Real-time Drowsiness Detection and Emergency Parking using EEG

Asim Javed, Muhammad Umair Arshad, Ehtesham Saeed and Noman Naseer
Department of Mechatronics Engineering and BioMedical, Air University, Islamabad, Pakistan

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Abstract: This paper presents a comprehensive method to prepare a highly accurate and efficient classification model to detect drivers drowsiness and a parking system for parking the car along the emergency lane. Vehicle accidents are rapidly increasing in many countries. *One of the most demanding technologies for the active prevention of such fatal road accidents are drowsiness monitoring systems since drowsiness is the leading cause of severe road accidents on motorways and highways. EEG is direct and effective, it directly measures the change in the brain's electrical activity compared to techniques of image processing, which are indirect in approach. The EEG signals, recorded from ten healthy subjects under the state of drowsiness playing a car simulator and were given the feel like they were driving a car. As a proof of concept, a scaled car based on computer vision would shift to autonomous mode on detection of the drowsy state of the driver. The EEG system detects drowsiness with an accuracy of 96.8%. The autonomous system is also able to process 50-60 frames per second and gives decision accordingly. The turning angle for the scaled autonomous car ranges between 0 to 30 degrees.

1 INTRODUCTION

Brain-Computer Interface (BCI) is an emerging technique that has made possible the communication between a subject's brain and an external device. The main idea is capturing the neuro signals of a person, which are the variations in voltages. The electroencephalography (EEG) based BCI has two techniques invasive and noninvasive. Invasive methods involve the insertion of electrodes into the subject's cranium, also called intracranial electrodes. The noninvasive techniques do not require such intrusions such that the electrodes are placed over the scalp. In the beginning, the researchers of BCI worked mostly in critical applications such as immediate control. Later on, they expanded their research, focusing on paralyzed patients' applications such as chess playing through brain control. Within the past decade, modern machine learning and signal processing techniques have led to a rapid increase of brain-related applications, including communication, prosthetic control, robotics, and security. A crucial and essential area considered by most researchers is the safety of people, with a significant focus on making their daily activities safer. Human error is one of the fatal cases and has led to more significant casualties. The BCI researchers believe human-safety to be a potent area for work.

A traffic accident, also known as Motor Vehicle Collison (MVC) due to a human error, may result in severe injury, property damage and even death. Non-human factors can also contribute to the risk of accidents, such as vehicle design, road design, or some natural cause, but human-caused factors such as lack of concentration, decision-making skills, and abilities, using drug drowsiness plays a significant role in fatal collisions. A 1985 published study for auto accidents believes that recklessness, drunkenness, and other human factors add up to almost 93 % of road crashes. Some typical driver's impairments include alcohol, physical impairment, distraction, drug use, drowsiness, and combinations. Falling asleep suddenly due to some sleep disorder or fatigue can lead to losing the car control ending up in an accident. National Highway Traffic Safety Administration (NHTSA) reports that 100,000 yearly vehicle crashes recorded are the direct result of the driver's drowsiness, resulting in 1550 deaths, 71000 injured (Wei et al., 2018). These numbers show that the drowsiness of a driver is a primary concern leading to road accidents.

Many methods were employed to prevent accidents caused by the drowsiness of a driver. However,

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electroencephalogram (EEG) led to a new research-able area. The EEG can be used to process almost all sorts of physical or behavioural activities. Also, EEG can report a person's central nervous system activity through a driving task and evaluate the consciousness and attention levels to prevent the possible risk. The following technique is non-invasive and requires the electrodes placing on the scalp.

An electroencephalography-based sleepiness detection system (ESDS) evaluates a subject's drowsiness range through brain activity. The main focus of ESDS research is to inhibit sleepiness-related accidents. (Balandong et al., 2018). EEG is primarily used to monitor the variations of brain neuro activity linked with drowsiness because signal changes in some EEG frequency bands depends on an individuals concentration. Most existing systems rely on multi-channel EEG devices, which are expensive and they require gel for conductivity. A cost- efficient method is proposed in this research. Single-channelled NeuroSky dry EEG headset which has the ability to obtain brain signals as 512Hz sampling rate. It uses SVM to detect drowsiness for training (Song et al., 2017). During the activity of drowsiness and awake states, the relative power of different EEG bands differ and thus provide important information, they can be used as features. Frontal, temporal and parietal regions of the brain show sensitivity to drowsiness. The EEG headset electrodes Fp1 and O1 must be considered during the study of drowsiness. (Majumder et al., 2019) The above mentioned papers suggests how effective electroencephalography can turn out to be for sleep detection.

Kulkarni, developed a method to detect vehicles on road using low cost raspberry pi and camera. The proposed method uses background subtraction method (Kulkarni and Baligar, 2020) Choudhury, pro- posed a method to detect cars on the road efficiently using Haar Cascade, for that two types of samples shall be required positive and negative; the positive samples will have the images of cars, and the negative will have environment samples photos that car may see on the road. We have employed this technique in our object detection algorithm. (Choudhury et al., 2017). Stevan Stevic´, propose an algorithm for detecting road lanes using Hough transform and performs and share field testing results, however Hough trans- form doesn't work efficiently on curved lanes (Stevic´ et al., 2020). For this Project, drowsiness detection is further followed by emergency parking of the car. Some researches show a few methodologies related to the performance of this task, including lane detection. Wu et al. have proposed a emergency parking system. The system is based on the spread of the lane markers close to the vehicle, this helps in determination of the lane markings (Wu et al., 2019).

Yang et al. have developed a method to detect road lanes. The first method using SSID was applied to detect vehicles after that a vehicle tracking method was used to compute trajectory lines (Yang et al., 2017). Kuo et al. conducted an image sensor experiment on a 1/10 miniature car which manoeuvred in a straight–curve–straight lane and validated better processing performance before and after the curves of lane. Within 5 per cent error, the lane detection algorithm achieves lane detection and cross track error in live situation, our system is inspired by this paper for autonomous car parking (Kuo et al., 2019). The above mentioned papers are the proof that the introduction of camera in a car, can lead to an efficient lane detection systems with minimal cost.

Figure 1: General Block Diagram of Image Processing

SSH, also known as Secure Shell or Secure Socket Shell, is a network protocol that gives users, particularly system administrators, a secure way to access a computer over an unsecured network. In addition to providing secure network services, SSH refers to the suite of utilities that implement the SSH protocol. Secure Shell provides strong password authentication and public key authentication, as well as encrypted data communications between two computers connecting over an open network, such as the internet. In addition to providing strong encryption, SSH is widely used by network administrators for managing systems and applications remotely, enabling them to log in to another computer over a network, execute commands and move files from one computer to an- other (Rouse, 2020).

Bablani et al. used KNN for EEG classification. k-Nearest Neighbor classifier is a non-parametric ap- proach, which classifies a given data point according to then majority of its neighbors. The KNN algorithm completes its execution in two steps, first finding the number of nearest neighbors and second classifying the data point into particular class using first step. It chooses nearest k samples from the training set, then takes majority vote of their class where k should be an odd number to avoid ambiguity, KNN has been employed in our system, because of it ability to deal with non linear data effectively. (Bablani et al., 2018). The past conducted experiments show that drowsiness detection using an EEG headset is more direct and effective than image processing. The data is directly being taken from the brain, and there is a low chance of error. The autonomous car uses state of the art canny edge detection algorithm, which has effective noise cancellation. The lane detection algorithm proposed can also effectively follow the straight and Curved lane. The algorithm is performing better on curved lanes compared to algorithms based on Hough transform. Owing to importance of the issue a system has been proposed, this system should detect drowsiness and fatigue accurately with near perfection and then autonomously take over the car and park it safely towards the emergency lane. The parking system utilizes a computer vision-based lane assistance sys- tem that detects road lane and then changes lane to an emergency as soon as a car or an obstacle comes ahead. The lane detection system can detect curves. EEG data preprocessing involves preprocessing, feature selection and classification. Some previous re- searches were used to develop a real-time system on drowsiness detection of a driver. These researches are related to this Project either directly or indirectly.

2 METHODOLOGY

The system has two phases and methodologies of each are discussed below.

2.1 Drowsiness Detection

To study the effects of drowsiness, the EEG signals are recorded, and several signals are preprocessed and classified. Noise removal is done using a high pass filter, less than 1 Hz as they can appear as offset; On the basis of preprocessing the EEG signals are further classified to primary waves using bandpass filters.

2.1.1 Data Recording

The EMOTIV EPOC+ headset when fixed on the scalp of the subject, the EmotivBCI application dis- plays feedback. The application is to assist the user in fitting the headset correctly. The headset acquires these signals, and this information is then transferred to a computer via Bluetooth. For getting better results, it is necessary to attain the best contact of sensors with the scalp. When electrodes are placed red- orange and green coloured circles are shown in the control panel to show the engagement of electrodes with brain surface. Once all the sensors on the control panel turn green, a successful connection between the headset and the subject has been established. Experiments were performed, during which the Emotiv Epoc+ was placed on the scalp to get the raw signals of a person's brain. The Emotiv Epoch has over 14 channels; electrodes can get the data from these channels. The electrodes consist of an assembly with felt pads soaked into a saline solution that increases con- ductivity. Thirteen healthy individuals participated in

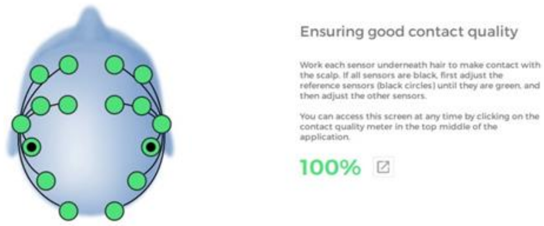


Figure 2: Connection Status

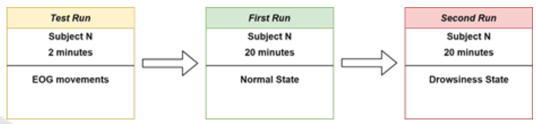


Figure 3: Timing Scheme

An experiment; all the participants were students of Air University. Before the experiment, all the participants were asked to avoid any medicine or coffee throughout the experiment. The participants were healthy individuals and were asked to complete their sleep before the experiment. The experiment had two phases; the first phase, the subjects were sitting comfortably on chairs; at the beginning of the trial, for each subject, 2 minutes of test run was conducted during which EOG movements were done as a test trial. The first trial involved 20 minutes of active state data from each subject. After recording the normal state from each subject, the participants were asked to join an overnight study program, such that they stayed awake the whole night. The next day in the morning, ten out of thirteen participants were declared drowsy based on the Chalder fatigue scale. After the head- sets' placement, the ten participants were asked to play an android car driving game. They were given 10 minutes duration to get themselves acquitted with the controls. After that duration, subjects played the game for 20 minutes each; the car control involved steering the phone. Thus they were given the feel like they were driving in real.

When people become fatigued and tired, they lose focus and repeatedly regain the lost concentration; such is a drowsy driver's behaviour. Current studies have revealed that when a person faces the loss of concentration, there is an abrupt increase in alpha and theta activity. A particular effect was also observed on the delta waves concentration. The waves mentioned above predominately originated from the occipital region during the normal and the wakeful state. Thus, channel O1 was selected for drowsiness detection. Thus this experiment involves getting data from a single dominant channel.

Figure 4: Data acquisition

2.1.2 Preprocessing and Feature Extraction

The raw data were first subjected to a median average filter; it was observed that it is not affected by the outlier values as much as the mean filter. The median filter creates a series of average subsets of the whole and thus smoothens the channel as shown in the figure (5) below.

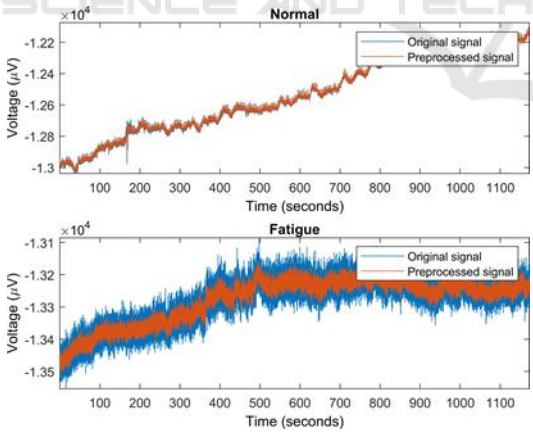


Figure 5: Median filter

Filter creation was necessary for obtaining the alpha, beta, theta, gamma and delta waves. Figure (6) shows the distinction between primary brain waves based on frequency. A bandpassb filter of order eight was designed with a passband ripple of 0.2. The passband frequency was specified based on the respective frequency. MATLAB's function designfilt() was used to generate the magnitude response of the filter, as shown in figure (7), such that the following graphs, as shown in figure (8) were obtained when the bandpass filter was applied. Power of signal can be expressed as

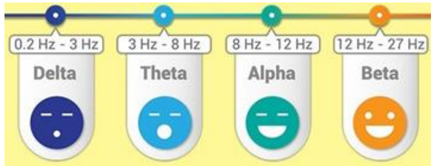


Figure 6: Brain primary waves

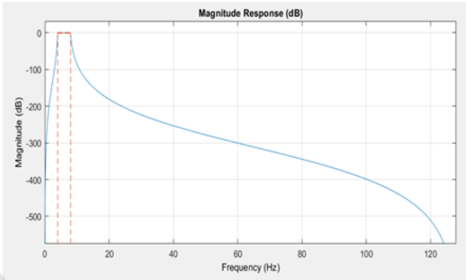


Figure 7: Magnitude Response

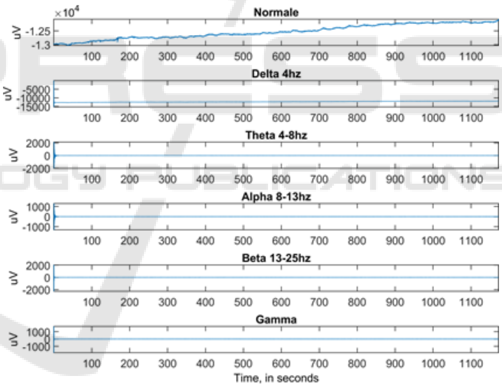


Figure 8: Filter Application on Normal data

$$P = \frac{V^2}{R} \quad (1)$$

Where V and R are voltage and resistance respectively.

$$n = \frac{N}{Fs} \quad (2)$$

Where n is Time frame, N is Number of samples and Fs is Sampling Frequency. To create features, power obtained through (1) is integrated concerning time to get energy, which further is converted into decibels (dB) to get more distinct features. The graph shows the spectral plot of alpha and theta waves both in the state of drowsiness and awake. The graph concludes that a sudden change occurs in alpha and theta power bands when the subject goes from an awake state to drowsy. This unprecedented change can be used as features as it enough to tell about the subject's state. The data is then passed through principal component analysis (PCA).

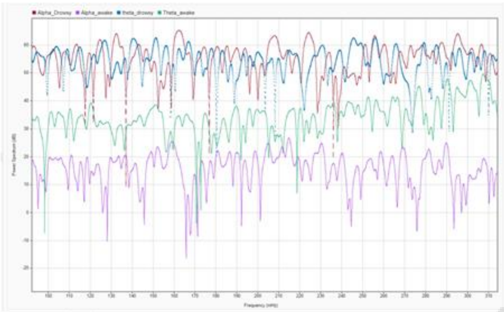


Figure 9: Spectral Analysis

Two components were taken; the first variance is 67 percent and the second coordinate is 17 percent. Thus these two components are chosen, thus reducing the chance of overfitting by providing a smaller model. Hence, principal component analysis (PCA) aims to determine new linearly independent components that can efficiently represent data. It was performed as follows. Data received through the above procedure is subjected to feature scal- ing, standardization, which is the Computation of transformed values by computing the difference of each feature of value from the mean of the feature's values. Further removal of outliers was performed as machine learning algorithms are sensitive to distribution, and the spread of any attribute value may result in misleading the training process. The MATLAB function isoutlier() checks for such data and marks them as 0, are also negated from the data stream.

$$XTrans\,formed = \frac{x - mean(x)}{Standarddeviation(x)} \tag{3}$$

Features in a dataset often contain information that is highly redundant such that they are highly correlated. In order to identify such correlations, a covariance matrix is computed. For two variables X and Y, covariance matrix has the following formula.

$$conv(X,Y) = \frac{1}{n-1}\sum_{i=1}^{i}(Xi - x)(Yi - y) \tag{4}$$

The eigenvector is a characteristic non zero vector that changes its value when multiplied by a scale value, which is the eigenvalue. The eigenvalue is represented by . Thus eigenvector of a matrix is for which the following value holds.

$$A\mathrm{U} = \lambda \mathrm{U} \tag{5}$$

The eigenvectors are arranged according to their eigenvalues, in decremental order. The new variables formed due to the linear combination of the starting features are not related but perpendicular to each other in Cartesian space. The principal components are arranged in order of rank of eigenvalues.

Figure (10) below is the scatter plot of the two principal components that tell most about the data.

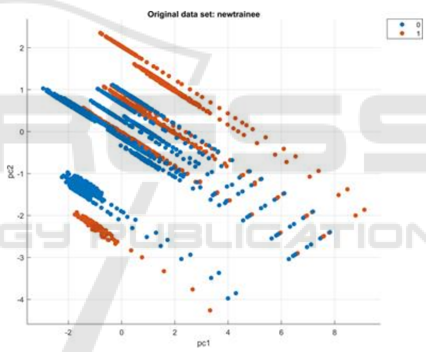


Figure 10: Scatter Plot of PCA Components

2.1.3 Classification

The classification algorithm used is K nearest mean neighbour's, also known as KNN. Cross-validation is used, where k is known as the number of groups the data will split up. A value of 5 was used for K such that the model each time was trained on five random sets, and 5 test sets from the aggregate data were selected to test the model. Cross-validation makes sure that the model is trained for every type of data. K fold was preferred over holdout since its ability to make the model more efficient and less sensitive to false negatives and false positives. KNN has the following steps for implementation; they are as follows.

- Select the K neighbors
- Using Euclidean distance using equation (6) calculate the distance of a new point from the K

neighbor

- Calculate the data points in each category among the neighbors that were computed in step (ii)
- The new data point is sent to the category where the distance to neighbor is the least.

2.1.4 Euclidean Distance

$$(x_2-x_1)^2-(y_2-y_1)^2 \tag{6}$$

2.1.5 Pros of KNN

- Easy Implementation
- Flexible features
- Easily handles multiple class labels

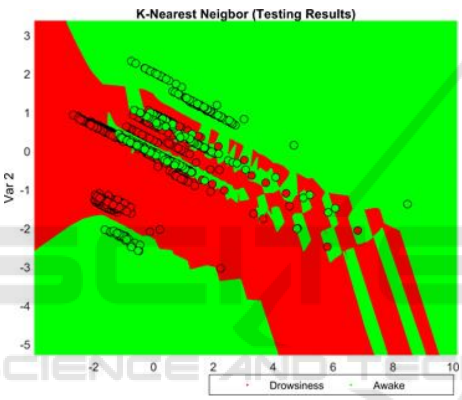


Figure 11: Classification of test set for first fold

The graph is shown above between two independent variables, pc1 and pc2, the red area marks for drowsiness and green marks for the awake state. The bubbles in the graph represent the testing data. The correct placement of these bubbles into the right area shows that data is correctly classified with minimal error.

2.1.6 Hyper Parameters Selection

To improve the model's performance, a MATLAB toolbox classification learner was used, which resulted in optimized hyperparameters like the number of neighbours, distant metric, and distant weight.

2.2 Car Parking System

To have better results, Image Processing (Open CV) was used for the lane following and car parking system. After getting raw data that was in the form of images, data was preprocessed. After the preprocessing region of interest was selected carefully. At turns, an error was used to steer the car for lane following. Object detection was the primary command to park the car immediately. The image processing algorithm has three stages perception, processing and output.

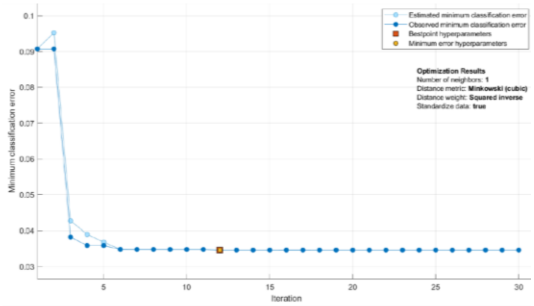


Figure 12: Hyperparameter Plot

2.2.1 Preprocessing

Raw Image is a matrix where each matrix member has 8-bit R, G and B values. In preprocessing smoothing filter was applied such that the Image only contains Black and white colour, so it reduces processing time. After that, the Image was converted into a greyscale, which improves accuracy. Region of interest ROI was selected according to the car and track size. Thresholding was applied to detect the lane, and canny edge detection was used to detect the lane's edges.

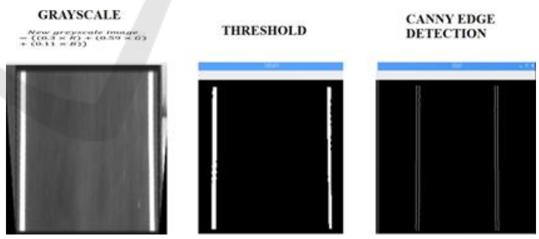
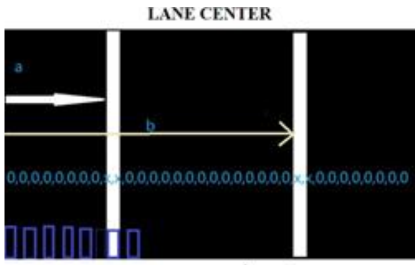


Figure 13: Pre Processing Stages

2.2.2 Error Calculation and Steer Control

The car's frame center is fixed while the turning lane center is changed with respect to the frame center. So the difference of frame center to lane center gives us an error, which is positive or negative for turning right and left, respectively. This error was used as steer input to follow the lane. For this error calculation purpose, a dynamic array having a length of a num- ber of pixels in the width of ROI (Region of Interest) was used. Since the project is proof of concept, thus for the manual control of the car was smartphone app based on WIFI.



$$Lane\ Center = \frac{b-a}{2} + a$$

$$Error = Lane\ Center - Frame\ Center$$

Figure 14: Error Calculation

2.2.3 Obstacle Detection and Car Parking

For obstacle detection, a machine learning-based object detecting classifier named HAAR Cascade was utilized. In order to get data trained, 300 positive and 50 negative samples were used. For data training, a windows program Cascade Trainer GUI was used to get the XML file. As soon as the object was detected in front of the car, the parking function activates, which turns on the indicator and detects whether the car is in the fast lane or normal then parks accordingly by gradually reducing speed. Open CV is also used to detect lanes, i.e. in the fast lane. The left line would be white, and the right would be Yellow and inversely in the normal lane.

2.3 Mode of Communication

Raw EEG API carried out the data transmission between the EEG headset and the MATLAB. Thus allows to program EmotivPRO, it was used to stream the recorded raw EEG data from EmotivPRO to MAT- LAB for real-time data processing. The communica- tion between Raspberry PI and MATLAB was suc- ceeded using Transmission Control Protocol (TCP). MATLAB was set as master, and Raspberry Pi was set as a slave. The next communication requirement was required between Raspberry Pi and ESP32, which as accomplished using Bluetooth.

3 RESULTS

The drowsiness detection system has an accuracy of 96.8 percent, and it outperforms many systems in the market. The system also can detect signals live. The EEG headset sends the signal to MATLAB us- ing Raw EEG API. In contrast, the MATLAB sends data if drowsiness was detected or not using a Trans- mission control protocol. Further, the RaspberryPi sends steer commands to ESP32 using Bluetooth.

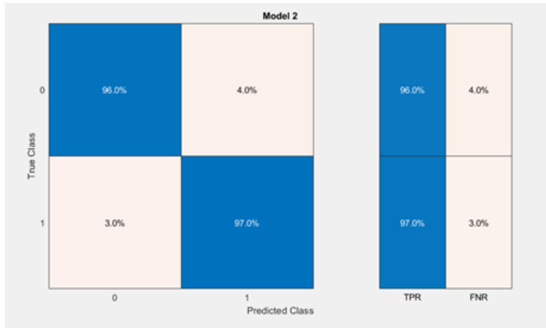


Figure 15: Confusion Matrix

The confusion matrix reports that, if a person was feeling drowsiness than there is 3 percent chance algorithm would report awake, and if a person is awake than there is 4 percent chance algorithm will report the per- son is feeling drowsy.

The accuracy and error is calculated as follows

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$Error = \frac{FP+FN}{TP+TN+FP+FN} \tag{8}$$

The next part of the system is the parking of miniature car which follows the track thus ensuring safe parking. Below are the results of successful of lane following covering each step.

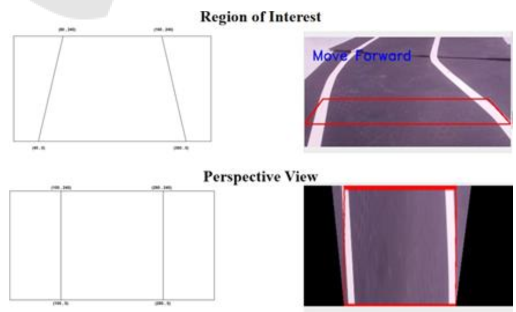


Figure 16: ROI and Perspective view

The above results prove that the designed system is fully capable and efficient is detect drowsiness and in successful parking of a car.

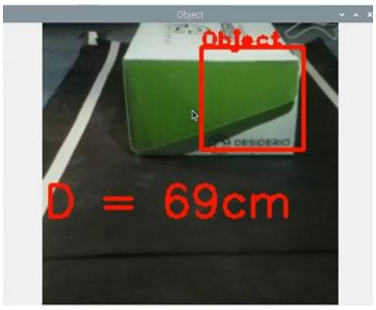


Figure 17: Object Detection

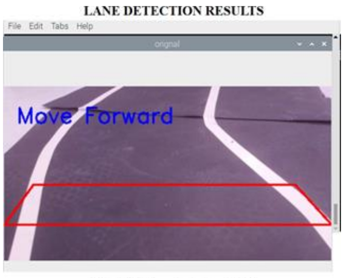


Figure 18: Final lane detection Result

4 DISCUSSIONS

The operational parameters and limitations and restriction's are discussed below

4.1 Operational Parameter

Following are the operational Parameter of our complete system:

- Proper Setup of EEG Headset
- Raspbian Buster and MATLAB Setup

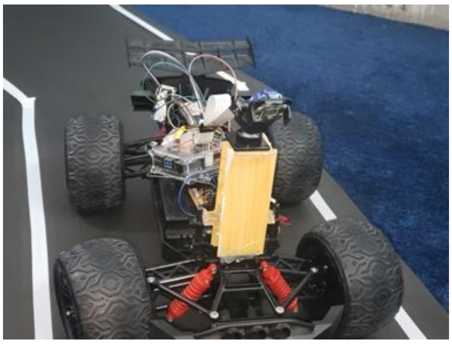


Figure 19: Autonomous Car

- Raspi Camera
- Properly Configured OpenCV for GCC compiler Environment
- Raspi Cam library
- Track Setup, i.e. Lane Width and colour
- Ensure communication between EEG Headset and Raspberry PI also between Raspberry PI and ESP32

4.2 Limitations and Restrictions

- User should not be on medication and must not be under the influence of Alcohol
- System is designed to work on Motorway
- While changing lane, the system does not consider any other vehicle
- The curves of the road should be less than 60 De- gree.
- Poor Lightning conditions were not considered during Experiments

5 CONCLUSIONS

Microsleep is due to an inadequate amount of sleep, and this type of sleep often occurs when driv- ing and lasts from 1 to 10s, which is enough to cause road accidents. Experiments showed that when a person shifts from an awake state to a drowsy state, the brain's occipital region is the most affected area. There is a sudden downward shift in alpha waves followed by the oscillation in the theta band. This shift works as a feature. After preprocessing, it goes to a machine learning algorithm that resulted in a system able to detect the driver's drowsy state with an accuracy of 96.8 percent with an ability to classify 10,000 observations per second; hence it is fast and accurate. Our study also suggests, instead of using many channels for drowsiness detection, only one channel O1 of the occipital region can effectively detect drowsiness. Many systems proposed in the past activated a buzzer or an alarm to awaken a driver, but such systems appeared meaningless when cars travel at a speed of 100 km/h. Hence an autonomous system is implemented on a miniature car as proof of concept. It parks the car itself after successful lane detection on to the parking lane, thus minimizing the risk of accident at maximum. In future, the drowsiness and the autonomous system can be implemented on a non-scaled vehicle.

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