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Drowsiness and Real-time Road Condition Detection using Heart Rate Sensor, Accelerometer and Gyroscope

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Abstract: In recent years, there is a considerable increase in the number of road accidents occurring in India. Most of them are related to driver errors and impaired driving conditions. In this research project, we propose a method to detect driver's drowsiness level by analysing the Heart Rate Variability (HRV) with the help of a Fast fourier transform in the frequency domain and a classifier to identify if the driver is drowsy or awake. To help reduce accidents due to bad driving condition, we analyze and report the condition of the road in real-time. This project uses a system of sensors to monitor the driver's biometric data and the inertial data of the vehicle. We connect the sensor system in the car to an Android mobile app through a cloud platform. The Android mobile app can receive emergency notifications in real-time and display the conditions of the road.

Keywords: Drowsiness Detection, Rash Driving, Crash Detection, Road Condition Monitoring

1. INTRODUCTION

According to the World Health Organization (WHO), approximately about 1.35 million people every year die and 20 to 50 million people suffer non-fatal injuries due to road-related accidents. Statistics show that 78% of accidents are due to driver's fault such as drowsiness, over speeding in populated areas and rash driving, while 2% accounts for the accidents due to bad road conditions [1]. Drowsy driving is hazardous as the driver loses his attention and becomes fatigued and can be threatening to him and aswell as other person who are travelling in the road. Rash driving on the roads can cause grave danger to the life of other people and the driver himself. These drivers accelerate and brake unevenly, turn sharply into a corner, overtake in a blind curve, and drive faster. Over speeding increases, the chance of an accident and driving at a higher speed than the specified speed limit can be dangerous. Poorly maintained roads with potholes and chipped roads can cause difficulty for both drivers and vehicles. Therefore road condition monitoring is obligatory for improving safety, obviating accidents and preventing vehicles from getting damaged and also it can help the government repair and maintain the road.

2. Literature Survey

Many solutions have been developed to assist drivers, especially in detecting drowsiness and alerting them. There are several widely used methods to detect driver drowsiness like Image processing which include eye blink detection, yawning detection, identification of head pose [2][3]. Then the physiological techniques include analysis of an electroencephalogram (EEG) or photoplethysmography (PPG) or Electrocardiography (ECG) signal and also by analyzing the driving behaviour. The image processing technique by eye blink duration, eye state, driver facial image and yawning monitor requires a costly and advanced camera to be installed within the car and positioned properly to detect the drowsiness, but it has its drawbacks like some drivers might be tall, and the device can't detect them properly[4][5][6]. Also, while travelling on bumpy roads, the device may get loose and can't monitor properly. In physiological techniques, EEG monitors our brain waves and depending on the frequency of the waves, we can predict the characteristics of our central neural system. However, according to K. Fujiwara's research paper [7], EEG can be uncomfortable and dangerous for drivers to wear as the device is attached to their head and due to movement of the vehicle it could give wrong readings. According to S. Kaplan, M. A. Guvensan, A. G. Yavuz and Y. Karalurt's survey paper[8] on drowsiness mentioned that EEG signals provide good accuracy while detecting drowsiness in a static state but can not be used in an

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application orientated as they are intolerant to movements. K. T. Chui and his Colleagues in their research [9] suggested that ECG signals can be used to detect drowsiness by using the Heart Rate Variability(HRV). HRV analysis is done by acquiring the inter-beat-interval(IBI) of the ECG signal. Also, M. Bolanos, H. Nazeran and E. Haltiwanger in their work [10] suggests that PPG signal can also be used for IBI calculation, and they have provided statistics suggesting that both PPG and ECG show similar results and ECG monitors the electrical activity of our heart to give us the heartbeat count. In contrast, PPG uses an optical method to discern blood volume change and it is a result of number times our arteries open due to contraction. Therefore ECG and PPG are similar. HRV analysis reflects on our Autonomic nervous system(ANS), and some papers concluded that sleep stage transformation reflects changes in the HRV[11][12][13].

HRV can be analyzed in two domains, namely Time domain analysis and frequency domain analysis. T. Hwang, M. Kim, S. Hong and K. S. Park in their work[14], they have performed Time domain analysis and used a 5-second window for analyzing it quickly but mentioned it could be less accurate. So some of the papers analyze in Frequency Domain dividing into three groups Very low frequency(VLF), low frequency(LF), high frequency(HF) by applying FFT to a 1-minute window of IBI and then by calculating LF/HF ratio. This ratio can be used for classifying drowsy or awake and usually LF/HF ratio decrease as a person becomes tired or drowsy[15][16].

In the field of road condition detection, many applications have been made in the past. Lars Forslöf and Hans Jones' work[17] uses a regression model based on accelerometer amplitude levels, RMS (root mean square) algorithms, measured vehicle speed and sample data length. It uses smartphones to collect the acceleration data, so it can be easily implemented in various places, but it has to be placed securely and firmly to get reliable data. Also, if different smartphones are used, it will be giving varied results. Adham Mohamed et al. have worked on a road monitoring system[18], which uses smartphones to capture data. Then filters are used to reduce noise and then a support vector machine model to classify the roads. As mentioned before, using smartphones has the disadvantage that orientation can't be maintained as the same. But the use of the machine learning model and filters improves the accuracy of classification. Jokela, Maria, Matti Kutila, and Long Le [19] presents a method and evaluation results to monitor and detect road conditions like ice, water, snow and dry asphalt using light polarization reflection from the road's surface. It uses a stereo camera to detect the road conditions by texture analysis which contrasts the content of the image. In another paper by Allouch and Azza [20], the authors have proposed a machine-learning algorithm to predict road quality. It uses an accelerometer and gyroscope sensor to collect data and GPS(Global Positioning System) for plotting the road location trace in Google map. Increased availability of cheap sensors with both accelerometer and gyroscope make this a viable solution. A similar paper by Gunawan and Fergyanto [21] has proposed a solution with an accelerometer sensor where the data is filtered, and then the variations in Z-axis, XY ratio, speed and acceleration are considered to classify the roads. Since it does not use a gyroscope, the results are less accurate compared to the others. A research paper by Jadhav, S., Zingade, S., Takawale, T., Dhaninkula, V., and Nimbalkar[22], the authors have used the gyration values obtained from a gyroscope to analyze the road, the complex calculations are done on the cloud, so it reduces the need for computing power.

3. Proposed method

Our method includes a hardware system, a cloud platform and an android app. The hardware system consists of a heart rate sensor, accelerometer, gyroscope and a raspberry Pi processor. The processor receives data from the sensors and update them to the cloud platform. In case of drowsiness detection, the alarm inside the car will be sounded. The cloud platform receives and analyses the data and then send notifications whenever necessary. The android app is capable of receiving these real-time notifications from the cloud platform about crashes and rash driving incidents. The reason why we choose raspberry pi instead of Arduino is that it very much high clock speed and it Is an independent computer. As we gonna use cloud platform we need to run more complex fucntions and also we need to perform more calculations as well as collect various parameters. The drowsiness, rash driving, crash detection and Road condition analysis could be implemented by using the AI(Artificial Intelligence) method and there are lots of scientist and there are lots of research papers which focuses on the AI based methods like Face detection method, Eye blink detection , Yawn detection and many other detection which AI are there but we choose to use PPG sensor and Sense Hat sensor as AI based methods need a large diverse datasets and would need it to be perfect to detect it accurately and also lighting would play an important role in these systems as during night light won't be sufficient for the camera to recongize the facial expressions.

A. Heart Rate Variability Analysis

Heart Rate Variability (HRV) is the oscillation of Inter-Beat-Interval and is an evaluation of the neurophysiological aspect of difference in a continuous heartbeat in a person, reflecting directly on the ANS of the human body and can be used to detect the condition of a person like stress, drowsiness and medical conditions [13][17][22]. Heart rate variability has linear and non-linear features. As we know HRV can be analysed in both time domain and frequency domain. Time domain is the most simplest method where either the heart rate of a person at any point in time or the time intervals between consecutive normal complexes are determined. In time domain for an continious ECG recording, the QRS complex are detected and the interval between adjacent QRS complex also can be detected. By

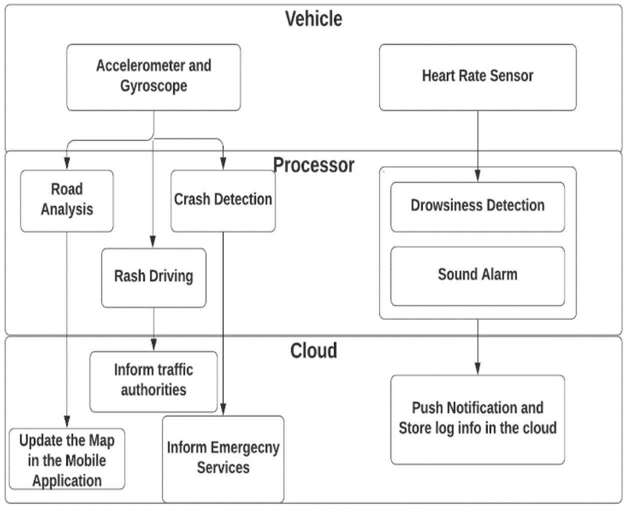

Figure 1. Block Diagram

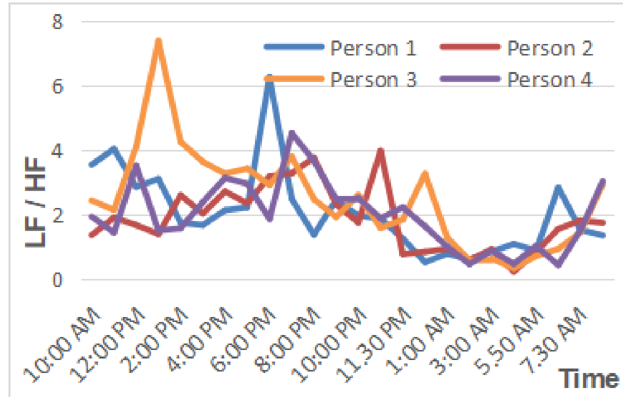

Figure 2. Difference in LF/HF ratio over a day

this method we can calculate the mena NN(normal to normal) interval, the mean heart rate, the difference between the longest and shortest NN interval, the difference between night and day heart rate and also Valsalva maneuver. In Frequency Domain we can use various spectral methods. Power spectral density (PSD) analysis can provide us with the basic information of how power (variance) distribution as a function of frequency will take place. Independent of the power spectral method used, only an approximate of the true PSD of the signal can be obtained by proper mathematical algorithms. This work has been implemented using a simple extraction of linear features as a long-term reading of IBI is necessary for the non-linear feature[23]. In Frequency Domain, there are three main power spectral components Very low Frequency(VLF), Low Frequency(LF), and High Frequency(HF) components which can be used as Short term recording of 1 min to 2 mins. The measurments of VLF, LF, and HF power factors is generally made in absolute values of power. The representation of LF and HF in regularized units depicts the controlled and balanced behaviour of a signal of the two branches of the autonomic nervous system(ANS) in a person.We perform spectral analysis on the heartbeat interval and normalize its power, then depending on the frequency, we can classify it as Low Frequency (LF) or High Frequency (HF). The LF values range between 0.04 Hz - 0.15 Hz, whereas HF values range from 0.15 Hz to 0.4 Hz. The ratio of LF/HF can help in the detection of drowsiness and fatigue [7]. The LF/HF ratio decreases as a person fall asleep from an awake state [12]. So to analyse the LF/HF ratio of a person when he is in awake and drowsy state, I had collected the Inter Beat Interval (IBI) data of 4 people over a day [24], processed the data and found the LF/HF ratio and plotted it in the Figure 2 and we can clearly see that at the night time when the person is in sleep state there is difference in the LF/HF ratio.

B. Road Condition Analysis

We monitor the Z-axis acceleration continuously to classify the condition of the road. The amount of deviation directly corresponds to the condition of the road. So the roads with higher acceleration values and more deviation are considered to be bad. For example, an ideal road will have zero acceleration in the z axis, but if the measured road has a mean of 1.5g, then it is a bad road with a rough surface or lots of potholes. The roads segments are also analyzed using peak detection algorithms every 30 to 45 seconds to count the number of potholes and bumps. The results including the GPS coordinates are updated to the database. The android app will then display this data on the map as line segments.

C. Crash Detection and Rash Driving Analysis

We use the X-axis acceleration as the parameter to analyze crashes. Because when the vehicle crashes, it decelerates rapidly in the X-direction, thus we can detect crashes by measuring the amount of g-force it experiences. Also, based on NHTSA (National Highway Traffic Safety Administration) crash data [25], the vehicle might experience an acceleration up to 60g (g = 9.8m/s2) during actual crash events. Thus we set the corresponding threshold in the software to detect and notify crashes. The emergency notification will be sent immediately when the specified threshold in acceleration is detected.

The vehicle's orientation and the acceleration in the X and the Y direction are monitored to identify rash driving incidents. Rash driving is reported if the vehicle is accelerated and decelerated rapidly, taking sharp turns at an unsafe speed or also if the vehicle is driven above the speed limit repeatedly. Sharp turns are identified with abrupt changes in the Y axis acceleration. The rash driving event is immediately flagged and stored in the database. If the driver repeats these incidents, the traffic authorities will be notified through email and push notifications.

D. Classifiers

1) Support Vector Machine :

Support Vector Machine also know as SVM is a simple machine learning algorithm that is used commonly by the people as it produces high accuracy with less computationl power and also it can be used for both classification and regression .

2) Logistic Regression:

Logistic Regression is used for envisioning the categorical dependent variable when a set of independent variable . Thereby the output can either Yes or No , 1 or 0, True or False. It is a very noteworthy algorithm as it has the ability to provide the probailty and can classify the data using dicrete and continuous datasets and aswell as It can easily classify the most effective variables used for the classification

3) Random Forest Classifier:

Random Forest Classifier is based on classification and Regression problems and it works based on the basis of ensemble learning which uses multiple classifiers to solve complex problem and it improves the performance of the model. If we have greater number of trees in the model leads to higher accuracy and it will prevent the problems of overfitting. Moreover it takes less time to train while compared to other algorithm.

4) K Nearest Neighbour Classifier:

K Nearnest Neighbour Classifier is a simple machine algorithm which works based on Supervised learning technique. It presumes the similarity between the data and available data and put these new data into the category that is most similar to available categories. It is also called lazy learner algorithm as it does not learn anything from the set immediately instead it will store the dataset and while classifying, it performs an action on the dataset.

5) Decision Tree Classifier:

Decision Tree also works based on Supervised learning technique. It is a tree structured type classifier where the node represent dataset features , branch will represent the decison rules and leaf nodes will represent the outcome. It usally mimics the human ability of thinking while making a decision and so it is very easy to understand.

6) Bagging Classifier:

Bagging is also known as boostrap aggregation which uses ensemble learning method to reduce variance with a noisy dataset. If we change our training dataset then the resulting decision can be quite different and in result predictions can be quite different. If there are large models to classify then it may take long time but it will not overfit the training data.

7) Gradient Boosting Classifier:

Gradient Boosting Classifier is one of the most dominant algorithms in the machine learning field. It is used to minimize the bias error of the model. It can handle any missing data as imputation is not required and also its a generalised algorithm which makes sure it can work for any differentiable loss function.

4. Hardware and software

A. Raspberry Pi:

Raspberry Pi is a low cost, credit-card sized portable computer. It is widely used by electronics hobbyists worldwide in areas like intelligent homes and weather monitoring projects. It can suit a variety of projects because of its low cost and modular and open design. Since it is popular, there are many sensors and attachments designed for Raspberry Pi, which makes using it more convenient.

B. PPG Sensor:

PPG sensor is an electrical device that uses optical technology and a photo detector to detect the changes in the volumetric difference of blood circulations. The variation in blood volume results from heart contracting, and a pulse signal is derived from it, and this pulse signal is similar to our heartbeat[10]. The light emitted by the sensor will reflect directly on the veins. This device can be placed under our fingertip or ear tips, So the PPG sensor can be mounted into the vehicle's steering wheel to measure the driver's pulse. In figure 3, we have shown the hardware setup we used for simulation which includes the PPG sensor, Raspberry Pi and a steering wheel.

Figure 3. Hardware Simulation Setup for PPG sensor

C. SenseHat:

SenseHat is an add-on board for Raspberry Pi. It has a five-button joystick, 8x8 LED array and includes the sensors like gyroscope, accelerometer, magnetometer, temperature, barometric pressure and humidity. SenseHat is designed to be easily attached and interfaced by the Raspberry Pi, so it also includes a Python library that allows us to program and read the sensor data efficiently. In Figure 4, we have shown the hardware setup implemented in a car using Raspberry Pi and a Sense Hat.

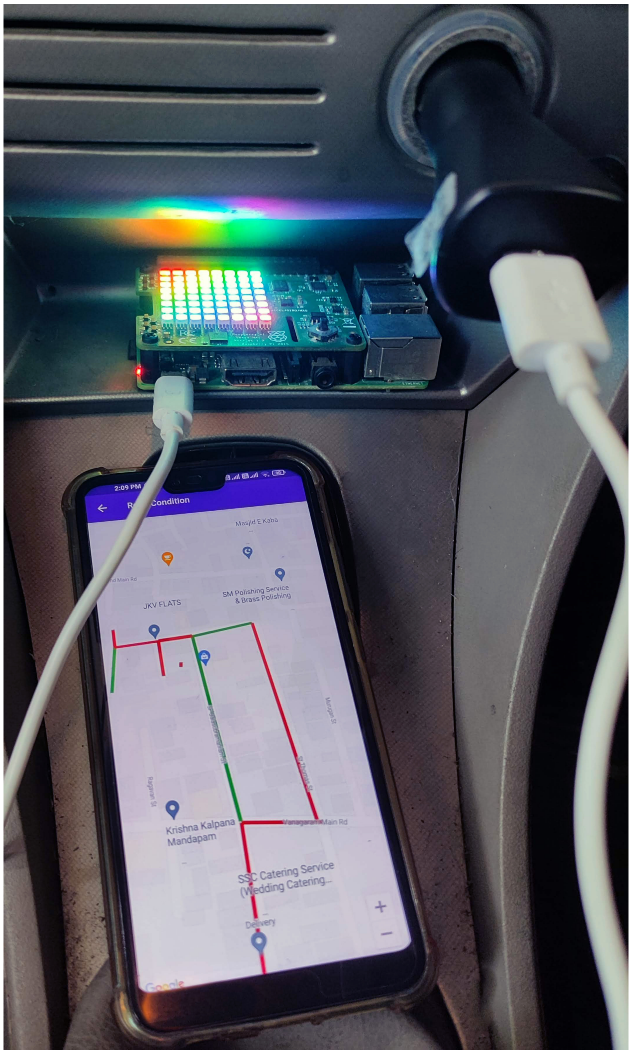

Figure 4. Hardware setup implemented using Sense Hat

D. Mobile App:

The Mobile app is written in Dart programming language using Google's Flutter framework. The app is used to monitor and visualize the data collected from the Raspberry Pi. The app has three menus : One to show the driver's current details, a screen to show the incident log and another one to display the conditions of the road on the map. The Figure 3 above also shows the road condition screen of the application. Firebase Cloud Messaging (FCM) is used to send and receive real-time notifications, Google Maps API to show the road condition, and we also use Firebase Authentication to allow only the authenticated users to access the data from the cloud. So with the help of this single android app, authorities can monitor the road conditions and repair it rapidly, they can also monitor car crashes and reckless drivers and take actions on them.

5. Process flow

When the fingertip is placed on the PPG sensor, we can read the data and identify the variation in blood pressure. To perform HRV analysis, we need to find the Peak-to-Peak interval of the successive signals known as Inter-Beat-Intervals (IBI). We have done Frequency-domain analysis in this project and it cannot be extracted using just the IBI rate, so the IBI data have to be interpolated and resampled at equal intervals. Then Spectral analysis on the signal is done using FFT with one or two-minute windows. We can then find the power spectral density of the signal and classify them into Low Frequency (LF) and High Frequency (HF), and we find the LF/HF ratio. To identify whether the person is drowsy or awake we need an classifier, so we considered 7 following classifiers: logistic regression (LR), support vector machine (SVM), k-nearest neighbour classifier (kNN), Random Forest classifier, Bagging classifier, Gradient Boost Classifier and Decision Tree Classifier and for each of the classifier the dataset which we collected were randomly divided into testing set and training set with a ratio of 3:7. Out of these 7, Gradient Boost classifier gave a marginally better accuracy, so we used Decision Tree classifier to predict the outcome when the LF/HF ratio is given as an input to the Decision Tree model. Hence depending on the value, it may be classified into a drowsy state or awake state.

Parallel to the drowsiness detection, the accelerometer and gyroscope sensors sense the environment and send the data to the Raspberry Pi several times each second. The data is first filtered to reduce noise, and then the individual axes are analyzed separately to identify crashes, rash driving and road conditions. The X-axis data is monitored first, and if the acceleration crosses the threshold for the crash, the collected data is sent to the cloud server and the email and push notifications are sent immediately along with the GPS coordinates acquired by the smartphone application. Then if the X-axis acceleration is less than the crash threshold but detects unsafe acceleration or deceleration, or if the gyroscope value indicates sharp turns or lane changes, it is classified as rash driving. This data is logged on the cloud server, and repeated incidents will be flagged and notified to traffic authorities. Meanwhile, the android app continuously keeps track of the GPS coordinates and updates them to the cloud. Using the Z acceleration data from the SenseHat, we can classify the road segments as good or bad by peak detection algorithms. Then the results along with the GPS coordinates are uploaded to the cloud database. The classified road segments are then retrieved by the app to show them on the map using Google Map's API.

6. Results

After implementing the proposed methodology with the optimized parameters, the application was deployed.. The figure 5 and 6 shows the accelerometer readings in a smooth road and a rough road, we can clearly see the large peaks in the rough road due to the potholes and bumps. This data is used to classify the roads as good or bad.

Then we tested the drowsiness detection system by simulating a driving environment using a steering wheel with the computer and we drove in a realistic Truck simulator and we monitored the LF/HF ratio and plotted it below as Figure 7, we can see that as driver becomes fatigue the LF/HF ratio decreases and when he felt drowsy around 01.20AM, the LF/HF ratio dropped significantly, the classifier classified the ratio as drowsy and alert was issued and the data will be updated to the cloud. As shown below the results of Accuracy in the Table I, The Gradient Boost classifier was chosen as it showed a better accuracy than logistic regression (LR), Random Forest Classifier, Bagging Classifier, Support Vector Machine (SVM) and k-nearest neighbor classifier (kNN) and the dataset is trained to classify the two states and predict the outcome, and the test average accuracy of 96.11% and F1 Score of 96.12% was achieved, which is better results than that in the research work published by T. Hwang [14], which has around average test accuracy 85% where they used time-domain analysis for classifying states and also from the Confusion matrix figure 13 of Gradient boosting as it has less false positive and false negative which is better than other classifiers Confusion matrix as show below in figure 8 to figure 14 , thus we chose Gradient boosting classifier

As shown in figure 15, the app shows the driver's current details like their drowsiness state, number of rash driving incidents etc. Then the road condition screen in figure 15 has markers to display the current condition of the road, green lines to show good roads and red lines to show rough and unsafe roads. The figure 15 shows the notifications that will be sent if a crash or rash driving incident is reported. By tapping the notification, the authorities can see the updated location of the vehicle.

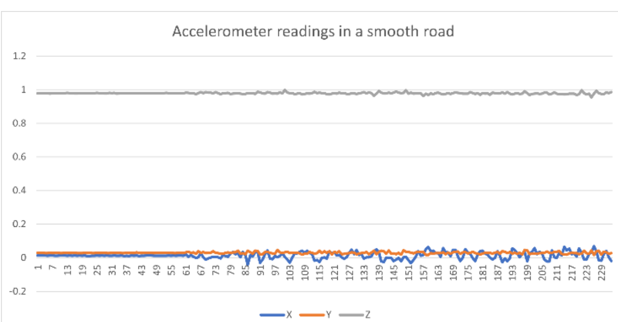

Figure 5. Accelerometer reading in a smooth road

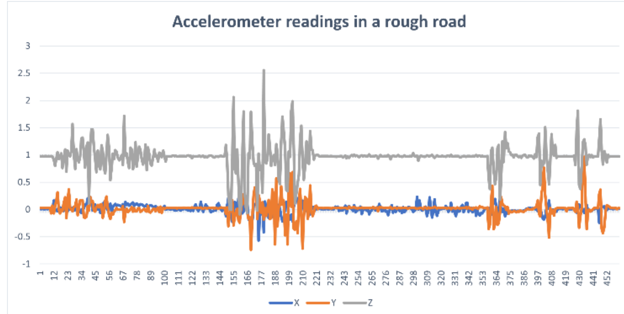

Figure 6. Accelerometer reading in a rough road

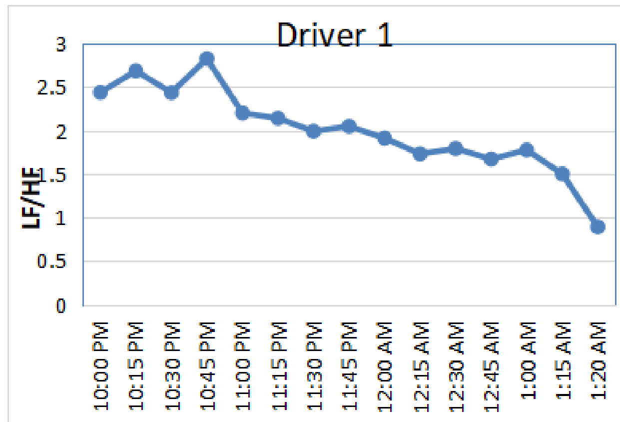

Figure 7. Results from Drowsiness Detection

TABLE I. Classification Accuracy

Classifier	Test Accuracy	F1 Score
Support Vector Machine	93.8%	93.84%
Logistic Regression	92.77%	92.80%
Random Forest Classifier	95%	94.796%
K-Nearest Neighbor Classifier	93.33%	93.33%
Decision Tree Classifier	94.441%	94.4%
Bagging Classifier	90.55%	90.58%
Gradient Boosting Classifier	96.11%	96.12%

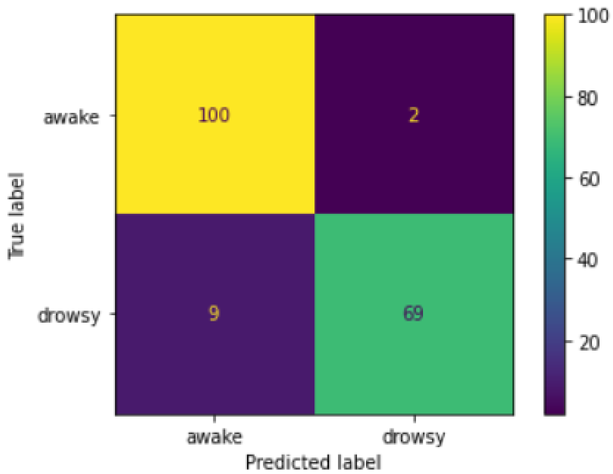

Figure 8. SVM Confusion matrix

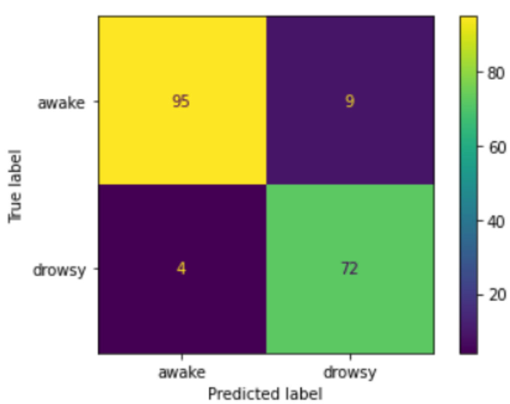

Figure 9. Logistic Regression Confusion Matrix

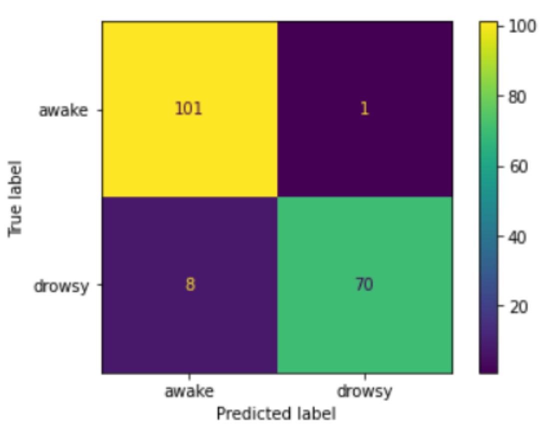

Figure 10. Random Forest Confusion Matrix

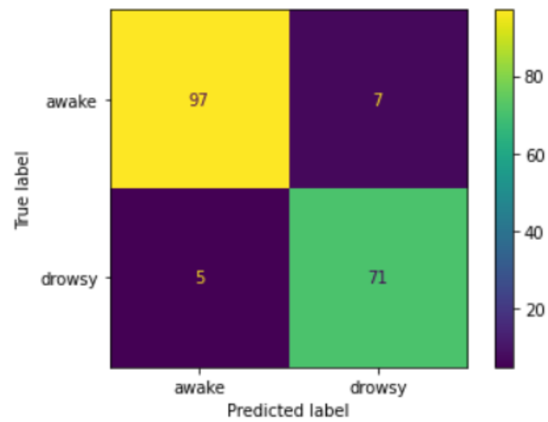

Figure 11. kNN Confusion Matrix

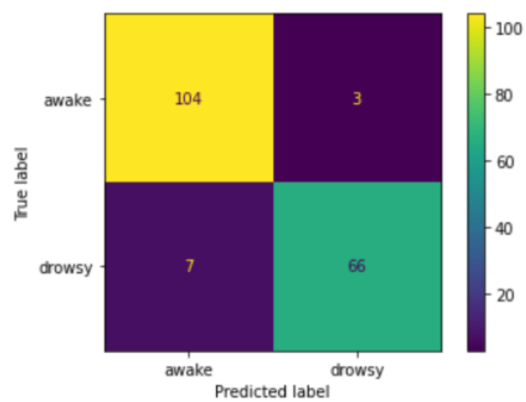

Figure 12. Decision Tree Confusion Matix

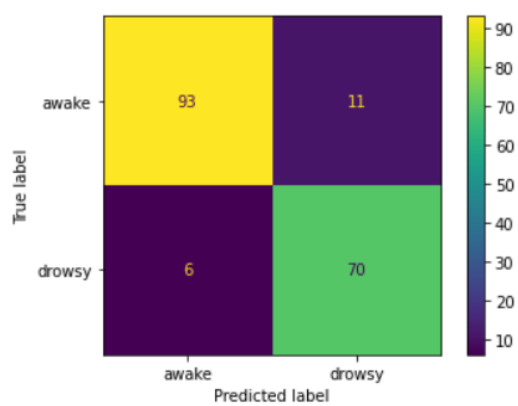

Figure 13. Bagging Confusion Matrix

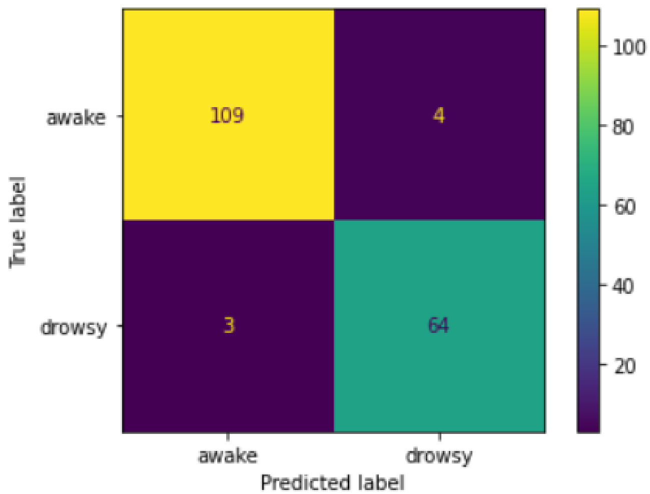

Figure 14. Gradient Boosting Confusion Matrix

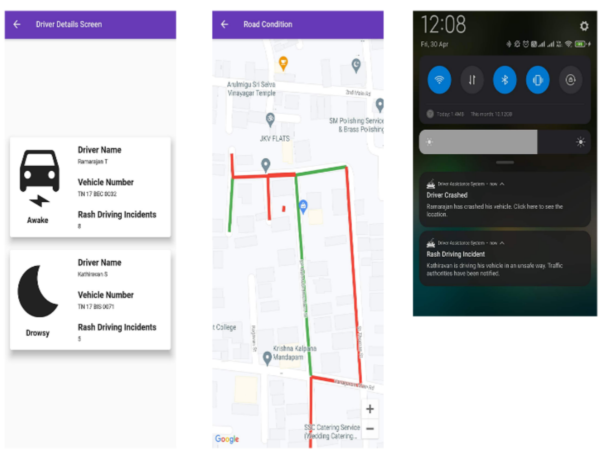

Figure 15. Screenshots of the mobile App

7. Conclusion and future scope

A drowsiness detection system has been developed to distinguish between the drowsy and awake state as there exists a major contrast between the bio signals of awake state and drowsy state, this can help to prevent the accidents related to drowsiness and in the future research HRV analysis can be a great foundation for monitoring the driver's health care system. The road condition is identified, and the corresponding coordinates are uploaded to the cloud database. An android mobile app is designed, and it can receive notifications about reckless driving behaviour, and vehicle crashes It also includes a real-time Map that can show the conditions of the road with coloured markers which can help people to know the condition of the road and plan their journey accordingly to reach the destination in time or during any emergency and people can easily access it the way just they use to monitor traffic in the map.The proposed method is inexpensive, easy to implement and easy to use. Moreover we can easily monitor via app and it produced a better result than the exisiting method which is published by T.Hwang[14]. Our project, as of now, uses pre-programmed algorithms to identify crashes, rash driving and road conditions. In the future, we can improve the detection accuracy by training a machine learning model based on the accelerometer and gyroscope data. Furthermore, we can improve the accuracy of the drowsiness detection by implementing the multimodal system by adding GSR signal to PPG or we can add an IR camera and PPG sensor to detect the drowsiness, and we can improve the accuracy.

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