EEG Stability Factor Estimation for Biometric Features using Machine Learning

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Abstract - *The human brain is responsible for the various different internal functions of the body to keep the individual alive. Humans interact with the various different things in the world and process it with the help of the brain and its nervous system. The nervous system communicates through the use of the electric impulses that are passed through the neurons. These electrical impulses can be measured using an EEG or an Electroencephalogram. It is one of the most useful approaches to measure the electrical activity of the brain. EEG can be used to perform an in-depth analysis of the brain and its activities and the responses can be mapped effectively. There are certain attributes that are related to the EEG mapping which have not been utilized. These attributes are the age, sex and other personal attributes of the individual which have been utilized in our approach. The introduction of such parameters would allow for the measurement of the mental stability factor of the subject in much more comprehensive and accurate manner. Therefore, the methodology depicted in this publication introduces machine learning approaches that utilize the various parameters along with the EEG signals to measure the mental stability factor of the subject accurately. The presented technique implements K Nearest Neighbors and Pearson Correlation along with the Hidden Markov Model and Fuzzy classification to yield accurate Mental Stability factor analysis.*

***Key Words*: K-Nearest Neighbors Clustering, Regression Analysis, Entropy Estimation, Pear-son Correlation, Hidden Markov Model, Fuzzy Classification, Mental Stability Factor.**

1. INTRODUCTION

The graph (EEG) is a recording of the electrical activity of the brain from the scalp. The recorded waveforms mirror the plant tissue's electrical activity. Signal in-tensity is very low and graph activity is measured in microvolts (mv). The human brain consists of several neurons, that neuron is the basic unit enjoying a very important role for the dominant behaviour of the physical structure of the brain and reaction to internal or external sensory stimuli. These neurons can act as info carriers between the physical world and the brain. Understanding the behaviour of the brain will be done by analyzing either signals or pictures from the brain. Human behaviour can be envisioned in terms of motor and sensory states like eye movement, lip movement, remembrance, attention, hand clenching, etc. These state that neurons associated with a specific signal frequency that helps to grasp the purposeful behaviour of brain structure. Electroencephalography (EEG) is a method that helps to record brain signals corresponding to varied states from the scalp. These signals neurons are typically classified as delta, theta, alpha, beta and gamma that support signal frequencies ranges from zero.1 Hertz to over one00 Hertz. This paper primarily focuses on graph signals and its characterization with relevancy varied states of the brain. It additionally deals with associate degree experimental setup utilized in graph analysis.

EEG helps decide seizure varieties associated with illnesses in patients with encephalopathy and so selects an anticonvulsant medication and performs prognosis of the disease. Electroencephalogram decides that in a multi-axial designation of encephalopathy, whether or not the seizure disorder is focal or generalized, upset or symptomatic or a part of a selected epileptic syndrome. Focal and generalized seizure disorders show some overlap of each clinical and electrographic manifestations, and also if the patient suffers from hemispheric brain disease then the boundaries are blurred. However, the abstract division of partial and generalized seizures / epileptic episodes continues to be valid and clinically helpful. However, once history isn't clear (non-witness "blackout" or transient loss of awareness), the graphical record might facilitate the differences between a partial seizure with focal IED and a complete seizure with generalized IED.

There are a variety of symptoms of encephalopathy with distinct graph options used in formative years of childhood. Some syndromes are distinct while others are disputed or might not be enclosed in current International League Against encephalopathy (ILAE) classification systems because of insufficient information.

EEG characteristics within the immune serum globulin embody generalized spike or polysipic and slow discharge at

3–5 Hertz, which is recognized as traditional background cerebral activity, and a comparatively high incidence of sensibility. Poly-sipic discharge is related to phenotypes within which miscellaneous predominates operate. In childhood with an absence of any brain disease, the benchmark is that the bilateral synchronous three Hertz spike-wave, generally between 5–10 seconds is produced, with the specific absence of seizures. The discharge is usually slightly quicker than three Hertz within the starting and slows down by the tip. Interregional graphical record is common, or, in some kids plagued by post-absence pain, might show runs of bone cadenced delta (15–40% of cases). Sensibility is unusual (<10%), and should be a marker of worsening illness. Juvenile traveller brain disease patients require additional data to point out polysipic discharge or spike-wave frequency on top of three Hz; the runs of the bone cadenced delta usually aren't found. Major poly septic wave discharge alongside major brain disease is additionally seen in pro-tective fold myoclonia. The absence of standing brain disease appears comparatively common during this syndrome. Generalized tonic-clonic seizures on rousing don't have any characteristic graphical record characteristics.

The EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the skull with wires. Electrodes analyze electrical impulses in the brain and send signals to a computer that records the results. Whenever large groups of these pyramidal cells are firing in a synchronized pattern, the power generated reaches the skull surface - this is what we record with EEG electrodes. Because electric fields are still very few, signals are usually amplified. EEG is a referential re-cording and not an absolute voltage - it always represents a relative increase or de-crease in power at a specific location. Changes in electric fields happen very rapidly - so with EEG, you will get insights into brain processes with much higher time resolution. The EEG allows you to record brain processes that occur immediately after the onset of visual or audio stimuli (there are already frequent brain processes following stimulation after 50–100 ms), but you may have prolonged busyness, You can also keep an eye on the state of the brain reflecting inspiration or drowsiness. This excel-lent time resolution gives your insight into the precise timing of brain processing.

Electroencephalography (EEG) may be an advanced signal and might need many years of coaching to be properly understood. Recently, deep learning (DL) has shown nice promise in processing electroencephalogram signals thanks to its capability to make smart feature representations from the information. Whether or not DL actually presents benefits as compared to a lot of conventional electroencephalogram-gram process approaches, however, remains an open question. EEG can be used to identify various different application domains like brain disease, sleep, brain-computer interfacing, and psychological feature and emotional watching. We tend to extract trends and highlight attention-grabbing approaches so as to predict future analysis and formulate recommendations. Numerous pieces of information were extracted for every study touching on 1) the info, 2) the pre-processing methodology, 3) the DL style decisions, 4) the results, and 5) the duplicability of the experiments. Our analysis reveals that the quantity of electroencephalogram recordings used across studies varies from 10 minutes to thousands of hours. As for the model, four-hundredth of the studies used convolutional neural networks (CNNs), whereas certain applications used recurrent neural networks (RNNs), most frequently with a complete set of three to ten layers. Moreover, a large number of studies trained their models on raw or pre-processed electroencephalogram data. Finally, the median gain in the ac-curacy of DL approaches over traditional baselines was 5.4% across all relevant studies. We tend to notice studies typically suffer from poor reproducibility: a majority of papers would be out of reach or not possible to analyze given the inaccessibility of their dataset and code.

This paper dedicates section 2 for analysis of past work as literature survey and section 3 concludes the paper with feasible statement of the literature study.

1.1 Literature Survey

This section of the literature survey eventually reveals some facts based on thoughtful analysis of many authors work as follows.

A. Vijayan [1] explains that emotion is a psychological expression of the mental state of a being which depends on its subjective involvement. Emotions play a key role in interpersonal relationships. If feelings may be sensed by the machine learning technique it would lead to better development. Only Facial emotions were being mostly used for emotion recognition in previous researches. The results are based on an EEG database called DEAP. The proposed technique ratifies to many related works different emotions such as happiness, fear, sadness, etc. The proposed methodology is proving to be more effective than present algorithms as a categorization accuracy of 94.097% was obtained.

A. Bhardwaj [2] estimates from the last few years there is much researched made on Emotion Prediction. Humans can easily understand the emotions of other person but it is impossible for the computer to do so. Most probably in the future, the approaches will depend on the brain-computer interface where it is mainly used to understand the human senses or emotions. The brain generates electrical signals which are measured by Electroencephalography. SVM is one of the popular supervised machine learning algorithms which is used analyze the data. Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) are two algorithms that are used to classify the EEG signal to predict seven different emotions.

S.Paul [3] presents a complex set of interactions among subjective and objective factors resulting in the arousal of feelings which is called an emotion governed by neural/hormonal systems and it is very hard to detect. Every emotion circumstance creates clear EEG signals in different brain regions. EEG gives a good method to identify emotion information. With the help of Electroencephalogram (EEG) signals emotions can be recognized. A successful classifier named Support Vector Machine (SVM) is used to classify the EEG signal. It was compared with different technologies such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and K Nearest Neighbor (KNN). The average prediction accuracy of SVM for positive emotions on the whole frequency bands is 84.50%,

W. Zheng [4] proposed an interdisciplinary field that encompasses research in computer science, psychology, neuroscience, and cognitive science is emotion research. In the proposed paper they have used DBN models for the construction of EEG signals they are categorized into three models such as positive, neutral and negative emotions. DBN models get higher accuracy and lower standard deviation than techniques like KNN, LR and SVM approach. Deep belief networks (DBNs) to investigate critical frequency bands and channels. The proposed experiment output shows that neural signatures related to, unlike emotions. The average accuracies of DBN, SVM, LR, and KNN are 86.08%, 83.99%, 82.70%, and 72.60%, respectively.

S. Chen [5] narrates with the help of EEG signals from peripheral signals a new emotion recognition method is introduced. The emotional labels feature new peripheral physiological features that are trained by SVM. With the help of EEG features a new peripheral physiological feature space using canonical correlation is created. Physiological signals have fascinated increasing attention due to its great dormancy during human-computer interaction. Researchers aim at finding the crucial frequency bands and channels for EEG-based emotion recognition with different techniques. By using peripheral physiological signals the method which recognizes emotions surpasses through EEG features as privileged information.

J. Teo [6] presents a prime endeavor in artificial intelligence applications in recent years. “Wearable EEG” has introduced a common (EEG) headset which has less recording channels and far lower signal resolution through virtual reality stimuli using only cheap, commercial-off-the-shelf electroencephalography for consistently reliable emotion recognition. Support Vector Machines (SVMs) and K-Nearest Neighbor (KNN) classifiers are used and their classification rates are between 65-89% accuracy for emotion recognition. The proposed approach of wearable EEG for emotion prediction as a cost-effective and user-friendly.

G. li [7] proposes a low-cost in-ear EEG device for recognition of emotion in a simple, inexpensive and in very popular style. As major technology players progress into the market, by introducing ever more inexpensive and reliable ear EEG devices with lofty resolutions and more functionality have become available to the everyday consumer. It contains three stages, data collection, feature extraction, and feature classification. Data collection contains completion of emotion inducible experiment, feature extraction includes WPT based signal decomposition and the last step feature classification uses SVM Classification using different kernels. Thus the artificial feature extracting gives the expected better result.

M. Degirmenci [8] investigates upgraded features of empirical mode decomposition (EMD) for emotion recognition by applying electroencephalogram (EEG) signals. Due to the non-stationary behavior of the signals, it is difficult to study emotion recognition through EEG signals. These signals are strained from the complicated neural activity of the brain. Data is collected from one channeled BIOPAC lab system and from visual evoked potentials of 13 female and 13 male volunteers for 12 pleasant and 12 unpleasant pictures of EEG signals are collected. An EMD-based method is used for emotion recognition to observe nonlinear and non-stationary characteristics of EEG signals. Support vector machine (SVM), Linear discriminant analysis (LDA), and Naive Bayes classifiers technique are used for the classification of features released from the IMFs, and their performances are compared with the other major technique.

C. Qing [9] estimates the fast development of computer and human-computer interaction technology. In the field of human-computer interaction, there is a high demand to build a more intelligent and humanized human-machine interface (HMI). The study presents a new interpretable emotion recognition technique by using machine learning and EEG signals. The technique first extracts attributes from EEG signals and classifies emotions using machine learning techniques. DEAP and SEED dataset is used to validate the proposed methodology. EEG-based emotion recognition accuracy is effectively improved through weighting coefficients based on the correlation coefficient and the entropy coefficient.

H. Lu [10] introduces a new technique in the mining industry for monitoring the status of the miners by using a human wearable helmet. In an extreme environment there is little research regarding human emotion recognition. The study of an emotional state plan is to recognize the brain area where the emotion feature is most obvious. The Human smart helmet is a part of the wearable safety device as the smartest helmets for humans are useful for monitoring the environment and making phone calls. In the proposed technique fusion algorithm for the anxiety, level parameter is used. The technique can accordingly be used for better operating safety and avoid improper miner operation.

J.Koya [11] discusses a Brain-Machine Interface (BCI) which is a technique that considers bio signal, acquired from a subject, and predicts certain attributes of the person's cognitive state. Latest machine learning concepts using LSTN (Long short term memory) recurring neural networks are used in the proposed technique where a convolution neural network is passed through neural networks. For proper emotion recognition, the LSTM technique performed a bit better than the traditional technique on the initial presentation with the data accuracy of 63.61%. In deep learning models there is decrease in performances due to time binning.

P. Zhong [12] explains emotion recognition as an important topic to study for affective computing, which aims at understanding human emotions depends on a variety of modules, such as audio-visual expressions, body language, physiological signals, etc. Emotion models can be broadly classified into discrete models and dimensional models. The emotion is classified in discrete structure e.g., anger, disgust, fear, happiness, sadness, and surprise according to Ekman's theory. The most informative regions in emotion recognition through Investigations on the neuronal activities disclose that pre-frontal, parietal and occipital regions are the most informative for Emotion Recognition.

R. Khosrowabadi [13] proposes an EEG-based emotion recognition system using the self-organizing map for boundary detection. Emotions are part of natural communication between humans. The identification of EEG in response to emotionally-related stimuli was tested. EEG features for classification extract is used to EEG signals for Magnitude squared coherence estimation magnitude squared coherence. KNN classifier is used for the classification of the EEG features. The output of the proposed system improves the accuracy of the EEG-based emotion recognition system.

T. Xu [14] presents Frontal EEG has widely used emotion recognition. Frontal EEG and VR effective scenes are a new framework for emotion recognition. For classification, data is collected from the 19 subjects. 3-channel frontal EEG by textile electrodes. Models such as GBDT (Gradient Boosting Decision Tree), RF (Random Forest) and SVM (Support Vector Machine) are used in the proposed system. The accuracy of 81.30% is achieved by prosed paper it gives better performance as compared to others. It can be used as a device for EEG emotion recognition in VR scenes.

C. Shahnaz [15] explains emotion classification can be executed in many ways such as happiness, sadness, fear, joy, anger, surprise and disgust this are six major emotion proposed by Ekman and Friesen. A new technique is proposed by wavelet analysis of Empirical Mode Decomposed (EMD) and Electroencephalogram (EEG) signals are responsive to music videos. Discrete Wavelet Transform (DWT) is carried out on the selected Intrinsic Mode Functions (IMFs) to get from EMD operation. EMD-DWT based higher-order statistical features provide good accuracy to the proposed methodology.

2. Proposed Methodology

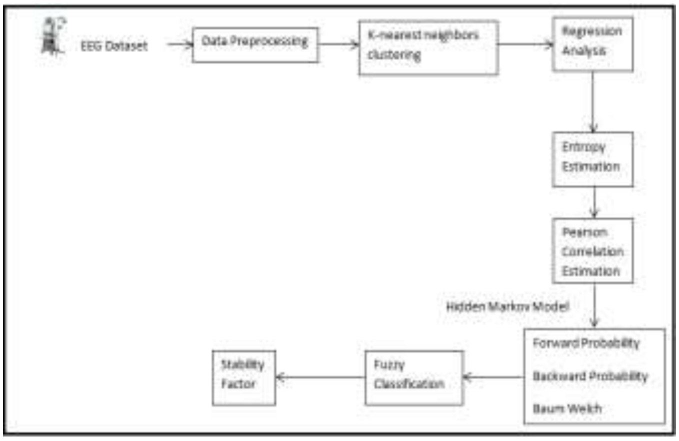

Fig. 1-: Overview of the proposed system

The Presented technique for the Biometric Feature measurement utilizes the EEG dataset along with machine learning approaches is detailed in fig.1 above. The various steps involved in the implementation of the presented system are explained below.

Step 1: Preprocessing and Labeling – An easy to understand and the interactive user interface is designed for the user to provide the details on the various attributes required in the system. The attributes provided are stored temporarily in the static format. The dataset required for this methodology is stored in the workbook format and is obtained through the following

URL : https://archive.ics.uci.edu/ml/datasets/EEG+Steady-State+Visual+Evoked+Potential+Signals#. This worksheet is then utilized by the java program through the utilization of the external JXL API and stored in the form of a double dimension list.

The double dimension list created now contains the dataset in a relevant format for processing, therefore, seven of the attributes given by the user are selected for performing the clustering mechanism which is highly useful for the determination of the EEG signal's functional outcome. The Seven Attributes are like Gender, Age, Smoker, Medical Treatment (Value in Yes/ no), Medical Supplement (Value in yes/ no), Systolic BP and BMI. The respective columns and their positions are utilized by labeling to collect the attributes in numerical format. The preprocessed data is then formed by storing the collected attributes form every row into a new row.

Step 2: K- Nearest neighbor Clustering – The previous step supplies the preprocessed list for the clustering purposes for this step. This procedure utilizes the K Nearest Neighbor for the clustering process through the steps given below.

[i] Distance Evaluation – The Euclidean distance of each of the rows and the four attributes selected is calculated with respect to the other rows through equation 1 given below. The four attributes which are selected for the purpose of Distance evaluation are Test Type, Test name, Number of Events and Test Duration.

The row distance R_D is appended at the end of each row as the mean of the distance calculated. The average distance A_D of the R_D is then calculated through the average distance of the preprocessed list obtained in the previous step.

$$RD = \frac{\sum_{i=0}^{n} \sum \sqrt{(Xi-Yj)^2}}{n-1} \_\_\_\_(1)$$

Where,

R_D - Euclidean Distance

X,Y- Attributes

n= Number of Rows in the Preprocessed List

[ii] Sorting – The list with the distances calculated and stored for the preprocessed data is then sorted in the ascending order using the Row distances R_D. The bubble sort algorithm is utilized for the purpose of sorting the list. This procedure allows the best clusters to be grouped together to make the process of selection of the clusters easier.

[iii] Data Point Estimation – The sorted list formed in the previous step is utilized for the purpose of estimating random data points. The data points have the aggregation range of 1 – 100 and are of integer data type. The size of the preprocessed list is then utilized for the purpose of normalizing the integers of the data points. An integer array is then utilized to store the data points for further processing.

[iv] Centroid Evaluation – In this step, the data points obtained in the previous step are utilized for the purpose of selecting the rows. The centroid list for the cluster formation is formed by storing the row distances R_D of the selected rows.

[v]Cluster Formation – The cluster boundaries are formed by the utilization of equation 2 given below. The Average distances A_D is then added and subtracted to get the range of the cluster from the respective selected R_D which is eventually a centroid value.

$$f(B) = \int_{i=0}^{n} (RD - AD) \rightarrow (RD + AD)] \_\_\_\_(2)$$

Where,

B - Cluster Boundary

R_D - Centroid

A_D- Average List Distance

n- Number of Centroids

The obtained cluster boundaries are gathering their respective row data from the preprocessed list to form the K clusters. And the remaining rows are labeled as the outliers to declare them a separate cluster, which in the end is appended with the formed clusters.

Step 3: Linear Regression and Entropy Estimation – The clusters formed in the previous step are utilized for the purpose of regression value estimations. The mean and standard deviation of the Row Distances of the clusters in order to measure the regression values of every single cluster is estimated. The obtained mean and standard deviations are used to create boundary from the mean to form the regression ranges. The resultant regression range obtained stipulates the best clusters that are suitable for the extraction of the EEG values according to the user input data. The Shannon Information Gain theory is utilized to estimate the entropy of the clusters obtained for the ranges of mean and standard deviation. This step is done to ensure the best possible clusters are selected to perform the mental stability factor measurement based on EEG through the entropy estimation technique.

The Entropy estimation is done by processing every cluster for counting different attributes in each row of the cluster. After the estimation and measurement of the count are then utilized for the comparing. If the count exceeds 2 then that row count R_C is expected to increase. The Information gain on such clusters is calculated using equation 3 given below. The clusters having some Mental Stability factor elements selected for the next process are considered on the condition that the information gain values for those clusters are equal to or more than 0.5.

$$IG(E) = -(X/Z)\log(X/Z) - (Y/Z)\log(Y/Z) \_\_(3)$$

Where

X= Row count R_C

Z= Cluster Elements Size.

Y= Z-X

IG(E) = Information Gain for the given cluster

Step 4: Pearson Correlation – The obtained Top clusters are used to measure their correlation for the user input to evaluate the Pearson correlation as given in equation 4. Based on this correlation the topmost clusters are identifying to feed to further into the Hidden Markov model to estimate the mental stability factor. The working strategy of Pearson correlation with the input data can be seen in the below mentioned algorithm 1.

$$r = \frac{\sum xy - \frac{\sum x \sum y}{n}}{\sqrt{(x^2 - \frac{\sum x^2}{n})}\sqrt{(y^2 - \frac{\sum y^2}{n})}} \qquad \text{\_\_\_\_\_\_\_\_(4)}$$

Where

x is User input label Array

y is Index label array

n is the array Size

r= correlation value in between -1 to +1.

Algorithm 1: Correlation Estimation

// Input: TOP Cluster List T_{CL},

// Input: GEN, AGE, SMOKE,MT[Medical treatment],

// Input: MS[Medical Supplement]

// Output: Correlation Factor List C_{FL}

0: Start

1: C_{FL} = Ø

2: **FOR** i=0 TO Size of T_{CL}

3: TMP_{LIST}= Ø

4: S_{CL}= $T_{CL\,[i]}$ [Single Cluster]

5: Y[ ]= Y[$S_{CL\ SIZE}$] , X[ ]= X[$S_{CL\ SIZE}$]

6: **FOR** j=0 TO Size of S_{CL}

7: Y[j]=j

8: **END FOR**

9: **FOR** k=0 TO Size of S_{CL}

10: R=$S_{CL[k]}$

11: IF (R== {GEN || AGE || SMOKE || MT || MS}

12: X[k]=k

13: ELSE

14: X[k]=0

15: **END FOR**

16: MEAN**=∑ Pearson Correlation(X,Y)**

17: MEAN**=**MEAN/ 5

18: $TMP_{LIST[0]}$=i, $TMP_{LIST[1]}$=MEAN

19: C_{FL}= C_{FL+} TMP_{LIST}

20: **END FOR**

21:**return** C_{FL}

Step 5: Hidden Markov Model – The estimation of the Hidden probability of the Mental Stability proneness is obtained through subjecting the clusters obtained to the Hidden Markov Model. In this process, the row distances are utilized to evaluate the mean and standard deviation. The range of the row distances for determining the quality of the data for Mental Stability factor Feature proneness is obtained by summation and applying differences. The maximum and minimum values determine the range obtained in the previous step based on the mean and standard deviation through which the list is sorted and then segregated into a probability cluster list.

The probability cluster obtained in the previous step is given as an input to the Baum Welch model for the estimation of the rows which have the most probability for the most accurate proneness to the Mental Stability Features.

Step 6 - Fuzzy Classification – This the final step in the evaluation of hidden factors for the Mental Stability Features. The fuzzy crisp values are calculated using the ranges like VERY LOW, LOW, MEDIUM, HIGH and VERY HIGH.

The count for all of the parameters measured is assessed for estimating their fuzzy crisp value positions. Based on the generated positions the Mental Stability factor is predicted for the given input by the user.

2. RESULT AND DISCUSSIONS

The presented technique for Mental Stability factor estimation based on EEG mapping through the use of the Hidden Markov Models and Fuzzy Classification implemented in the java programming language through the utilization of the Net Beans Integrated Development Environment. The proposed methodology is implemented on a machine comprising of a standard configuration such as the Intel Core i5 processor coupled with 500GB of storage and 4GB of RAM. The database responsibilities are handled by the MySQL database server.

The RMSE or the Root Mean Square Error is employed for the purpose of assessment of the error introduced in the mental stability evaluation through the Electroencephalographic mapping data. For the process of attaining the error rate, two assessment parameters are deployed for this purpose. The number of expected Mental Stability factors and the number of users evaluated Mental Stability factors are the two correlated and continuous entities that are employed for this initiative.

The error rate of the proposed methodology is calculated through Equation 5 given below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{1,i} - x_{2,i})^2}{n}} \quad \_\,(5)$$

Where,

$\sum$ - Summation

$(x_1 - x_2)^2$ - Differences Squared for the summation in between the no. of expected Mental Stability factor evaluations and the no. of user evaluated Mental Stability factor evaluations

n - Number of samples or Trails

Table 1: Mean Square Error measurement

Experiment No	No of expected Mental Stability Factor Evaluations	No of user evaluated Mental Stability Factor Evaluations	MSE
1	10	9	1
2	10	8	4
3	10	9	1
4	10	8	4
5	10	9	1
6	10	9	1
7	10	8	4

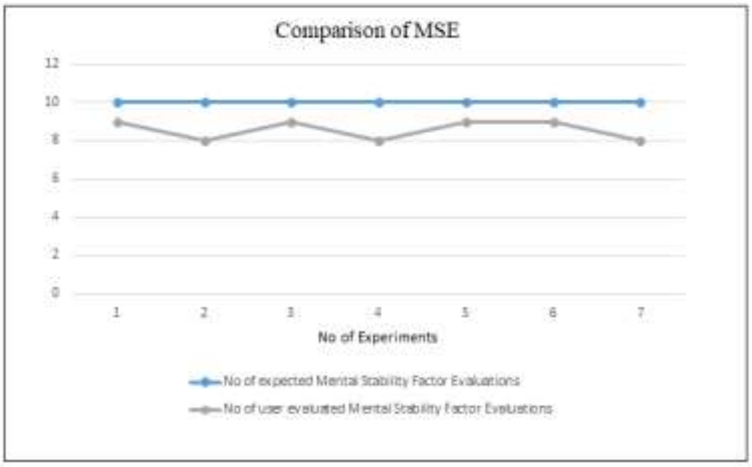

Chart.1 Comparison of MSE in between No of expected Mental Stability factor Evaluations V/s No of user evaluated Mental Stability factor Evaluations

Chart 2 above illustrates the graphical representation of the experimental data given in Table 1 above. The graph plotted demonstrates the Mean Square Error rate between the number of expected Mental Stability factor evaluations and the number of users evaluated Mental Stability factor evaluations for a large collection sequence of experimentation that is accomplished under meticulous analysis. There is a substantial number of trials that are executed in each experiment. The values of MSE and RMSE measured through the experimental outcomes are 2.28 and 1.5 respectively. The calculated values of RMSE for the Mental Stability factor evaluations of the EEG data are extraordinary and according to the criteria of the research which demonstrates good accuracy offered by the HMM approach in terms of RMSE factor.

3. CONCLUSIONS

EEG is one of the most powerful techniques that have been utilized for the purpose of achieving visual representation of the internal activities of the brain. The EEG signal can be used to effectively perform the mapping of the human brain and its functioning for an individual. Therefore, this paper has been focused on achieving the estimation of the Mental stability factor of a particular subject through the use of these EEG signal data. There have been previous researches that have been performed for this purpose. The difference between those researches and our proposed methodology is that our approach utilizes attributes regarding the subject such as their age and sex. Therefore, this research utilizes these parameters along with the EEG signal data and achieves the mental stability evaluation through the use of innovative machine learning approaches. The proposed system utilizes KNN and Pearson correlation catalyzed by the HMM and the Fuzzy classification paradigm to achieve highly accurate mental stability factor evaluations. The presented technique has been extensively tested for errors through extensive experimentation which has yielded highly positive results.

For future research, the methodology can be enhanced further through the introduction of more features such as Educational Qualifications and IQ level of the subject for improving the accuracy substantially.

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