HALLUCINATION AND DELUSION PREDICTION IN EEG WITH NEURAL NETWORK

Gopinath M P, Aarthy S L, Suresh Kumar N, Chebrolu Sai Prasanna Abhinav
School of Computer Science and Engineering, 632014 VIT, Vellore, Tamil Nadu, India

Abstract:

Schizophrenia is a chronic mental illness that impacts men than women causing an abnormality in emotion, thinking, speech, lifestyle, and social behaviour. Delusions, Hallucinations, Epileptic seizures, Disorganised Speech, catatonic behaviour, emotional flatness, lack of motivation, etc., are commonly observed symptoms. In this paper, the study is conducted by examining the patients through Electroencephalogram (EEG) and its variations in Interictal Epileptiform Discharges (IEDs) before, during and after the attack of seizures extracted. The outputs during the cognitive tasks correlated with clinical observations. The graphical results are proven to be potential in accurately assessing patients suffering from epileptic seizures and schizophrenia.

1. Introduction:

Richard Cannon was a pioneer in the documentation of Neurophysiology of Animals in 1875 and has taken five more decades for the onset of electrical pursuit on humans. A German psychiatrist, Hans Berger, initiated the EEG (Electroencephalogram) in human beings in 1924. The electrical impulses generated in the brain can record through an electrophysiological technique called EEG. The EEG is known for consummate temporal sensitivity. It is widely used to assess vital cerebral activities. It can determine sub-clinical seizures, epilepsy, unusual spells and is patient-friendly. In most of the known cases of epilepsy, during an epileptic seizure, notable deviations can be observed in EEG during the attack, pre and post-seizure, and its recordings. Interictal (in between attack) variations are observed commonly in most epilepsy patients. Interictal Epileptiform Discharges (IEDs) show notable variations like Spike, with a duration of less than 70 µsec duration and sharp wave with a spike and wave for duration ranges 70 - 200 µsec. Due to its versatility in applications, EEG is quoted in various clinical procedures. For instance, due to its sensitivity in responding to neurological variations, EEG monitors the depth of anaesthesia during surgical procedures. It's potential in keeping an eye on the changes that occur due to ischemia or infarction. There are certain temporary neurological activities concerning specific stimuli which can study through EEG by considering the average of its waveforms to obtain evoked potentials (EPs) and event-related potentials (ERPs). These values effectively analyse visual, auditory, somatosensory, and other higher-end cognitive functions.

The Electroencephalogram is thought to be principally generated by cortical pyramidal neurons in the cerebral cortex that is oriented perpendicularly to the brain's surface. The neural activity detected by the EEG is the summation of the excitant and inhibitory postsynaptic potentials of relatively large groups of neurons firing synchronously. Conventional scalp or cortical surface–recorded EEG cannot register the momentary local field potential changes arising from neuronal action potentials. An unfortunate reality of EEG is that cerebral activity may be overwhelmed by other electrical activity generated by the body or the environment. To be seen on the scalp surface, the minuscule, cerebrally induced EEG voltages must first pass through multiple biological filters that reduce the signal amplitude and spread the EEG activity out more widely than its source vector. Cerebral voltages must traverse the brain, CSF, meninges, the skull, and skin prior to reaching the recording site where they can detect.

Additionally, another biologically generated electrical activity (by scalp muscles, the eyes, the tongue, and even the distant heart) creates massive voltage potentials that frequently overwhelm and obscure cerebral activity. Temporary detachments of the recording electrodes (called "electrode pop" artifact) can further erode the EEG or even imitate brain rhythms and seizures. The bottom line is that biological and environmental electrical artifacts frequently interfere with the interpreter's ability to identify normal rhythms and pathological patterns accurately. Fortunately, artifacts possess many distinguishing characteristics readily identifiable by well-trained, careful observers.

A typical EEG display graphs voltage on the vertical domain and time on the horizontal domain, providing a near real-time collection of ongoing cerebral activity (Figure 1). With digital recording and review, the interpreter can change several aspects of the EEG display for convenience and intelligibility of the data. The interpreter can adjust the sensitivity (also known as [aka] "gain") of the recording, in microvolts per millimetre, to either increase or reduce the display height of waveforms. One may also alter the amount of time displayed, which is sometimes referred to as an epoch and used to be known as "paper speed." Shorter intervals can be viewed with a few seconds on a computer screen, a distinct advantage for viewing very brief EEG events such as epileptiform spikes.

Conversely, the time scale may expand to display longer segments of EEG over several minutes to look at slowly evolving rhythmic discharges. Digital filters may also apply to reduce artifacts in specific settings. Still, they must use with great caution since they also filter EEG activity of interest and severely distort EEG waveforms.

EEG uses the principle of differential amplification or recording voltage differences between different points using a pair of electrodes that compares one active exploring electrode site with another neighbouring or distant reference electrode. Only through measuring differences in electrical potential are discernible EEG waveforms generated. By convention, when the active exploring electrode (termed G1, for "Grid 1," a historical pattern from analogue amplification) is more negative than the reference electrode (G2), the EEG potential is directed above the horizontal meridian (i.e., an upward wave). If the opposite is true, where the reference electrode is more negative, the EEG potential vector is directed below the horizontal meridian (downward potential).

A related technique to the EEG is MEG, which does not record electrical activity but rather utilises sensors to capture magnetic fields generated by the brain. MEG provides complementary information to the EEG by demonstrating the action of cerebral magnetic dipoles. Since magnetic fields are less degraded by the head's biological filters than electrical activity, MEG dipoles may produce more accurate locations for cerebral epileptiform generators than EEG. A detailed review of MEG is beyond the scope of this review.

1.1 EEG and Schizophrenia

Electroencephalography (EEG) is the procedure of recording thebrain's electrical activity from the scalp, with electrodes attached to different skull locations. The EEG is used to diagnose other diseases and disorders. Electroencephalography (EEG) estimates electrical movement along the scalp, generally employing physically set cathodes at various areas or a headset gadget intended for that reason. EEG is progressively utilised as a low-goal conclusion instrument for general psychological action and as a marker of the current stage and status of the brain at a given time because of its adequacy as a versatile, fast arrangement recordable instrument. Past investigations utilising EEG have included strategies that help to recognise emotions [1,2], assess intellectual levels through cognitive tasks [3,4], measurement of range of activity area in control based gadgets [5], diagnosis and evaluation epileptic seizures in correlation with clinical findings [6] and numerous other related techniques. Because of a massive absence of signal affectability contrasted with different apparatuses, such as fMRI, EEG has not come out as a proficient or authentic information extraction technique for locating and investigating psychological or mental ailments. Contemporary computational examinations have proposed that most changes in utilitarian availability are seen in schizophrenia patients [7], and predominant variations in the theta-recurrence movement are apparent, too [8]. Earlier studies to analyse schizophrenia utilising EEG have concentrated on conventional ERP (Event-Related Potential) investigation, specifically scrutinising properties around N100 and P300 [9,10]. Similarly, the latest report has recommended adding a machine learning-based mechanism to frisk a pair of P300 characteristics [11], indicating massive precision in segregation and grouping.

Likewise, in the majority of the cases, performing a full-scale EEG-based investigation needs recording from patients for quite a long time. Though not directly related to psychological illness, recording from subjects has to consider. Practically, it is time-consuming and strenuous for execution —particularly when utilising a complex multielectrode arrangement. The test is to locate a dependable segregating innovation to observe the reactions of the sound subjects also, schizophrenia patients using restricted information. In the extension of this research, the proposed strategy depends on the contribution of only one cathode. It takes less than a minute to record the data from a subject to accomplish precisely accurate segregation, grouping, and classification result.

1.2 EEG signal disadvantages:

The present research scrutinises whether the required or adequate information is available on EEG data, gathered over a short interval of time, probably less than a minute—to separate between two individuals, one healthy and the other diagnosed with schizophrenia and undergoing regular internal medication as prescribed. Our primary concern here is to study whether the data extracted from the only electrode be sufficient to obtain the classification or not. The secondary problem is to determine whether the severity of the disease can estimate through chronicity, the number of hospitalisations, usage of medicines, and other generic parameters though not directly used from the data available in our model. There are many studies in the area of sleep and wakefulness. However, it is considered that arousal maintenance state, i.e., long-distance driving, humdrum works, etc., is a different physiological state from the usual sleep onset. Recently, we have analysed that EEG signals in the arousal maintenance state against sleepiness to capture such physiological state [1].

Time-frequency analysis revealed that the EEG signals while subjects were trying to maintain restlessness against drowsiness had wide bandwidth than EEG signals in usual sleep onset because of the EEG desynchronisation [7], [8]. It can consider that neuron activities from the frontal lobe, which coordinates behaviour, to the hypothalamus, which coordinates wakefulness and sleep, were raised to maintain a wakefulness state against sleepiness. In the previous studies, The portion of this work was supported by Grant-in-Aid in Scientific Research (C) by the Ministry of Education, Culture, Sports, Science and Technology of Japan (No. 20560406 and No. 24560534). H. Yoshida is with the Department of Computational Systems Biology, Faculty of Biology-Oriented Science and Technology, Kinki University, 930 Nishi Mitani, Kinokawa, Wakayama 649-6493, JAPAN. S. Kikkawa is a research fellow at Kinki University and Humanoid Robotics Institute of Waseda University. However, EEG analysis was done only in the occipital area because blinking artifacts were mixed in the EEG signals in the frontal area and made it challenging to analyse the activities of the frontal region. Remarkably, there are many blinks when people try to maintain a wakeful state against sleepiness. Blinking artifact is a potential difference between the cornea and retina in the eye. The former is optimistic concerning the latter. When the eyelids blink or are closed, the eyeballs rotate upward. The potential change by the eyeball movements is recorded from the electrodes on the scalp with the EEG signals. Though more frequency components of the signals with the blinking artifacts are in the delta (up to 4 Hz) and the frequency bands theta (from 4 to 8 Hz), the other elements are still in the alpha (from 8 to 13 Hz) and beta (above 13 Hz) frequency bands. All frequency elements of the blinking artifacts develop an obstacle to the EEG analysis. Hence, eliminating the blinking artifacts will benefit the estimation of brain activity.

2. Cognitive Task: Reverse task from 100

The Mean Square Error (MSE) helps assess the magnitude of errors accurately and is thus applied here in estimating the variation between the estimated values of the proposed model. As the Squaring avoids fiddling by converting errorsinto an absolute value, the results would be close and accurate. The physical interpretation of the hyperplane would be nearer to the values obtained for actual data on the cloud in the validation set. A swift response close to the target values can be attained for a network as the Lila's MSE is accurate to 10-25. Apart from this, the exact Validation and Regularisation performed by the network are to be assessed to identify the overall performance of the EEG signal & system. Here, the gradient obtained is the gradient of square of the error function, and hence the error is calculated from:

Error = (known target – variable output)

concerning the anonymous, unknown biases and weights. Usually, the Optimisation of Weights and Biases are done in the Steepest Descent Method by reducing or minimising the sum of squares of errors concerning the Training Objective. Still, the speed of descent is reduced to preserve the search values. The Momentum is also added to prevent the flyback of values. The outcomes of Gradient Descent with Momentum are as in Fig 2.

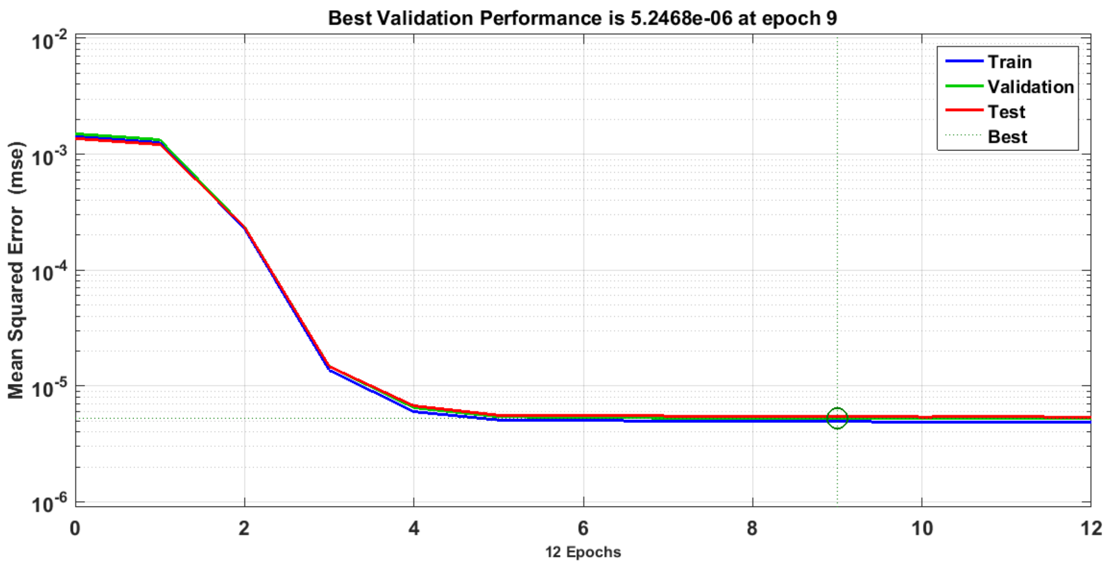

fig 1: Performance for Reverse Task from 100

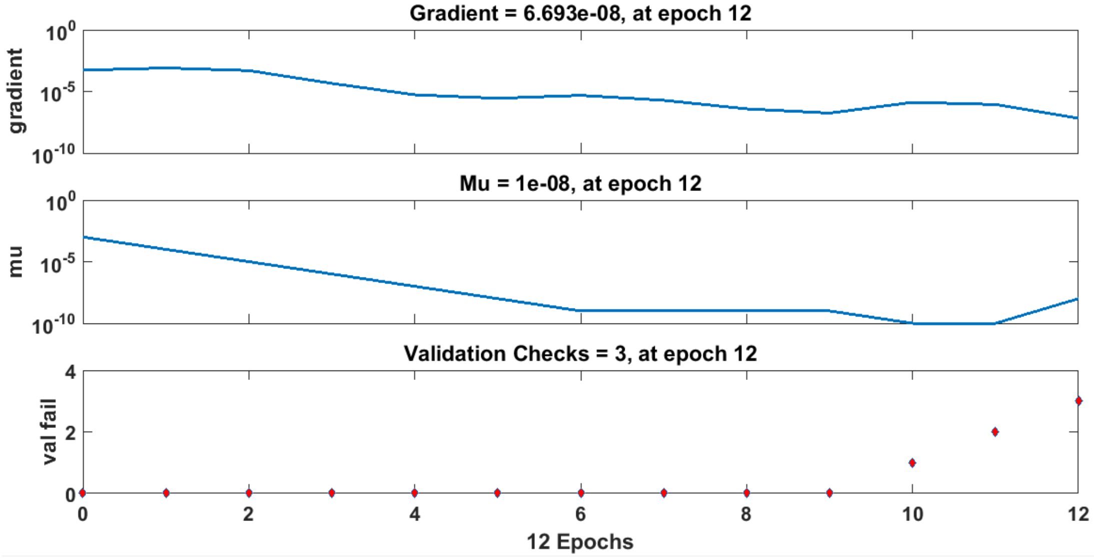

fig 2: Performance for Reverse Task from 100

Error histogram is defined as the histogram of the errors between the Target Entities and Predicted or Anticipated Entities considered on feedforward neural network. The Error histogram is usually negative as the predicted hallucination and delusion differ from desired entities. The vertical bars in the histogram are called Bins, as in figure 3. The entire range of errors is divided into 30 tiny bins.

The number of samples available on the dataset for the respective bin represents the instances for different abnormality classification. For example, at the center of the graph, if a container is found corresponding to the error of 0.001502, approximately 150 being the height of the container corresponds to the training dataset. The Validation and Test datasets lie between 150 and 200, which means that most of the errors found in the sample datasets belong to this range. The X-axis, which corresponds to error, has Zero Error Line and a Zero Error Value. However, in this scenario, Zero Error Point lies below the bin with center 0.00152.

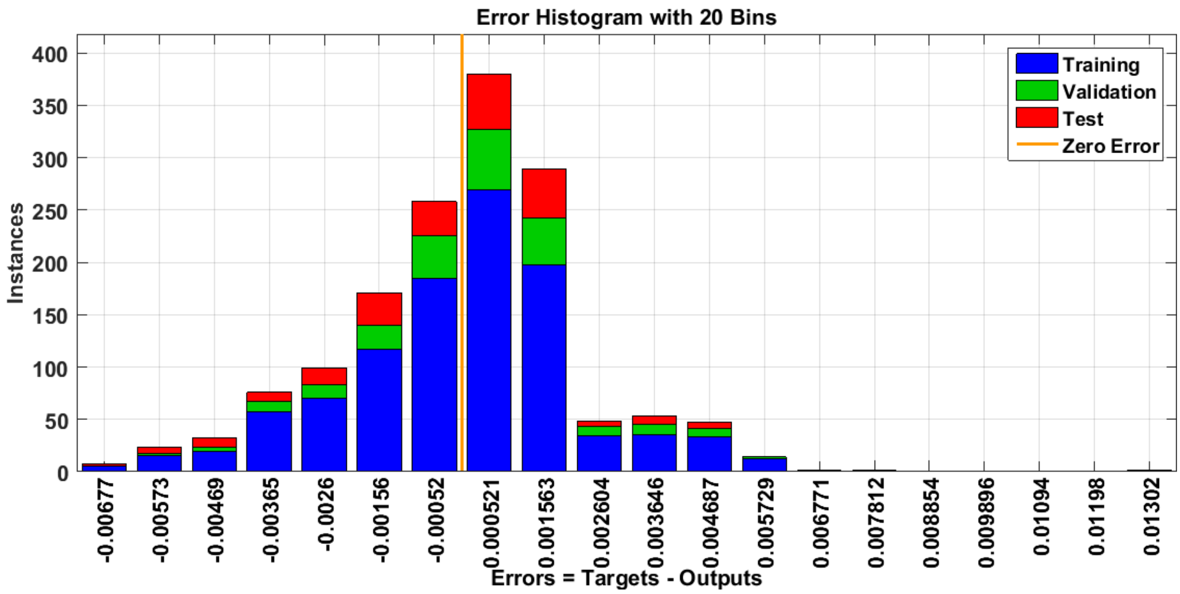

fig 3: Histogram for Reverse Task from 100

The prediction results on a Classification Problem are summarised in a Confusion Matrix as shown in figure 4. The Broken Values and Count Values for every class summarise the number of correct and incorrect predictions for hallucination and delusion. It helps to understand the confusion in the classification model while predictions are made. As the confusion matrix identified the errors and their nature, we can surmount the limitation of the classification matrix.

Fig 4: Confusion Matrix for Reverse Task from 100

3. Cognitive Task: Eye Rotation

The task, Eye Rotation, shows the EEG signal variation from the brain of a Schizophrenia patient during the job. The eye rotation happens from left to right, top to bottom, and vice-versa. The stimuli change during the clockwise and anti-clockwise movements, affecting neural activities. The trained neural network to predict the variation of EEG signals. The network model reached the best performance at seven epochs, as shown in figure 5. The gradient and mu of the trained model were low, as shown in figure 6. The validation of the trained model to detect error was negligible, as shown in figure 7. The said stimuli impact halogenations and delusions, visible in the graph and confusion matrix. More the variations, the higher the intensity ofsymptoms. The task is repeated randomly for a better valuation and the observations to be noted. On a comprehensive observation, it is found that the variations in the Confusion matrix and histogram are prevalent in comparison with a healthy person, as shown in figure 8.

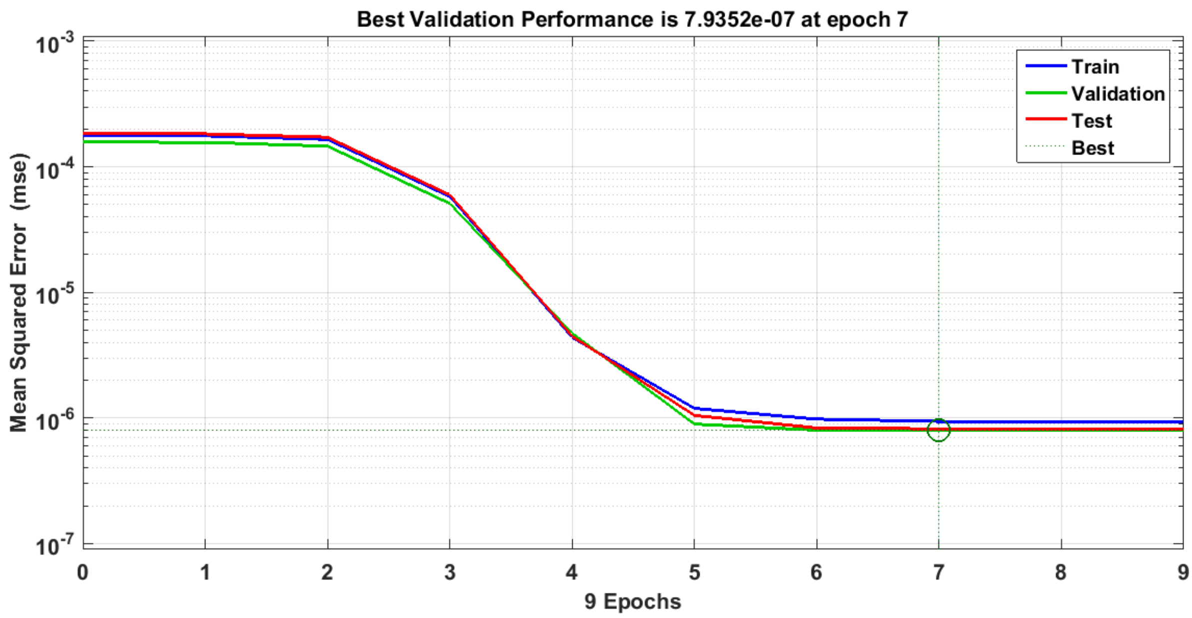

fig 5: Performance for Eye Rotation

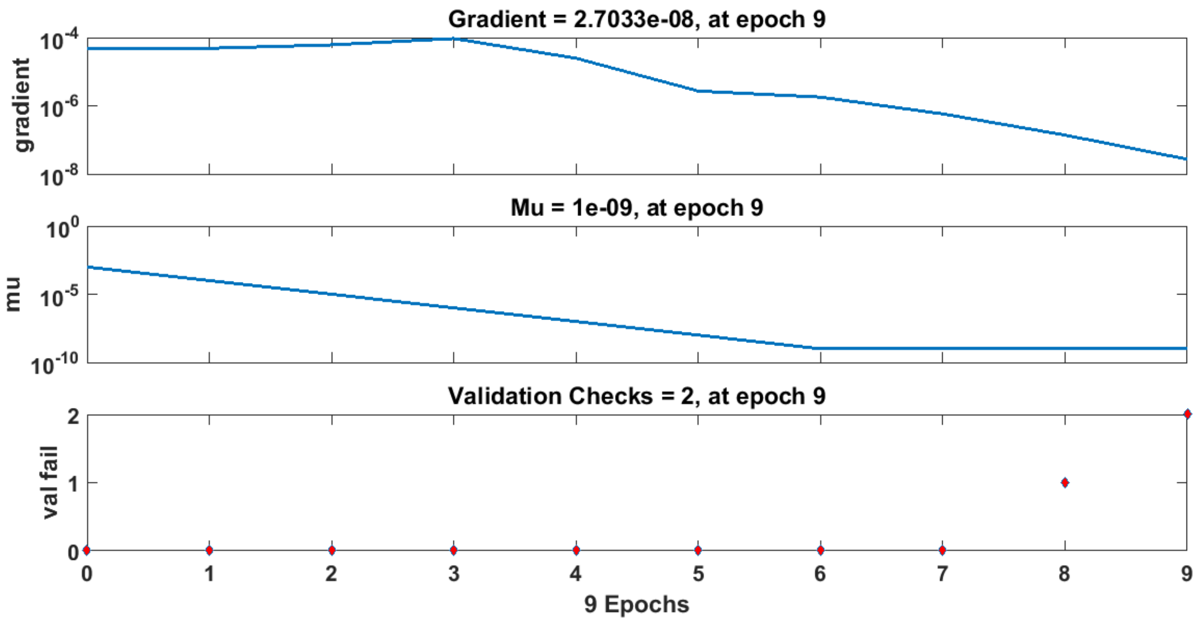

fig 6: Performance for Eye Rotation

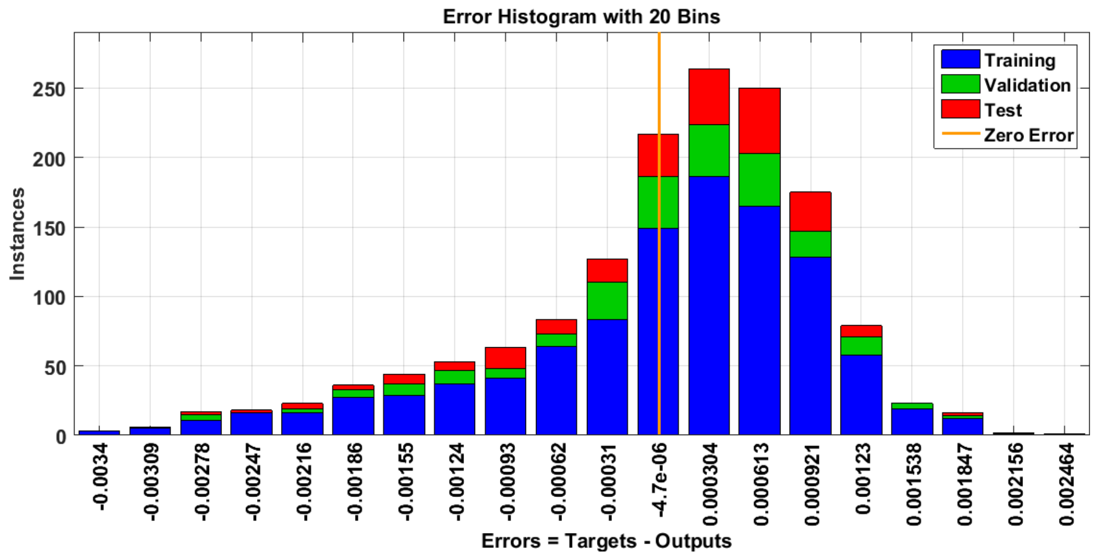

fig 7: Histogram for Eye Rotation

fig 8: Confusion Matrix for Eye Rotation

4. Cognitive Task: Asking Question

The trained neural network model for EEG signal is acquired while answering a question; a lot of thought processes are involved in the backend in the brain. The brain, which implies Neurons are the most responsible for understanding the question, thinking and giving an answer. The stimuli caused have to be adequately streamlined to get an appropriate solution. The signal variation due to hallucination and delusion detects from EEG signals by training the neural network model. The neural network model reached the best-trained model at 22 epochs as in figure 9, and the gradient, mu, is shown in figure 10—the error histogram between the trained model and actual result shown by error histogram as in figure 11. Due to the changes in the functioning of Neurons, halogenations, and delusion, the capability to understand and respond is abnormal compared to average persons. Hence, the changes are vividly visible in the graph and confusion matrix as in figure 12.

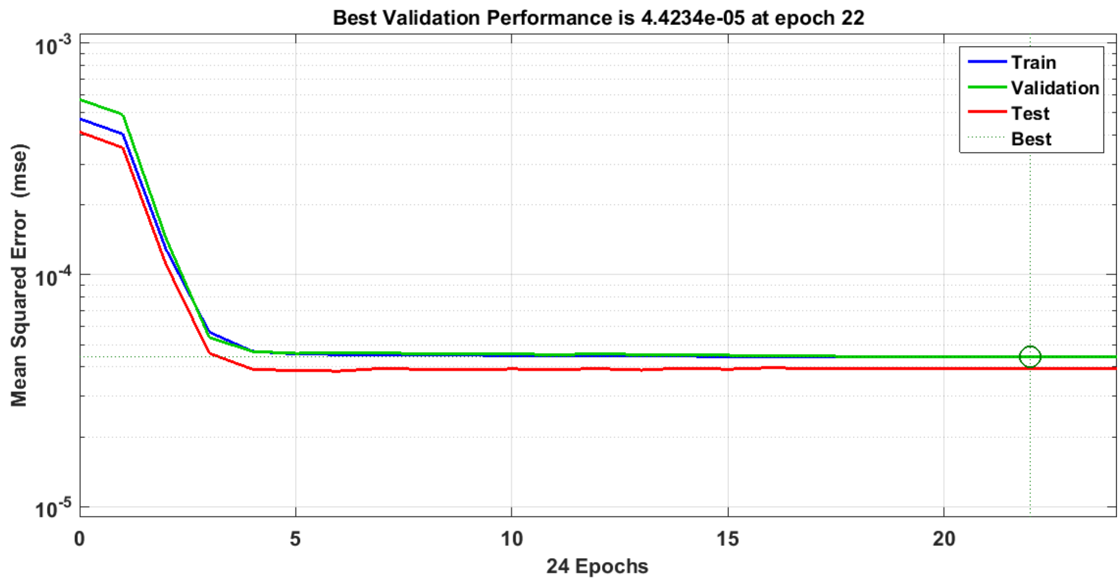

fig 9: Performance for Asking Question

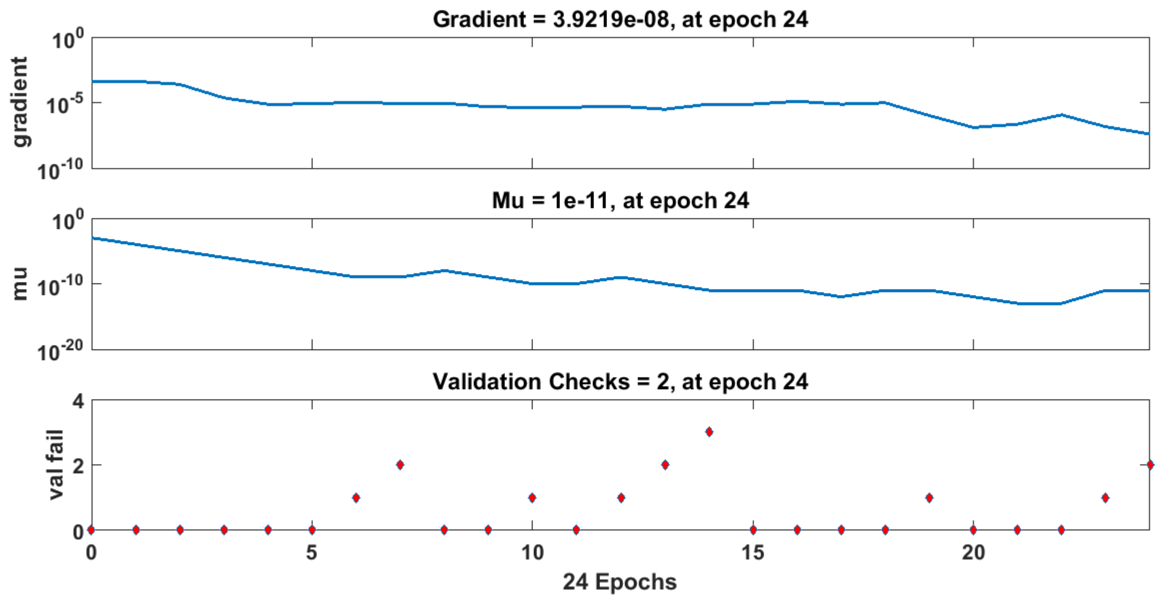

fig 10: Performance for Asking Question

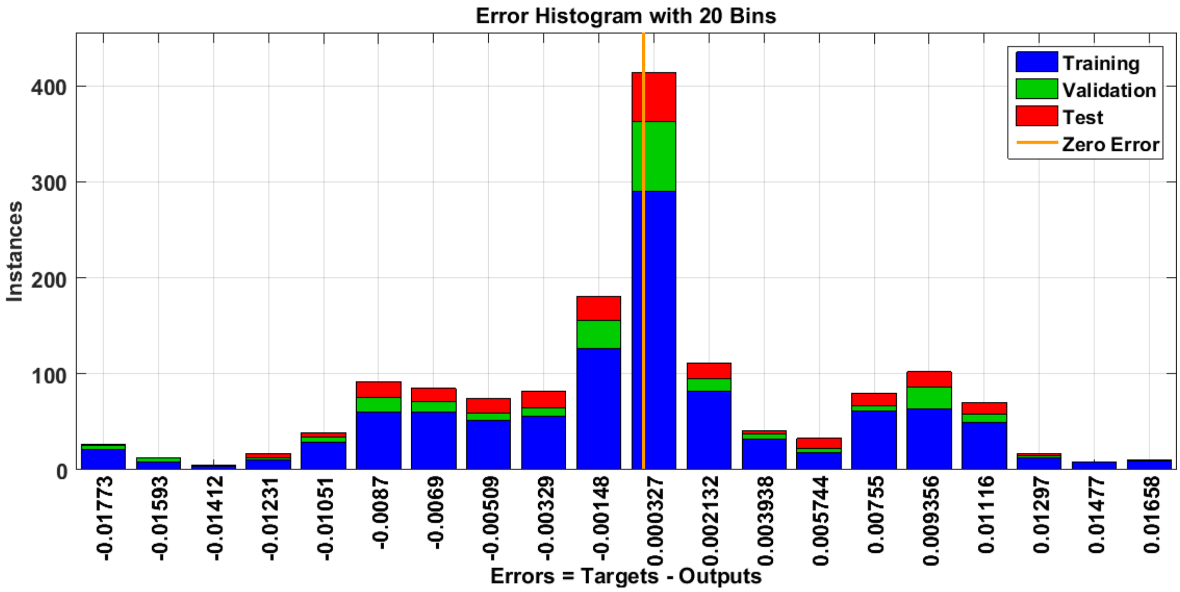

fig 11: Histogram for Asking Question

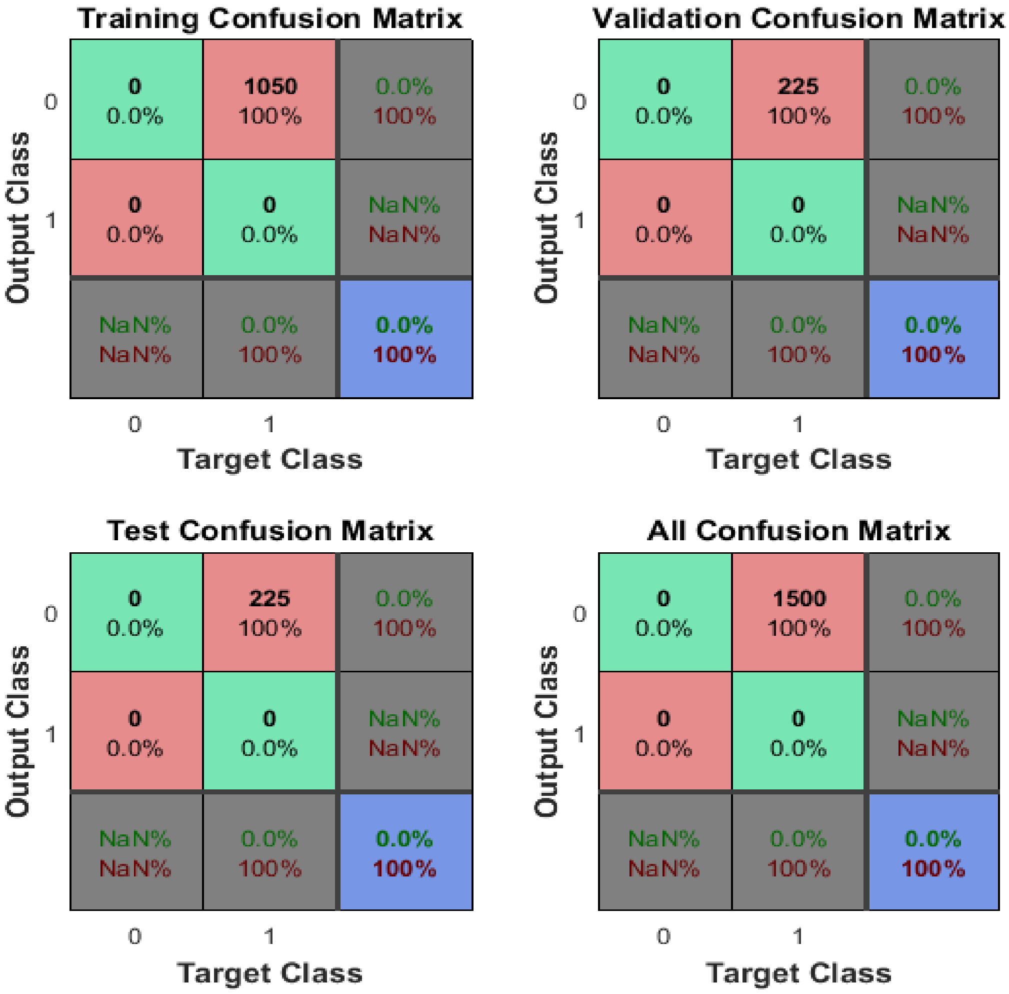

fig 12: Confusion Matrix for Asking Question

5. Conclusion:

The proposed method to assess the intensity, stage, and chronicity of schizophrenia and associated epileptic seizures through EEG is found to be potential and proven to be accurate for clinical findings. The cognitive tasks to mention counting numbers in reverse order, rotating the eyes, and asking questions have shown considerable variations at different attack stages. The age group, gender, intensity, etc., affect the results extracted through EEG. As this method is found to help identify the patient's stage, it would emerge as a diagnostic technique for doctors to prescribe further treatment for practical, quick, and long-lasting relief from the symptoms of mentioned mental illness.

References

[1] S. Ganguly and R. Singla, "Electrode Channel Selection for Emotion Recognition based on EEG Signal," 2019 IEEE 5th International Conference for Convergence in Technology (I2CT), Bombay, India, 2019, pp. 1-4, DOI: 10.1109/I2CT45611.2019.9033929.

[2] G. Zhao, Y. Zhang, G. Zhang, D. Zhang, and Y. -J. Liu, "Multi-target Positive Emotion Recognition from EEG Signals," in IEEE Transactions on Affective Computing, DOI: 10.1109/TAFFC.2020.3043135.

[3] J. Sun et al., "Abnormal Dynamics of EEG Oscillations in Schizophrenia Patients on Multiple Time Scales," in IEEE Transactions on Biomedical Engineering, vol. 61, no. 6, pp. 1756-1764, June 2014, DOI: 10.1109/TBME.2014.2306424.

[4] F. Li et al., "Differentiation of Schizophrenia by Combining the Spatial EEG Brain Network Patterns of Rest and Task P300," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 27, no. 4, pp. 594-602, April 2019, doi: 10.1109/TNSRE.2019.2900725.

[5] Z. Cao et al., "Extraction of SSVEPs-Based Inherent Fuzzy Entropy by Wearable Headband EEG in Migraine Patients," IEEE Transactions on Fuzzy Systems, vol. 28, no. 1, pp. 14-27, Jan. 2020, DOI: 10.1109/TFUZZ.2019.2905823.

[6] K. Huang, S. Lee and C. Chang, "Association of Methylation Profiles of Mitochondrial Genes with Schizophrenia," 2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI), Kumamoto, 2016, pp. 1184-1185, DOI: 10.1109/IIAI-AAI.2016.222.

[7] T. Wang, A. Bezerianos, A. Cichocki and J. Li, "Multikernel Capsule Network for Schizophrenia Identification," in IEEE Transactions on Cybernetics, DOI: 10.1109/TCYB.2020.3035282.

[8] S. K. Nataraj, F. Al-Turjman, A. H. Adom, R. Sitharthan, M. Rajesh and R. Kumar, "Intelligent Robotic Chair with Thought Control and Communication Aid Using Higher-Order Spectra Band Features," in IEEE Sensors Journal, DOI: 10.1109/JSEN.2020.3020971.

[9] D. Ahmedt Aristizabal et al., "Identification of Children At Risk of Schizophrenia via Deep Learning and EEG Responses," in IEEE Journal of Biomedical and Health Informatics, DOI: 10.1109/JBHI.2020.2984238.

[10] Y. Li, R. Zhou, R. Xu, J. Luo, and S. Jiang, "A quantum mechanics-based framework for EEG signal feature extraction and classification," in IEEE Transactions on Emerging Topics in Computing, DOI: 10.1109/TETC.2020.3000734.

[11] M. -P. Hosseini, A. Hosseini and K. Ahi, "A Review on Machine Learning for EEG Signal Processing in Bioengineering," in IEEE Reviews in Biomedical Engineering, DOI: 10.1109/RBME.2020.2969915.