“Effective Automated Driver Drowsiness Detection System based on Machine Intelligence Techniques”

Major Project Report

Submitted in Partial Fulfillment of the Requirements for the Degree of

BACHELOR OF TECHNOLOGY

IN

INFORMATION AND COMMUNICATION TECHNOLOGY

By

Khushi Naik

(19BIT064)

Under the Guidance of

Prof. (Dr.) Nitin Singh Rajput

Department of Information and Communication Technology, School of Technology, Pandit Deendayal Energy University, Gandhinagar 382426

May 2023

Certificate of Originality of Work

I hereby declare that the B.Tech. Project entitled "Effective Automated Driver Drowsiness Detection System based on Machine Intelligence Techniques" submitted by me for the partial fulfilment of the degree of Bachelor of Technology to the Dept. of Information and Communication Technology at the School of Technology, Pandit Deendayal Energy University, Gandhinagar, is the original record of the project work carried out by me under the supervision of Prof. Nitin Singh Rajput.

I also declare that this written submission adheres to University guidelines for its originality, and proper citations and references have been included wherever required.

I also declare that I have maintained high academic honesty and integrity and have not falsified any data in my submission.

I also understand that violation of any guidelines in this regard will attract disciplinary action by the institute.

Name of the Student: Khushi Naik

Roll Number of the Student: 19BIT064

Signature of the Student:

Name of the Supervisor: Dr. Nitin Singh Rajput

Designation of the Supervisor: Assistant Professor

Signature of the Supervisor:

Place: Pandit Deendayal Energy University

Date: 10th May 2023

Certificate from the Project Supervisor/Head

This is to certify that the Major Project Report entitled "Effective Automated Driver Drowsiness Detection System based on Machine Intelligence Techniques" submitted by Ms. Khushi Naik, Roll No. 19BIT064 towards the partial fulfilment of the requirements for of degree in Bachelor of Technology in the field of Information and Communication Technology Engineering from the School of Technology, Pandit Deendayal Energy University, Gandhinagar is the record of work carried out by her under my supervision and guidance. The work submitted by the student has in my opinion reached a level required for being accepted for examination. The results embodied in this major project work to the best of our knowledge have not been submitted to any other University or Institution for the award of any degree or diploma.

Dr. Nitin Singh Rajput
Name and Sign of the Supervisor

Name and Sign of the Industry Supervisor

Name and Sign of the HoD

Name and Sign of the Director

Place: Pandit Deendayal Energy University

Date: 10th May 2023

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ABSTRACT

This project discusses the development of an effective automated drowsiness detection system using machine learning and deep learning techniques. Drowsy driving is a significant safety concern that can result in accidents, injuries, and even fatalities. To address this issue, we have developed a model that uses machine intelligence techniques such as computer vision, machine learning as well as deep learning. The proposed system combines several machine intelligence techniques to detect drowsiness accurately. Computer vision techniques are used to analyze facial features such as yawning and eye movements to detect signs of drowsiness. The Dataset used is a video dataset and was collected by researchers at the University of Texas, Arlington. The system's performance is evaluated using various metrics, including accuracy, sensitivity, roc curve, f1 score and specificity. The results show that the proposed system is highly effective in detecting drowsiness, with an average accuracy of over 80%.

The proposed model also works in real-time scenarios. The model with the best performance is used for real-time drowsiness detection. Video captured from the webcam is used as the input for the algorithm and with the help of camera calibration, the model detects whether the person in front is drowsy or alert.

Our proposed system is a promising and reliable tool to enhance driving safety by detecting drowsiness accurately. The results of our study demonstrate the potential of machine intelligence techniques to address practical issues such as driver fatigue and improve human life quality. The proposed model has practical applications and can be used in real-world scenarios to prevent road accidents caused by driver fatigue. With the increasing adoption of machine learning and deep learning techniques in various domains, our research provides new insights into the use of these technologies in addressing road safety concerns.

INDEX

Chapter No.	Title	Page No.
	Acknowledgement	**i**
	Abstract	**ii**
	Index	**iii**
	List of Figures	**iv**
	List of Tables	**vi**
	Nomenclature	**viii**
1	**Introduction**	1
	1.1 Introduction/ Prologue/Background	1
	1.2 Motivation	2
	1.3 Objective	2
	1.4 Problem Statement	2
	1.5 Approach	3
	1.6 Scope of the Project	3
	1.7 Organization of the Rest of the Report	3
2	**Literature Review**	4
	2.1 Previous Approaches to Solve the Problem	4
3	**Software Design/Methodology**	8
	3.1 Proposed System	8
	3.2 Methodology	9
5	**Results and Discussion**	12
6	**Conclusions and Future Scope**	19
	References	20

LIST OF FIGURES

Figure No.	Title	Page No.
1.1	Approach Flowchart	3
3.1	Proposed System	8
3.2	Facial Landmarks	10
4.1	Confusion Matrix Of Random Forest Classifier	12
4.2	Confusion Matrix Of Decision Tree Classifier	12
4.3	Confusion Matrix Of Naïve Bayes Classifier	12
4.4	Confusion Matrix Of Logistic Regression Classifier	12
4.5	Confusion Matrix Of XGB Classifier	13
4.6	Confusion Matrix Of KNN Classifier	13
4.7	Confusion Matrix Of Ensemble Classifier	13
4.8	Confusion Matrix Of MLP Classifier	13
4.9	Confusion Matrix Of CNN Classifier	13
4.10	Accuracy Of Classifiers	14
4.11	F1 Score Of Classifiers	15
4.12	Precision Of Classifiers	15
4.13	Sensitivity Of Classifiers	16
4.14	Specificity Of Classifiers	16
4.15	ROC Curve Of Classifiers	17
4.16 - 18	Real-time Drowsiness Detection Through Webcam	18

LIST OF TABLES

Table No.	Title	Page No.
4.1	Accuracy Of Classifiers	14
4.2	Previous Work - Proposed Work	17

NOMENCLATURE

Greek

μ	Mean
σ	Standard Deviation

Subscripts

n	Feature
m	Person

Abbreviations

EAR	Eye Aspect Ratio
MAR	Mouth Aspect Ratio
MOE	Mouth Aspect Ratio over Eye Aspect Ratio

CHAPTER 1 INTRODUCTION

1.1 Prologue

With rapid development and evolution in technology, science has come a long way in the past 50 years. The automobile industry has shown immense growth, starting from a bicycle to now automated vehicles. But with that, the risk of accidents has also increased. In India, the number of car accidents reported in 2021 was 4,12,432 which claimed 1,53,972 lives and caused injuries to 3,84,448 people[19]. According to some reports, 40% of these accidents were caused by drowsiness or fatigue in drivers. Researchers have been trying to find a solution for alerting the driver for the past many years. The advent of machine learning has enabled the development of various intelligent systems that can perform complex tasks with high accuracy. One area that has been extensively explored is transportation safety. Machine learning (ML) has been used to develop systems that can detect and prevent accidents caused by human errors, such as driver drowsiness. In recent research progress ML was used for detecting fatigue in drivers, Random Forests, Decision Trees, Regressors, and KNN. While these algorithms have shown promising results individually, they may not always perform well in real-world scenarios due to variations in the data. To address this issue, ensemble learning, which involves combining the output of multiple machine learning algorithms, has gained popularity. Ensemble learning has improved the accuracy and robustness of machine learning models, making them more reliable in real-world applications. Ensemble methods can be broadly classified into two categories: aggregation-based methods and meta-learning-based methods. Aggregation-based methods, such as Majority Voting and Bagging, combine the output of multiple machine-learning algorithms by averaging or voting. Meta-learning-based methods, such as Stacking and Boosting, train a meta-learner that combines the production of numerous base learners. In this work, we propose a novel approach for detecting drowsiness in drivers by ensembling multiple machine learning algorithms. We explore the effectiveness of various machine learning algorithms and their ensembles in detecting drowsiness using a Voting Classifier in drivers using eye-tracking data from a video dataset. Furthermore, we have employed two deep learning algorithms; MLP and CNN. The algorithms' results are then compared to find the model with the best performance and accuracy. The dataset we have used here is taken from the University of Texas, Arlington.

The research aims at finding out the accuracy of the machine learning algorithms mentioned above and suggesting the best-suited algorithms amongst them. It also aims to use the ensemble method to get the best results. We have calculated other parameters such as sensitivity, f1 score, precision, recall, and roc curve. The algorithm's input is given using a webcam, and the model then detects whether the person sitting in front of the camera is drowsy or alert in real time. The proposed model highlights the power of ML and DL methods to tackle practical issues in detecting drowsiness in drivers. It demonstrates the potential of machine intelligence techniques in addressing real-world problems and improving human life quality.

1.2 Motivation

The percentage of deaths caused due to drowsiness in drivers has increased. In this project, we aim to solve this problem by implementing an alert system that can detect actions such as yawning or eye closure. Various classification methods, including ML and DL models, will be used to alert the driver. In the end, a real-time drowsiness detection system will be implemented.

1.3 Objective

This project aims to design a system for drivers using ML and DL techniques. The rising number of accidents caused by drowsy drivers has become a significant concern for road safety. Therefore, our primary motivation is to implement an alert system that detects signs of drowsiness, such as yawning or eye closure, and warn the driver before any mishap occurs. We will explore various classification methods and compare their accuracy and adaptivity to real-time situations. This project's successful implementation will provide a reliable and effective solution to the problem of drowsy driving, ensuring safer roads for everyone.

1.4 Problem Statement

This study's main objective is to provide a solution for drowsiness detection in drivers using different ML and DL algorithms. We intend to give a comparison of other models based on their accuracy and adaptivity to the real-time situation.

1.5 Approach

We started by collecting the video dataset. Our next step was to pre-process the data by resizing it. For determining the key facial features such as the eyes and mouth. After performing normalization, we applied different machine learning and deep learning classifiers. We later compared each classifier by evaluating them on various performance parameters. The Figure below provides a general architecture of the proposed system.

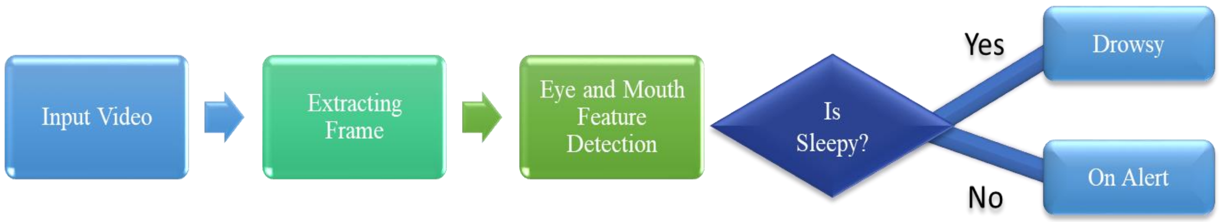


Fig 1.1: Approach Flowchart

1.6 Scope of the Project

The primary aim of this project is to detect signs of drowsiness such as yawning or eye closure and alert the driver before any accidents occur. To achieve this goal, we collected the video dataset and performed preprocessing and feature extraction. This project will provide an effective and dependable solution to the problem of drowsy driving and an opportunity in exploring advanced machine learning and deep learning techniques and their practical applications in real-world settings.

1.7 Organization of the Rest of the Report

Chapter 1 introduction provides a brief overview of the project and its objectives. Further, Chapter 2 Literature Review discusses the existing research on drowsy driving and detection systems, Chapter 3 Methodology describes the data collection and methods involved in reaching the results, Chapter 4 discusses the results and analysis of the models and the end Chapter 5 concludes the overall project and explains the future scope.

CHAPTER 2 LITERATURE REVIEW

2.1 Previous Approaches to Solve the Problem

Pachouly [1] in their research used a convolution neural network model for the analysis and extraction of details of the driver. In order to train the model they used the dataset from Media Research Lab. After training the model, facial features are extracted which will help detect the exact movement of the eyes. The frequency of yawning was analysed using OpenCV and Dlib in Python. Through their model, they could achieve an accuracy of 94%.

Colbran [2] worked towards classifying the distracted drivers from the set. The author used two types of CNN models namely, VGG-16 and GoogleNet. The dataset used consists of 22400 training and 79727 testing images and later it was labelled based on nine possible classifications. He then classified the test data as to which class it belongs. Using the proposed method he got a log loss of 0.28554.

Mohanty [3] in their research proposed that the Eye Aspect Ratio (EAR) i.e., the duration of closing eyes while driving can help us get the status of the driver’s drowsiness. Later on, using the KNN algorithm they tried to reform their model to detect the level of drowsiness. For this, it was then classified into three groups and based on the blinking rate an alarm is set for different stages in real time.

Nikitha [4] compared two machine learning algorithms/ classifiers, novel random forest and logistic regression, in order to detect fatigue and drowsiness in the driver (age more than 35 years preferably). This research was concluded by obtaining the accuracy score of both of these classifiers. Novel random forest performed better with 63.20% accuracy.

Ramzan [5] worked on drowsiness detection by taking into consideration the three main categories, including Behavioural, Vehicular, and Physiological parameter-based techniques. However, the vehicular-based technique isn’t reliable as there can be some other factors affecting the change in patterns. In this paper, the author has proposed three models, including SVM, HMM, and CNN. Here, HMM showed the best results in terms of accuracy. Although it has also been mentioned that SVM 2 is much less complex it is used widely in this area.

Samy Bakheet [6] and other researchers, with the help of HOG(Histogram of Oriented Gradient) and Naive Bayes Classifier, developed a model that detects drivers' drowsiness while driving the vehicle. The model performed with 85.62% accuracy. The dataset used was NTHU-DDD which is publicly available. The limitation was that the data was generated in a lab, and the model was trained on that data, thus, the results might vary for the actual driving scenario.

Banerjee [7], is based on various components of the perceptron. In this study, the researchers have talked about the structure as well as multiple components of the perceptron. The researchers have mentioned different activation functions such as Step, Sigmoid, Tanh, Relu, etc. Moreover, they have shown the vital role of the decision boundary in the training process of the perceptron. In the end, they talked about the multilayer perceptron used for the types of classifications that are linearly not separable.

For the detection of the drowsiness of drivers in real-time, researcher Jabbar [8] has developed a real-time drowsiness detector using a multilayer perceptron algorithm. They have developed an algorithm for facial landmarks, they intended and succeeded in creating this model, which is compressed to a lightweight model. They used the NTHU (National Tsing Hua University) dataset and performed the study on videos of 18 studies. The proposed model resulted in more than 80% accuracy for all the different cases.

As driver safety has been a critical issue, researcher Chirra [9] has proposed a CNN-based algorithm that includes a SoftMax layer at the end for classifying whether the driver is sleepy. In this method, the researchers have used PCA and LDA to extract the facial features and regions of the face. Here they have used four convolutional layers and a fully connected layer. The model reported an accuracy of 96.42%. Although we do have devices such as ECG, EOG, etc which give desired results, they have yet to be widely accepted due to their practical limitations.

Researcher Samiee [10] used a data fusion approach to detect the robustness of signal loss during the drowsiness detection of drivers. They used a driving simulator to collect the data. They have considered 12 drivers with controlled sleeping conditions. In this fusion approach, if at any time any algorithm fails, the system still functions appropriately without any complication. In the input layer of the algorithm, they have provided eye status, lateral position, and steering wheel angle.

The inputs were connected to 3 MLP networks and trained using backpropagation. In the best-case scenario, the loss calculated was 6.85%. Furthermore, after some improvements, the final loss calculated was 3.89%.

Deep learning has been observed as a better alternative for learning features and handling facial variations. The researcher Markoni [11] has provided a solution using CNN and LSTM models to analyze the drowsiness. Extracting the features for the process has been considered a difficult task, so the haar-like part is widely used. After the feature extraction, the next step is to classify it, which is done using the Ada-Boosting algorithm. However, this algorithm has certain limitations when the driver is wearing glasses or when the illumination changes. The results show that CNN performed better results as compared to LSTM.

Due to the rapid increment in road accidents due to drowsiness or fatigue in drivers, researcher Yarlagadda [12] developed a drowsiness detection system using RNNs and LSTM algorithms. They collected a video dataset of 30 drivers, each person recording for approximately 10 minutes. They have extracted facial features with the help of facial landmarks. They removed the eyes, mouth, and face for eye closure and blinking rate, head position, and mouth opening and closing to detect yawning. The achieved accuracy is 97.25%. If the model detects the driver drowsy, then it turns on an alarm to alert the driver, which helps in causing any accident due to drowsiness.

Arslan [13] has implemented a live camera in front of the driver to analyze the results which they have obtained using the CNN model. In the proposed method, they have used “Viola-Jones” for face detection by processing one frame of image at a time. After checking each frame the eye feature is extracted from the frame using the Haar cascade classifier. They have used 75% of the data for training and the rest 25% of the testing. The CNN model is structured in such a way that it has three convolutional, ReLu and Pooling layers including a SoftMax classification layer. In the end, they have compared results by running the model on different epochs and learning rates. The maximum accuracy which they could obtain was 97.8%.

Researchers at UTA (University of Texas Arlington), Ghoddoosian [14] have developed a model for drowsiness detection using a Multiscale Hierarchical Long Short-Term Memory algorithm. They considered the connection between eye blinking and drowsiness to determine whether the driver is drowsy or not while driving. They have used the RLDD(Real-Time Drowsiness Dataset) dataset comprised of 60 participants and 30 hours of video footage. Their system processed 35-80 frames per second. They used 3 labels, Alert, Low Vigilant and Drowsy for classification. They implemented fully connected layers and regression unit in the HM-LSTM model. They achieved an accuracy of 65.2%.

CHAPTER 3 SOFTWARE DESIGN/METHODOLOGY

3.1 Proposed System

This study is completely focused on detecting drowsiness and fatigue in drivers using machine learning algorithms, their ensemble and deep learning algorithms. Ensembling them provides better accuracy and better results than each individual algorithm. Below are the steps performed for calculating accuracy and different parameters in order to analyse the algorithms' performance and find the best-performing model.

Step 1: Data collection and Pre-processing

Step 2: Feature Extraction

Step 3: Feature Normalisation

Step 4: Machine Learning Algorithms

Step 5: Ensemble Voting Classifier

Step 6: Deep Learning Algorithms

Step 7: Performance evaluation by calculating parameters

Step 8: Real-time Drowsiness Detection

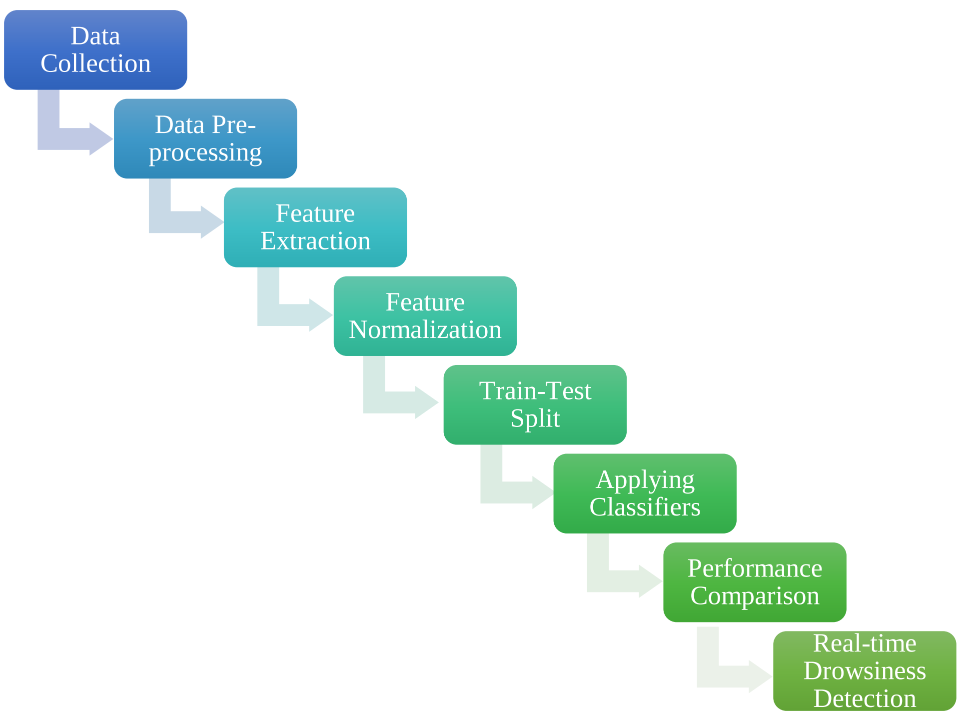


Fig 3.1 Proposed System

3.2 Materials and Methods

3.2.1 Data Set and Pre-processing

Collecting the dataset was the most challenging part of this research since we needed help finding an ideal video dataset. After some findings, we came across the dataset collected by the researchers at the University of Texas, Arlington. It contains videos of 60 participants and 180 videos, each average of 10 minutes long. We have extracted 240 frames per video and 10560 frames in total. We have pre-processed the data by resizing it for simplicity in feature extraction.

3.2.2 Feature Extraction

We have used some formulas to extract the features and calculate their ratios. We have calculated four different ratios; that are, EAR, MAR, Pupil Circularity and MOE. Figure 3.2 represents the facial landmarks where points 37 to 68 are the only essential points since we need to monitor the eye and mouth movements. For eye movements such as blinking, eye closure for a longer time, points P1 to P6 are used for both the eyes and to monitor mouth movements such as yawning, points A to H are used. The equations below are derived by using the points P1 to P6 and A to H from Figure 3.2.

$$EAR = \frac{||p2-p6|| + ||p3-p5||}{2*||p1-p4||} \tag{1}$$

$$MAR = \frac{|EF|}{|AB|} \tag{2}$$

$$Circularity = \frac{4*\pi*Area}{Perimeter^2} \tag{3}$$

$$Perimeter = Distance(p1, p2) + Distance(p2, p3) + Distance(p3, p4) + Distance(p4, p5) + Distance(p5, p6) + Distance(p6, p1) \tag{4}$$

$$Area = \frac{Distance(p2, p5)}{4}^2 * \pi \tag{5}$$

$$MOE = \frac{MAR}{EAR} \tag{6}$$

By using these aspect ratios, we have extracted eyes and mouth from the faces captured from the videos.

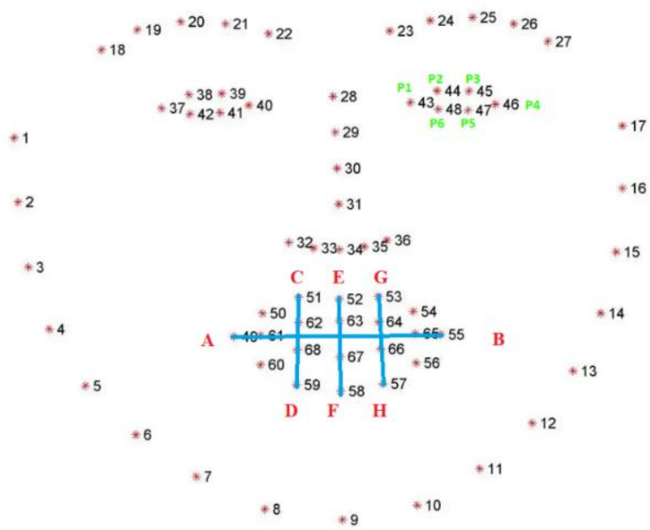


Fig 3.2 Facial Landmarks

3.2.3 Feature Normalization

In order to perform feature normalization, we have taken the first three frames of each individual in the dataset and used them as the baseline. We have used a mathematical equation for the normalization of the features.

$$Normalised\ Feature_{n,m} = \frac{Feature_{n,m} - \mu_{n,m}}{\sigma_{n,m}} \qquad (7)$$

These features were stored in a .csv file after for classification purposes. For classification, we are going to implement various ML and DL algorithms.

3.2.4 Classification Algorithms

To implement the classifiers, the train-test split is 77.27%. Following are the algorithms that we have implemented as well as we have calculated their accuracy, f1 score, sensitivity/ recall, precision, receiver operating characteristics, specificity and confusion matrix.

1. Random Forest Classifier
2. Decision Tree
3. Naïve Bayes
4. Logistic Regression
5. Extreme Gradient Boosting
6. K-Nearest Neighbour
7. Ensemble of all classifier
8. Multilayer Perceptron

9. Convolutional Neural Network

In order to calculate these performance measures, we have drawn these four values, TP(True Positive), TN(True Negative), FP(False Positive) and FN(False Negative). We have two classes here, Alert and Drowsy. The performance parameters are explained below:

- **Confusion Matrix:** A confusion matrix is made up of four values calculated according to the classes we have i.e., TP, TN, FP and FN.
- **Sensitivity:** Sensitivity/ Recall tells us how many of the actual positive cases we were able to predict correctly with our model.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (8)$$

- **Precision:** Precision tells us how many of the correctly predicted cases turned out to be positive.

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP+FP}} \quad (9)$$

- **Specificity:** Specificity is to predict a true negative for each category available.

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN+FP}} \quad (10)$$

- **F1 Score:** F1 score is used for real-world datasets where classes are imbalanced. It is better for evaluating model performance than the accuracy parameter.

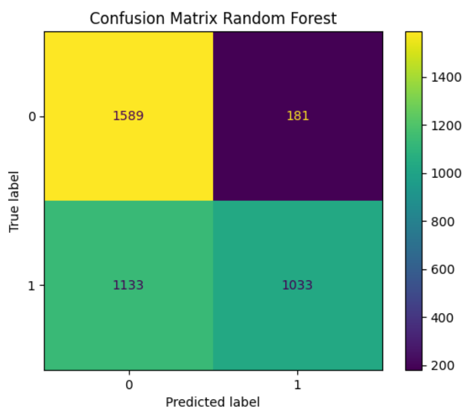
$$f1\ Score = 2 * \frac{(\mathrm{Precision} * \mathrm{Recall})}{\mathrm{Precision+Recall}} \quad (11)$$

- **ROC(Receiver Operating Characteristic):** ROC curve is used to show the performance of any classification model at all the classification thresholds.

With the help of these performance parameters, the algorithm having the best accuracy and performance is found and further used to detect drowsiness.

CHAPTER 4 RESULTS AND DISCUSSION

The proposed system calculates how the various classifiers perform in order to detect drowsiness and fatigue in drivers. In this project, as mentioned we have used machine learning classifiers such as logistic regression, naïve bayes, decision trees, extreme gradient boosting, and K nearest neighbours. Moreover, the ensemble of these classifiers in order to get the best possible performance out of them to properly and efficiently detect the driver's attention on the road. Moreover, two DL algorithms, MLP and CNN are employed. For the purpose of finding the best-performing algorithm, different performance parameters are calculated such as a confusion matrix to properly summarise and visualise the algorithm's performance. The confusion matrices of all the classifiers are shown below:



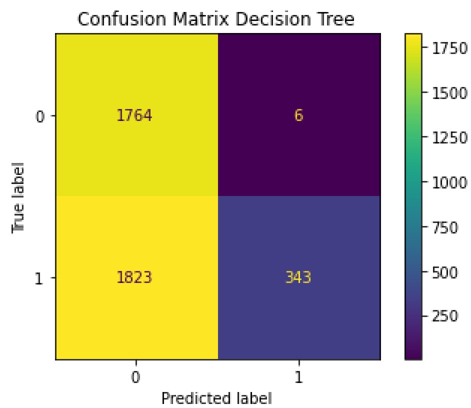
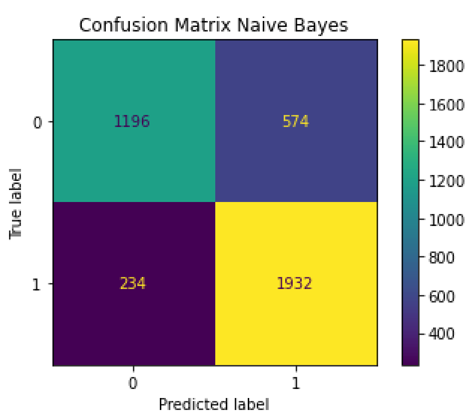


Fig 4. Random Forest Classifier **Fig 4.2 Decision Tree Classifier**



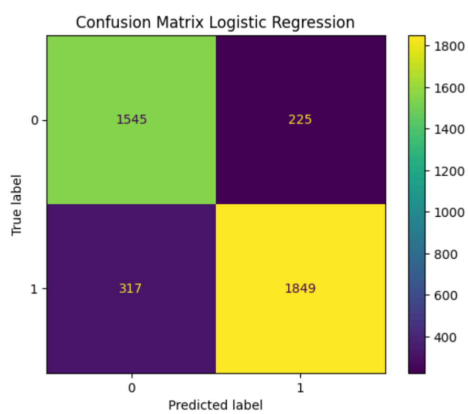
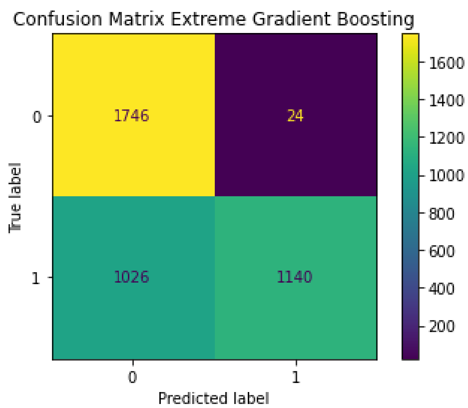


Fig 4.3 Naïve Bayes Classifier **Fig 4.4 Logistic Regression Classifier**



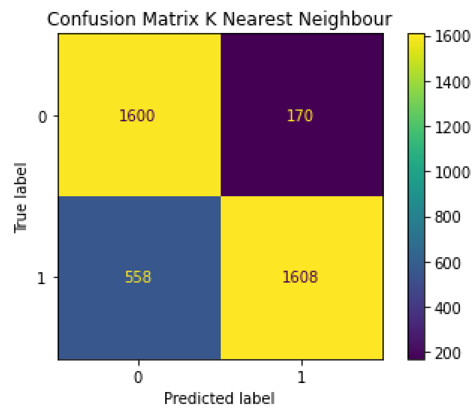
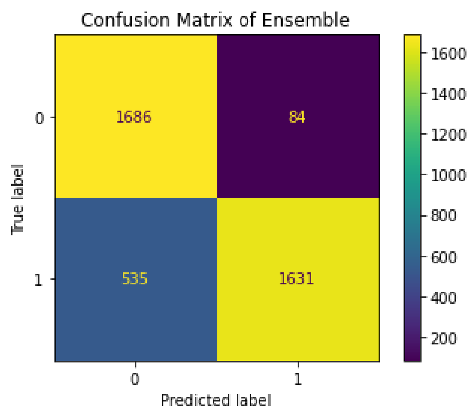


Fig 4.5 XGB Classifier **Fig 4.6 KNN Classifier**



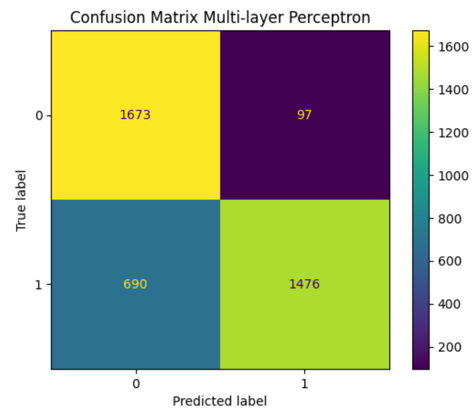


Fig 4.7 Ensemble Classifier **Fig 4.8 MLP Classifier**

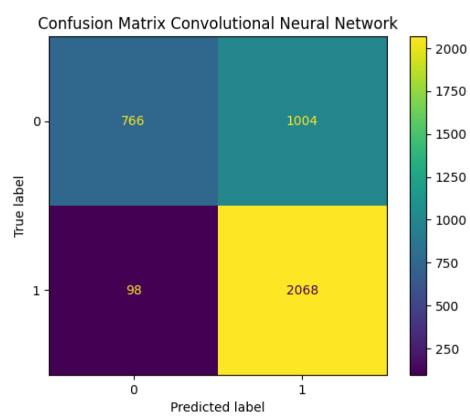


Fig 4.9 CNN Classifier

The accuracy obtained from all the algorithms is shown in the table below as well as we have also plotted an accuracy curve for these classifiers.

Table 4.1 Accuracy of Classifiers

Model	Accuracy
Logistic Regression	0.861280
Naive Bayes	0.794715
KNN	0.815040
Decision Tree	0.535315
Random Forest	0.757876
XGB Boosting	0.733231
Ensemble	0.842733
Multilayer Perceptron	0.857724
Convolutional Neural Network	0.720020

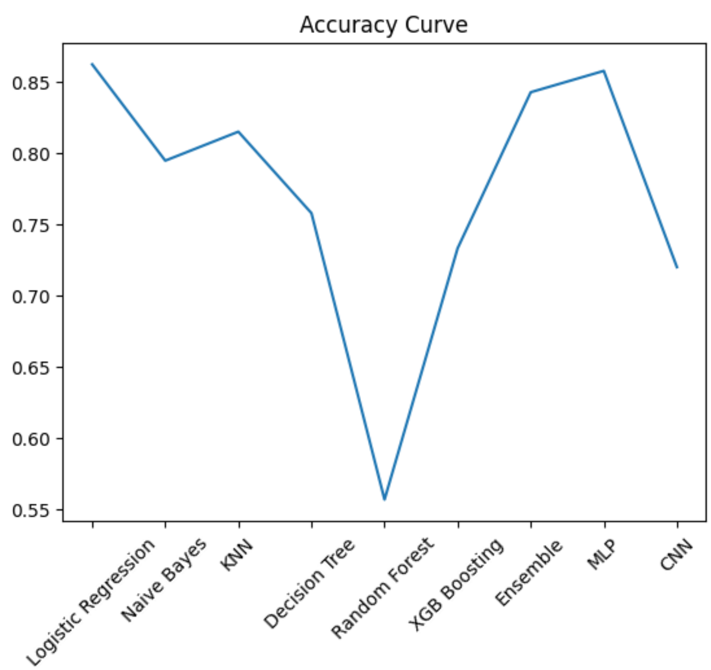


Fig 4.10 Accuracy Of Classifiers

In real-world problems where the dataset's classes are imbalanced, we cannot rely on accuracy since it might give false results, so we calculate the F1 score to avoid such problems. Apart from F1 score some other performance parameters such as precision, recall and specificity are also calculated to understand the model's performance accurately. We have also plotted curves for F1 Score, Sensitivity, Specificity and Precision.

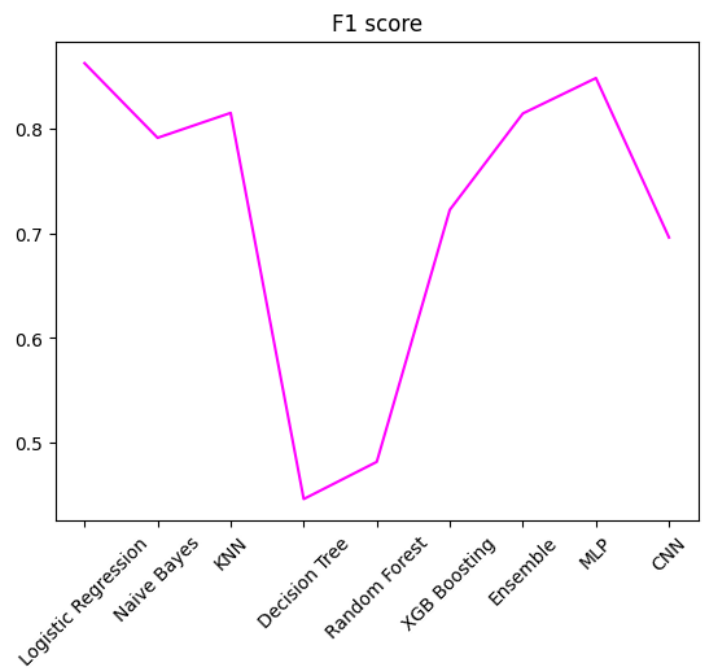


Fig 4.11 F1 Score Of Classifiers

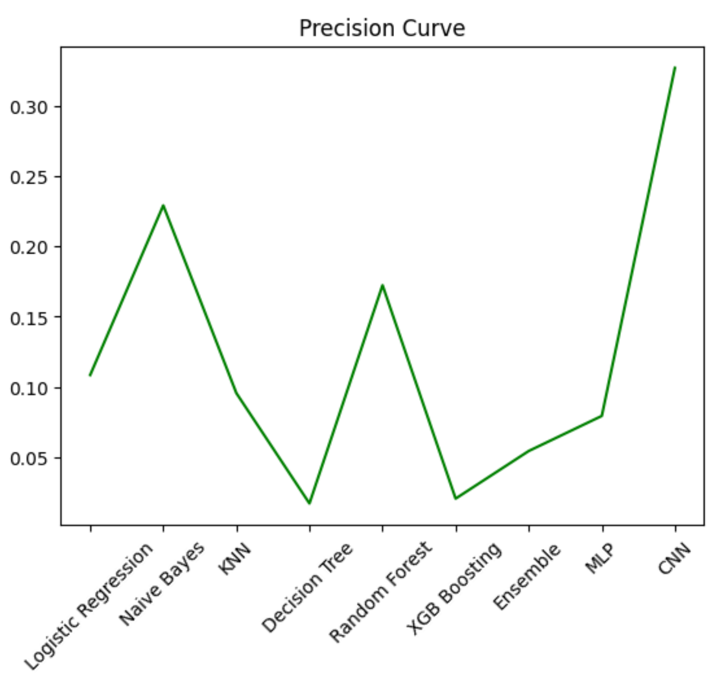


Fig 4.12 Precision Of Classifiers

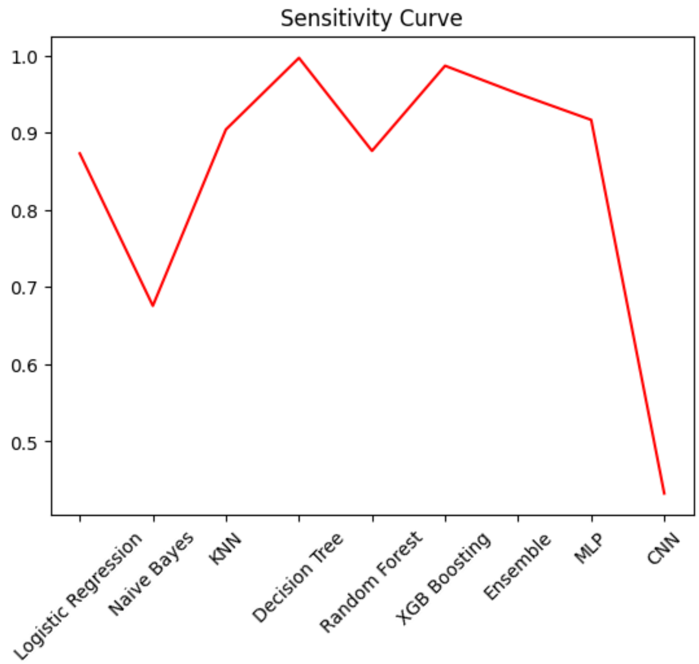


Fig 4.13 Sensitivity Of Classifiers

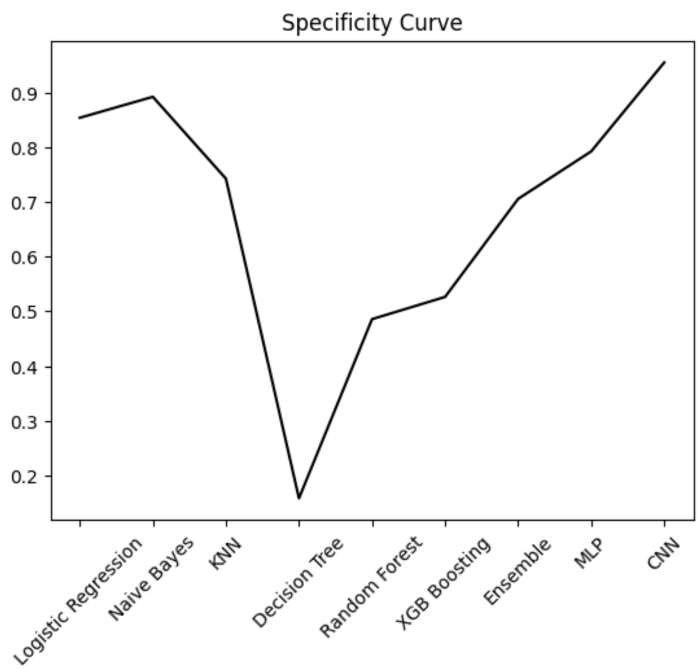


Fig 4.14 Specificity Of Classifiers

The Receiver Operating Characteristic curve maximizes all the True Positives and minimizes False Positives. Generally, if the curve is more to the top-left corner, the model tends to perform better. Here we have plotted the ROC curves for all classifiers.

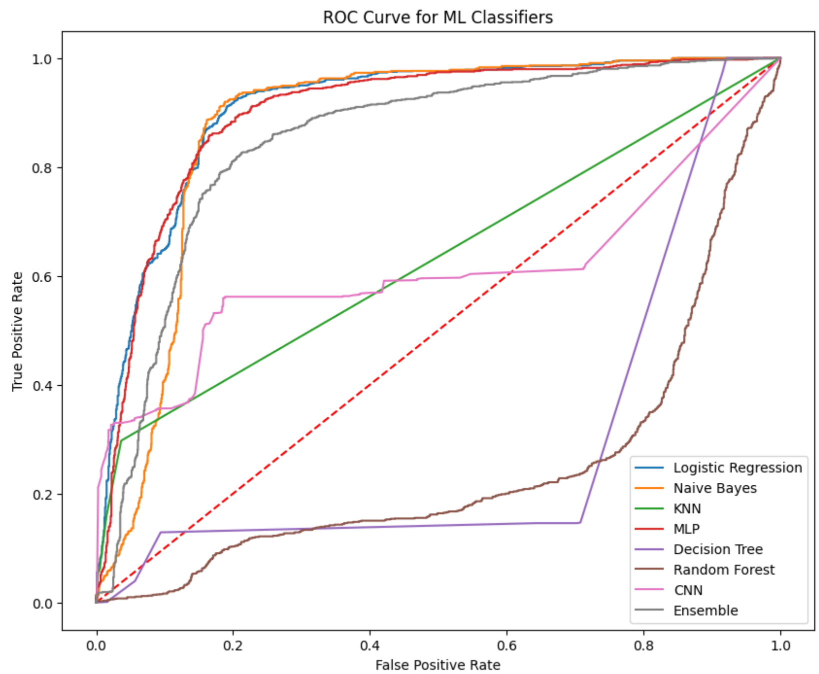


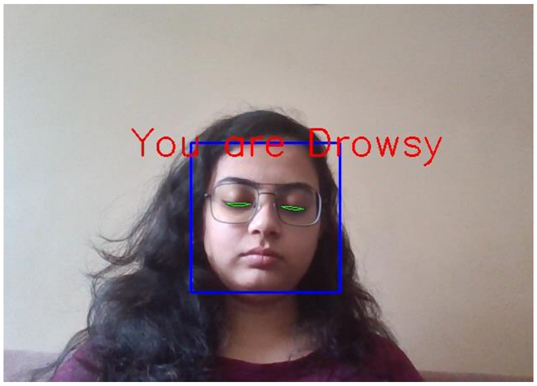
Fig 4.15 ROC Curve Of Classifiers

To validate our developed model, we have compared and analysed the proposed system's accuracy with other recent models. Here is the analysis's summary presented in tabular form in Table 4.2.

Table 4.2 Previous Work - Proposed Work

Author	Classifier	Accuracy
[4] 2022	Novel Random Forest	63.2%
[9] 2022	Support Vector Machine	56.9%
[10] 2020	MOL-TCE	62.84%
[11] 2020	Logistic Regression	75.67%
[14] 2017	Multilayer Perceptron	82%
[15] 2020	Convolutional Neural Network	61.7%
Proposed Work	Logistic Regression	86.12%
	Ensemble	84.27%
	Multilayer Perceptron	86%
	Convolutional Neural Network	72%

Looking at the outcomes of the comparison, Logistic Regression and Multilayer Perceptron performed well with the obtained dataset. Additionally, with the help of these two algorithms, a real-time drowsiness detection system is created. The input is taken from the webcam and the results are shown below:



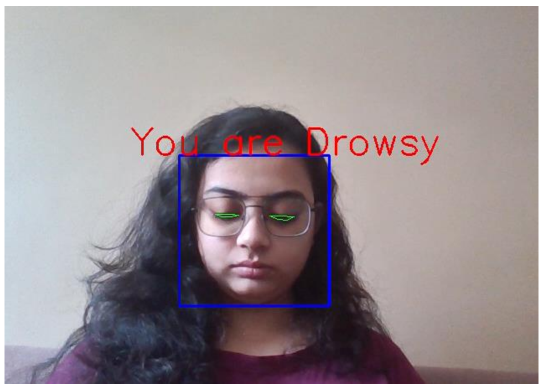


Fig 4.16 - 4.18 Real-time Drowsiness Detection Through Webcam

These results show that whenever the eyes are closed, the person is yawing and not paying attention, and the system alert them by a beeping sound with a text written as “You are Drowsy”. Here is the link to the video: https://drive.google.com/drive/folders/1-6igUGqSWVJY9_64v2UlPYcgixTYxnoB?usp=sharing

CHAPTER 5 CONCLUSIONS AND FUTURE SCOPE

The main purpose of this study is to monitor and detect drowsiness, and fatigue in drivers, and monitor their attention while driving in order to avoid accidents. With the help of various machine learning and deep learning algorithms, the proposed system aims at calculating multiple performance parameters in order to analyze the classifier's performance. From the results we have obtained, it can be concluded that the Logistic Regression classifier performed best with an accuracy of 86.12%. The voting classifier of the ensemble learning gave an accuracy of 84.27% and while the deep learning classifier MLP provided an accuracy of 86%. Calculation of various parameters such as f1 score, precision, sensitivity, specificity and roc curve helped understand the classifiers better. We have implemented a webcam which detects the drowsy and non-drowsy state. The proposed system can work efficiently on any video dataset provided. Usually, research has shown that deeper learning models work better with real-time scenarios. However, it is crucial to acknowledge that the performance of deep learning models is heavily dependent on the characteristics of the dataset. Therefore, future research should explore the effectiveness of other deep learning models and evaluate their performance with a more diverse dataset.

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