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Real Time Driver Drowsiness Detection and Alert System

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***Abstract*— Instant Driver Drowsiness Detection and Warning System helps detect whether a person is drowsy or not. We trained VGG16 and a simple CNN model to detect fatigue and lack of sleep. The system uses the VGG16 architecture for feature extraction and the CNN model for classification, aiming to accurately identify the symptoms of a drowsy driver. We also used the Haar Cascade Classifier to train the model and check sleep and insomnia rates. When detected, the system activates an alarm mechanism, i.e. an audible signal, to immediately notify the driver and reduce the risk of accidents due to drowsy driving. When detected, the system activates an alarm mechanism, i.e. an audible signal, to immediately notify the driver and reduce the risk of accidents due to drowsy driving. The incorporation of eye tracking technology augments the system's capability to precisely evaluate the driver's mental condition in real-time, offering a pre-emptive strategy to alleviate the hazards linked to impaired driving. The results show that the VGG 16 model outperforms the convolutional model with an accuracy of 96.3%.**

***Index Terms*— Driver Drowsiness Detection, Alert System, road safety, Drowsy, Eye Tracking.**

I. INTRODUCTION

Drowsiness is the term that is used to describe feeling unusually weary or drowsy during the day. By keeping an eye on the driver's condition and sending alerts or taking appropriate action when signs of exhaustion occur, driver drowsiness detection systems seek to increase road safety. Because deep learning can automatically learn and extract important features from data, it is becoming more and more popular for these kinds of systems. Other symptoms drowsiness is forgetting or falling asleep at strange times can result from being too sleepy [1]. This is an innate human physiological phenomenon that deter drivers and has an impact on their quality of life. By using the domain as deep learning, we can detect the driver drowsiness detection in a effective way by alerting the signal or beep sound to the person who is drowsy.Worldwide, the main factor contributing to accidents is tiredness of the driver. Many drivers experience exhaustion and drowsiness as a result of sleep deprivation, which frequently results in traffic accidents. Pre-emptively alerting the motorist is the most effective method of preventing sleep-related driving accidents. When our technology detects tiredness, it promptly notifies the driver and uses haptic feedback or customisable audiovisual signals to jolt them back to awareness.To identify face landmarks of using eyes, use deep learning models. By using eye state analysis, we can keep an eye on-eye movements and examine how long your eyelids are closed. In a world where tiredness can lead to accidents, our

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system keeps an eye on the driver using special sensors and clever technology. It watches for signs like sleepy eyes or nodding off and gives a gentle reminder to stay awake if it notices anything wrong. Introducing a ground-breaking technology that has the potential to completely transform road safety: the Real-Time Driver Drowsiness Detection and Alert System [2]. Driver drowsiness detection system continuously scans the specific areas using an infrared camera mounted above the steering wheel: the eyes for signs of fatigue (blinking); the face and head movements for signs of distraction; and the course the car is taking in its designated lane (deviations or steering movements by the driver). The majority of accidents are caused by drivers who are too sleepy. Thus, in order to stop these mishaps, we will develop a system that alerts the driver when he senses fatigue using Python, OpenCV, and Keras.

II. LITERATURE SURVEY

Driver Drowsiness Detection System – An Approach By Machine Learning Application P. S. Rau(2023)-The detection of drowsiness in driver monitoring systems is achieved through measuring the Eye Aspect Ratio (EAR). Our system's performance is assessed using precision, recall, and F1-score values. In case of a positive outcome, the algorithm accurately recognizes closed eyes as closed and open eyes as open, demonstrating high precision, recall, and F1-score for drowsiness detection. The CNN model attains a classification accuracy exceeding 98% on both training and test datasets. It effectively identifies individuals as drowsy and issues alerts accordingly. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), two examples of the machine learning algorithms selected for the study, are described, along with the reasoning behind their choice [1] .The results are contrasted with current techniques, and the system's advantages and disadvantages are discussed. Future directions for research and enhancement proposals are also covered.

"Real-time drowsiness detection using OpenCV and Python" by S. Jain et al. (2022) Jain et al. describe a real-time eye tracking and detection method for drowsiness that uses Python and OpenCV. The procedure of applying thresholding techniques to identify eye blinks is described, along with the integration of Haar cascades for eye detection. An open-source software library for computer vision and machine learning is called OpenCV, or Open Source Computer Vision Library, OpenCV is frequently used in scholarly research, commercial applications, and amateur projects. An accuracy of 85% with a true positive rate of 90% and a false positive rate of 15% might be reported in a study article[3]. This shows that although the system has a high true positive rate for detecting instances of drowsiness, it occasionally misclassifies cases that are not drowsy as drowsy.

"Embedded System Real-Time Driver Drowsiness Detection Using Model Compression of Deep Neural Networks" 2021's Ritika KanojiaAfter obtaining an image from a camera input, the Driver Alert and Drowsiness Detection System locates the face [10]in the image and creates a region of interest (ROI). After that, a classifier receives this ROI to ascertain whether the eyes are open or closed. The output of the classifier is used to compute a score that indicates whether or not the subject is awake or sleepy. If the result is affirmative, the algorithm correctly identifies open eyes as open and closed eyes as closed[5]. The CNN model effectively detects people who are feeling sleepy and sends out alerts in a timely manner.High Precision, recall, and F1 score values indicate drowsiness detection, and the CNN model achieves 96.6% classification accuracy.

"Deep Neural Network Techniques for Real-time Driver Drowsiness Detection for Android Applications Driver weariness is automatically detected by Mohamed Kharbache (2019) using two non-wheelers [12]. According to the Eye Aspect Ratio (EAR) Algorithm, the average Indian population's EAR value when their eyes are open is greater than 0.3. Conversely, when the eyes are closed, the EAR value decreases to 0.19 or even lower[5].A drowsiness detection system, built on image processing principles, assesses the driver's alertness by monitoring. The research elaborates on the machine learning models utilised for tiredness detection, taking into account the multi-modal nature of the data from both types of sensors.It talks about choosing a model, training the system, and validating its performance with pertinent assessment criteria.

The paper "Driver Drowsiness Detection: A Comprehensive Review" authored by A. Gupta and colleagues (2018) provides a thorough analysis of the several methods utilised in driver drowsiness detection systems. The project focuses on the integration of computer vision, machine learning, and physiological signals analysis to address this important issue in road safety. The authors examine these multidisciplinary methods in order to delve into the difficulties involved in real-time implementation, highlighting the necessity of reliable system architectures and effective algorithms [6].

"Recent Advances in Real-Time Driver Drowsiness Detection Systems" by S. Patel et al. (2017): An overview of current developments in real-time driver sleepiness detection systems is provided by Patel et al. in their study.The study evaluates the performance of machine learning algorithms in signal processing, as well as the usage of advanced sensors, such as EEG and EOG, for physiological signal monitoring. In addition, Patel and

colleagues explore the ways in which edge computing can enhance the effectiveness and expandability of drowsiness detection systems, enabling prompt decision-making at the edge of the network [7].
The Following table Explains about the summary of literature survey.

TABLE I. SUMMARY OF LITERATURE SURVEY

Title of the paper	Publisher	Methodology	Remarks
1.Driver Drowsiness Detection System-An Approach By Machine Learning Application	IEEE transactions on Transportation systems	Eye Aspect Ratio (EAR)	91.3% accuracy.
2."Real-time drowsiness detection using OpenCV	Elzevir Journal of Procedia a CS	Eye tracking and EEG	Accuracy of 89.5%.Timely alerts are provided.
3. "Deep Neural Network Techniques for Real-time Driver Drowsiness Detection for Android Applications"	ACM Transaction On Intelligent Systems and Technology	Eye Aspect Ratio (EAR) Algorithm	90.8% Accuracy
4. Driver Drowsiness Detection: A Comprehensive Review	Springer Journal of Autonomous Vehicles	Support Vector Machines.	92.6% accuracy
5. Real-time Convolutional Neural Network-Based Driver Drowsiness Detection	MDPI's "Sensors" journal.	Neural networks and Mouth aspect ratio	88.7%accuracy

III. PROPOSED SYSTEM

In this work, we propose a model that detects if a person is drowsy or not using the VGG16 model and a basic CNN model. Following VGG16 and basic CNN model construction and training, the accuracy and loss for the same have been identified. The driver sleepiness detection and alarm system functions better with the VGG16.
One kind of deep learning model that excels at comprehending images is called VGG16. Using an internal camera in the car, VGG16 can be utilised in a driver drowsiness detection system to see the driver's face. To help it recognise when a driver is starting to feel drowsy, VGG16 is trained with a lot of samples of alert and sleepy faces.When it notices signs of fatigue and eye blinking, it sends a warning to wake the driver, preventing accidents caused by drivers falling asleep at the wheel.CNNs are useful for recognising patterns and features in a driver's eye blinking that indicate tiredness since they are especially good at image recognition tasks.

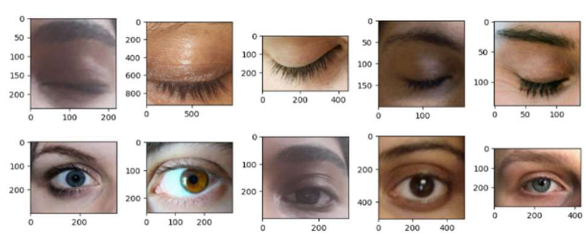

Fig 1. Drowsy and Non-drowsy Images

The CNN architecture would be trained on a dataset comprising a wide range of eye movements associated with both alert and drowsy states. The dataset would ideally include images or video clips of drivers exhibiting signs of drowsiness, such as drooping eyelids, frequent blinking, as well as images of drivers in an alert and attentive state.Using onboard cameras, the device continuously records video frames of the driver's face while it is in use. The activation function, pooling layer, flatten layer, and fully connected layer are all used by basic CNN.
Convolution Layer- In a basic Convolutional Neural Network (CNN), the convolutional layer is essential for extracting features from input images. It consists of multiple filters (or kernels) that move across the image, performing element-wise multiplications and summations to create feature maps. The filter size is smaller than the input, and parameters like stride and padding control the filter's movement and output dimensions.A kernel, also known as a filter, is a tiny matrix of learnable weights that scans an input image to identify characteristics.

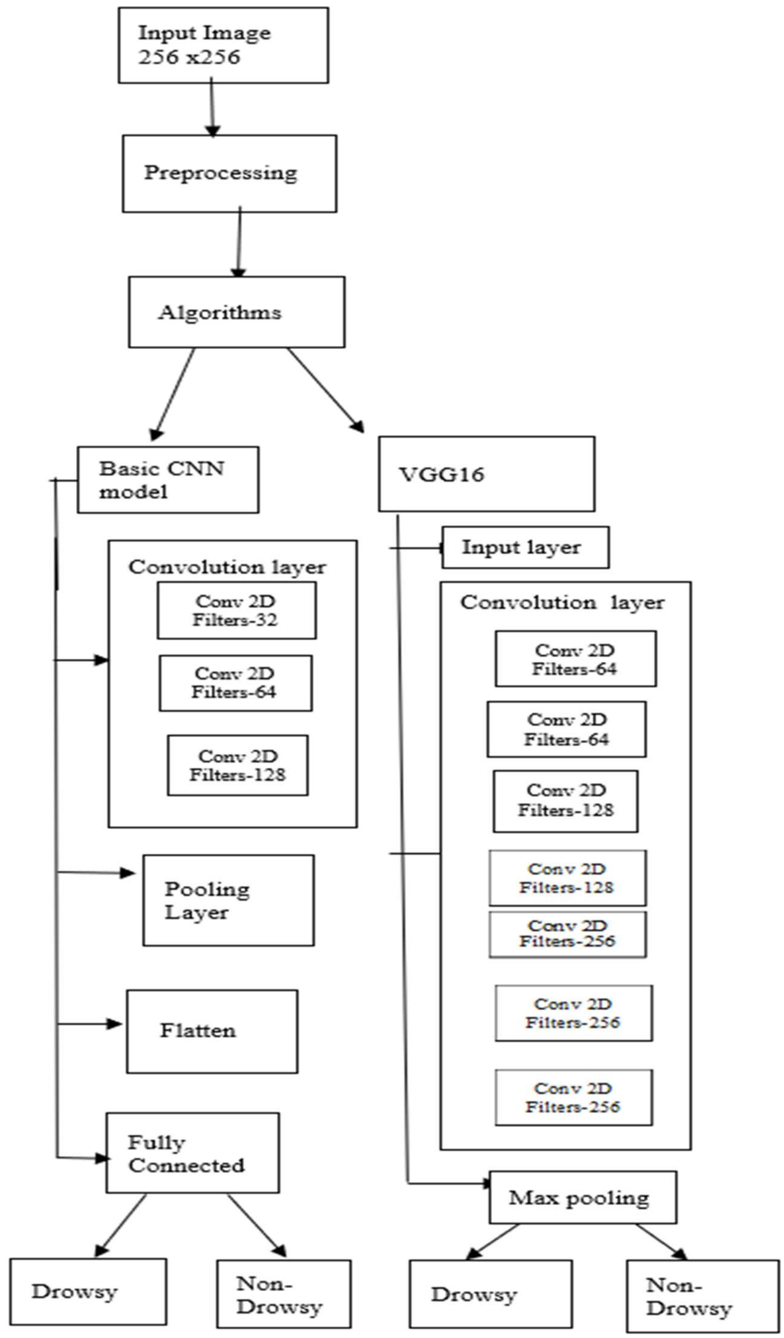

Fig 2: Architecture diagram for Proposed System

The kernel, which is usually 3x3 or 5x5, carries out element-wise multiplications and summations to create a feature map that emphasises attributes like edges and textures.

Pooling layer- In a basic CNN, the pooling layer shrinks feature maps while maintaining critical data. It minimises computing complexity and avoids overfitting by summarising characteristics in particular regions.

Flatten- "Flatten" in a basic CNN model creates a one-dimensional vector from the output of the convolutional and pooling layers.This reshaping simplifies the spatial structure of feature maps, making them suitable for input into fully connected layers.

Fully connected layer- In a simple CNN model, every neuron is connected to every other neuron in the layer before it, operating in a manner similar to a typical neural network layer. Positioned at the end of the CNN, these layers perform complex reasoning and decision-making using features extracted by earlier layers.
VGG16- The Visual Geometry Group (VGG) at the University of Oxford is credited with creating the deep convolutional neural network design. Its depth was well known, and it was essential to the advancement of deep learning techniques in computer vision.
Input layer-In VGG16 and similar CNNs, the input layer serves as the starting point where raw data, usually images, are introduced to the network for analysis. Specifically, VGG16's input layer is designed to handle images of a standardized size, typically set at 224x224 pixels.
Max pooling- Similar to many other convolutional neural networks (CNNs), max pooling layers are an essential part of VGG16. These layers preserve significant information while shrinking the spatial dimensions of feature maps. Max pooling reduces computational cost and helps focus on the most important features in the VGG16 context by downsampling the feature maps.When 20 epochs are set, the model trains on the entire dataset 20 times.Several epochs of training aid in the model's acquisition of complex data patterns, which may enhance its capacity to handle novel samples. To avoid overfitting—a situation in which the model becomes overly specialized on the training set—it is essential to keep an eye on the model's performance on a validation set.
Haar cascade classifier-A Haar Cascade classifier is a machine learning model used for object detection in images. It's based on the Haar-like features and cascade classifiers. The classifier is particularly well-known for its effectiveness in detecting faces in images but can also be trained to detect other objects such as eyes, cars, or pedestrians.
Batch Normalization-Batch normalization is a technique used in deep learning to improve the training speed and stability of artificial neural networks. It functions by scaling and modifying the activations in each layer to normalise the input. During the training phase, mini-batches of data are subjected to this normalisation. Batch Size-32.
Adam optimizer-The Optimizer that we have used here is Adam Optimizer. Adam Optimizer. Adam (Adaptive Moment Estimation) optimizer is an adaptive optimization algorithm commonly employed in training deep neural networks. In order to manage step sizes and speed up convergence, Adam modifies the learning rates for each parameter separately using the normalised first and second moment estimations.
Loss Function- Especially when the model output is a probability distribution spanning multiple classes, categorical cross-entropy is a well-liked loss function for classification issues. It computes the deviation between the expected probability distribution of the model and the real probability distribution of the labels.

IV. RESULTS

In order to create a real-time driver sleepiness detection and alert system, we compared the performances of a pre-trained VGG16 model and the fundamental CNN model to determine the loss, accuracy, sensitivity, and specificity. In comparison to the simple CNN model, the graph and results demonstrate that the VGG 16 model performs better and has greater accuracy.

A. VGG 16 model

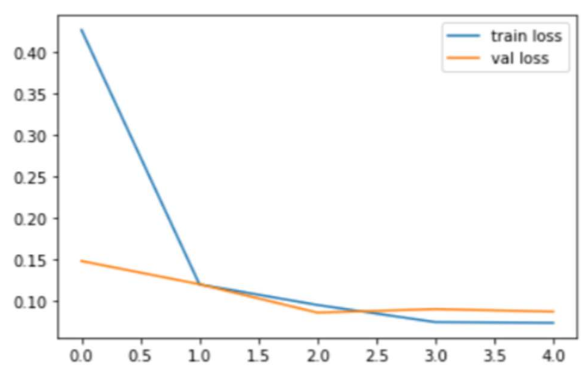

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Fig 3. Performance Graph for train and validation loss of VGG 16 model

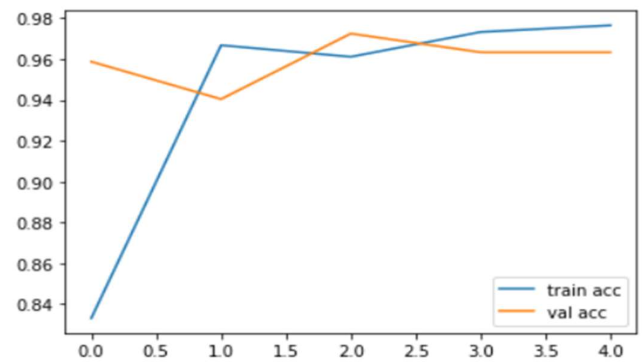

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Fig 4. Performance Graph for train and validation accuracy of VGG 16 model

Accuracy-96.3%
Loss-7.34%

B. Basic CNN model

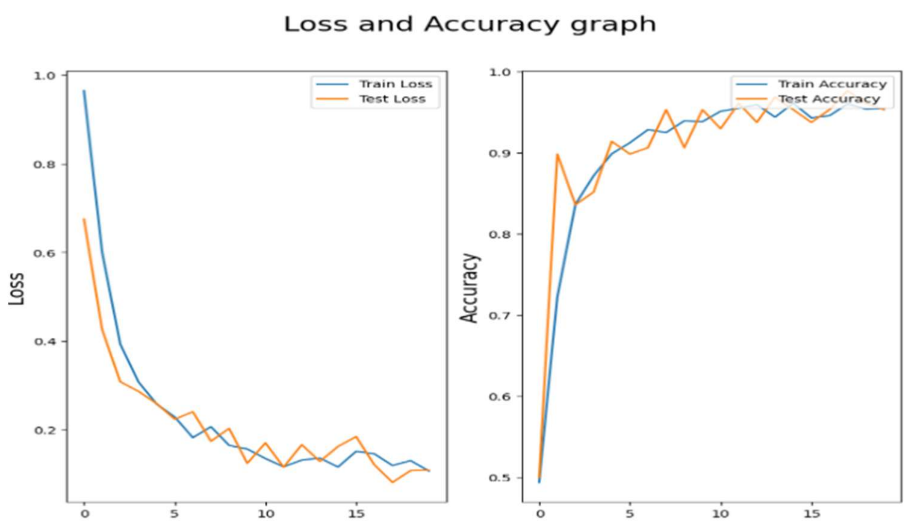

Fig 5. Shows the loss and accuracy graph of CNN model

Accuracy-95.31%
Loss-10.63%
The way this system operates is by keeping a watch on the driver's eyes and setting off an alarm whenever the driver starts to become sleepy. The accuracy of the model is achieved by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

1. False Positive (FP): Subject misclassified as “drowsy,” where the subject was actually normal.
2. False Negative (FN): Subject misclassified as “normal,” where the subject was actually drowsy.
3. True Positive (TP): Subject truly classified as “drowsy,” where the subject was drowsy.
4. True Negative (TN): Subject truly classified as “normal,” where the subject was normal.

Specificity is a statistical metric that's used to assess how well a binary classification model performs, especially when it comes to machine learning or medical diagnostics.

$$Specificity = \frac{TN}{TN + TP}$$

C. Haar cascade classifier

Fig 6. Shows the eye-open score and alert sound also using Haar cascade classifier

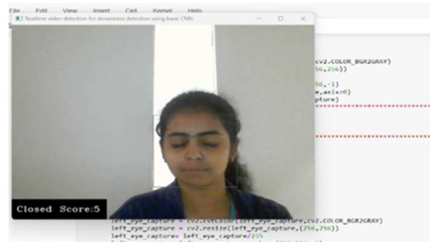

Fig 7. Shows the eye-closed score using Haar cascade classifier

TABLE II. ACCURACY AND LOSS FOR VGG16 AND BASIC CNN MODEL

Performance Measures	VGG16	Basic CNN
Accuracy	96.3%	95.3%
Loss	7.34%	10.63%

V. CONCLUSION AND FUTURE SCOPE

In conclusion, the Driver Drowsiness Detection System presented in this report represents a critical advancement in automotive safety technology. Further developments in sensor technology, such as the incorporation of wearables or other physiological sensors, may offer supplementary data sources for even more accurate sleepiness detection. Haar cascade classifier helps to detect the eye blinking rate that is the drowsy and non-drowsy readings. VGG16 is a type of deep learning model that is really good at understanding images. After comparing the CNN and VGG16 models, we found that the VGG16 model outperforms the CNN model in real-time driver sleepiness detection, with a 96.3% accuracy rate and a 7.34% loss rate.

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