PROJECT REPORT

Drowsy Driving Detection System by Analyzing and Classifying Brain Waves

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BONAFIDE CERTIFICATE

Certified that this project report **" DROWSY DRIVING DETECTION SYSTEM BY ANALYSING AND CLASSIFYING BRAIN WAVES"** is submitted by *ARAVIND JYOTHI, SUBHA R, VIGNESHWARAN SANTHALINGAM.*

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ABSTRACT

The increase in number of accidents by the day is a dangerous situation that needs to be mitigated. If the data from recent past is taken into account, one can see that the number of road accidents has grown exponentially. In fact, one can go so far as to say that the roadways record the highest number of accidents in comparison to other modes of transport. This statistic can put anybody ill at ease since the majority of the people in India use the roadways as a major mode of transportation. Although drowsy driving is not the only contributor to the situation, it remains the principal or major issue and can pose a grave threat if it is not averted. Specifically, in India, this project would be critically helpful to mitigate the loss to life and property. This project thus aims to reduce the number of accidents due to drowsy driving.

Using an EEG headset which consists of multiple EEG sensors and inbuilt Bluetooth transmitter, brain wave data is transmitted to the system. The collected data is input to the prediction model which decides whether the driver is losing consciousness or not. The prediction model is trained by using the Auto Regressive and Integrated Moving Average (ARIMA) time series algorithm to predict whether the person is losing consciousness. This can be used to trigger an alarm/warning mechanism.

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CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Travelling long distances takes a toll on any individual and drivers are not alone in that. This can lead to exhausted drivers who become drowsy on the road while driving, leading to loss of life and property. The cause of drowsy driving [1] cannot be helped but its effect can still be handled in such a way so as to safeguard valuable human lives. A number of grievous accidents are caused due to this alarming issue. There is a serious call to mitigate these circumstances.

Statistics show that each day a grievous accident happens in India and most other accidents are deaths of people on two wheelers. Moreover, it has also been shown that Tamil Nadu is the state with the maximum number of road accidents per year [2]. This just goes to show the defects in the current road safety systems. Although there is no denial that the road safety systems in place now do their best bit, it still is not enough considering in the current boom in the number of people using personal transport. There is also an increase in the number of high speed automobiles used by the general Indian public and thus there is a jump in the number of rash driving incidents. All these goes to show that current rules need to be reformatted in place in favor of new rules and mechanisms to enable more safe travel. Moreover there is no reliable system to help curb such incidents. Though many devices had already been made to prevent drowsy driving and to ensure safety to the driver and the public, they all have some kind of drawback and are not completely fool proof. The proposed system uses Electroencephalograph (EEG) [3] to combat accidents.

The project can go a long way in reducing if not completely nullifying the situation. It can also be extended to include several other dangerous issues on roadways.

1.2 OBJECTIVES

The objectives of the project are to develop a system to detect whether the driver is feeling drowsy. The detection system is supposed to alert the driver when they are about to lose their consciousness. This project aims to prevent accidents which occur due to drowsy driving. The ultimate aim of the project is to ensure better road safety in rural and urban road areas and to avoid life and property loss. This project will help long distance and heavy motor vehicle drivers to stay focused to reach their destination safely.

1.3 INNOVATION

The project overcomes the defects in the existing systems that deal with Drowsy and Drunken Driving detection. In this project, the detection is made with the help of EEG which is a foolproof method [3]. Unlike other systems which use Electrooculogram (EOG) or Electrocardiogram (ECG) or the angular tilt , EEG can predict whether the driver is drowsy or not without ambiguity since it deals with brain waves that are specific to the physiological conditions of the driver. EEG overcomes the ambiguity surrounding systems using image processing techniques and angular tilt [4]. EEG method is said to be foolproof since the brain waves cannot be duplicated by any other aspect. This system helps to address and mitigate the major contributor to accidents unlike the existing systems.

1.4 PROBLEM DEFINITION

The project analyses and classifies different types of Brain Waves based on which prediction is done to determine whether the driver is losing consciousness. The EEG data is sampled and the corresponding brain wave frequencies alpha, beta, gamma, theta, delta are extracted from the sampled data. Each of the frequencies correspond to a specific function which is used to determine the brain state. This extracted data is used to build a ARIMA time series model to predict if the driver is drowsy or not.

1.5 SCOPE OF PROJECT

The project can be expected to curb the number of drowsy driving incidents that occur in the subsequent months of release of this project commercially. Consequently, this can help reduce the destruction to life and property and thus result in safer road travel. The EEG or brain wave detection sensor can produce a plot of the driver's brain waves that can help to give an idea to find out if the driver has dozed off or not. This can subsequently help to prevent drowsy driving.

1.6 ORGANIZATION OF THE REPORT

The rest of the report is organized as follows: Chapter 2 presents the literature survey on drowsy driving detection systems. Chapter 3 outlines the architecture and design of the system proposed. Chapter 4 explains about the implementation details and the discussion of results. Chapter 5 contains the conclusions and some possible avenues for future research on the topic.

CHAPTER 2
LITERATURE SURVEY

McIntire *et.al*. [5] proposed a system to measure eye blink metrics from an eye tracker in relation to change in vigilance parameters and cerebral blood flow velocities. The system measured the blink frequency and duration which changed significantly over time during the study. The authors proposed that the blink frequency and duration increased when the performance decreased and with respect to decrease in right cerebral blood flow velocities. It was estimated that the eye blinks can be an indicator of arousal levels. The system used a two IR sensitive cameras and a linear array of IR-illuminating light emitting diodes (LEDs) mounted on a set of eyeglass frames as eye trackers. The system used a predefined threshold for calculating the number of blinks based on median blink rates. The system also used a trans-cranial Doppler unit to measure cerebral blood flow velocities in middle cerebral arteries in both left and right hemispheres for each participant. The study was conducted by simulating critical tasks in an isolated environment without distractions for participants. However, real world tasks which cause the change in perceived change in cerebral blood flow velocities were not considered which thus does not overcome the possibility that the system may fail in case the participant sleeps when during a critical function that was not considered in the study.

Garg *et.al*. [6] proposed a system in which an iris recognition system in relation with a heat variation sensor and a camera is used to determine if the driver is drowsy or not. Iris recognition system is used to authenticate the user and is used to provide security to the system. The driver's eyes are monitored with a camera using image processing system. The variation in the heat in the driver’s body is measured with the help of infrared thermal sensor which is used to perceive if the driver is drowsy or not. The infrared camera is used to monitor the driver’s eyes constantly. The temperature change will be due to exhaled gas plume of normal breathing patterns, which will lower in volume as the driver begins to hypoventilate , thus increasing their blood level of carbon dioxide which is in most part the reason for early drowsiness associated with sleep. The combination of closure of eyes and a decrease in body temperature, which is a physiological response to hypoventilation thus initiating drowsiness, will trigger the alarm. Detections are based on predefined templates that are matched against the images from the current scenario.

Mesharam *et.al*. [7] proposes a system that continuously monitors the head movements of the driver to determine if the driver is falling asleep to prevent the risk of road accidents. The paper proposes a technique which utilizes the hybrid of geometric and feature based algorithm for head pose estimation, so that both head and eye blink pattern are enough to provide information about the driver's drowsy condition. The proposed method includes face detection, eye region extraction, eye blink rate pattern, head postures. In the face detection phase, a sub window identifies the face region and discards the noise from the background. The center nodal point is extracted to localize eyes on the face. The eye region extraction method analyzes all possible regions of interest in the eye to determine the suitable condition for extraction of eye region areas. The characteristics of the eye region on human face are analyzed, the summation of the gray pixel values in each part in the eye region is similar regardless whether glasses are worn or not.

Eskandarian *et al*. [8] proposed a smart algorithm for determining vehicle driver drowsiness detection. The paper describes an experimental analysis of drivers who were subjected to drowsiness conditions in a truck driving simulator and evaluates the performance of a neural network based algorithm which monitors only the drivers' steering input. The paper proposes that a correlation exists between the change in steering and the state of drowsiness which can be effectively used for detection. The driver behavior, performance and eye closure were observed during testing and off-line observation of video data. The paper proposes two different phases for determining driver drowsiness. An Artificial Neural Network was trained to learn steering input of commercial truck drivers under different driving states (alert and drowsy). This system was used to detect truck driver drowsiness based on steering activity. The training of the neural network was based on the learning of the phase-I steering performance degradation. The system used a neural network architecture of a three-layer, feed forward network. The error-propagation supervised learning algorithm was used to update the weights.

There have been quite a few other research papers that use vehicle based measures (acceleration, steering wheel position) [9,10], head pose estimation / angle of tilt between the head and neck [11,12], eye tracking [13,14] to detect drowsy driving.

CHAPTER 3
PROPOSED SYSTEM

3.1 OVERVIEW OF THE PROPOSED SYSTEM

This project utilizes the characteristics of brain waves obtained from EEG or Electroencephalograph to determine the state of the driver. There are 5 types of Brain Wave Frequencies: Gamma, Beta, Alpha, Theta, Delta. Each of these frequencies have specific characteristics and is essential to optimal brain functioning as shown in Fig 3.1. EEG is used to note the frequency patterns in the brain waves. Each of the brain waves has a specific function using which can be used to determine the brain state.

3.2 TYPES OF BRAIN WAVES

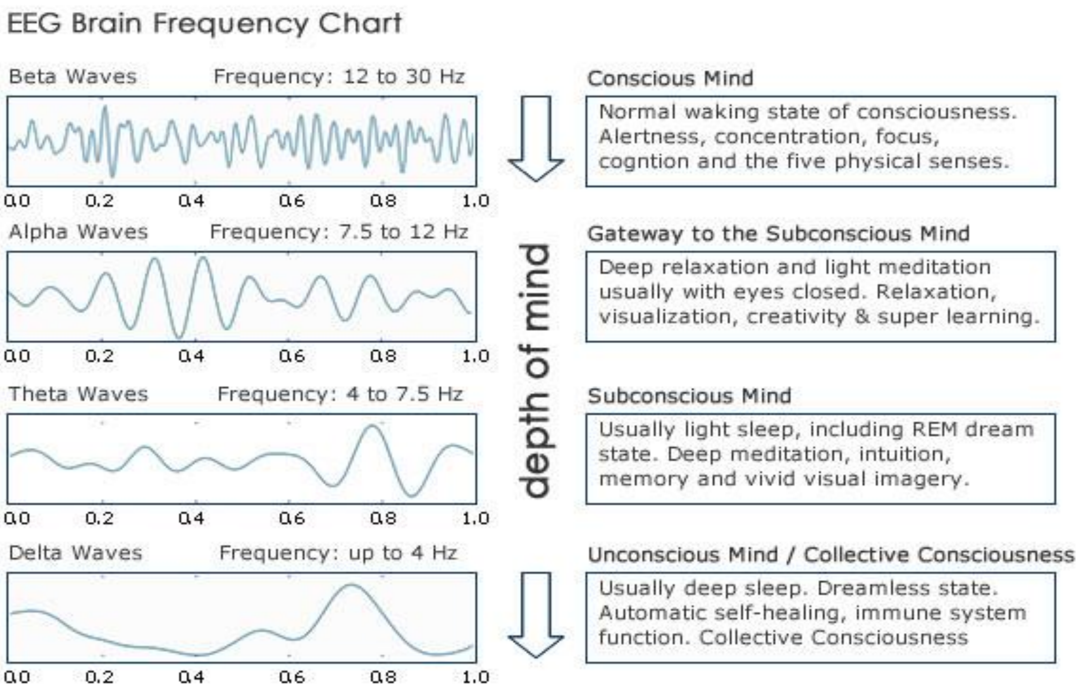

Fig 3.1 EEG Brain Frequency Chart

3.2.1 Gamma Waves:

Gamma Waves are useful in higher mental tasks and cognitive reasoning. They are important for memory, learning and processing of information. The frequency range of gamma waves is from 40 Hz to 100 Hz. Too much of gamma results in stress and anxiety. When gamma waves are optimal, it’s useful in REM Sleep, learning, perception and cognition.

3.2.2 Beta Waves:

These waves are seen usually when a person is awake. They involve logical thinking, conscious thought. Concentrated focus can lead to generation of beta waves. Excess Beta waves indicate stress. Scarcity of the waves indicate daydreaming, low cognition and depression. The frequency of these waves is from 12 Hz to 40 Hz, when high.

3.2.3 Alpha Waves:

Alpha Waves bridge the gap between sub-conscious and conscious. Alpha waves are an indication of calmness. Scarcity of alpha waves are indicative of Obsessive Compulsive Disorder (OCD), Insomnia and high stress. Excess of the alpha waves makes the mind too relaxed. The frequency range of the Alpha waves is between 8 to 12 Hz. Consumption of Alcohol causes an increase in Alpha waves.

3.2.4 Theta Waves:

Theta waves are involved mostly during daydreaming and sleep. Raw emotions are felt in relevance to theta waves. Excess of these waves will cause Depression and impulsive decisions. Depressants increase theta waves. The frequency is of the range 4 to 8 Hz.

3.2.5 Delta Waves:

Delta waves are most often found in children and infants. Delta waves are associated with the deepest levels of sleep. Excessive levels of alpha waves lead to injuries to brain and learning disabilities. Natural amount of these waves lead to deep sleep. The frequency range of delta waves is of the range 0 to 4 Hz.

3.3 ARCHITECTURE DIAGRAM

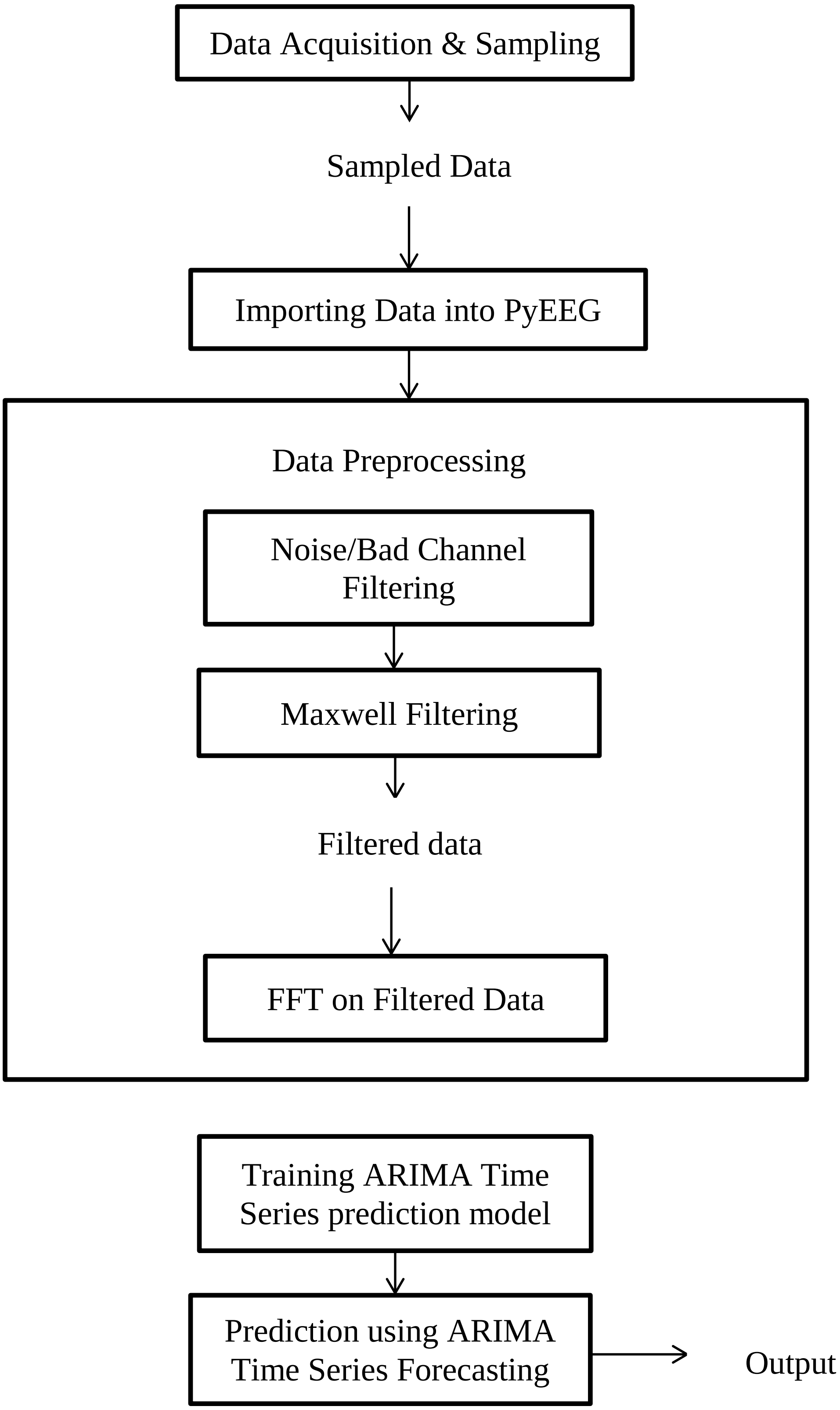

Fig 3.2 Architecture Diagram

3.4 DATA ACQUISITION

3.4.1 EEG SENSOR (NEUROSKY MINDWAVE)

The sensor uses the TGAM1 module, a single AAA Battery with automatic wireless pairing. It uses Bluetooth V2.1 to transfer the sampled data into the system. The sensor has a static Headset ID (headsets have a unique ID for pairing purposes).The sensor shown in Fig 3.3 measures raw-brainwaves and provides EEG signal quality analysis which can be used to detect poor contact or whether the device is off the head.

Fig 3.3 NeuroSky MindWave Sensor for brain wave detection

The sensor outputs a single continuous EEG signal which can be sampled at a rate of 500/s and transferred to the system using the inbuilt Bluetooth Transmitter in the sensor. The sampled data is stored in CSV files and the features are extracted using this sampled signal and python libraries MNE Python [15], PyEEG [16] packages. Some of the features include: High Alpha, Low Alpha, Beta, Theta, Delta, Power Spectral Intensity (PSI), Relative Intensity Ratio(RIR), Petrosian Fractal Dimension(PFD), Higuchi Fractal Dimension(HFD), Hjorth mobility and complexity, Spectral Entropy, SVD Entropy, Fisher information, Approximate Entropy (ApEn), Detrended Fluctuation Analysis(DFA) and Hurst Exponent.

3.5 IMPORTING DATA INTO PyEEG

PyEEG uses standard NumPy datastructures to store data that correspond to EEG. The datasets that are obtained from drowsy, conscious persons are imported into PyEEG using NumPy arrays. Numpy arrays are tables of elements (usually numbers), all of the same type, indexed by a tuple of positive integers.

3.6 DATA PREPROCESSING

Data preprocessing describes any type of processing performed on raw data to prepare it for another processing procedure. Data preprocessing transforms the data into a format that will be more easily and effectively processed for the purpose of the user. It organizes data for more efficient access and feature extraction, which pulls out specified data that is significant in some particular context. Analyzing data that has not been carefully screened for such problems can produce misleading results. Thus, the representation and quality of data is first and foremost before running an analysis. Often, data pre-processing is the most important phase of a machine learning project.

3.6.1 NOISE REMOVAL / BAD CHANNEL FILTERING

Filtering can help to select certain frequencies, such that either some frequencies are removed, or possibly that some filters remain. There are a number of types of filters:

Low-pass filter: 'Low' frequencies below a certain value are kept, while high frequencies are removed. This is also known as a high-cut filter. It may help to think of the audio version of this, which would be something that removed all the high notes from a sound.

High-pass filter (a.k.a Low-cut): The same as above, but only high frequencies remain, and only those below a certain value are removed.

Band-pass filter: This filter selects only frequencies between a lower and upper bound. The band-cut filter which functions opposite to that of the band-pass filter, which removes all frequencies in a particular range.

Notch filter: This is a special type of band-cut filter, that removes a single frequency. It is also possible to combine multiple notch filters, to remove a particular set of single frequencies, useful for things like removing electricity noise.

3.6.2 FAST FOURIER TRANSFORM

The Fast Fourier transform (FFT) algorithm samples a signal over a period of time and divides it into its frequency components. The components are single sinusoidal oscillations at distinct frequencies each with their own amplitude and phase. The FFT algorithm computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IFFT). Fourier analysis converts a signal from its original domain to a representation in the frequency domain and vice versa. An FFT rapidly computes such transformations by factorizing the DFT matrix into a product of sparse (mostly zero) factors. Hence, it manages to reduce the complexity of computing the DFT.

3.7 TIME SERIES ANALYSIS

A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time. Thus it is a sequence of discrete-time data as shown in Fig 3.4. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data. Time series forecasting is the use of a model to predict future values based on previously observed values.

PyEEG provides the bin_power function that can perform Fast Fourier Transform on the Filtered Data to obtain the required alpha, beta, gamma, theta components as shown in Fig 3.5. The component values in the EEG are normalized against the total values to obtain the comparable values.

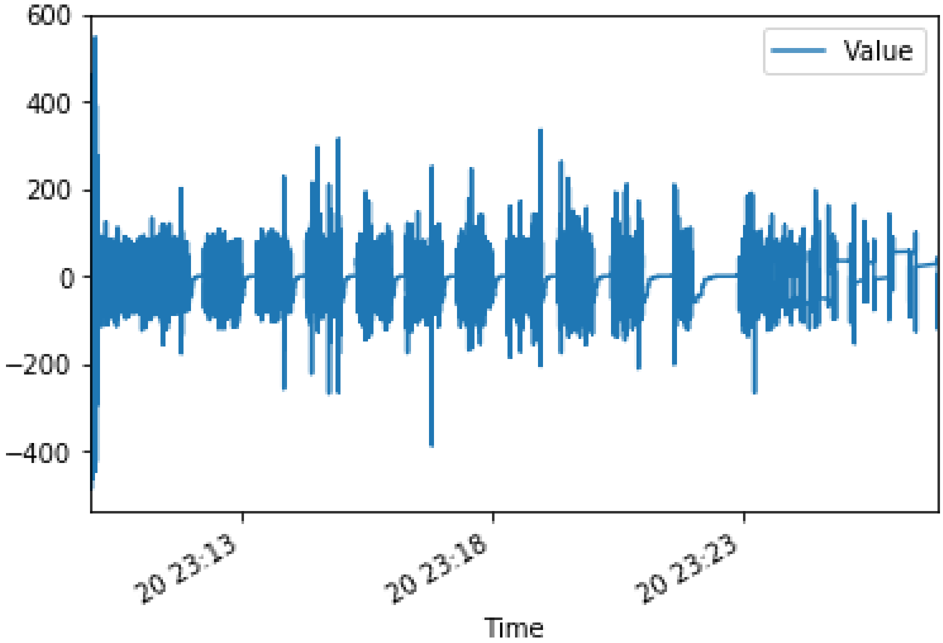

Fig:3.4 The raw input time series

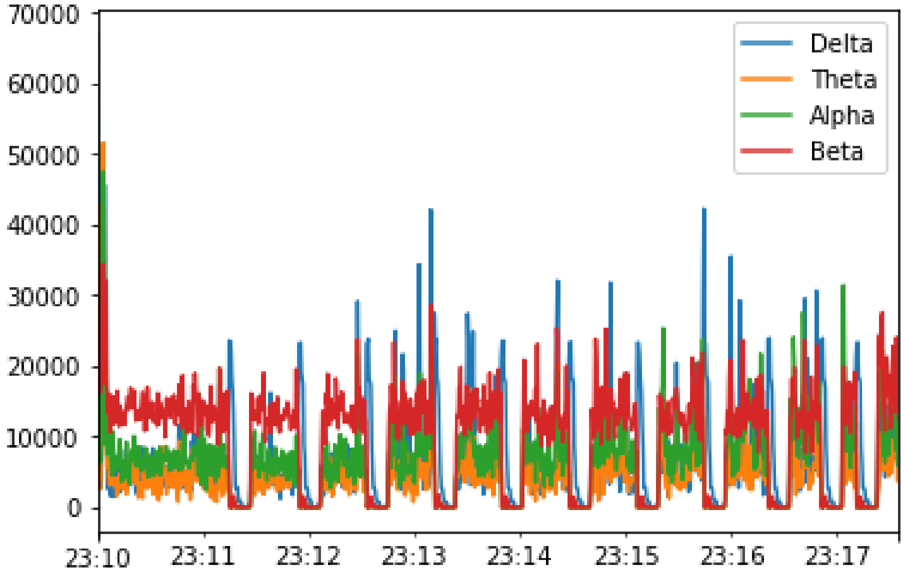

Fig:3.5 Raw signal split into its components: Alpha, Beta, Delta and Theta

3.7.1 ARIMA Time Series Forecasting

The Auto Regressive Integrated Moving Average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. ARIMA models are applied in some cases where data show evidence of non-stationarity. Since the data from the brain signals are capable of showing unsteady variations, the ARIMA model would be better suited for the application. The ARIMA model has been applied to a sample dataset and checked for the stationarity based on the Dickie-Fuller Test.

CHAPTER 4
IMPLEMENTATION AND RESULT DISCUSSION

4.1 IMPLEMENTATION SPECIFICATION

PYTHON

The 64-bit, 3.6.3 python version is used. Python 3.6 is the recent release of the Python language, and it contains many new features and optimizations. NumPy is a library for the Python programming language, adding support for large, multi-dimensional arrays and matrices, along with a large collection of high-level mathematical functions to operate on these arrays. The Pandas package is very useful for Time Series Analysis as it contains all the necessary functions and data structures to handle a continuous series of values. The popular Matplotlib is used for plotting graphs. Jupyter Notebook programming environment was used for implementation. The feature extraction process from the raw EEG signal is done using a python module called PyEEG.

PyEEG

PyEEG is a python module exclusively designed for extracting features from input EEG Signals. Though originally designed for EEG, PyEEG can also be used to analyze other physiological signals that can be treated as time series, especially MEG signals that represent the magnetic fields induced by currents of neural electrical activities. PyEEG's target users are programmers working on computational neuroscience. It does not contain functions to import data of various formats or export features to a classifier. This is due to the modularity and composition principles of building open source software which indicate that small programs that can work well together via simple interfaces are better than big monolithic programs. PyEEG only uses functions in standard Python library and SciPy, the de facto Python module for scientific computing.

JUPYTER NOTEBOOK

The Jupyter Notebook is an open-source web application that allows users to create and share documents that contain live code, equations, visualizations and narrative text. It is used for the functions such as data cleaning, data visualization, data transformation, numerical simulation, statistical modeling and machine learning.

4.2 SYSTEM MODULES

4.2.1 UNCONSCIOUS DATASET

The unconscious data pertaining to the situation when the driver is drowsy is extracted by placing the NeuroSky Brain Wave sensor on the participant under study, who is fluctuating between drowsiness and sleep. Since the system is required to detect if the drivers are drowsy before progressing to sleep, data sampled at that particular state is required. The unconscious data are sampled into a file against time measure which is shown in figures 4.1 and 4.2. Hence the EEG values are variable based on time, signifying that time series analysis is the best possible method for analyzing such data. The sensor samples at the rate of 500/s or 500 Hz. Hence multiple values pertaining to a single second in time are obtained. These values are divided into epochs, which are discrete measureable intervals in time.

The significance of dividing the time series data into epochs is that, the system is required to identify that the driver is drowsy before he is about to fall asleep and the division helps in training the system for such a scenario. Thus analyzing time series data and forecasting based on time series prediction model can help to determine the objective.

	A	B	C
1	Time	Value	
2	23:09:41	56	
3	23:09:42	56	
4	23:09:43	50	
5	23:09:44	53	
6	23:09:45	44	
7	23:09:46	37	
8	23:09:47	41	
9	23:09:48	43	
10	23:09:49	43	
11	23:09:50	43	

Fig:4.1 Sample Unconscious Data

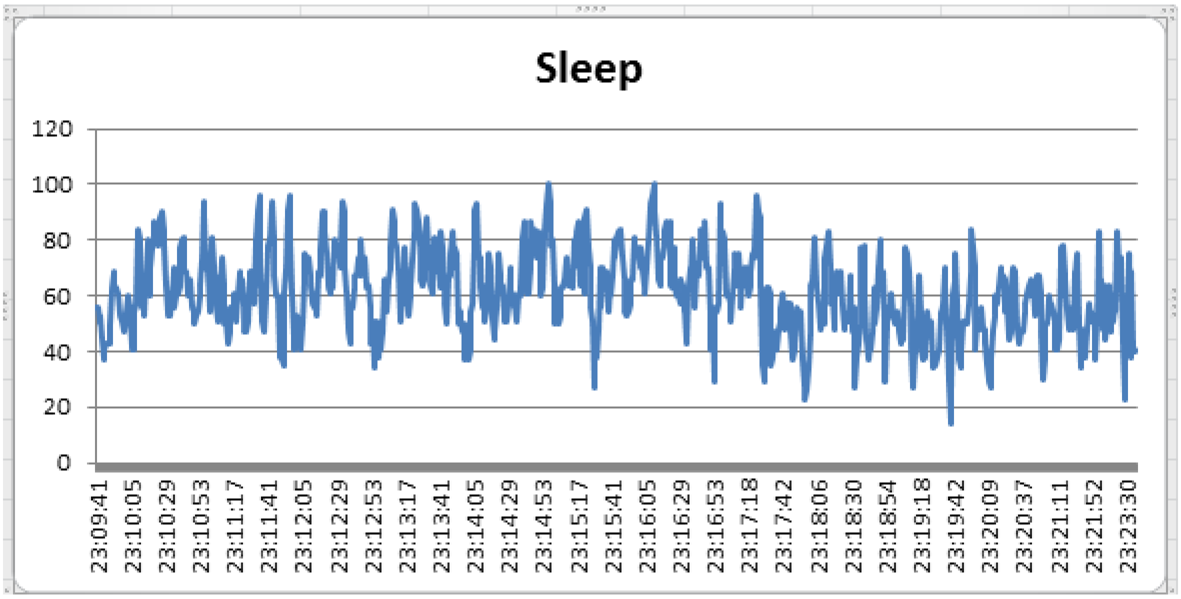

Fig:4.2 Sample unconscious raw EEG Signal

4.2.2 CONSCIOUS DATASET

Similar to the unconscious dataset, the conscious data shown in Fig 4.3 are extracted from the participant under study. The data can be visualized by a time series plot as shown in Fig 4.4

	A	B
1	Time	Value
2	23:09:41	60
3	23:09:42	75
4	23:09:43	64
5	23:09:44	48
6	23:09:45	43
7	23:09:46	40
8	23:09:47	29
9	23:09:48	34
10	23:09:49	34
11	23:09:50	34

Fig: 4.3 Sample Conscious Dataset

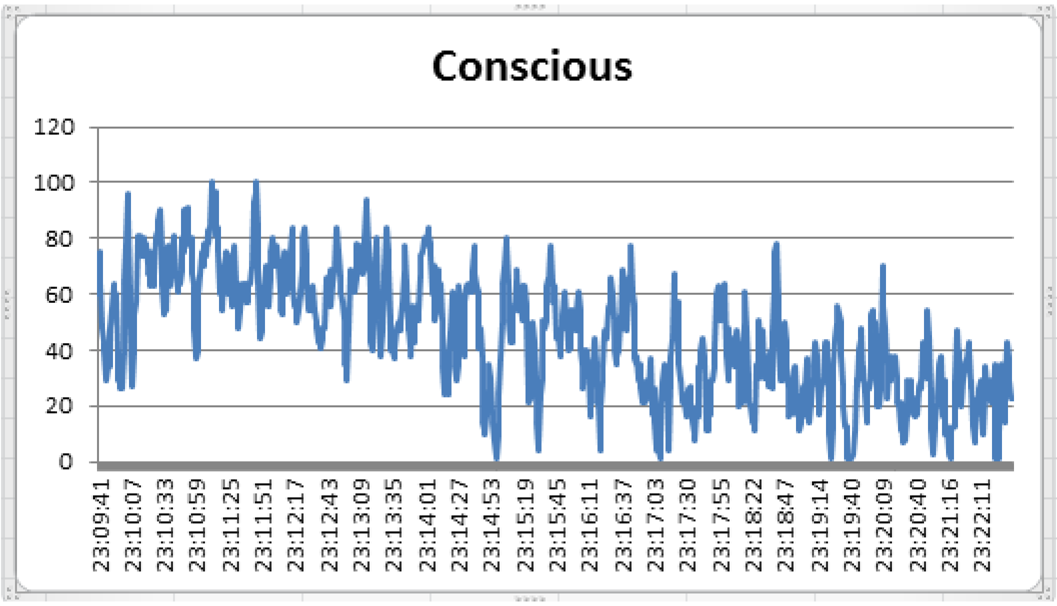

Fig: 4.4 Sample conscious raw EEG signal

4.3 RESULTS AND DISCUSSION

The modules proposed in the project include preprocessing raw EEG data (noise/bad channel removal, maxwell filtering), dividing the EEG data into Epochs and time series analysis of the sampled EEG data. The output is the expected values of alpha, beta, gamma, theta for the next epoch which can be used to determine the driver's state. The results are determined based on the output values of the EEG components.

The project focuses on analysis of the EEG data and identifying useful patterns in the EEG data based on time series analysis. The advantage of the system is that it uses EEG to extract driver information, since EEG is unambiguous and cannot be duplicated by any other physiological aspect of the person.

From the analysis, it is seen that firstly the raw signal can be split up into the major components such as Beta, Alpha, Theta and Delta by using bin_power from the PyEEG Module. The Fig 4.5 shows the extracted Beta wave being plotted.

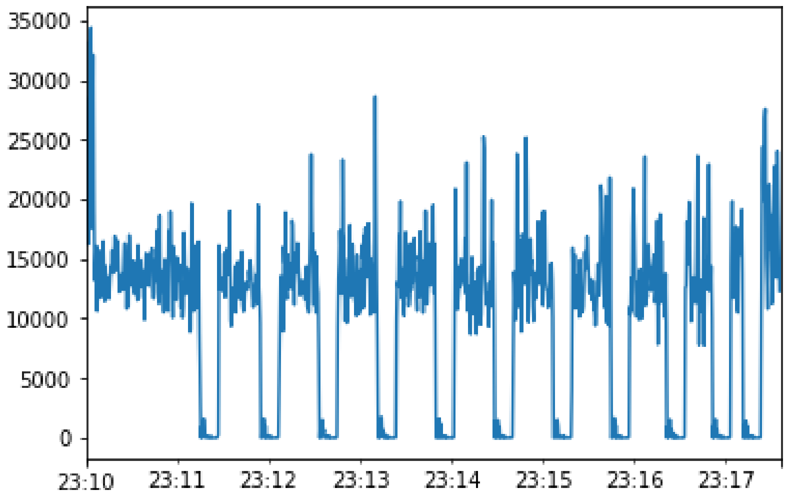

Fig: 4.5 Beta Wave Plot: Extracted from the raw signal

The extracted signals are stored in data-frames in pandas as shown in the Fig. 4.6 .

Out[24]:

	Delta	Theta	Alpha	Beta
2017-12-19 23:10:00.000	66967.607213	2.629728e+04	2.970435e+04	3.318235e+04
2017-12-19 23:10:00.500	44627.953217	4.292298e+04	2.117908e+04	2.136383e+04
2017-12-19 23:10:01.000	14499.432685	3.110694e+03	7.624004e+03	2.050524e+04
2017-12-19 23:10:01.500	6031.714406	2.531559e+03	7.536532e+03	1.621922e+04
2017-12-19 23:10:02.000	2712.837504	3.843056e+03	6.361775e+03	2.072157e+04
2017-12-19 23:10:02.500	20338.295479	2.694895e+04	2.751465e+04	2.846539e+04
2017-12-19 23:10:03.000	17313.665628	2.992978e+04	4.161394e+04	2.900749e+04
2017-12-19 23:10:03.500	25656.378576	5.162075e+04	4.747597e+04	3.442705e+04
2017-12-19 23:10:04.000	45667.456683	2.679977e+04	3.544084e+04	1.755379e+04
2017-12-19 23:10:04.500	26436.479182	1.433437e+04	8.911995e+03	2.554039e+04
2017-12-19 23:10:05.000	14062.121775	7.856979e+03	1.507807e+04	3.213525e+04
2017-12-19 23:10:05.500	5834.037953	5.797267e+03	7.472385e+03	1.945855e+04
2017-12-19 23:10:06.000	2612.794732	6.886028e+03	8.098902e+03	1.319407e+04
2017-12-19 23:10:06.500	5827.901348	3.670407e+03	1.044599e+04	1.479116e+04
2017-12-19 23:10:07.000	5090.386673	3.104800e+03	1.144903e+04	1.608707e+04
2017-12-19 23:10:07.500	1586.465786	3.548717e+03	7.533779e+03	1.063819e+04
2017-12-19 23:10:08.000	1706.871728	3.369785e+03	6.475098e+03	1.384858e+04
2017-12-19 23:10:08.500	7290.667021	3.239402e+03	4.610035e+03	1.444662e+04
2017-12-19 23:10:09.000	5363.391550	4.295825e+03	1.079469e+04	1.568237e+04
2017-12-19 23:10:09.500	1536.458513	3.495787e+03	8.502761e+03	1.174234e+04
2017-12-19 23:10:10.000	2138.698514	3.078979e+03	5.727216e+03	1.183240e+04

Fig 4.6 Extracted values from raw EEG signal

The time series analysis is performed on the beta wave extracted as it is known that these waves show the attentiveness and level of consciousness of a person. The data is stored and contains about 350,000 records out of which about 35,000 records are used for testing purposes and the remaining is used for testing purposes. In the initial forward validation testing, the results of the validation testing are shown in Fig 4.7.

```
>Predicted=34.200, Expected= 44
>Predicted=44.000, Expected= 43
>Predicted=42.600, Expected= 37
>Predicted=37.000, Expected= 35
>Predicted=34.900, Expected= 35
>Predicted=35.100, Expected= 33
>Predicted=33.200, Expected= 29
>Predicted=28.900, Expected= 25
>Predicted=24.900, Expected= 23
>Predicted=22.900, Expected= 20
>Predicted=20.400, Expected= 13
>Predicted=13.200, Expected=  4
RMSE: 5.905
```

Fig: 4.7 Prediction results with RMSE performance metric using forward validation

The ARIMA forecasting model is used for the prediction and get better performance as shown in the Fig 4.8.

```
[[ 28.60000038  27.64970024]]
[[ 29.70000076  30.33247721]]
[[ 32.09999847  28.98689715]]
[[ 36.59999847  32.16987157]]
[[ 38.70000076  37.90679496]]
[[ 37.29999924  38.26971913]]
[[ 35.70000076  34.53575694]]
[[ 34.59999847  32.87028759]]
```

Fig. 4.8 Arrays containing predicted and expected values for ARIMA model.

The ARIMA model gives a RMSE of about 0.59 which is lower than the walk forward validation error rate. The scatter plot between the expected and predicted output by the model is given in Fig 4.9. From the figure, it is seen that there is a high correlation between predicted and expected output for the time series.

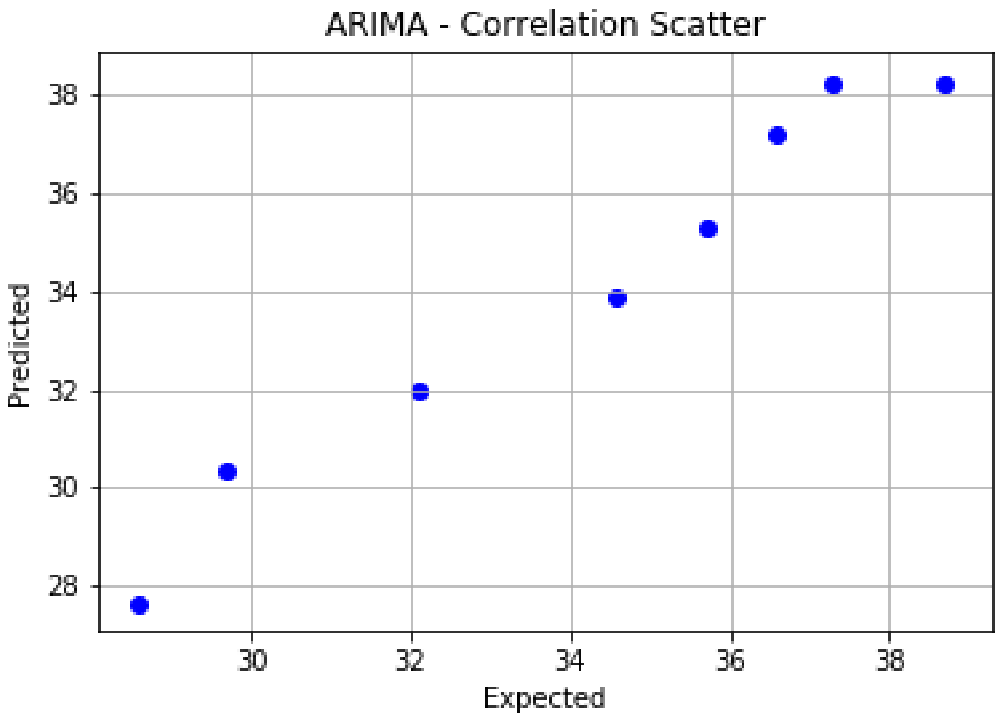

Fig 4.9 The Scatter plot of expected and predicted output for ARIMA

Performance Metric	Proposed Method		Previous Methods	
	Walk Forward Validation	ARIMA Time Series Modeling	Smart algorithm	Mobile phone based detection
RMSE	5.905	0.59	0.2	0.65

Table 4.1: Performance Metrics

CHAPTER 6
CONCLUSION AND FUTURE WORK

The system would help to tackle drowsiness which is the major contributor to road accidents. It uses Electroencephalograph(EEG) to determine the driver's state to prevent accidents caused due to drowsy driving. This can help to reduce/mitigate the destruction to life and property.

Signal Processing has been a widely researched topic complete accuracy in separating signals has not yet been completely achieved. With better separation procedures, the accuracy of the current system can be improved. In this project, the PyEEG module is used to split the waves into Alpha, Beta, Delta and Theta and use a time series as an input. Since time series is used, it is only possible to train the model using a single raw signal converted into its constituents.

However, in the future, the signals can be trained using a Recurrent Neural Network (RNN) and Long Short Term Memory (LSTM). The neural network architecture can use multiple raw signals to train the system. The model can then be used to test data. The system can be extended to include solutions for several other road accident causes. Processing of the sampled EEG data can be done over the cloud to ensure a relatively non-intrusive technique. This system can be implemented as a product which can be manufactured and can be mass produced if a low cost sensor can be found to retrieve brain waves.

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