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Driver Drowsiness and Alcohol Detection for Automotive Safety Systems

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Abstract

Driver drowsiness and alcohol impairment are major causes of traffic accidents, making road safety a main concern. This study highlights the importance of addressing these issues through improved driver monitoring technologies. A prototype combining MQ-3 alcohol sensors, and facial detection was created, integrating with IoT via a Raspberry Pi to monitor and alert on drowsiness and alcohol levels. The developments use the NTHU-DDD dataset, which supports a supervised learning approach to develop a reliable drowsiness detection model. The study explored various machine learning algorithms such as Logistic Regression, Support Vector Machine (SVM), Random Forest (RF), K-nearest neighbors (KNN), Gradient Boosting Classifier, and Gaussian Naive Bayes, with Random Forest and Gradient Boosting emerging as top performers, particularly suited to complex non-linear data. The system effectively used supervised learning techniques to differentiate drowsy and non-drowsy images and exhibited consistent accuracy in detecting drowsiness, especially when the driver's face was centered. However, accuracy decreased when faces were tilted, highlighting areas for refinement. Moreover, the environmental tests on the MQ-3 sensor demonstrated its sensitivity to alcohol presence, even distinguishing the intensity based on beverage type and concentration. The findings underscore the efficacy of using sensor-based technologies in real-world conditions and provide a foundation for optimizing the system's detection capabilities across various scenarios.

Keywords: Driver Drowsiness; Alcohol Impairment; NTHU-DDD Dataset; Gradient Boosting; MQ-3 Sensor.

1. Introduction

In our modern world, the ongoing challenges of road accidents caused by driver drowsiness and alcohol impairment remain pressing concerns for the safety of the public [1, 2]. According to an expert from the University Kebangsaan Malaysia (UKM) Centre for Research in Psychology and Human Wellbeing, highlights the strong link between a short period of sleep, commonly known as microsleep, and a person's ability to function on a daily basis [3]. The Malaysian Institute of Road Safety Research (MIROS) highlights the role of driver drowsiness as a major contributor to accidents involving various vehicles, including cars, trucks, and buses [4-6]. Besides, the Deputy Housing and Local Government (KPKT) Malaysia reveals a concerning statistic, stating that between 2016 and 2020, 771 accidents were attributed to alcohol influence, resulting in 44 fatalities [7]. Additionally, nationwide operations under the codename "Ops Mabuk" led to a significant number of arrests, totaling 1,249, as reported by the Deputy Head of Bukit Aman Traffic Investigation

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and Enforcement Department (JSPT) [8, 9]. Faced with these distressing numbers and potential hazards associated with driving under the influence and drowsiness, there has been a surge in research and technological advancements focusing on driver monitoring systems. The primary objective is to detect and mitigate driver drowsiness, ultimately aiming to reduce the risks on the road.

Researchers have made progress in creating accurate techniques for identifying intoxication from alcohol and detecting driver drowsiness over the years. Jadaalli et al. [10] and Archana et al. [11] proposed systems that utilize an eye blink sensor and an alcohol sensor which is MQ3 to detect and address potential dangers related to drowsiness and alcohol consumption while driving. The eye blink sensor continually tracks the eye blink rate in order to identify the driver's level of fatigue. Additionally, both systems employ a buzzer to warn the driver in case of detected drowsiness or alcohol consumption. Both systems have limitations affecting their accident prevention effectiveness. The reliance on drivers consistently wearing the eye blink sensor frame assumes continuous usage, impacting drowsiness detection if forgotten or removed during driving. Fit discomfort for some drivers may lead to non-compliance, posing a risk as drivers may choose not to wear or remove the sensor during the journey.

Varghese et al. [12] developed an integrated system for detecting driver drowsiness and alcohol intoxication using machine learning technology. This system utilizes non-intrusive methods such as face detection and analysis of core facial features to detect drowsiness, while also incorporating an alcohol sensor for detecting alcohol consumption. The system uses a Support Vector Machine (SVM) classifier to segregate the data into drowsy and alert states, with an accuracy rate of F1 scare 0.98. Kao & Chan [13] investigated the usage of face characteristics to identify fatigue. The study employed K-nearest neighbors Sigma (KNN-Sigma) and gradient-weighted class activation mapping (Grad-CAM) to analyze how individual neurons focus their attention and gather features. The results revealed that combining facial and eye signals produced the highest recognition accuracy, with an impressive area under the curve (AUC) value of 0.935.

Gupta et al. [14] proposed a system, which is a real-time system for monitoring a driver's state while driving. The goal of the system is to spot when the driver is getting sleepy, yawning, or showing other signs of drowsiness, and also if there's any risk, the system is designed to alert the driver. The system employs various methods like Histogram Oriented Gradient (HOG), SVM, Local Binary Patterns (LBP), and dlib facial landmarks to find the face, identify the driver, and calculate the aspect ratio of the mouth and eye for spotting yawning and eye closure. The system has a dynamic timer that adapts thresholds for continuous yawning and closed eyes as driving time goes on. If the driver yawns for over four seconds or closes the eyes for more than two seconds, the system sounds an alarm. Roja et al. [15] developed a system aimed to detect driver drowsiness using machine-learning techniques, highlighting the importance of continuous monitoring to reduce accidents caused by fatigue. The system uses algorithms, including the Haar cascade for detecting facial features and the PERCLOS method to analyze eye closure, enabling it to assess drowsiness levels with reasonable accuracy. By examining eye behavior, it also addresses the problem of driver distraction and makes sure that drivers maintain their attention on the road. While the system demonstrated a 78% accuracy rate in detecting drowsiness and distraction, this may not be good under all driving conditions or for every driver.

Theivadas & Ponnan [16] introduced a machine learning-based system designed to detect driver fatigue and improve road safety. Using SVM as its technique, the system integrates tools like OpenCV and Dlib to analyze 68 facial landmarks, with a particular focus on monitoring the driver's eye status. When signs of drowsiness are detected, it promptly alerts the driver through auditory or tactile signals. The system demonstrated impressive performance, achieving a 94% accuracy rate in fatigue detection. However, the system needs to go through comprehensive testing in diverse scenarios to ensure the system's reliability in real-world applications. Further research is recommended to enhance its effectiveness across varying environments.

2. Research Method

2.1. Methodology

Two key methodologies were implemented: a drowsiness detection system and an alcohol detection system. Both systems operate in parallel, utilizing real-time monitoring and threshold-based decision mechanisms to identify potential risks and provide timely alerts. The process for driver drowsiness detection includes a number of steps that are intended to monitor the driver's face in real-time and identify indicators of drowsiness that are shown in Figure 1. In order to recognize the driver's face, the system first takes a video feed from a camera and applies a face detection algorithm. A facial landmark identification method is used to extract the facial landmarks, after which the system determines the Mouth Aspect Ratio (MAR) and Eye Aspect Ratio (EAR) for both eyes. The system uses a decision point to determine whether the EAR and MAR are below their respective threshold values. If both values are above the threshold, the system alerts the driver by buzzing the buzzer. The system will then use a GSM module to send an SMS notification to the vehicle owner or relatives. The system continues to monitor the driver's face if both the EAR and MAR are below the threshold.

For the alcohol detection system, the process starts with initializing the MQ-3 sensor and other necessary components, waiting for the sensor to stabilize, and then reading the alcohol level from the sensor. After that, the system acquires the readings from the MQ-3 sensor and sends the data to the cloud. The alcohol level is then compared to a predetermined threshold, and if it is above the threshold, the warning system is activated, which is the buzzer beep and sending an alert message to the driver's relative via the GSM module. The warning system is turned off if the alcohol level is below the threshold that is set. Throughout operation, the system repeatedly performs this action.

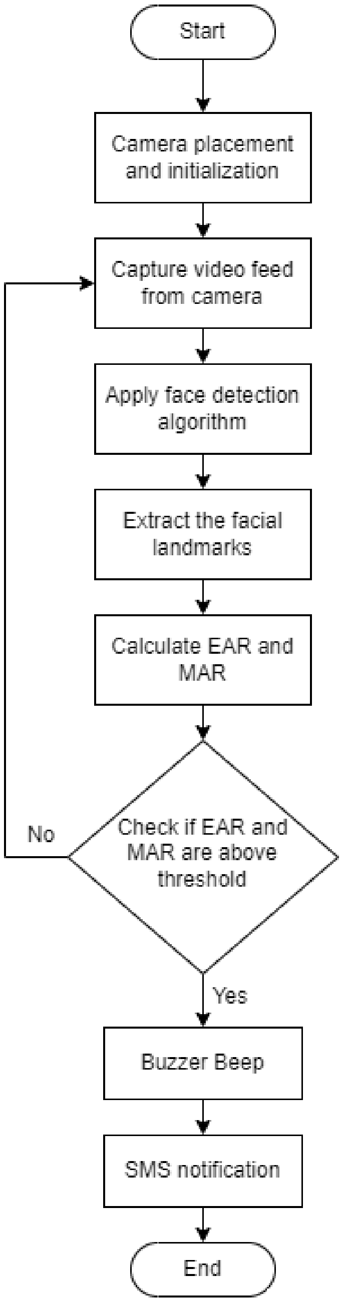

Figure 1. Drowsiness Detection Flowchart

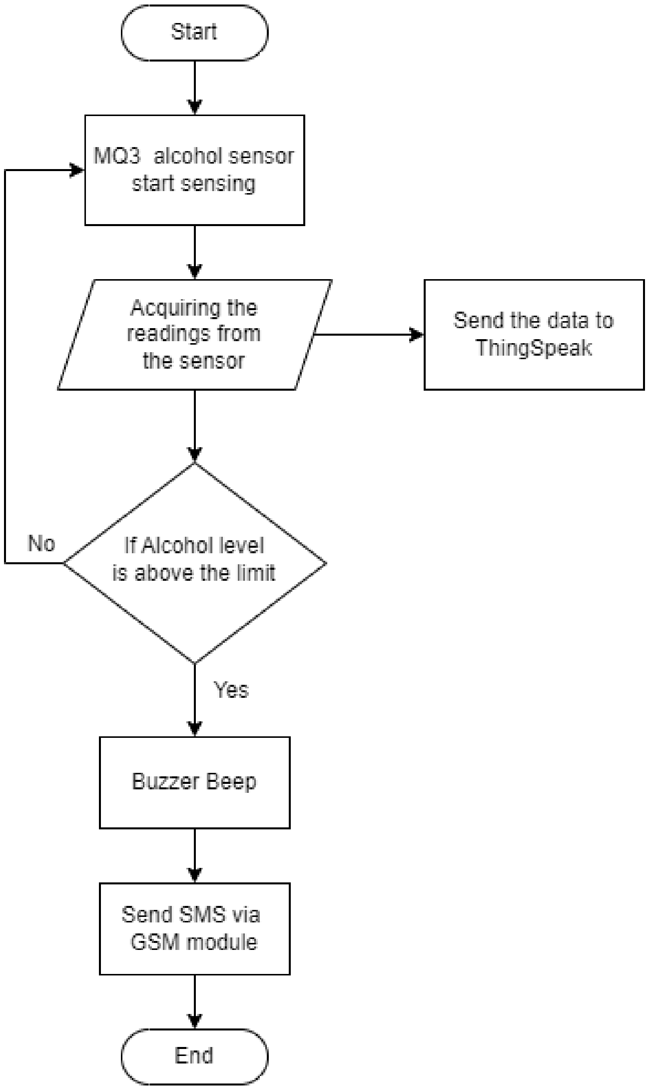

Figure 2. Alcohol Detection Flowchart

2.2. Dataset

The NTHU-DDD dataset consists of videos, which were designed for driver drowsiness detection. The videos have a resolution of 640×480 and were stored in the AVI format. Figures 3 shows example snapshots of the NTHU-DDD dataset. The dataset is divided into three parts such as training, evaluation, and test purposes. The training set encompasses 360 videos, while the evaluation dataset comprises 20 videos. The dataset contained diverse driving situations captured through visual sensors, such as cameras and active infrared sensors [17].

Figure 3. NTHU-DDD dataset [18]

The dataset featured 36 drivers of varied ethnicities, recorded based on the presence of glasses and the illumination conditions like glasses, bare face, sunglasses, night glasses, and night bare face. The dataset also recorded the drivers engaging in a range of driving scenarios. The sequences were captured under normal driving, yawning, slow blink rates, falling asleep, and scenarios under different day and night illumination conditions. As a part of the dataset's pre-processing, the videos have been segmented into images and labelled as either drowsy or non-drowsy. Figure 4 shows example snapshots of the pre-processed images [17].

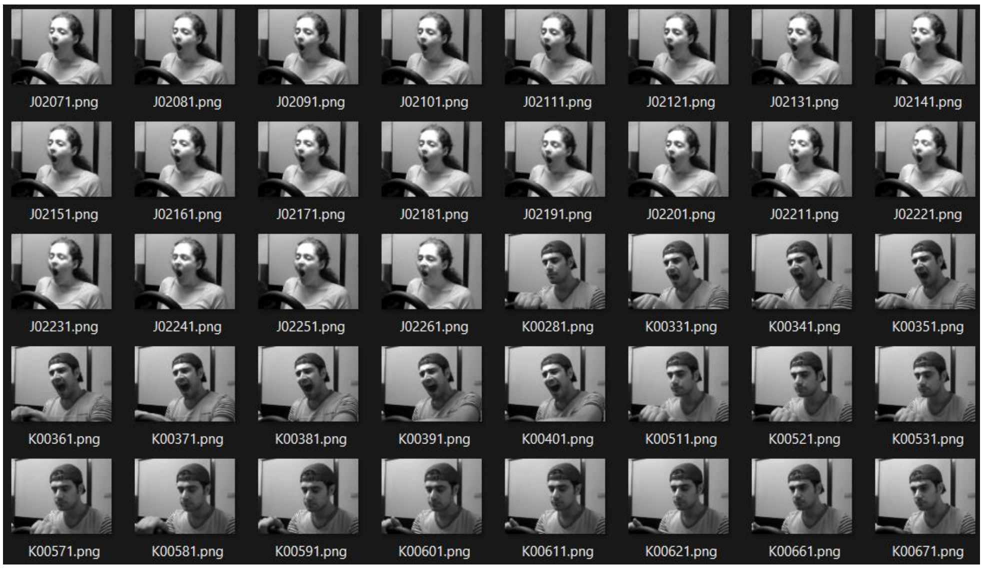

Figure 4. Pre-Processed NTHU-DDD Dataset [18]

2.3. Pre-Processing

This section discusses the pre-processing methods that are used to optimize the training of a drowsiness detection model by refining a video dataset. The initial step involves converting the video dataset into a format that is suitable for training the model. By removing frames from the video clip, temporal dynamics of the scene are captured in snapshot form. Then, the retrieved frames are subsequently saved into high-resolution images to guarantee significant visual information, which improves the clarity of face features like eyes and mouth.

Followed by the extraction of frames, the dataset is organized into two categories, including drowsy and non-drowsy images. Each category is then stored in separate files, and corresponding labels are assigned to facilitate supervised learning. This segmentation sets the stage for the model to learn the distinguishing features between instances of drowsy and non-drowsy. The next stage of pre-processing focuses on making sure the data is relevant and of high quality. In order to accomplish this, an intensive cleaning process is initiated in order to remove any instances of blurry images. Images with blurry pixels can introduce noise and make the model perform worse. So, one of the most important pre-processing steps is to recognize and remove the blurry images to enhance the dataset's overall clarity and reliability. The entire pre-processing workflow guarantees that the dataset is cleaned, arranged, and optimized for insightful analysis and the development of the model, providing a strong basis for the research's next phases.

2.4. Detection using Supervised Learning Algorithms

2.4.1. Logistic Regression

Logistic regression and Naive Bayes share a similar approach of determining weighted features from the data, achieved by applying logarithms and combining them linearly. In both methods, traits are multiplied by respective weights and summed [19]. The main difference between Naive Bayes and logistic regression is the way of classification process.

In logistic regression, a type of regression analysis, data is fitted to a logistic function to figure out how likely something is to happen. This method looks at both categorical and numerical predictor factors [20]. This is how the logistic regression hypothesis is written:

$$h_\theta(x) = g(\theta^T x) \tag{1}$$

The sigmoid function is shown by the function g, which is written as:

$$g(z) = \frac{1}{1+e^{-z}} \tag{2}$$

As shown in Figure 5, the sigmoid function has special features that constrain values within the [0, 1] range.

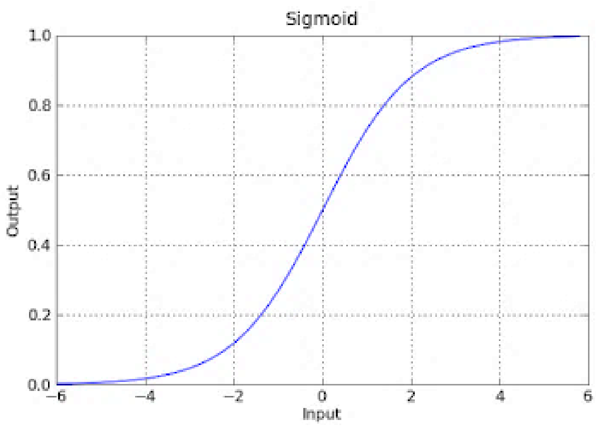

Figure 5. Sigmoid Logistic Function [20]

2.4.2. Support Vector Machine

SVM is a robust machine learning algorithm commonly used for sorting things into categories or predicting values. The way SVM works is by figuring out the best possible dividing line, which is hyperplane in a space with lots of dimensions. This line efficiently separates data points into different groups, as illustrated in Figure 6. The strength of SVM lies in its ability to handle complex datasets, especially those that are not linearly separable, through the use of kernel functions. SVM strives to find a hyperplane that maximally separates different classes while minimizing classification errors.

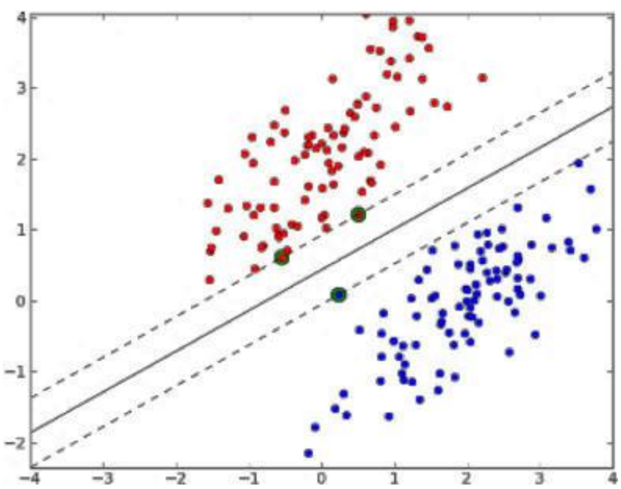

Figure 6. Hyperplane in a High-Dimensional Space [21]

2.4.3. Random Forest

RF stands as a robust and versatile ensemble learning algorithm widely utilized in machine learning tasks such as classification and regression. This approach involves creating many decision trees while training and then picking the most common class for sorting things or the average prediction for estimating values [22]. Every decision tree is built by utilizing a random subset of the training data and a random assortment of characteristics. This introduces diversity and mitigates the risk of the model becoming excessively specialized and prone to overfitting. The collective decision-making process of multiple trees enhances the overall predictive accuracy and generalization ability of the model. The fundamental concept behind RF lies in the aggregation of individual decision trees to create a more reliable and resilient predictive model.

2.4.4. K-Nearest Neighbors (KNN)

KNN is a straightforward and flexible machine learning technique, mostly used for categorizing and making predictions. The KNN looks at the surrounding points to decide how to classify or predict something for a given data point. It's like letting the nearby crowd influence the decision. The “K” in KNN refers to the number of neighboring data points considered in this decision-making process.

2.4.5. Naïve Bayes

Bayesian classification, a form of supervised learning, operates on a probabilistic model to address predictive challenges. The method embraces uncertainty by assigning probabilities to outcomes, offering a principled approach to model uncertainty. The significance lies in the ability to generate explicit probabilities for hypotheses and effectively handle input data noise [20].

Consider a basic probability distribution represented by two numbers, which is written as $P(x_1, x_2)$. By using Bayes' rule, can get the following equation:

$$P(x_1, x_2) = P(x_1|x_2)P(x_2) \tag{3}$$

Adding another class variable, written as c, to this leads to the following equation:

$$P(x_1, x_2|c) = P(x_1|x_2, c)P(x_2|c) \tag{4}$$

Further, if change the situation from two variables to more than two variables and assume that a set of variables x_1, ..., x_N are conditionally independent given another variable c, the statement changes to:

$$\mathrm{P}(x|c) \prod_{i=i}^{N} P(x_i|c) \tag{5}$$

2.4.6. Gradient Boosting

In the area of supervised learning, gradient boosting is an effective and popular ensemble learning method. This method makes predictions more accurate by adding weak learners, like decision trees, one by one until there is a strong predict model [23]. Gradient boosting works by gradually improving predictions and reducing errors by fitting new models to the remaining mistakes of the earlier ones. The gradient of the loss function serves as a guidance during this repeated boosting process, which makes it easier to create a highly accurate and adaptive model. In the context of this driver drowsiness model, Gradient Boosting serves as the sole machine learning methodology, demonstrating to be able to handle complicated patterns in the data and improve the model's capacity to predict driver drowsiness.

3. Results and Discussion

3.1. Experimental Results

In the pursuit of identifying the most effective machine learning algorithm for a classification task, an experiment was conducted using six algorithms, which are Logistic Regression, SVM, RF, KNN, Gradient Boosting, and Gaussian Naive Bayes. The implementation of many different types of machine learning techniques enabled a full evaluation of each algorithm's performance through an efficient dataset analysis. The experiment used default parameters in order to capture each algorithm's actual capabilities without the need for extra tuning. This method helped to draw attention to the underlying advantages and disadvantages of the various algorithms in light of the particular traits of the NTHU-DDD dataset.

As shown in Table 1, the results of the experiment indicate significant differences in testing accuracy between several machine learning algorithms using the NTHU-DDD dataset. The differences in accuracy can be linked to the inherent features of every algorithm and its suitability for the dataset. The results revealed that RF and Gradient Boosting Classifier emerged as the top performers, achieving impressive testing accuracies of 90.04% and 91.79%, respectively. This superior performance can be attributed to their ability to capture complex non-linear relationships within the data, making them well-suited for challenging classification tasks. The Gradient Boosting Classifier performed slightly better than RF, potentially due to its ability to iteratively correct errors and optimize performance.

Table 1. Experiment Result

Algorithm	Logistic Regression	SVM	RF	KNN	Gradient Boosting	Naive Bayes
Training Accuracy	0.830999066	0.760971055	1.00	0.893557423	0.941176471	0.877684407
Validation Accuracy	0.873134328	0.78358209	0.932835821	0.895522388	0.940298507	0.917910448
Testing Accuracy	0.858208955	0.753731343	0.900447761	0.850746269	0.911373134	0.880597015
Total Computation Time (minutes)	1.40	1.48	1.82	1.40	1.40	1.45

On the other hand, the SVM exhibited a lower accuracy of 75.37%. This algorithm is known for its effectiveness in handling linearly separable data, but SVM struggled in this scenario where the data exhibited non-linear patterns. The low performance of SVM is also indicating that the structure of the dataset might not be entirely consistent with its inherent assumptions. Logistic Regression also demonstrated a lower accuracy of 86.82%. While Logistic Regression excels in problems with linearly separable data, the non-linear nature of our dataset presented a challenge for this algorithm. Gaussian Naive Bayes achieved a moderate accuracy of 88.06%. KNN, with an accuracy of 85.07%, also faced challenges in capturing the complex relationships within the data. These algorithms rely on similarity measures between data points, and the non-linearity of the dataset hindered its performance.

In terms of computation time, the algorithms varied in their efficiency. RF required relatively longer training times of 1.82 minutes that can be attributed to its ensemble nature, where RF builds multiple decision trees during training and combines their outputs. This ensemble approach, while enhancing predictive accuracy, requires additional computational resources compared to individual decision tree algorithms. The algorithm's complexity and the ensemble strategy contribute to its relatively longer training duration compared to some of the other algorithms in the experiment. SVM and Gaussian Naive Bayes consume slightly less computational time, with the time of 1.48 minutes and 1.45 minutes, respectively. KNN, Gradient Boosting Classifier, and Logistic Regression are the optimal algorithms, completing its computation in 1.40 minutes. From a practical standpoint, computation time is a critical factor in real-time drowsiness detection systems, where model predictions are required for timely intervention. Gradient Boosting's performance in both accuracy and computational efficiency makes it a promising candidate for deployment in real-world applications.

3.2. Hyperparameter Tuning

Among the evaluated machine learning algorithms, Gradient Boosting Classifier emerged as the most promising model for drowsiness detection. A targeted hyperparameter tuning is implemented as shown in Table 2, resulting in an iterative process aimed at improving the performance of the model. The tuning parameters are carefully selected based on their important functions that impact the Gradient Boosting Classifier's learning dynamics. Three key hyperparameters are selected for tuning, which are learning rate, number of estimators, and subsample.

The reason for modifying these specific parameters is because of their interrelated impact on the boosting process. Changing the learning rate affects the step size, whereas changing the number of estimators and subsample directly affects the model's complexity and data sampling method. This study aimed to find the proper balance, making sure that the Gradient Boosting Classifier obtains the highest prediction performance.

Table 2. Gradient Boosting Classifier Hyperparameter Tuning

Learning rate	Number of estimators	Subsample	Test Accuracy	Computation Time (m)
0.01	50	0.7	0.910447761	1.52 minutes
0.01	50	0.8	0.910447761	1.73 minutes
0.01	50	0.9	0.910447761	1.75 minutes
0.01	100	0.7	0.917910448	1.77 minutes
0.01	100	0.8	0.910447761	1.79 minutes
0.01	100	0.9	0.910447761	1.72 minutes
0.01	200	0.7	0.902985075	1.73 minutes
0.01	200	0.8	0.910447761	1.79 minutes
0.01	200	0.9	0.910447761	1.75 minutes
0.1	50	0.7	0.917910448	1.75 minutes
0.1	50	0.8	0.917910448	1.77 minutes
0.1	50	0.9	0.917910448	1.82 minutes
0.1	100	0.7	0.910447761	1.81 minutes
0.1	100	0.8	0.925373134	1.76 minutes
0.1	100	0.9	0.932835821	1.77 minutes
0.1	200	0.7	0.910447761	1.84 minutes
0.1	200	0.8	0.917910448	1.80 minutes
0.1	200	0.9	0.910447761	1.82 minutes
0.2	50	0.7	0.932835821	1.85 minutes
0.2	50	0.8	0.910447761	1.75 minutes
0.2	50	0.9	0.910447761	1.77 minutes
0.2	100	0.7	0.888059701	1.58 minutes
0.2	100	0.8	0.888059701	1.83 minutes
0.2	100	0.9	0.902985075	1.67 minutes
0.2	200	0.7	0.910447761	1.79 minutes
0.2	200	0.8	0.902985075	1.79 minutes
0.2	200	0.9	0.895522388	1.82 minutes

3.3. Setup of IoT Prototype

Setting up the prototype requires connecting MQ-3 alcohol sensor, MCP3008, Logitech webcam, buzzer, Raspberry Pi display, and GSM module to the Raspberry Pi 4 Model B, as illustrated in Figure 7. The MQ-3 alcohol sensor is connected to the MCP3008, which acts as an intermediary component in the connection sequence. This connection is important because the MCP3008 works as an analog-to-digital converter, converting analog signals from the MQ-3 sensor into a digital format that the Raspberry Pi can analyse.

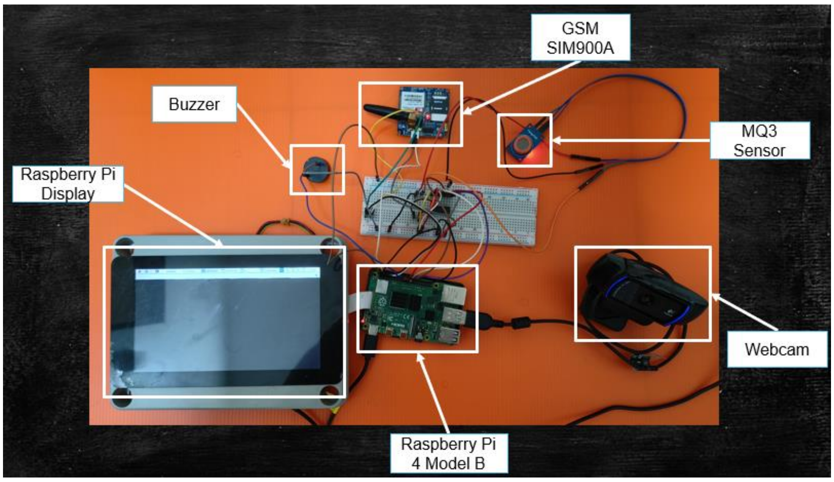

Figure 7. Functional Prototype

Subsequent to the hardware setup, the coding process is used to enable the parallel functionality of the drowsiness detection and alcohol detection components. The tuned model, which is discussed in Section 3.2 is then converted into a .h5 format and integrated into the system as the predictive model for drowsiness detection. Based on the certain features obtained from facial landmarks, this model determines whether an individual shows signs of drowsiness. The eye aspect ratio and the vertical distance between the top and lower lip are important predictor factors. There are functions to compute these ratios, with the resulting binary value like 1 or 0, which indicate the presence or absence of drowsiness. Depending on the outcome, the system adjusts the system's state and triggers specific actions, such as activating a buzzer and sending an alert SMS. The system is included to automatically relay the information to the drivers designated emergency contacts using the GSM Module as shown in Figure 8. This feature ensures that loved ones are promptly informed of the potential risks, allowing for appropriate actions to be taken. Additionally, a warning message pops up on the Raspberry Pi display when the system detects that the driver is either drowsy or under the influence of alcohol as shown in Figure 9. This feature serves to alert co-passengers during travel.

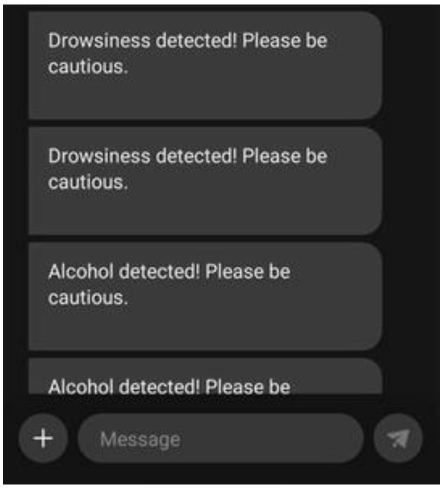

Figure 8. Alert Messages Sent to Emergency Contact

Figure 9. Warning Messages on the Raspberry Pi Display

Subsequently, the collected data from the MQ3 sensor and the binary value like 1 or 0 representing the drowsiness detection, is transmitted to the cloud-based platform ThingSpeak. The integration with ThingSpeak facilitates the centralized storage and real-time monitoring of crucial information. The prototype automatically transmits the specific data to the ThingSpeak channel, allowing for remote access and analysis.

3.4. Testing

The accuracy and responsiveness of the developed system are assessed through testing methods. This ensures that the prototype consistently identifies drowsiness and the presence of alcohol.

3.4.1. Drowsiness Detection

To assess the driver drowsiness detection system, tests were conducted in a car with a strategically placed camera on the dashboard as shown in Figure 10. Ten participants aged between 20 to 30, participated in the testing phase. The testing conditions involved various positions, which are face centered, face tilted at 30-degree angle, face tilted at 40-degree angle, and presence or absence of spectacles. Participants performed several actions such as closing their eyes, yawning, and maintaining normal states. The collected data under these conditions serves as a valuable resource for evaluating the system's performance and reliability.

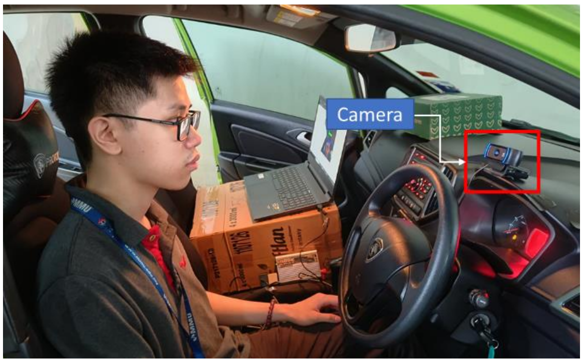

Figure 10. Drowsiness Detection Testing

The system consistently demonstrated effective drowsiness detection in scenarios with a centered face, accurately identifying drowsiness in one to six test cases as shown on Table 3. The system's reliability relies on its analysis of facial features, facilitated by clear visibility of the eyes and mouth. Focusing on key facial regions enables the detection of subtle signs like eyelid drooping and mouth movements. The centered face as shown in Figure 11 provides a detailed view, allowing the system to detect various facial expressions related to drowsiness. Overall, the system's proficiency in utilizing facial features underscore its ability to deliver accurate and reliable results in detecting drowsiness.

Table 3. Drowsiness Detection Test Case

Test Case	Face in Centre	Face Tilted 30°	Face Tilted 40°	Wear Specs	Not Wear Specs	Eyes Closed	Yawn	Normal	Expected Result	Reported Result
1	Yes	No	No	No	Yes	Yes	No	No	Drowsiness detected	Drowsiness detected (10 cases)
2	Yes	No	No	No	Yes	No	Yes	No	Drowsiness detected	Drowsiness detected (10 cases)
3	Yes	No	No	No	Yes	No	No	Yes	No drowsiness detected	No drowsiness detected (10 cases)
4	Yes	No	No	Yes	No	Yes	No	No	Drowsiness detected	Drowsiness detected (10 cases)
5	Yes	No	No	Yes	No	No	Yes	No	Drowsiness detected	Drowsiness detected (10 cases)
6	Yes	No	No	Yes	No	No	No	Yes	No drowsiness detected	No drowsiness detected (10 cases)
7	No	Yes	No	No	Yes	Yes	No	No	Drowsiness detected	Drowsiness detected (10 cases)
8	No	Yes	No	No	Yes	No	Yes	No	Drowsiness detected	Drowsiness detected (8 cases)
9	No	Yes	No	No	Yes	No	No	Yes	No drowsiness detected	No drowsiness detected (10 cases)
10	No	Yes	No	Yes	No	Yes	No	No	Drowsiness detected	Drowsiness detected (9 cases)
11	No	Yes	No	Yes	No	No	Yes	No	Drowsiness detected	Drowsiness detected (9 cases)
12	No	Yes	No	Yes	No	No	No	Yes	No drowsiness detected	No drowsiness detected (10 cases)
13	No	No	Yes	No	Yes	Yes	No	No	Drowsiness detected	Drowsiness detected (6 cases)
14	No	No	Yes	No	Yes	No	Yes	No	Drowsiness detected	Drowsiness detected (1 cases)
15	No	No	Yes	No	Yes	No	No	Yes	No drowsiness detected	No drowsiness detected (5 cases)
16	No	No	Yes	Yes	No	Yes	No	No	Drowsiness detected	Drowsiness detected (7 cases)
17	No	No	Yes	Yes	No	No	Yes	No	Drowsiness detected	Drowsiness detected (1 cases)
18	No	No	Yes	Yes	No	No	No	Yes	No drowsiness detected	No drowsiness detected (6 cases)

Figure 11. Face in Center

In the scenarios where the face is tilted at a 30-degree angle, as shown in Figure 12, the system consistently demonstrated its effectiveness in detecting drowsiness. This capability can be attributed to the system's reliable facial feature analysis, which allows the system to capture and extract relevant features, including eye and mouth movements. However, challenges occurred in extracting the Mouth Aspect Ratio (MAR) value during yawning, especially when the face was tilted. As seen in Table 3, Test Case 8 indicated that the system failed to detect drowsiness during yawning in two participants, while Test Case 11 showed one participant could not detect drowsiness in the presence of yawning. These findings highlight the complexity of identifying a driver's yawn, particularly at a 30-degree angle.

Figure 12. Face Tilted 30 Degree Angle

In scenarios with a 40-degree tilted face as shown in Figure 13, the system faced challenges in consistently detecting drowsiness. While successful detection occurred in some instances, the majority proved difficult. The specific angle posed a considerable obstacle, making it challenging for the system to detect signs of drowsiness consistently. Table 3 data revealed variations in detecting drowsiness when eyes were closed. Instances like Test Case 13 and 16 showed successful Eye Aspect Ratio (EAR) value extraction from one side of the face, enabling detection. However, this capability wasn't uniform, as some participants could not trigger detection when their eyes were closed. This inconsistency underscores the challenge of maintaining detection under the 40-degree tilted face scenario. The system also struggled to detect drowsiness during yawning at a 40-degree angle. Limitations arose from an inability to capture the entire face while yawning, impacting efficacy. Test cases 14 and 17 highlighted that only one participant out of 10 could trigger detection during yawning due to the system's inability to capture the entire facial region reliably. These findings underscore the influence of facial orientation on system consistency and stress the need to address challenges associated with specific head positions for optimizing drowsiness detection.

Figure 13. Drivers with spectacles

Testing drivers with spectacles, as shown in Figure 14, aimed to assess its impact on face and drowsiness detection. Results from test cases 4, 5, and 6 demonstrated the system's consistency in drowsiness detection, highlighting its performance in handling spectacles. The system recognized facial expressions and detected signs of drowsiness even with drivers wearing spectacles. These findings confirm that the system is capable of overcoming possible obstacles created by spectacles, ensuring consistent and reliable performance in drowsiness detection.

Figure 14. Drivers with spectacles

3.4.2. Alcohol Detection

As for measurement of alcohol content thresholds, the formula presented by Rafidi and Ismail [7] have been used in this study. From the formula, the alcohol content limit for the MQ3 sensor was set at 39. Wang et al. [24] use MQ-3 sensor to evaluate responses in different indoor and outdoor environments. The findings shows that sensor responses are more inconsistent outdoor, while stable in indoor. Besides that, humidity has a significant effect on the MQ-3 sensor, impacting its accuracy and reliability for gas detection [24]. All the tests will take place in a car, where humidity levels are generally higher [25], sensor drift may become a concern over time. Therefore, regular recalibration of the MQ-3 sensor is recommended to maintain measurement accuracy in real-world conditions. After the calibration process, the environmental factors impact tests were conducted using the MQ3 sensor with some substances such as perfume, hand sanitizer, and disinfectant spray. The tests were carried out inside a car, which is similar to the actual environment, to replicate the real-world situations. As shown in Figure 15, the MQ3 sensor was placed at the steering wheel to make sure the MQ3 is close to the driver's breath to get correct readings. The main motive of the environmental impact test was to find out the effects perfume, hand sanitizer, and disinfectant spray have on the MQ3 sensor. This would help to understand how these chemicals might affect in real life scenarios.

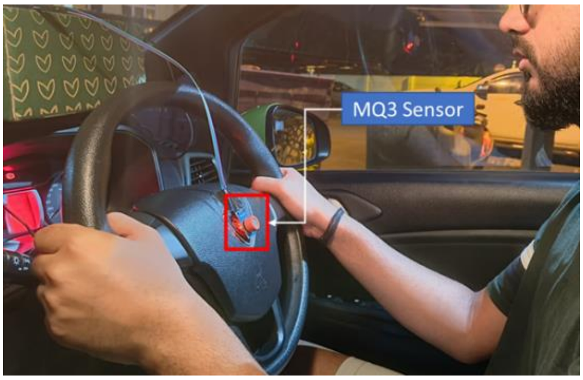

Figure 15. Environmental Factors Impact Test

Based on the graphs presented in Figure 16, the alcohol values obtained from the MQ3 sensor are observed for different substances during the environmental impact tests. Notably, the disinfectant spray shows the highest value at 34.98, followed by the hand sanitizer at 32.65, and the perfume at 21.41. Even though these substances are very different, the MQ3 sensor successfully detected its alcohol presence during the tests. It's important to note that, although the sensor identified alcohol's existence in the substance, none of the substances reached the designated alcohol detection range, which is 39.

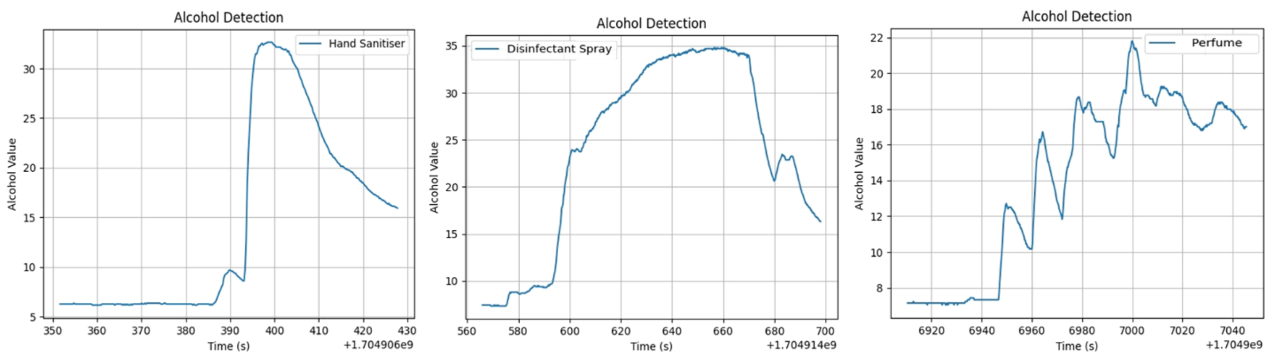

Figure 16. Environmental Factors Impact Test on Hand Sanitizer, Disinfectant Spray and Perfume

Three participants, aged between 20 and 27, were involved in this phase of the experiment. The test protocol involved the examination of three different alcohol beverages, which are 320ml of beer, 500ml of beer, and 180ml of vodka. Each participant was assigned to test with only one type of alcohol beverage to ensure a focused and controlled approach to the assessment. This test aims to explore the sensor's effectiveness in detecting alcohol presence across varying beverage types and quantities, which provides insights on the performance under different alcohol-related scenarios.

Based on Figure 17, the alcohol detection testing involved three different alcohol beverages. The first participant consumed 320ml of Beer and exhaled in front of the MQ3 sensor, resulting in a peak alcohol value of 35.68. Following this, the second participant, after consuming 500ml of Beer, exhaled towards the MQ3 sensor, revealing a higher alcohol value of 41.15. Lastly, the third participant consumed 180ml of vodka, exhaling in front of the MQ3 sensor, with the highest alcohol value recorded at 44.83. In particular, the analysis has shown that 180ml of Vodka displayed the highest value, with 500ml of Beer ranking second, and 320ml of Beer exhibiting the lowest alcohol concentration. This observation underscores the difference in alcohol levels across different alcohol beverages. Notably, both 180ml of vodka and 500ml of beer displayed a substantial increase in alcohol levels upon the initiation of alcohol detection by the MQ3 sensor, emphasizing its relatively high alcohol content.

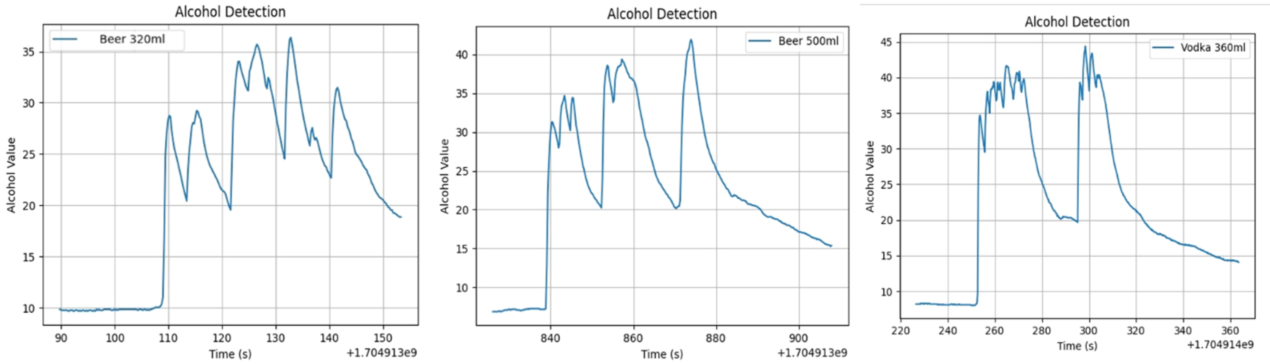

Figure 17. Test using Beer 320ml, Beer 500ml and Vodka 360ml

3.5. Discussion

The drowsiness detection testing underscores the system's proficiency in accurately identifying and extracting EAR and MAR values when the driver's face is positioned at center. At a 30-degree tilt angle, the system faces a moderate challenge in detecting the driver's face, which is leading to potential difficulties in obtaining EAR and MAR values. Furthermore, the EAR value can still be extracted from a substantial portion of the driver's face. This means that most of the time the drowsiness can be detected when the driver closes the eyes. The extraction challenge intensifies at a 45-degree tilt angle, significantly impacting the system's ability to identify the driver's face. In such a situation, the EAR value can only be extracted from a limited portion of the driver's face, resulting in drowsiness detection occurring intermittently. The extraction of MAR values proves even more challenging, particularly at higher tilt angles, highlighting the system's limitations in detecting drowsiness when the driver yawns and tilts their face. The correlation between the degree of face tilt and the extraction challenges emphasizes the need for further refinement.

In the context of the alcohol detection system, the outcomes of the environmental impact tests revealed the MQ3 sensor's ability to detect substances such as hand sanitizer, disinfectant spray, and perfume. Despite these substances not being classified as alcoholic beverages, the MQ3 sensor still responded to their presence. The presence of these substances may contribute to background noise in the sensor's readings, making it difficult to consider and account for such interferences when interpreting and relying on the alcohol detection system's results. In conclusion, the interference from environmental elements may lead to false positives or inaccuracies in the alcohol detection system. The issue comes from the sensor's inability to differentiate between alcoholic beverages and other substances with similar chemical properties during its operation.

4. Conclusion

Drivers’ drowsiness and alcohol detection systems enhance road safety by monitoring two crucial aspects, which are alcohol impairment and drowsiness. The implementation of drowsiness detection was realized by training the model with six machine learning algorithms, which are Logistic Regression, SVM, RF, KNN, Gradient Boosting Classifier, and Gaussian Naive Bayes. Through the evaluation, the best-performing machine learning algorithm is selected, and further enhancements are made through hyperparameter tuning. In terms of alcohol detection, the system employs an MQ3 alcohol sensor calibrated to calculate Blood Alcohol Concentration (BAC) based on specific factors. This BAC is then translated into a numeric value using a dedicated formula within the sensor's predefined range. In conclusion, this IoT-based system not only successfully detects driver drowsiness through behavioral patterns and machine learning techniques but also ensures reliable alcohol detection by leveraging a calibrated alcohol sensor.

For driver drowsiness detection, the future enhancement of models implies the use of more extensive datasets. While the current dataset is valuable, expanding the dataset to include many head tilts, face angles, and lighting conditions, as well as increasing the number of images per class, would facilitate better training of the model. Additionally, the dataset should include a diverse range of ethnicities, which is important because different facial features can affect the ability of the system to detect certain signs of drowsiness. The dataset also lacks variety in lighting conditions; things like bright sunlight, nighttime, or low-light settings can all change how facial features are captured and affect the model’s ability to detect drowsiness accurately. The dataset also does not include other factors such as different weather settings, for example, when it is raining or there is fog or glare from the sun, which can all interfere with drowsiness detection as well. Including these factors in the dataset would help improve the model’s performance since it would allow better recognition and classification accuracy. Currently, the system was only tested in a stationary car, which was a controlled environment. The current system testing didn't include any real-world or simulated driving tests under varying lighting, noise, and environmental conditions. Future testing will consider such scenarios to further validate system performance. In alcohol detection, future work could explore non-invasive microfluidic sensing patches as a backup solution. These patches measure ethanol levels in sweat, providing an alternative method when conventional sensors like MQ3 fail. Integrating such technologies enhances robustness, especially in scenarios where breath analysis may be obstructed if a drunk person wears a mask or covers the mouth. Additionally, open-air environments with external noise create challenges for accurate alcohol content readings, making innovative solutions like microfluidic sensing patches crucial for improving system performance.

5. Declarations

5.1. Author Contributions

Conceptualization, A.S., S.Y., and K.V.; writing—original draft preparation, A.S., S.Y., and K.V.; writing—review and editing, S.F.A.R., J.N.M., and A.A.; supervision, S.Y. All authors have read and agreed to the published version of the manuscript.

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

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5.4. Acknowledgements

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5.5. Conflicts of Interest

The authors declare no conflict of interest.

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