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Real Time Driver Fatigue Detection System Based on Multi-Task ConNN

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ABSTRACT Changes and progresses in information technologies have played an important role in the development of intelligent vehicle systems in recent years. Driver fatigue is an important factor in vehicle accidents. For this reason, traffic accidents involving driver fatigue and driver carelessness have been followed by researchers. In this article, a Multi-tasking Convulational Neural Network (ConNN*) model is proposed to detect driver drowsiness/fatigue. Eye and mouth characteristics are utilized for driver's behavior model. Changes to these characteristics are used to monitor driver fatigue. With the proposed Multi-task ConNN model, unlike the studies in the literature, both mouth and eye information are classified into a single model at the same time. Driver fatigue is determined by calculating eyes' closure duration/Percentage of eye closure (PERCLOS) and yawning frequency/frequency of mouth (FOM). In this study, the fatigue degree of the driver is divided into 3 classes. The proposed model achieved 98.81% fatigue detection on YawdDD and NthuDDD dataset. The success of the model is presented comparatively.

INDEX TERMS Convolutional neural network, driver fatigue detection, PERCLOS, FOM.

I. INTRODUCTION

According to World Health Organization (WHO) statistics, traffic accidents cause millions of people to lose their lives every year. Statistics assert that most of the fatal accidents are due to driver fatigue and carelessness. The American Automobile Association reported that 7% of all accidents and 21% of fatal traffic accidents were caused by tired drivers [1]. The US National Highway Traffic Safety Administration (NHTSA) states that only 2.2% to 2.6% of total annual fatal accidents in the USA between 2005 and 2009 stemmed from driver fatigue. Accidents that caused only material damage are not included in these results. According to reports in 2009, about 30,000 injury accidents (2.0% of all injuries in 2009) stemmed from driver fatigue [2]. In 2017, Foundation for Traffic Safety's study found that in a normal week, 42.4% of drivers were driving without at least one or more days of sleep, less tha n six hours of sleep, and were serious for the majority of drivers (87.9) and they perceive what they see as unacceptable behavior (95.2%). However, about 3 out of 10 drivers (30.8%) admit that they drove cars even though they were too tired to keep their eyes open in previous months[3].

The process of falling asleep in the vehicle is a gradual event. Due to monotonous driving conditions and other environmental factors, the driver can change from normal to drowsiness. Therefore, the first critical issue to be identified in the fatigue detection system is how to detect drowsiness accurately and early [4]. In this article, it is recommended to monitor driver fatigue in real time using a behavioral model on drivers. Behavioral fatigue detection methods can be applied without distracting the driver and can capture this gradual transition.

Liu *et al.* [5] proposed an algorithm for classifying eye condition operating on the radial basic function (RBF) neural network. In their study, with the results of classification, fatigue detection parameter PERCLOS and blink frequency were used. Coetzer and Hancke [6] compared artificial neural networks (ANN), support vector machine (SVM) and AdaBoost classification algorithms in their 2011 study. Kır Savaş and Becerikli [7] found that driver fatigue is due to the blindness of the driver's eyes. They used principal component analysis and Adaboost to classify eye data and finally used PERCLOS for driver fatigue detection. Luo *et al.* [8] used the AdaBoost algorithm to find the exact position of the eyes in different driving conditions under different lights. They used the characteristic parameters of PERCLOS and

*Convulational Neural Network has been abbreviated as ConNN, not CNN or CoNN, CNN has been used as the abbreviation of Celluar Neural Network and CoNN has been used as the abbreviation of Cooperative neural networks in the leterature as a long time.

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eyes for fatigue detection. Zhang *et al.* [9] whose system determines the driver fatigue depending on the yawning of the driver provided a tension detection system comprising a face detector, a nose detector, a nose tracker and a stretch detector. They developed a nose tracking algorithm by combining the Kalman filter with a special open source Track-Learning-Detection (TLD) monitor. Lyu *et al.* [10] developed a method based on face level to define drowsiness. This method extracts effective face identifiers and classifies driver face states with Random Forest (RF). F-DDD and NTHU-DDD data sets are used for classification. Ma *et al.* [11] devised a system based on ConNN architecture to alert tired drivers during the night. Their work includes the current depth frame of the two-stream ConNN architecture and the temporal information of neighboring depth frames. Classification was carried out on their own dataset. Zhang *et al.* [12] studied the problem that sunglasses affect the detection of driver fatigue. To solve this problem, they used infrared videos (IRF database) and created a model based on the ConNN architecture. They tried to detect fatigue using PERCLOS. Junaedi and Akbar [13] tried to detect the eye in every frame to detect fatigue. From the detected eye, PERCLOS was calculated using the iris regions of the left and right eyes. In the study, YawDD video data set was used for classification. Huang *et al.* [14] built the FDCN (fatigue detection convolutional neural network) architecture based on the ConNN architecture. They used Wild (CEW) and ZJU database for classification. Miah *et al.* [15] conducted a fatigue detection study based on the condition of the eye. The position of the eyes and the average distance of them were determined. In the study, when the eye is closed, the result is reached by considering the closed period to determine the state of drowsiness. In the study, when the eye is closed, the result is reached by considering the closed period to determine the state of fatigue. Reddy and Swathi [16] investigated a segmentation algorithm using the Threshold method. In the study, the segmented region having the maximum area within the mouth region classifies the frame on the YawDD dataset as a stretch frame. Kır Savaş *et al.* [17] tried to detect driver fatigue using the SVM algorithm. In their studies, PERCLOS uses the number of yawns, the inner region of the mouth opening and the number of blink for the determination of driver fatigue on their own dataset. Recently, interest in deep learning methods has been increasing in image processing studies [18]. Gwan *et al.* [19] classify fatigue and mild sleepiness based on physiological, behavioral, and driving performance of the driver. Subsequently, a variety of 32 features are extracted from the drives for the classification of mild sleepy states, and logistic regression, support vector machines, the neighbor classifier, and random forest (RF) algorithms are used. Ursulescu *et al.* [20] use the Viola-Jones method to detect and monitor the driver's eyes. The degree of fatigue is determined by the driver's eyes closed. Gu *et al.* [21] present a multitasking hierarchical ConNN scheme for fatigue detection system and propose a multi-scale pooled (MSP-Net) convolutional neural network (ConNN) model. PERCLOS and FOM are used for fatigue detection and the system is tested on the embedded platform. Liu *et al.* [22] proposed a driver fatigue detection algorithm based on facial analysis. They used MB-LBP (Multi-block local binary patterns) and Adaboost algorithm to classify the driver's eye and mouth position. They used PERCLOS for fatigue detection of the driver. Finally, the fatigue rating of the driver was estimated with the Fuzzy Inference System. Wang *et al.* [23] present a dual-stream consistency detection system based on deep learning for fatigue detection. They argue that their approach has generalization potential in fatigue detection and general image recognition tasks. Xing *et al.* [24] devised a driver fatigue detection system that recognizes and monitors the face of the drivers with a face recognition system. The system tracks the duration each driver drives, as well as the driver's face and eyes. In this study, the fatigue status of the driver is evaluated with PERCLOS. Ji *et al.* [25] used a multi-task cascade convolutional neural network for fatigue detection. Finally, for further analysis of driver fatigue, the two characteristics between the eye and mouth condition are combined to form a fatigue judgment model. In this article, drive fatigue (not tired, less tired and very tired) is detected using a ConNN model that runs behavior-based multi-task on drives. Each convolutional layer creates its own feature maps and aims to shrink the layer. For this purpose, it uses the information of the previous layer. The goal is to make the maps to be more generalized and to reduce the complexity of the extracted feature.

The experimental results are tested on the videos in the YawDD [26] and NTHU-DDD [27] databases. Comparison of the results obtained with the classification reports and the results of the studies on the same databases in the literature are given in tables. Finally, the weaknesses of the study and possible studies that can be done for its development are mentioned.

II. DATASETS

A. YawDD VIDEO DATASET

YawDD includes two video data sets with various facial characteristics used for mouth detection and monitoring for testing algorithms and models for yawn detection. In the first data set, a camera is placed under the car's front mirror. Each participant has three / four videos. Each video has different mouth conditions such as normal speech / singing and stretching. In this data set, there are 322 videos of different ethnic groups of male and female drivers with or without glasses and sunglasses. In the second data set, the camera is installed on driver's line of sight. This data offers 29 videos of male and female drivers' wearing sunglasses or sunglasses, from different ethnicities [28]. Some samples of dataset in YawDD is shown Fig. 1.

B. NTHU DROWSY DRIVER DETECTION (NTHU-DDD) DATASET

The NTHU-DDD video data set consists of 5 different scenarios. The data set comprises of a group of male and female

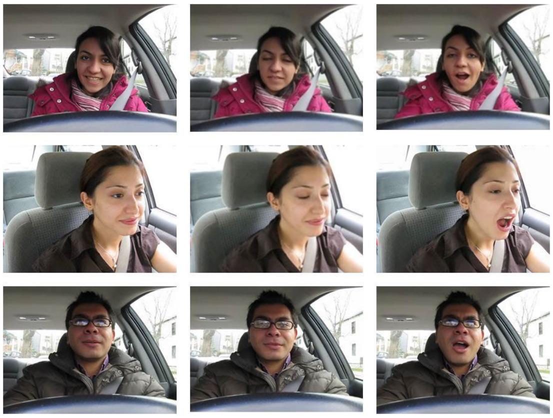

FIGURE 1. Some samples of dataset in YawDD.

FIGURE 2. Some samples of dataset in NthuDDD.

drivers from different ethnic groups. Each frame in the video is labeled with "fatigue" or "not fatigue". Videos consist of different types of "fatigue" and "not fatigue" activities, including day and night. Videos are 640 × 480 pixels, 30 frames per second in AVI format without audio [29]. Some samples of dataset in NthuDDD is shown Fig. 2.

III. PROPOSED APPROACH

In our previous work, we [7], [17] designed a two-label (fatigue/not fatigue) system for driver fatigue detection and SVM and Adaboost algorithms were used for classification. In this study, driver fatigue detection is performed with Multi-task ConNN using raw data obtained from different data sets in the literature. The model of driver fatigue detection system is shown Fig. 3. In recent driver fatigue detection systems, most studies have focused on using limited visual cues [15]. However, human fatigue is a complex mechanism and depends on the dynamic cohesion of various cues [16], which means that outcomes and situations can be improved. Fatigue is a condition that requires continuity, and instant decisions cannot be made while driving. Fatigue at a predetermined time point is considered a factor for fatigue at the present time point, and time varies according to the behavior of individuals. For example, yawning is a major symptom of fatigue, but it does not always occur before the driver sleeps. This should be considered as a preliminary step during fatigue detection and should be evaluated in consideration of the eye conditions of the driver. Otherwise, if something is not detected for a while, the probability of fatigue may be calculated incorrectly.

A. PRE-TRAINED STAGE

Dlib [28], [29], a platform-independent programming library created in the C ++ programming language, contains this face pointer data set created by Sagonas et al. The Dlib Library's pre-trained facial landmark detector is used to predict the location of 68 x-y coordinates that map facial landmarks in the facial zone [30]. Detecting facial landmarks is a critical subject in terms of facial zone shapes estimation. In this study, the dlib library is used to detect and track the faces of the drivers in real time videos. Therefore, important facial structures are detected on the face zone using shape estimation methods. Detecting facial landmarks are demonstration Fig. 4.

In order to be used in the Multi-Task ConNN model, YawDD and Nthu-DDD video datasets are first resized from 640 × 480 resolution to 320 × 240. Then, face, mouth and eye regions were determined by using Dlib algorithm on these resized images. It is determined whether the mouth is open / closed and the eye is open / closed on these identified areas and the opening is labeled according to the closed state. The opening states are labeled as "1", and the closed states as "0".

When training data is being prepared, the videos include blinking for the eye or opening before closing the eye, or looking at other angles. If 80% of the eye opening is open when labeling the data, the label value is considered 'open' and in the remaining cases it is considered 'closed'. Likewise, during speech or opening the mouth at random situations are different from yawning. If 80% of the mouth opening is open, label value is considered 'open' and in other cases 'closed' in order to prevent errors during detection and to label these situations correctly. In each training, 20% of the training data is chosen as random verification data. The selection of verification data is consistent with the dataset distribution. The results of eye and mouth detection are shown Fig. 5.

B. FATIGUE DETECTION

Fatigue parameters based on face markers:

1) PERCENTAGE EYE CLOSURE (PERCLOS)

PERCLOS is the percentage of squares that appear to be closed to the total squares of the human eyes in a given time frame. In other words, PERCLOS can be defined as a fatigue analysis method that shows the ratio of closed eyes depending on the number of open and closed eyes [31]. This value can be calculated as in (1);

$$f_{PERCLOS} = n_{close}/N_{CloseandOpen} \times 100\% \tag{1}$$

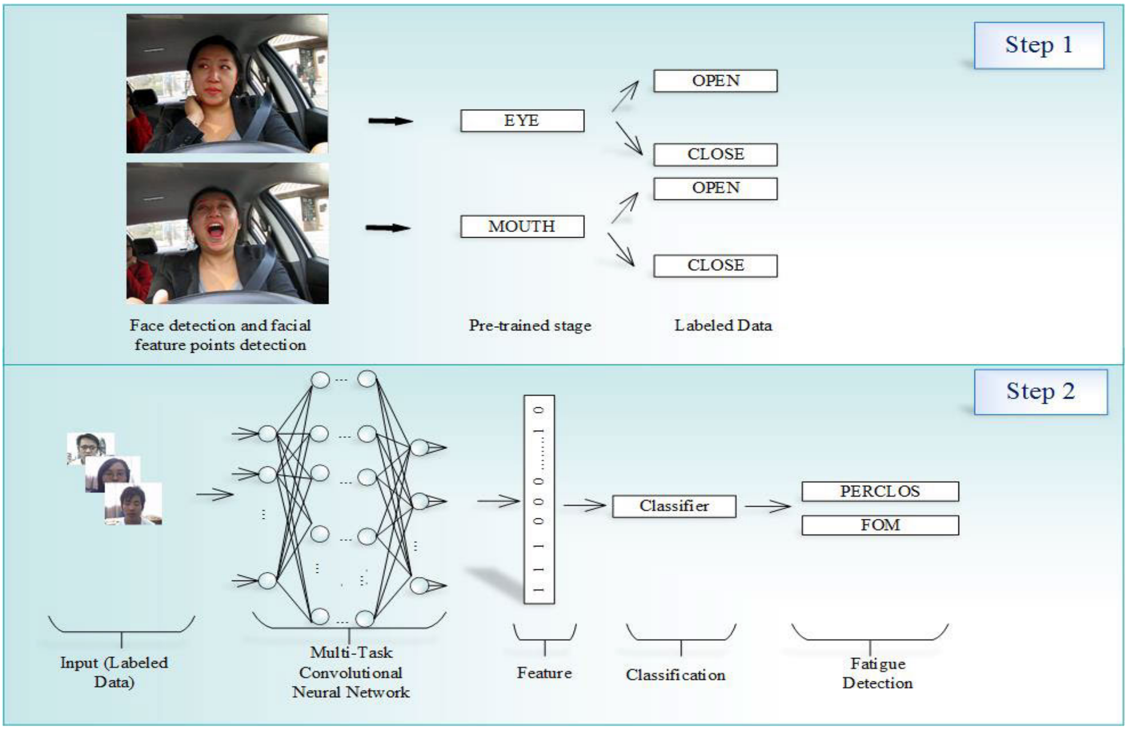

FIGURE 3. Proposed model of driver fatigue detection system.

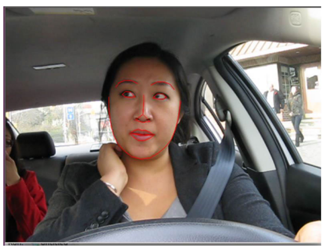

FIGURE 4. Detecting facial landmarks.

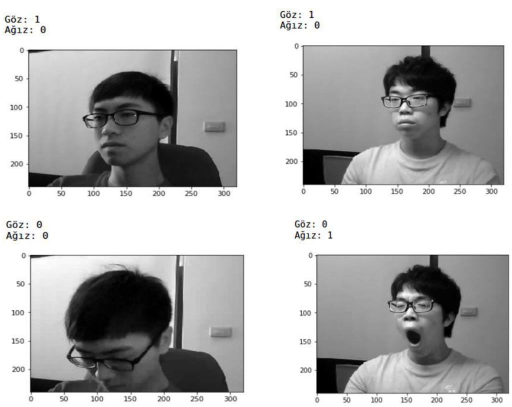

FIGURE 5. The results of eye and mouth detection.

$N_{CloseandOpen}$ represents the total number of open and n_{close} represents closed eye frames at a given time and represents the number of closed-eye frames at a close, specific time.

In the literature it has been determined that a driver blink approximately 10 times per minute under normal conditions. High or low PERCLOS is a method used in the literature to detect eye fatigue [32].

2) FREQUENCY OF MOUTH(FOM)

FOM is the ratio shown as a percentage of squares that open to total squares in a given time frame. Calculation of FOM (2) is similar to PERCLOS calculation.

$$f_{FOM} = n_{open}/N_{CloseandOpen} \times 100\% \tag{2}$$

n_{open} is the number of open mouth frames in a period, $N_{CloseandOpen}$ represents the total number of frames in a period.

IV. EXPERIMENTAL RESULT

Two different dataset (YawDD and NthuDDD) are used in the study for training and testing. With the dlib algorithm, the location of 68 points in the face region is captured on determination of the frequency range. Therefore, PERCLOS and FOM are calculated within the fixed the video to determine the driver eye and mouth regions. Thus, mouth and eye status information is labeled. Labeled data is classified by multi-task ConNN. In order to calculate fatigue parameters accurately, a certain frequency range is required (total number of frames: N). The frequency range to be used here is kept constant within the study and the number of frames is fixed. Each new frame is removed and the last frame is removed. Thus, the frequency range remains constant. Fig. 6 shows the

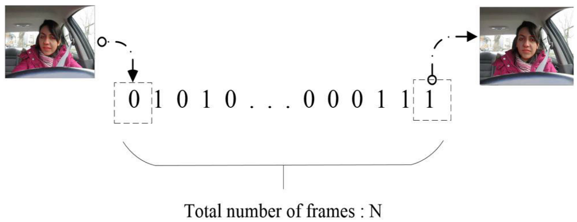

FIGURE 6. Work of frequency queue.

frequency range, and according to these values the decision mechanism (certain threshold value) is formed.

In the proposed study, during the training process, the data sets are divided into training set, validation set and test set. The distribution of the data set of the YawDD and Nthu-DDD architectures used in the multi-task architecture is shown in Table 1.

TABLE 1. Distrubition of dataset.

Dataset	YawDD dataset	Nthu-DDD dataset
Training	41600	23943
Validation	10800	4964
Test	10910	5000
Total	**62910**	**33907**

In the study, since both the eye and the mouth were simultaneously classified on the images during the training phase, the sunglass driver data contained in the YawDD and Nthu-DDD dataset was not used. Stochastic Gradient Decent (SGD) [33] optimization algorithms are used in the training of the proposed model. SGD parameters batch size = 64, 0.6 momentum and 0.0005 weight distortion is used. The training speed is started at 0.01 for all trainable layers.

Fig. 7 shows Multi-task ConNN model. Depending on the width of the mesh, the filter size was determined as first (12,15,20) and second (6,8,10) in three convolution layers, respectively. Two experiments were conducted to select network structures including convolution layer capacity, nonlinear activation function and pooling method. First experiment: Conv1(12,5,1) - A - Pool1(2 $\times$ 2) - Conv2(15,5,1) - A - Pool2(2 $\times$ 2) - Conv3(20,4,1) - A - Pool3 - FullyCon1 (512) - A - FullyCon2 (128). Second experiment: Conv1(6,5,1) - A - Pool1(2 $\times$ 2) - Conv2(8,5,1) - A -Pool2 (2 $\times$ 2) - Conv3(10,4,1) - A - Pool3 - FullyCon1 (128).

Both experiments were tested with SGD optimization algorithm [33] the second experiment gave a better result for the multi-task ConNN model shown in Figure 7. To improve performance, the original images were resized and the new size was 320 $\times$ 240. For the first and second convolution layers 5 $\times$ 5 filter size and for the third convolution layer the filter size 4 $\times$ 4 was selected. The maximum docking method was selected for each docking layer. A non-overlapping 2 $\times$ 2 core was used which is the same as most ConNN-based approaches. Therefore, the size of the output property map is 27 * 37. The multi-task ConNN model has been tested on YawDD and NthuDDD datasets. The results are shown in Fig. 8 and Fig. 9.

TABLE 2. Model losses on traınıng and validation data for YawDD dataset.

Epoch	Training Loss	Validation Loss
1	0.7983	0.7624
20	0.6895	0.6819
40	0.4048	0.4007
60	0.3782	0.3993
80	0.3135	0,3094
100	0.1765	0.1556

The training loss and validation loss values given in Table 2 show the values of training loss and validation loss in the epochs 1, 20, 40, 80, 100, as indicated in the graph in Figure 8 (a). The accuracy- of epoch graph of our model is given in Figure 8 (b). According to the results, it is observed that loss value decreases in given epoch values. Thus, the model we designed worked successfully for YawDD dataset.

The training loss and validation loss values in Table 3 show the training loss and validation loss values in the epochs 1, 20, 40, 80, 100 indicated in the graph in Figure 9 (a). The accuracy-of epoch graph of our model is given in Figure 9 (b). According to the results, it is observed that loss value decreases in given epoch values. Thus, the model we designed worked successfully for NthuDDD dataset.

TABLE 3. Model losses on traınıng and validation data for NthuDDD dataset.

Epoch	Training Loss	Validation Loss
1	1.0029	0.9565
20	0.2203	0.2010
40	0.1542	0.1549
60	0.1307	0.1194
80	0.1172	0.1007
100	0.0993	0.0927

The validation, test, and avarage accuracy of our model on each dataset is shown in Table 4. The comparison of the obtained avarage accuracy with the other approaches in the literature is shown in Table 5.

TABLE 4. Detection validation, test and avarage accuracy on each dataset.

	YawDD	NthuDDD	Accuracy (Avarage)
Validation accuracy	98.96%	98.92%	98,94%
Test accuracy	98.49%	98.89%	98,69%
Proposed approach	98.72%	98,91%	**98,81%**

When drivers fatigue, they will have series of behavioral reactions such as eyes closed or yawning. Therefore, it can be accepted, drier fatigue can be calibrated bu calculating the PERCOS and FOM parameter. According to

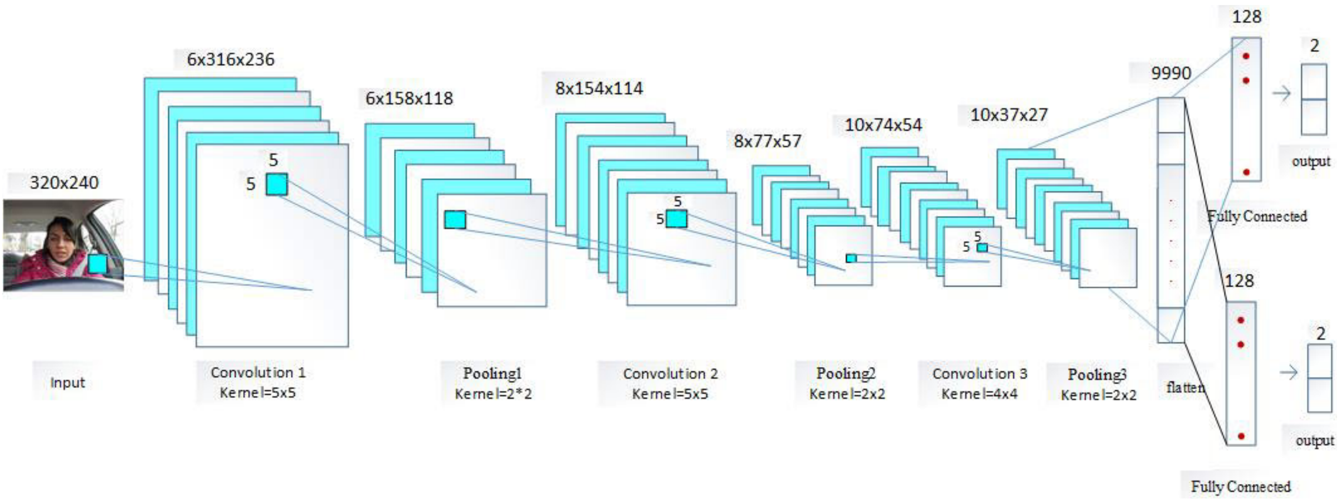

FIGURE 7. Multi-task ConNN model.

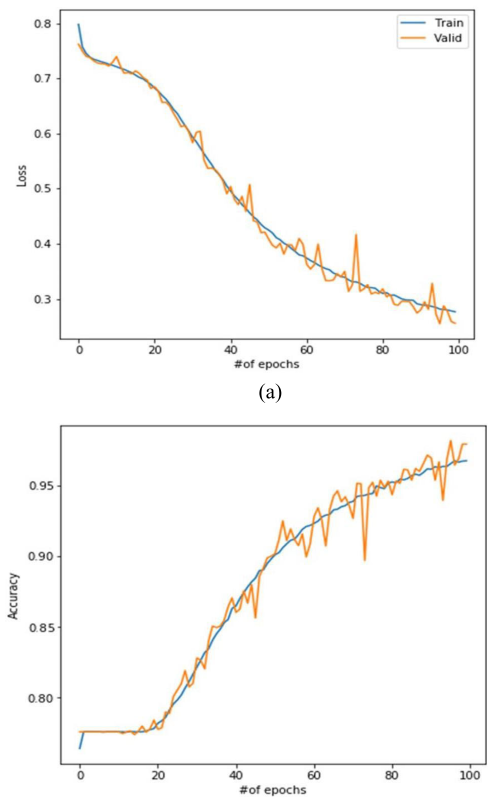

FIGURE 8. (a) The multi-task ConNN model has been tested on YawDD dataset. (model losses on training and validation data). (b) The multi-task ConNN model has been tested on. YawDD dataset. (model accuracy on training and validation data).

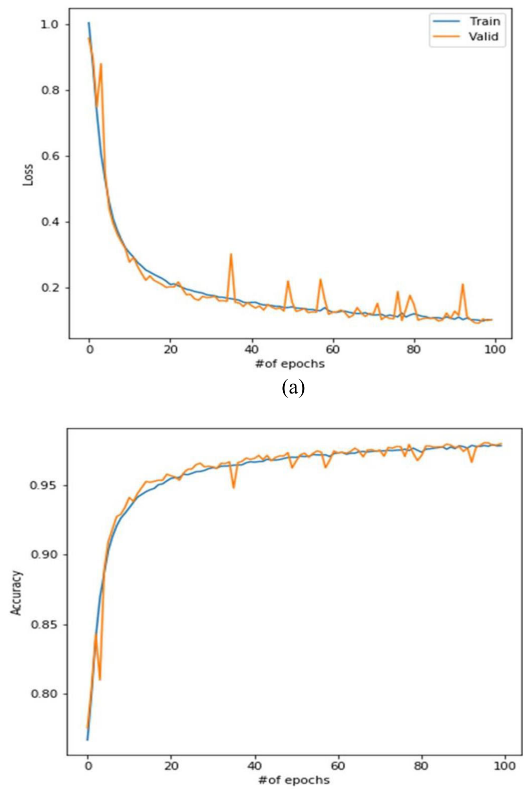

FIGURE 9. (a) The multi-task ConNN model has been tested on NthuDDD dataset. (model losses on training and validation data). (b) The multi-task ConNN model has been tested on NthuDDD dataset. (model accuracy on training and validation data).

literature [9], [12], the fatigue status for the driver was determined when the PERCLOS threshold $f_{PERCLOS} > 0.24$. Furthermore, when $f_{FOM} > 0.16$, it is determined that the stretching symptoms indicate fatigue. Fatigue status of the driver is divided into three levels. The first type is a very tired level and this evaluation consists of two stages. The first one is only when the eye closure time exceeds 5 sec ($n_{close} > 150$ frames). In this case, the system gives a warning regardless of yawning. The other controls the eye condition and the yawning state together. If the closing time of the

TABLE 5. Multi-task accuracy compared with other approaches.

	Year	Dataset	Accuracy (Avarage)
Zhang et al [9]	2015	YawDD	92%
Gu et al. [21]	2018	EMD,ZJU,CEW	96.89%
Ji et al [25]	2019	YawDD	98.42%
Proposed approach	2019	YawDD, NthuDDD	**98.81%**

driver's eyes $f_{PERCLOS} > 0.24 \,||\, f_{FOM} > 0.16$, the driver is extremely tired. In the second type of fatigue, the driver closes his eyes $f_{PERCLOS} = 0.15 \sim 0.24$ || If $f_{FOM} > 0.16$, it is observed that the driver is getting tired, else the driver is less tired. The third type is normal. Here, the driver has no signs of fatigue and can drive normally. In this study, PERCLOS and FOM threshold values are tested on test videos.

V. CONCLUSION

In this article, Multi-task ConNN models is used to detect driver fatigue in real time. The Dlib algorithm is used to accurately identify the driver's eye and mouth information. Then, the system is trained with Multi-task ConNN models for the determination of fatigue parameters. The frequency range to be used here is kept constant within the study and the number of frames is fixed. Finally, depending on fatigue parameters, fatigue is evaluated as "very tired, less tired and not tired". These situations are also dynamically tested and coded at certain periods that maintain their continuity. The accuracy performance of the system tested in real time is very robust. The proposed system can model the interactive relationship between eye, mouth and sub-states. Fatigue at a predetermined time point is considered a factor for fatigue at the present time point, and time varies according to the behavior of individuals. The system runs successfully. One of the most powerful features of the study is that it is a faster and more powerful system with a single model without creating a separate ConNN model with two different architectures. In our future work, the head condition, which is as important as the eye and mouth condition, will be added to the system and the system will be integrated into an embedded system.

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