DROWSINESS DRIVER DETECTION SYSTEM USING CONVOLUTIONAL NEURAL NETWORK

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Abstract – **Drowsy driving is dangerous and this is also one of the causes of traffic accidents. Recognizing the importance of this, we propose a system to recognize whether the driver is drowsy or not based on facial features. The system applies deep learning techniques using convolutional neural networks CNN on the combination of 2 datasets: the Real-Life Drowsiness Dataset RLDD and the real drive for driver drowsiness detection SUST Dataset. The proposed algorithm uses the cascade object detector (Viola-Jones algorithm) for detecting and extracting the driver's face from images, the images extracted from the videos of RLDD will act as the dataset for training and testing the CNN model. A comparison between models is described in this paper.**

Keywords – **Drowsiness Driver Detection, Convolutional Neural Network,**

I. INTRODUCTION

Traffic accidents are considered one of the biggest disasters that threaten human life and health. Its consequences are very heavy and incalculable, not only affecting the spirit but also easily leading to poverty, backwardness and disease. The World Health Organization(WHO) estimates that around 1.3 million people die each year as a result of road traffic crashes, and up to 50 million are injured or disabled [1]. Traffic accidents are in the 8th rank among the causes of death in the world, and it is predicted that if no measures are taken, it may rise to the 5th rank [2]. The cause of the accident is mentioned as over speeding, drunken driving, distractions to driver, red light jumping, avoiding safety gears like seat belts and helmets, non-adherence to lane driving and overtaking in a wrong manner [3]. In addition to the reasons mentioned above, drowsiness or fatigue is also one of the causes of traffic accidents. The effects of drowsy driving are more severe than most people realize. Drowsy driving is a particular concern, as it can lead to car accidents and other types of traffic incidents. According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving is responsible for an estimated 100,000 crashes, 71,000 injuries, and 1,550 deaths per year in the United States alone [4]. It can be seen that drowsy driving is very dangerous, and detecting a drowsy driver is also important and useful for road users.

There is an increasing interest in building intelligent in-vehicle systems, called Driver Assistance System (DAS) [5], [6]. Driver Drowsiness Detection (DDD) systems are a primary area of research in DAS. These systems aim to identify signs of drowsiness in drivers at the earliest possible stage and provide an alert to the driver so that they can take appropriate measures before they become sleepy. In most cases, sleepiness does not occur suddenly but is usually preceded by observable indications [6], [7]:

- Physiological-based signs
- Vehicular-based signs
- Behavioral-based signs

DDD systems are designed to identify sleepiness indicators based on one or more of these signs. Each sign has the advantages and the disadvantages.Tab.1 shows the advantages and limitations of all the three measures approaches [6], [8]:

TABLE I
Three measures approaches

Approach	Accuracy	Comfortability	Cost	Limitations
Physiological	High	Low	High	Sensitive to drivers' movements and health
Vehicular	Low	High	High	Dependency on enviroment and vehicle type
Behavioral	Medium	Hight	Low	Illumination dependency

Physical signs like pulse rate, heart rate, breathing rate, and body temperature are gathered through intrusive sensors that are connected to the driver's body, but this method can be uncomfortable and distracting. Vehicular-based signs, on the other hand, involve sensors attached to the vehicle's parts that analyze various metrics like lane departure, steering wheel movements, and braking patterns. Lastly, behavioral signs rely on non-invasive methods like cameras and computer vision techniques to extract behavioral characteristics such as eye closure ratio, eye blinking, head position, facial expressions, and yawning. Based on the above approaches, this study will develop a system to detect drowsy drivers through a number of noticeable behaviors [6]. The research accomplished in this paper is within the field of monitoring the drivers' visual behaviors from a video to detect drowsiness, using computer vision and deep learning-based approaches. The main contributions of this paper are:

- Propose a driver drowsiness detection model that uses convolutional neural networks.
- Create new dataset by combining the real-life drowsiness dataset and the real driver for drive drowsiness detection.
- Study the effect of changing the position of the layers in the CNN model.

The remainder of this paper is organized as follows. In Section 2, we review related work in driver drowsiness detection. We summarize the information of the dataset and approaches to DDD nowadays. In Section 3, we clarify the proposed method of this study. Experiments and Results are presented in section 4 and section 5, respectively. , we conclude the paper in Section 5 and discuss future work in Section 6.

II. RELATED WORK

In this paper, we provide a brief overview of current datasets and their methods of collection, as well as a summary of some behavioral-based techniques for detecting drowsiness.

A. *Drowsiness Driver Datasets*

Table 2 presents a short summary of drowsiness-related datasets in literature, which are publicly (or partly) available at the time of writing [9].

We provide specific information of the datasets that are used a lot in the problem of detecting drowsy drivers.

1) NTHU dataset: This video dataset was collected by NTHU Computer Vision Lab. The entire dataset (including training, evaluation, and testing dataset) contains 36 subjects of different ethnicities recorded with and without wearing glasses/sunglasses under a variety of simulated driving scenarios, including normal driving, yawning, slow blink rate, falling asleep, burst out laughing, etc., under day and night illumination conditions [54] The author use an active infrared(IR) illumination to acquire IR videos in the dataset collection [54]. The dataset is divided into training, evaluation, and testing sets. The testing videos are produced by mixing videos of different driving scenarios.

TABLE II

Comparison of DMS-related datasets, Purpose: The original usage of dataset, People: The number of participants, Environment: A way of collection, Type: The type of data

Dataset	Purpose	People	Environment	Type
CCDWC [10]	Eye Blinking	-	simulated,act	video
OUD [11]	Eye Status	23	simulated,real	video
RDD [12]	Drowsiness	33	car,act	video
MBD [13]	Drowsiness	23	car,real	video
DDD [14]	Eye closeness	21	car,act	image
SRV [15]	Eye closeness	319	lab,act	image
ADD [16]	Head Pose	1	lab,act	-
SBE [17]	Eye Blinking	-	lab,act	video
MHE [18]	Head/Eye Motion	2	car,act	-
SEU [19]	Drowsiness	20	car,act	image
AOD [20]	Drowsiness	21	simulated,act	video
MCSO [21]	Drowsiness	15	simulated,act	video
CDL [22]	Drowsiness	49	simulated,real+act	video
FDU [23]	Drowsiness	20	car+simulated,-	video
HCV [24]	Eye Status	-	car,act	-
AOY [25]	Yawing	12	simulated,real	video
MOD [26]	Eye Blinking	6	simulated,act	video
DFD [27]	Eye Status	-	-,act	video
TES [28]	Eye Status	-	car,act	image
EBB [29]	Eye Blinking	3	lab,act	video
IRF [30]	Eye Status	20	lab,act	video
HDB [31]	Eye Status	-	lab,act	video
DAS [32]	Eye/Mouth Status	5	car,act	-
DHD [33]	Drowsiness	-	car,-	video
DFD [34]	Eye Status	-	lab,act	-
HPA [35]	Eye Blinking	-	car,act	-
DSD [36]	Drowsiness	14	car,act	-
VAO [37]	Drowsiness	5	car,act	video
MDC [38]	Drowsiness	35	lab,act	video
Eyeblink8 [38]	Eye Blinking	4	lab,act	video
DriveAHead [39]	Head Pose	20	car,real	video
ZJU [40]	Eye Blinking	20	lab,act	video
NTHU [41]	Drowsiness	36	simulated,act	video
YawnDD [42]	Yawning	107	car,act+real	video
DROZY [43]	Drowsiness	14	lab,real	video
CEW [44]	Eye Closeness	-	-,-	image
RT-BENE [45]	Eye Blinking	15	lab,act	frame
300-VW [46]	Facial ldmk	-	natural,-	video
RLDD [47]	Drowsiness	60	lab,real	video
DMD [48]	Comprehensive	37	car+simulated,real+act	-
Drive&act [49]	Behavior	12	simulated,act	-
Pandora [50]	Driver Pose	22	lab,act	video
DD-Pose [51]	Head Pose	27	car,real	frame
CMU-PIE [52]	Head Pose	72	lab+car,real+act	image
SUST [53]	Drowsiness	19	-,-	video

Fig. 1. NTHU Dataset

2) *YawnDD dataset:* The dataset was created in two different sets, from the camera placed on the front mirror of the car and the camera placed on the driver's panel. The dataset consists of videos of 57 male and 50 female participants in three different situations: normal driving (no talking), talking or singing while driving, and yawning while driving in a parked vehicle. It is a suitable data set for face and mouth recognition studies, as well as being useful for yawn detection. [42], [53]

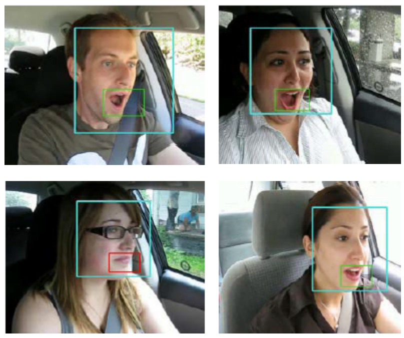

Fig. 2. YawnDD Dataset

3) *RLDD dataset:* A total of 180 videos were collected for this dataset, with each video lasting approximately 10 minutes. The videos were taken from three different burstings: alert, low vigilant, and drowsy, and were recorded by 60 participants,51 were male and 9 were female. They were given 20 days to prepare three videos and were instructed to record the videos in their natural environment (such as at home, work, or school) when they felt alert, low vigilant, or drowsy. The videos were taken from an arm's length away, with the participant's face visible and in accordance with the driving

video. Participants used their mobile phones or webcams to take the videos. [47], [53]

Fig. 3. RLDD Dataset

4) SUST dataset: SUST dataset is a real drive dataset for driver drowsiness detection created by Sivas University of Science and Technology. The dataset contains 2 groups of videos, with a total of 19 drivers aged between 24 and 42, 3 females and 16 males. Participants recorded a video of their driving moments with their phones in their vehicles at a desired time. The presented SUST-DDD, on the other hand, is a dataset consisting of videos recorded by the cameras of their phones when drivers feel tired and normal during real driving.

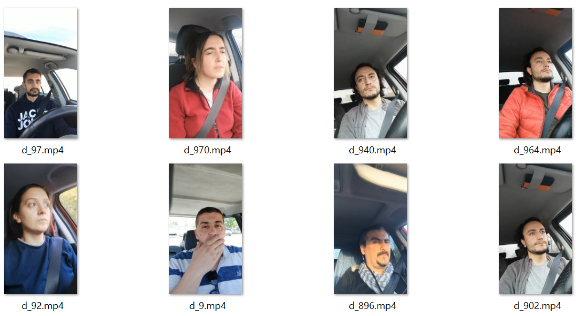

Fig. 4. SUST Dataset

B. Drowsiness Driver Existing Approaches

There are 3 techniques that can be applied to detect a drowsy driver [6], [9]:

- Physiological-based Techniques: based on Physiological measures: Electroencephalogram (EEG), Electrooculography (EOG), Electromyography (EMG), Heart Rate Variability (HRV),etc.By using a combination of these physiological measures, it is possible to detect and monitor drowsiness in a driver and take appropriate action to prevent accidents.
- Vehicle-based Techniques: based on Vehicle measures, the use of technology to monitor the behavior and performance of a vehicle and its driver in order to detect signs of drowsiness or impairment. It includes steering wheel sensors, accelerometer, lane departure warning systems, vehicle speed, etc.
- Behavioral-based Techniques: based on behavioral measures, such as eye movements, head position, reaction time, yawning,etc.

1) Physiological-based Techniques: For Physiological-based Techniques, we detect the drowsiness driver by targeting the heart rate, pulse rate, brain activity, body temperature, etc . [55]. It is the early stages that can cause physiological changes in the human body. Drowsiness is measured in this category by attaching electronic devices such as sensors to the driver's body. The most frequently used physiological measures use different signals including electroencephalography (EEG), electro-oculogram (EOG), electromyography (EMG), electrocardiography (ECG) [56]. The EEG technique utilizes the electrical signals produced by the human brain to detect brainwaves, and it is employed in various applications such as diagnosing epilepsy and monitoring sleep disorders [56], [57].The EOG method is utilized to track the movement of the human eye, and it measures the corneo-retinal potential, which is the potential difference that exists between the front and back of the eye. This technique is employed to measure the corneo-retinal standing potential [56], [58].EMG technique assesses and records the electrical signals generated by muscles, using surface electrodes that are placed in contact with the skin of the subject [56], [59].The ECG method is capable of monitoring and assessing the cardiac activity of a driver, which includes parameters such as heart rate, rhythm, and electrical activity, while they are driving [56], [60]. ECG and EEG signal integration is used to detect drowsiness and improve performance [61]. SVM classifier is used to classify drowsiness based on the notable features of ECG and EEG. The combination of ECG and EEG performed better than either signal alone. To predict driver tiredness, a combination of EEG and forehead EOG signals is also employed in conjunction with a g discriminative graph regularized extreme learning machine(GELM) [62]. Moreover, a driver's cognitive state can be classified using an EEG measurement method, independent component and power-spectrum analyses, correlation evaluations, and a linear regression model [63] In a Virtual Reality (VR) environment, the sleepiness detection system attained an average accuracy of 88.2%.

TABLE III
Analysis of physiological based techniques
measure1: *approximate entropy, sample entropy, renyi entropy and recurrence quantification analysis*, measure2: *power spectral density and differential entropy horizon electrooculogram vertical electrooculogram* , measure3: *Complexity of EMG,ECG and EMG sample entrophy.*

Reference	Signals	Measurement parameter	Classification algorithm	Accuracy
[61]	ECG EEG	HR, HRV, Time and frequency	SVM	80.90%
[64]	EEG	measure1	ELM ELM-RBF SVM classifiers	94.7% 95.6% 94.7%
[62]	ELEG Forehead EOG	measure2	GELM	prediction correlation coefficient-0.8080 RMSE value 0.0712
[63]	EEG	33-channel EEG data	Linear Regression	88.2%
[65]	ECG EMG	measure3	Multiple Regression	91%

2) Vehicle-based Techniques: It is difficult to anticipate driver tiredness using vehicle measures [66].In [67] five input parameters like centerline of the road, lateral acceleration, steering wheel angle, yaw rate and steering wheel velocity are considered and classification was done using a combination of CNN and LSTM deep learning algorithms.The steering wheel angular velocity is considered and time series analysis is done on it to identify the fatigue condition in [68]. Smart steering wheels in [69] can be utilized to improve driver safety. Sensors mounted to the steering wheel can detect the presence or absence of the driver's hand. Another study on steering angular movement was conducted by attaching sensors to it [70]. By taking the supplied deviation into account, the system linearizes the approximation entropy using adaptive piecewise linear fitting. The sleepiness state is determined by the wrapping distance between the linear feature series. Despite extensive research on the vehicle-based measure, it remains difficult to be recognized as a detection system. It may be more successful when combined with physiological and behavioral assessments.

TABLE IV
Analysis of vehicle-based techniques
input1: *road centerline,lateral acceleration,yaw rate,steering wheel angle,steering wheel velocity*, method1: *44 sessions in a fixed-base driving simulating monotonous night-time highway drives* , method2: *bus driving simulator (BI301Semi) 39 bus drivers with different driving professions*, alg1: *feature selection using neuro-fuzzy systems SVM classifier*

Reference	Input parameters	Data collection method	Classification algorithm	Accuracy
[67]	input1	method1	CNN, LSTM	96.0%
[68]	Steering wheel data	method2	alg1	98.5%
[69]	Steering wheel	Sensors	Threshold of comparator	100% reliability
[70]	Steering wheel angle	Sensors	Binary decision classifier	78.01%

3) Behavioral-based Techniques: Many researchers have done effective work with the help of various measures utilized for driver sleepiness detection due to the high demand for driver drowsiness detection approaches. The authors of [59] tested several data combinations using physiological, behavioral, and vehicle-based variables. With a detection mean square error of 0.22 and a prediction mean square error of 4.18 min, the behavioral measure has demonstrated its strength in both detection and prediction.

TABLE V
Analysis of behavioral-based techniques
mater1: *SCANeR Studio, faceLAB, pulse plethysmography*, data1: *21 participants simulated car for 110mins*, data2: *NTHU-drowsy driver detection benchmark dataset*, mater2: *Sensors, Logitech C920 HD Pro Webcam*, mater3: *web-cam of the laptop*, alg2: *Image processing, Decision making algorithm*, data3: *55 min of video, in which 130 drowsiness events have occurred*, data4: *videos of 30 subjects (with ages ranging from 20 to 55 years)*

Author	Materials	Method/Algorithm Used	Dataset	Accuracy
[71]	mater1	Aritificial Neural Networks	data1	95.0%
[72]	RGB input video	Deep networks	data2	73.06%
[12]	mater2	Deep Neural Networks	Custom Dataset	89.5%
[73]	mater3	alg2	data3	90%
[74]	Camera	Artificial Neural Networks	200 image dataset	100%
[75]	HD Camera	Deep Belief Network	data4	96.7%

To learn and identify tiredness, a deep drowsiness detection network [72] is being created. The network takes an RGB input video of a driver and uses three deep networks to learn facial motions and head gestures. The output of the three layers, together with the softmax classifier, aids in the detection of drowsiness. For rapid and accurate face detection, Multi-task Cascaded Convolutional Networks (MTCNN) are used [56]. The human visual system processes images to detect driver fatigue [73] To improve the resilience of the drowsiness detection system, the energy levels in the image frames are modified and predicted using a better decision-making algorithm. Moreover, the processed images can be used to examine the status of the eye, whether it is open, half-closed, or closed [74]. An artificial neural network with a hidden layer network and an auto-encoder network can be employed for this aim. A Deep Belief Network (DBN) [75] is utilized to classify driver sleepiness expressions and a high-definition camera is employed to extract face landmarks and textures. Behavioral measurements have recently become popular among researchers. A thorough and accurate report is still a struggle in today's world.

III. Proposed Methods

This section presents a summary of the suggested approach, which involves creating a dataset and utilizing a specific methodology to train a CNN model. The objective of this model is to distinguish images of the driver as either being Drowsy or Non-Drowsy. Figure 5 shows the architecture of the proposed model.

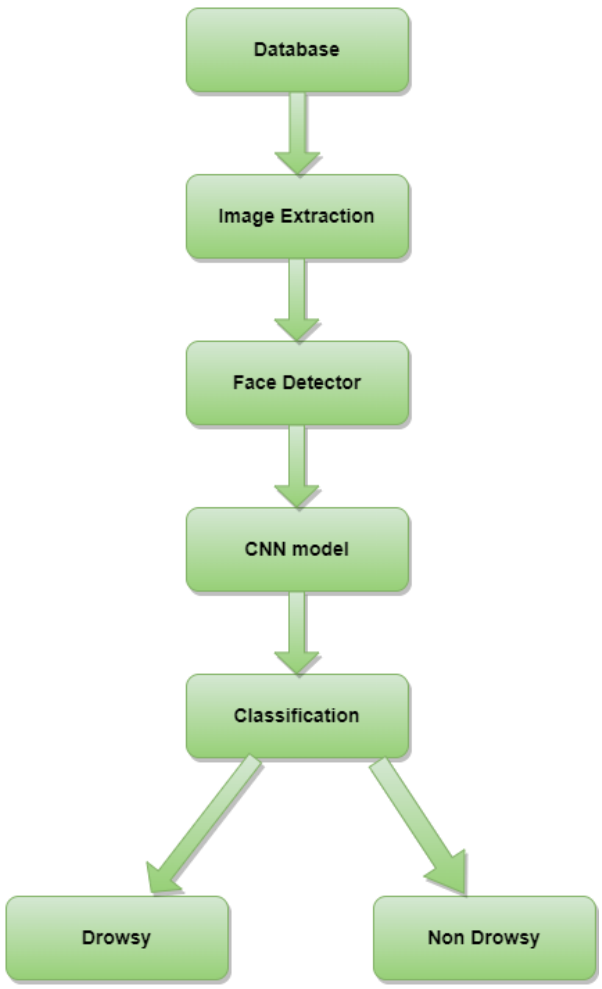

Fig. 5. Proposed System Architecture

A. *Dataset and Preprocessing*

Regarding the creation of the dataset, this research will concentrate on the analysis of the University of Texas in Arlington's Real-Life Drowsiness Dataset (UTA-RLDD) [47] and Sivas University of Science and Technology SUST dataset - the real driver dataset [53] for driver drowsiness detection. We combine two these datasets to create new dataset for this study.

1) RLDD Dataset and SUST Dataset: RLDD Dataset and SUST Dataset are the set of videos. Two data sets are divided into two labels : drowsy or non-drowsy. There are 60 objects available in the RLDD Dataset while SUST Dataset contains 19 drivers. The dataset includes both men and women, varied in age, lighting conditions, wearing glasses, hats,...

2) Preprocessing: Video preprocessing happens in 2 stages: extracting images from video and data augmentation.

a) Extracting Images from Video Frames:
The frames of each image were extracted from videos as images based on time position using OpenCV in Python. After that, the Viola-Jones algorithm has been used to extract the face from images. Viola-Jones algorithm is a machine-learning technique for object detection proposed in 2001 by Paul Viola and Michael Jones in their paper [76]. The algorithm was primarily conceived for face detection. The Viola-Jones algorithm is based on four main ideas, which we'll discuss in the sections below:

- Haar-like features
- Integral images for accelerating the feature computation
- AdaBoost learning for feature selection
- Cascade of classifiers for fast rejection of windows without faces.

From a set of images consisting of many faces belonging to 2 labels, we proceed to select images to create a dataset for the model. Images were selected based on eye characteristics and the act of yawning. When extracting images from video, it is inevitable that the data will be noisy, for example an image of a person with eyes closed can be in both drowsy and non-drowsy labels.

b) Data Augmentation:
In addition, one way to improve the performance of a drowsy driver detection model is through the use of data augmentation techniques. Data augmentation involves generating new training samples from existing ones by applying various transformations to the original images.In this study, we propose the following method for data augmentation using the Keras ImageDataGenerator class. This method creates an ImageDataGenerator object that applies the following transformations to the training data:

- Rescaling the pixel values to be in a range of [0, 1].
- Randomly applying shearing transformations to the images.
- Randomly zooming in or out of the images.
- Filling in any gaps created by the previous transformations using the nearest neighbor method.
- Randomly flipping the images horizontally.
- Randomly shifting the images horizontally and vertically.

These transformations increase the diversity of the training data, helping the model generalize better to new images. The resulting augmented dataset can then be used to train a drowsy driver detection model using a convolutional neural network (CNN) architecture.

B. Drowsiness Driver Detection based on CNN

Convolution Neural Networks (CNN) are used in the initial module for detecting driver fatigue and other aforementioned driver statuses. The proposed CNN model for detecting driver drowsiness is depicted in Fig.6:

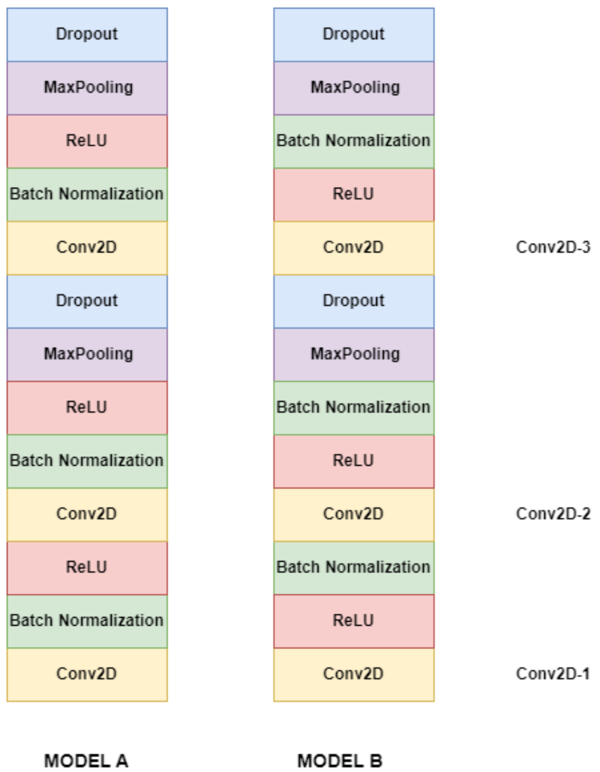

Fig. 6. The CNN units architecture for model A and model B

This study focuses on developing a CNN model that includes the following basic layers:

- Convolutional layer: Use the Conv2D layer as the first layer for the model to learn the local features of the input image. This class uses a filter to scan the image and compute the feature features
- ReLU layer: After calculating the feature features, the ReLU (Rectified Linear Unit) layer will be used to generate non-linear contours and de-skew. This layer can be placed before or after the Batch Normalization layer.
- BatchNormalization layer: The Batch Normalization (BN) layer is used to normalize the output features of a Conv3D layer or a ReLU layer before they are passed on to the next layer. This layer helps to speed up convergence and reduce overfitting during network training.
- Pooling layer: Pooling layer has the effect of simplifying the output information. That is, after completing the calculation and scanning through the layers, go to the pooling layer to remove unnecessary information. From there, produce the results as desired by the user.

The model takes as input images with shapes (227, 227, 3), which are common for the dataset. In addition, the dropout layer, the Flatten layer, and the Dense layer are used. The dropout layer applies dropout regularization with a rate of 0.5, which randomly sets 50% of the outputs of the previous layer to zero during training to prevent overfitting. The Flatten layer in a neural network is used to flatten the output of the previous layer into a 1D vector. This is often used as a transition from the convolutional/pooling layers to the fully connected layers in a neural network. The flattened output is then passed to the fully connected Dense layer which has 2 output units and a sigmoid activation function. The sigmoid function is used to predict the probability of the input image belonging to one of two classes. In the other hand, this study will explore the impact of the ReLU layer on the performance of the model. Model A and Model B have the same number of layers and include the same layer types, but they have a difference with respect to the location of the Batch Normalization layer: Model A places the Batch Normalization layer before the ReLU layer while Model B puts it in reverse, ReLU is placed before Batch Normalization layer.

IV. EXPERIMENTS

A. Dataset

This study creates a new dataset based on two published datasets: RLDD Dataset and SUST Dataset. The new dataset has 17029 images belonging to 2 labels, of which Non Drowsy has 8281 images and Drowsy has 8748 images. We divide the dataset into 3 training sets, validation sets and test sets with a ratio of 60 - 20 - 20.

B. Experiment Results

The experimental platform for this study was Google Collab with GPU 15 GB. Model A and Model B are trained end-to-end for 30 epochs. We used the 'adam' optimizer, cross-entropy loss function and a batch size of 128. We conducted two experiments on each dataset (Model A and Model B). The accuracy, precision, recall, and F1 score are the evaluation metrics used to evaluate the performance of the proposed models in both experiments. The accuracy and loss for the training set and validation set of Model A and Model B are described in Fig 7, Fig 8, Fig 9, and Fig 10. After 5 epochs, the accuracy of Model A and Model B start to grow and both reach above 0.85. However, the accuracy of Model B is not stable. Moreover, it can be seen that Model B is not as stable as Model A through the Loss histogram on two datasets.

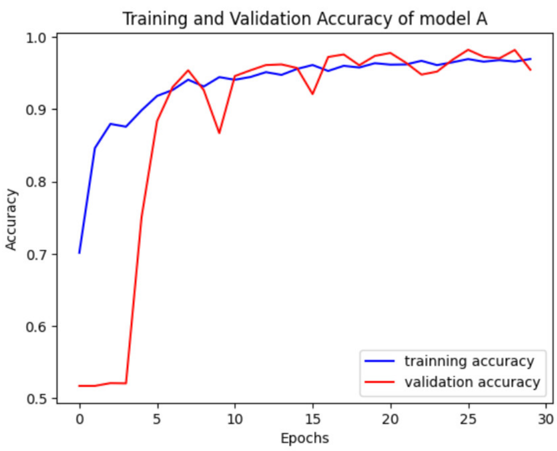

Fig. 7. Accuracy of Model A for training set and validation set

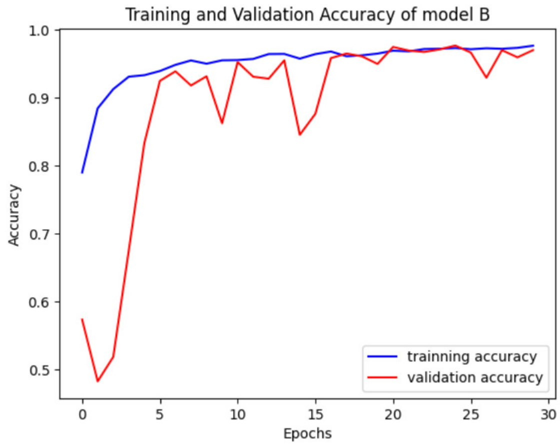

Fig. 8. Accuracy of Model B for training set and validation set

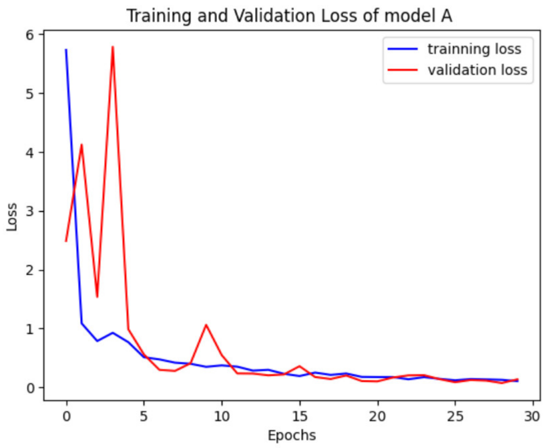

Fig. 9. Loss of Model A for training set and validation set

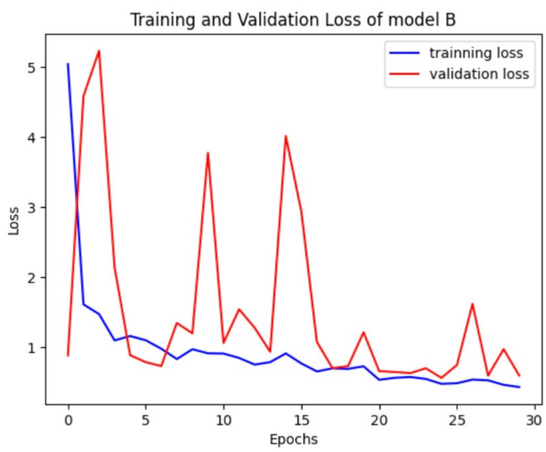

Fig. 10. Loss of Model B for training set and validation set

The general trend of the accuracy curves was increasing and decreasing for the loss curves. Table VI compares the accuracy, precision, recall, and F1 score between Model A and Model B:

TABLE VI
Comparision between Model A and Model B for classification report

		precision	recall	f1-score	support
Model A	Non Drowsy	0.92	0.99	0.96	1645
	Drowsy	0.99	0.92	0.95	1761
Model B	Non Drowsy	0.96	0.97	0.97	1645
	Drowsy	0.98	0.97	0.97	1761

Batch normalization is a technique commonly used in neural networks to help speed up convergence and model stability. However, the position of the Batch normalization in the neural network, especially in the Convolutional Neural Network (CNN), can affect the performance of the model. When the Batch normalization is placed after the ReLU layer, the model goes through the ReLU computation before normalizing the input value of the next layer. In contrast, when the Batch normalization is placed before the ReLU layer, normalization is applied before the ReLU calculation. This ensures that the output of the ReLU layer is not affected by the normalization work of the Batch normalization while preserving all input values of the ReLU layer. Usually, placing the Batch normalization before the ReLU layer is often more heavily advertised in CNN because it helps to keep all the input values of the ReLU layer and helps the learning model to have more important features. But in some cases, the model which Batch Normalization layer placing after ReLU layer gives better result.

V. CONCLUSIONS

This paper proposed an efficient framework for driver drowsiness detection based on combining two datasets. Face detection also approaches are examined in this study. In addition, we investigated the effect of adding the Batch Normalization layer in two different places in CNN (before or after the activation function). The goal of this study was to prove that other positions of the Batch Normalization layer than the suggested one can speed up the training of the model and avoid overfitting on one dataset but not the other. From the results, it can be concluded that the performance of the proposed model is highly affected by selected positions of the Batch Normalization. In future research, other methods for enhancing the performance of the proposed model will be considered. Another direction for future works would be using hand gesture recognition inspired by [6] for drowsiness activity when the drivers rub their eyes or yawn with hand assistance layer.

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