Enhancing Driver Safety Using Deep Learning Models

Ishaan Shokeen
Department of Electronics and Computer Engineering
Amrita School of Engineering, Bengaluru
Amrita Vishwa Vidyapeetham, India
bl.en.u4eac22022@bl.students.amrita.edu

Krishnendu M Uday
Department of Electronics and Computer Engineering
Amrita School of Engineering, Bengaluru
Amrita Vishwa Vidyapeetham, India
bl.en.u4eac22027@bl.students.amrita.edu

Manju Venugopalan
Department of Computer Science and Engineering,
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India
v_manju@blr.amrita.edu

***Abstract*— This proposed work emphasizes the critical role of eye movement detection, particularly open and closed eye states, in identifying drowsiness, providing a clear focus on the project's main technological approach and its importance for road safety. The proposed model ensures constant checks on the driver's safety and provides necessary observations on their behavioral activities. To ensure effective drowsiness detection, different methodologies such as Convolutional Neural Networks (CNN), customized Neural Networks and Recurrent Neural Networks (RNN) were employed for image processing. The CNN model achieved the best results. Two different data sources from Kaggle provided various training images for the model to operate in different scenarios. The proposed model aims to achieve accurate predictions across various case scenarios and to develop the most efficient model for real-time detection and alert systems, ensuring driver safety. Among the models our system gives the best result using CNN reporting an accuracy of 98.53%, and precision, recall and F-score of 98.71%, 98.04% and 98.37% respectively.**

I. INTRODUCTION

Drowsiness detection has emerged as a critical area of research in the field of intelligent systems, with profound implications for transportation safety, occupational health, and overall public safety. According to the latest data released by road transport and highways minister Nitin Gadkari, 1,47,913 people were killed in road accidents in 2017, with Uttar Pradesh reporting the maximum number of 20,124 road accident fatalities, followed by Tamil Nadu with 16,157 deaths.[1] The consequences of drowsiness extend beyond road safety, affecting productivity and increasing the risk of accidents in workplaces, especially those involving heavy machinery and critical operations.

By addressing the challenges associated with drowsiness detection, we try to contribute to the ongoing efforts to enhance safety and productivity in high-risk environments. The findings of this study have the potential to inform the design and deployment of next-generation drowsiness detection systems, ultimately reducing the incidence of drowsiness-related accidents and improving overall safety standards.

Machine learning plays a significant role in impacting research by refining decision making and improving the accuracy of predictions. The ability to analyse extensive datasets and study hidden patterns increases research in various fields like healthcare, environmental science, astronomy and finance. Though Machine learning helps to drive innovation, it also brings ethical challenges such as concerns over data privacy, fraudulent impersonation and potential biases in algorithms, which must be addressed to ensure fair and reliable outcomes. Overall, machine learninghas become an essential tool in advancing research and moulding the future for various domains.

Incorporating Machine Learning (ML) [1,2,3] into the drowsiness detection system [4,5,6] greatly enhances its precision and reliability. Utilizing Convolutional Neural Networks (CNN), the system accurately identifies open and closed eye states, which are critical for detecting drowsiness. With extensive training on diverse datasets, the ML models achieve high accuracy in real-time scenarios, ensuring prompt alerts and continuous monitoring. This integration not only optimizes the system's performance but also significantly improves road safety by reducing the risk of accidents due to driver fatigue. To achieve the above, we have used a machine learning algorithm with a CNN model to generate an efficient prototype to overcome to problem. We have used binary cross entropy to distinguish between open and closed eye images upon the datasets available and also deploy it for real use scenario. This model is even integrated with 3 other deep learning model that have been tested and trained on many datasets for a more precise result.

The rest of the paper is distributed into different sections with section II containing some related works by different researchers, section III containing our dataset information, section IV having our proposed methodology which in-depth explains the working of our model, section V containing the result, and the conclusion and future works are discussed in section VI.

[1] https://www.financialexpress.com/india-news/40-of-highway-accidents-occur-due-to-drivers-dozing-off/1659901/

The major contributions of our papers are:

- Incorporating CNN, ANN and RNN helped to arrive at the best model.
- Binary entropy mechanism that helps us in ensuring more accurate results.

II. RELATED WORKS

Alshaqaqi and team [7] proposed an advanced technique for identifying driver fatigue. Although specific details regarding the year of publication and data set are not provided, the paper outlines a sophisticated algorithm designed to detect, track, and analyse the driver's face and eyes. The system specifically measures the PERCLOS (percentage of eye closure) to gauge the driver's alertness level. By utilizing visual data and artificial intelligence, the system is capable of automatically identifying signs of drowsiness. This development is particularly significant as it aims to reduce the high incidence of accidents caused by driver fatigue. Continuous improvement and refinement of this detection system are essential to effectively address this critical safety issue. Bajaj and team [8] presented an innovative method for detecting driver fatigue. Despite the absence of detailed information about the specific data set, the paper describes an architecture that integrates features from facial expressions and behaviours to improve detection accuracy. The system tackles the challenge of real-time driver drowsiness detection by employing advanced techniques, including MS-RCNN and other algorithms. These methods enable high-accuracy classifications, both binary and multi-class, thereby contributing significantly to the development of a comprehensive distraction detection system.

Magán and team [9] investigated the application of deep learning methods for detecting driver fatigue utilizing UTA-RLDD dataset. They used a combination of Convolution Neural network (CNN) and Recuring Neural Network (RNN) to analyse the sequence if images. The study reported a 65% accuracy on train data and a 60% accuracy on test data. Despite these outcomes, the research highlights the ongoing need to improve the accuracy of both training and testing data to enhance the overall efficacy of the detection system.Dipu and team [10] presented an enhanced drowsiness detection system leveraging Convolutional Neural Networks (CNN). The objective of this system is to detect driver fatigue accurately and efficiently to reduce the incidence of vehicle accidents caused by drowsiness. The dataset used is derived from various sources online, including videos provided by the University of Ottawa. The model demonstrated over 90% accuracy in typical conditions but showed limitations in low-light scenarios. To address these, the study suggests augmenting the dataset with more low-light images and further improving the SSD_MOBILENET architecture.

Almazroi and team [11] have introduced an innovative system aimed at enhancing driver safety using the MS COCO dataset, the architecture integrates the MobileNet V3 Single Shot Detector (SSD) and a Keras classifier with OpenCV. The research reports an outstanding F1 score of 99.7% for object detection. Nonetheless, the study underscores the importance of incorporating additional factors such as weather conditions, vehicle conditions, and the driver's sleep hours to further refine and improve the system's performance and reliability.

Avigyan Sinha and team [12] have designed a system to detect drowsiness in the 2020 utilizing a custom dataset comprising video frames of drivers. They employed a modified LeNet CNN architecture for feature extraction and classification, achieving high accuracy in drowsiness detection under various conditions. The system outperformed traditional methods, demonstrating robustness and real-time capabilities. Future work aims to enhance robustness under diverse lighting conditions and integrate multimodal data for improved accuracy.

Jasprit and team [13] utilized the NTHU-DDD dataset to compare various deep learning architectures, focusing on the effectiveness of different models in detecting driver drowsiness. The results indicate significant improvements in detection accuracy, highlighting the efficiency of convolutional neural networks. Future work suggests enhancing model robustness and expanding the dataset for broader application scenarios. Caio and team [14] have formed a system which utilize the National Tsing Hua University (NTHU) Drowsy Driver Detection dataset. The architecture employed includes a modified LeNet for its simplicity and performance, along with YOLOv3 for face detection. The results indicate high accuracy in detecting drowsiness using hybrid measures combining physiological and behavioural data. Future work suggests integrating additional datasets and improving real-time detection capabilities.

Savas and team [15] have generated a Real time drowsiness detection system based on multitask convolution neural network which utilizes 2 datasets namely YawDD and NTHU-DDD datasets. The architecture employs a Multi-task Convolutional Neural Network (ConNN) to classify both mouth and eye information within a single model, achieving a 98.81% accuracy rate in detecting driver fatigue. Future work aims to enhance real-time detection capabilities and address diverse lighting conditions for improved accuracy and reliability. Sanghyuk and team [16] have presented a work on driver drowsiness detection based on the NTHU-drowsy driver detection benchmark dataset. The architecture combines three deep networks: AlexNet, VGG-FaceNet, and FlowImageNet. The system achieves a detection accuracy of 73.06%. Future work aims to improve accuracy by refining the feature representation and ensemble methods.

III. DATASET DESCRIPTION

We have incorporated two datasets containing virous visual eye data via Kaggle. The source and content of the dataset has been provided along with Table 1. [2] [3]

TABLE I. DATASET STATISTICS

Data Partition	Dataset 1	Dataset 2
# Instances in Train data	1080	2900
# Instances in Test data	120	322

IV. METHODOLOGY

For the implementation of our ML model, we have incorporated three deep learning models through the two datasets after some data preprocessing. The images of the datasets varied by sizes and dimensions, so they have to be

[2] https://www.kaggle.com/datasets/dheerajperumandla/drowsiness-dataset

[3] https://www.kaggle.com/datasets/tauilabdelilah/mrl-eye-dataset

resized using NumPy and then used into our ML models for training and testing. Binary Cross-entropy is the loss functions used for the evaluation matrix to measure the difference between the actual and predicted binary outcome of the model. The detailed explanation of the working of the model is given as follows:

A. Dataset Preparation

The images were first sorted into an array of their length and then grouped by their corresponding labels using 1's and 0's. These images then were reshaped into a common size of 100x100 for better evaluation. To further reduce the load onto the system and model the RGB images were converted to grayscale as shown in Fig 1.

The images were then subjected to our 3 models CNN, RNN and deep neural network as shown in Fig 2,3 and 4 respectively. The model with the features extracted then were compiled using binary cross entropy and Adam optimizer to give us the accuracy of the model.

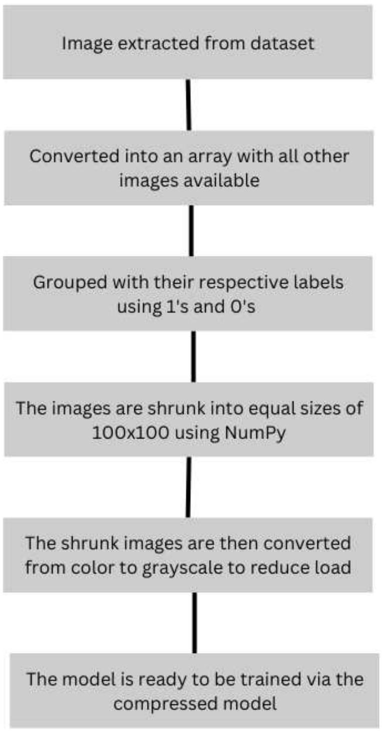

Fig. 1 Dataset Preparation

B. Model Training

Three deep learning models have been developed to train and test upon the dataset provided and provide the best result for each case scenario. The models used are as follows:

1) Convolution Neural Network (CNN)

The above model consists of 3 convolution layers, 2 max pooling layers, a flatten and a dense layer.

The convolution layers help in the detection of various features in the image like texture, edges etc. The consecutive layers build upon the previous features extracted, helping in more accurate results. The pooling layers are applied after each convolution layer that helps in reducing the spatial dimensions of the input image and find more detailed features from the reduced image size and generate an output with more detailed features. The flatten layer coverts the 2D feature map into a 1D vector, which is required by the dense layer, where the first dense layer contains the high-level feature, and the second layer contains the output of the image processed earlier.

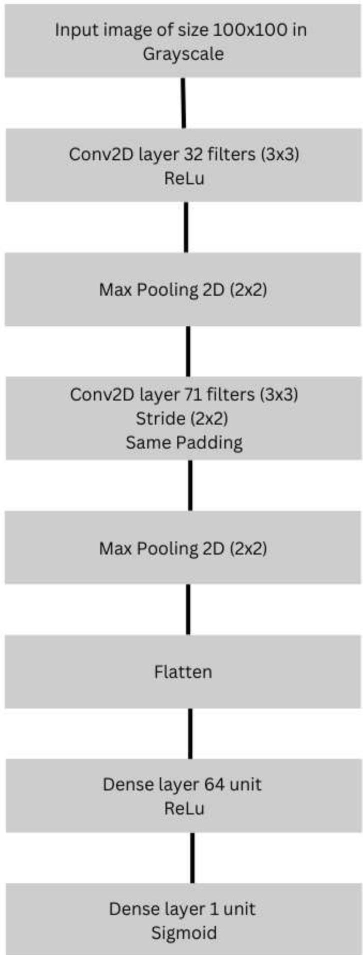

Fig. 2 Convolution Neural Network

2) Recurrent Neural Network (RNN)

The above model consists of 2 LTSM (Long Short-Term Memory) layer which validates an input of 100x100 sized grayscale image.

The LTSM layer excepts input data and has 32 units (neurons). Each neuron can capture patterns across the row of sequence. It works on every sequence one after the other until the entire data is interpreted. The second LTSM layer has 64 neurons that continues processing from first LTSM layer filtering out more features. The dense layer contains of 64 neurons that connects to each neuron from the previous LTSM layer that allows the model to connect to its more complex and less complex layers. The second dense layer consists of a single neuron that helps in giving the output of the overall layers which is activated via sigmoid that helps in binary classification.

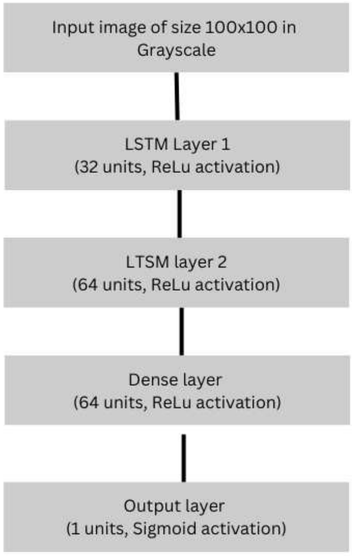

Fig. 3 Recurrent Neural Network

3) Customized Neural Network

The model consists of flatten and several dense layers for prediction of the input data.

The flatten layer is used to covert the 2-dimensional data into 1 dimensional (100x100 => 10000 element vectors). The dense layer starts with 512 neurons that extracts simple features from the input layer. The following layers contain 256,128 and 1 neuron respectively, which picks up the major high-level features from the previous layers, filtering the data more precisely which is activated via sigmoid for binary classification.

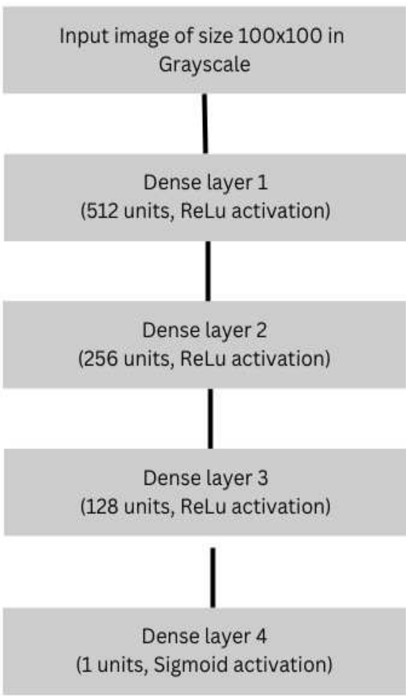

Fig. 4 Customised Neural Network

C. Model Testing

After the successful training of our data, the model is tested by inputting various unlabelled data of the eyes and checking what the model lacks. As shown in fig. 5 we take inputs via the allocated camera using OpenCV module. To detect the precise location of the eye in human body we have used two data files which can extract out our face and eyes from human body through a given image. We tend to focus more on the accuracy of eye detection through different lighting and angles so that we can utilize the method in almost all situation leaving no drawbacks. Once we are able to detect the eyes and capture its movement, the eye is cropped out into a new image to get us a representation of the eyes only. The images are then sent through the NumPy model as mentioned above where it is compressed into smaller sizes. The input after running through the model then predicts the output and alerts the user accordingly.

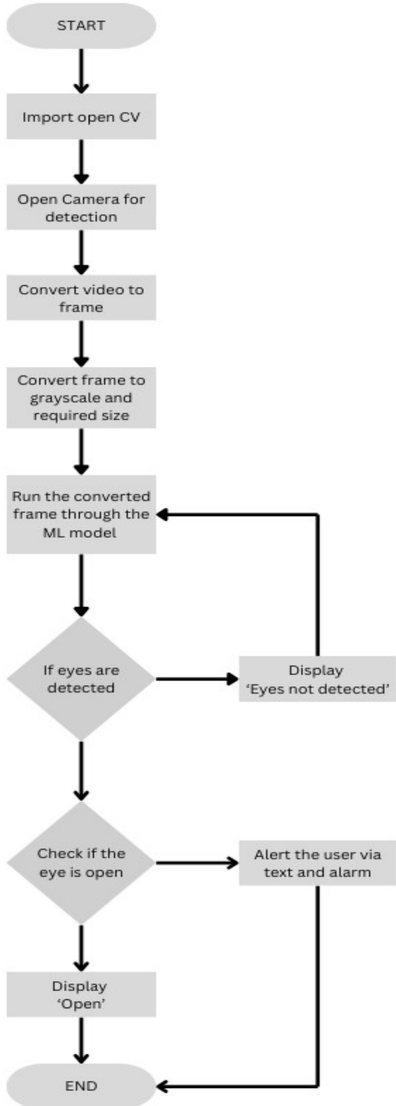

Fig. 5 Model Testing

V. RESULTS

The three models were trained on the training data and evaluated on the test set. After the evaluation of the system, the three models CNN, CuNN and RNN and 2 datasets the values obtained are shown in Table II. The F-measure reported is the best at 98.37% and 96.43% on Dataset1 and Dataset 2 respectively. The customised neural network reports the second-best results and RNN results are combatively poor. The CNN model is projected as the proposed model for drowsiness detection.

The model accuracies of the three experimented models varying with epochs are showcased in Fig.6 to Fig. 11.

TABLE II. MODEL PERFORMANCE ACROSS THREE MODELS

Model	Dataset	**Accuracy**	**Pre**	**Recall**	**F_Measure**
CNN	**Dataset 1**	98.53	98.71	98.04	**98.37**
	Dataset 2	98.78	99.60	94.11	**96.43**
CuNN	**Dataset 1**	86.63	84.76	85.77	85.26
	Dataset 2	94.24	94.65	92.44	93.12
RNN	**Dataset 1**	54.71	46.54	41.36	43.79
	Dataset 2	77.38	85.72	63.16	72.73

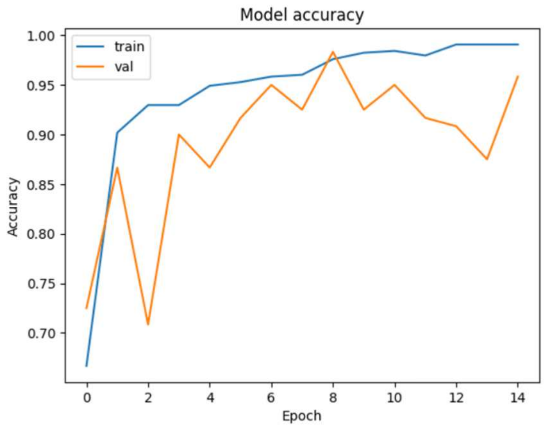

Fig 6. Dataset 1 and CNN

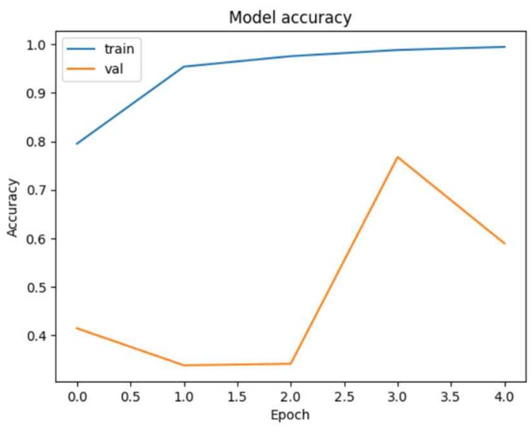

Fig 7. Dataset 2 and CNN

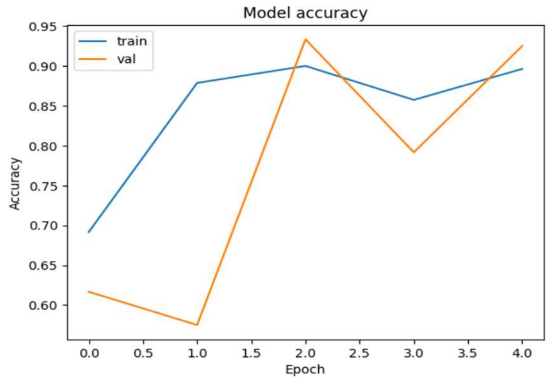

Fig 8. Dataset 1 and CuNN

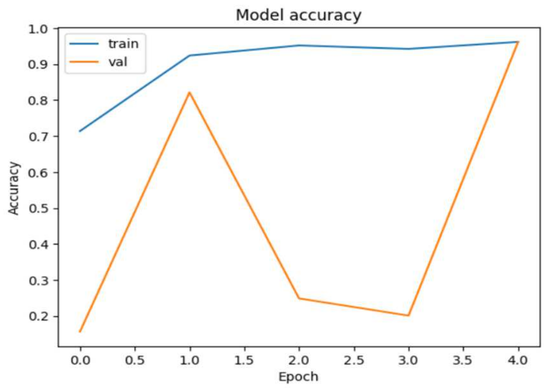

Fig 9. Dataset 2 and CuNN

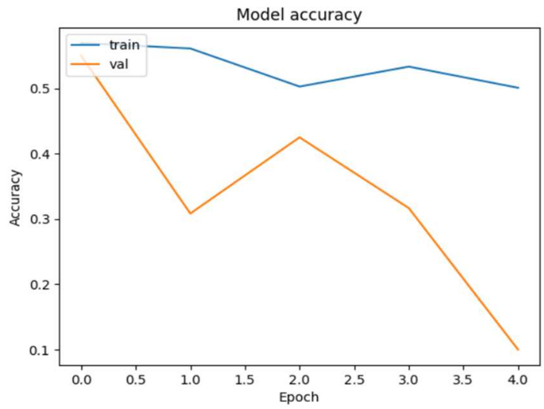

Fig 10. Dataset 1 and RNN

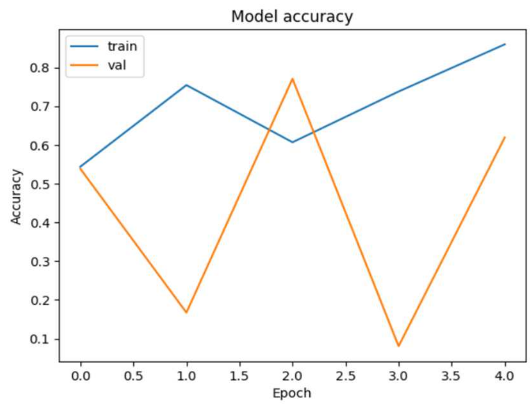

Fig 11. Dataset 2 and RNN

To find the real time validity of the model, we ran the model through various images of different scenarios and are able to continuously detect the active results obtained via the ML model. Fig 12 and Fig 13 depict the output of the model when tested on the test images.

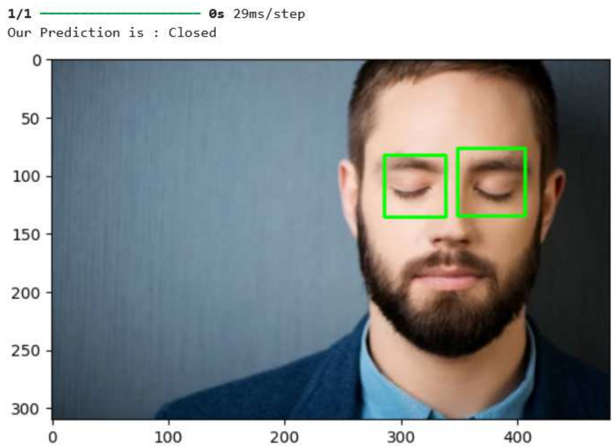

Fig 12. Positive instance predicted by the model

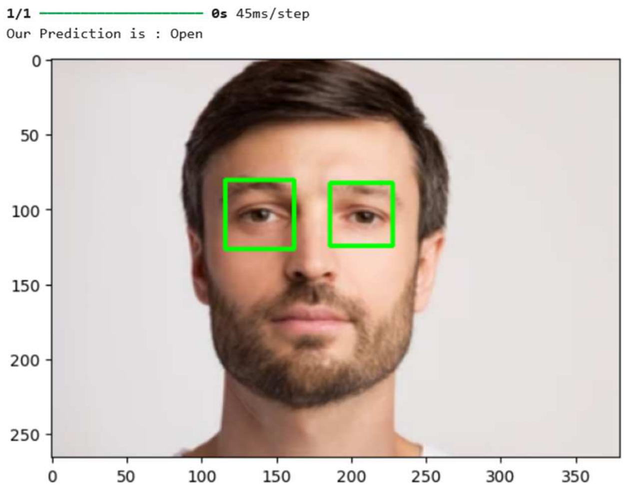

Fig 13. Negative instance predicted by the model

This model when implemented in real life is able to predict the output based on user live video. An alerting mechanism has also been integrated in the model for alerting the drivers. Fig. 14, Fig. 15 and Fig. 16 shows the output based on real time input.

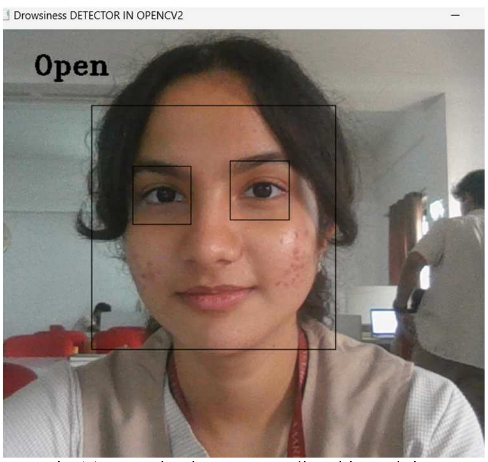

Fig 14. Negative instance predicted in real time

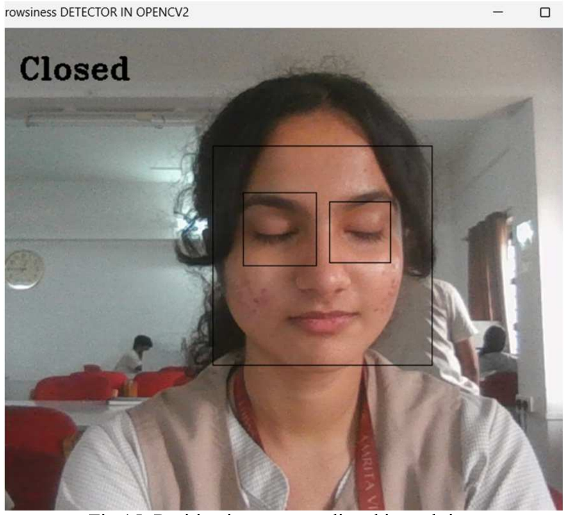

Fig 15. Positive instance predicted in real time

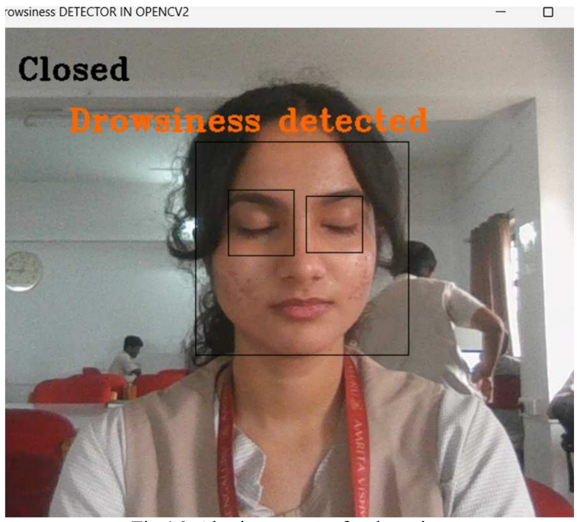

Fig 16. Alerting system for detection

VI. CONCLUSION AND FUTURE WORK

Three models which include CNN, Customized CNN and RNN were successfully implemented to detect drowsiness behaviour. All three models gave were successfully able to classify the data inputs into the respective classifications and Convolution Neural Network (CNN) gave us the best output among all the tested models with an accuracy score of 98.5%. Drawbacks like complex learning models and lower accuracy were successfully overcome by the system and the variety of models used in training were able to address various minor issues faced earlier.

Despite the higher accuracy of our model, the problem cannot be solved just by eye tracking features. There are various other factors such as poor lighting, various camera angle and tricking of the model that heavily affect the output and the accuracy of the model. Driver's behaviour, facial expression should also be bought to consideration for a more accurate result that is more likely to catch drowsiness at the right time. Even factors such as eye size, the

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