DRIVER DROWSINESS DETECTION USING DEEP LEARNING

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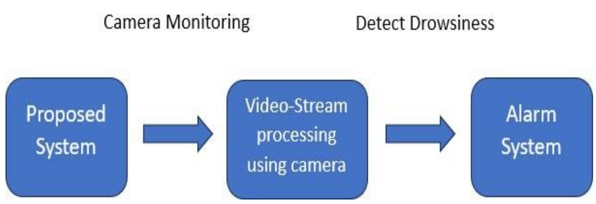
Abstract- **Every day many road accidents are happening across the world and many people are losing their lives in these accidents. The majority of these incidents are caused by drowsy drivers. Drivers with Sleepiness and exhaustion are the critical issues contributing to road accidents. So, a real-time drowsiness detection model using deep learning algorithms is used to avoid these incidents before they occur. By these algorithms, the sleepiness of the driver is detected by identifying the facial landmarks. Convolutional neural networks (CNNs) are used in the proposed system to extract essential features from images of faces taken with an onboard camera. A buzzer alarm is activated when drowsiness is detected to alert the driver and remind them to take the appropriate safety precautions. The accuracy of our well-trained model is 95.5% which helps in easy detection of drowsiness.**

Keywords **- Eye tracking, Yawning detection, Drowsiness detection, Deep learning, Convolution neural network, processing images.**

I. INTRODUCTION

According to reports from the World Health Organization 98% of road accidents are caused by driver faults which include an estimated of nearly 1.3 million people dying every year worldwide. One main reason for such accidents is caused by drowsiness of the drivers. Studies show that drivers driving for long continuous hours and at night are found to be more susceptible to such accidents. Fatigue, which is due to long time traveling is one significant reason for driver drowsiness. To make the roads safer and protect lives, the development of advanced driver assistance systems becomes crucial.This proposed project describes a better solution to detect Drowsiness and fatigue to avoid road accidents. Based on behavior like eye closing, opening, and yawning drowsiness identification process requires a camera. A study of the techniques for sleepiness detection by computer vision is specifically carried out, with an emphasis on the usage of facial reference points.

The primary goal of this conference paper is to provide a user-friendly, cost-effective, and accurate procedure for detecting driver fatigue while driving. To develop this drowsiness detection system, we used CNN architecture. This neural network processes the images that are given in the dataset and recognizes objects. In the First stage, images are processed by the Har cascade algorithm by the OpenCV tool, in the second stage required features like eyes and faces are detected. Here we are using the Harr Cascade algorithm which is. In stage three feature extraction is done by CNN and in the final stage it predicts the output. If sleepiness is detected, an alarm is activated to warn the driver before the accident occurs.



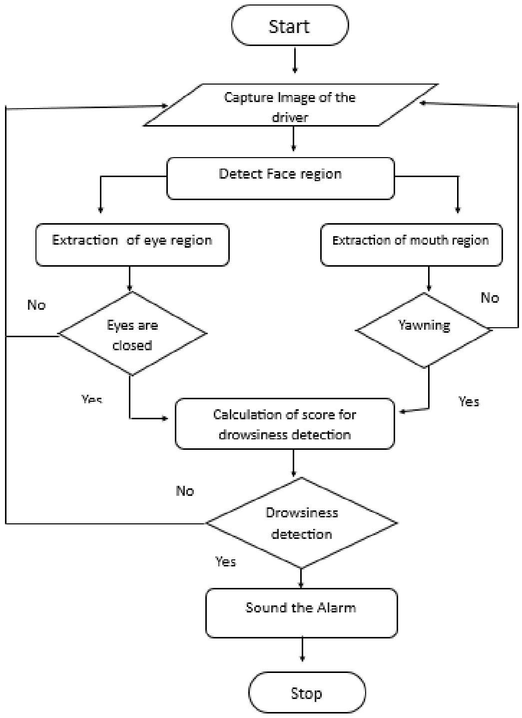
The remaining sections of the paper were arranged as follows: Section II included the literature review, Section III covered the study methodology, Section IV covered the results and analysis, and Section V covered the conclusion.
Our project aims to prevent road accidents through a system called "Detecting driver drowsiness". Using a camera, the system recognizes signs of drowsiness such as closed eyes and yawning. A trained CNN model is used to analyze the driver's facial characteristics, notably their eyes, and lips, once the camera has taken a picture of them. The system extracts

II. REVIEW OF LITERATURE

The [12] proposed work focused on real-time driver drowsiness detection using Convolutional Neural Networks (CNNs), VGG-16,19.In contrast, our approach accompanied the pretrained VGG-16 model with OpenCV and Harr-cascade algorithm as well as the inclusion of an alarm system to activate. The key differences include the type of deep learning algorithm used and alert.
The study [9] was highly sophisticated in its data gathering and processing. In contrast, our research focused on an alternative strategy utilizing deep learning, Convolutional neural networks, the Haar-cascade technique, and the VGG-16 model. The main difference is related to data sources and techniques used Barua et al. used physiological data like EEG and EOG coupled with contextual information, whereas our approach made use of computer vision algorithms on image data. Our approach is based on analyzing facial features which can be more accessible and discreet for real-world applications. The author of [10] utilized multi-channel second-order blind identification techniques, likely involving physiological data. Their method is complicated and would need specialized sensors and equipment, whereas our approach is more approachable and based on computer vision. Research [11] focused on real-time drowsiness detection using eyelid closure as the key measure. Their method targets primarily eye-related movements whereas our research also targets mouth regions like yawning movements.

III. METHODOLOGY

characteristic features and determines whether the driver is sleepy or not. An alarm will sound right away to warn the driver if the model detects signs of drowsiness, such as closed eyelids or yawning, in the driver.



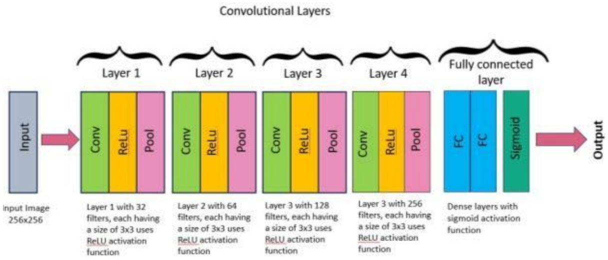
a. *Algorithm*

Object identification using the fatigue detection system is a task related to object detection. We take images by capturing them from the camera. Among all the available algorithms of deep learning, we used the Har cascade algorithm which is popular and significant for object detection.

The input images from the inserted camera are converted into grayscale images which contain only white and black intensity values and do not contain any color information. This grayscale conversion simplifies the processing and reduces computational load. In the grayscale photos, faces can be detected using the Harr Cascade algorithm. The algorithm uses a pre-trained Harr Cascade classifier, which can identify faces using patterns of certain features that have been learned. To identify potential face areas, the classifier moves over the picture at various sizes and locations. After the detection of the face, a region of Interest is extracted around the detected face. Another Harr Cascade classifier is employed to identify the features like eyes and mouth within the region of Interest This classifier is trained to recognize the eye patterns like opening and closing of eyes and facial movements like yawning. Our system also makes use of a pre-trained model called VGG-16, which is very effective at extracting essential parts from images. Relevant features like mouth and eyes are obtained using the model. These obtained features can be sent into a classifier as input to determine the degree of drowsiness of the driver.

b. *Convolution neural network architecture*

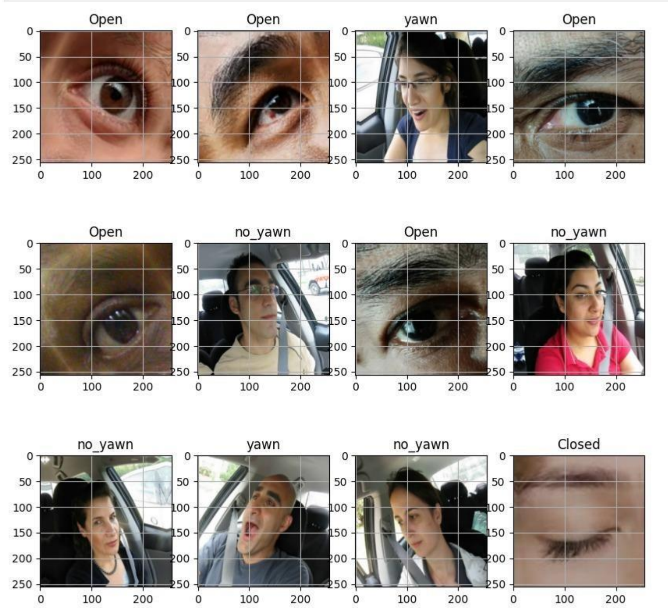
After the detection of eyes and face by using the Harr Cascade algorithm, the resulting Region of Interest which is detected by the Harr Cascade classifier is further processed as input to CNN. For feature extraction, CNN uses several convolutional and pooling layers. Our model starts with a Conv2D layer with 256 filters, and a ReLU activation function is followed by a kernel size of (3,3). Several low-level layers are learned by this layer from input images. After the Convolutional layer, a MaxPooling2D layer is added with a 2×2 pool size which helps to minimize the spatial dimensions and preserve the essential data. ReLU activation function and Maxpooling2D layers, which extract higher level features from the input, are added after the first three convolutional layers, Conv2D with 128 filters, Conv2D with 64 filters, Conv2D with 32 filters, and a 3x3 kernel, to repeat the pattern. A "Flatten" layer, the last layer, flattens the 3D features into a 1D vector. The Dropout layer is followed by two dense layers that are fully connected.



The first dense layer consists of 64 units using a ReLU activation function, while the second dense layer consists of 4units using a Softmax activationfunction. The last layer has 4 units, which correspond to the followingclasses: Open, Closed, Yawn, and No Yawn. To prevent overfitting during training, a Dropout layer with a dropout rate of 0.5 is included. The system is built using the sparse categorical cross-entropy loss, accuracy, and Adam optimizer as the labels are integers.

c. *pre-defined model VGG-16*

The output of the base VGG16 model is subjected to global average pooling (GlobalAveragePooling2D) to decrease the spatial dimensions and provide a fixed-length feature vector for each image. A dense layer of 512 units and a ReLU activation function are added to the model to improve it. This layer assists in learning more complicated characteristics from the data that VGG16 collected. The last Dense layer, which has two units and a softmax activation function, is introduced for binary classification (Open vs. Closed eyes). The output of the base VGG16 model is subjected to global average pooling (GlobalAveragePooling2D) to decrease the spatial dimensions and provide a fixed-length feature vector for each image. A 512-unit dense layer with a ReLU activation function is included to enhance the model. With the help of the characteristics that VGG16 collected, this layer aids in learning more complex features. The final Denselayer is added for binary classification (e.g.: Open vs. Closed eyes, Yawn vs. no Yawn), and it has two units and a Softmax activation function. CNN focuses on identifying drowsiness usingfacial and eye images, as well as the pre-defined VGG16 model that distinguishes between open and closed eyes. These two strategies will be combined to increase the efficacy of driver sleepiness detection.

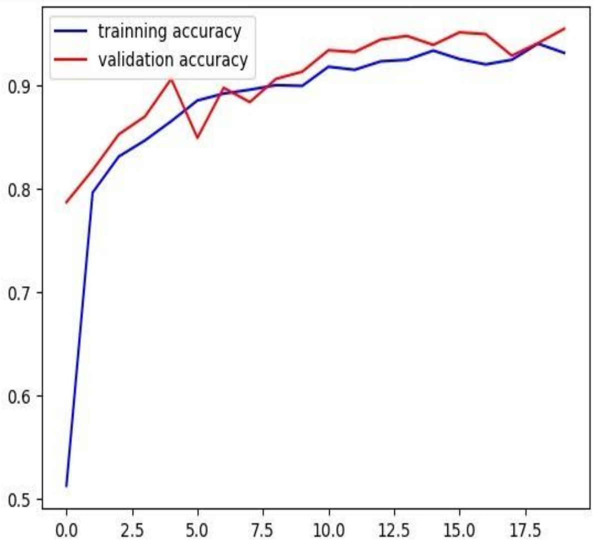


The entire dataset is split into training and testing sets. Out of 8000 images that are present in the dataset,6000 images are utilized in the training set for CNN training, 1000 images are used for the testing, and the remaining images i.e.,1000 images are used for the validation to evaluate its performance.

IV. RESULTS AND ANALYSIS

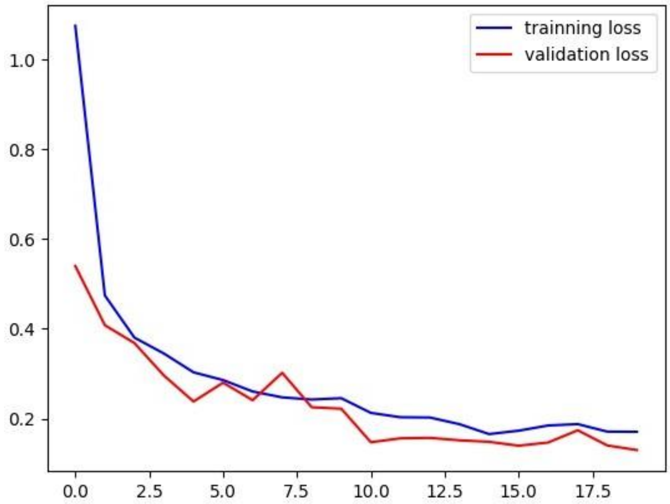
In this section, we demonstrate results obtained during training and validation of the driver sleepiness detection system using CNN. The model is trained for 20 epochs and the results of it were evaluated by tracking the performance metrics.

The following graphs explain the accuracy of training and validation and the loss of movement and validation.

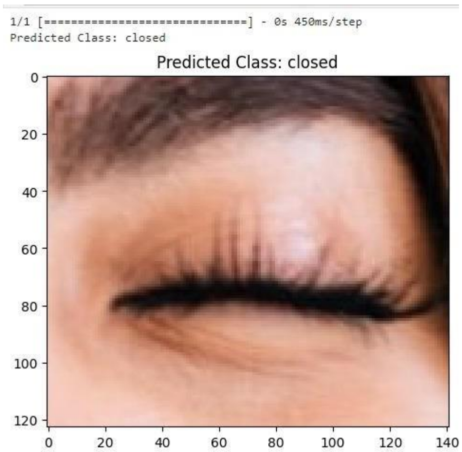


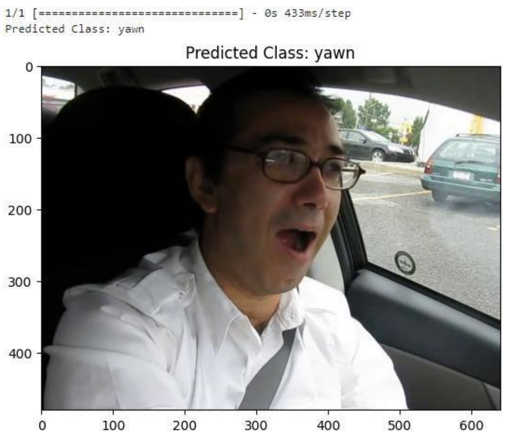
The above graph shows the accuracy of training and validation, the accuracy of training steadily increases, obtaining around 93.17% accuracy by the 20th epoch. This demonstrates that the model is learning to recognize patterns in the training dataset that are related to sleepiness and non-drowsiness.

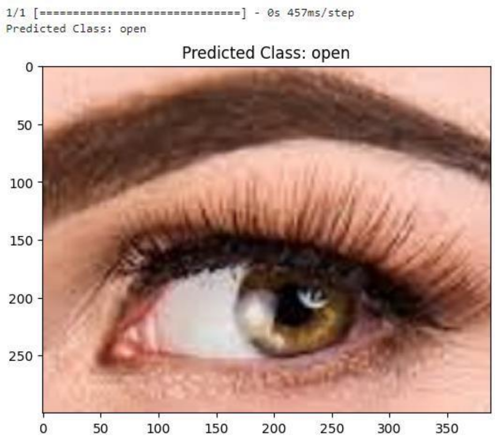
Conversely, the accuracy of validation demonstrates a similar trend and, by the 20th epoch, had reached about 95.50% accuracy. This shows that the model performs equally well on both the validation set and the training set, indicating that the model generalizes to new data successfully.



The above graph represents training and validation loss throughout the training process. The training loss decreases steadily as the model learns from the data, reaching a value of approximately 17.09% at the 20th epoch. This decrease in loss indicates that the model is effectively minimizing the errors during training. The validation loss follows a similar pattern, decreasing until it stabilizes around 13.03% at the 20th epoch. As the validation loss remains relatively low in comparison to the training loss, this behavior shows that the model generalizes well to new data with less difficulty.







V. CONCLUSION

In conclusion, the conference paper introduces a driver fatiguesolution that effectively detects and addresses sleep issues using deep learning techniques. This newly proposed feature detects drowsiness in drivers and alerts them with an alarm on the analysis of the condition of theireyes, face, and mouth. The Har cascade algorithm is used to extract the areas of the face, eyes, and mouth from the images. This employs CNN architecture which is constructed to process the images and extract features like eyes and faces. The accuracy of the model is 95.5%. A SoftMax layer is utilized in the CNN classifier for classifying output as drowsy or not drowsy. The training data is classified into eyes opening, eyes closing, yawning, and not yawning based on the facial landmarks from the open CV. The model assesses the driver'sstatus and informs them with an alarm sound when it continually anticipatessleepiness as an output. The model successfully captures the key properties for identifying driver tiredness, as evidenced by the training accuracy and validation accuracy both improving steadily across the epochs.

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