers are classified with CNN and identified as the cause of detection. The classification of the cause of distraction is very essential to avoid the risk. The cause of the distraction is dissimilar, and it needs to be found and dealt with accordingly [14]. The images from the dashboard of the vehicle are gathered and subjected to neural networks and then, the category of distraction is recognized [15]. Deep learning has shown better performance in visual representation tasks. Particularly, CNN has achieved high accuracy in image recognition tasks [16]. Various deep learning methods such as VGGNet, GoogLeNet, recurrent neural network (RNN), and AlexNet attain progressive results in time series problems and language issues like machine translation and speech recognition [17].

1.1 MOTIVATION OF THE STUDY

In recent years, the integration of the Internet of Things (iot) with advanced machine learning techniques has shown significant potential in enhancing road safety by detecting driver distractions. One promising approach involves leveraging Convolutional Neural Networks (cnns) combined with Long Short-Term Memory (LSTM) networks to accurately identify and predict distracted driving behaviors. This research aims to optimize feature tuning in such models to improve the performance and reliability of driver distraction detection systems deployed on iot platforms. The motivation for this research is:

a. Increasing Road Safety:

i. High Accident Rates: Driver distraction is a major cause of road accidents globally. According to the World Health Organization, a significant percentage of road traffic accidents are due to distracted driving. Detecting and mitigating such distractions can potentially save countless lives.

ii. Preventive Measures: By identifying distractions in real-time, appropriate preventive measures can be taken, such as alerting the driver or taking control of the vehicle, thereby reducing the risk of accidents.

b. Advancements in Machine Learning:

i. Effectiveness of CNNs and LSTMs: CNNs are highly effective in feature extraction from visual data, while LSTMs excel in sequence prediction tasks. Combining these two architectures can enhance the model's ability to understand and predict driver behavior over time.

ii. Optimal Feature Tuning: Fine-tuning the features extracted by CNNs and processed by LSTMs can significantly improve the accuracy and efficiency of distraction detection models.

c. Advancements in Machine Learning:

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ii. Optimal Feature Tuning: Fine-tuning the features extracted by CNNs and processed by LSTMs can significantly improve the accuracy and efficiency of distraction detection models.

d. Integration with IoT Platforms:

i. Real-time Data Processing: IoT platforms enable real-time data collection and processing from various sensors installed in vehicles. This allows for immediate detection and response to driver distractions.

ii. Scalability and Deployment: IoT platforms facilitate the deployment of driver distraction detection systems on a large scale, ensuring that a wide range of vehicles can benefit from this technology.

e. Challenges in Driver Distraction Detection:

i. Variability in Distractions: Driver distractions can vary widely, from using a mobile phone to interacting with passengers. Developing a model that can accurately detect such a wide range of distractions requires robust feature extraction and processing.

ii. Real-time Constraints: Ensuring that the detection system operates in real-time with minimal latency is crucial for practical deployment. This necessitates efficient feature tuning and model optimization.

1.2 OBJECTIVE

a. Enhance Detection Accuracy: Improve the precision and recall rates of driver distraction detection models by optimizing feature extraction and tuning processes.
b. Minimize Latency: Develop models that can operate with minimal delay, ensuring timely detection and response to distractions.
c. Ensure Robustness: Create models that can reliably detect various types of distractions under different driving conditions.
d. Facilitate Deployment: Design models that can be easily integrated into existing IoT platforms for widespread use.

The motivation behind this research is to leverage the strengths of CNNs and LSTMs in creating an optimal feature tuning model for driver distraction detection. By integrating these advanced machine learning techniques with IoT platforms, we aim to develop a robust, accurate, and scalable solution that enhances road safety by mitigating the risks associated with distracted driving.

1.3 RESEARCH GAP AND CHALLENGES

The existing works have faced various challenges that are shortly given as follows.

a. The existing detection models produce the dissimilarity between the classified data and the public dataset, which results in performance loss. So the adoption of hybrid deep learning approaches will enhance the existing problems.
b. The existing model does not consider any spatial-temporal correlation, and so, the improved LSTM can be incorporated to deal with the spatial-temporal forecasting problems.
c. The detection of facial information is unclear in the existing model, so, the fine-tuning of features using CNN variants is implemented to detect the drowsy and fatigue drivers and provide high recognition accuracy.

d. The recognition of distracted drivers was focused on a single angle with low image quality, which may lead to affect the proper detection. Hence, improved deep-learning approaches have to be developed to detect the behaviour of drivers at different angles with better prediction accuracy.

1.4 RESEARCH CONTRIBUTION

The major significance of this work is described here.

a) To adopt an advanced driver distraction detection model with the help of an IoT platform along with the intelligent deep structured model and optimization algorithms for accurately detecting distracted behavior to avoid road accidents. This performance improvement in the designed model is done and so, it can be applied to the driver assistance systems to find appropriate solutions for drivers.

b) To implement the optimal feature tuning model with the nine variants of CNN such as "LeNet, AlexNet, VGG 16, GoogleNet, ResNet, Inception-ResNet, DenseNet, Xception, and mobileNet" for obtaining the optimized features with the help of a novel SA-GFRO algorithm to improve the classification performance.

c) To suggest the deep structured technique named M-LSTM for categorizing the distracted behaviors by their actions using the proposed SA-GFRO by the parameter optimization to improve the classification accuracy and precision of the suggested method.

d) To validate the efficacy of the offered distracted driver detection approach with different meta-heuristic approaches and classifiers using several quantitative metrics.

The remaining section of the developed model is described as follows. The section II explains the related works and the problems. In section III, the proposed distracted driver behavior model and its dataset description is depicted. In section IV, the optimal feature tuning model is carried out. In section V, the developed M-LSTM and the proposed algorithm are introduced. In section VI, the attained results of the proposed model are discussed. In section VIII, the developed distracted driver detection with IoT is summarized.

1.5 THESIS STRUCTURE

This thesis was organized and divided into 5 chapters, The first chapter was divided into 5 sections such as introduction, Problem statements, research contribution and thesis orginaziton. While the second chapter included the literature review, related work, we present our methodology in chapter three and in chapter four we discussed explained the ruslts that get out after implementation of our methodology. The last chapter, called chapter five included the conclusion and the future work.

2. LITERATURE SURVEY

2.1 BACKGROUND

IoT technology is becoming ubiquitous in today's society, affecting every aspect of our lives. One of the technologies that can help with today's problems is the Internet of Things (IoT), which is also quite affordable [18] This technology is a component of a new industrial revolution that is bringing previously unheard-of levels of efficiency to a number of industries, including smart cities, e-health applications, the automotive sector, and agriculture [19]. In addition to the incredible results of IoT technology, the countless features of IoT platforms provide a multitude of devices and apps. According to the well-known adage that characterizes two sides of a coin, this technology entails security issues related to user data confidentiality, access control, public infrastructure, emerging threats, etc. [20] Although implementing IoT platforms serves the primary goal of increasing efficiency, there are a number of security risks that come with IoT devices since they create a lot of data that is sent to the internet[21]. The primary obstacles are large volumes of data, heterogeneity, collectivity, and extra aspects of Internet of Things services.

In order to enhance driver convenience and vehicle safety, driver monitoring systems have long been essential. The extraction of features is an essential step in the identification of driving behavior [22].

During the digital development and the artificial intelligence revolution in areas of life, especially the industrial field. Detecting driver distraction and determining his behavior while driving a vehicle is one of the most important topics in industrial and academic fields that researchers are currently focusing on [23]

Human life and safety are among the most important things in our world, and driver distraction threatens human life and exposes them to danger while driving [24].

Driver distraction is defined as shifting attention toward a competing activity away from important driving activities, such as Using phone while driving, talking with the person next to the driver, trying to reach an object in the back seats, eating or drinking something while driving and focus on using the stereo and radio buttons while driving without due attention and observing the correct driving conditions, etc [25].

Traffic accidents cause the death of many people, an estimated 1.9 million people annually, according to World Health Organization statistics for the year 2023. [26].

We find that most of the causes of these accidents are the result of driver distraction, so driver distraction is the main factor causing these accidents that pose a great danger to people's lives, and which often lead to direct death or serious injuries that sometimes end in death [27].

This important study addresses all the factors that may affect the driver while driving the vehicle and distract him.

Using the techniques of artificial intelligence, machine learning and deep learning algorithms that were used in this thesis in order to build a system that can identify driver behavior and detect whether a car driver is distracted or not.

Therefore, this system can be used in several fields and applications in daily life, including developing the driver's command and control system, developing the autonomous driving system for the driver's safety and controlling the vehicle the moment his attention is distracted, which helps the traffic police recognize the speed of the vehicle. The cause of the accident, and it is also likely that this system will be developed and adopted by self-driving car manufacturers.

2.2 RELATED WORKS

In 2020, Omerustaoglu *et al.* [28] proposed a new model to incorporate sensor data into an image-based driver distraction detection method to enhance the simplification capability of the system. Two-stage driver distracts detection systems were assembled to analyze the nine distracted behaviors. Transfer learning and fine-tuning methods were adopted to create a vision-based CNN approach. Then, the image data and sensor were linked together to create the LSTM-RNN approach. With the fusion of these two techniques and the incorporation of the sensor data was given into the visual-based driver distraction detection method, it has increased the overall efficacy of this proposed technique using a benchmark dataset.

In 2020, Kumar *et al.* [29] proposed a new CapsNet-based model to detect the distraction behavior of drivers. This method was similar to the CNN model and has reduced parameters close to CNN. The results have determined the distraction of drivers and prevent the risk of accidents. The driver's inattention, hand movements, and other activities were possible to monitor and alter them from the cause of high risk. This suggested model has outperformed well on real-life data and the classification accuracy was increased for commonly used metrics.

In 2019, Botta *et al.* [30] planned to create a real-time and non-invasive of visual distraction detection model using real-life data and vehicle dynamics. The data were attributed to the direct resolution of output weights. The presence of null elements in the matrices has caused run-time errors in the trained network. Various genetic approaches were involved to explore the input weights. The proposed method has shown better performance on pseudo pseudo-inversion model.

In 2021, Huang *et al.* [31] have suggested a new driver behavior detection model. The DBD model has low accuracy due to insufficient data, and the negligence of texture information and multi-level structure. Then, a new approach with the support of Mish was introduced. The gradient saturation was prevented and ensured a better driving behavior model. The weight data was used to train the Mish from the first process. The simulation outcomes of the offered model have attained high accuracy, real-time performance, and simplification while tested with other traditional techniques.

In 2021, Zhang *et al.* [32] have introduced a deep learning network compiling of three modules. The multi-scale feature fusion has aimed to study spatio-dependency from different modalities and temporal dependence from all modalities. ConvLSTM Encoder-Decoder model was utilized to perform the classification phase. In the detection process, the UMMFN reconstruction error was calculated to resolve the fine-grained detection. The validation of the offered approach over other existing approaches has given significant performance.

In 2020, Huang *et al.* [33] have developed a Hybrid CNN Framework (HCF) with a deep learning approach. The pre-trained techniques like Xception, ResNet50, and Inception V3 have enhanced the accuracy of a driving detection system. These pre-trained models were required to extract the behavior features of drivers. The obtained features from the pre-trained model were independent. The extracted features were integrated to attain inclusive information. Finally, HCF was applied to detect the hand movements and anomalies. An enhanced dropout algorithm was proposed to prevent the overfitting problems associated with training data. The offered HCF method has gained a higher accuracy rate and helped the drivers to sustain safe driving.

In 2021, Pal *et al.* [34] proposed a CNN-based model to detect and classify distracted drivers and provided a probable solution to the trouble. The activities of the drivers were monitored with a CNN model and the warning signals alerted the drivers to prevent the risk of accidents. This suggested model has taken ten dissimilar classes to classify the behavior of drivers. Hence, nine drivers were distracted by some events and one was driving safely. When one driver was found distracted, he would be warned with an alarm to avoid the chances of an accident.

In 2021 Rao *et al.* [35] proposed a CNN-based approach to detect the distracted driver's behavior with the data collected from the vehicle cameras. The images were contrasted with the PCA technique and reduced the correlation of pixel matrices. Also, multi-layered CNN model was evaluated and the parameters were optimized. The offered approach has enlarged the accuracy in detecting distracted drivers and outperformed the other machine learning approaches.

In 2018, Zhang *et al.* [36] developed a novel color visual saliency segmentation algorithm, which was utilized to enhance and normalize color values to capture color information. The author has implemented a Radial Symmetry Transform (RST) algorithm to enhance the computation efficiency and also decrease the false alarm rate. At last, the simulation findings have revealed that the recommended method enlarged the robustness and achieved a better accuracy rate.

In 2019, Minhas *et al.* [37] investigated diverse approaches to detect the driver’s drowsiness according to the openness and closeness of eyes for detecting the driver’s drowsiness. Based on the situations of the unavoidable effect, adequate details of the driver’s situation are transmitted to the Police Base station.

In 2021, Akrout *et al.* [38] developed a fusion system according to the detection of somnolence, yawn, and 3D head pose estimation. The major scope of this recommended method is to identify the driver's uncommon action by investigating the behaviors of the face. In the end, the recommended method was validated by publically available databases and revealed the advanced performance of the recommended fusion system.

2.3 PROBLEM STATEMENT

The risk of accidents on the road is increased owing to the behavior of drivers. Distracted driving can be detected and to prevent the risk of impacts by implementing various learning approaches. The existing advanced features and challenges of the designed distracted driver detection model are discussed in Table 1.

LSTM-RNN [28] has video screening to detect the actions of drivers and includes mobile sensors to detect the backward and forward motions of drivers. However, it suffers from performance loss such as the viewpoint of camera and non-identical car models and it requires data from multiple drivers to increase the reliability.

DDBD [29] specifically tackles the distraction caused by the usage of mobiles and has shown promising results in posture classification. But, it does not detect visual features like face and eye movements and it is unable to detect the drowsiness of drivers.

Genetic pseudo-inversion [30] analyzes the real-time visual distractions. However, it causes overlapping of data. DDBD-HBCL [31] generalizes high performance in real-time applications and has gained high accuracy in training the behavior images of drivers. But, it is hard to recognize the characteristics of drivers due to poor image quality.

UMMFN [32] increased the quality of the driver's visual awareness and introduced microphones to analyze the sounds and voice. But, it cannot detect all facial expressions due to low light.

HCF [33] assists the drivers in maintaining safe driving habits and resolves the convergence problem and maximizes the training speed. But, it is incapable to detect the behavior of drivers from all angles, and detection of driver's behavior is impossible at night.

CNN [34] monitors the driver's state and prevents from accidents and also recognizes the behavior of the driver via a sound alert or vibration in the seat. However, it occur mis-classification errors and it causes overfitting problems.

PCA-CNN [35] brightens the captured driving images and it also reduces the data noise. However, it takes a long time to train the recognition model. These challenges help in implementing a new driver distraction model using IoT and deep learning.

Table 2.1: Reviewing Different Detection Models Of Driver's Distraction.

Author [citation]	**Techniques**	**Advantages**	**Disadvantages**
Omerustaoglu *et al.* [28]	LSTM-RNN	• It has video screening to detect the actions of drivers. • It includes mobile sensors to detect the backward and forward motions of drivers.	• However, it suffers from performance loss such as the viewpoint of camera and non-identical car models. • It requires data from multiple drivers to increase reliability.
Kumar *et al.* [29]	DDBD	• It is suitable for the real-world environment related to the driver distraction model. • It has shown promising results in posture classification for the distracted driver detection model.	• It does not detect visual features like face and eye movements. • It is unable to detect the drowsiness of drivers.
Botta *et al.* [30]	Genetic pseudo-inversion	• It analyzes real-time visual distractions.	• It does not have the ability to handle other types of distractions like face or eye movements and non-visual features like drowsiness detection.
Huang *et al.* [31]	DDBD-HBCL	• It generalizes high performance in real-time applications. • It has gained high accuracy in training the behaviour images of drivers.	• It is hard to recognize the characteristics of drivers due to poor image quality.

Table 2.1: Reviewing Different Detection Models Of Driver's Distraction" Table Continoued".

Zhang *et al.* [32]	UMMFN	• It increased the quality of the driver's visual awareness. • It has introduced microphones to analyze the sounds and voice.	• It cannot detect all facial expressions due to low light.
Huang *et al.* [33]	HCF	• It assists the drivers in maintaining safe driving habits. • It resolves the convergence problem and maximizes the training speed.	• But, it is incapable of detecting the behavior of drivers from all angles. • The detection of a driver's behavior is impossible at night.
Pal *et al.* [34]	CNN	• It monitors the driver's state and prevents from accidents.	• However, it has misclassification errors that affect the efficacy of the developed approach.
Rao *et al.* [35]	PCA, CNN	• It brightens the captured driving images. • It recognizes the behaviour of the driver via a sound alert or vibration in the seat.	• However, it has less generalization ability.

3. METHODOLOGY

3.1 DETECTION OF DRIVER DISTRACTION MODEL USING IOT NETWORK AND DEEP STRUCTURED MODEL

3.1.1 IoT Framework for Smart Vehicular Network

Intelligent Transport Systems (ITS)-based IoT seeks more attention in the research areas for solving the issues related to road safety. An efficient approach needs to be developed for minimizing the traffic hazards and also for saving the lives of the people, which also reduces the death rate increase due to accidents. Very essential research is progressed for these problems and also for gradually decreasing the response time through the accident. Diverse techniques are developed based on these perspectives, especially in the Vehicular Ad-hoc Network (VANET), where all the moving vehicles are represented to be the node. Here, the accidents are detected and reported through the alert messages using the radio frequency module. Another approach is implemented with limited switches for detecting an accident, in which mobile communications are utilized for transmitting the alert message, and accident location can be tracked with the help of the Global Positioning System (GPS) module. Alternatively, Smartphones are used for detecting vehicle crashes with an Android app, in which the system computes the tilt angle variations through the accelerometer sensor detects the speed with the GPS, and finally, sends an accident alert decision. Certain systems concentrate on some of the preventive methodologies for saving human lives. Similarly, some approaches focus on avoiding drunken driving through the installation of alcohol sensors into the steering wheel. Further, it stops the driver from driving when the person is identified to be intoxicated on calculating his/her alcohol content in the oxygen. Here, the data is collected from diverse sensors and also used in the event logs for extracting the essential features for the accident detection model. Also, numerous computational models are utilized for detecting accidents, which employ regression trees, neural networks, and nearest neighbors. These systems employ IoT sensors for collecting data to detect accidents after it occur. Thus, it is not essential for road safety, where the core aim is to detect the accident prior to its occurrence. Also, the driver's behavior is said to be the major factor for accidents and so, IoT technology plays a major role in collecting effective data regarding distracted driver behaviors. The main problem is that utilizing single sensors for collecting the data in accident detection may produce a false positive rate. The general architecture of IoT-aided detection of driver distraction is depicted in Fig. 3.1.

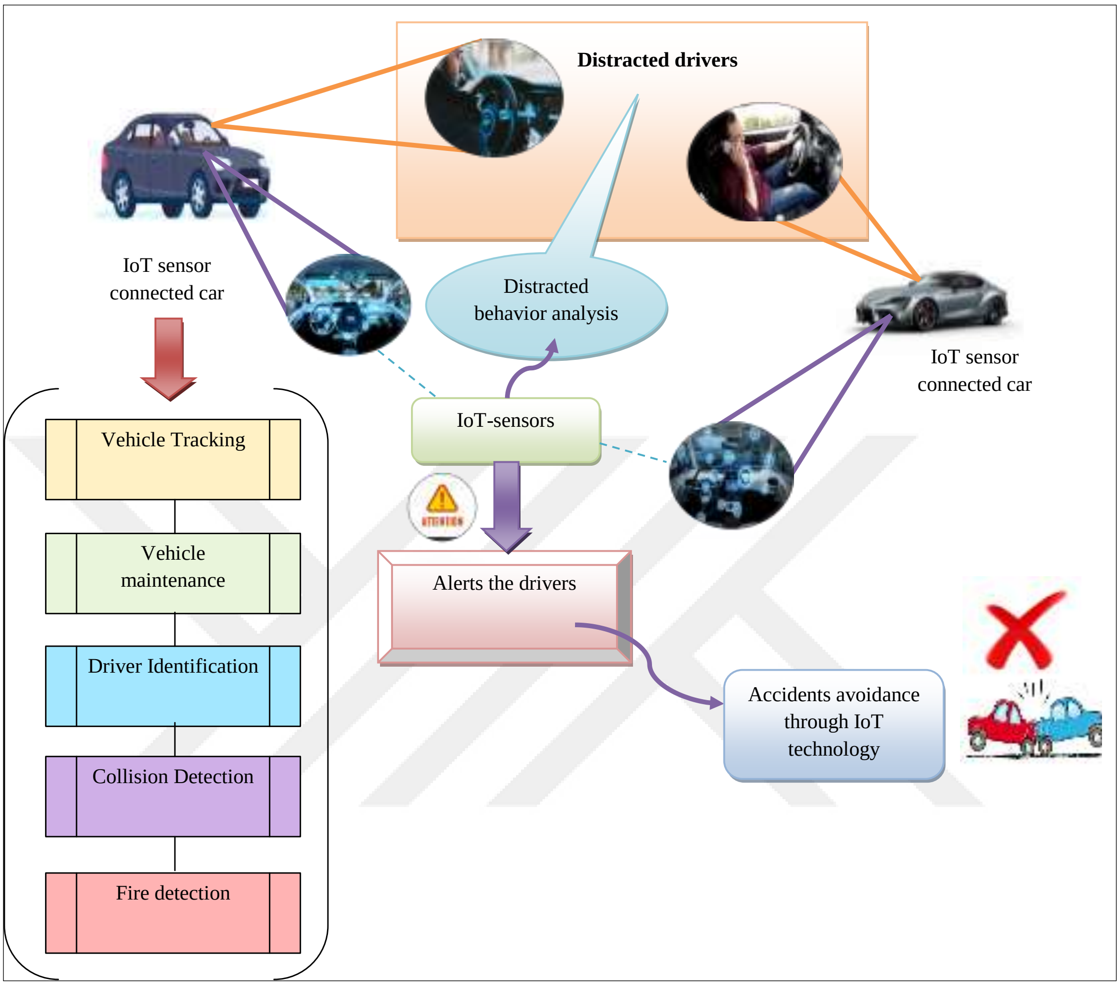

Figure 3.1 : Smart Vehicular Network Based Iot For Accident Prevention.

3.1.2 Recorded Datasets

The offered detection of driver distracted approach gathers the data from two different datasets that are given as follows.

a) Dataset 1: The developed model collects the required images from the State Farm Distracted Driver Detection database [39]. Here, the dataset is incorporated with the driver images, who perform certain actions like texting, makeup and reaching behind, talking on the phone, and eating. The data is involved with ten categories for predicting the behavior of driver distraction using both the train and text data.

b) Dataset 2: The dataset has been collected by some Turkish centers for teaching car driving. All cars for driving lessons are equipped with schools to monitor the activities and efficiency of the driver and coach. This work, in turn, takes advantage of this dataset in order to monitor the driver's dispersal during the activities that occur while driving. Note, that all these videos are recorded and published on the YouTube channels of those centers. They refer to the names of the schools that were used to collect the dataset and the links to their YouTube pages as follows:

a. The first school was named “BalgatKeremSürücüKursu” and its link on [40].
b. The second school called is “e direksiyonEnes ŞAHİN” and its link is on [41].
c. The third school is named “DireksiyonGeliştirmeMerkezi” and its link on [42].
d. The fourth school is “DireksiyonEğitimi Mustafa ÖzkanAkademi” and its link on [43].

The considered images for the developed model are indicated asIM_p^{indriv}, where $p = 1,2, \ldots, P_,$ and Pvisualize the average of garnered driver images from the corresponding dataset. The ten classes of sample images are shown in Fig.3.2 and .3.3.

Class Explanation	**1**	**2**	**3**
(1): “Safe Driving"			
(2): “Texting-Right”			
(3): “Talking on the Phone-Right			
(4): “Texting-left”			
(5): “Talking on the phone-left”			
(6): “Operating the Radio”			

Figure 3.2: Sample Distracted Driver Images From Dataset 1.

(7): “Drinking”			
(8): “Reaching behind.”			
(9): “Hair and makeup”			
(10): “Talking to passenger”			

Figure 3.2. Sample Distracted Driver Images From Dataset 1. "Figure Continued".

Figure 3.3 : Sample Distracted Driver Images From Dataset 2 As The Real-Time Data.

3.1.3 Proposed Architecture and Description

Various types of evidence have revealed that distracted driving is the major cause of vehicle accidents and crashes. For influencing safe driving, different approaches are developed in detecting distracted driver behaviors that mainly focus on some driving contexts and gaze behaviors. Based on these aspects, it is very significant to perform the accurate detection of driver behavior for practical counter-measures. Yet, there is no clear definition for the distraction but sometimes, it may cause misunderstanding about the distraction to be overlapped or inattention of driver behaviors such as workload and drowsiness.

Further, driver distraction is defined to be “the diversion of attention away from activities critical for safe driving towards a competing activity that causes accidents”. This is also expanded by integrating with the driver inattention concept which means no attention or insufficiency towards the critical activities on the safe driving. Also, the existing models suffer from inadequate performance in the data collection and are also not many representatives of the driving population that show distracted behavior as a secondary task. Hence, IoT technology can be involved in collecting efficient data regarding distracted driver behaviors to achieve effective classification performance.

Moreover, computer vision-based approaches overtake all other algorithms mainly with the help of hardware computations, neural networks, and camera technology, and also can extract complex data features. Deep learning frameworks like CNNs are used broadly for processing complex images. On the other hand, the detection of driver behavior can lead to overfitting problems and also causes detection failures in practical applications when using a single pre-trained model for feature extraction. Hence, it is essential to adopt a novel detection of driver-distracted approach using an optimal feature tuning model that is pictorially presented in Fig. 3.4.

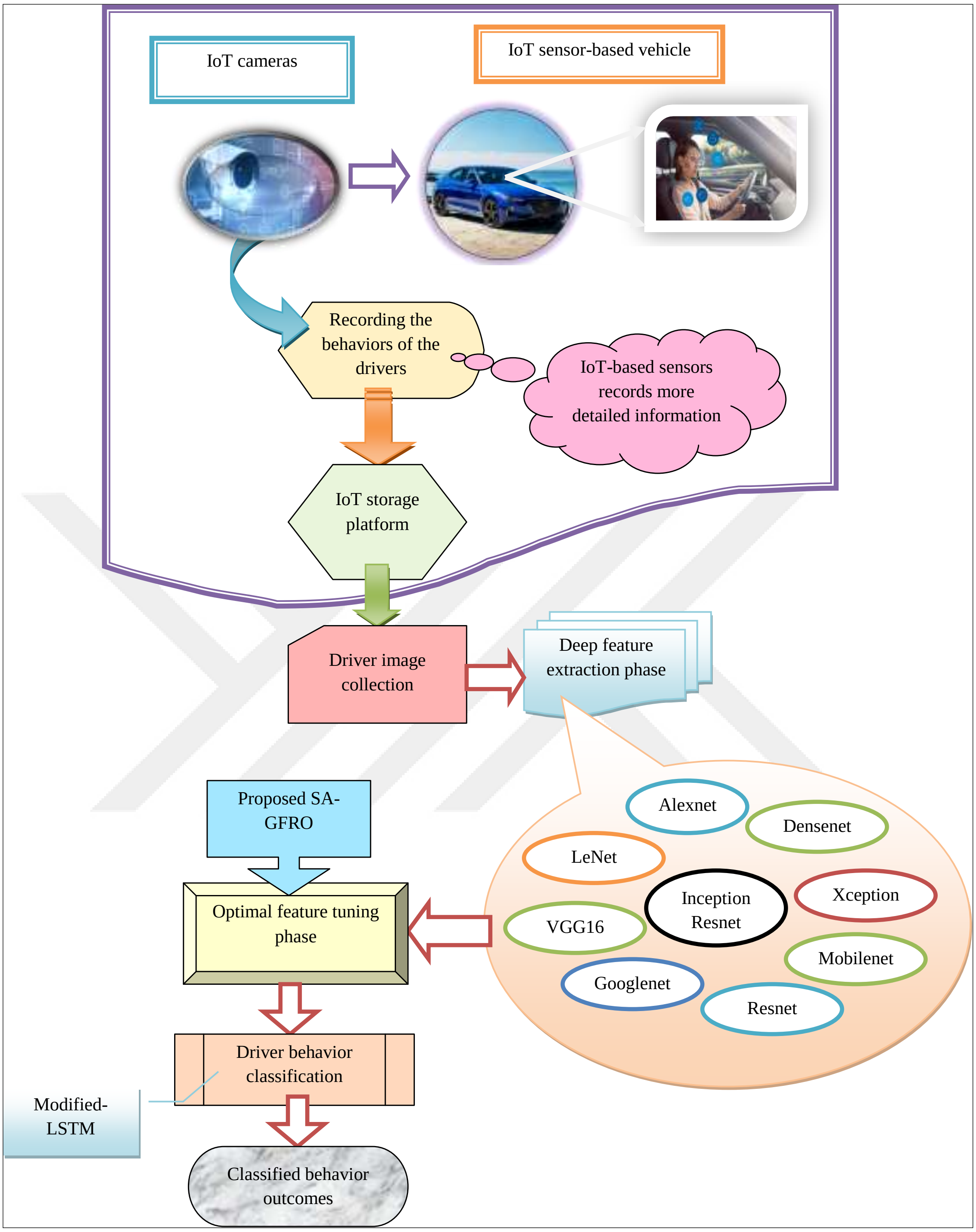

Figure 3.4: Proposed Distracted Driver Behaviour Model with IotT and Deep Learning Approaches.

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The developed driver distraction detection model is implemented using IoT technology and deep structured approaches along with optimization algorithms. The required images of the driver's behaviour are collected with the support of IoT for generating more detailed information from the image. The collected images are fed into diverse variants of CNN such as ResNet, VGG16, Xception, Inception-ResNet, GoogleNet, DenseNet, MobileNet, AlexNet, and LeNet to acquire the attributes of the distracted behaviours of the driver. These combined features extraction model is developed for acquiring the more precise features of the images without any loss of information. The extracted features are then considered for choosing the accurate features by tuning through the proposed SA-GRFO to enhance the efficiency of the suggested model. The optimal features are used for the categorization stage, where the modified LSTM is involved in classifying the behaviours of distracted drivers. The core aim of the developed approach is to improve the accuracy and precision of the proposed driver distraction identification model.

3.2 OPTIMAL FEATURE TUNING MODEL USING IMPROVED META-HEURISTIC CONCEPT

3.2.1 Feature Extraction by Different Variants of CNN

The recommended detection of driver distracted model utilizes the optimal feature tuning model with various variants of CNN like Resnet, VGG16, Xception, Inception-Resnet, Googlenet, Densenet, Mobilenet, Alexnet and Lenet for extracting the deep features. The fascinating application areas for CNN are speech recognition, video processing, natural language processing, and object detection. It has great learning capacity owing to the usage of much extraction of feature phases which is utilized to learn representations from data automatically. The spatial or temporal correlation is a significant feature for CNN variants and also it can have the ability to extract valuable characteristics from data. Owing to these precocious features, the CNN variants are picked for this work.

a. LeNet [44]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} for extracting the features to detect distracted driver behavior using LeNet. It is a common CNN model with integration of convolutional, activation, pooling, and fully connected layers. It is also comprised of a supplementary set of convolutional, pooling, and activation layers for enhancing the classification performance by introducing the non-linearity function into the network. Here, the convolutional layer implies the convolution operation to acquire the attributes. When the size of deep features is increased, the size of the filter is kept to be 5×5, and the filter size will be gradually increase. The convolutional and pooling layers are performed with the extraction of features, where the extracted features are obtained for the proposed model from the pooling layers of LeNet. The acquired features from the pooling layer of LeNet are presented asFE_g^{lenet} that is counted to be 150528.

b. AlexNet [45]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} for extracting the features for detecting distracted driver behavior using Alexnet. The convolution layers are used for acquiring the image features. Then, the pooling layers are used for reducing the size of the obtained features simplifies the network computation complexity. Finally, the fully connected layers are utilized for changing the 2D-feature vector into a 1D-feature vector. The acquired features from the pooling layer of AlexNet are presented asFE_h^{alex} that is counted to be 3072.

c. VGG16 [46]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} for extracting the features for detecting distracted driver behavior using Vgg16. It is according to the CNN architecture that helps to extract the features since it has the capacity to get more than 1000 features from a single image. This method contains one pooling layer and three convolution layers, which are repeated to make 16 layers of architecture. In every convolution layer, the filters with 3×3 size are presented at all the layers. The last stage is used for estimating the low-level features along with the filters, which are used for obtaining high-level as well as moderate-level features over the segmented images. The features get though the pooling layer of VGG16 are represented byFE_i^{vg16} that is counted to be 150528.

d. GoogleNet [47]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} for extracting the features for detecting the distracted driver behavior using the Googlenet approach. Convolutional filters under different sizes are utilized for getting various receptive fields. The training phase is initiated with the input deep features in the Googlenet, which is given into the three convolution layers. These layers extract the low latitude features with the help of 3×3 kernels in addition to the one max pooling layer. Then, the three pooling layers are incorporated into the network to get the features with high dimensions from the input deep features. The acquired features through Googlenet's pooling layer are represented asFE_j^{gonet} that is counted to be 268203.

e. ResNet [48]: The proposed distracted driver detection model uses the ResNet50 technique for extracting significant features from the input imagesIM_p^{indriv}. This approach is developed with the skipping connections and also with nearly three layers of ReLU and batch normalization. The remaining block presented in the ResNet is depicted as shown in Eq. (9).

$$Ol = J(in, U + in) \tag{3.1}$$

Here, the residual map is given by the function$J$ and the output layer is depicted by $Ol$and the input layer is indicated byin. The acquired features through the ResNet50's pooling layer are indicated byFE_k^{resnet} that is counted to be 784.

f. Inception-ResNet [39]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} to extract the features for detecting the distracted driver behavior using Inception-ResNet-v2. It is used to obtain the features for the classification process. The reason for choosing the residual connection is that it rejects the degradation problems at the time of deep structure and ensures the significant feature information such as location, color, size, and texture. The acquired features from the pooling layer of Inception-ResNet-v2 are presented asFE_k^{inres} that counted to be 150528.

g. DenseNet [50]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} for extracting the features for detecting distracted driver behavior using DenseNet. This network is composed of various dense blocks along with the transition layer architecture that will overlap the multilayer neural network. Neighboring Convolutional neural networks are combined to form the residual block. The acquired features from the pooling layer of DenseNet are presented asFE_l^{den} that is counted to be 150528.

h. Xception [51]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} to extract the features for detecting distracted driver behavior using the Xception model. The input deep featuresIM_p^{indriv} are termed as convolutional kernels that are given for getting the image features. Here, the obtained outcome is depicted in Eq. (10).

$$B_P = f(CK_P * B_{P-1} + c_P) \tag{3.2}$$

Here, the activation function is expressed by$f(\cdot)$, convolution operation is symbolized by"$*$", convolution kernel is shown byCK_P, an outcome from P^{th}convolution layer is considered byB_P and the offset parameter is depicted byc_P. The features obtained through the Xception's pooling layer are represented asFE_m^{xcep} that is counted to be 150528.

i. MobileNet [49]: The proposed distracted driver detection model uses the input imagesIM_p^{indriv} to extract the features for detecting distracted driver behavior using MobileNet. Depth-wise convolution is "the step of filtering the input without creating new features". Thus, the process to produce new features is called combined point-wise convolution. Finally, the concatenation of two layers was called depth-wise separable convolution. This model utilizes the depth-wise convolutions to imply a single filter to the input and then uses 1x1 convolutions (point-wise) for generating the linear combination of output from a depth-wise layer. The acquired features from the pooling layer of Mobilenet are represented asFE_p^{mob} that is counted to be 268203.

3.2.2 Optimal Feature Tuning Model

The extracted features from all the variants of CNN such as Resnet, VGG16, Xception, Inception-Resnet, Googlenet, Densenet, Mobilenet, Alexnet, and Lenet are considered individually for tuning and obtaining the optimal features. The solutions (each model) are given in the proposed SA-GFRO for obtaining more accurate results in the classification phase. If the features from LeNet obtain the bounding value of 0, then these features won't be selected as the optimal feature. It is necessary to acquire the bounding value of 1 for the extracted feature while processing with the proposed SA-GFRO. Then, the features with the bounding value of 1 are selected for the optimal tuning model. The optimal feature tuning model with the suggested SA-GFRO is depicted in Fig. 3.5.

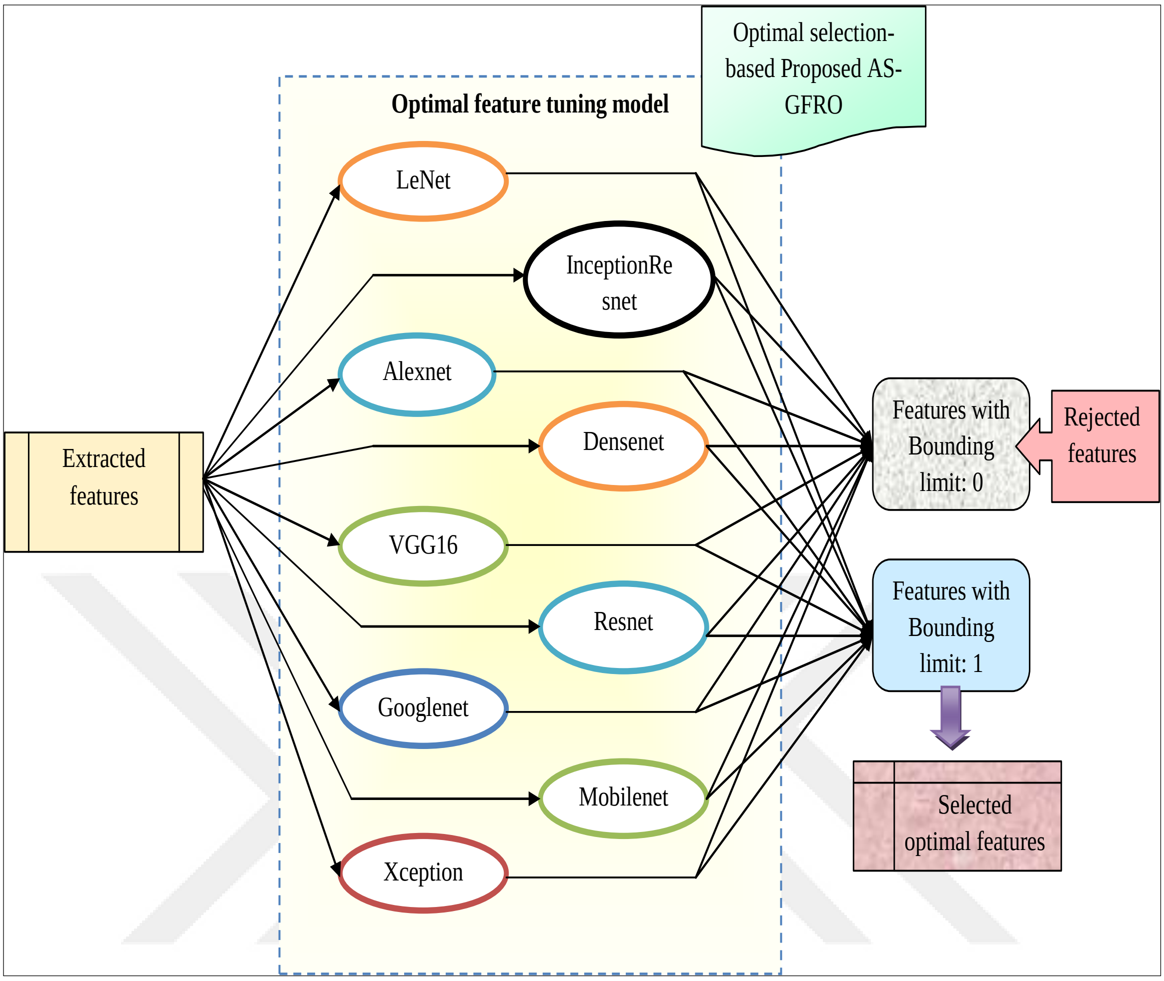

Figure 3.5: The Procedure of Optimal Feature Tuning Model Using Nine CNN Variants.

3.2.3 FEATURE CONCATENATION

The optimal features from the nine CNN versions are combined for utilization in the classification phase. The optimal features from the Resnet, VGG16, Xception, Inception-Resnet, Googlenet, Densenet, Mobilenet, Alexnet, and Lenet are concatenated into a single set of deep features that is denoted by $FT_t^{conc} = \begin{Bmatrix} FE_h^{alex}, FE_i^{vg16}, FE_j^{gonet}, FE_k^{resnet}, FE_k^{inres}. FE_l^{den}, FE_m^{xcep}, \\ FE_p^{mob} \end{Bmatrix}$, where$h = 1,2, \ldots, T$and the total number of extracted features is represented by$T$.

3.3 MODIFIED LSTM ARCHITECTURE FOR IOT-ENABLED DRIVER DISTRACTION DETECTION

3.3.1 LSTM Model

The concatenated featuresFE_l^{con} are utilized in the M-LSTM [28] for classifying distracted driver behaviors to avoid traffic accidents. To enhance the effectiveness of the, the recurrent structures are utilized, where there is no necessity to store the output in the external memories. The recurrent structures presented in this classifier reduce the complexity while computing the network. Four different modules are presented and they are “cells, input gate, output gate and forget gate”. The cell holds the data that are further moved to the input and output gate. The forget gate is employed to determine the information passed over the network which is shown in Eq. (11).

$$cl_{tl} = \sigma(Bl_{cl} \cdot [kl_{tl-1}, (FE_l^{con})_{tl}] + wl_{cl}) \tag{3.3}$$

Here, a sigmoid activation function is denoted asσ , and the resultant output obtained from the hidden state is expressed bykl_{tl}. The weight matrices are represented as$Bl_{cl}, Bl_{gl}, Bl_{hl}, Bl_{ql}$, the cell output is indicated bygl_{tl}, the forget gate is denoted byGl_{tl}, the input variable is represented byFE_l^{con} and the output gate is shown byql_{tl}. The involved biased values at these gates are portrayed by$wl_{cl}, wl_{fl}, wl_{hl}, wl_{ql}$. Further, the input gate is designed in Eq. (12).

$$gl_{tl} = \sigma\left(Bl_{gl} \cdot [kl_{tl-1}, (FE_l^{con})_{tl}] + wl_{fl}\right) \tag{3.4}$$

A new cell gets updated with the sigmoid function, where the new vector $\hat{G}l_{tl}$ is generated as given in Eq. (13).

$$Gl_{tl} = tan\,k\,l\left(Bl_{hl} \cdot \left[kl_{tl-1}, \left(FU_{g*}^{opt}\right)_{tl}\right] + wl_{hl}\right) \tag{3.5}$$

The old cell is upgraded into the novel cell by connecting the previous state with the forget gate. Moreover, it also incorporates certain parameters into it as depicted in Eq. (14).

$$Gl_{tl} = gl_{tl} * Gl_{tl-1} + cl_{tl} * \hat{G}l_{tl} \tag{3.6}$$

At last, the outcome gate offers the cell state based on the outcome obtained through the sigmoid of the output gates that are depicted in Eq. (15) and Eq. (16).

$$ql_{tl} = \sigma\left(Bl_{ql} \cdot [kl_{tl-1}, (FE_{l}^{con})_{tl}] + wl_{ql}\right) \tag{3.7}$$

$$kl_{tl} = ql_{sl} * tan\,k\,l(dl_{tl}) \tag{3.8}$$

The sigmoid activation function in the network is expressed by σ and the hyperbolic tangent is represented by $tanh$.

3.3.2 Proposed SA-GFRO

The suggested detection of driver distracted model with IoT employs the offered SA-GFRO for tuning the number of suitable hidden neurons and epochs of LSTM and performs the optimal feature tuning model for improving the overall efficacy of the developed approach. GFRO [52] algorithm is chosen for the proposed model as it has the potential to solve real-time optimization issues and also able to balance the exploitation and exploration phases. However, it suffers from issues related to local optimum and does not achieve the required convergence rate. To resolve these conventional challenges of GFRO, an enhanced algorithm named SA-GFRO is developed with adaptive features. Thus, the SA-GFRO algorithm is developed for solving the baseline issues. In the proposed SA-GFRO, the step size equation cc is estimated using the improved concept according to best fitness and current fitness values.

GFRO [52] is the meta-heuristic algorithm based on the behavior of the grass plant's regeneration and their fibrous root system. Here, the population is produced in a random manner and the seeding process is used to distribute into the solution into the search space. After performing the optimization process, a newly generated population is obtained that is in the range of$Pl_{new}^{m} \leq Pl_{new} \leq Pl_{new}^{n}$, where the terms $Pl_{new}^{m}$and$Pl_{new}^{n}$are denoted as the lower range and upper range among the population variable. The new population is comprised of several parameters like a best value that is computed in Eq. (9).

$$gg_{bst} = min\big(f(swrm)\big) \in r^{D} \tag{3.9}$$

Here, the term$f$ denotes the mean square error function and$D$ represents the problem dimension. The elementPl_{new}includes the total number of grassesgs that are acquired through the best valuegg_{bst}, which are frequently diverted by the basic grassesgs_L that involve the step size less thanPl_{new}^{n}. It is shown in Eq. (10).

$$gs = \left\| (0.5 \times Pl) \times \left(\frac{avrg(MSE)}{avrg(MSE) + min(MSE)} \right) \right\| \tag{3.10}$$

Here, the computation $(0.5 \times Pl)$equals to the maximum number of newly produced grass branches. The final methodology ofPl_{new}^{n} consists of new grass that is computed through$(Pl - gs - 1)$that can also be changed by the influence of survived best initial grassesSG_{gr}that is shown in Eq. (12). Further, all the newly generated greasesgs_L are computed using Eq. (11).

$$\begin{aligned} gs_L = ones(gs, 1) \times gs_{bst} + 2 \times max(Pl_{new}^{n}) \\ \times (\sigma(gs, 1) - 0.5) \times gs_{bst} \end{aligned} \tag{3.11}$$

$$\begin{aligned} SG_{gr} = gs_L + 2 \times max(Pl_{new}^{n}) \\ \times (\sigma(Pl - gs - 1,1) - 0.5) \times Pl_{new}^{n} \end{aligned} \tag{3.12}$$

Here, the variableσnotes the arbitrary value that is in the interval of$[0,1]_{,}$ and the one's column vector is indicated by$ones(\cdot)$and then, the new population is described in Eq. (13).

$$Pl_{new} = [gs_{bst}; gs_m; SG_{gr}] \tag{3.13}$$

Here, the absolute rate of minimization in the MSE is considered, which needs to be less than or equal to already defined variables like tolerance value$\varepsilon_{,}$ and then, the global stack gets increased and obtained to the maximum predefined value. Further, the next local search is given in Eq. (14).

$$Q = \min_{j=1,\ldots,Pl}(MSE) \tag{3.14}$$

$$BST_{MIN} = \min_{k=1,\ldots,itr}(Q) \tag{3.15}$$

$$\left|\frac{min_{j=1,\ldots,Pl}(MSE) - gs_{bst}}{min_{j=1,\ldots,Pl}(MSE)}\right| \leq \varepsilon \tag{3.16}$$

Then, the locally changed best values for the hair root location are computed in Eq. (17).

$$q_{gs_{bst}}(1,j) = avrg(gs_{bst}) + gs_{bst}(1,j) + cc_2 \times (\sigma - 0.5) \tag{3.17}$$

Here, the variablecc_2refers to the random variable of ccthat is the step size equation updated with the adaptive concept of fitness in the proposed SA-GFRO. This is shown in Eq. (18).

$$cc = \frac{bstfit}{fit(j)} * Pl \tag{3.18}$$

Finally, the stopping conditionε_{sc}will be verified and terminated during the iterations. The pseudo code of the suggested SA-GFRO is given in Algorithm 1.

Algorithm 1: Proposed SA-GFRO
Initialize the overall grass population
Determine the parameters
Compute the fitness function for entire grass solutions
Arrange the solution according to their fitness value
Compute the step size formulation using the Eq. (18).
While (until the stopping criteria) do
Update the new branch grasses using Eq. (11)
Update the survived best initial grasses using Eq. (12)
Satisfy the condition related to the tolerance value ε given in Eq. (16).
End While
Update the hair root location using the Eq. (17)
Return the best optimal solution
End
End

The proposed SA-GFRO has enhanced its searching behavior on high-dimensional search space. It also ensures the superior convergence in acceleration and provides most effective global optimal solution. The flow diagram of the recommended SA-GFRO algorithm is visualized in Fig.3.6 and .3.7.

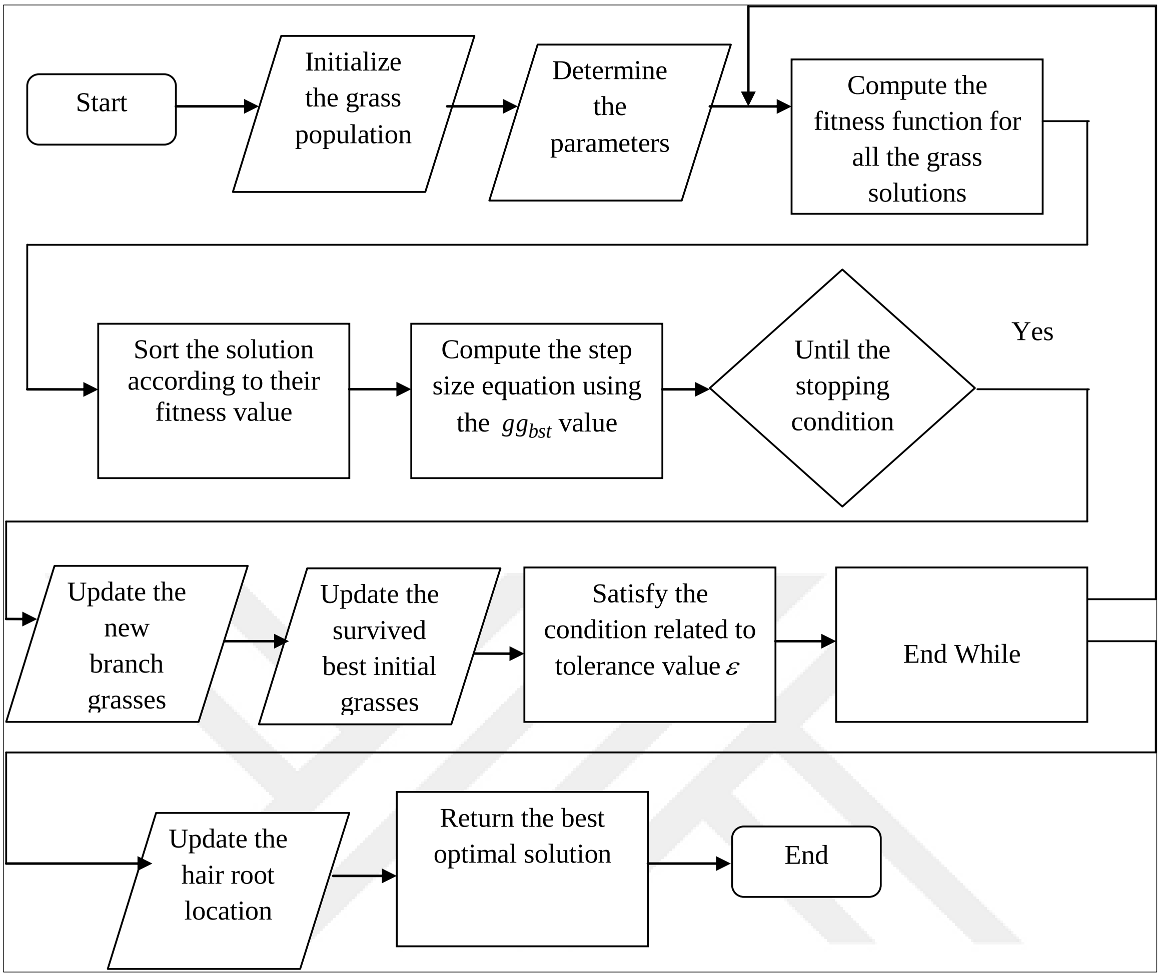

Figure 3.6: Dataflow Diagram for The Suggested SA-GFRO.

Adaptive optimization is a concept that performs dynamic recompilation on the section of the algorithm based on the current iteration. Whereas, self-adaptive optimization can continuously modify the network to improve the algorithm's performance based on runtime behavior. The major intent of using the self-adaptive optimization concept is to adaptively provide priority to pertinent strategies on diverse issues in the optimization process. It is utilized to enlarge the applicability of the developed SA-GFRO algorithm. In addition, the purpose of the self-adaptive concept is to analyze issues like combinatorial optimization problems, multi-objective optimization problems, and global numerical optimization problems. Hence, the offered SA-GFRO approach offers better efficiency through self-adaptive behavior.

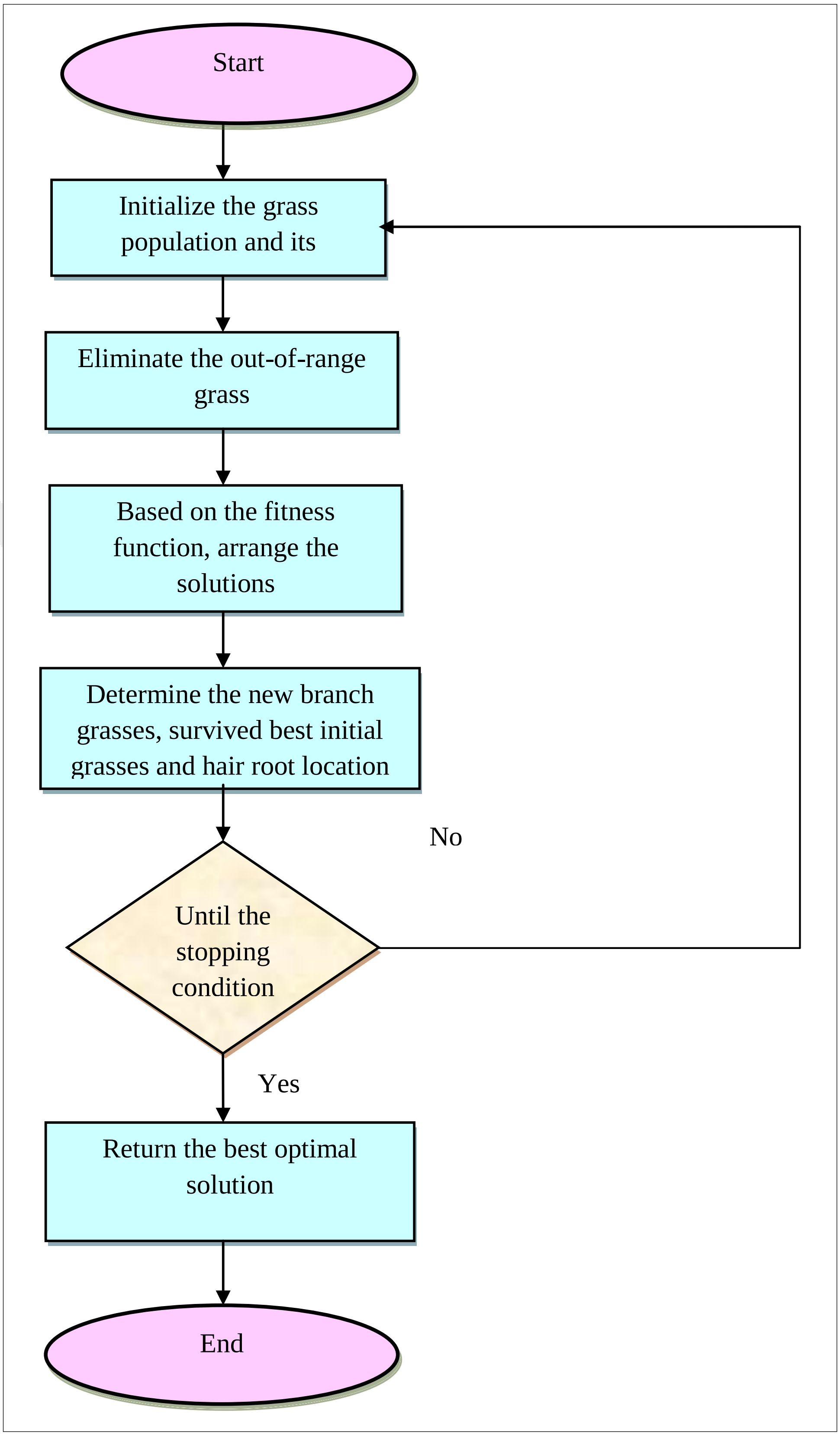

Figure 3.7: Flowchart of the Suggested SA-GFRO.

3.3.3 Modified LSTM Model

The developed model detects the distracted behavior of the driver in an accurate manner using the LSTM along with the aid of suggested SA-GFRO. The detection outcomes from the proposed model are obtained as different classes of driver's behavior that may be safe and distracted activity. The main intention of the developed approach is to improve the detection accuracy as well as precision that is formulated in Eq. (17).

$$Ofn = \underset{\left\{HN_{lstm}^{hn}, Ep_{lstm}^{ep}\right\}}{\arg\min} \left(\frac{1}{Ay + \Pr} \right) \tag{3.19}$$

Here, the variable HN_{lstm}^{hn} denotes the hidden neurons and Ep_{lstm}^{ep} is presented as epochs of the LSTM, respectively. The offered SA-GFRO is used for tuning the hidden neurons in the interval of $[5,255]$ and the epoch counts in the range of $[5,20]$. Accuracy Ay is "the closeness of the measurements to a specific value" as given the Eq. (18).

$$Ay = \frac{(ip+in)}{(ip+in+jp+jn)} \tag{3.20}$$

Here, "the true positive and true negative values are shown as ip and in, respectively, and false positive and false negative values are given as jp and jn, respectively". Precision Pr is "the fraction of relevant instances among the retrieved instances" given as in Eq. (19).

$$Pr = \frac{ip}{ip+jp} \tag{3.21}$$

The detection of distracted behaviors of drivers is performed with the implemented O-LSTM as shown in Fig.3.8.

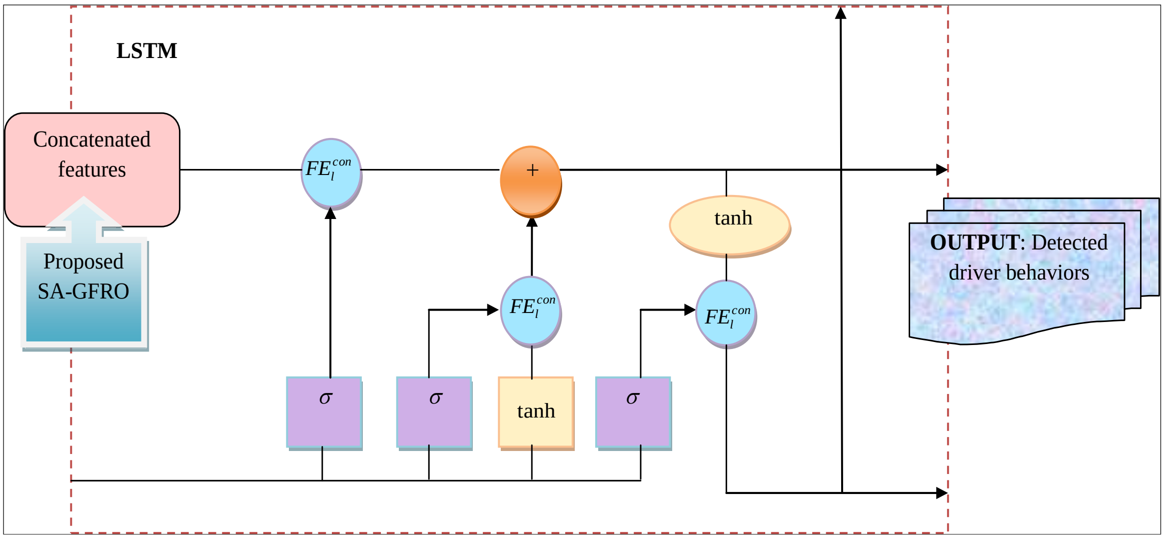

Figure 3.8: LSTM-Based Distracted Driver Behaviour Classification with IoT.

4. RESULTS AND DISCUSSIONS

4.1 SIMULATION SETUP

The experiments were carried out by performing the comparisons between the developed and baseline heuristic algorithms and also with the classification techniques. The population size was considered as 10 and maximum iterations were observed to be 10 for the experiments to validate the efficacy of the recommended distracted driver detection model. The proposed HSWOA was compared with other meta-heuristic algorithms such as "Spider Monkey Optimization (SMO) [53], particle swarm optimization (PSO) [54], Jaya Optimization (JA) [55] and GFRO-LSTM [52] and machine learning algorithms like Deep Neural Network (DNN) [56], Recurrent Neural Network (RNN) [57], Convolutional Neural Network (CNN) [34], and LSTM-RNN [28]". The platform utilized for estimating the recommended distracted driver detection model was Python and certain simulation validation was employed for testing the developed approach using diverse quantitative metrics. The parameters of the recommended SA-GFRO-LSTM method are shown in Table 2.

Table 4.1: Parameters of the SA-GFRO-LSTM Method.

Techniques	**Parameters**	**Description**	**Range**
GFRO	E_{oc}	Standard Potential	[0,1.2]
	A	Tafel Line Slope	[0,1]
	$I_{o,a}$	Anode	[0,100]
	$I_{o,c}$	Cathode	[0,100]
	B	Constant	[0,1]
	I_L	Current Limitation Density	[0,10,000]
	R_Ω	Area-Specific Resistance	[0,1]
LSTM	HN_{lstm}^{hm}	Hidden Neurons	[5,255]
	Ep_{lstm}^{ep}	Epochs	[5,20]

4.2 EFFICIENCY METRICS

The efficiency metrics used for the developed distracted driver detection model are given as follows.

(a) MCC: It is a metric to analyze binary classifications performance while testing that is equated in Eq. (40).

$$MCC = \frac{ip \times in - jp \times jn}{\sqrt{(ip+jp)(ip+jn)(in+jp)(in+jn)}} \tag{4.1}$$

(b) Specificity: It is the quantity of correctly recognized negative observations that are computed in Eq. (41).

$$SPTY = \frac{in}{in+jp} \tag{4.2}$$

(c) NPV: It is the sum of all positive and negative observations that is computed in Eq. (42)

$$NPV = \frac{in}{in+jn} \tag{4.3}$$

(d) F1-score: It is computed from the recall and precision values while testing that is in Eq. (43)

$$F1 = 2 \times \frac{2ip}{2ip+jp+jn} \tag{4.4}$$

(e) FDR: It is to compute the predicted number of false positive observations according to precision values that are given in Eq. (44).

$$FDR = \frac{jp}{jp+ip} \tag{4.5}$$

(f) Sensitivity: It is the quantity of correctly recognized positive values as in Eq. (45).

$$SEN = \frac{ip}{ip+jn} \tag{4.6}$$

(g) FPR: It is the quantity among the counts of false events incorrectly classified as positive (false positives) as in Eq. (46).

$$FDR = \frac{jp}{jp+in} \tag{4.7}$$

(h) FNR: It is the quantity of positive observations that produce false test outcomes with the corresponding test that is shown in Eq. (47)

$$FNR = \frac{jn}{jn+ip} \tag{4.8}$$

4.3 DATASET 1 VALIDATION WITH DIFFERENT CLASSIFIERS

The evaluation is done to estimate the efficacy of the offered approach with baseline GFRO-LSTM provides 4.54%, 3.2%, 5.56%, and 7.95% higher accuracy than the comparative algorithms like SMO-LSTM, PSO-LSTM, JA-LSTM, and GFRO-LSTM, respectively when observing at the learning percentage of 70. While noticing other measures for the implemented model, it is revealed that the highest performance rate has been obtained on detecting the distracted behaviors of the drivers. Thus, the implemented model has scored better efficiency than the baseline models.

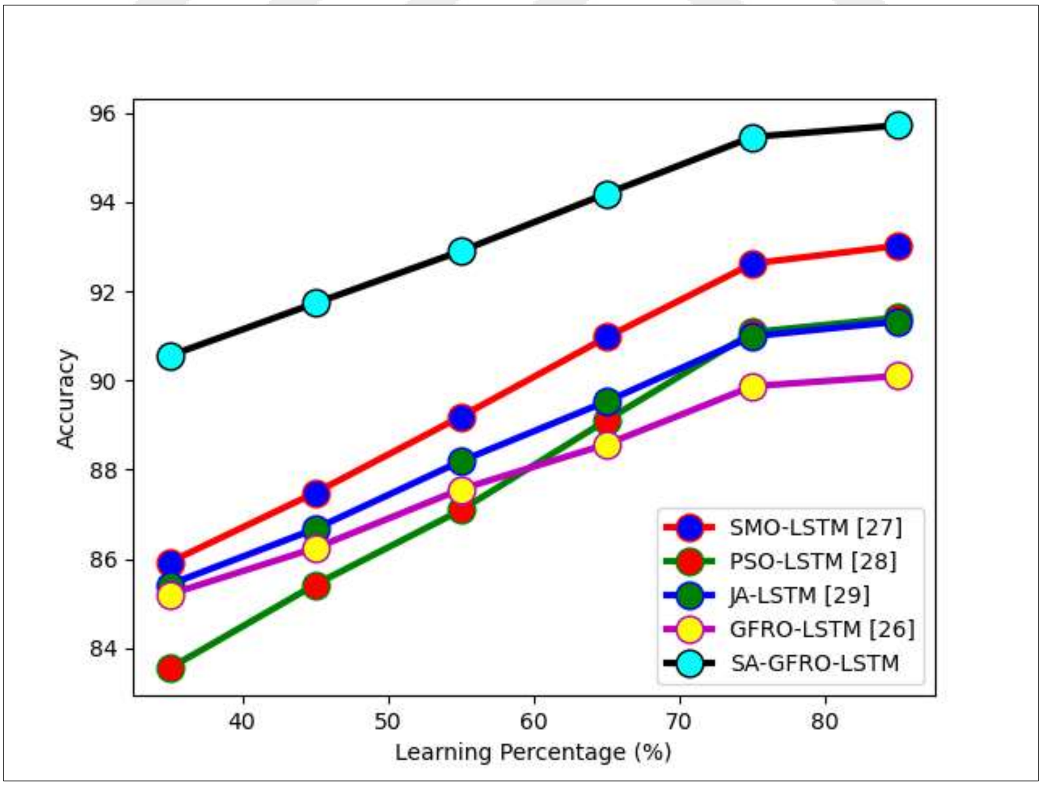

Figure 4.1: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding : A) "Accuracy".

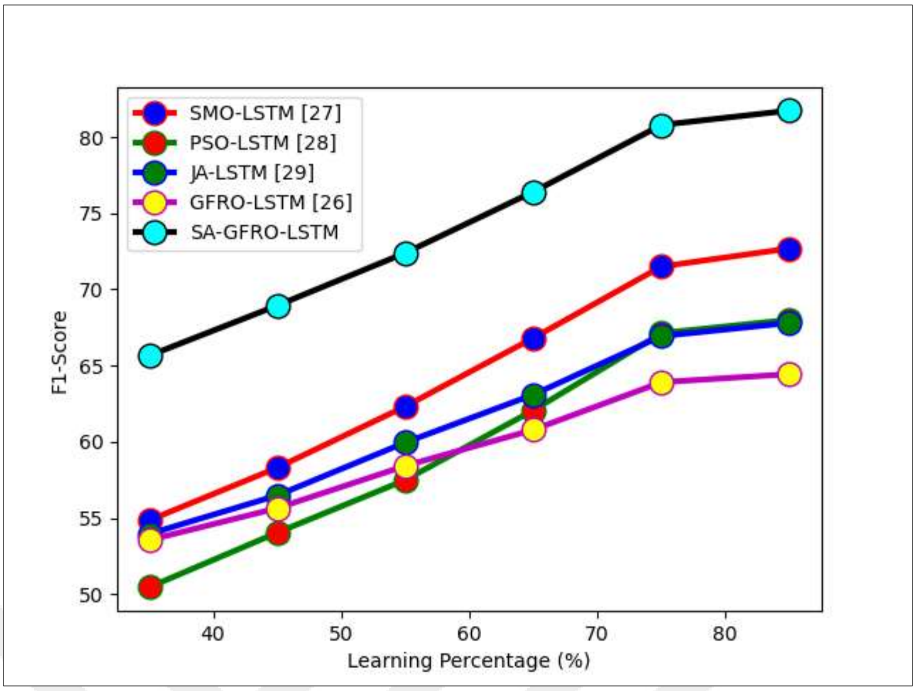

Figure 4.2: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding : B) "F1-Score".

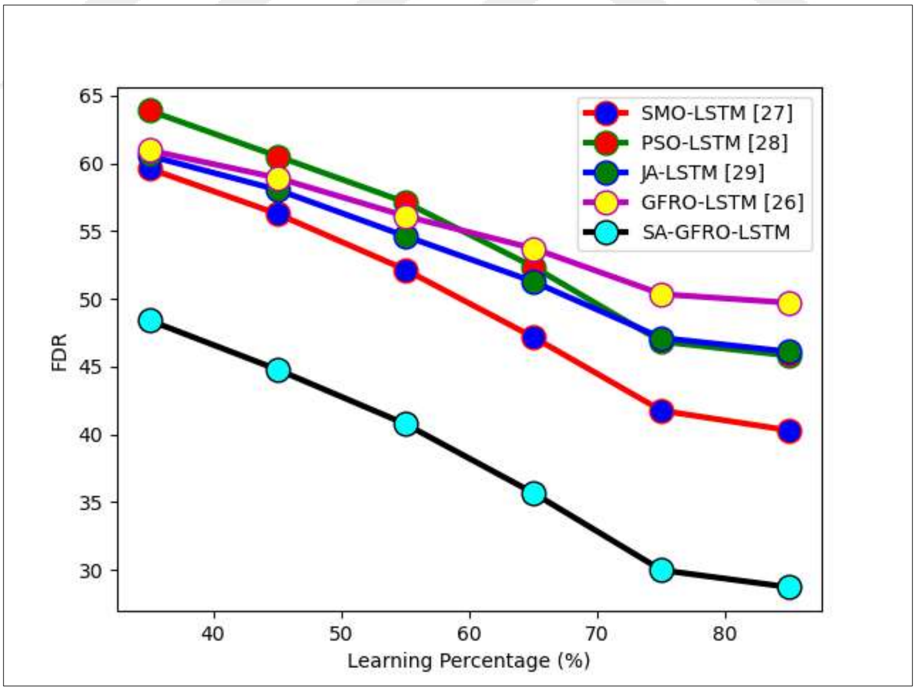

Figure 4.3: Recommended Detection of Driver Distracted Model Evaluation with Baseline Meta-Heuristic Algorithms Regarding: C) "FDR".

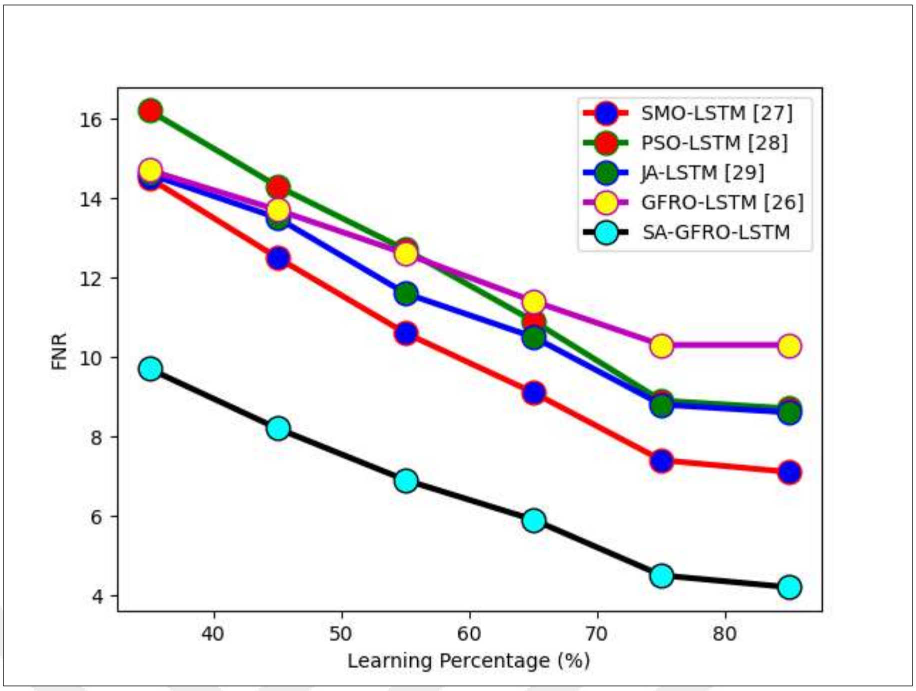

Figure 4.4: Recommended Detection Of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding :D)"FNR".

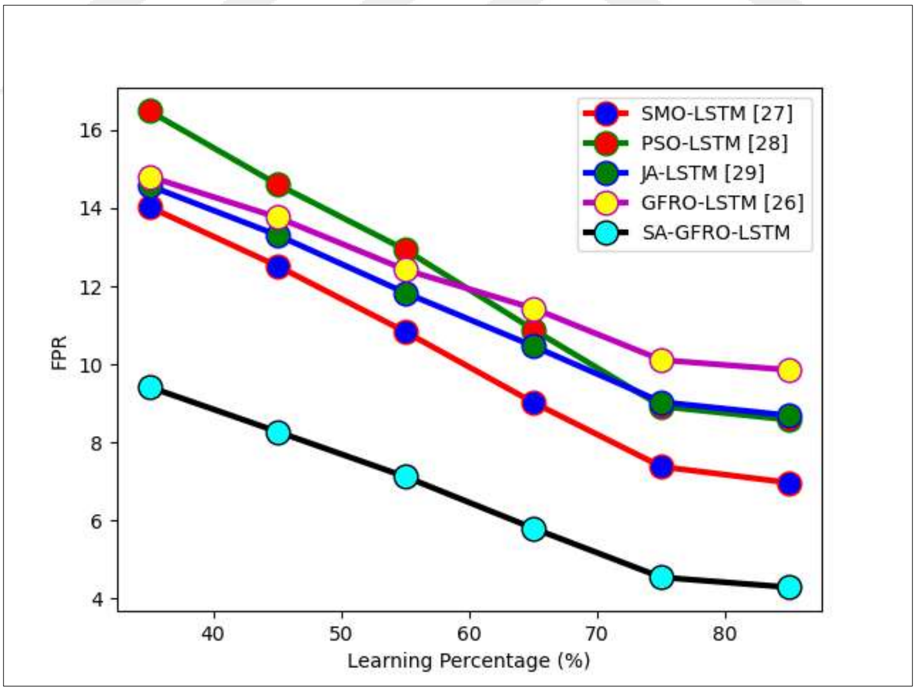

Figure 4.5: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding : E) "FPR".

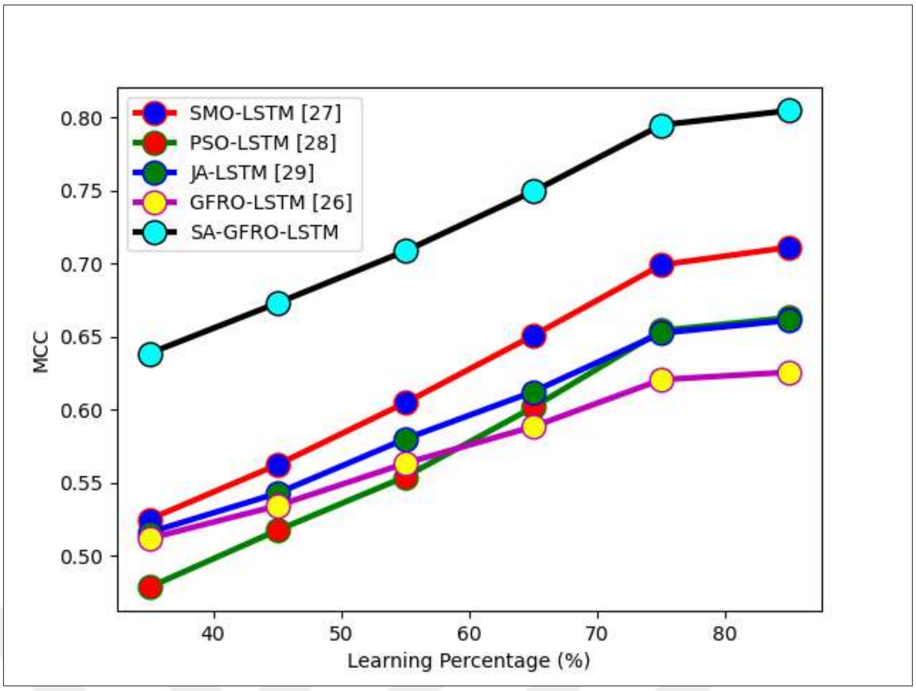

Figure 4.6: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding : F) "MCC".

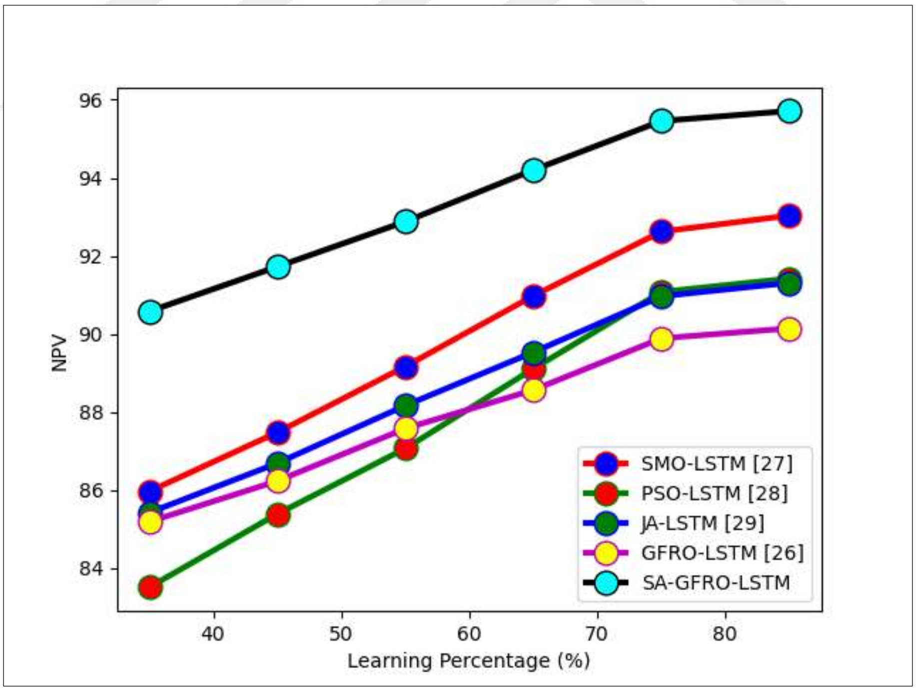

Figure 4.7: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding : g) “NPV".

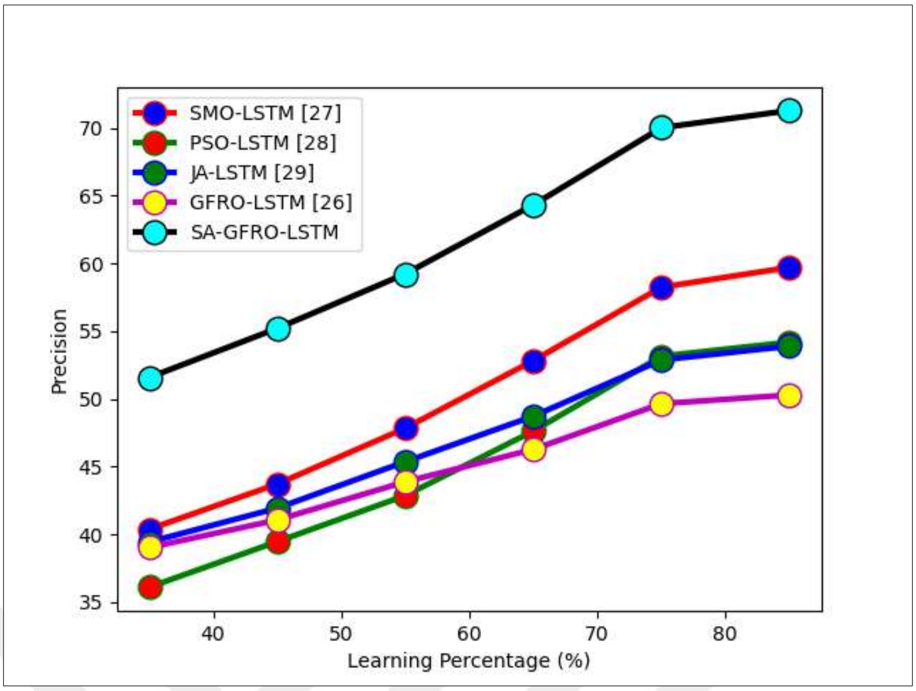

Figure 4.8: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding: h) “Precision".

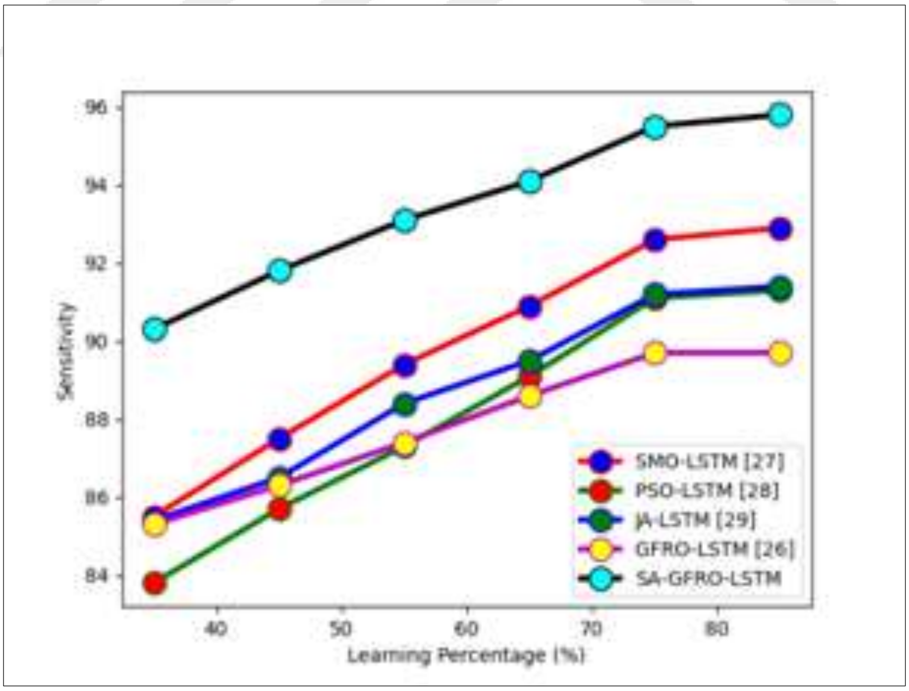

Figure 4.9: Recommended Detection of Driver Distracted Model Evaluation With Baseline Meta-Heuristic Algorithms Regarding i) "Sensitivity".

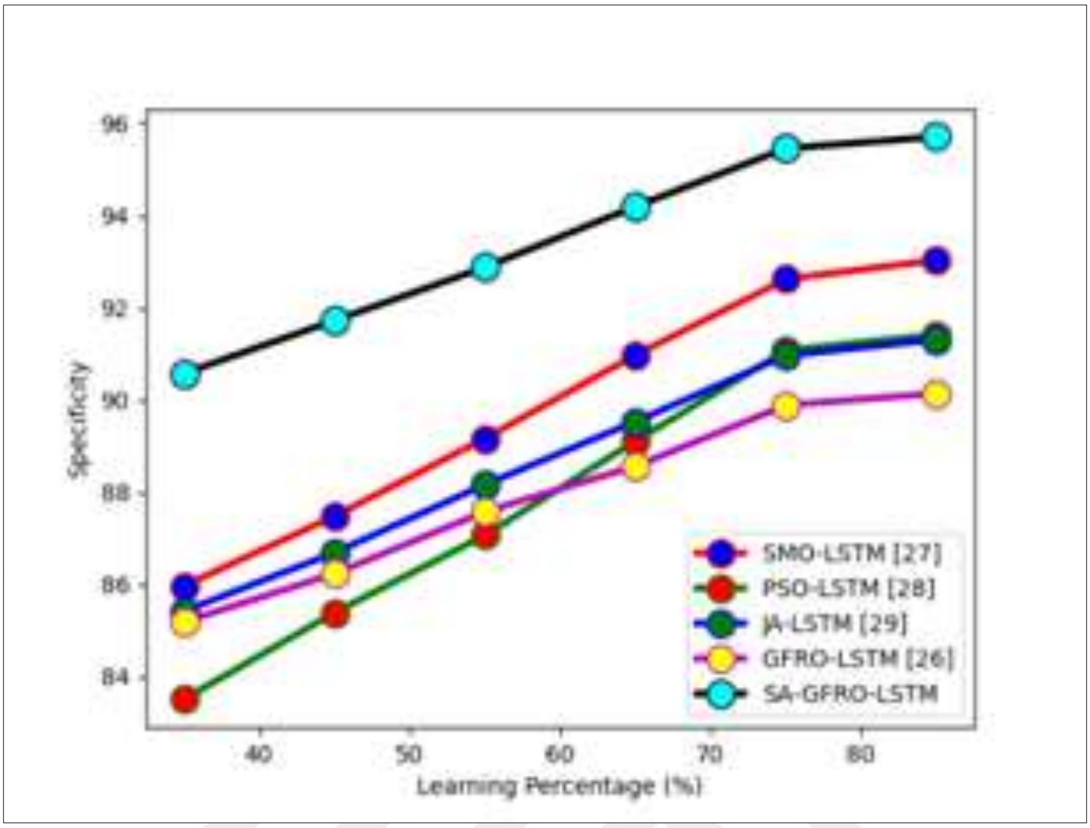

Figure 4.10: Recommended Detection of Driver Distracted Model Evaluation with Baseline Meta-Heuristic Algorithms Regarding : j) "Specificity".

4.4 DATASET 1 VALIDATION WITH DIFFERENT CLASSIFIERS

The estimation of the developed model is done by performing the comparison with different classification techniques at different learning percentages as depicted in Figures below. The developed SA-GFRO-LSTM secures superior accuracy, which is observed to be 0.6%, 1.3%, 1.4%, and 3.6% than the DNN, RNN, CNN, and LSTM-RNN, respectively at the learning percentage of 35. When analyzing the negative metrics such as FNR, FDR, and FPR the developed model stays at the lower position that shows the minimum error occurrence in detection performance. Thus, the distracted behaviours of the driver have been detected with high accuracy when tested with the baseline techniques.

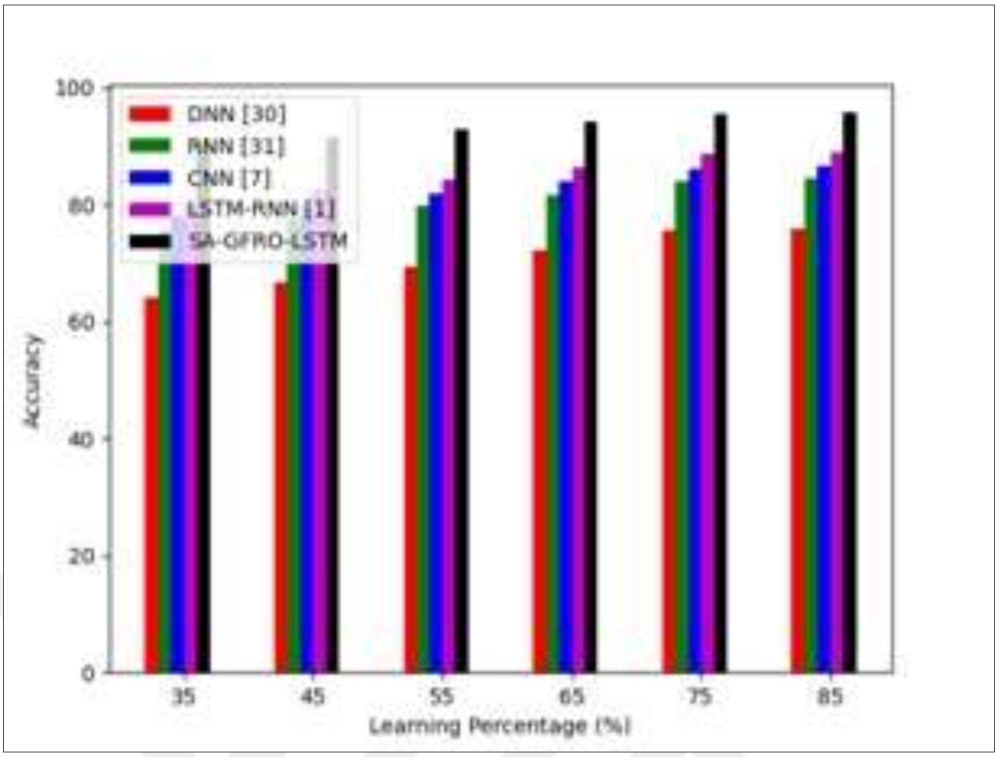

Figure 4.11 : Accuracy Validation of The Recommended Detection Of Driver Distracted Model Model with Existing Classifiers Regarding: “(A) Accuracy.

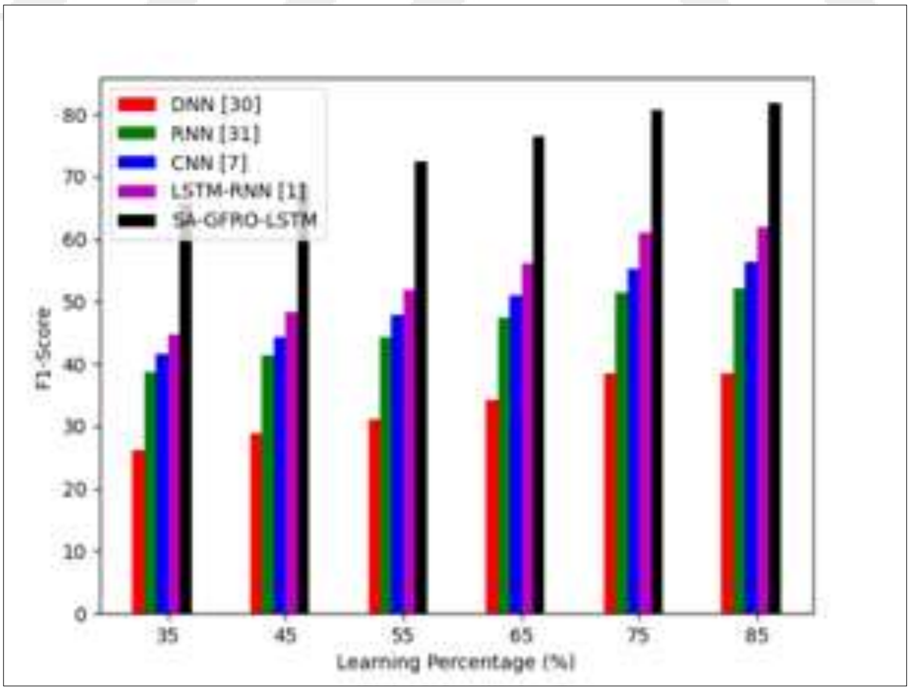

Figure 4.12: Accuracy Validation of The Recommended Distracted Driver Detection Model With Existing Classifiers Regarding :“ (B) F1-Score.

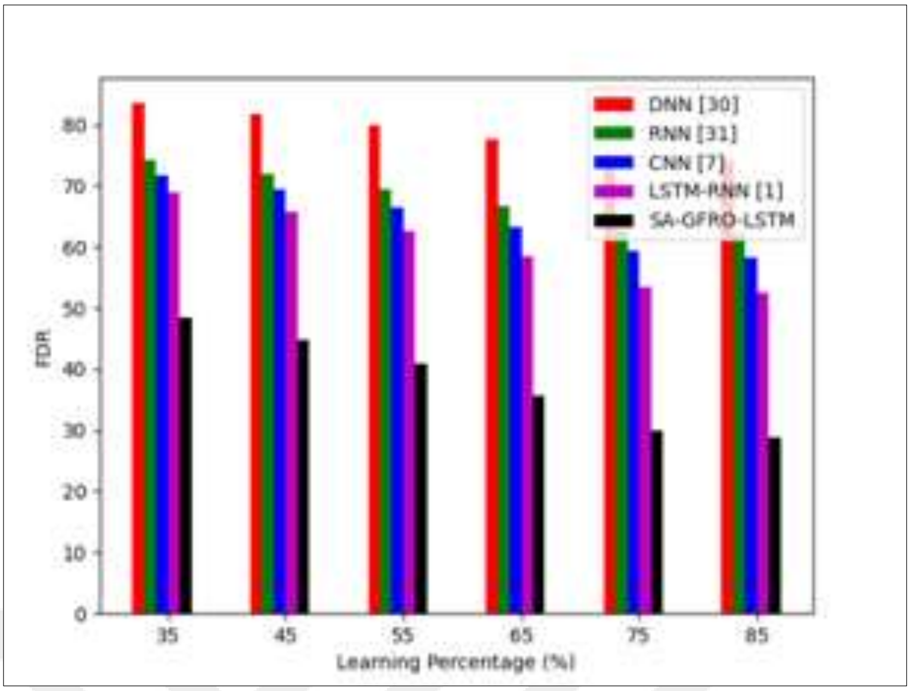

Figure 4.13: Accuracy Validation of The Recommended detection of Driver Distracted Model with Existing Classifiers Regarding:(C) "FDR".

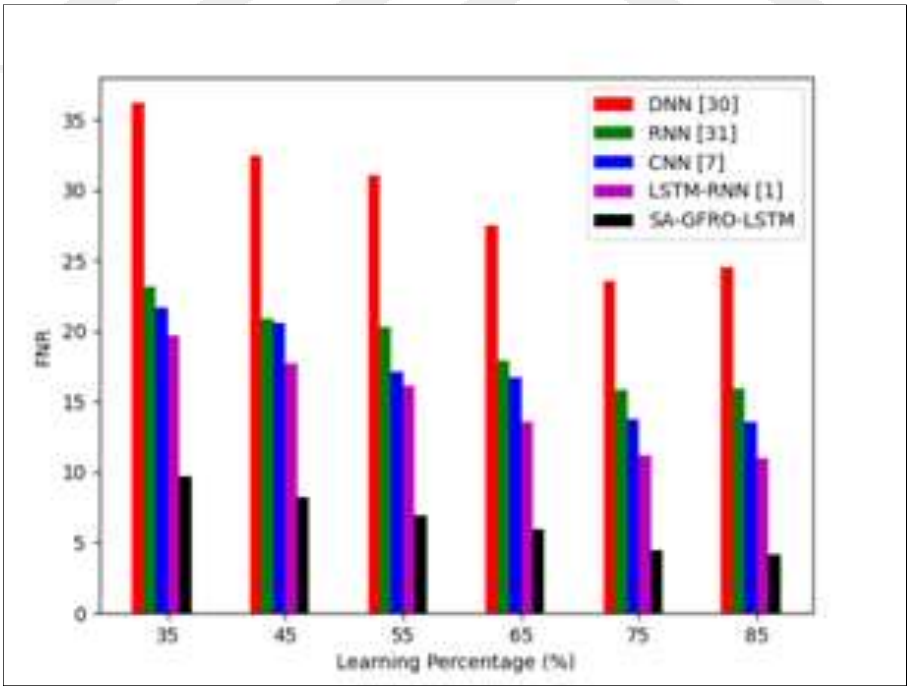

Figure 4.14: Accuracy Validation of The Recommended Detection Of Driver Distracted Model Model With Existing Classifiers Regarding : (D) "FNR".

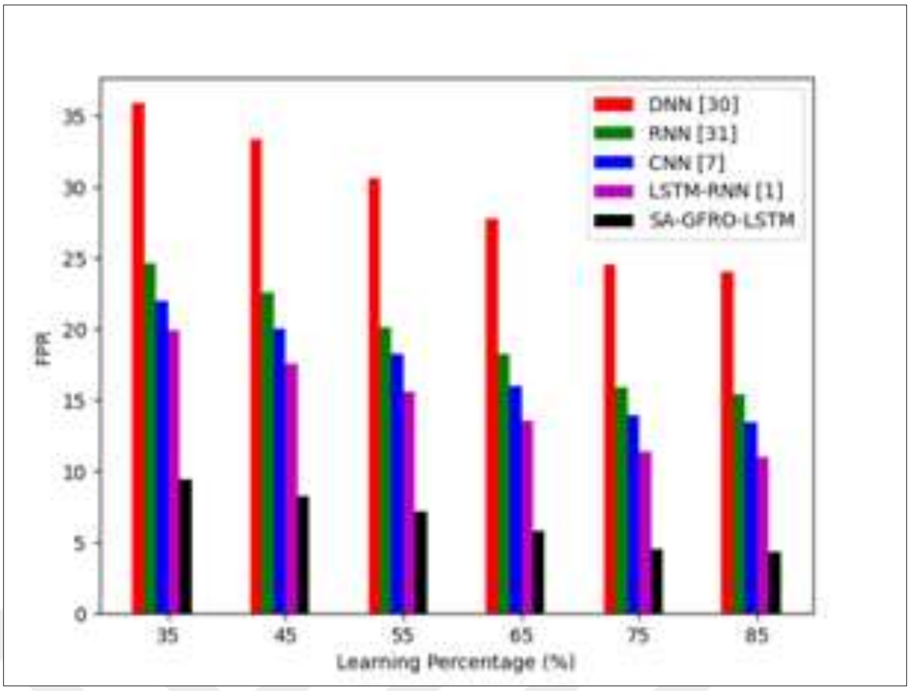

Figure 4.15: Accuracy Validation of The Recommended Detection of Driver Distracted Model With Existing Classifiers Regarding : E) “FPR,

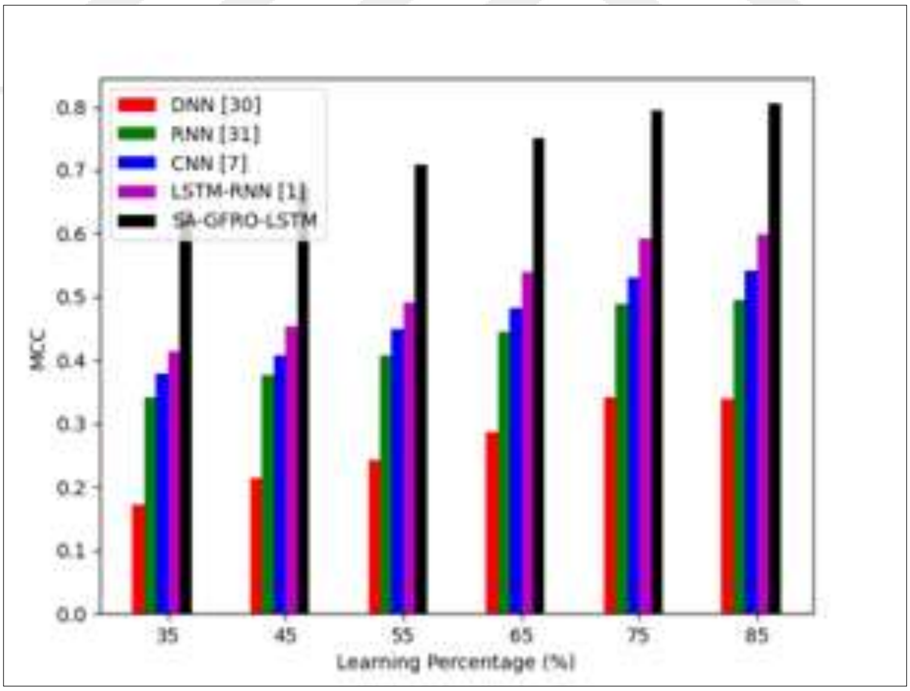

Figure 4.16: Accuracy Validation of The Recommended Detection of Driver Distracted Model With Existing Classifiers Regarding: f) “MCC".

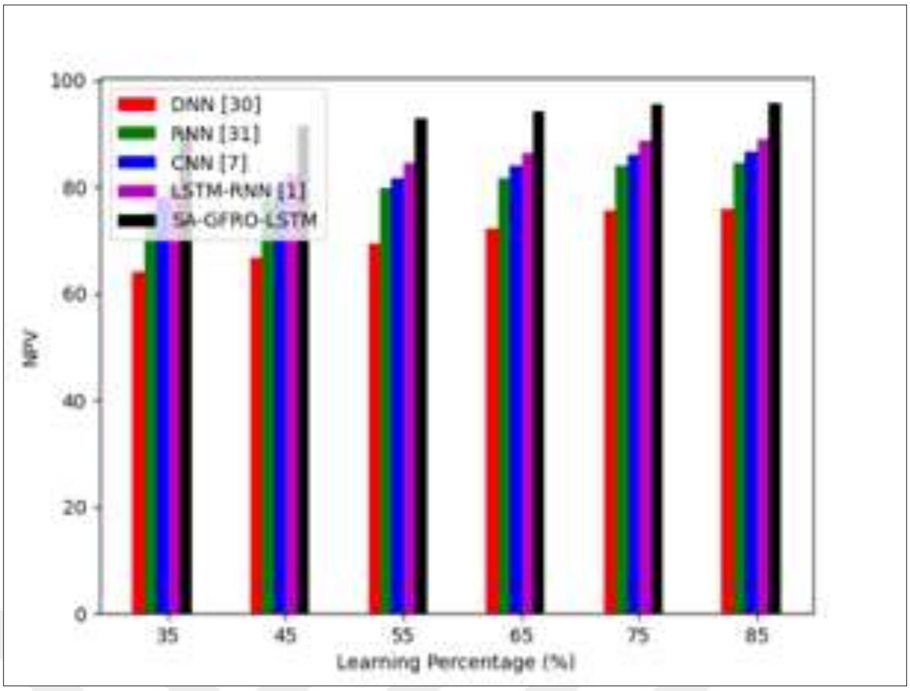

Figure 4.17: Accuracy Validation of The Recommended Detection of Driver Distracted Model With Existing Classifiers Regarding : g) " NPV.

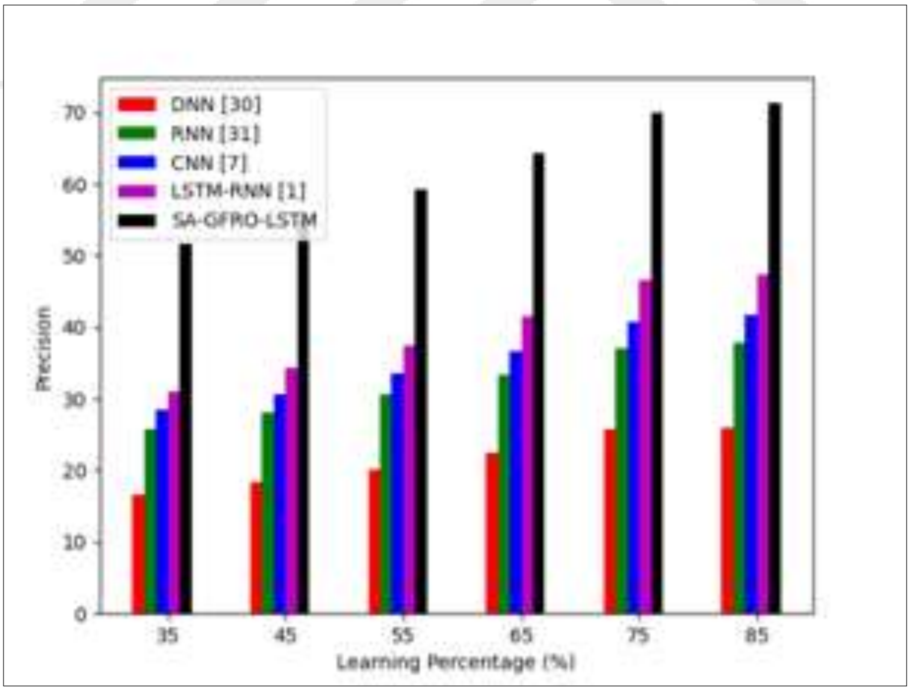

Figure 4.18: Accuracy Validation of The Recommended Detection of Driver Distracted With Existing Classifiers Regarding : h) "Precision".

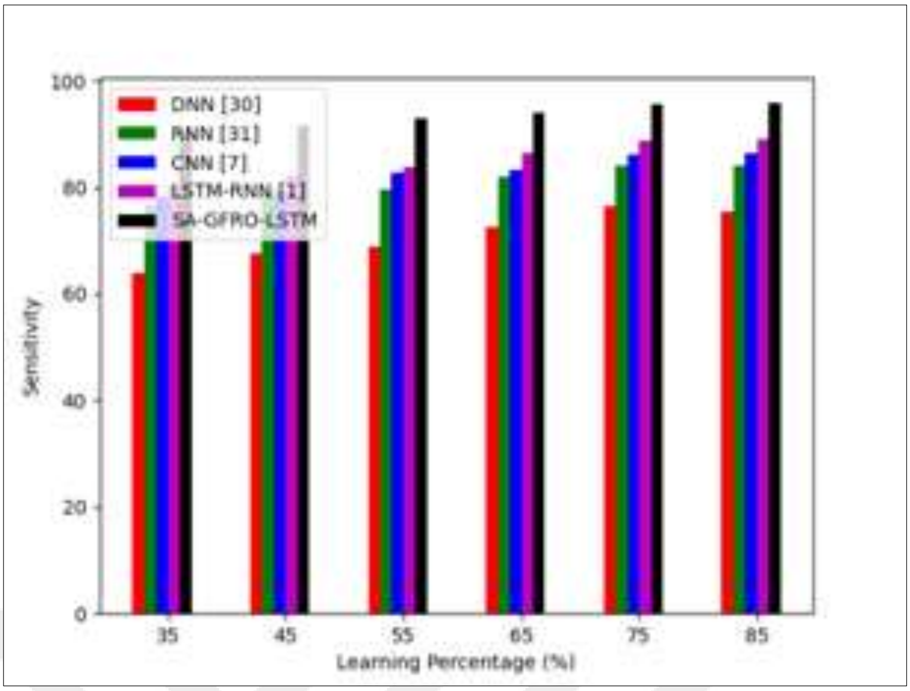

Figure 4.19: Accuracy Validation of The Recommended Detection of Driver Distracted Model With Existing Classifiers Regarding: i) “Sensitivity".

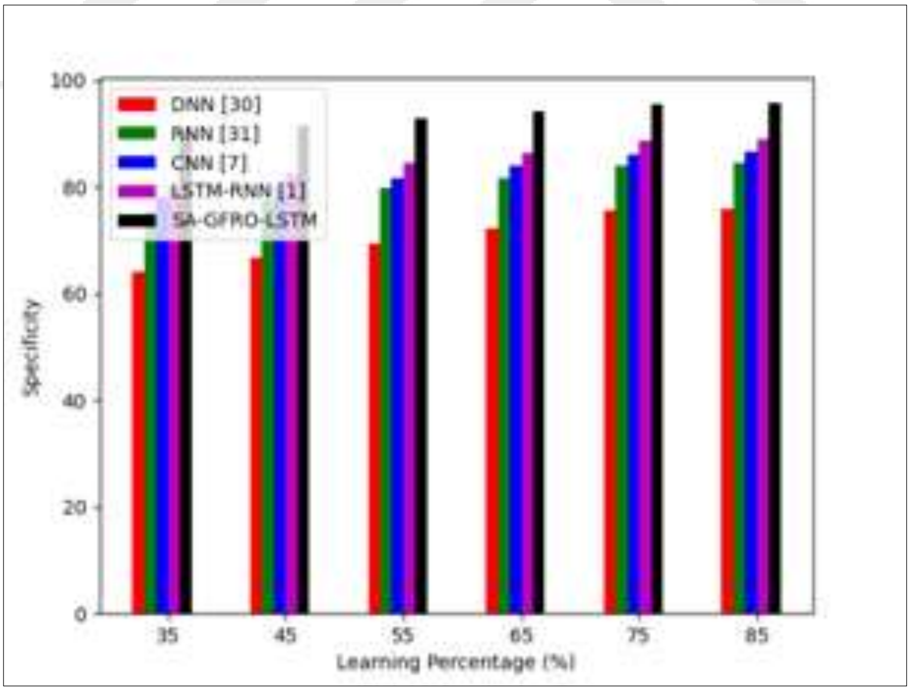

Figure 4.20: Accuracy Validation of The Recommended Detection of Driver Distracted Model With Existing Classifiers Regarding: j) “Specificity”.

4.5 DATASET 2 VALIDATION WITH DIFFERENT META-HEURISTIC ALGORITHMS

The developed SA-GFRO-LSTM-based detection framework is evaluated by comparing it with the various optimization algorithms that are depicted in Figures below. by considering different observations with varying learning percentages. The suggested SA-GFRO-LSTM provides 3.52%, 4.76%, 4.76%, and 6.02% better accuracy when compared to SMO-LSTM, PSO-LSTM, JA-LSTM, and GFRO-LSTM, respectively. The efficacy of the offered approach was revealed to be the best among the comparative algorithms.

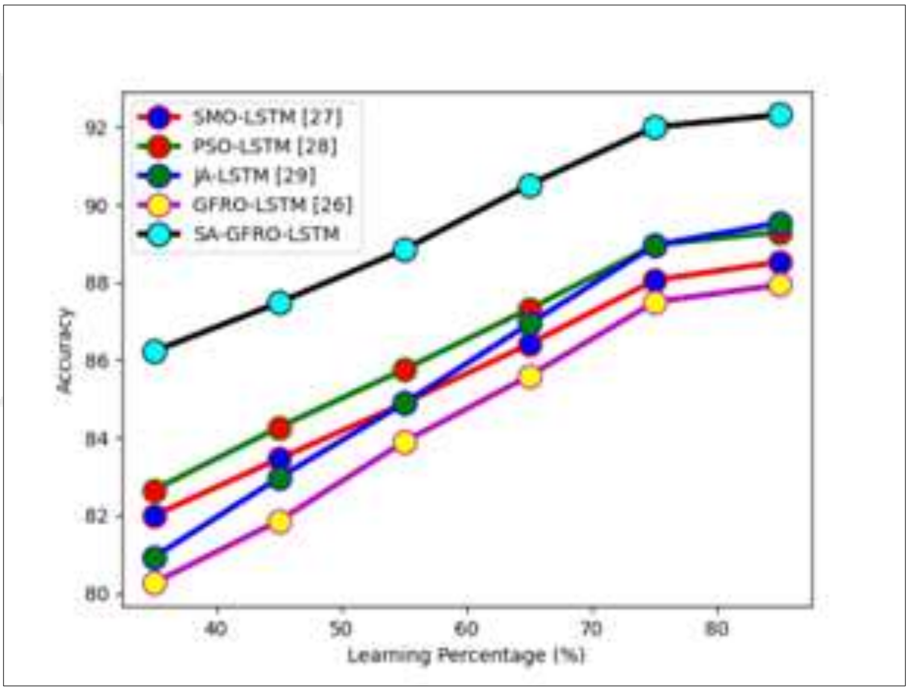

Figure 4.21: Estimation on Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding “(a) "Accuracy".

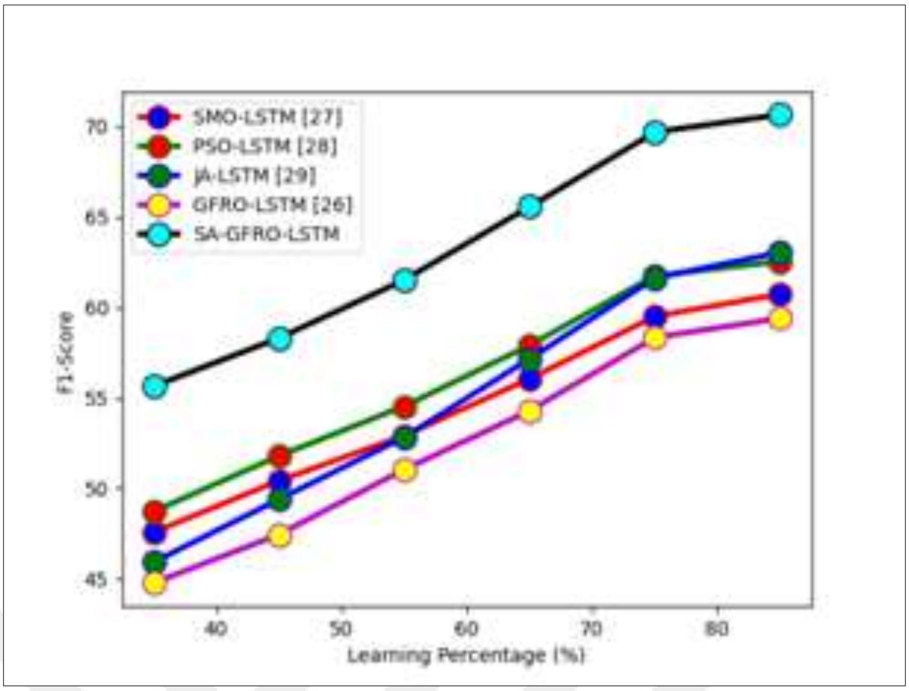

Figure 4.22: Estimation on Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding “ (b) "F1-Score"**.**

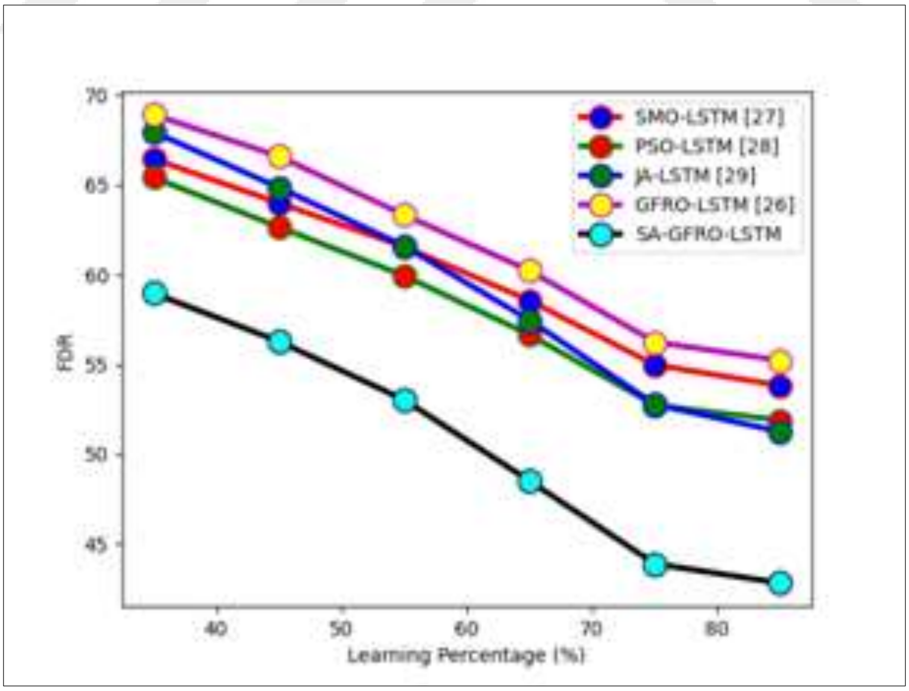

Figure 4.23: Estimation on Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding: (c) "FDR".

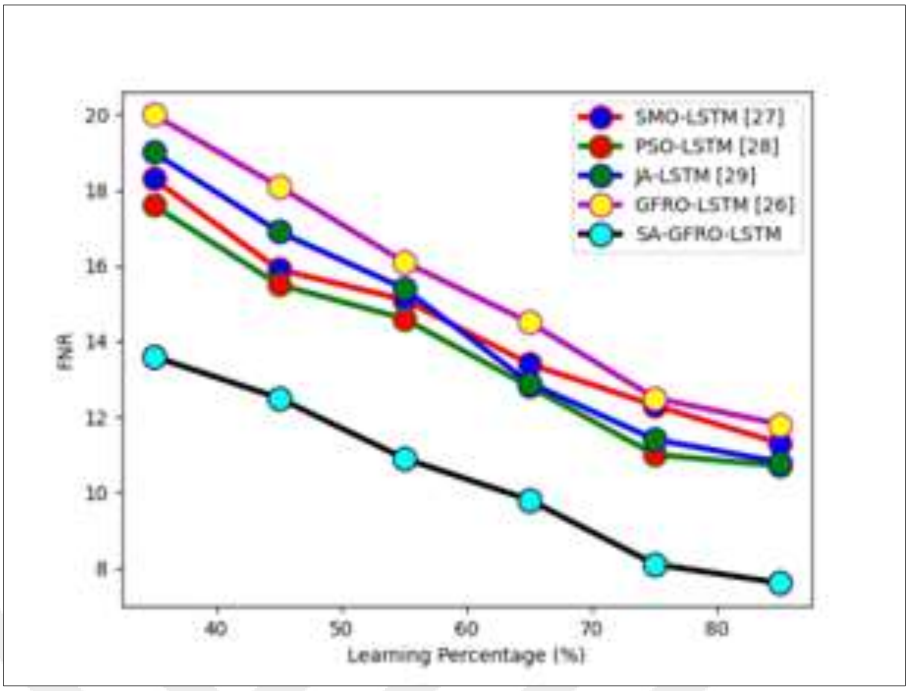

Figure 4.24: Estimation on Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding : (d): “FNR".

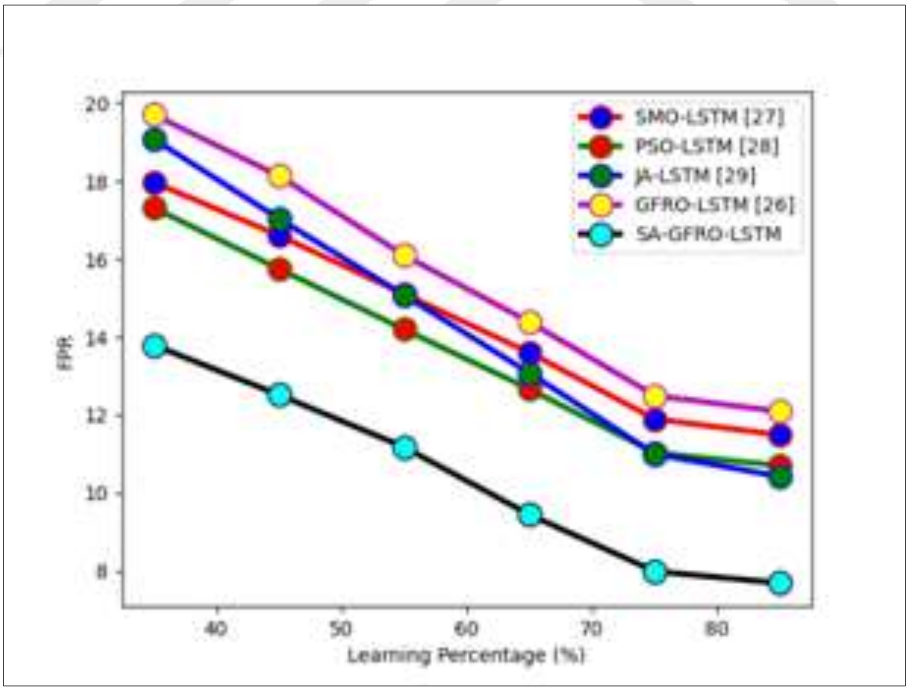

Figure 4.25: Estimation on Recommended Distracted Driver Detection Model with Conventional Meta-heuristic algorithms Regarding : (e) “FPR".

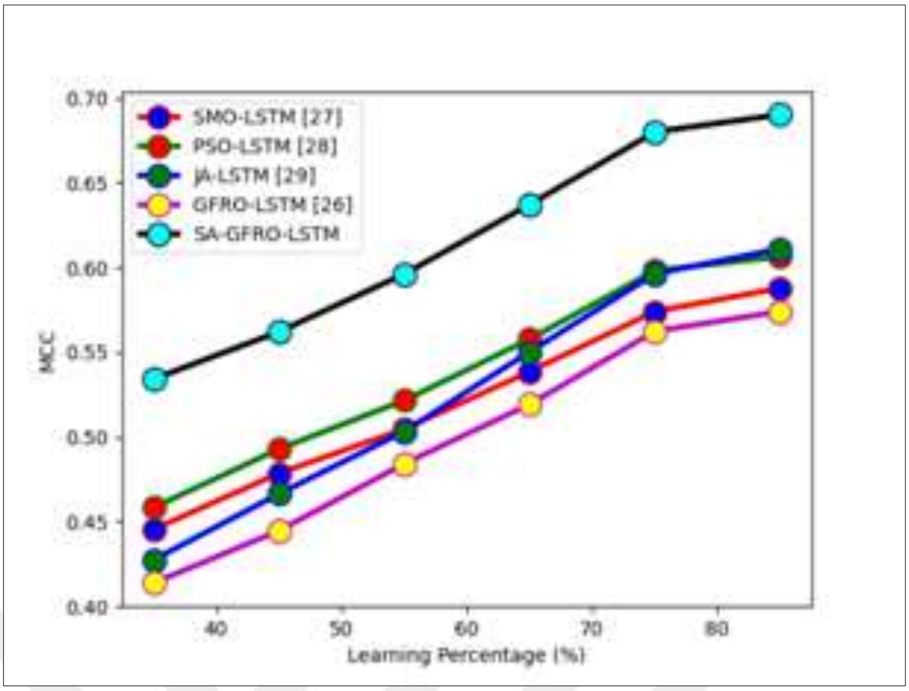

Figure 4.26: Estimation On Recommended Detection of Driver Distracted Model with Conventional Meta-Heuristic Algorithms Regarding: (f) “MCC".

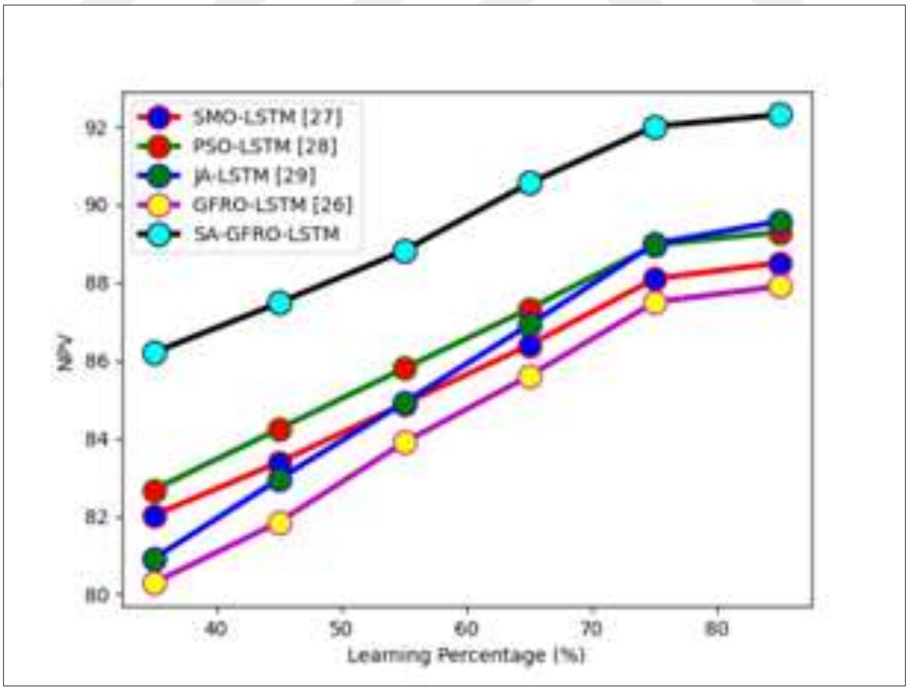

Figure 4.27: Estimation On Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding: (g)“ NPV.

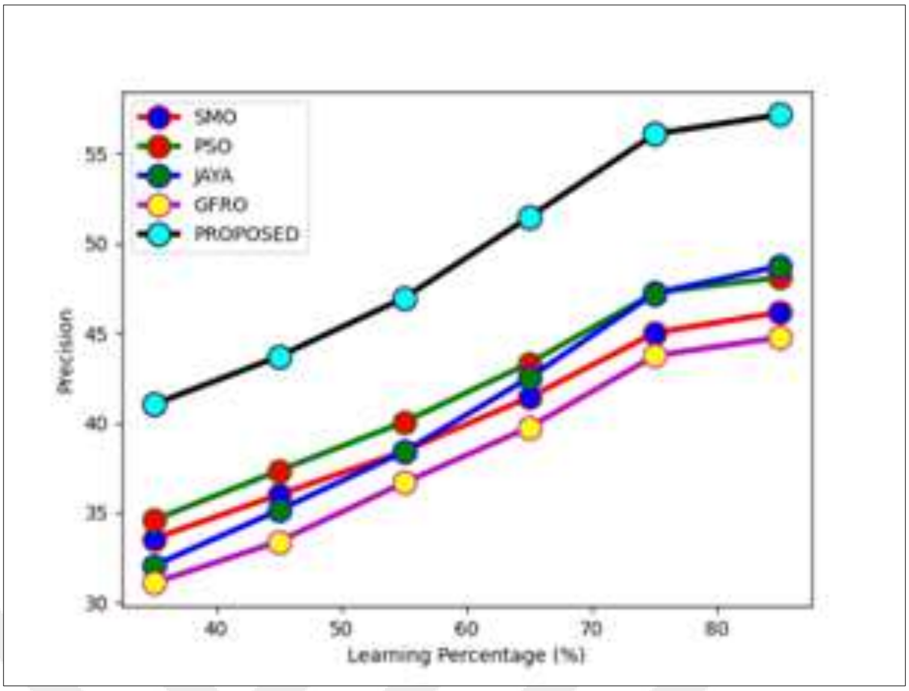

Figure 4.28: Estimation On Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding: (h)“Precision".

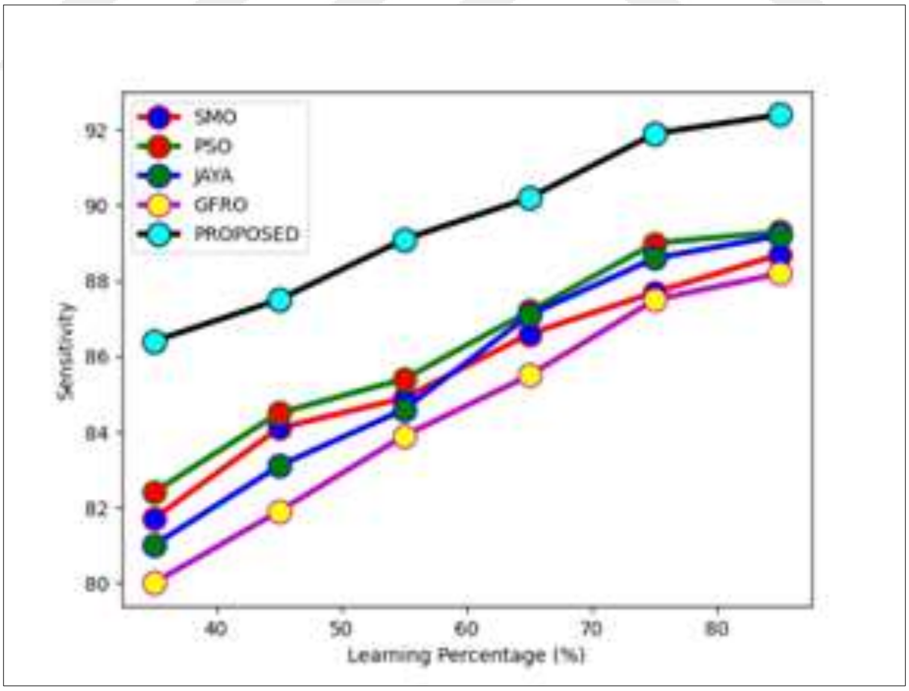

Figure 4.29: Estimation On Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding: (i) “Sensitivity".

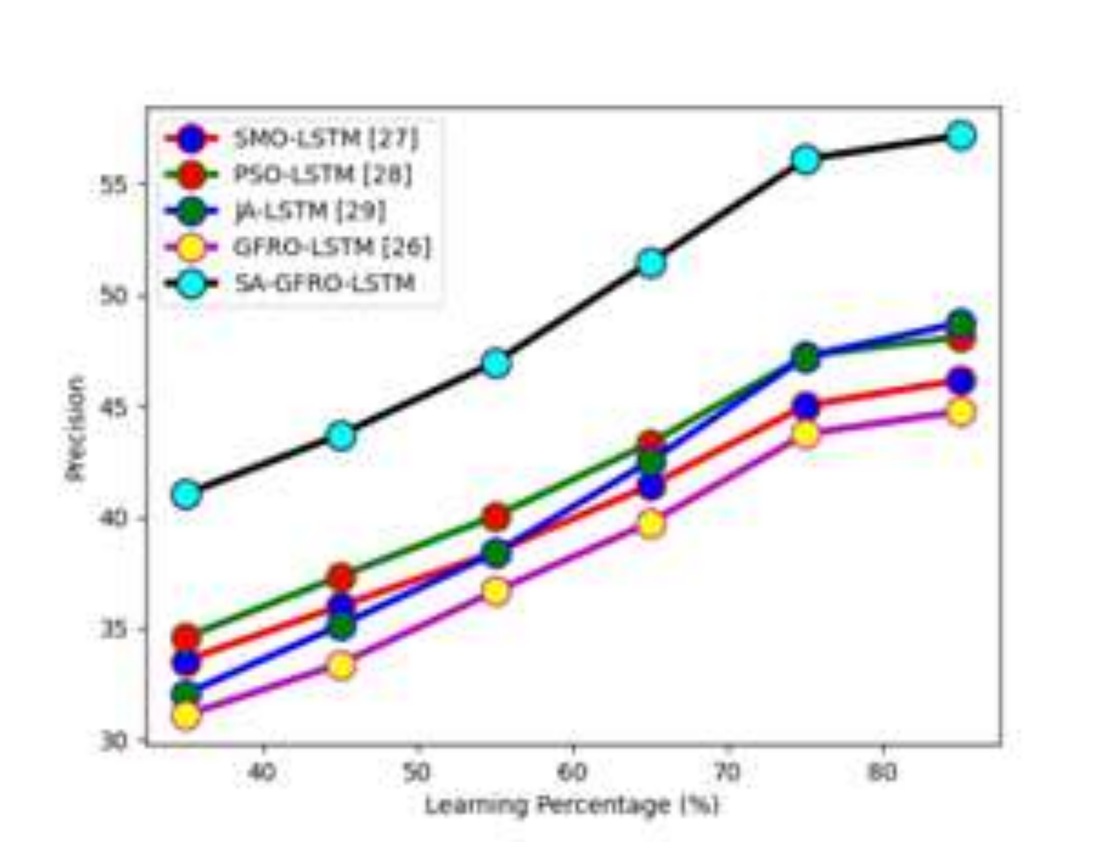

Figure 4.30: Estimation On Recommended Detection of Driver Distracted Model With Conventional Meta-Heuristic Algorithms Regarding: (j) “Specificity”.

4.6 EVALUATION OF THE PROPOSED MODEL WITH VARIOUS ALGORITHMS

The effectiveness of the developed distracted driver detection model is made into comparison to show the betterment of the model with different classification strategies as displayed in Figures below. by considering the learning percentage. The implemented SA-GFRO-LSTM gives 42.85%, 66.67%, 85.18%, and 63.3% higher precision than the DNN, RNN, CNN, and LSTM-RNN at the learning percentage of 35. Hence, the superior efficacy of the developed model is achieved, which is observed through the analysis with existing models.

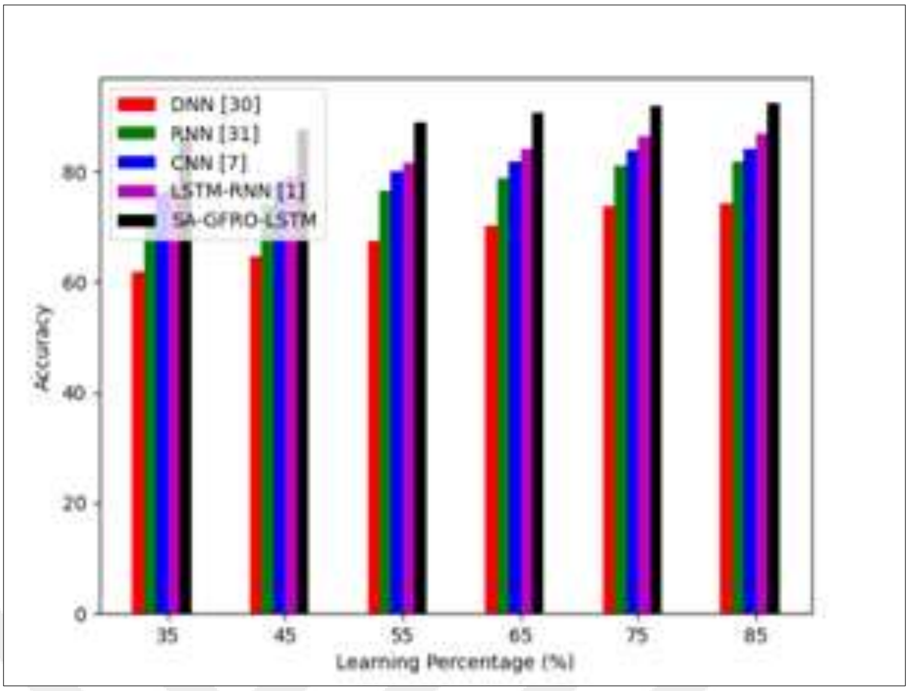

Figure 4.31: Accuracy Validation Of The Offered Detection of Driver Distracted Model with Existing Classifiers Regarding: “(a) Accuracy".

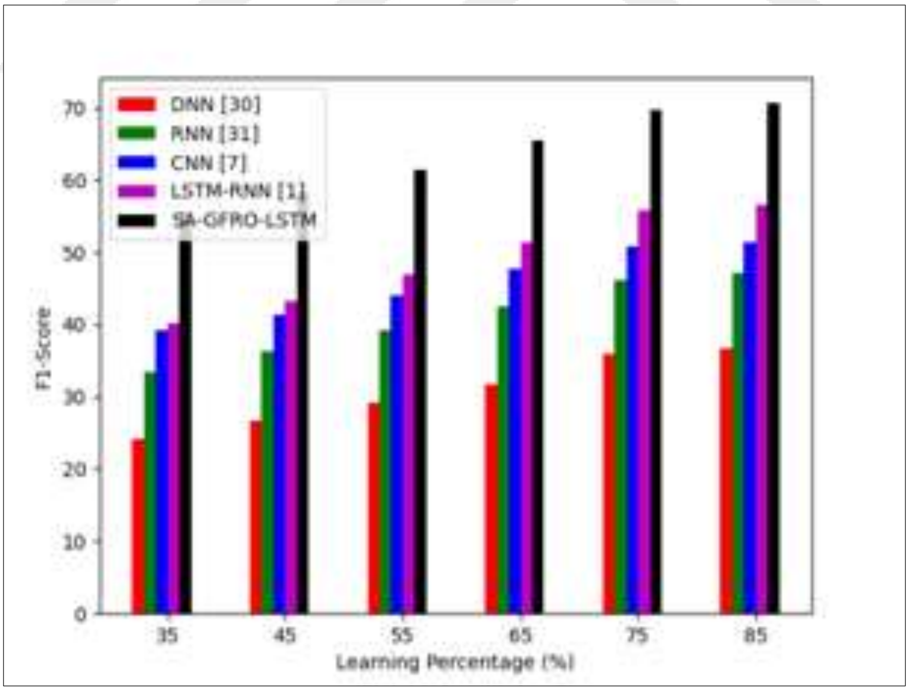

Figure 4.32: Accuracy Validation Of The Offered Distracted Driver Detection Model With Existing Classifiers Regarding “(b) F1-Score,”.

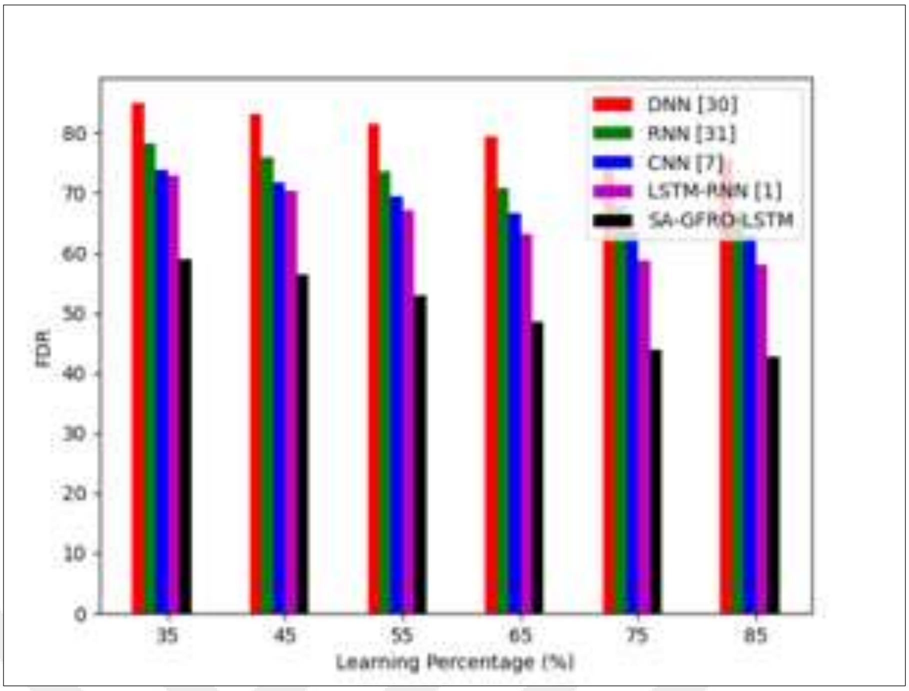

Figure 4.33: Accuracy Validation Of The Offered Detection of Driver Distracted Model with Existing Classifiers Regarding: " (c) FDR".

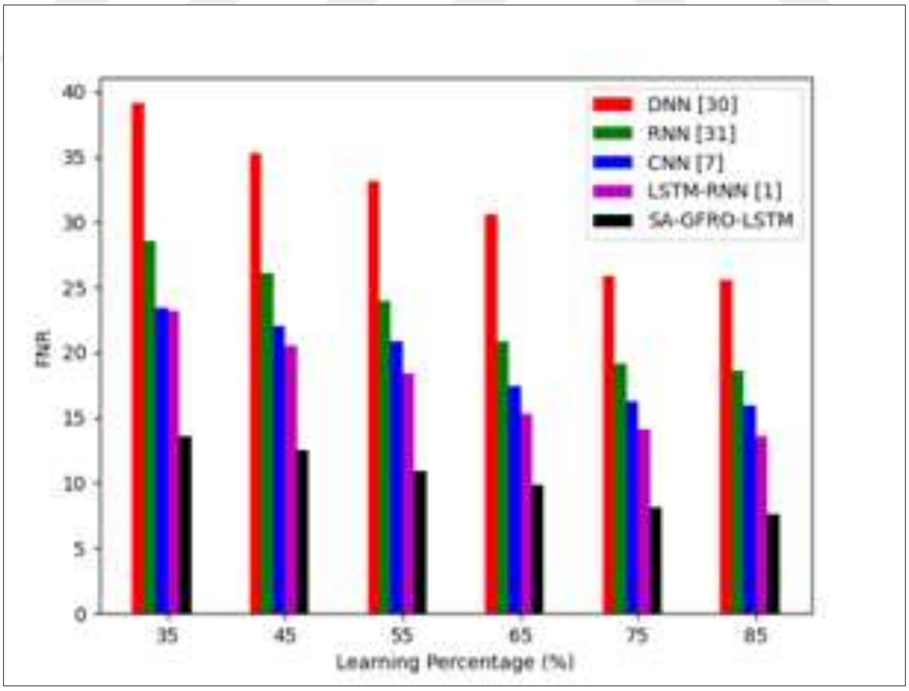

Figure 4.34: Accuracy Validation of The Offered Detection of Driver Distracted Model with Existing Classifiers Regarding: (d) "FNR".

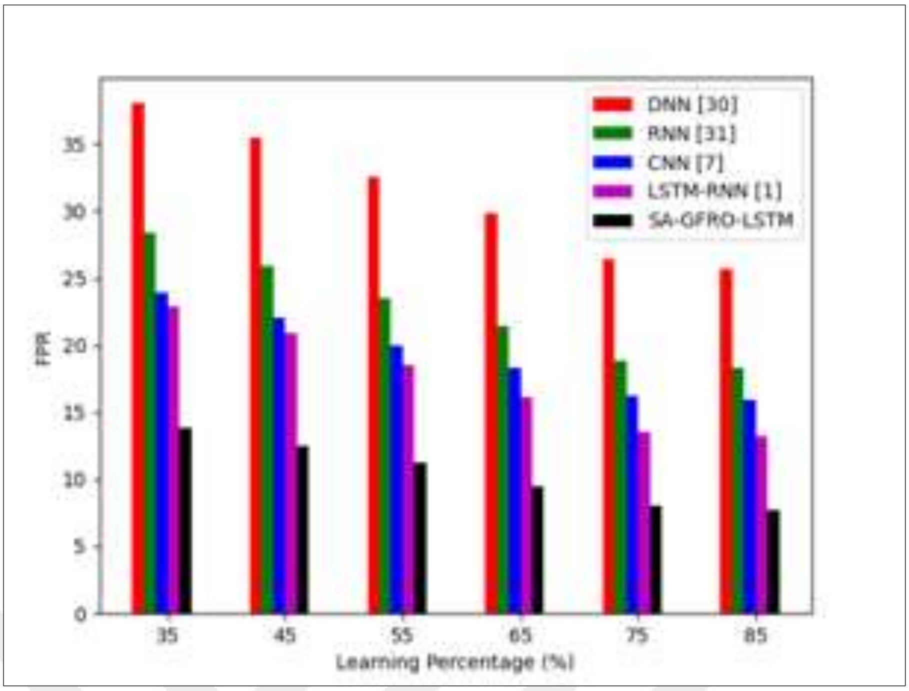

Figure 4.35: Accuracy Validation Of The Offered Detection of Driver Distracted Model With Existing Classifiers Regarding: (e) “FPR".

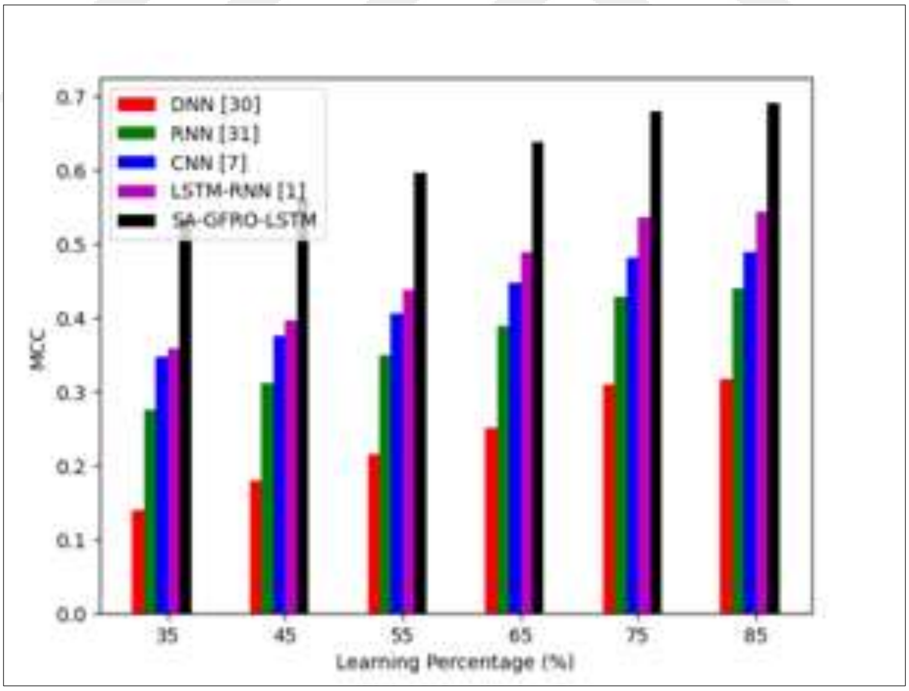

Figure 4.36: Accuracy Validation Of The Offered Detection of Driver Distracted Model With Existing Classifiers Regarding: (f) “MCC"**.**

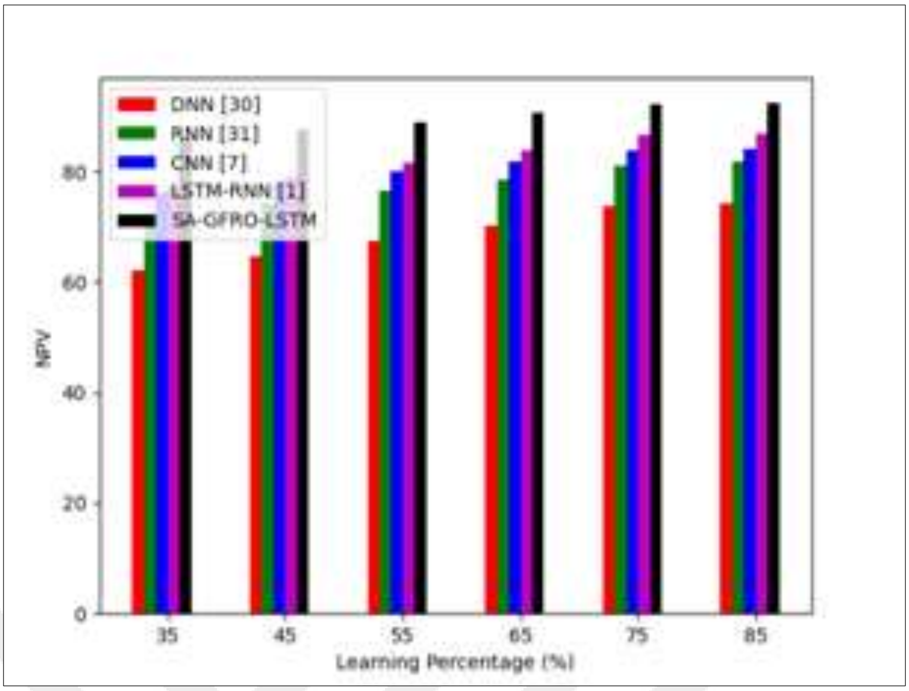

Figure 4.37: Accuracy Validation Of The Offered Detection of Driver Distracted Model with Existing Classifiers Regarding: (g) “NPV".

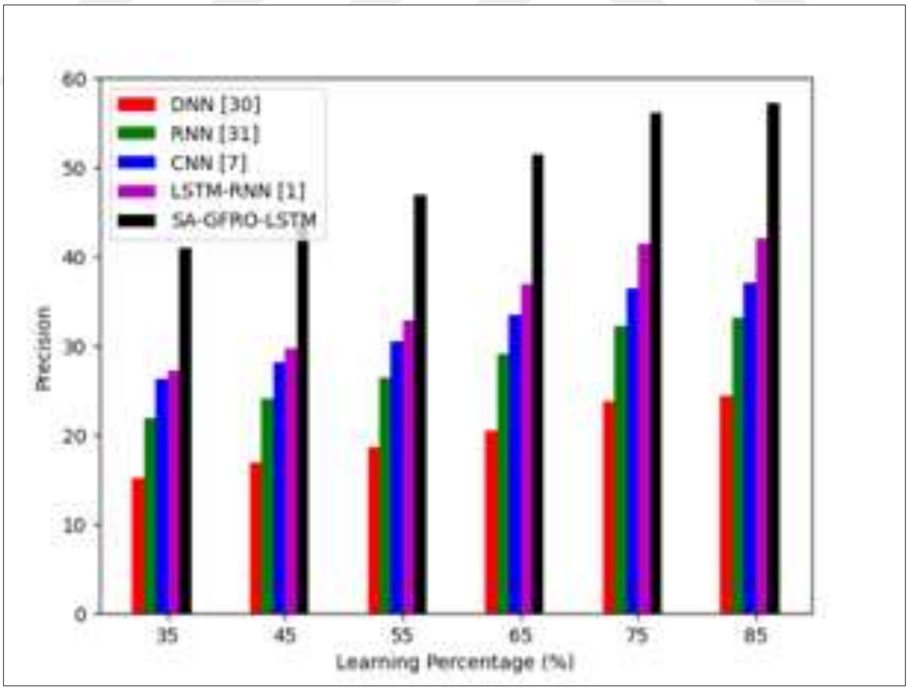

Figure 4.38: Accuracy Validation Of The Offered Detection of Driver Distracted Model With Existing Classifiers Regarding: (h) "Precision".

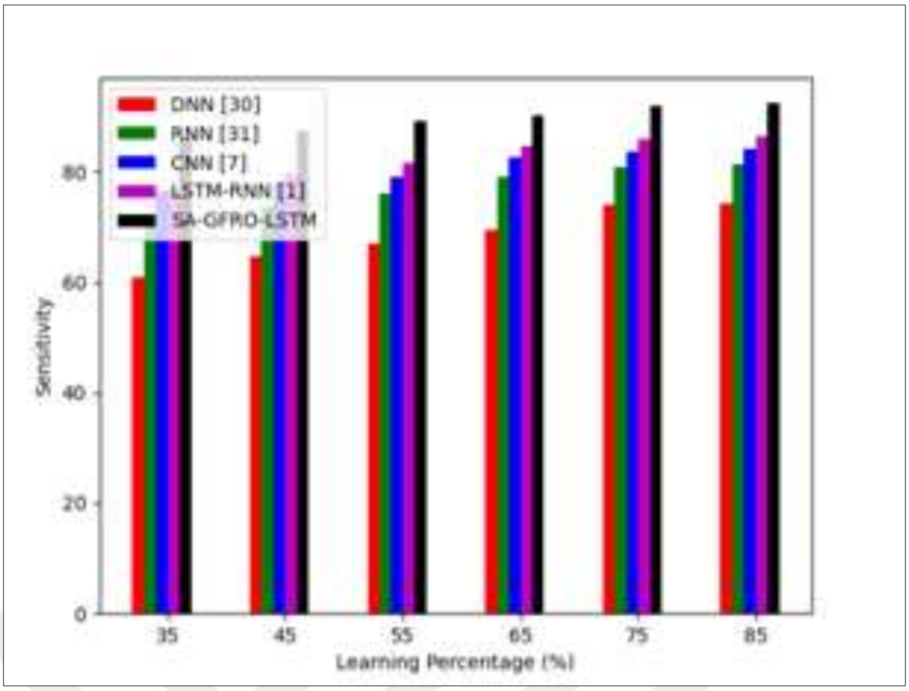

Figure 4.39: Accuracy Validation of The Offered Detection of Driver Distracted Model with Existing Classifiers Regarding: (i) " Sensitivity".

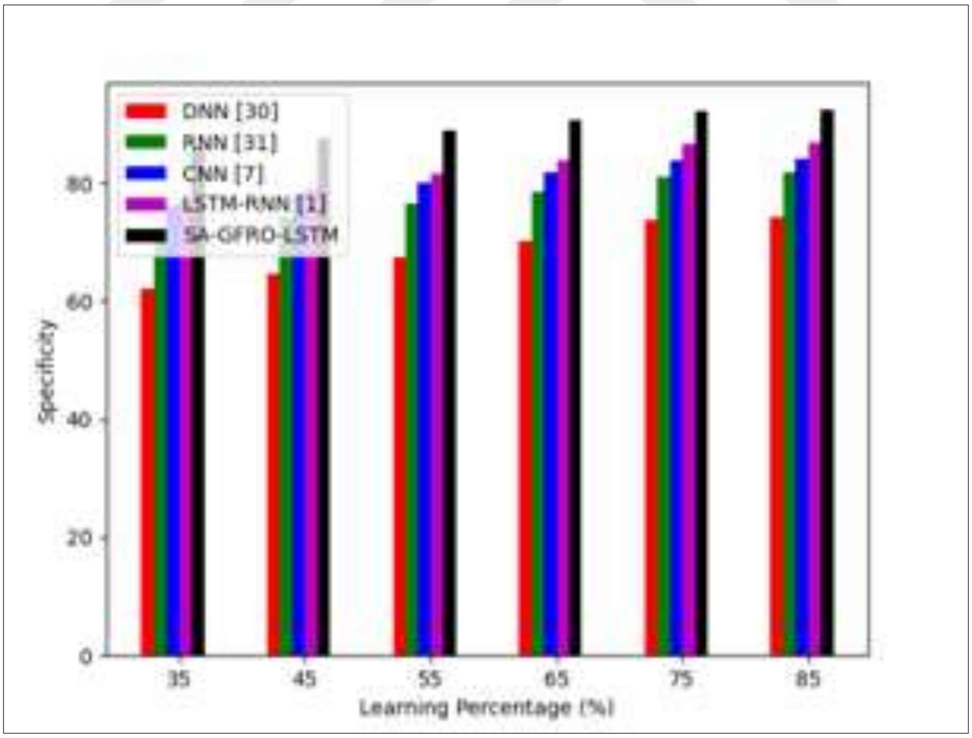

Figure 4.40: Accuracy Validation of The Offered Detection of Driver Distracted Model With Existing Classifiers Regarding: (j) "Specificity".

4.7 EVALUATION OF THE PROPOSED MODEL WITH VARIOUS ALGORITHMS

The implemented distracted driver detection model is compared with various heuristic algorithms as shown in Table 3. The developed SA-GFRO-LSTM is 3.06%, 4.8%, 4.91%, and 6.22% superior to the SMO-LSTM, PSO-LSTM, JA-LSTM, and GFRO-LSTM, respectively at the accuracy analysis. The developed model has showcased the effectiveness of accurately detecting the distracted behaviours of the drivers when correlating with the diverse algorithms.

Table 4.2 : Overall Efficacy of The Recommended Model.

Measures	**SMO-LSTM [53]**	**PSO-LSTM [54]**	**JA-LSTM [55]**	**GFRO-LSTM [52]**	**SA-GFRO-LSTM**
Dataset 1					
"Accuracy"	92.62	91.08	90.99	89.87	95.46
"Sensitivity"	92.6	91.1	91.2	89.7	95.5
"Specificity"	92.6222	91.0778	90.9667	89.8889	95.4556
"Precision"	58.239	53.1505	52.8696	49.6403	70.0147
"FPR"	7.3778	8.9222	9.0333	10.1111	4.5444
"FNR"	7.4	8.9	8.8	10.3	4.5
"NPV"	92.6222	91.0778	90.9667	89.8889	95.4556

Table 4.3 : Overall Efficacy of The Recommended Model.

“FDR”	41.761	46.8495	47.1304	50.3597	29.9853
“F1-Score”	71.5058	67.1334	66.9358	63.9116	80.7953
“MCC”	69.9162	65.4181	65.2437	62.0545	79.5036
Dataset 2					
“Accuracy”	88.06	88.97	88.96	87.5	92
“Sensitivity”	87.7	89	88.6	87.5	91.9
“Specificity”	88.1	88.9667	89	87.5	92.0111
“Precision”	45.0205	47.265	47.2281	43.75	56.105
“FPR”	11.9	11.0333	11	12.5	7.9889
“FNR”	12.3	11	11.4	12.5	8.1
“NPV”	88.1	88.9667	89	87.5	92.0111
“FDR”	54.9795	52.735	52.7719	56.25	43.895
“F1-Score”	59.498	61.7412	61.6134	58.3333	69.674
“MCC”	57.4175	59.8284	59.6323	56.25	68.0188

4.8 EVALUATION ON PROPOSED MODEL BASED ON DIFFERENT CLASSIFIERS

The developed driver distraction detection model is evaluated for its performance regarding different metrics as shown in Table 4. The proposed SA-GFRO-LSTM provides 24.86%, 13.42%, 9.8%, and 6.45% elevated performance in accuracy than the DNN, RNN, CNN and LSTM-RNN, respectively. On observing analysis results, it is confirmed that the developed model provides enhanced efficiency in detecting the distracted behaviours of the drivers than the comparative techniques.

Table 4.4: Overall Evaluation Of Implemented Driver Distraction Detection Model With Different Classifiers**.**

Measures	**DNN [56]**	**RNN [57]**	**CNN [34]**	**LSTM-RNN [28]**	**SA-GFRO-LSTM**
Dataset 1					
“Accuracy”	75.6	84.13	86.04	88.67	95.46
“Sensitivity”	76.4	84.2	86.2	88.8	95.5
“Specificity”	75.5111	84.1222	86.0222	88.6556	95.4556
“Precision”	25.7412	37.0762	40.6604	46.5165	70.0147
“FPR”	24.4889	15.8778	13.9778	11.3444	04.5444
“FNR”	23.6	15.8	13.8	11.2	4.5
“NPV”	75.5111	84.1222	86.0222	88.6556	95.4556

Table 4.5: Overall Evaluation Of Implemented Driver Distraction Detection Model With Different Classifiers**.**

“FDR”	74.2588	62.9238	59.3396	53.4835	29.9853
“F1-Score”	38.5081	51.4827	55.2564	61.0519	80.7953
“MCC”	34.0887	48.923	53.0104	59.1248	79.5036
Dataset 2					
“Accuracy”	73.68	81.11	0.83.77	86.42	92
“Sensitivity”	74.1	80.9	0.83.7	85.9	91.9
“Specificity”	73.6333	81.1333	0.83.7778	86.4778	92.0111
“Precision”	23.7958	32.2696	0.36.4388	41.3776	56.105
“FPR”	26.3667	18.8667	0.16.2222	13.5222	7.9889
“FNR”	25.9	19.1	0.16.3	14.1	08.1
“NPV”	73.6333	81.1333	0.83.7778	86.4778	92.0111
“FDR”	76.2042	67.7304	0.63.5612	58.6224	43.895
“F1-Score”	36.0233	46.1363	0.50.7734	55.8518	69.674
“MCC”	30.9243	42.938	0.48.1251	53.5353	68.0188

4.9 EVALUATION OF PROPOSED MODEL BASED ON RECENT DIFFERENT DEEP LEARNING STRATEGIES

An evaluation of the distracted driver detection method is given in Table 5. The accuracy of the proposed SA-GFRO-LSTM provides 2.76%, 4.01%, 3.91%, and 2.61% more advanced than DDBD, DDBD-HBCL, UMMFN, and HCF for dataset 1. The precision of the proposed SA-GFRO-LSTM provides 4.53%, 5.13%, 3.75%, and 2.44% elevated performance than DDBD, DDBD-HBCL, UMMFN, and HCF for dataset 2. Hence, the proposed distracted driver detection model provides more advanced performance than the existing methods.

Table 4.6: Evaluation Of Proposed Detection of Driver Distracted with Different Classifiers**.**

Metrics	**DDBD [19]**	**DDBD-HBCL [21]**	**UMMFN [22]**	**HCF [23]**	**SA-GFRO-LSTM**
Dataset 1					
“Specificity”	90.13	90.01	92.15	93.40	95.90
“Sensitivity”	90.25	89.70	91.91	93.53	95.87
“F1-Score”	90.14	89.77	91.97	93.43	95.86
“FDR”	9.98	10.15	7.97	6.68	4.16
“Precision”	90.02	89.85	92.03	93.32	95.84
“FPR”	9.87	9.99	7.85	6.60	4.10
“FNR”	9.75	10.30	8.09	6.47	4.13
“NPV”	90.13	90.01	92.15	93.40	95.90

Table 4.7: Evaluation Of Proposed Detection of Driver Distracted with Different Classifiers**.**

"Accuracy"	90.19	89.85	92.03	93.47	95.89
"MCC"	80.39	79.71	84.06	86.94	91.77
Dataset 2					
"Accuracy"	86.37	88.50	89.71	91.42	95.89
"Sensitivity"	86.61	88.43	89.64	91.46	95.87
"Specificity"	86.13	88.57	89.78	91.38	95.90
"Precision"	86.03	88.41	89.64	91.28	95.84
"FPR"	13.87	11.43	10.22	8.62	4.10
"FNR"	13.39	11.57	10.36	8.54	4.13
"NPV"	86.13	88.57	89.78	91.38	95.90
"FDR"	13.97	11.59	10.36	8.72	4.16
"F1-Score"	86.32	88.42	89.64	91.37	95.86
"MCC"	72.74	77.00	79.42	82.84	91.77

4.10VALIDATION OF THE DEVELOPED MODEL REGARDING MULTIPLE DIFFERENT CLASSES OF DISTRACTION ACTIVITY

The estimation of the designed model regarding multiple different classes of distraction activity using the deep learning model for datasets 1 and 2 is shown in Fig.4.42 and 4.43. The accuracy of the recommended approach was achieved at 93.6% in a safe driving class. While taking the texting left class, the accuracy of the offered approach is attained as 94.1%. Moreover, a better accuracy rate can be achieved in the class “Talking to a Passenger” for datasets 1 and 2. Thus, the simulation findings of the developed model have revealed that it attains better accuracy on all classes of driver behaviors for all datasets.

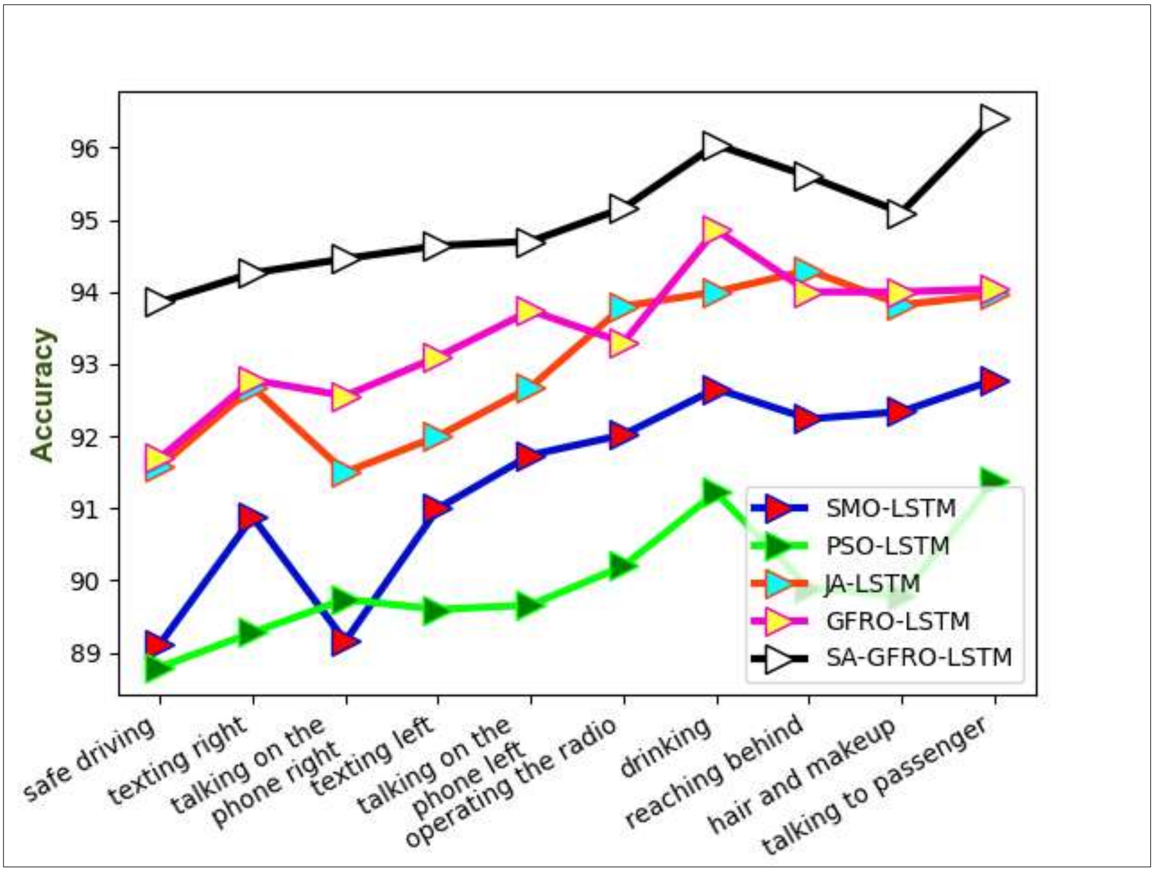

Figure 4.41: Validation Of the Developed Model Regarding Multiple Classes Of Distraction Activity For Dataset 1 With Respect To (A) Algorithms.

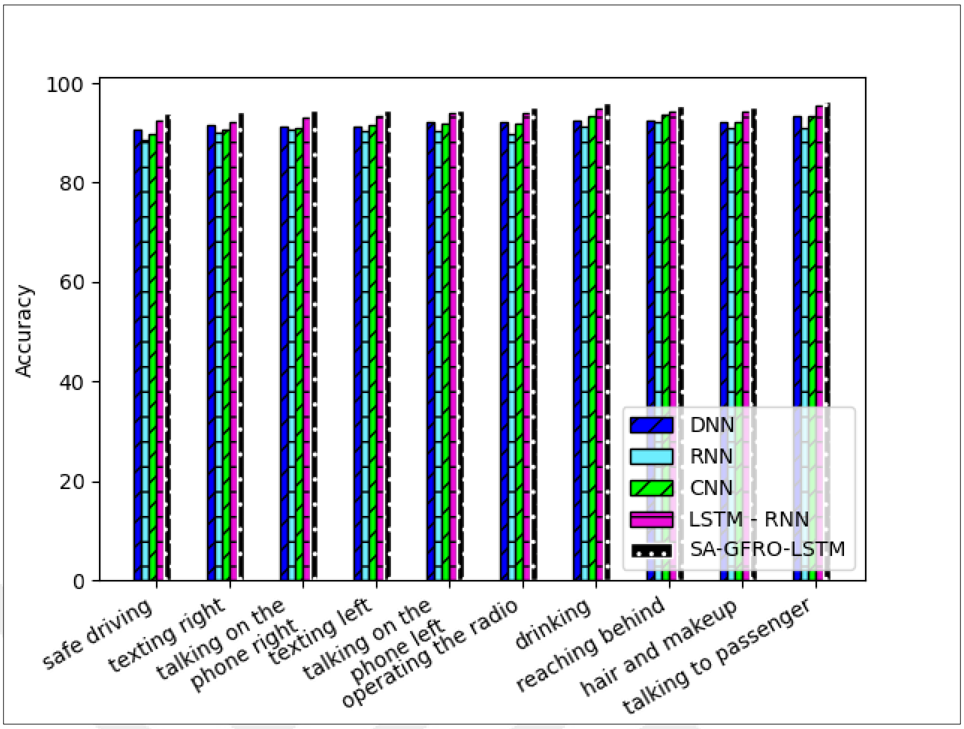

Figure 4.42: Validation of the Developed Model Regarding Multiple Classes of Distraction Activity for Dataset 1 with Respect to (A) Classifier.

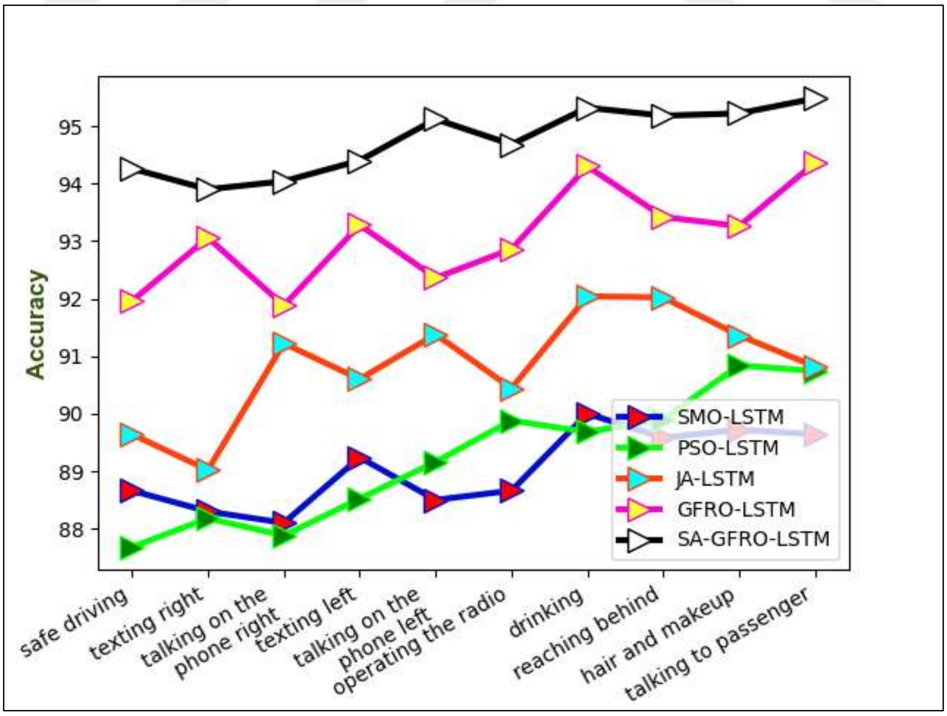

Figure 4.43: Validation of the developed model regarding multiple classes of distraction activity for dataset 2 with respect to (a) Algorithms**.**

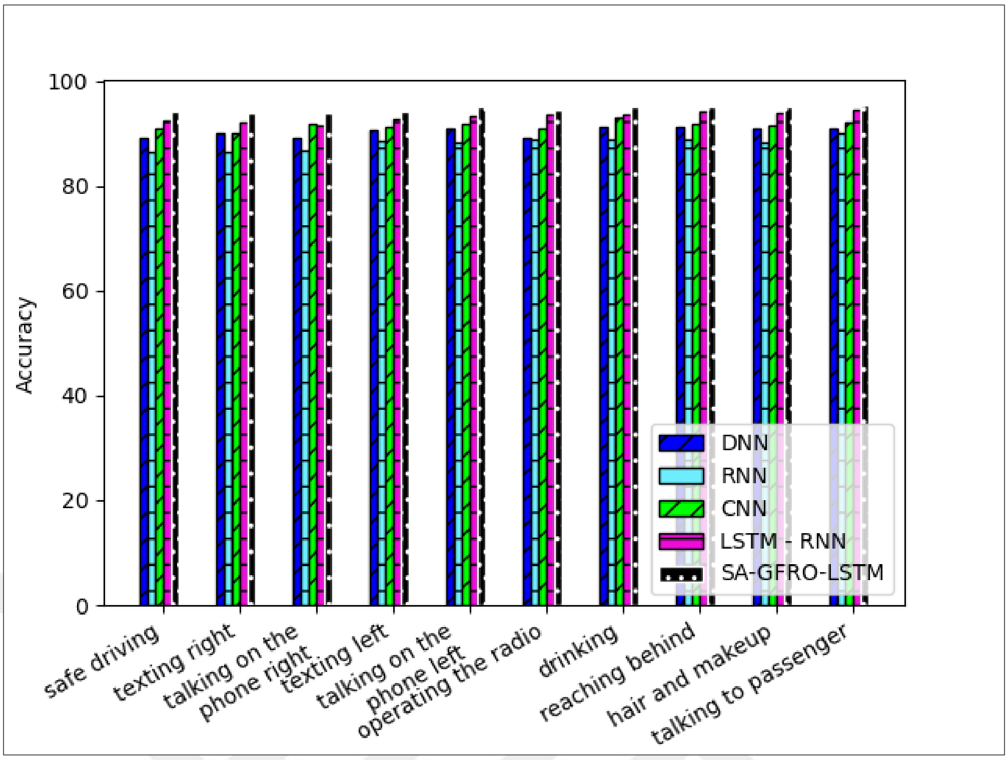

Figure 4.44: Validation of The Developed Model Regarding Multiple Classes of Distraction Activity for Dataset 2 with Respect to (B) Classifiers.

5. CONCLUSION

This Dissertation has introduced a novel detection of a driver-distracted model using suggested SA-GFRO along with the offered M-LSTM approach with the IoT sector. The gathered input images using IoT were initially given into the different variants of CNN. These extracted features were considered for the selection model using the proposed SA-GFRO to get the best features for detection. Then, the best features were given to the developed M-LSTM for detecting the distracted behaviors of the drivers. The parameters in the LSTM were tuned with the support of developed SA-GFRO to elevate the detection performance. The comparison has been shown that 24.86% superior to DNN, 13.42% better than RNN, 9.8% improved CNN than, and 6.45% higher than LSTM-RNN when considering the accuracy analysis. Hence, it was confirmed that the developed distracted driver detection model has elevated efficiency in detection using developed M-LSTM with the help of developed M-LSTM when compared with the baseline algorithms.

5.1 FUTURE WORK

A drawback of this work is that the real-time dataset is not considered and also needs to collect data from more drivers to increase the reliability of the system. In the future, we will try to improve the reliability of the model by collecting more public as well as real-time data. Especially, the data related to multiple drivers and driving styles will be added that helps to enhance the generalization ability of the distracted action detection model.

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