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DRIVER DROWSINESS DETECTION SYSTEM USING CNN

Sampradeepraj.T
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
t.sampradeepraj@klu.ac.in

Shyam Sundar Reddy.G
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9920004618@klu.ac.in

Bharath Kumar.V
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9920004685@klu.ac.in

AnilKumar P
Department of Electronics and Communication Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9920004689@klu.ac.in

Yedukondalu.P
Department of Computer Science and Engineering
Kalasalingam Academy of Research and Education
Krishnankoil, Virudhunagar, India
9920004662@klu.ac.in

Abstract - One of the major causes of traffic accidents is driver fatigue. We can use the condition of our eyes to determine how tired we are, but wearing sunglasses would affect how our eyes are feeling. Our faces hold a lot of valuable information. In this paper, we propose an eye state recognition method based on convolution neural network (CNN), eventually calculating percentage of eyelid closure over the pupil over time (PERCLOS), blink frequency to detect the fatigue, in order to solve the aforementioned problems and make the algorithm keep the accuracy and real-time at the same time. The findings of the experiments demonstrate that the suggested method can successfully detect fatigue and has a high recognition accuracy of the state of the eyes when wearing glasses.

I. INTRODUCTION

Many peoples are died every year in road accidents due to lack of awareness of the driver. Being tired, fatigue, and microsleeping are the main causes of road accidents. According to the US Department of Transportation, drowsy driving contributed to an estimated 91,000 crashes that were recorded by the police in 2017. An estimated 50,000 people were hurt and nearly 800 individuals died as a result of these collisions. So, therefore it is very important to build a model that can detect the driver drowsiness and alert the driver to wake up and saves the lives of the passengers. The drowsiness detection system's goal is to help reduce accidents involving both passenger and costly vehicles. Before the driver completely went to sleep, the system will identify the early signs of tiredness and alert them that they can no longer drive the car safely. An application Deep learning model at the backend and a user-friendly interface was created using the concepts and principles of Deep learning. A user interface can be created to solve the issue of distracted driving. The goal of this work is to offer a user-friendly model that has been trained to identify driver sleepiness. In order to do this, a detailed investigation of the development and testing of user interfaces was conducted. Between the user and the computer (application), the user interface serves as a barrier.

The main goal of user interface design is to make sure that, with the UI's final iteration, any user can understand what happens as each job progresses naturally. The user interface must be straightforward enough to prevent confusion and complexity in the tasks that a user must do. Also, it is impressive to be able to identify and comprehend the GUI's component parts and the principles that must be followed for an efficient interface design process.

a)Justification :

The main reason to use CNN is it has a special feature called spatial extraction as compared to the normal Neural Network, By having this feature CNN extract the particular portion of the image. For example if we want to train the images having eyes it only takes eyes by neglecting the backround image due to this it reduces the number of layers of CNN and produce better accuracy as output.

II. LITERATURE REVIEW

Jabbar, R. Shinoy, M.Kharbeche, M.Al-Khalifa, K. Krichen, M. and Barkaoui in 2020, is focusing on Driver Behavior monitoring system using Convolutional Neural Network it will take 22 subjects from different ethnicities for sleepy ,nonsleepy and night conditions. The resolution of 640*480 at 30 frames per second containing different subjects enacting regular and drowsy driving behaviors. The facial landmark coordinates which are extracted from the images using the DLib Library as represented in the algorithm. The presented model is based on the CNN approach with five layers as told in [1].

Tanveer Khan, M. A. The possibility of detecting drowsiness for positive BCI (brain computer interface) via hemodynamic response caused drowsiness is being researched by M. J. Qureshi, J. Naseer N., and Hong K. S. (2019). Two different

deep learning architectures—namely, DNNs (Deep Neural Networks) and alert/drowsy, respectively—were employed in this study to detect and measure strength. The first layer of the hidden layers, which uses a thick layer construction, has 19 neurons, and the last layer has 200 neurons. The color map images generated from each time window for all channels were categorized using the CNN (Convolution Neural Network) architecture. The characteristics were then passed via a dense layer with 128 neurons, a 50% reduction layer, and a fully linked layer as told in [2].

Agarwal, A., & Kumar, M. (2019). Driver drowsiness detection system. International Journal of Innovative Technology and Exploring Engineering, 8(7), 1450-1453. | This article presents a driver drowsiness detection system which uses a combination of eye tracking and heart rate monitoring. The system is based on a convolutional neural network (CNN) and a support vector machine (SVM). The article discusses the various challenges faced in the development of the system such as the accuracy of the detection, the robustness of the system, and the complexity of the system. The results of the system showed that the system was able to detect drowsiness with an accuracy of 98%.

In this paper, pre-existing features for facial landmark detection is used. The methodology uses 68- facial landmark (a predefined landmark) for shape prediction in order to identify various regions of the face like eye brows, eye, mo etc [3].

Hasan, Paul, & Babu, 2021 describes a nighttime, real-time system for detecting driver fatigue. By using one shape predictor and then calculating the eye aspect ratio, mouth opening ratio, and yawning frequency, facial landmarks on the driver's face are located. Drowsiness is determined by these parameter values. An adaptive thresholding approach is used to establish the thresholds. Machine learning methods were also implemented offline. The suggested method was examined on the Face Dataset and in real-time. The experimental results show the robustness and precision of the system[4] .

Miranda, Villanueva, Buo, & Merabite, 2018) suggests a gadget to avoid sleepiness because the incidence of car accidents in the Philippines has been rising year after year. The installation of standard rumble strips on highways, GPS, speed limiters, sensors, and other signal processing studies are examples of current safety measures that are utilised to increase driver awareness. The device uses the internet of things to enable the automobile owner to monitor the driver's level of fatigue at all times during business hours. The subject of the new study is eyelid movement, which was not covered in the earlier investigation. The proposed technology continuously monitors the driver's eyelid movements and, if tiredness is detected, alerts him with a noise of unknown origin. By internet connection from the web application, it automatically delivers the report to the automobile owner [5].

In their research "Bias Correction in Driver Drowsiness Detection Systems Using Generative Adversarial Networks," Mkhuseli Ngxande and Michael Burke suggest utilising generative adversarial networks to lessen bias in vehicle drowsiness detection systems (GANs). The authors point out that driver drowsiness detection devices are playing a bigger role in lowering accidents brought on by fatigued driving. Yet, some driver categories, such as senior drivers or those with specific medical issues, may be unfairly targeted by these systems. The authors suggest employing GANs to create synthetic data that represents all drivers, including those who might be underrepresented in the training data, in order to solve this issue. In order to create synthetic images of drivers with various degrees of tiredness, they modify the CGAN design[6].

Using a convolutional neural network, Hashemi, Mirrashid, and Beheshti Shirazi describe a system in 2020 for real-time driver sleepiness detection (CNN). They described the technologies for detecting drowsiness that are now in use, including as tracking the driver's eye, head, and physiological signals. Some techniques do have drawbacks, too, include being influenced by outside influences, being intrusive, or needing specific tools. In order to identify tiredness, they suggested a CNN-based method that analyses the driver's facial features in real-time. The method uses transfer learning to optimise a pre-trained CNN model after being trained on a dataset of photos of awake and sleepy drivers. In terms of detecting sleepiness, the CNN model had an accuracy of 96.5% and a precision of 95.2%[7].

Krishnaraj, N., Elhoseny, M., Thenmozhi, M., Selim, M. M., & Shankar, K. (2020) proposed a deep learning model for real-time image compression in the context of the Internet of Underwater Things (IoUT). The paper begins by discussing the need for image compression in underwater environments due to the limited bandwidth available for data transmission. The authors also highlight the challenges associated with traditional image compression techniques, such as lossy compression leading to significant loss in image quality[8].

III. MODEL ARCHITECTURE:

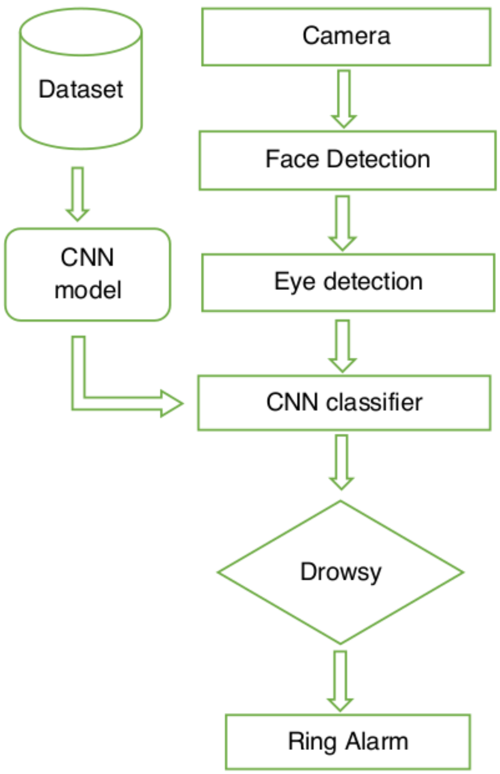

Figure-1 Architecture diagram for driver drowsiness system

In the above figure-1 we explain the working flow of our paper, At first our model is trained with some of the eyes images dataset. This images are taken from the Kaggle dataset. This CNN model detect the face and eye and identify whether the eye is closed or not. If eyes is closed and for some amount of time the model feels that the driver is drowsy and alert the driver.

IV. DATASET DESCRYPTION:

With the help of the Drowsiness dataset available on the Kaggle platform, we trained the CNN model in this study. For categorizing photos into Open Eyes, Closed Eyes, Yawning, or No-Yawning, the original dataset has four classes. However, the purpose of work is to categorize tiredness according to whether the eyes are open or closed. Thus, we will use four classes from the dataset. There are 2900 photos in all, divided into four categories, in the dataset. There is no need to balance the dataset because it is already balanced. Class labels include Open Eye, Closed Eye

V. METHODOLOGY

Gather a database of images showing both awake and sleepy drivers. Using a webcam, you can capture footage of drivers and mark the frames in which they appear to be nodding off. Gather enough images for your model to be trained. Make the photographs grayscale and resize them to a standard size. For CNN input, resize the photos to a standard size. Adjust the pixel values to lie within the range of 0 and 1. Identify and pinpoint the driver's eyes in each frame of the video using OpenCV.

Convolution Neural Network:

Due to their proficiency at effectively processing image data, convolutional neural networks (CNNs) are frequently used in systems for detecting driver drowsiness. Convolutions, which involve swiping a filter over the image and computing dot products to produce a feature map, are a technique used by CNNs to identify patterns and features in images. Convolutional neural networks (CNNs) are utilised in driver sleepiness detection systems because of their capacity to learn intricate visual properties from still photos or moving video frames. The driver drowsiness detection system can inform the driver when indicators of tiredness are found by evaluating the camera footage in real-time using a CNN. By doing this, accidents brought on by drowsy or distracted drivers may be avoided. In these systems, CNNs can be applied in the following ways:

Face detection and tracking: A important stage in driver sleepiness detection systems is the detection and monitoring of faces in real-time video feeds, which can be accomplished using CNNs. This makes it possible for the system to constantly see the driver's face and look for indicators of tiredness.

Eye detection and tracking: CNNs can be utilised for eye detection and tracking, which is an important sign of tiredness in drivers. The device can tell if a driver is starting to nod off by monitoring their eye movements and blinking patterns.

Feature extraction: CNNs can be used to extract features from the pictures or video frames that the system has taken. These characteristics may include things like head motions, eye movements, and facial expressions, which can all be utilised to identify whether the driver is starting to nod off.

Classification: CNNs can be used to categorise the driver's level of tiredness after features have been retrieved. This might entail teaching the network to identify patterns linked to various degrees of somnolence, like slow blinking or head nodding.

In general, CNNs are an effective tool for driver drowsiness detection systems because they can automatically evaluate massive volumes of data in real-time and find tiny patterns that may suggest fatigue. CNNs can increase driver safety by warning them when they are growing drowsy and should take a break utilising a combination of face and eye tracking, feature extraction, and classification.

Architecture of the CNN :-

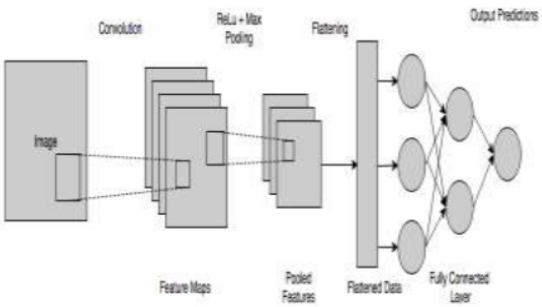

Figure-2 : Sample Architecture of CNN

max_pooling2d (MaxPooling2D)	(None, 16, 16, 32)	0
conv3 (Conv2D)	(None, 16, 16, 64)	18496
batch_normalization_2 (BatchNormalization)	(None, 16, 16, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 8, 8, 64)	0
conv4 (Conv2D)	(None, 8, 8, 64)	36928
batch_normalization_3 (BatchNormalization)	(None, 8, 8, 64)	256
dropout_1 (Dropout)	(None, 8, 8, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 64)	0
conv5 (Conv2D)	(None, 4, 4, 64)	36928
batch_normalization_4 (BatchNormalization)	(None, 4, 4, 64)	256
conv6 (Conv2D)	(None, 4, 4, 64)	36928
batch_normalization_5 (BatchNormalization)	(None, 4, 4, 64)	256
conv7 (Conv2D)	(None, 4, 4, 64)	36928
batch_normalization_6 (BatchNormalization)	(None, 4, 4, 64)	256
dropout_2 (Dropout)	(None, 4, 4, 64)	0
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 64)	0
flatten (Flatten)	(None, 256)	0
fc1 (Dense)	(None, 128)	32896
dropout_3 (Dropout)	(None, 128)	0
fc2 (Dense)	(None, 128)	16512
dropout_4 (Dropout)	(None, 128)	0
fc3 (Dense)	(None, 2)	258

Total params: 227,554
Trainable params: 226,786
Non-trainable params: 768

Figure-3 : CNN calculations of the model

a)Convolution Layer :

The convolution layer applies a filter to an array of pixels in order to extract features from the input image as it is the first layer to do so. This layer will preserve the correlation between the pixels by learning image features, by using small squares of input data. This is essentially a mathematical operation that produces a feature map from two inputs, the image matrix and the filter.

b)Polling Layer :

A pooling layer reduces the pattern length of function map. It enables to system quicker as it reduces the full range of parameters a community desires to system. The output of a pooling layer is a pooled function map. Two methods to create a pooled function map.

• Max pooling
• Average Pooling

Average pooling differs from max-pooling as it keeps statistics this is much less essential in a pooled function map. Max pooling throws away those much less essential features, with the aid of using selecting the most cost of the pooled function map

c)Flattening :

Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. We flatten the output of the convolutional layers to create a single long feature vector. And it is connected to the final classification model, which is called a fully-connected layer. In other words, we put all the pixel data in one line and make connections with the final layer. After this the image matrix of flatten layer is forward to fully connected Dense layer in order to produce output.

Data is flattened when it is made into a 1-dimensional array for input into the following layer. We flatten the convolutional layer output to produce a solitary, lengthy feature vector. Additionally, it is linked to the last classification model, also known as a fully-connected layer. To put it another way, we connect the last layer to the single line containing all the pixel data. In order to provide output, the image matrix from the flatten layer is then forwarded to the densely connected fully connected layer.

VI. RESULT

This model is trained with a 200 epoch values with 128 batch size. The batch size is a number of samples processed before the model is updated. The number of epochs is the number of complete passes through the training dataset.

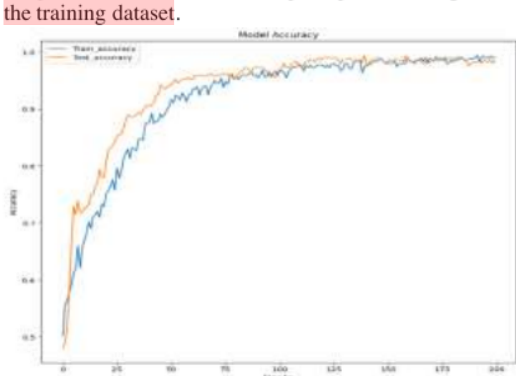

Figure-4: Train_accuracy and Test_accuracy

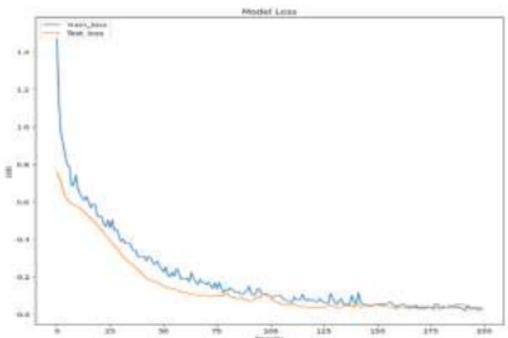

Figure-5: loss and val_loss

	precision	recall	f1-score	support
0	0.99	0.98	0.99	169
1	0.98	0.99	0.98	122
accuracy			0.99	291
macro avg	0.98	0.99	0.99	291
weighted avg	0.99	0.99	0.99	291

Figure-6: Classification Report of the Driver Drowsiness model

Figure-7 : Detection of drowsiness from webcam

In the above figure-7 we show the drowsiness that is detecting from the webcam where we use the open cv library in python to open web cam. We load our trained CNN model in this open cv implementation to know whether the driver is feeling drowsy or not. If the driver closes the eyes alarm ring to alert the driver

Despite good results, when the model is tested on a completely new person, that was not included in dataset, a neural network struggles to identify drowsiness in a person's fascial expression and suggesting a person is aware most of the time. Efficient gesture that is recognized in other people is slight head falling. On the other hand, all the videos of captured subjects, even ones recorded later, were recognized successfully. The Accuracy of our model is 98%.

VII. CONCLUSION

In this article, we suggest a technique for eye state-based driver fatigue identification. High accuracy is offered by the eye state detection technique. We can determine the PERCLOS and blink frequency parameter using the state of the eyes, which allows us to identify drowsy driving early enough to prevent mishaps.Experimental findings demonstrate that our approach produces a significantly more reliable and precise state recognition. The technique can be used as long as you are donning glasses. In order to increase the real-time performance and detection precision, we plan to integrate additional fatigue parameters into our system and optimise the parameters of the existing model.

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