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MACHINE LEARNING BASED DRIVER DROWSINESS DETECTION USING EMOTION ANALYSIS

A.R. DEEPA
Koneru Lakshmaiah Education Foundation, Guntur. Email: deepaamuth@gmail.com

MOUSMI AJAY CHAURASIA
Muffakham Jah College of Engineering & Technology, Hyderabad India. Email: mousmi.ksu@ieee.org

PERAM SAI HARSHA VARDHAN
Koneru Lakshmaiah Education Foundation, Guntur. Email: saiharshachowdary999@gmail.com

GANISHETTI RITWIKA
Koneru Lakshmaiah Education Foundation, Guntur. Email: ritwikaganishetti03@gmail.com

YASWANTH CHOWDARY
Koneru Lakshmaiah Education Foundation, Guntur. Email: Yaswanthchowdarynettem@gmail.com

MAMILLAPALLI SAMANTH KUMAR
Koneru Lakshmaiah Education Foundation, Guntur. Email: samanthmamilla@gmail.com

Abstract

Driver drowsiness is a critical issue contributing to road accidents worldwide. Traditional methods for detecting drowsiness in drivers primarily rely on physiological signals and facial recognition. However, these methods may not capture the nuanced emotional states of drivers, which can also be indicative of drowsiness. This paper presents a novel approach to driver drowsiness detection using machine learning techniques and emotion analysis. In experimental evaluations, our system demonstrated promising results in terms of accurately detecting drowsiness-related emotions in drivers. By integrating emotion analysis with traditional physiological indicators, our approach offers a more comprehensive and robust drowsiness detection system. This can lead to enhanced road safety by providing timely warnings to drowsy drivers, potentially preventing accidents and saving lives. Our research represents a significant step towards improving driver safety through the integration of emotion analysis and machine learning in drowsiness detection systems. Future work will focus on refining the model, exploring additional data sources, and integrating this technology into existing vehicle safety systems.

Keywords: Driver Drowsiness; Eye Detection; Yawn Detection; Blink Pattern; Fatigue.

1. INTRODUCTION

In recent years, road safety has emerged as a critical concern due to the increasing number of accidents caused by driver drowsiness and fatigue. According to the World Health Organization (WHO), road traffic accidents are a leading cause of fatalities globally, with a substantial portion attributed to human error, especially drowsy or fatigued driving. Detecting and mitigating driver drowsiness is a paramount challenge for ensuring road safety and reducing the associated human and economic costs.

Traditional methods of drowsiness detection primarily rely on physiological indicators, such as eye closure duration, yawning frequency, or steering wheel movements. While these methods have been valuable, they often lack precision and may lead to false

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alarms. In contrast, recent advancements in machine learning techniques have opened new avenues for more accurate and robust drowsiness detection systems. Emotion analysis, as a subset of affective computing, has gained prominence in understanding human behavior and mental states. Emotions play a crucial role in determining a person's cognitive and physiological state, making them a valuable indicator of drowsiness. By leveraging machine learning algorithms and emotion analysis techniques, it is possible to create a driver drowsiness detection system that can identify subtle changes in a driver's emotional state, thus providing a more reliable indicator of drowsiness.

This paper presents a novel approach to driver drowsiness detection that integrates machine learning techniques with emotion analysis. We propose a system capable of continuously monitoring the driver's emotional responses through various sensors, such as facial recognition cameras and physiological sensors. The collected emotional data are then processed using machine learning algorithms to classify the driver's emotional state and identify signs of drowsiness.

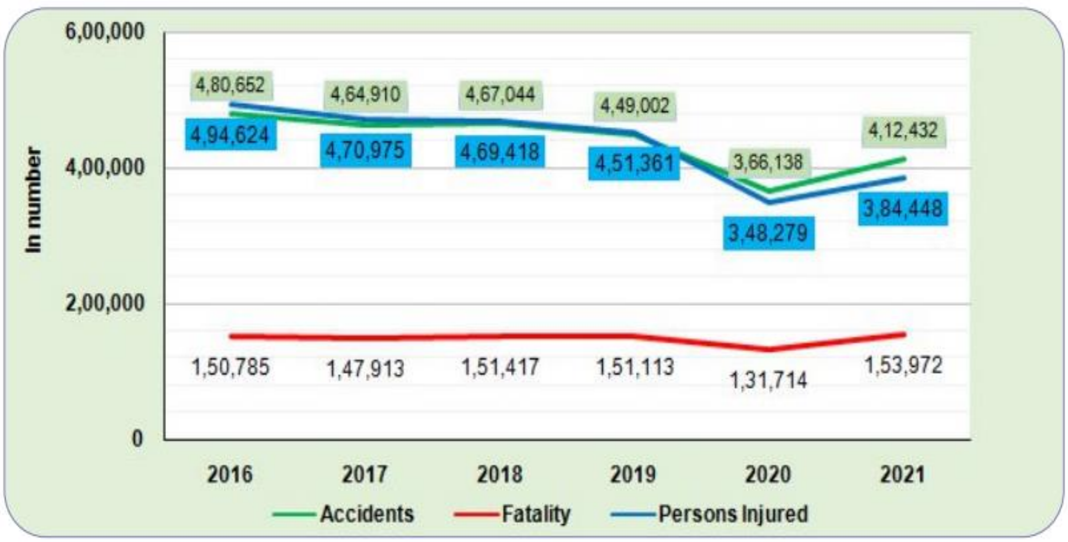

Figure 1: Statistical analysis of accidents due to driver fatigue and reckless driving from 2016 to 2021

2. LITERATURE REVIEW

To prevent traffic accidents brought on by fatigued drivers, numerous researchers are actively searching for solutions. Five types of driving, including regular driving, driving while fatigued, driving while inattentive, driving while inebriated, and driving while distracted, have been created from the extensive research data. Some of the important study findings that were presented were used in the construction of the proposed system with increased performance.

"Emotion-Based Driver Drowsiness Detection Using Deep Learning" by M. S. Hossain, M. M. A. Hashem, et al. (Published in 2020).Drowsiness, defined as the state of sleepiness when one needs to rest, can cause symptoms that have great impact over the

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performance of tasks: slowed response time, intermittent lack of awareness, or microsleeps (blinks with a duration of over 500 ms), to name a few examples [1]. In fact, continuous fatigue can cause levels of performance impairment similar to those caused by alcohol [2,3]. While driving, these symptoms are extremely dangerous since they significantly increase the probabilities of drivers missing road signs or exits, drifting into other lanes or even crashing their vehicle, causing an accident.

The Karolinska Sleepiness Scale (KSS) was used by Zhang et al. (2020) to create a model for detecting driver drowsiness. The suggested model combines the Time Cumulative Effect (TCE) and Mixed Effect Ordered Logit (MOL) models. The proposed model produces a 62.84% better accuracy than the current models, according to the experimental analysis, which compared the MOL-TCE model with the non-MOL-TCE models. A contextual algorithm was developed by McDonald et al. (2018) to identify sleepy driving. The method has a lower false-positive rate than the current PERCLOS, which is the current standard for the driver drowsiness detection system, and was merged with the Dynamic Bayesian Network algorithm (DBN).

Phanikrishna et al. (2021) developed an autonomous classification algorithm for detecting driver drowsiness using wavelet packet transform. The wavelet packet transform was derived from the singlechannel Electro-Encephalogram (EEG) data of the driver. The real-time sleep analysis is carried out by the suggested model with a 94.45% accuracy. Taherisadr et al. (2018) used Mel-Frequency Cepstrum in the two-dimensional transform and Convolution Neural Network (CNN) to construct a model for determining the driver's attention [16]. The developed model generates a two-dimensional MelFrequency Cepstrum representation of the ElectroCardiogram (ECG) detected from the driver. The analytical results demonstrate that the created model outperforms the existing drowsiness detection methods. when a car. Lee et al. (2017) created a system that uses correlation analysis on ElectroCardiography (ECG) and Photoplethysmogram (PPT) data to determine driver drowsiness. Experimental research demonstrates that this noise replacement model is superior to the PPT method in spotting driver intoxication.

The main focus of Kumar et al. (2020) was on implementing surveillance systems employing embedded devices and signal processing techniques. The system concentrates on drowsy driving identification, alcohol intake detection, and crash detection for better vehicle control. The results of the experiments show that this method is more precise and effective than the present analogue system. Kowalczuk et al. (2019) developed a versatile driver monitoring system by recognising the driver's emotions [19]. The final emotion was calculated using the Kalman filter, which interprets emotions as digital data, and the system understands the driver's actual interior sensations. The technology has no preference when it comes to determining driver fatigue. In order to identify urban crimes, Li et al. (2020) proposed a technique for evaluating facial expression and emotion links. In order to determine the relationship between the emotion and the driving pattern, the Facial Expression Recognition (FER) was developed and put to practise [20]. It works by recognising the user's emotion based on their facial expression. Wang et al. (2021) investigated the evaluation of several deep learning- and machine-based categorization techniques for images. Both very big datasets, like the

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MNIST dataset, and small datasets, such the COREL1000 dataset, were used in the study. The experimental results demonstrate that deep learning improves recognition accuracy on large datasets, while classical machine learning performs better on small datasets.

The proposed model is an integrated model, which detects the drowsiness of the driver and identifies the emotion of the driver to avoid reckless driving which is one of the vital causes of road accidents.

3. PROPOSED MODEL

Two modules make up the suggested model: one that detects driver drowsiness and another that looks at the driver's emotions to prevent irresponsible driving. Gathering data from the driver sensing module, preprocessing the data, and deep learning using Convolution Neural Network (CNN) are the three procedures contained in the first module for identifying driver drunkenness. Fig. 2 represented the three phases and their respective responsibilities.

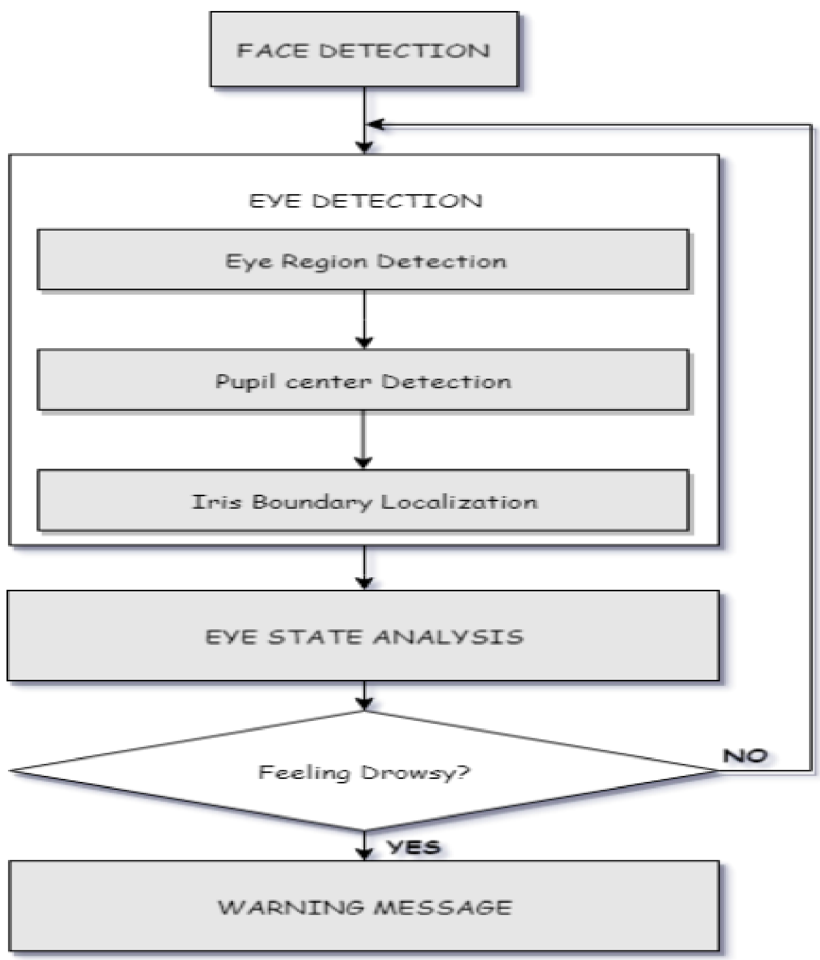

Figure 2: Proposed drowsy detection system process

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3.1 Data Gathering Phase

The data gathering phase serves as the initial training stage for our proposed model, where we aim to categorize driver behavior into multiple levels: normal, fatigue, aggressive, disturbed, and alcohol consumption. This phase involves not only collecting information about the driver's multi-level behavior but also monitoring the vehicle's acceleration system by examining key metrics such as revolutions per minute (RPM), speed, and throttle position. To analyze the vehicle's acceleration, we focus on linear acceleration measurements. These measurements take into account both acceleration and gravity along the three-dimensional axis (x, y, and z), enabling us to determine the vehicle's linear acceleration accurately. By analyzing the linear acceleration data, we can classify the driving mode into various multi-level categories, including normal, aggressive, drunken driving, reckless driving, and more. To train the driver drowsiness detection phase of our model, we utilize a specialized Driver Drowsiness Detection (DDD) dataset. Additionally, for training the driver emotion analysis phase, we employ the extended Cohn-Kanade dataset (CK+). These datasets, collected during the experimental training phase, serve as reference values for subsequent live testing. During live testing, we capture images of the driver's face and process them to extract important features, particularly focusing on the eye blinking factor and its frequency. We analyze these features under various conditions, including normal driving, fatigue, drunkenness, and aggression. The data collected during live testing is compared against the trained values stored in a local database. This comparison helps us determine the current state of the driver, whether they are showing signs of drowsiness, fatigue, or other emotional states, and take appropriate actions to ensure their safety.

3.2 Pre-Processing Phase

The preprocessing phase is a crucial step that is performed before applying the data to the convolutional neural networks (CNNs). When the raw data is directly fed into the CNNs without preprocessing, it often results in errors in the output data. Therefore, the preprocessing phase plays a vital role in transforming the raw data into a format that is acceptable by the CNNs. In the context of the driver fatigue monitoring system, the preprocessing phase involves measuring the input image in the time domain representation. The labeled data is categorized into multiple levels, including normal, aggressive, drunken, and fatigue. This categorization helps in accurately identifying the different states of the driver. The time interval considered in the proposed system is a critical aspect of the preprocessing phase. It is set to 1.0 second, aiming to detect driver distraction. Selecting an appropriate time interval is essential to prevent overlapping of input samples, which could result in data loss and inaccurate analysis. At the same time, the time interval should be as small as possible to effectively capture even minute levels of driver distraction. By carefully selecting the time interval in the preprocessing phase, the driver fatigue monitoring system can ensure accurate detection of driver distraction while minimizing data loss. This step is crucial in achieving reliable and precise results in the overall system. The Recurrence Plot (RP) is employed to view the recurrent states and in the proposed model, the Recurrence Plot in the time series on temporary data

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which is measured to make digital images with spatial properties in the frequency domain. The mathematical expression for the Recurrence Plot is given as in Eq. (1).

$R^{x}_{a;b}$ ¼ aðR_T jjX_a $X_b$jjÞ

(1) Here the $R_{a,b}$ is the recurrence plot, while the R_T is the recurrence threshold, whereas α is the Heaviside function of the temporal data. The algorithm for the time domain windowing and generating the recurrence plot is illustrated in the Tab. 1.

Table 1: Algorithm for time domain windowing and generating recurrence plot

Input:
$X^i = \sum(Xn^i)$; i=1,2,3....n
$X_i = (X_{1i} + X_{2i} + X_{3i} + \ldots + X_{ni})$ Output:
Window size: 150
Sliding window: sw = 1
Recurrence threshold R_T
Recurrence Plot function: using equation 1
for samples $X^i \epsilon$ self-dataset do for
representations r ϵ rep (X^i) do
Image $_{150X100} = R_{a,bx}$ end
Image = concatenate (Image ^{X}) end

In the proposed system, the captured image of the driver was converted from the time domain and the recurrence plotting is performed using the PyRQA toolbox for the analysis of recurrence quantification and to generate the recurrence plots in a massive parallel pattern. The plotted image was of 50 x 50 pixels dimensions stored in the grayscale format. The quantity of samples measured and the plotted images for each level were listed in Tab. 2.

Table 2: Quantity of measured samples for each level of driving and images plotted

Driving Pattern	Number of Measured Samples	Number of Image plotted
Normal	3812	3517
Fatigue	4289	4122
Drunken	4119	3927
Reckless	5023	4962

The preprocessed input images with 50 X 50 pixels are sampled and reconstructed to 150 X 100 pixel images which are ready to feed as input to the adjacent stage of Convolution Neural Networks.

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3.3 Deep Learning Phase

The deep learning phase serves as the culmination and essential processing component of our proposed driver fatigue detection model. This phase encompasses two critical processes: firstly, feeding the preprocessed image into Convolutional Neural Networks (CNN), and subsequently, producing an output that mirrors the driver's behavior and classifying it into one of the previously mentioned four levels. Our choice of employing Convolutional Neural Networks (CNN) in the driver drowsiness monitoring system stems from several advantages over traditional Neural Networks. Neural Networks often involve intricate procedures for training datasets, requiring extensive training of all datasets, which can be a time-consuming and complex process. In contrast, Deep Neural Networks (DNN) embrace low-level representations at the initial stages and progressively fuse them into higher-level representations at the final DNN layer. CNN, a subset of Artificial Neural Networks (ANN), is particularly well-suited for a wide range of applications due to its simplified processing. In our model, the output image from the preprocessing phase, sized at 150 X 100, is fed into all the channels of the convolutional neural network. The majority of CNN layers are responsible for extracting features from the input image. Ultimately, the final layer of the CNN performs maximum classification of the processed image, categorizing the observed image into one of the following states: normal, fatigue, drunken, or reckless. For a visual representation of the CNN architecture in our proposed model, please refer to Figure 3.

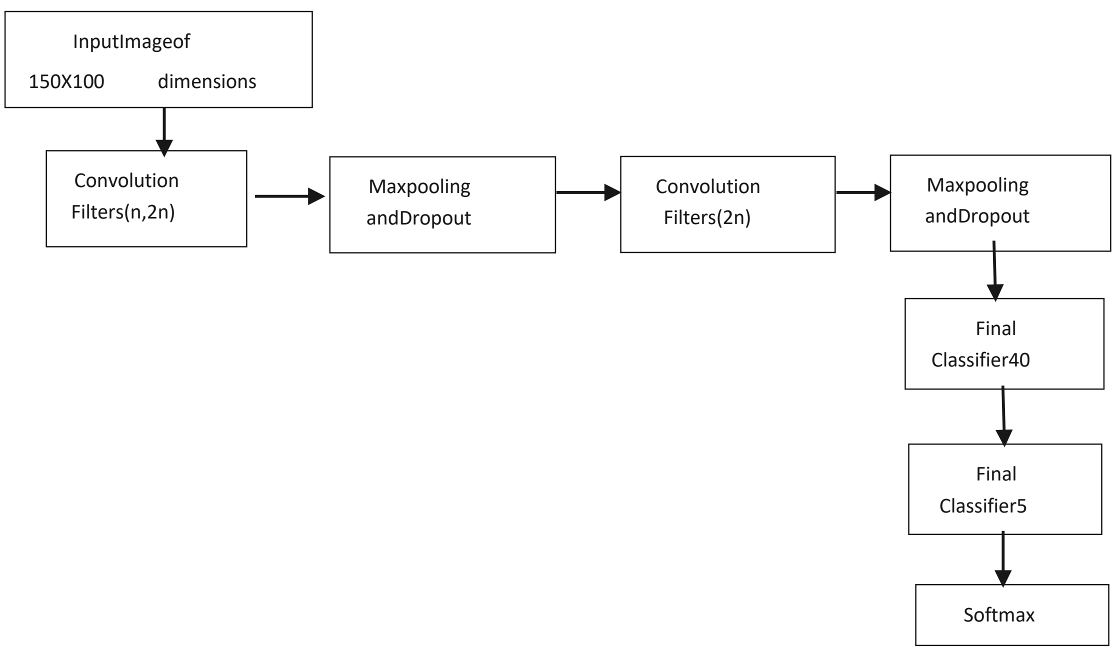

Figure 3: Proposed CNN architecture with two layers of convolution

The proposed CNN model of the driver drowsiness detection system possesses two levels of convolution filters with an order (n, 2n). These two levels of combined convolution filters reduce the complexity of the model and also decreases the distraction detection time to 1.0 sec which leads to the rapid detection and alerting of the driver drowsiness

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detection. The algorithm for the training and testing of measured data using Convolution Neural Network is exemplified in Tab. 3.

Table 3: Algorithm for training and testing data using CNN

```
Input:
    Training Image (X_train, Y_train)
    Testing Image (X_test, Y_test)
Convolution Process: Initialize
the Parameters
    Batch size: 50
    Epochs: 25
    Drop rate: 0.25 Pool size: (2,2) for
    convolution layer (n, 2n) = (2,4)
     for filter size (2,3,4,5)
      do
       filter size (10,20)
       model.add (conv2D(2*filter count, (filter size, filter size)
       model.add (maximum pooling2D, pool size)
      end
     model.add(Dense(quantity_levels,activate = softmax)
     losses.catoegorial- cross entropy, optimizing = optimizer ()
     model.evaluate ( )
    end end
```

The trained data were compared with the test data to classify the input data in any of the four levels classified under driver behavior detection. The preceding subsection describes the later module of the proposed system in detecting the emotion of the driver.

3.4 Emotion Detection System

The emotion detection system is underpinned by a Convolutional Neural Network (CNN) that operates through distinct processes and layers. It takes as input the pre-processed data from the previous module, which is represented as an image with dimensions of 150 X 100 pixels, in order to determine the driver's emotional state. In this system, the input image is treated as a test image and is compared against a set of trained images to classify the driver's emotion into multiple levels, including normal, anger, disgust, fear, happiness, and sadness. To facilitate emotion detection, the Convolutional Neural Network for this process accepts input images of 50 X 50 pixels. As a result, the pre-processed data, originally sized at 150 X 100 pixels, is normalized to transform it into a digital image with dimensions of 50 X 50 pixels. This reduction in image dimension is a prerequisite for the onboard computer to perform emotion diagnosis using the Convolutional Neural Network framework. The entropy of the CNN, a crucial aspect of its functioning, is defined according to the specific parameters and processes set forth in our system's design. This entropy calculation plays a key role in the network's ability to discern and categorize the driver's emotional state accurately.

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(2) The layer 1 and 2 in the convolution network classifies the 50 X 50 pixel image and the final layer magnifies the image to fix the emotion under any of the aforementioned categories. During the training process of the data, the following augmentation properties were implemented.

Brightness range: 75% to 100%

Rotation interval: ±2 degree

Sheer range: ±2%

Zoom transformation interval: ±2%

The tested images are normalized to a determined case using the mathematical relationship as mentioned Eq. (3).

n0 ¼ ~~n nmin~~ (3) nmax nmin

The final magnified output from the layer 3 of the convolution neural network is of 150 X 150 pixel dimension and based on the classified emotion of the driver, a prerecorded song is played using the controller to neutralize the mentality of the driver so as to avoid reckless driving.

4. EXPERIMENTAL RESULTS

This section explores the proposed model, which consists of two modules, and analyzes the experimental results to evaluate its accuracy. The first module uses Convolution Neural Networks (CNN) to classify driver fatigue and other driver states. The analysis of the experimental results focuses on the accuracy level and error rate of driver state detection. Initially, the accuracy level of CNN is compared with traditional classifiers such as KNN and SVM, along with their derived classifiers. Figure 4 provides a comparative analysis of CNN and conventional classifiers in terms of accuracy percentage. CNN exhibits scalable features for handling large datasets and efficiently classifies images through multiple convolution operations. As depicted in Figure 4, the multi-layer CNN proves to be more accurate in predicting and classifying the driver's state compared to other classifiers. Moreover, the accuracy of the classifier improves with longer processing durations. However, it is important to note that the driver drowsiness detection system must possess a minimum duration to accurately determine driver distraction. The proposed model utilizes two levels to extract features that identify the drowsy state of the driver. Choosing three or more levels would result in overfitting the model and reduce accuracy. To summarize, the experimental analysis demonstrates that the proposed model, utilizing a multi-layer CNN, achieves high accuracy in predicting the driver's state. It effectively classifies driver fatigue and other states, while considering the processing duration and avoiding overfitting.

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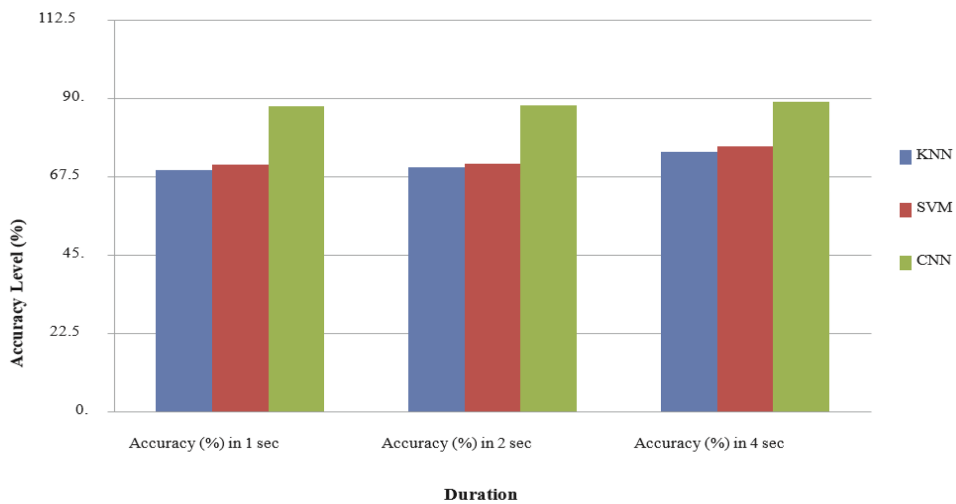

Figure 4:

The accuracy level of different classifier types was compared in terms of accuracy percentage. Figure 5 illustrates the 4 x 4 confusion matrix of the two-level convolutional neural network, which includes four predefined states of the driver. On the other hand, Figure 6 presents a qualitative analysis of the proposed model, where the trained datasets of the two-level convolutional neural network are compared with the testing data to evaluate the model's performance.

In Figure 6, it can be observed that the training and testing data accuracy match precisely, indicating that the proposed model is able to accurately detect the driver's state. The model achieves an impressive accuracy percentage of 93% and can classify the driver's state into one of the four categories: normal, fatigue, drunken, and reckless.

In summary, the experimental results demonstrate that the proposed model, utilizing a two-level convolutional neural network, performs exceptionally well in accurately detecting and classifying the driver's state. The model achieves an accuracy rate of 93% and successfully categorizes the driver's state into one of the predefined classes.

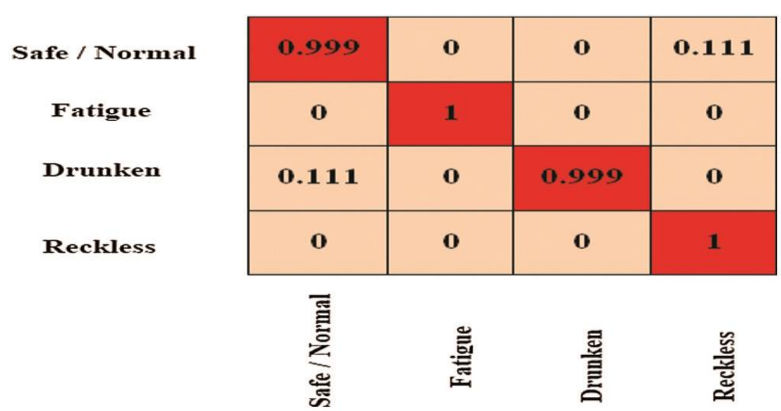

Figure 5: Confusion matrix of driver multi-level classification

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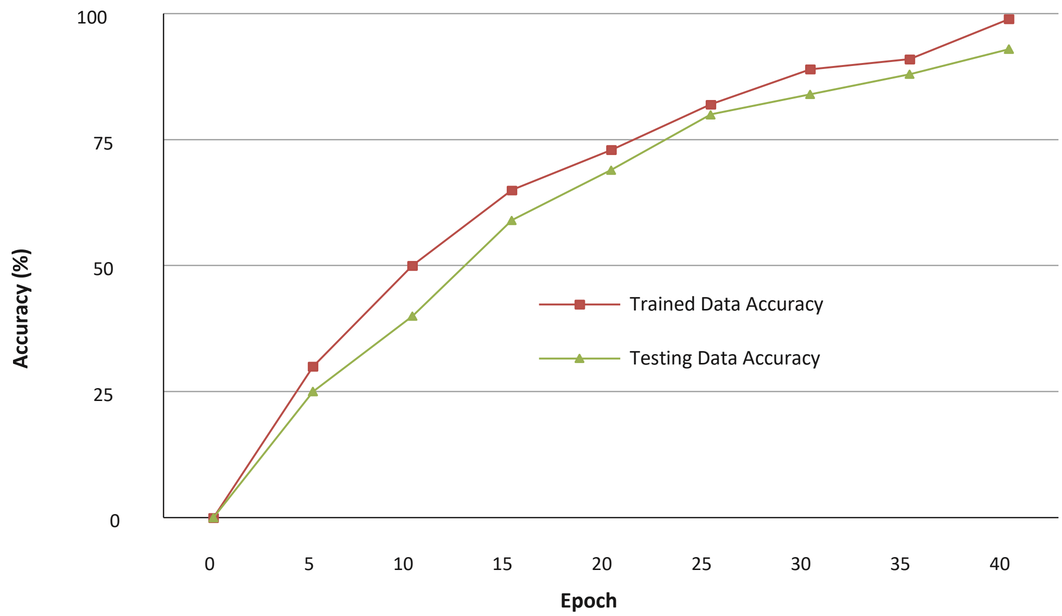

Figure 6: The accuracy level between the trained and test data

Figure 6: The accuracy level between the trained and test data was analyzed for multiple epochs. Figure 7 presents the error analysis of the proposed model, demonstrating that the trained data exhibits a lower error rate compared to the testing data. Furthermore, as the epoch level increases exponentially, the error rate diminishes to a negligible level. In addition, Figure 8 displays the confusion matrix of the Convolutional Neural Network for the six different emotion levels of the driver. The experimental results indicate a strong alignment between the predicted and test levels, validating the effectiveness of the designed model in accurately detecting driver fatigue emotions. The findings of the analysis highlight that the proposed model performs efficiently and achieves a high level of accuracy in detecting driver fatigue emotions. By reducing the error rate and effectively aligning with the test data, the model demonstrates its capability to accurately classify and detect different emotion levels. Overall, these results contribute to the validation of the proposed model and its potential for accurately detecting and classifying driver fatigue emotions, thereby enhancing safety measures on the road.

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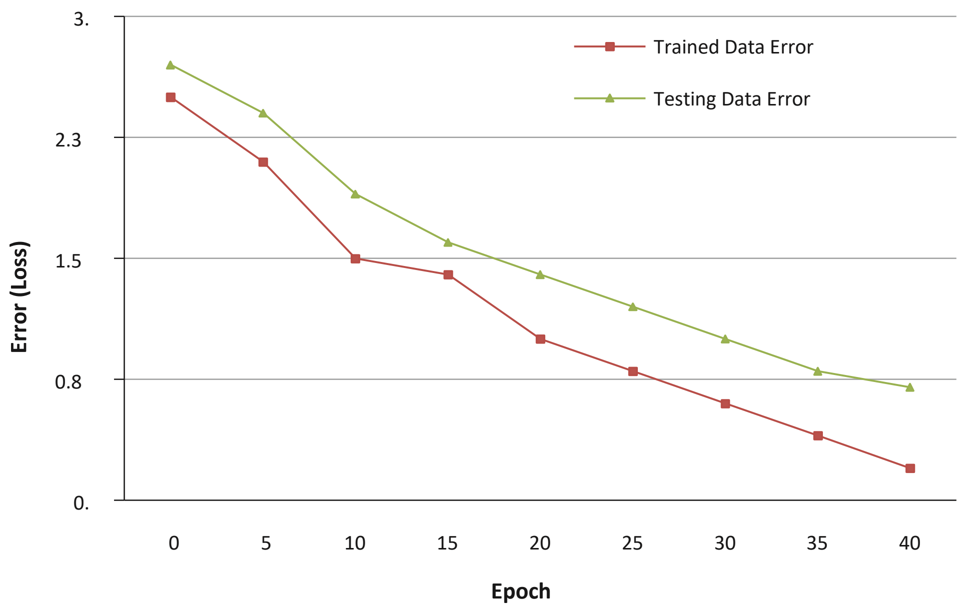

Figure 7: Error level for multiple epochs between trained and test data

	Normal	Anger	Disgust	Fear	Happiness	Sadness
Normal	1	0	0	0	0	0
Anger	0	1	0	0	0	0
Disgust	0	0	1	0	0	0
Fear	0	0.20	0	0.80	0	0
Happiness	0	0	0.10	0.10	0.80	0
Sadness	0	0	0	0	0	1

Figure 8: Confusion matrix for the CNN in detecting the driver emotion

5. CONCLUSION

The Convolutional Neural Network (CNN) has emerged as a prominent technology in the fields of Machine Learning and Automation Systems. Its remarkable properties and features have made it a valuable tool in various applications. One such application is the driver drowsiness detection system, which aims to reduce road accidents. Despite the development of more efficient models, road accidents continue to occur at an alarming rate. This is often due to the extended duration required for distraction detection in existing models.

To address this issue and improve accuracy, a proposed model has been introduced that incorporates two-level convolutional neural networks. This model is capable of classifying both driver behavior and emotion in a reduced detection duration. Experimental results have demonstrated that the proposed models align well with the trained data. Furthermore, the error rate between the trained and test data has been minimized, indicating a high level of accuracy.

The experimental analysis and comparative statements have shown that the proposed model achieves an accuracy level of 93% in detecting both driver behavior and emotion. This suggests that the proposed system, known as the Automatic Driver Emotion Detection System (ADEDS), holds great potential for reducing road accidents and preventing the loss of valuable lives in the future.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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