# Neural Network Based Drowsiness Detection Using Electroencephalogram

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## Abstract

*Driver drowsiness is one of the main factors in many traffic accidents. It can be detected by monitoring physiological signals in order to detect drowsiness with the change in the patterns of the EOG, EEG and ECG signals. The main issue in such a technique is to extract a set of features that can highly differentiate between the different drowsiness levels. In this work, a new system for driver's drowsiness detection based on EEG using Neural network is proposed. This uses physiolo- gical data of drivers to detect drowsiness. These include the measurement of brain wave by using 25 channels EEG and approaches based on EEG signals. EEG data is converted into excel sheet from where we detect the alpha waves, which are indicators of drowsiness. The result shows the Roc graphs and confusion matrix for the samples which gives the combined accuracy result which is 81.8%.*

## 1. Introduction

Many traffic accidents are caused by drivers falling asleep while driving. So it would be beneficial to develop a way to detect the drowsiness before it occurrence and to be able to warn the driver in time. Many systems have already been developed which are based on the vehicle behavior like steering wheel movements, focusing on the driver physical behavior i.e. based on recording of head movements, heart rate variability or grip strength. System uses a video camera for the tracking of eye movements have also been developed. Till now no system has proved to be sufficiently reliable.

### 1.1 Drowsiness

Drowsiness is the transition state between awakening and sleep during which a decrease of vigilance that is the capacity of keeping oneself attention on a task is generally observed. It is the state where a person is almost asleep or very lightly asleep. During drowsiness Reaction time is slower, vigilance is reduced and information processing is less efficient, which can generate abnormal driving. Moreover, as drowsiness is the transition between awakening and sleep, it induces an increase of the number and the duration of blinks and yawns. Fatigue which means an extreme tiredness that result from physical or mental activity and the amount of sleep during night is the most common factors of drowsiness. Other factors contributing are the amount of light, sound, temperature and oxygen contents.

### 1.2 Effects of Drowsiness on Driving

Most people would agree that the effects drowsiness has on driving are nothing but negative. According to Virginia Commonwealth University, the second leading cause of distraction on the road is driver drowsiness, estimated to cause 12 % of the crashes related to distraction. The leading cause (16%) is looking at crashes, vehicles, roadside incidents or traffic. Driver distraction is involved in approximately 20 to 30 % of all vehicle crashes. According to the National Highway Traffic Safety Administration (NHTSA) drowsiness leads to crashes because it impairs parts of the performance that are important to safe driving. Impairments like slower reaction time, reduced vigilance, deficits in information processing are also suggested. This corresponds with the statement that making small mistakes, called lapses, is one of the most likely aspects of performance by a sleepy person. A Canadian driver fatigue and alertness study has found the following characteristic consequences of drowsiness:

Increased lapses of attention

- Increased information processing and decision making time
- Increased reaction time to critical events
- More variable and less effective control responses

• Decreased motivation to sustain performance
• Decreased psycho physiological arousal like brain waves and heart activity

• Increased subjective feelings of drowsiness
• Decreased vigilance like watchfulness
• Decreased alertness like readiness

Drowsy driving is sometimes also compared with driving under the influence of alcohol. Although the level of alcohol influence can be measured it is hard to exactly know when alcohol makes the driving dangerous. When it comes to drowsiness, it is even harder since there are no practical and reliable tests that can be used for example by the police at the roadside. The National Highway Traffic Safety Administration (NHTSA) statistical investigations and evidence from car crashes has been used to set up the following characteristics of a typical crash related to drowsiness:

The problem occurs during late night, early morning or mid afternoon.
• The crash is likely to be severe
• A single vehicle leaves the roadway
• The crash occurs on a high-speed road
• The driver does not attempt to avoid a crash
• The driver is alone in the vehicle

The best way to avoid the risks that are enclosed with driving in a too drowsy state is to take a break and sleep for a while till one feels alert again.

## 1.3 Methods used for drowsiness detection

Drowsiness can be measured through focusing on the driver physiological behavior, focusing on the vehicle behaviour, focusing on the driver physical behavior. The different methodologies are described below.

### 1.3.1 Physiological measures

Physiological measures have frequently been used for drowsiness detection as they can provide a direct and objective measure. Possible measures are EEG, eyelid closure, eye movements, heart rate, pupil size, skin conductance and production of the hormones adrenaline, noradrenaline and cortisol. EEG has shown to be a reliable indicator of drowsiness. The amount of activity in different frequency bands can be measured to detect the stage of drowsiness or sleep. Several studies also reveal that eye parameters such as blink duration, blink frequency, delay in lid reopening and the occurrence of slow eye movements are good indicators of drowsiness. These parameters can be measured by EOG. A decrease in heart rate and an increase in heart rate variability have shown to be indicators of drowsiness, as well as decrease in pupil size, spontaneous pupillary movements and decrease in skin conductance. A decreased production of adrenaline, noradrenaline and cortisol are other possible indicators of drowsiness.

### 1.3.2 Self report

Self-report refers to the subjective rating made by the driver and can be obtained through various rating scales. It is important that the scales are displayed in such a way that they are Unobtrusive and don't alert the driver, since that would affect the drivers state. Various rating scales have been constructed, for example the Karolinska Sleepiness Scale (KSS). This is a subjective sleepiness scales which allows drivers to directly evaluate their own drowsiness.With the help of this scale driver can evaluate his own level of drowsiness that whether he is at the alert stage, extremely alert stage or at the drowsiness stage. Karolinska Sleepiness Scale (KSS) is shown below

**Table 1.** Modified version of KSS

| Karolinska Sleepiness Scale<br>Here are some descriptors about how alert or sleepy you might be feeling right now. Please read them carefully and then circle the number that best corresponds to the statement describing how you feel at the moment. | |
|---|---|
| 1 | Extremely alert |
| 2 | Very alert |
| 3 | Alert |
| 4 | Rather alert |
| 5 | Neither alert nor sleepy |
| 6 | Some signs of sleepiness |
| 7 | Sleepy – but no difficulty Remaining awake |
| 8 | Sleepy, some effort to keep alert |
| 9 | Extremely sleepy, fighting sleep |

### 1.3.3 Vehicle movement measures

Vehicle movement measures include steering wheel movements, lateral position, speed variability and reaction time. The studies have indicated that the steering wheel variability of the vehicle increases with the amount of drowsiness. The steering movements becomes larger and its occurring is less often, and the lateral position variability increases as the driver gets drowsier. Also, the speed variability of the vehicle increases and the minimum distance to any lead vehicle decreases. The time of reaction to any unexpected events also becomes longer with increased drowsiness.

### 1.3.4 Driver physical behavior

These kinds of systems focus on the drivers' visual attention. Face, mouth and eye tracking algorithms are used to detect the face. Once the mouth, the eyes and the face are located, it is easier to detect eye blinking and yawning and calculate their duration and frequency. Duration and frequency of yawning or eye blinking too high indicates a decrease in attention. The gazing of eyes can be calculated with the position of eyes and the face or using a stereoscopic camera. Then it allows the driver to be warned when he is not looking at the road.

### 1.3.5 Expert ratings

Expert ratings refers to the rating made by an observer and are made on a similar scale as theself-report. Results from earlier studies indicate that these ratings are reliable and consistent. The observer looks for behavioural indicators of drowsiness, for example eyelid closures, yaws, a vacant stare, body movements or the head falling backward or forward.



## 2 Techniques used for detection of drows--iness

## 2.1 Electrooculogram (EOG)

Electrooculographic is used to monitor the visual activity through blinking detection and characterization.

### 2.1.1 Origin of the EOG signal

Electrooculography is a technique used to measure the difference in potential between the front and back of the eye ball of the eyes. The EOG can be used for detection of eye movements and blinking of eyes. The eye is a dipole having the positive cornea in the front and the negative retina in the backward direction of the eyes and the potential between cornea and retina lies in the range of 0.4 – 1.0 mV. When the eyes are fixed straight ahead of a steady baseline potential which is measured by electrodes placed around the eyes. During the movement of the eyes, a change in potential is detected because the poles come closer or farther away from the electrodes. The sign of the change depends upon the direction of the movement of the eyes.

### 2.1.2 Measurement of EOG

EOG is measured by placement of the electrodes around the eyes. Generally silver-silver chloride coated electrodes are used as they provide negligible drift and develop almost no polarization potentials. The electrodes must be placed as near the eyes as possible in order to increase the measured potential. The issues with the EOG measurement are the artefacts that arise from potential of muscles and small electromagnetic disturbances which can be induced in the cables. In order to reduce the impedance between the electrode and skin, the skin should be cleaned carefully before measuring it and electrode paste must be used. It is necessary to separate horizontal eye movements from vertical eye movements, and eye movements from eye blinks. By using different kinds of electrode placements the obtained recordings can be either vertical or horizontal.

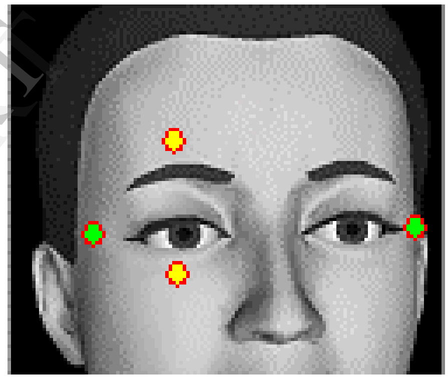


**Figure 1.** Electrode placement

In vertical recording electrodes are placed under and above the eye, and in horizontal recording they are placed at the outer edges of the eyes. Vertical recording is usually monocular, which means that the recording is made across one eye, whereas horizontal recording usually is binocular. Figure1 shows how the electrodes are placed. Eye blinks are detected by using vertical recording. During the measurement of the blink related features, the sampling frequency should be high that must be atleast 500 Hz as a high resolution is required in order to measure small differences , for example blink duration. The DC recording is preferred during the filtering of the low frequency components which makes the detection of long blinks difficult. One problem with DC recordi--ng however, is the risk of slow baseline drift, which makes it important to monitor the EOG signal and adjust for the drift during the measurement.

### 2.1.3 Blink detection

An eye blink is defined as when the upper and lower lids are touching each other and the eye is temporarily hidden. A typical blink has an amplitude of 400 μV which lasts for about 200 - 400 ms. A blink can be detected in the EOG by its sharp rise and fall. Blinks in the EOG signal are always referred to as blink artefacts. It is necessary to be able to distinguish eye blinks from vertical eye movements, as a change in the form of the blink artefact can be used for hypovigilance detection. Parameters which are used to describe the blink behaviour of eyes, that are extractable from the EOG signal,for example blink frequency [blinks/minute], amplitude or eyelid opening level [mV] and duration [ms]. According to Andreassi (2000), a relaxed person blinks about 15-20 times per minute, although only 2-4 are needed from a physiological viewpoint.
When performing cognitive tasks the blink frequency drops to as little as 3 blinks per minute, whereas an increase in blink frequency indicates reduced vigilance. A common definition of blink duration is the time difference between the beginning and the end of the blink, where the beginning and end points are measured at the point where half the amplitude is reached. However, this definition will cause a problem when a vertical eye movement occurs at the same time as the blink, since this causes a vertical shift in the signal. The amplitude thus becomes difficult to define. As this is often the case, a better definition of blink duration is the sum of half the rise time and half the fall time in the blink complex. The first part of the duration is measured from half the rise amplitude to the top, and the second part is measured from the top to half the fall amplitude.

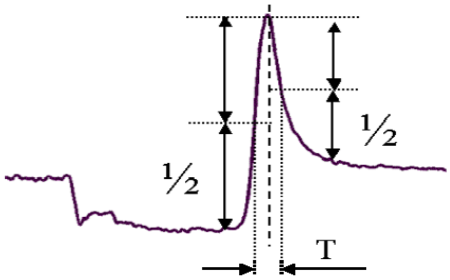



**Figure 2.** Definition of blink duration, T, in EOG

The reason for measuring the beginning and end points where half the amplitude is reached is because of the difficulties to exactly determine the beginning and end points of the blink complex in the EOG signal. The points where half the amplitude is reached, however, can be determined more exactly, as they are rather unaffected by small errors in the location of the blink beginning and end points. The definition of a blink is separated from that of an eye closure. The definition of eye closure is commonly a blink with duration exceeding one second. When using the definition of blink duration described above the definition of eye closure will instead be a blink with duration exceeding 0.5 seconds.

## 2.2 Electroencephalogram (EEG)

Electroencephalography measures the electrical activity of the brain from electrodes placed over the scalp.

### 2.2.1 Origin of the EEG signal

Electroencephalography is a method for measuring the electrical activity generated by the nerve cells of the brain, mainly the cortical activity. The EEG-activity is present all the time and recording show both random and periodic behaviour. The main origin of the EEG is the neuronal activity in the cerebral cortex, but some activity also originates from the thalamus and from subcortical parts of the brain. The rhythmic activity is due to the synchronous activation of the nerve cells. The signal is classified on the basis of its amplitude and frequency range. The recorded pattern differs during the different sleep stages, but also when performing cognitive tasks, focusing attention, preparing manual tasks or by brain diseases, for example epilepsy or tumours.

### 2.2.2 Classification of EEG Signal

The EEG-signal can be classified on the basis of its amplitude and frequency range. The patterns most reliable in consistence and occurrence are beta waves (15-30 Hz), alpha waves (9-14 Hz), theta waves (4-8 Hz) and delta waves (1-3 Hz). [12] Table 3.1 shows the frequency and state represented by the four waves. During drowsiness change in all these four waveforms can be seen.

***Beta waves*** (15-30 Hz) are common in the alert condition, during physical activity and when performing cognitive tasks. They can also be present in the first stages of sleep. The beta waves are irregular and have a small amplitude (2-20 μV) and relatively high frequency.

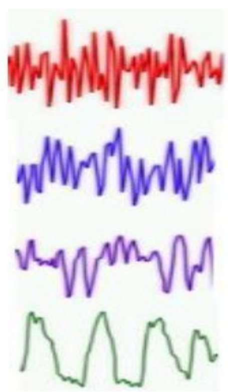
***Alpha waves*** (9-14 Hz) are common in the awake and relaxed condition and can be used as a first measure of drowsiness. They are rhythmic and have an amplitude of 20-60 µV. When drowsiness appears the first sign is a rise in alpha activity. Later in the process the alpha waves diminish and are replaced by theta waves. When alpha activity shows during relaxation, a sudden exposure to a cognitive task will make it disappear and be replaced by beta activity. This state is called alpha blocking.

**Table 2.** EEG Rhythms

| Type | Frequency(Hz) | Normally |
|---|---|---|
| Delta | 1-3 | Deep sleep |
| Theta | 4-8 | Appears as consci-ousness slips into Drowsiness |
| Alpha | 9-14 | Relaxed awareness and in attention |
| Beta | 15-30 | Associated with active thinking |

***Alpha waves*** (9-14 Hz) are common in the awake and relaxed condition. They are rhythmic and have an amplitude of 20-60 µV. When drowsiness appears the first sign is a rise in alpha activity. Later in the process the alpha waves diminish and are replaced by theta waves. When alpha activity shows during relaxation, a sudden exposure to a cognitive task will make it disappear and be replaced by beta activity. This state is called alpha blocking.

***Theta waves*** (4-8 Hz) have an amplitude of 20-100 µV and will occur in the early stages of sleep. There exist two types of theta activity, one that is associated with performance of cognitive tasks and one associated with the early stages of sleep.



Beta wave 15-30 Hz

Alpha wave 9-14 Hz

Theta wave 4-8 Hz

Delta wave 1-3 Hz

**Figure 3.** Various frequencies in EEG signal

*Delta waves* (1-3 Hz) occur during the deepest sleep or by brain tumours. Their amplitude is in the range 20-200 µV. Existence of frequencies in the delta range in the awake condition is not normal and probably due to artefacts, but can also be an indicator of a brain tumour.

### 2.2.3 Measurement of EEG

EEG was developed by the German psychiatrist Hans Berger in 1929. EEG is normally registered by placing about 20 electrodes on the scalp, but as many as 256 electrodes can be used. The number and the placement are dependent on the purpose of the recording. The advantage of using a large number of EEG channels is to obtain spatial information on how the EEG energy is shifting from one frequency band to another.

The signal is either measured pair-wise between two electrodes on the scalp (bipolar recording) or between each electrode and one reference site (monopolar recording). The reference site is usually one ear or the nose. The sampling frequency should be at least 128 Hz. The measured signal is small, only a few microvolts (compared to EOG ~100 µV), which requires a large amplification factor. Amplification is necessary to minimize the load on the body, which reduces the current density between the skin and the electrodes. A high Current density otherwise implies polarization of the electrodes. The amplification can make it difficult to separate the real signal from artefacts.



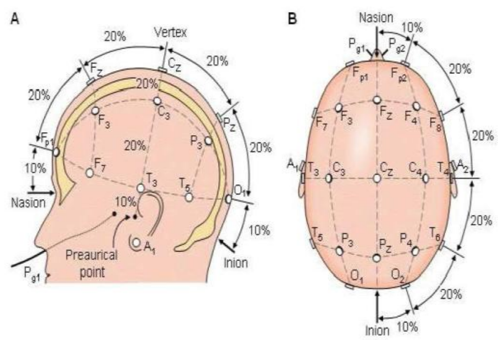



**Figure 4.** 10-20 system

An international system for positioning of the electrodes has been constructed which is called the International 10/20 system. The name indicates that the electrodes are placed at positions 10 % and 20 % of the distance between four anatomical landmarks. The landmarks are the nasion (bridge of nose), the inion (projection of bone at the back of the head) and the left and right preauricular points (depressions in front of the ears). The points are labelled with a letter and a subscript index. The letters refer to the regions of the brain; F = frontal, O = occipital, C = central, P = parietal and T = temporal. The subscript indices are z which indicates the midline and numbers indicating the lateral placement and degree of displacement from the midline. An odd number refers to the left hemisphere, an even to the right. The number gets higher the farther away it is from the midline. Figure 4 shows how the electrodes are placed.

## 3 Components required for drowsiness detector

In general, the development of a drowsiness detector requires the following components:
**1**.a reliable measure of the subject's current drowsiness.
**2**. a well-defined threshold for sleepiness at which the ability to perform is substantially reduced.
**3**.objective behavioural symptoms and biosignals which includes appropriate sensors and software that indicate such a critical point of sleepiness in advance.
**4**. a body of knowledge which can be applied on an individual level. With the large changes in biosignal variations which are related to fatigue are reported to occur in an individual, group means are not sufficient.

### 3.1Scale used for the drowsiness detection

There are two types of scales which are subjective sleepiness scales like the Karolinska Sleepiness Scale (KSS) which allows drivers to directly determine their own drowsiness and Objective Sleepiness Scales (OSS) which is used by expert doctors in order to determine the drivers' drowsiness after driving.

**Table 3.** OSS Criteria

| Objective sleepiness score | $\alpha$ and $\emptyset$ cumulative duration | Blinks and eye movements |
|---|---|---|
| 0 | Negligible | Normal |
| 1 | Less than 5s | Normal |
| 2 | Less than 5s or Less than 10s | Slow Normal |
| 3 | Less than 10s or More than 10s | Slow Normal |
| 4 | More than 10s | Slow |

## 4 Implementation of Drowsiness Detectio- -on using video EEG signal

STEP 1: Subject is asked to sit in front of Camera with EEG Electrodes placed on his Head and silence is maintained so that Subject can easily goes to drowsiness state.

STEP 2: BrainTech EEG Software captures the signals from 25 different Channels.

STEP 3: When the Subject starts sleeping the recording is stopped.

STEP 4: Raw EEG Data without Filter implementation on software side is converted from EEG format to Excel Sheets using converter provided by Clarity Medical.

STEP 5: Loading of EEG Signal in MATLAB.

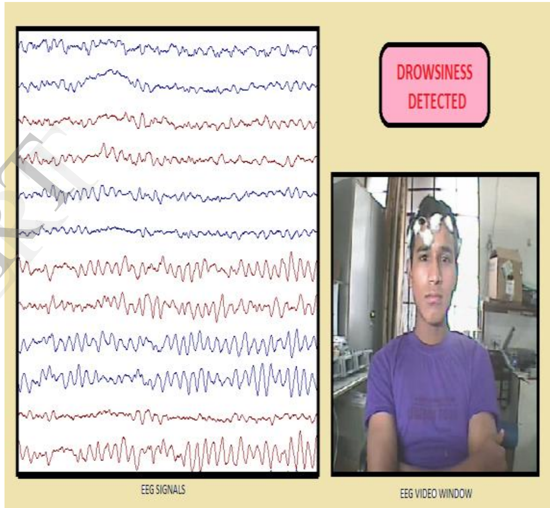



**Figure 5.** GUI window showing current video frame and the combine EEG signal.

STEP 6: Applying Preprocessing using Haar and Symlets Family on Loaded Signal

STEP 7: Calculation of Entropy of the same signal

STEP 8: Applying EEMD to extract different IMF's.

STEP 9: Resultant output is given as input to pertained neural network system for drowsiness detection.

STEP 10: Concluding percentage of correctness by applying for different datasets.

## 5 Methodology

The purpose is to design a drowsiness detection algorithm which can work off-line, inspired by the OSS. Thus the methodology to achieve the objectives can be summarized as follows:

***Step 1* The EEG power spectrum is computed using a Short Time Fourier Transform**

The EEG power spectrum is computed using a Short Time Fourier Transform (STFT) to calculate the relative power into the different EEG bands every second.

The short-time Fourier transform (STFT) is a Fourier-related transform which is used to evaluate the sinusoidal frequency and phase content of a signal. The EEG power spectrum is evaluated using a Short Time Fourier Transform (STFT). The power spectrum is computed every second on a window of two seconds using Welch's periodogram method. The overlapping window between the previous and next value is 1 second. Then, the relative powers in each band are calculated as the ratio of the power in one band and the power of the whole EEG spectrum. Only the range [1-30]Hz is used because activity below or above this range is likely to be artefactual

***Step 2* The relative power of the alpha band is median filtered using a sliding window**

The relative power of the alpha band is median filtered using a sliding window to reject abnormal values.

Median filtering is used to smooth the $\alpha_{\mathrm{rel}}$ signal and to reject abnormal values. The median is the value separating the higher half of a population from the lower half. Compared to the mean, the median is known for its robustness towards outliers, as far as the number of outliers is lower than half the length of the population. Here, the median of the relative powers is calculated every second, before performing MCT, using a sliding window of 10s.

***Step 3* A Means Comparison Test (MCT) is computed at last to compare the energy to a reference level**

A Means Comparison Test (MCT) is computed at last to compare the energy to a reference level which is learnt at the beginning of the recording while the patient is not supposed to be drowsy. The method of MCT is inspired by and is applied on the relative powers in the alpha band. A moving window is compared to a fixed reference window.

***Step 4* A Variances Comparison Test (VCT) is computed on the raw EEG data**

A Variances Comparison Test (VCT) is computed on the raw EEG data to detect high amplitude artifacts. Information on the occurrence of artifacts can be used as an index of reliability on the “drowsy decision.

An artefact is an electric perturbation of the EEG signal due to patient movements or measurement problems. Artefacts pollute the whole EEG band and it is quite impossible to extract reliable EEG information when an artefact occurs. There are several types of artefacts. They may be due to ocular movements, face muscles movements or measurement devices problems such as electrode unstuck.

The method of VCT is inspired by and is directly applied on the raw EEG. The principle is the same than the MCT: the variance of a moving window is compared to the variance of a reference window. Let us consider two independent populations with normal distributions. Their lengths are n1 and n2 and their experimental variances are $s_1^2$ and $s_2^2$. Then, the variable:

$$F = \frac{s_1^2}{s_2^2}$$

follows a Fisher law with k1= n1-1 and k2= n2-1 liberty degrees. The variances equality is then tested by a bilateral test with a confidence threshold λart: F λart/2<F < F1- λart/2.

The general purpose of this algorithm is the detection of drowsiness. The MCT detects a bursts, which are indicators of drowsiness. The reference is calculated on a fixed window which is chosen at the beginning of the signal, assuming that the driver is completely awake when he begins driving. So, the mean calculated on the moving window is compared with the wakefulness reference. If the bilateral test is higher than the threshold, the driver is then considered as drowsy, otherwise he is considered as awake.

## 6 Results

EEG Sample numbers are noted down in the excel file for drowsy state using “TakeSamples” utility. These samples list of 15 samples is copied to “NNTraining” utility with Result state of 2. In NNTraining utility 15 Random samples for awake state are taken with state of 1. Now all the 87 Samples with both Awake and Drowsy state are used to train Neural Network for Pattern recognition.

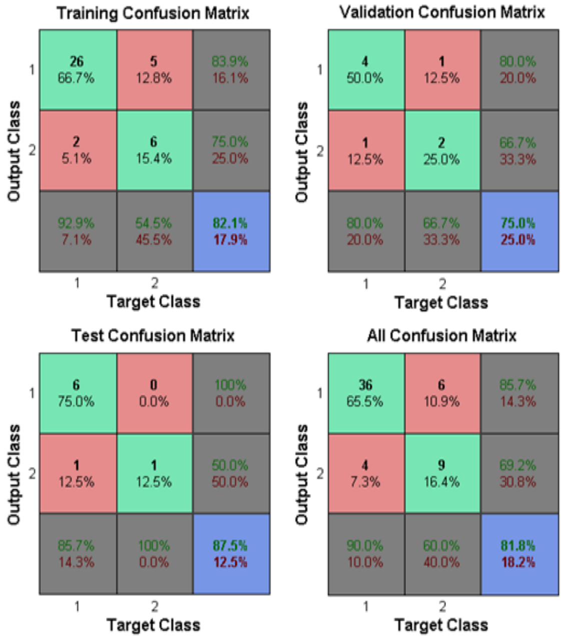



**Figure 6.** Confusion Matrix for Trained Neural Network

In NNTraining Program, input sample numbers are used to capture Samples to generate IMF's of the same and are saved as Inputs for NPRTool. The respective state i.e. 1 and 2 are saved as feature Outputs for NPRTool. After saving all the Inputs and outputs, nprtool is opened to train the Network for Pattern recognition.

NPRTool is retrained again and again to achieve maximum accuracy having lowest error rate. The output of the Training is shown graphically in the confusion matrix in Figure 6.

In this confusion matrix graph, feature at 1 shows awake State and 2 shows drowsy state. The green boxes represent samples which are accepted with accuracy results greater or equal to 0.5 and Red boxes shows samples which are not accepted. In the blue box shows the final results.

In Training Confusion Matrix 70 % samples were used to train the neural network i.e. 61 samples were used. These are presented to the network during training, and the network is adjusted according to its error and training the network achieved 82.1 % results. After Network Training, 15% samples i.e. 13 samples were used to validate the network. These samples are used to measure network generalization, and to halt training when generalization stops improving. The results achieved during validation are 75 %.

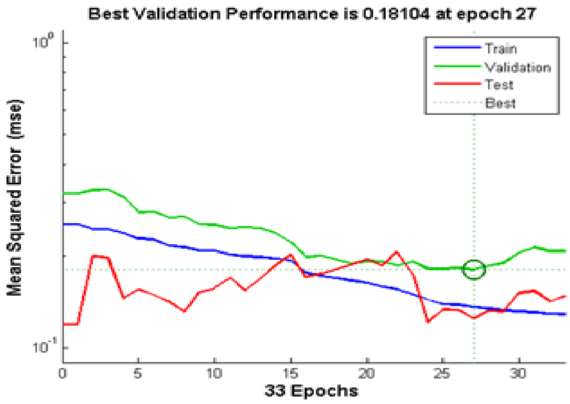



**Figure 7.** Best Validation Performance Graph

The validation performance is shown in the graph in Figure 7. The best validation performance is show at the 27th epoch as the MSE (mean squared error) is lowest at this point. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

In the next stage remaining 15 % samples are used to Test the network. These samples have no effect on training and so provide an independent measure of network performance during and after training. Test confusion matrix shows accuracy of 87.5 % result as shown in figure 5.1. The combined accuracy results are shown in all confusion matrix in the last box and we achieved 81.8% results.

A histogram is a way to graphically represent the distribution of data in a data set. Each data point is placed into a bin based on its value. The histogram is a plot of the number of data points in each bin.

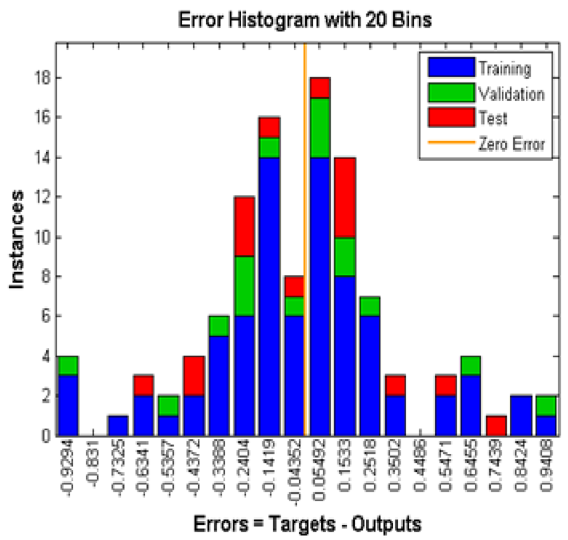



**Figure 8.** Error Histogram

Here the blue bars represent training data, the green bars shows the validation data, and the red bars gives the testing data. The histogram can give an indication of outliers, which are data points where the fit is significantly worse as compared to the majority of data. The Error histogram graph shows maximums number of instances are near the zero error area which shows better performance of the trained network.

Neural network training receiver operating characteristics are shown in figure 9 below for all the different stages of trained network generation. The ROC curve is a plot of the true positive rate (sensitivity) versus the false positive rate (specificity) as the threshold is varied.

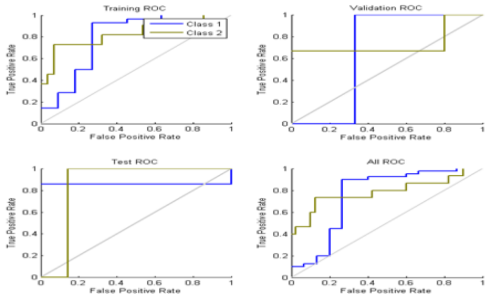



**Figure 9** ROC Graphs

Class I in blue color shows True positive rate v/s false positive rate for Awake stage Samples and Green color shows for Drowsy stage. In all ROC Graph the performance of drowsy stage samples is better and above the Required Level.

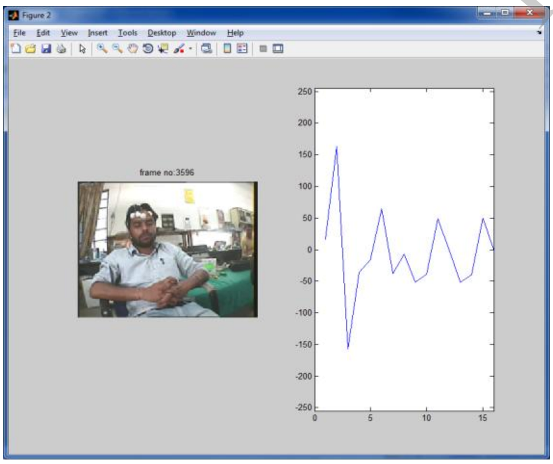



**Figure 10** Main GUI Window Showing Current Video Frame and the respective Combined EEG Signal

The network generated by NPR Tool is saved as TrainedNet which is used in the "FinalGUI" application to detect drowsiness in the EEG. As the TrainedNet is ready to scan the EEG data for drowsy patterns, it is used in the GUI program for the recording taken on same pattern as described earlier for drowsiness detection. Samples are taken to generate IMF of the EEG signal for all the channels combined together and this IMF is passed as input to the TrainedNet. TrainedNet gives output in decimal form which is rounded off to match the two states i.e.Awake or Drowsy.

## 7 Conclusion

In this present work, driver's drowsiness detection system is formed using the information from brain using 25 channels EEG. This system uses physiological data of drivers to measure or detect drowsiness**.** This detection system is based on a means comparison test , which is applied on the EEG relative power, calculated in the alpha band. The results of the MCT test are then merged using neural networks. The results show the 81.8% of true detection and 18.2% of false detection using the twenty five EEG channels. A high-amplitude artefact detection system has been developed and combined to the drowsiness detector. EEG based Drowsiness Detection system is best suited for detecting Drowsiness due to high computation speed and portability. It can be easily used into real time applications as long term monitoring is possible. Hence it can be easily used for driving application.



## 8 Future Scope

The next step of this work can be to add an eye blinks and yawn detection system thanks to a high frame rate camera and to merge the decisions to obtain a highly reliable automatic drowsiness detector. This work has been done using 25 channels EEG, in future work higher number of channels can be used in order to increase the accuracy of the system.

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