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Precise Driver's Drowsiness Detection Using a Combination of Proven Methods with a Neuro-Dynamic Structure

Ghazal Abdolbaghi[1], Alireza Yazdizadeh[2*]

[1, 2] Department of Electrical Engineering Control, Shahid Beheshti University, Tehran, Iran
*Corresponding Author Email: a_yazdizadeh@sbu.ac.ir

Abstract

Drowsiness can impair reaction time, increasing the risk of severe accidents. Many current studies concentrate on a single symptom of drowsiness, which can lead to false alerts. This paper presents a new method for detecting drowsiness in real time. The proposed approach utilizes four deep learning architectures based on convolutional neural networks: AlexNet for extracting environmental features, ResNet50V2 for recognizing hand gestures, VGG-FaceNet for facial feature extraction, and FlowImageNet for analyzing behavioral features. To maximize the benefits of the aforementioned methods, we suggest using a single-layer neural network. Since drowsiness is a dynamic phenomenon, capturing its evolving features requires a dynamic neural network with adaptive delays, specifically an Adaptive Time Delay Neural Network (ATDNN) with adjustable weights. Our implementation of this neuro-dynamic approach on the NTHUDDD and our custom datasets demonstrates that it achieves greater accuracy (99.1% and 98.6%, respectively) compared to existing methods in the literature.

Keywords

Adaptive Time Delay Neural Networks (ATDNN), Convolutional Neural Network (CNN), Drowsiness Detection, Neuro-Dynamic structure.

INTRODUCTION

Drowsiness represents a transitional state between full wakefulness and consciousness, causing slower reaction times and impaired memory [1]. The US National Highway Traffic Safety Administration reports that drowsiness contributes to about 100,000 traffic accidents each year worldwide, leading to over 1,500 deaths and more than 70,000 injuries [2]. This problem is widespread globally. Since drowsiness greatly affects driving safety, detection systems are essential as they offer early warnings before drowsiness becomes critical and hazardous.

Machine Learning (ML) has been applied across numerous fields, offering substantial benefits like high accuracy, adaptability to various datasets, effectiveness with both small and large datasets, and scalability regarding data volume and computational resources [3]. In drowsiness detection systems, as in other areas, machine learning techniques are utilized. Different models, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Recurrent Neural Networks (RNNs), are used to train on datasets and identify key features related to drowsiness.

Datasets for developing driver drowsiness detection systems fall into three primary categories: 1) vehicle-based like steering wheel angle, lateral and longitudinal acceleration 2) facial-based like rapid blinking and yawning 3) biological signals such as electroencephalography (EEG) and electrocardiography (ECG) [4]. While biological signals offer high accuracy, they are also intrusive, as they necessitate the attachment of sensors to the driver, which can be uncomfortable and distracting during driving. In many works they used a combination of these methods for example a combination of vehicular and facial, vehicular and biological, and vehicular and biological methods. This way can help to get a more accurate result. Also, considering different symptoms in one group simultaneously can give a better result compared with experimenting with just one symptom.

Despite various methods developed by researchers for detecting drowsiness, existing approaches continue to encounter significant challenges. Relying on a single symptom of drowsiness often results in unreliable and inaccurate outcomes. Additionally, static machine learning models lack memory and are unable to track drowsiness over time. To overcome these limitations, this paper presents a new approach for drowsiness detection and its contributions are as follows:

1-This paper utilizes four deep learning architectures based on convolutional neural networks: AlexNet for extracting environmental features, ResNet50V2 for recognizing hand gestures, VGG-FaceNet for extracting facial features, and FlowImageNet for analyzing behavioral features. Each model is pretrained through transfer learning, with extra layers incorporated to improve performance, thereby harnessing the combined strengths of an integrated framework.

2-To fully leverage the advantages of the previously mentioned methods, we propose employing a single-layer neural network. Given that drowsiness is a dynamic process, capturing its changing characteristics necessitates a dynamic neural network with adaptive delays, specifically an Adaptive Time Delay Neural Network (ATDNN) with adjustable weights.

The rest of the paper is structured as follows: Section 2 provides a literature review of previous studies related to this work. Section 3 outlines the proposed method within the overall detection framework. Section 4 details the experimental results from the training and testing phases of the proposed method. At last, the paper will be concluded.

LITERATURE REVIEW

Researchers have explored various methods for detecting drowsiness, including facial, biological, and vehicular techniques [5]. Facial detection methods identify drowsiness by analysing features such as eye blinking rate, yawning, nodding, head movements, and eyebrow raising [6]. A summary of the factors considered in these three types of drowsiness detection techniques is illustrated in Figure 1. Facial detection approaches rely on video recordings of the driver to assess signs of drowsiness. However, using cameras for this purpose presents challenges, especially in conditions with variable lighting or when drivers wear glasses, sunglasses, masks, or have their heads turned away from the camera. Facial-based methods primarily use two approaches: facial landmarks and machine learning techniques. Landmark-based methods typically calculate the Eye Aspect Ratio (EAR) in the eye region and the Mouth Aspect Ratio (MAR) in the mouth region to detect yawning and predict drowsiness.

Biological-based drowsiness detection methods often require direct physical contact, making them intrusive. These techniques monitor physiological indicators such as heart rate, heart rate variability, pulse rate, respiration patterns, breathing frequency, body temperature, and electrical activity of the brain and eyes. Devices like Electroencephalograms (EEG), Electrooculograms (EOG), Electromyograms (EMG), and Electrocardiograms (ECG) are commonly used for these measurements. However, a major limitation of this approach is the need for drivers to be physically connected to monitoring equipment, which can be uncomfortable and impractical for continuous use. These measurement tools fall into two main categories: signal-based and image-based. The former relies on signal processing, while the latter depends on image analysis.

In contrast, vehicle-based methods offer a non-intrusive alternative, as they do not require direct interaction between the driver and monitoring sensors. These techniques assess driving behavior by analyzing parameters such as steering angle fluctuations, steering angular velocity, lateral and longitudinal acceleration, deviation angle, displacement from the road's centerline, and vehicle speed [5]. This approach allows for drowsiness detection without interfering with the driver's comfort or mobility.

In [7], a real-time drowsiness detection system was developed using facial features like Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Videos were recorded in a real driving environment and converted into frames. Facial landmarks were extracted using a Haar Cascade classifier and the Dlib library, combined with a logistic regression classifier. This approach achieved 92% accuracy with Dlib but dropped to 86% using Haar Cascade, due to its poor eye detection. A limitation of this method is that relying on MAR and EAR metrics may lead to inconsistent accuracy, as threshold values can vary between individuals.

In [8], the study focused on detecting drowsiness through the eyes using the MediaPipe library [9] to extract the eye region. Researchers trained three deep learning models—ResNet50v2, InceptionV3, and VGG-16—on this region, achieving real-time detection. MediaPipe's face mesh method was employed to identify 468 facial landmarks, from which four were selected to define the eye region. ResNet50v2 achieved the highest accuracy of 99.71%. However, the study mainly focused on the eyes, neglecting other potential drowsiness indicators.

In [10], a drowsiness detection system was developed using four deep learning models, combined through a simple averaging method. FlowImageNet analysed facial expressions and behaviours like nodding, while AlexNet focused on environmental factors such as lighting and glasses. VGG-FaceNet extracted facial features like lips and eyebrows, and Res-Net captured hand gestures related to yawning. A threshold of 0.24 was used to indicate drowsiness, yielding an accuracy of 85%. This relatively low accuracy suggests limited precision, possibly due to the model's focus on specific features while neglecting others like head movements and drooping cheeks.

Most studies primarily focus on the eyes and mouth, overlooking other drowsiness indicators such as raised eyebrows, head movements, and drooping cheeks, which can affect the accuracy of predictions. While bio-signal methods like EEG and ECG provide high accuracy, these devices are expensive, not typically available in vehicles, and are often intrusive, causing discomfort for the driver.

To assess driver drowsiness, we use the levels described in [11], which are based on [12] but with some modifications to the scales. The authors categorized drowsiness into five levels, as detailed in Table 1. Fig.1 illustrates the levels of drowsiness for both the international dataset and the dataset prepared by the authors of this paper.

Table 1. Drowsiness levels [11].

Drowsiness Levels	Features
1-Not Drowsy	Line of sight moves fast and frequently. Facial movements are active, accompanied by body movements.
2-Slightly Drowsy	Line of sight moves slowly. Lips are open.
3-Moderately Drowsy	Blinks are slow and frequent. There are mouth movements.
4-Significantly Drowsy	There are blinks that seem conscious. Frequent yawning.
5-Extremely Drowsy	Eyelids close. Head tilts forward or falls backward.

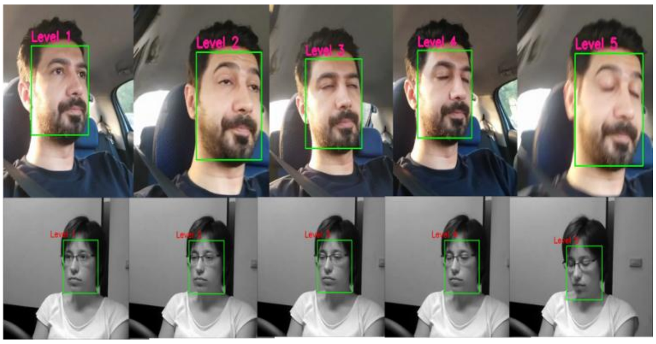

Figure 1. Five levels of drowsiness in two datasets

In this study, we introduce a framework that incorporates four distinct models. Rather than relying on a straightforward and conventional approach of averaging and merging multiple models, we implement an intelligent weighting mechanism. This approach adjusts the weight of each branch within a single-layer neural network, which is positioned at the output of the four selected models. Given the dynamic nature of the drowsiness process, we develop an Adaptive Time-Delay Neural Network to extract adaptive rules and establish a neuro-dynamic structure. The specifics of the proposed framework are detailed in the following section.

FRAMEWORK

Instead of using a basic voting method, this study employs a smart weighting approach by adding a layer at the output of the four models. Recognizing that drowsiness develops gradually over time, a neuro-dynamic structure is adopted with adaptive weight adjustment rules. In the structure of ATDNN, each neuron is described by a delay associated with all the weights. The framework is depicted in Fig.2.

Next, we analyse the layers added to each model through transfer learning and outline the weight adjustment rules for each branch in the dynamic mode. We selected the Exponential Linear Unit (ELU) as the activation function because it yielded better results. Notably, all models use the sparse categorical entropy loss function, which is optimal for multi-class classification and offers better performance than other loss functions. The formula for this loss function is given in (1). The formula of this loss function is shown in (1)

in which y_i is the true label and $\hat{y}_i$ is the predicted value.

$$H(\hat{y}, y) = -\frac{1}{N(num\_class)} \sum_{i=1}^{N} \log(\hat{y}_i, y_i) \tag{1}$$

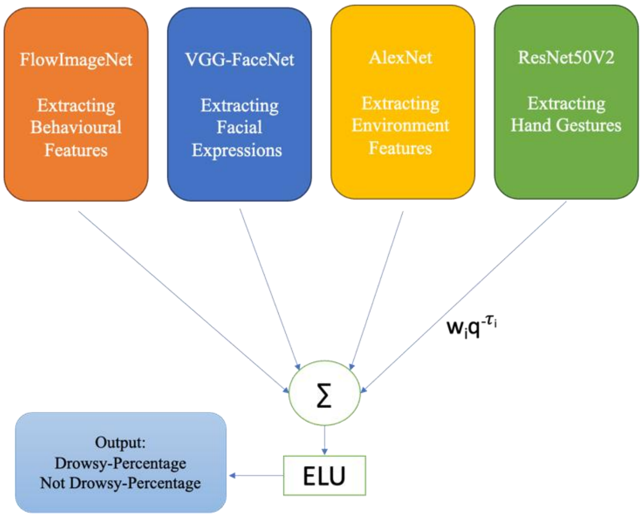

Figure 2. Framework of the proposed method

Adaptive Time-Delay Neural Networks (ATDNNs) have been introduced and applied in various fields, such as system identification for wind turbines [13] and turbo generators [14]. These networks closely resemble the structure of multi-layer feedforward neural networks, with only minor differences. In a typical neural network, each neuron computes the sum of its weighted inputs and processes this sum through a nonlinear activation function. In contrast, ATDNNs incorporate a time-delay for each weight associated with a neuron. The specific delays are chosen based on the application at hand, enabling the network to capture relationships between events occurring over time. This dynamic representation of input and output in a neuron is achieved by introducing a delay in each neuron's connection [13]. As illustrated in Fig.2, the time-delay is integrated, and the input-output relationship of the neuron is described by (2).

$$y(t)=\sigma(\sum_{i=1}^{N} w_i x_i(t-\tau_i)) \tag{2}$$

In (2), we represent the weights of neurons, τ_i is the delay, σ is the nonlinear activation function, $x_i(t-\tau)$ is the ith input with a delay, w_i is ith weight, and the summation is for i from 1 to Nth layer. It is important to note that in this formula, the output of the neuron at time *t* depends on previous input values, resulting in dynamic behaviour. This dynamic method is subsequently adjusted adaptively to appropriately represent various classes of nonlinear systems. This phenomenon is significant in drowsiness detection, as it does not occur suddenly but rather imposes itself on the driver dynamically, reducing alertness.

The layers shown are added to the pre-trained ResNet50V2, VGG-FaceNet, AlexNet, and FlowImageNet models using transfer learning to enhance performance (see Fig.3, Fig.4, Fig.5, and Fig.6). We compute the dynamic weighting rules to develop the smart weighting model. The dynamic weighting rules for each structure are detailed in (3), (4), (5), (6), (7), (8), (9) and (10). These weighting rules show the output of the jth neuron in the Lth layer at time t is denoted by $O_j^l(t)$. The weight and associated delay connecting the jth neuron in the lth layer to the ith neuron in the (L-1)th layer are denoted by w_{ji}^l and τ_{ji}^l, respectively. It is noticeable that j varies from 1 to N^L, i varies from 1 to N^{L-1}, and τ_{ji}^l varies from 0 to $\tau_{\max}$. Also, $net_j^l(t)$ is the weighted input of the jth neuron in the lth layer at time t. The weights Δw_{kj}^l and delays $\Delta\tau_{kj}^l$ adaptation laws in the following equations in this structure and others are based on these parameters.

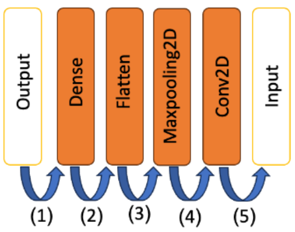

Figure 3. The layers added to a pre-trained ResNet50V2 structure

$$\frac{\partial O_k}{\partial w_{kj}}=\sigma'(net_k^5(t))[O_j^4(t-\tau_{kj}^5)+\sum_{p=1}^{N^4} w_{kp}^L\sigma'(net_p^4(t-\tau_{kp}^5)).....$$
$$\sum_{q=1}^{N^1} w_{lq}^2\sigma'(net_q^1(t-....-\tau_{lq}^2))w_{q2}^1\frac{\partial O_k^5(t-\tau_{kp}^5-...-1)}{\partial w_{kj}^5}].\mathrm{Re}LU'(X_{Conv,ijk}).X_{input,l} \tag{3}$$

$$\frac{\partial O_k}{\partial \tau_{kj}}=\sigma'(net_k^5(t))\sum_{p=1}^{N^4} w_{kp}^5\sigma'(net_p^4(t-\tau_{kp}^5)).....$$
$$\sum_{q=1}^{N^1} w_{lq}^2\sigma'(net_q^1(t-....-\tau_{lq}^2))w_{q2}^1\frac{\partial O_k^5(t-\tau_{kp}^5-...-1)}{\partial \tau_{kj}^5}+w_{q1}^1\frac{\partial u(t-\tau_{kp}^5-...-1)}{\partial \tau_{kj}^5}] \tag{4}$$

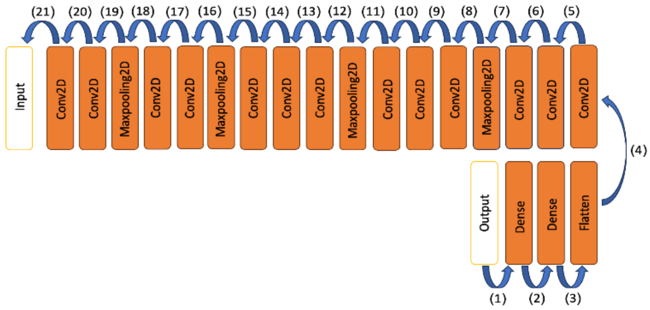

Figure 4. The layers added to a pre-trained VGG-FaceNet structure

$$\frac{\partial O_k}{\partial w_{kj}}=\sigma'(net_k^{21}(t))[O_j^{20}(t-\tau_{kj}^{21})+\sum_{p=1}^{N^{20}} w_{kp}^L\sigma'(net_p^{20}(t-\tau_{kp}^{21}))....$$
$$\sum_{w=1}^{N^1} w_{wv}^2\sigma'(net_w^1(t-\tau_{kp}^{21}...-\tau_{wv}^2))w_{w2}^1\frac{\partial O_k^{21}(t-\tau_{kp}^{21}....-\tau_{w2}^1-1)}{\partial w_{kj}^{21}}.$$
$$\mathrm{Re}LU'(X_{Conv13,ijk}).X_{input,l} \tag{5}$$

$$\frac{\partial O_k}{\partial \tau_{kj}}=\sigma'(net_k^{21}(t))\sum_{p=1}^{N^{20}} w_{kp}^L\sigma'(net_p^{20}(t-\tau_{kp}^{21}))....$$
$$\sum_{w=1}^{N^1} w_{wv}^2\sigma'(net_w^1(t-\tau_{kp}^{21}...-\tau_{wv}^2))w_{w2}^1\frac{\partial O_k^{21}(t-\tau_{kp}^{21}....-\tau_{w2}^1-1)}{\partial \tau_{kj}^{21}}$$
$$+w_{w1}^1\frac{\partial u(t-\tau_{kp}^{21}....-\tau_{w2}^1-1)}{\partial \tau_{kj}^{21}} \tag{6}$$

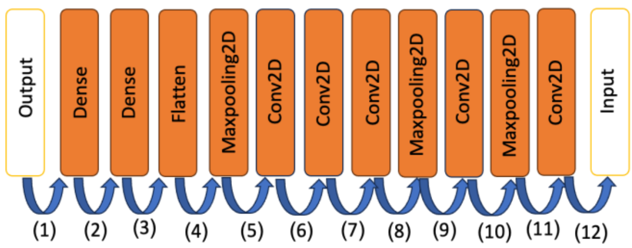

Figure 5. The layers added to a pre-trained AlexNet structure

$$\frac{\partial O_k}{\partial w_{kj}}=\sigma'(net_k^{13}(t))[O_j^{12}(t-\tau_{kj}^{13})+\sum_{p=1}^{N^{12}} w_{kp}^L\sigma'(net_p^{12}(t-\tau_{kp}^{13}))....$$
$$\sum_{f=1}^{N^1} w_{sf}^2\sigma'(net_f^1(t-\tau_{kp}^{13}...-\tau_{sf}^2))w_{f2}^1\frac{\partial O_k^{13}(t-\tau_{kp}^{13}....-\tau_{f2}^1-1)}{\partial w_{kj}^{13}}].$$
$$\mathrm{Re}LU'(X_{Conv5,ijk}).X_{Input,l} \tag{7}$$

$$\frac{\partial O_k}{\partial \tau_{kj}}=\sigma'(net_k^{13}(t))\sum_{p=1}^{N^{12}} w_{kp}^L\sigma'(net_p^{12}(t-\tau_{kp}^{13}))....$$
$$\sum_{f=1}^{N^1} w_{sf}^2\sigma'(net_f^1(t-\tau_{kp}^{13}...-\tau_{sf}^2))w_{f2}^1\frac{\partial O_k^{13}(t-\tau_{kp}^{13}....-\tau_{f2}^1-1)}{\partial \tau_{kj}^{13}}]$$
$$+w_{f1}^1\frac{\partial u(t-\tau_{kp}^{13}....-\tau_{f2}^1-1)}{\partial \tau_{kj}^{13}} \tag{8}$$

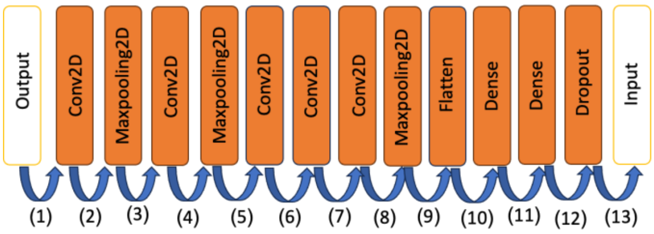

Figure 6. The layers added to a pre-trained FlowImageNet structure

$$\frac{\partial O_k}{\partial w_{kj}} = \sigma'(net_k^{14}(t))[O_j^{13}(t-\tau_{kj}^{14}) + \sum_{p=1}^{N^{13}} w_{kp}^{L} \sigma'(net_p^{13}(t-\tau_{kp}^{14}))....$$
$$\sum_{h=1}^{N^1} w_{fh}^2 \sigma'(net_h^1(t-\tau_{kp}^{114}...-\tau_{fh}^2))w_{h2}^1 \frac{\partial O_k^{14}(t-\tau_{kp}^{14}....-\tau_{h2}^1-1)}{\partial w_{kj}^{14}}].$$
$$\mathrm{Re}LU'(X_{Conv5,ijk}).X_{Input,l} \tag{9}$$

$$\frac{\partial O_k}{\partial \tau_{kj}} = \sigma'(net_k^{14}(t))\sum_{p=1}^{N^{13}} w_{kp}^{L} \sigma'(net_p^{13}(t-\tau_{kp}^{14}))....$$
$$\sum_{h=1}^{N^1} w_{fh}^2 \sigma'(net_h^1(t-\tau_{kp}^{114}...-\tau_{fh}^2))w_{h2}^1 \frac{\partial O_k^{14}(t-\tau_{kp}^{14}....-\tau_{h2}^1-1)}{\partial \tau_{kj}^{14}}]$$
$$+w_{h1}^1 \frac{\partial u(t-\tau_{kp}^{14}....-\tau_{h2}^1-1)}{\partial \tau_{kj}^{13}} \tag{10}$$

RESULTS

We evaluated our proposed method using multiple datasets, including the widely recognized NTHUDDD dataset on drowsiness and a custom dataset we created as in Fig. 7. The NTHUDDD dataset is an academic dataset developed by the Computer Vision Lab at National Tsing Hua University in China [15]. Initially introduced at the Asian Conference on Computer Vision in 2016, it was designed for detecting driver drowsiness using video recordings. This dataset comprises high-speed infrared video footage in AVI format, with a resolution of 480 × 640 pixels.

To evaluate the effectiveness of the proposed method on a custom dataset, we compiled data in a real driving environment involving 15 individuals—12 males and 3 females. This dataset includes subjects under diverse conditions such as daylight, nighttime, and both with and without glasses. During data collection, we made a concerted effort to capture behaviours like yawning, raised eyebrows, slow blinking, head movements, and nodding.

EVALUATION

To evaluate our classification task, we used a confusion matrix and examined four metrics: accuracy, precision, recall, and F1-score. The results are summarized in Table 2. The confusion matrix, which includes true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), is illustrated for two different scenarios (see Fig.8). Fig.9 and Fig.10 show the accuracy and loss metrics throughout the training process for these scenarios. The goal during training is to minimize the output loss when processing training data. The training results for both scenarios show a steady increase in accuracy and a consistent decrease in loss for both training and validation, indicating that the proposed method is effective. Specifically, in scenario 1, the TP and TN values for predicting drowsy and not drowsy states are both 99% as in Fig. 8.

Figure 7. Frames of our dataset

Table 2. The results of evaluation parameters on the proposed method with two datasets.

Num	Scenario	Label	Precision	Recall	F1-Score	Support	Accuracy
1	Neuro-Dynamic Structure on NTHUDDD	Drowsy	0.987	0.987	0.986	1010	**0.991**
		Not-Drowsy	0.995	0.985	0.986	1153	
2	Neuro-Dynamic Structure on our dataset	Drowsy	0.979	0.979	0.979	1010	0.986
		Not-Drowsy	0.993	0.978	0.985	1153	

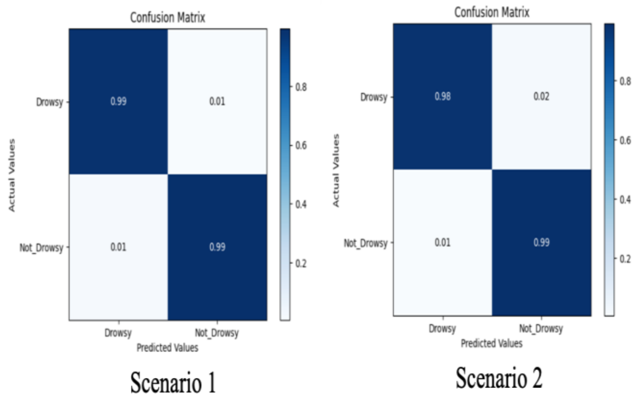

Figure 8. Confusion matrix for two scenarios

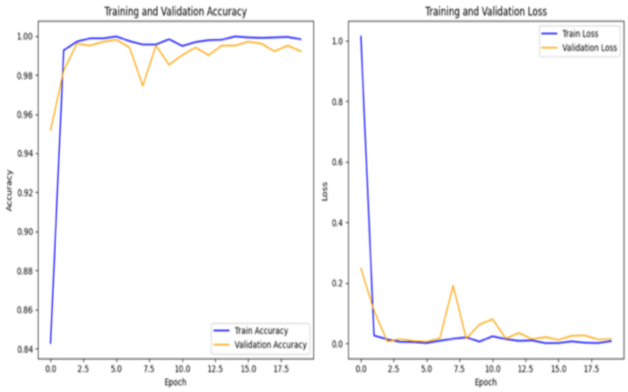

Figure 9. Metrics for scenario1: Accuracy and Loss

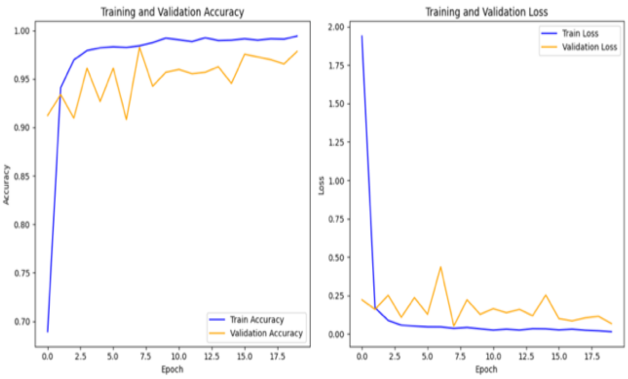

Figure 10. Metrics for scenario 2: Accuracy and Loss

Tables 3 and 4 compare the accuracy of two approaches: simple voting and the static model. The results clearly demonstrate that the static model significantly outperforms the simple voting method across both datasets. The implementation results of the proposed structure on these datasets are shown in Fig.11. A key advantage of this structure is its ability to accurately detect drowsiness even when yawning with hands covering the face, as evidenced by the high accuracy shown in Fig.12.

Table 3. Comparison of accuracy between two states on NTHUDDD dataset.

Structure	Accuracy	Voting	Neuro-dynamic Structure
AlexNet	92.73	87.47	**99.1**
VGG-FaceNet	83.03		
ResNet50v2	84.12		
FlowImageNet	90		

Table 4. Comparison of accuracy between two states on our dataset.

Structure	Accuracy	Voting	Neuro-dynamic Structure
AlexNet	92	86.49	**98.6**
VGG-FaceNet	81.93		
ResNet50v2	82.68		
FlowImageNet	89.35		

Figure 11. Evaluation of proposed structure on two datasets

Figure 12. Detecting drowsiness even yawning with hand

CONCLUSION

This study employed four convolutional neural network architectures—AlexNet, Res-Net50V2, FlowImageNet, and VGG-FaceNet—and combined their results using a neuro-dynamic structure. Initially tested on the NTHUDDD dataset, a leading resource for sleepiness detection, the proposed approach proved to be more effective than the individual methods. The method was also validated on a custom dataset created for this study, demonstrating its robustness across various datasets. The dynamic technique showed substantial improvements over previous methods like averaging. Ultimately, the neuro-dynamic architecture achieved accuracies of 99.1% and 98.6% on the two datasets, respectively. Given its high accuracy, the system is well-suited for real-world applications and could be integrated into hardware for use in vehicles. In future work, this system is expected to be implemented for signal data, which is distinct from image data. Additionally, by incorporating all three categories of data—vehicle-based, biological-based, and facial-based—we can achieve a more comprehensive assessment of drowsiness. Furthermore, this system could be applied to lateral and longitudinal vehicle speed data, as well as vehicle trajectory tracking, since driving behaviour can serve as an indicator of driver drowsiness.

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