Driver Drowsiness Detection

Machine Learning - UML501
Project Report

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1. Github Link

https://github.com/prachi040803/MLProject_DriverDrowsinessDetection

2. Introduction

In terms of road safety, tired drivers significantly contribute to global accidents. Our project tackles this issue by suggesting a practical way to check if a driver is tired, focusing on detecting drowsiness. Understanding the need to quickly respond to a drowsy driver and avoid accidents, we present a new approach to create a real-time drowsiness detection system.

Our system works smoothly by analyzing the driver's face through images and videos captured real-time. What makes our method different is that it doesn't bother or influence the driver. This special quality lets our model accurately understand the real condition of the driver, quietly keeping an eye on signs of drowsiness. Committed to making roads safer, our project provides a reliable solution, aiming to prevent accidents and save lives.

3. Problem Statement

Drowsy driving poses a substantial threat, contributing to a staggering 25% of all car accidents. Fatigue and driving together is a deadly combination. The alarming reality is that drowsy driving encompasses instances where drivers are not fully attentive to the road, potentially leading to momentary episodes of unconsciousness. This issue highlights a critical road safety concern, emphasizing the urgent need for effective measures to detect and mitigate the risks associated with drivers operating vehicles while in a tired and fatigued state.

4. Dataset

The University of Texas at Arlington Real-Life Drowsiness Dataset (UTA-RLDD) was created for the task of multi-stage drowsiness detection, targeting not only extreme and easily visible cases, but also subtle cases when subtle micro-expressions are the discriminative factors. Detection of these subtle cases can be important for detecting drowsiness at an early stage, so as to activate drowsiness prevention mechanisms. Subtle micro-expressions of drowsiness have physiological and instinctive sources, so it can be difficult for actors who pretend to be drowsy to realistically simulate such expressions. The UTA-RLDD dataset is the largest to date realistic drowsiness dataset. The RLDD dataset consists of around 30 hours of RGB videos of 60 healthy participants.

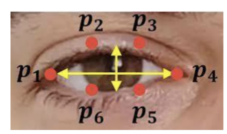
4.1 Feature Extraction

Given below is the set of features that we used for training the dataset:

I. Eye Aspect Ratio

It is the ratio of the height of the eyes to the diameter of the eyes. The calculation of the length of the eyes is done by taking the average of two distinct vertical lines drawn across the eyes, p1 and p4 are diametrically end points horizontally.

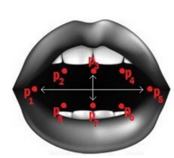
$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\,\|p_1 - p_4\|}$$



II. Mouth Aspect Ratio

On the same lines as EAR, MAR also measures the ratio of height of mouth to the diameter of mouth. Our hypothesis was that as a driver becomes drowsy, they are likely to yawn more and lose control over the actions of their mouths, which makes the MAR higher than usual. Here, EF and AB are lines joining vertical and horizontal end points.

$$\mathrm{MAR} = \frac{\|p_2 - p_8\| + \|p_3 - p_7\| + \|p_4 - p_6\|}{2\,\|p_1 - p_5\|}$$



III. Pupil Circularity

It is a metric which is interrelated to EAR, but it places a greater emphasis on the pupil and not the entire eye. For instance, someone who has half-opened their eyes or almost closed is going to have a much lower PUC value as compared to someone who has fully opened their eyes due to the squared term in the denominator. Just like the EAR, the hypothesis was that when a driver feels drowsy, their pupil circularity will decline.

$$\text{Circularity} = \frac{4 * \pi * \text{Area}}{\text{perimeter}^2}$$

IV. Mouth Over Eye Ratio

This is the ratio of the Mouth Aspect Ratio to the Eye Aspect Ratio. This value should increase as the driver gets more drowsy.

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

All these features point to the changing facial orientation of the driver, and help us detect if their eyes are closing or blinking too fast, and also if the person is yawning. Hence, we will be able to detect if the driver is fatigued and drowsy. Subsequently, we can alert the driver.

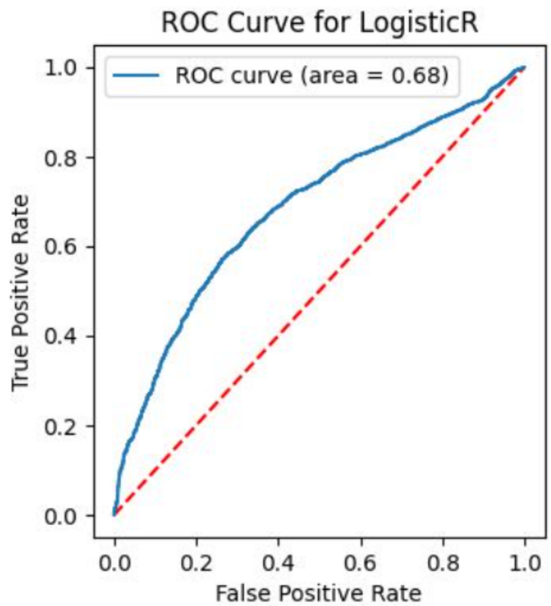
5. Methodology

5.1 Models

I. Logistic Regression

Despite its name, logistic regression is used for binary classification problems. It models the probability that an instance belongs to a particular category. The output is transformed using the logistic function to constrain it between 0 and 1. It's a linear model with a logistic activation function.

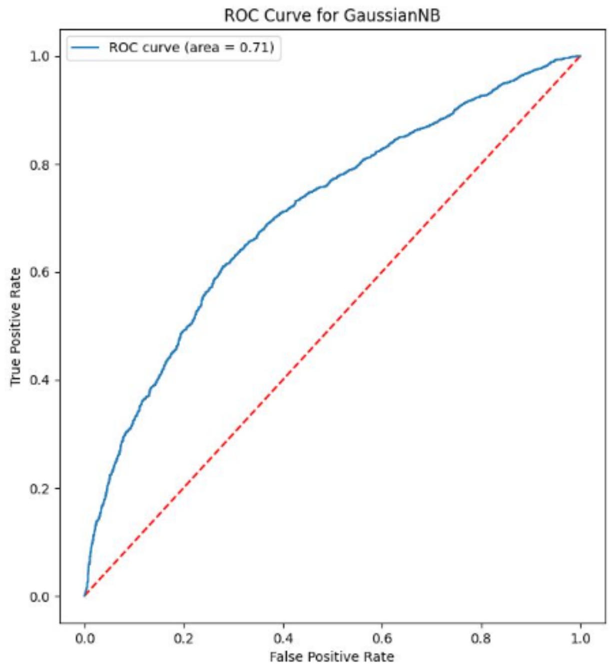
Accuracy = 0.6507



II. **Naive Bayes**

Based on Bayes' theorem, it assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. Despite its "naive" assumption, it performs surprisingly well in many real-world situations. It's computationally efficient and easy to implement.

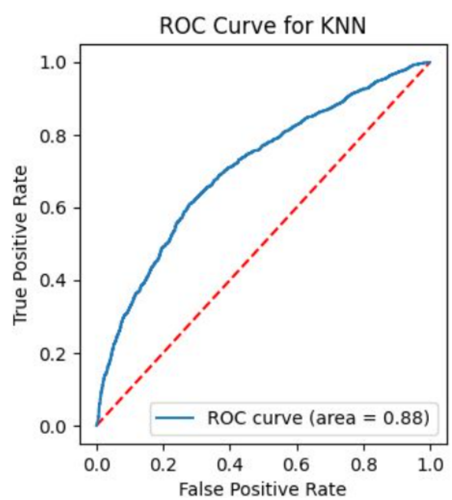
Accuracy = 0.6355



III. **K-Nearest Neighbors**

KNN is a non-parametric and lazy learning algorithm. Given a new instance, it looks at the k-nearest training instances (in feature space) and assigns the majority class (for classification) or the average value (for regression) of these neighbors to the new instance.

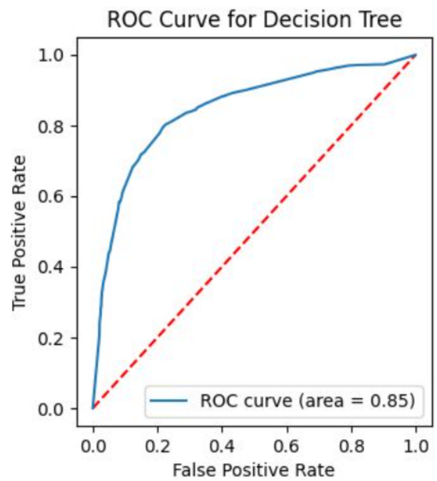
Accuracy = 0.8110



IV. **Decision Trees**

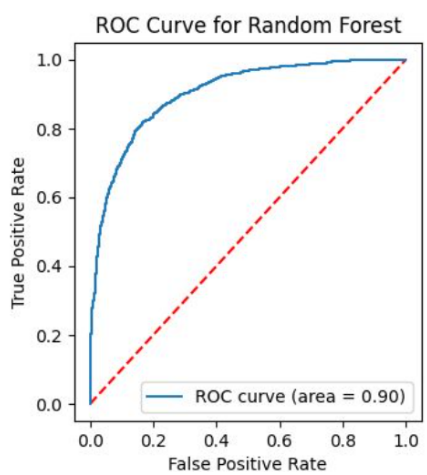
Decision trees recursively split the dataset into subsets based on the most significant attribute at each level. The process continues until a stopping criterion is met, such as a maximum depth or a minimum number of samples

in a leaf node. Decision trees are interpretable and can handle both numerical and categorical data.
Accuracy = 0.7861



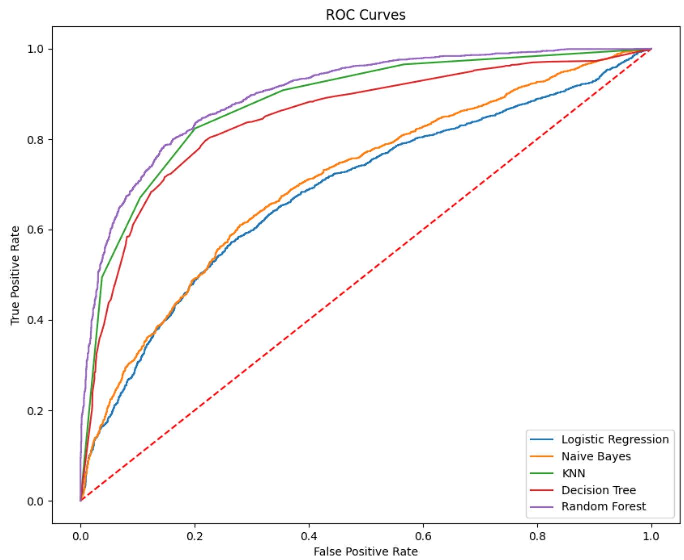
V. **Random Forest**

Random Forest is an ensemble of multiple decision trees. It builds a set of decision trees and merges them together to obtain a more accurate and stable prediction. Each tree is trained on a random subset of the training data, and the final prediction is often the majority vote (for classification) or the average (for regression) of the individual tree predictions.
Accuracy = 0.8209

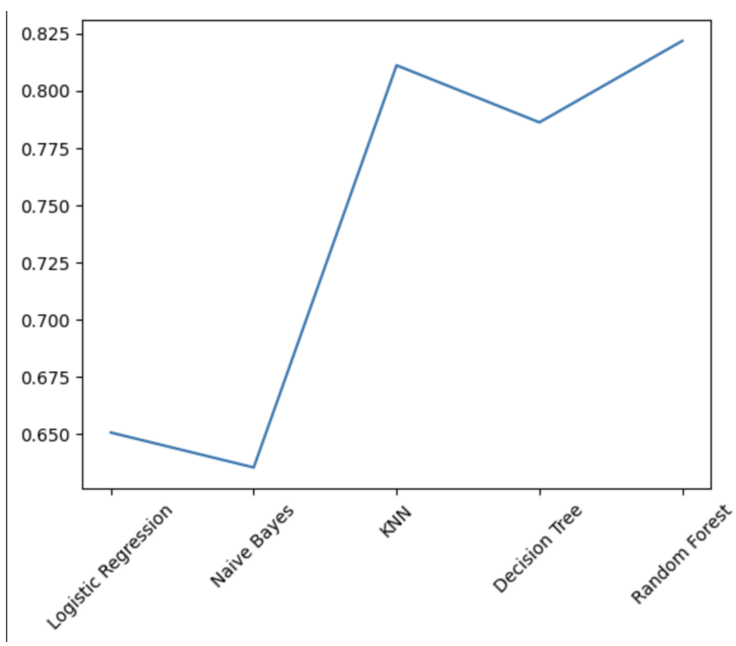


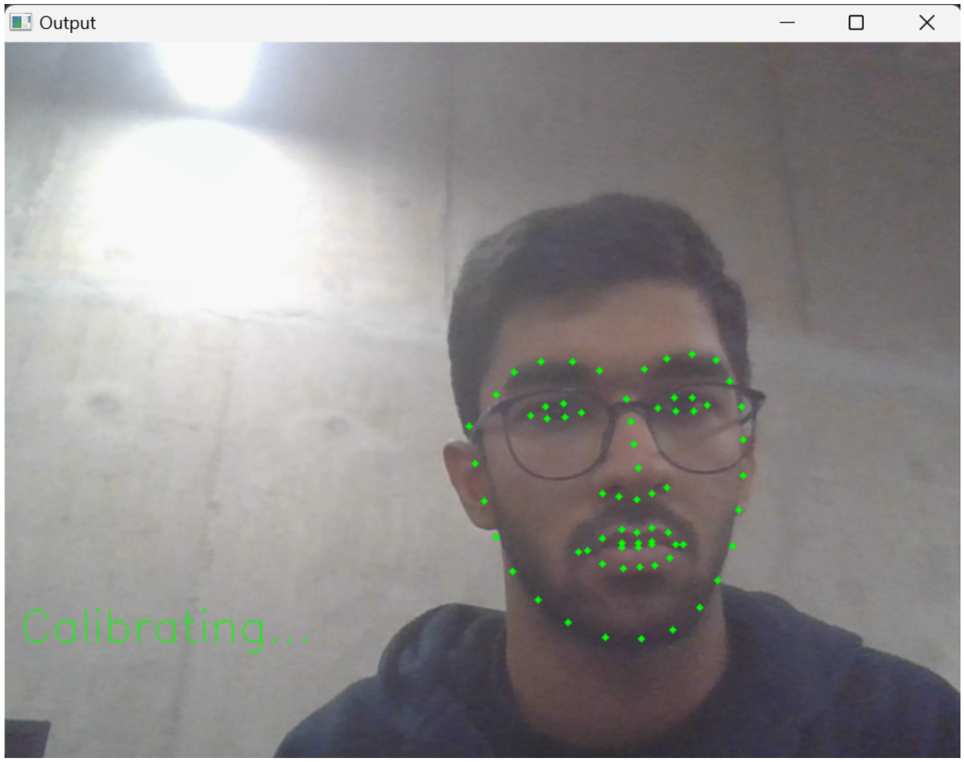
6. Outputs

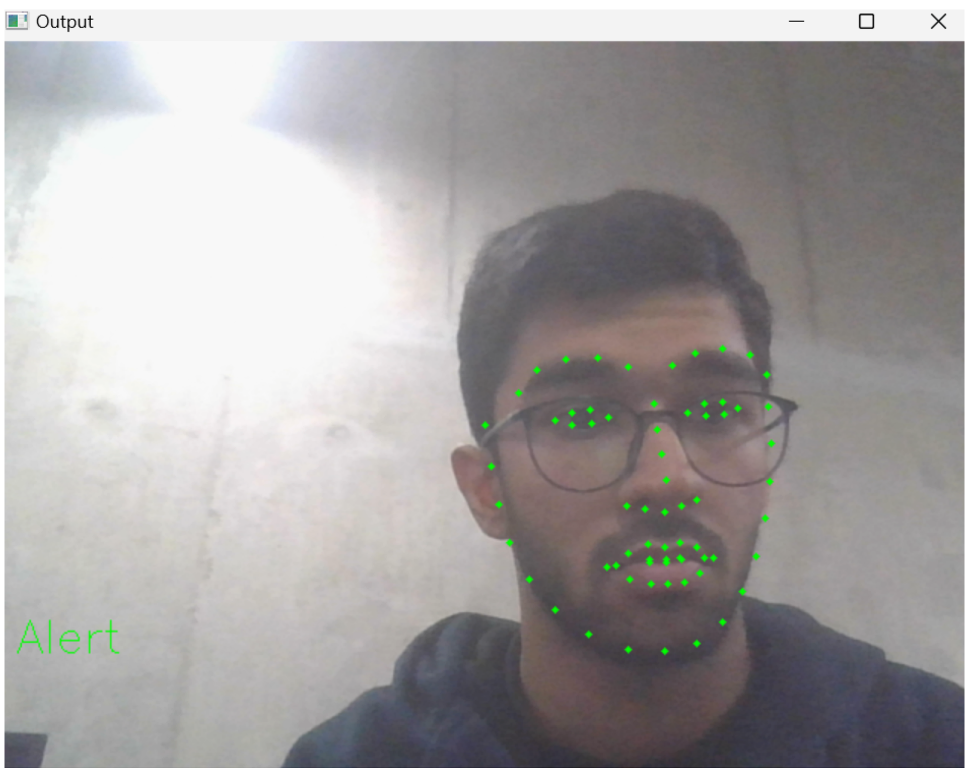
6.1 ROC Curves Comparison

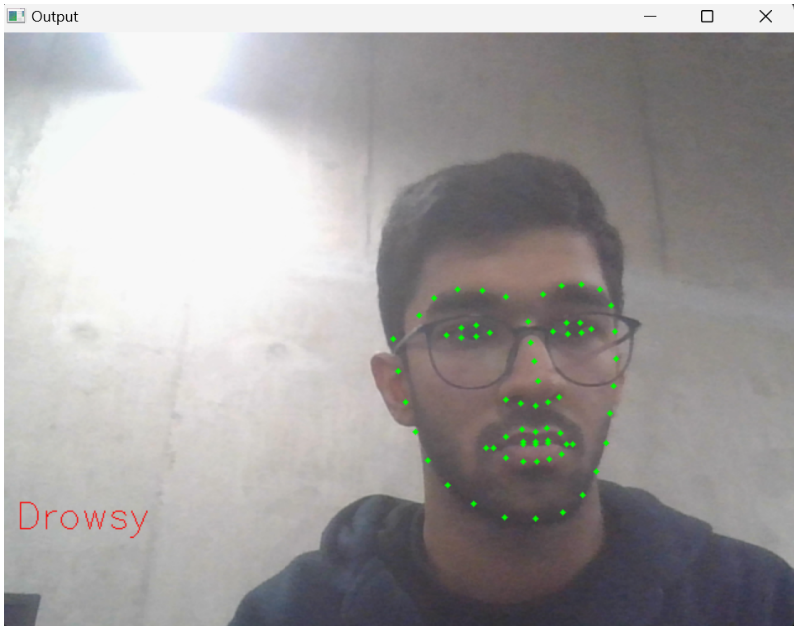


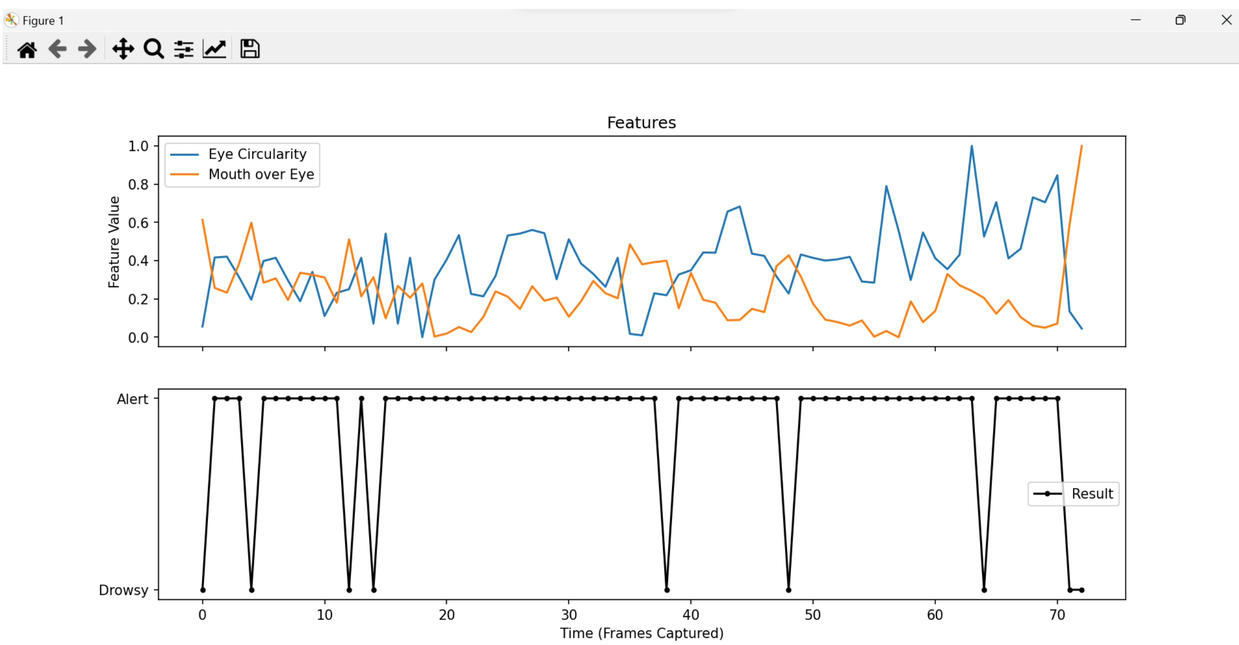
6.2 Accuracy Comparison




Output
Calibrating...


Output
Alert





7. Conclusion

In this project, we successfully developed and implemented a model for driver drowsiness detection, aiming to enhance road safety by mitigating the risks associated with drowsy driving. Our primary focus was on creating a robust and accurate system capable of identifying instances of driver drowsiness in real-time.

Current Model Performance

Our current model, which utilizes Logistic Regression, Naive Bayes, KNN, Decision Trees and Random Forest, has achieved a **highest accuracy of 82%** in the case of **Random Forest** Model.

To further advance the accuracy and effectiveness of our drowsiness detection system, we are considering the exploration of more advanced neural network architectures. Convolutional Neural Networks (CNNs) and Long Short-Term Memory Networks (LSTMs) are potential candidates that could better capture spatial and temporal dependencies within our dataset.