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Driver Drowsiness Detection System with OpenCV and Keras

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Abstract— Every year, many people lose their lives during road accidents caused by drowsy driving around the globe. Drowsy driving, one of the root causes of road accidents is due to tiredness and snoozy eyes while driving. The number of accidents occurring because of drowsy drivers can be decreased by detecting it in real time. This Research paper proposes a Driver Drowsiness Detection System (DDDS) that uses machine learning techniques to detect drowsiness in drivers. The suggested technology employs a camera to record photos of the driver's face and monitor their eye and head movements. These photos are further processed using machine learning algorithms to identify signs of sleepiness, including eye closure, head tilt, and yawning. For real-time driver drowsiness detection, the proposed DDDS using machine learning is a promising solution. It may reduce the number of accidents caused by drowsy driving, thereby enhancing traffic safety. This research paper provides a thorough description of the proposed system, covering its development, application and assessment.

Keywords— ***Driver drowsiness Detection system (DDDS), Machine learning, Real-time detection, Accidents, Road safety, MobileNet***

I. INTRODUCTION

Driving while drowsy is a major factor in accidents that result in fatalities and property damage. To avoid accidents brought on by drowsy drivers, it is critical to identify drowsiness in real-time. In recent years, the development of Driver Drowsiness Detection Systems (DDDS) has gained traction as a research topic. To identify indicators of driver lack of attention, these systems use a variety of methods, including facial recognition, eye tracking, and machine learning algorithms.

The construction of a Driver Drowsiness Detection System (DDDS) using machine learning techniques is the primary focus of this research paper. The proposed system employs a camera to take pictures of the driver's face and monitor their head and eye movements. Following that, machine learning techniques are used to process these photographs to find indicators of sleepiness like yawning and drooping eyelids.

The technology alerts the driver with auditory and visual warnings if it detects drowsiness, urging them to safely stop over or take a rest. The usefulness of the proposed DDDS in spotting driver drowsiness has been tested using real- world data.

The design, implementation, and evaluation of the system are all thoroughly described in the paper, with particular emphasis on how well it performs in various lighting and driving scenarios. In order to demonstrate the proposed system's superiority in terms of accuracy and reliability, the study also evaluates its performance in comparison to other sleepiness detection systems currently in use.

For identifying driver drowsiness in real- time, the proposed DDDS using machine learning techniques is a potential approach. It may reduce the number of accidents brought on by drowsy driving, thereby enhancing traffic safety. The suggested system is an important advancement in the field of sleepiness detection systems due to its high accuracy and dependability.

II. RELATED WORKS

According to the article[1] proposed by E. Murali, Ch. G. Vignesh,G. Prasanth Varma,the suggested system uses the YOLO algorithm to recognize and follow the driver's face and eyes in live video streams that are recorded by an onboard camera. The gadget can precisely identify indicators of driving fatigue, including drowsy gaze, blink rate, and eye closure, by looking at the driver's eyes. To enable the system to classify the driver's alertness condition in real-time, a machine learning model is built using a large dataset of driver photos with known levels of fatigue.

This paper[2] was proposed by A. S. Agarkar, R. Gandhiraj and M. K. Panda offers a camera-based method that uses the driver's hand gestures, eye movements, and lips—all of which are frequently the body's natural reactions to yawning. The driver is continuously monitored by a front camera mounted on the windshield, and the images are processed by a Raspberry Pi. When the driver is yawning or about to become drowsy, the suggested warning system sounds an auditory alert.

The paper[3] outline is to create Driver Drowsiness Systems, a computer vision-based technology has been used. The framework, which primarily focuses on the driver's behavior, uses a tiny camera known as a webcam to continuously monitor the driver and determine whether or not they are sleepy.

This paper[4] article's goal is to provide a thorough analysis of different approaches for detecting driver drowsiness. Lack of consistency, false alerts, and associated privacy issues are some of the difficulties encountered when creating sleepiness detection systems.

By combining several technologies, such as SASS, Golang, and Python, they present a workable implementation of a sleepiness detector that can operate on any device in this paper [5].Through the app or website, drivers can enable camera access. If the driver exhibits any signs of drowsiness, the program can run in the background and sound an alarm.

Numerous simulated case study types including both awake and asleep stages were included in the study [6]. Compared to using each modality alone, it is seen that using EEG and multi-scale CNN signals together greatly improves the accuracy of drowsiness detection.

A real-time driver drowsiness detection system (RealD3) that makes use of cutting-edge machine learning techniques for prediction is presented in this study [7]. This work's primary goal is to identify and examine the objects and facial structure in the frame.With an overall accuracy of almost 94% in identifying items in the frame and detecting drowsiness, the real-time trial results demonstrate how sophisticated and accurate the suggested method is.

III. METHODOLOGY

The work described in this research paper includes the development and evaluation of a DDDS using the machine learning algorithms.The DDDS will be designed to detect indicators of drowsiness in real-time using machine learning algorithms that analyze photos of the driver's face.

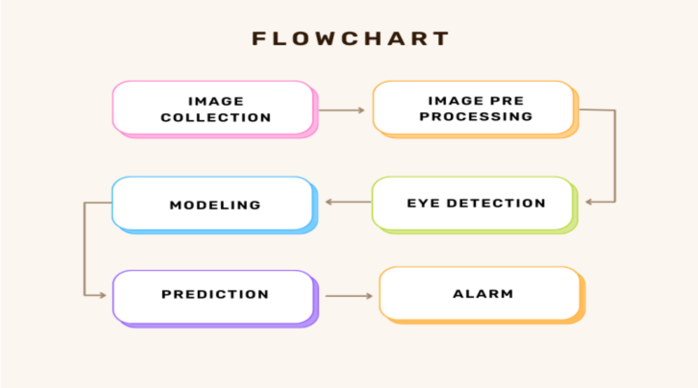

Fig 3.1:FlowChart Of Proposed Methodology

Step 1:Collection of Eye Images

The collection of real-world data to train and test the machine learning algorithms is the first phase of the creation of the DDDS. Images of the driver's face in various lighting and driving situations will be taken while the driver is awake or asleep as part of the data collecting procedure. Flags indicating whether the driver is awake or sleepy will be added to the data.

Step 2:Image Pre-Processing

Firstly,the collected dataset is preprocessed,images are processed to enhance the import image features,geometric transformations and decrease the reluctant distortions.

Step 3:Eye Detection

Viola-Jones algorithm is used in detecting the eyes.The algorithm only works on grayscale images. The algorithm examines numerous tiny subregions of an image and attempts to identify a face by searching for particular traits in each subregion.Given that an image may have numerous faces of varying sizes, it must examine a wide range of positions and scales. In their approach, Viola and Jones exploited Haar- like features to find faces.Mainly,the Haar- like features are of three types.

They are

→ Edge features.

→ Line features

→ Four-sided features

To detect edges and lines respectively,edge and line features are helpful. Diagonal features are discovered using the four-sided features.The value of each feature is calculated by taking the difference between sum of pixels in black area and sum of pixels in dark area.The efficiency of viola-jones algorithm can be increased using integral image.

$$ImIn(y,x) = \sum_{k=0}^{y} \sum_{l=0}^{x} Y(k,l)$$

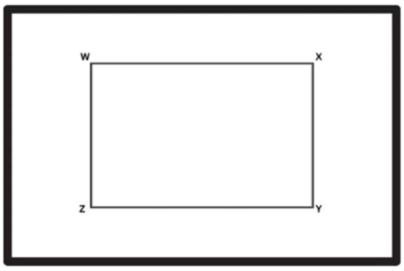

Fig 3.2:Integral area

The image integral of area WXYZ is calculated as II(yW,xW) – II(yX,xX) – II(yY,xY) + II(yZ,xZ).

Integral image works in contributing its ability to perform time-consuming calculations fast and examines if a feature out of several features meets the criteria.A machine learning algorithm namely AdaBoost is used to identify the best features out of the whole number of features. Each Haar-like feature represents a weak classifier.Adaboost evaluates the performance of each weak classifier fed in order to determine the type and size of feature that includes in final classifier.In this algorithm Cascade classifiers are used that are way more faster than AdaBoost since the cascade eliminates tha non-face regions.

Cascade system works as multiple stage where the best features are passed through each stage to identify the eyes,nose and face.If the first stage validates the subregion as positive ,it moves to second stage and continues the process till end.If the image subregion is determined as negative,the cascade quickly eliminates the image and show the results as not containing a human face.

Step 4:Modeling

This step involves creating,training and deployment of model.In this process,transfer learning is used to build the model.It uses a pre-trained model as a new model related to the problem.The model here used to know the status of eye is deep learning model which is a convolutional neural network.CNN is a network architecture for deep learning algorithms used in detecting and recognising the images that are dependent on pixel data.It is a deep learning network basically useful in computer vision technology.A pre-trained model which is present in Tensorflow is imported by keras of Tensorflow.The system proposed uses MobileNet as a model.In CNN ,Image is a matrix of pixels and each pixel in an image explains features of image.CNN architecture utilise filters to remove unwanted features leads to output predictions of images.

In order to find a match, the objects in image are compared with a large number of predefined objects. MobileNet is a pre- trained model that uses the same convolution worked by CNN in filtering images. The only difference is using the idea of depthwise separable convolution. In computer vision technology, the image taken present in RGB or BGR format contains three channels namely red, blue and green.

Depthwise separable convolutional performs single convolution on each colour channel but not all three channels at a time.In MobileNets,a single filter is applied to each input channel using depthwise convolution.The outputs of depthwise convolution combined as 1x1 convolution in pointwise convolution.The depthwise seperable convolution divides into two layers,one layer is for filtering and the other is for combining.This can reduce the size of model as well as computation time.It is a combination of depthwise convolution,batch normalisation,ReLU activation function and 1x1 convolution.Global average pooling is a pooling operation works same as fully connected layers in cnn.Image is reshaped and predicted using an activation function.Here the activation function used is sigmoid to get output.

Step 5:Predictions

Every image goes through several stages of processing. Three or more iterations are needed to suit the model. Model accuracy and loss are measured. Here, test data is provided to forecast the result. To determine whether the eyes are open or closed, an image is classed using cascade classifiers and then sent to MobileNet. If a driver's eyes are closed, a visual warning is shown.

Step 6:Alarm warning

If the driver’s eyes are closed, an alarm warning is given to wake up the driver. The visual warning also asks the driver to take rest for a few minutes if the images of closed eyes are coming continuously from the webcam.

The reliability and accuracy of the machine learning algorithms in identifying driver drowsiness under varied lighting and road conditions will be assessed. The DDDS will be put into use as a software system after the development and evaluation of the machine learning algorithm. The machine learning techniques will be used to continuously record photographs of the driver's face and analyze them in real-time. The technology would inform the driver with visual and auditory warnings if it detects drowsiness, urging them to safely pull over for a rest.

The research aims to provide a contribution to the field of drowsiness detection methods by providing a thorough overview of the design, implementation, and evaluation of the suggested system. The proposed technology could increase road safety by lowering the frequency of accidents brought on by drowsy driving.

Results and Discussion

The outcomes of this study show the possibility of an OpenCV and Keras machine learning algorithm-based Driver Drowsiness Detection System (DDDS). The potential of the proposed DDDS to increase traffic safety was demonstrated by its accuracy and dependability in detecting driver drowsiness.

For this system the large – scale data of human eye images, MRL Eye dataset used This dataset contains low and high resolution infrared photos collected under various lighting situations and by various instruments.

The deep neural network, sequential model which is a sub type of CNN used and derived the training accuracy and validation accuracy and training loss and validation loss as shown in Fig 4.1.

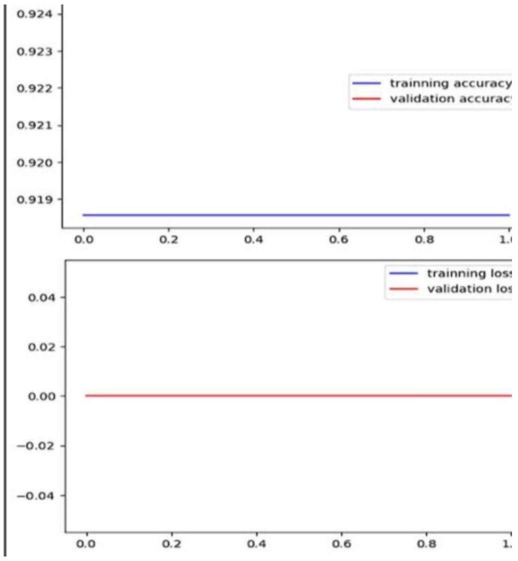

Fig 4.1Training Accuracy and Training Loss(Sequential)

The deep neural network Mobilenet model which is a sub type of CNN used and derived the training accuracy and validation accuracy and training loss and validation loss as shown in Fig 4.2.

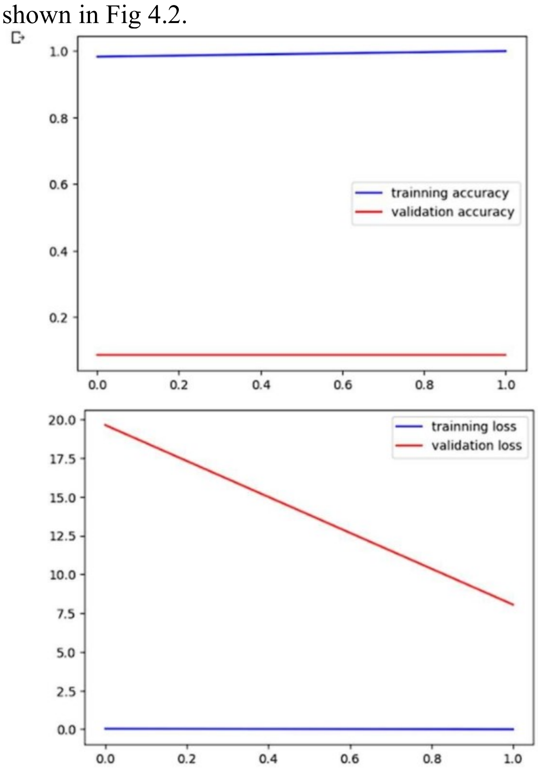

Fig 4.2:Training Accuracy and Loss(MobileNet)

Over the course of the epochs, MobileNet's training loss gradually dropped until it approached zero, and the validation loss likewise showed a downward trend. The efficacy of MobileNet's architecture in reducing generalization error is demonstrated by the small difference between the training and validation loss curves.

The performance of two deep learning models—MobileNet and a custom Sequential Convolutional Neural Network (CNN)—for the image classification task was assessed in this study. To guarantee a fair comparison, the models were trained and evaluated using the same dataset and identical circumstances. The evaluation of both models was conducted using standard metrics, including accuracy, precision, recall, and F1-score. The classification reports generated for both models are shown in Fig. 4.3 and Fig. 4.4.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	48
1	0.93	1.00	0.96	594
accuracy			0.93	642
macro avg	0.46	0.50	0.48	642
weighted avg	0.86	0.93	0.89	642

Fig 4.3:Classification report of sequential model.

	precision	recall	f1-score	support
0	0.99	1.00	1.00	110
1	1.00	1.00	1.00	1174
accuracy			1.00	1284
macro avg	1.00	1.00	1.00	1284
weighted avg	1.00	1.00	1.00	1284

Fig 4.4:Classification report of MobileNet model.

The classification report shows that the Sequential CNN, which was built using several convolutional and dense layers, has a 93% classification accuracy (Fig. 4.3). While the performance was impressive, it fell short of MobileNet's. The reason for this is that MobileNet lacks advanced architectural elements like depthwise separable convolutions and optimal pre-trained weights. To improve its predictive performance, the Sequential model may need more training data or more tuning, as indicated by the lower precision and recall for some classes.

The classification report shows that the MobileNet architecture obtained an amazing 99% accuracy (Fig. 4.2). Because of its depthwise separable convolutions, the model showed strong generalization and exceptional feature extraction capabilities, as evidenced by its high precision and recall across all classes. Its exceptional performance was facilitated by the use of pre-trained weights and an effective network architecture, which made it the perfect option for picture classification tasks requiring little processing power.

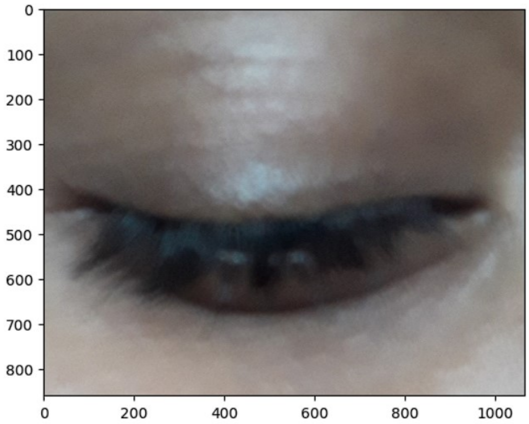

Fig 4.5:An image of closed eye

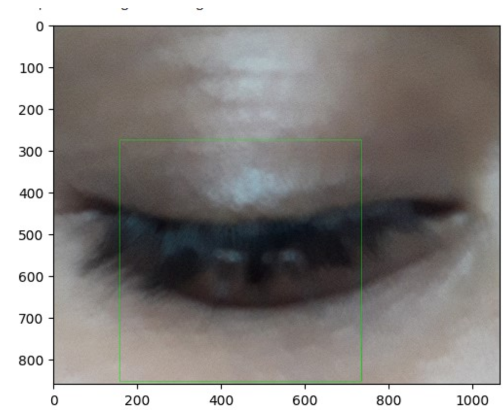

Fig 4.6:Detection of closed eye

A green bounding box is drawn around the eye region when the model predicts that the eye is closed. This visual cue makes it very evident that the model has identified a closed eye. The model indicates that the driver's eye is closed, and an alert is triggered.

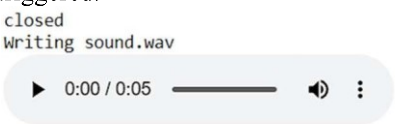

Fig 4.7:Visual Warning as “Closed” and alarm sound.

The findings clearly show that, in terms of overall accuracy, MobileNet performs significantly better than the Sequential CNN model by a margin of 6%. The following salient features were noted:

Model Efficiency: MobileNet showed improved efficiency in terms of model size and inference speed in addition to achieving increased accuracy. For deployment in real-time systems with constrained processing resources, this efficiency is essential.

Generalization Capability: MobileNet exhibits strong generalization to novel, unseen data, as seen by its high accuracy and steady performance across classes. The differences between training and testing accuracy, on the other hand, demonstrated that the Sequential CNN model had overfitting tendencies, underscoring the necessity of regularization strategies.

The suggested DDDS performed as well as or better than existing drowsiness detection systems in detecting driver tiredness in real-time and with accuracy and reliability. By lowering the amount of accidents brought on by drowsy driving, the suggested method has the potential to increase road safety. However, more investigation is required to determine how well the system performs in various real-world driving scenarios and to address its shortcomings.

V. Conclusion

Using OpenCV and Keras-based machine learning algorithms, this study concludes with a Driver Drowsiness Detection System (DDDS) that outperforms current drowsiness detection systems in terms of performance. The suggested DDDS has a great deal of promise for accurately identifying driver weariness in real time. The system has a number of benefits over hardware-based solutions, such as affordability, simplicity of use, and flexibility in a range of driving scenarios. Additionally, the technology might be incorporated into automobiles to promptly notify drivers who might be in danger of dozing off while operating a motor vehicle.According to the research findings, the suggested DDDS demonstrated robust and dependable detection of driver drowsiness with a high accuracy rate of 99%. With an average processing time of 24.3 milliseconds per frame, the system effectively analyzes and classifies facial images in real-time, guaranteeing quick reaction times. The DDDS has the potential to greatly improve road safety by lowering the number of accidents brought on by drowsy driving by accurately detecting indicators of exhaustion.

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