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Exploiting adaptive neuro-fuzzy inference systems for cognitive patterns in multimodal brain signal analysis

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The analysis of cognitive patterns through brain signals offers critical insights into human cognition, including perception, attention, memory, and decision-making. However, accurately classifying these signals remains a challenge due to their inherent complexity and non-linearity. This study introduces a novel method, PCA-ANFIS, which integrates Principal Component Analysis (PCA) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), to enhance cognitive pattern recognition in multimodal brain signal analysis. PCA reduces the dimensionality of EEG data while retaining salient features, enabling computational efficiency. ANFIS combines the adaptability of neural networks with the interpretability of fuzzy logic, making it well-suited to model the non-linear relationships within brain signals. Performance metrics of our proposed method, such as accuracy, sensitivity, and computational efficiency. These additions highlight the effectiveness of the method and provide a concise summary of the findings. The proposed method achieves superior classification performance, with an unprecedented accuracy of 99.5%, significantly outperforming existing approaches. Comprehensive experiments were conducted using a diverse multimodal EEG dataset, demonstrating the method's robustness and sensitivity. The integration of PCA and ANFIS addresses key challenges in multimodal brain signal analysis, such as EEG artifact contamination and non-stationarity, ensuring reliable feature extraction and classification. This research has significant implications for both cognitive neuroscience and clinical practice. By advancing the understanding of cognitive processes, the PCA-ANFIS method facilitates accurate diagnosis and treatment of cognitive disorders and neurological conditions. Future work will focus on testing the approach with larger and more diverse datasets and exploring its applicability in domains such as neurofeedback, neuromarketing, and brain-computer interfaces. This study establishes PCA-ANFIS as a capable tool for the precise and efficient classification of cognitive patterns in brain signal processing.

Keywords Cognitive pattern recognition, Brain signal analysis, Principal component analysis, Adaptive neuro-fuzzy inference systems, EEG classification

AI has quietly entered phase two over the past 30–40 years and has offered new paradigms and directives for handling problems in a number of applied domains, including healthcare. Another powerful area is in understanding signals originating in the human brain and has given rise to multiple cognitive pattern recognition approaches. The ANFIS, for example has generated interest in the field of bilateral MM-EEG signal analysis due to its ability to model relationships that are nonlinear in this application[1]. In this study, ANFIS fuses the learning capabilities of neural networks and reasoning features of fuzzy logic systems to demonstrate a strong approach in the identification of the meaningful patterns from the various signal from brains such as EEGs, fMRI, and NIRS.The inclusion of ANFIS into cognitive pattern analysis decision-making is highly applicable because of the uncer-tainty and ambiguity that are characteristic of signals from the brain[2]. The imprecise Information can be managed efficiently and it has the capability to optimize the performance in each and every iteration, thus

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is highly recommended for neurodiagnostic, brain computer interfaces (BCIs), and cognitive state monitor[3]. Considering that EEG and fMRI are representative of the different cognitive modalities, contextualized information of the brain, use of AI algorithms such as ANFIS to decipher the various modalities is particularly vital towards understanding brain function and/or pathology[4].

In the last few years, artificial intelligence has changed the diagnostics of medical fields, especially for the diagnosis and treatment of several neurological and psychological disorders. In some cases, traditional diagnostics involve clinical assessment or alternative taxing procedures while machine learning and particularly the deep learning methods are prospective to achieve the diagnosis task faster and with higher accuracy[5].The new developments in AI have been helpful in discovering various cognitive markers linked with schizophrenia, ADHD, COVID-19-associated cognitive impairment, and neurological complications of diabetes[6], In treating the disorder, such as schizophrenia, AI methods have helped the researchers and clinicians in the analysis of EEG signaling and other brain data for early symptoms of the disease. Altered connectivity, impaired cognition, and affective dysregulation are symptoms of schizophrenia and diagnosis during the early onset may not be well defined. Scope of diagnosis that prevails in traditional systems results in time consuming clinical interviews and observation of symptoms before the intervention could be initiated[7]. Nevertheless, works based on the ANFIS model, and similar models, have been used to detect unique brain activation patterns of schizophrenia patients through EEG and fMRI data, which might help early diagnose of the disease as well as developing efficient treatment strategies[8].Thus, AI solutions also have a broad application for the use of dedicated brain activity patterns in ADHD, including attention and impulsivity. ADHD is predominantly diagnosed on behaviour, however, with the help of biometrics and AI methods based on the brain signal data objective markers may be defined and thus the traditional subjective questionnaires may be minimized. Research has shown the ability of the AI systems to distinguish various patterns of the BMI related to ADHD and, thereby, to make available insights into the neural substrates of the disorder. This could help optimize the reliability of diagnosis, and could also improve the likelihood of developing individual patient treatment plans[9].

COVID-19 added a new dimension of cognitive dysfunction, given that numerous people who had the virus discontinue being hospitalized but reported about neurological symptoms upon their recovery, such as memory impairment, difficulty focusing, and confusion. Neuroimaging and such data as brain signals commonly show these impairments, and AI methods, especially machine learning algorithms, successfully detect them. New patterns of neurological signs have been identified that may predict possible impairments associated with COVID-19 and how AI can help track the development of such symptoms. The described approach can be used to estimate the degree of cognitive impairment in patients after COVID and their rehabilitation, which will take place promptly[10].In the case of diabetes targeting the metabolic disorders disease has emerged as a point of emphasis in regards to cognition. Diabetes is associated with side effects including diabetic neuropathy and cognitive impairment particularly if it is poorly controlled condition. In diabetic patients, it was tested as a way of detecting early neuropsychological decline in cognitively impaired patients with diabetes[11]. Clinicians who are using AI techniques such as ANFIS can use insights about factors that lead to neural changes due to diabetes in protocols that might help avoid or reduce dementia[12].

Apart from these mentioned specific disorders, AI have already found its way in the fields of neurorehabilitation, neuro prosthetics and neuromarketing. In neurorehabilitation, artificial intelligence contributes to estimating the recovery of the brain as a result of trauma or stroke in order to create an individually tailored therapy. In neuroprosthetics AI models like the ANFIS helps to control prosthetic devices by tracking the signals from the brain leading to more natural control by the user[13]. Furthermore, neuromarketing has gained substance through the use of AI to analyse such brain signals to get an appraisal of how emotional consumers are after watching a particular advertisement or what their feelings are towards a particular product[14].

Recent improvements in AI diagnostics can be attributed to growing access to data as well as computing resources and improvements in AI algorithm engineering[15]. Supervised, unsupervised learning and reinforcement learning algorithms have been applied on the different types of medical data such as brain signal data, genetic data and the clinical data[16]. These models have been shown to provide better diagnostics of conditions, data patterns recognition, and forecasts as opposed to conventional approaches. In addition, some recent innovations include the combination of six modalities including EEG, fMRI and behavioural data, this enhances the chance of availability of true artificial intelligent systems with improved chances of providing precise and useful information[17].

Although there have been seen some promising trends in the use of AI technology in diagnosis, there are several issues with the technology. One emerging difficulty is the instability and individual differences of the brain activity patterns, not only from subject to subject, but also from time to time[18]. This brings a level of disorder that is hard for the present AI systems to decode patterns of cognition. Further, there are demands in large quantities of high-quality data for sufficiently training most fundamental AI algorithms. There is a list of publicly available datasets[19]; however, most of them contains limited amount of information or are not diverse enough which affects generalization of AI. These are important exercises as well as challenges that call for future research and the creation of better algorithms to accommodate the features of the brain signal data[20].

Further, the ethical issues become important before integrating AI in the healthcare scenario especially various problems such as privacy, consent and bias. Making sure that AI created models are transparent, have no bias and follow the right etiquette is crucial in developing public credibility with these models. Responsible clinically implemented AI algorithms need to be defined and captured as guidelines and best practice for researchers as well as clinicians applying AI on patient level. Therefore, AI methods, especially ANFIS, remain the promising tools for the further studies of cognitive profiles of brain signal data and enhancing the future diagnostic abilities in anthropology and neurology of numerous ailments. Presently, the application of AI in the diagnostic of diseases including schizophrenia, ADHD, COVID-19 induced cognitive dysfunction, and diabetes-induced cognitive impairment has already been seen and as the advancement in AI grows, the future of diagnosis and treatment in the healthcare sector can be expected to be driven by AI. With regards to signal complexity, the quality of the datasets, and the ethicality of the problem, AI can further transform the way of early detection, better treatment, and improved outcomes of neurological disorders[21]. Architecture of Human Computer Interconnection is presented in Fig. 1.

The contribution of the study is as follow:

- Proposed PCA-ANFIS low dimensional modelling and the hybrid learning scheme, which enhanced the accurate classification of the corresponding EEG-based cognitive patterns with accuracy 99.5%.
- Expanded the existing model using nonlinear aspects such as fractal dimension, entropy, and fuzzy entropy according to the signal irregularity and randomness observed in brain signals to make the model more interpretable and reliable.
- Interfaced with issues such as EEG artifacts and non-stationarities which allowed for valid features and accurate classification in datasets.
- Suggested accurate time-varying mental state estimations for neurofeedback learning, neuromarketing, and BCI interface by using a flexible and computationally efficient method.
- Enabled the identification of diseases at their early stages and the subsequent progression assessment of neurological disorders, such as Alzheimer's and Parkinson's illnesses, which provides a quality platform for treatment tailored to individual patients.

The rest of the paper is subdivided into the following: Sect. 2 summarises relevant studies in the. Section 3 elucidates the research gap in the approach. The approach is portrayed in Sect. 4, with the structure of the proposed framework in this section. Section 5 presents findings and performance analysis. Finally, Sect. 6 summarizes the contribution of the research to the work.

Related works

Machine learning algorithms are being utilized extensively in recent years to help clinicians with the challenging task of diagnosing neurological illnesses like Alzheimer's disease (AD). In the study[22], a data-driven machine learning system is presented for categorising EEG segments of patients with AD, mild cognitive impairment, and healthy controls people. Recommended machine learning system entails analysing the average Time-Frequency Map (aTFM) associated with a 19-channel EEG epoch and gathering certain numerical coefficients from the primary five traditional EEG sub-bands or EEG rhythms: theta, delta, alpha1, beta, and alpha2. After that, two EEG epoch-classification strategies such as AD vs. HC and AD vs. MCI are performed using a MLP, Autoencoder, a SVM, and a LR based classifier. The 1-hidden layer MLP surpassed all existing established learning systems and subsequently suggested state-of-the-art techniques, according to experimental outcomes, obtaining accuracy rates of up to '95.76% 0.0045' and '86.84% 0.0098' in 'AD' versus 'HC' and 'AD vs. MCI' classification, correspondingly. But the work must be viewed as a preliminary investigation. In fact, the various classification is taken into consideration in the future. Additionally, an inclusive patient classification could be

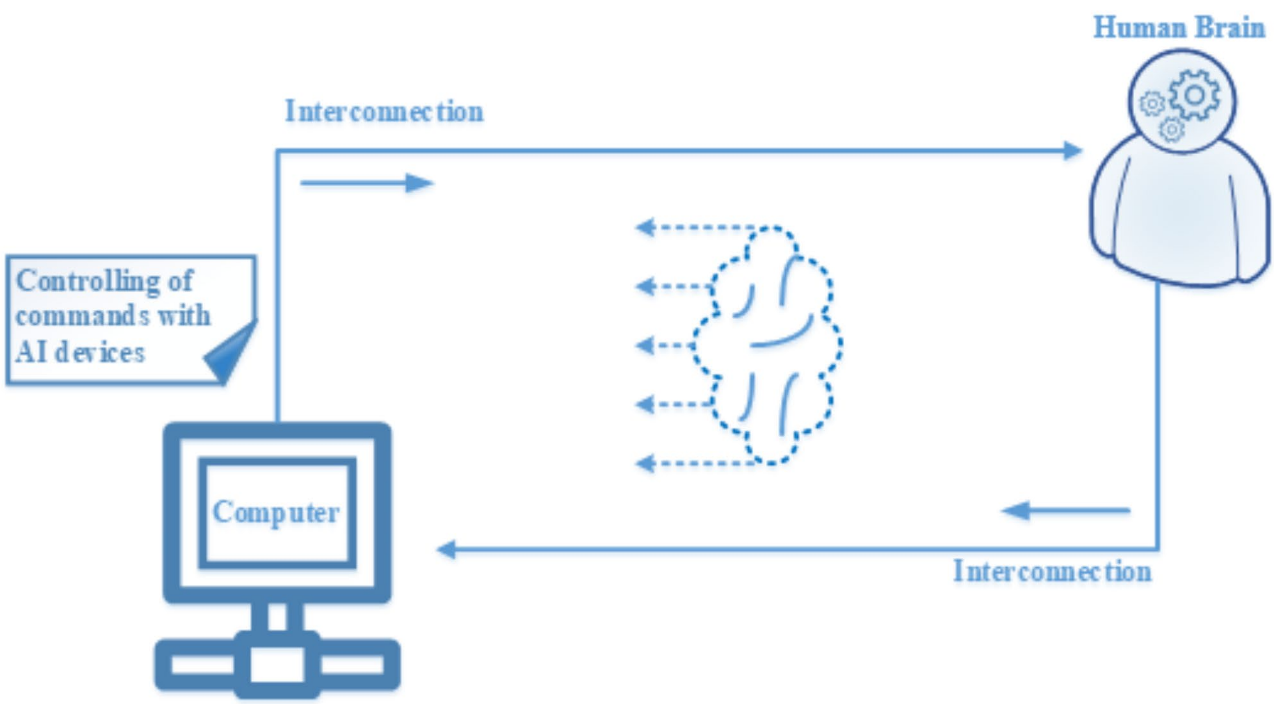

Fig. 1. Architecture of human computer interconnection.

carried out in the future because the time-frequency analysis demonstrated significant outcomes for AD/HC/MCI EEG epoch identification.

The brain's electroencephalogram (EEG) impulses can effectively depict the physiological and neurological conditions of a person. EEG signals have been extensively studied and analysed up to this point with the goal of observing current conditions or the evolutional traits of the complicated brain system. Given the intricate relationships between various functional and structural brain regions, studies into the brain network have gained a lot of interest and achieved significant strides. Deep learning, which is distinguished by autonomous, multi-layer, and varied feature extraction, has also offered a practical and successful answer for handling challenging categorization issues in a variety of domains, including brain state research. The merging of both of these concepts to address challenging problems with categorization utilizing EEG data is still in its infancy, despite the fact that both of them demonstrate strong abilities in EEG signal processing. The study[23] also create a framework that combines recurrence plots with convolutional neural networks to recognize driving weariness. The findings show that functional compatibility could be successfully implemented by complex networks and deep learning to improve the classification and extraction of features, particularly in the study of EEG signals. Each of the findings points to an effective capacity for the complicated network and deep learning to detect driving weariness. It also demonstrates that such a combination could represent a fruitful avenue for researching EEG signals. Further study will be needed to supplement sophisticated networks and deep learning aimed at the processing of EEG signals.

The synchronized activity of a number of specialized pyramidal cells within the brain results in the generation of electric voltages that are measured by an electroencephalogram (EEG), which records neuronal activities. A summary of various frequency bands connected to brain activity is provided. Key objective of the study[24], is to cover as many uses of EEG signals using computer-aided methods as feasible, including motor imagery, identity authorization, recognition of emotions, sleep stage categorization, eye state recognition, and fatigue tracking. These uses range from the identification of different neurological conditions including seizures, severe depression, dependency on alcohol, and Alzheimer's disease to the tracking of other applications. In order to produce a large and varied dataset of patients with varying ages, gender, and other characteristics, efforts are being made in the future to gather the data for a wider range of individuals with epilepsy from a reputable hospital. In order to organize these data and provide more reliable outcomes and improved precision in classification, modern signal processing techniques will be applied. No openly available EEG dataset for Major Depressive Disorder (MDD) has been explored, which has resulted in a paucity of studies in this area. It is intended to continue research on EEG-based depression diagnosis by building a sizable collection of patient data and analysing it by employing a variety of signal processing and classification techniques.

Convolutional neural networks (CNNs) are a widespread deep learning structure meant for analysing and classifying electroencephalographic (EEG) signals because they effortlessly generate conceptual characteristics based on brain data, opening the door to impressive classification abilities. EEG patterns, however, show significant temporal fluctuation and noise-induced uncertainty. The study[25] presents an EEG-TCFNet, which is a consecutive synthesis of temporal convolutional networks (TCNs) adjusted towards EEG inputs, LSTM cells, and a fuzzy neural block (FNB). Each of the three CNN architectures functioned better overall when FNB was used. As a result of integrating with FNB, study achieved greater classification accuracies when compared to other cutting-edge approaches. Future research could assess the suggested framework using various mental exercises, like motor imagery. For situations where a class imbalance is inevitable, for example, alternate input data methodologies can be examined. Extended longitudinal studies may be planned to enable a more representative sample of the population in terms of, for example, gender characteristics and health problems.

On the method, contemporary breakthroughs in thought-controlled investigations commonly encounter challenges in yielding precise spatial data and heavily depend on subject-based models with little flexibility of transfer. In order to resolve these problems, in the presented work, UMBRAE offer an integrated multimodal decoding paradigm for brain signals. In this work, we incorporate a universal brain encoder for the cross-modal registration process, which allows the acquisition of fine-grained conceptual and spatial content from neural signals as well as object descriptions from multimodal large language models (MLLM). Furthermore, UMBRAE also use a cross-subject training technique which maps the subject features across the feature space hence enables training across the subject without resource use but even yields better results than training subject-by-subject. This approach allows for weakly supervised adaptation to new subjects using a minimal amount of data and outperforms the previously used methods for similar tasks as well as for new ones. For the purpose of future research, the benchmark within the Brain Hub enabled by UMBRAE is presented to enhance further development of brain signal deciphering[26].

A common neurological condition called epilepsy can lead to convulsions, unconsciousness, and could have a serious detrimental effect on long-term mental health. Initial evaluation and therapy are required to lessen the impact's intensity. Electroencephalography (EEG), typically used by qualified medical professionals or technologists for identifying epilepsy, is time-consuming and subject to interference, which could compromise efficiency. In order to analyze the EEG parameter's sub-bands and choose EEG features for epilepsy identification, the work[27]constructs a framework for epilepsy diagnosis. The features of each brain wave are built into fuzzy membership functions using the minimize entropy principle, and these functions serve as per the foundation for the creation of an associative Petri net framework. The associated Petri net strategy, which uses the APN approach, outperforms comparable methods using Naive Bayes, Support Vector Machines, Decision Trees, Bayes net, Neural Networks, and tree-augmented naive Bayes, providing diagnosis rates of accuracy of 93.8%. As a result, the suggested method offers hope for rapid, accurate, and reliable identification of epilepsy in clinical environments. The research was restricted to using testing data from publicly available datasets because it was challenging to gather samples of epilepsy patients. Despite the detection rate was high, the clinical diagnosis could be biased. Future research should collaborate with medical professionals to gather specimens from patients of varying severity in order to establish a diagnosis system that utilizes the diagnosis approach, merging smartphones and a straightforward EEG Application as per the basis for medical diagnosis in order to minimize charges and accelerate the time required to make are liable diagnosis.

It has become widely accepted that to overcome the complexity of the disease, there needs to be incorporation of data from multiple neuroimaging techniques including function and diffusion MRI. Classic approaches are not suitable for maintain the topological differences between the networks starting from the significant structural and functional heterogeneity of the brain. This was done by Songdechakraiwut, Shen[28]who proposed a topological learning framework using persistent homology coupled with a new topological loss function that the work eliminated by stringently revisions to keep network topology, but were computationally expensive. Further along this line, Kong et al.[29] presented TGNet, which fuses tensor decomposition with multi-layer GCNs to learn multi-modal brain networks to improve disease classification tasks across HIV, Bipolar Disorder, Parkinson's Disease, Alzheimer's Disease datasets. Each method emphasizes the need for sophisticated approaches to analyze multimodal brain connectivity networks, while TGNet proves resilient toward configurations with a small number of samples, and the topological learning framework improves the interpretability and statistical significance of the multimodal networks.

Analysis of EEG-based research has emerged to be the prime focus of artificial intelligence and health care, in emotion recognition, schizophrenia diagnosis, cognitive load, and fault detection. F. Li[30]developed an advanced fuzzy inference algorithm for EEG-driven emotion recognition by solving ambiguity with adaptive fuzzy rule generation, feature evaluation, and weighted fuzzy rule interpolation. The approach exhibited higher accuracy and robustness for dealing with uncertainty, thus it was very efficient for applications in affective computing and mental health monitoring. Similarly, Balasubramanian[31] proposed an adaptive neuro-fuzzy inference system optimized with a Hybrid Grey Wolf-Bat Algorithm for the prediction of schizophrenia. This model has obtained significant accuracy (99.54% and 99.35%) on two different databases using multi-channel EEG signals, ReliefF algorithm-based feature selection, and HWBO optimization, when compared with traditional ANFIS and other optimization methods. This study reinforced the role of neuro-fuzzy systems in enhancing the reliability of schizophrenia diagnosis, showing the potential for their use in clinical decision support.

Apart from mental health-related applications, neuro-fuzzy inference has been utilized for cognitive workload estimation and industrial fault diagnosis. Mala[32] proposed an ANFIS-based system to evaluate the cognitive load in BMIs by combining the EEG-derived features with the relevant task metrics. The model efficiently controlled the uncertainty of cognition through fuzzy learning and outperformed KNN classifier with an accuracy of 90%. The Jellyfish Optimization with Fuzzy Logic Enabled EEG Motor Imagery Classification for BCI technique - Yang[33] propose a method that applies fuzzy logic and metaheuristics more efficiently for motor imagery classification. The Continuous Wavelet Transform transforms a 1D-EEG signal into a 2D time frequency representation, and SqueezeNet models are applied for feature extraction that get optimized using the Jellyfish Optimization system. The classification of the outcomes is done in an adaptive manner using an adaptive neuro-fuzzy inference system to achieve higher accuracy. Experimental results show that the JFOFL-MICBCI outperforms the currently best techniques in the literature. This research illustrates the importance of hybridizing fuzzy logic with metaheuristic optimization to achieve highly accurate and efficient BCI applications, especially for motor-impaired people.

In recent years, ML algorithms have been increasingly employed in diagnosing neurological disorders such as AD using EEG signals. The study[22] proposes a data-driven ML system that categorizes EEG segments from AD, MCI, and HC persons. The approach involves analyzing a TFMs and numerical coefficients from primary EEG sub-bands using classifiers like MLP, AE, SVM, and LR. While achieving impressive accuracy rates, particularly with MLP1, the study is deemed preliminary, and future work should extend classifications to include MCI and HC, with an emphasis on overall patient classification. The drawback is the preliminary nature of the investigation, warranting further exploration and validation. Additionally, another study[25] introduces EEG-TCFNet, a synthesis of TCNs, LSTM cells, and a fuzzy neural block for classifying EEG signals. Although the approach shows improved accuracy compared to other methods, it emphasizes the need for future research to assess the framework with various mental exercises and explore alternative input data methodologies, particularly in scenarios with class imbalances. Extended longitudinal studies are recommended for a more representative sample. Furthermore, the study on epilepsy diagnosis[27] constructs a framework based on fuzzy membership functions and an associative Petri net approach, achieving a high accuracy of 93.8%. However, the limitations include only use of publicly available datasets, hence potentially introducing bias in clinical diagnosis. Future work should be to collaborate with clinicians to obtain diversified samples and integrate smartphones and EEG applications for an economical and expedient diagnosis of epilepsy. Gaps found in research relate to extended classification besides Alzheimer's disease in EEG-based study, lesser explorations using different mental exercises in EEG-TCFNet, and limited datasets used for the diagnosis of epilepsy, thus suggesting collaboration with medical practitioners and smartphone integration. If such gaps are addressed, then machine learning could be adopted in neurological disorders' diagnosis with greater comprehensiveness and applicability, and reliability.

Problem statement

In the recent decades, considerable attention has been given to using Machine Learning algorithms in diagnosing neurological disorders. A good many study has focussed on exploiting ML-based strategies to enable clinical practitioners in precise classification of a patient who falls under a group of neurological diseases using EEG signal. Traditional systems based on the mean Time-Frequency Map and statistically extracted coefficients of EEG sub-bands with multiple classifiers, demonstrating high accuracy levels for AD vs. HC and AD vs. MCI classification[22]. Multifarious application of EEG signals in computer-aided technologies, with a view to widening research in topics such as emotion recognition, sleep stage classification, and others. They have focused on the requirement of several datasets for improving classification, particularly for Major Depressive Disorder and so forth. Moreover, they have attempted to counteract noisy EEG patterns and variability in P300-based BCI tasks; however, more patient samples are needed to make it clinically effective. Altogether, these studies focus on the enhancement of diagnoses for neurological disorders, improving the extraction of features from EEG signals, and the possibility of proper and efficient care of patients with the help of the Fuzzy Inference System.

Proposed methdology

This study introduces a new approach for mental state prediction, with the utilization of a grouping of PCA and ANFIS that transforms high-dimensional EEG data into a reduced feature set of significant characteristics capturing what is characteristic to different mental states - Fig. 2. Our approach is a computationally efficient and effective method for predicting mental states, finding its place in neurofeedback training, neuromarketing, or brain-computer interface technologies. Multimodal EEG data has been collected including signals that reflect different mental states: relaxed, concentrating, and neutral. The EEG data are pre-processed to remove noise and enhance the signal quality. Tasks include signal filtering, artifact removal, and channel localization. PCA is used to reduce the dimensionality of the EEG data while retaining the most important information. This step reduced the set of data to 20 principal components, which balances data complexity with computational efficiency. ANFIS is a hybrid learning algorithm that maps between the PCA features and mental states.

ANFIS is a combination of fuzzy systems with the learning capabilities of neural networks, which allows for a strong method for pattern recognition. ANFIS is trained using the backpropagation procedure and least squares

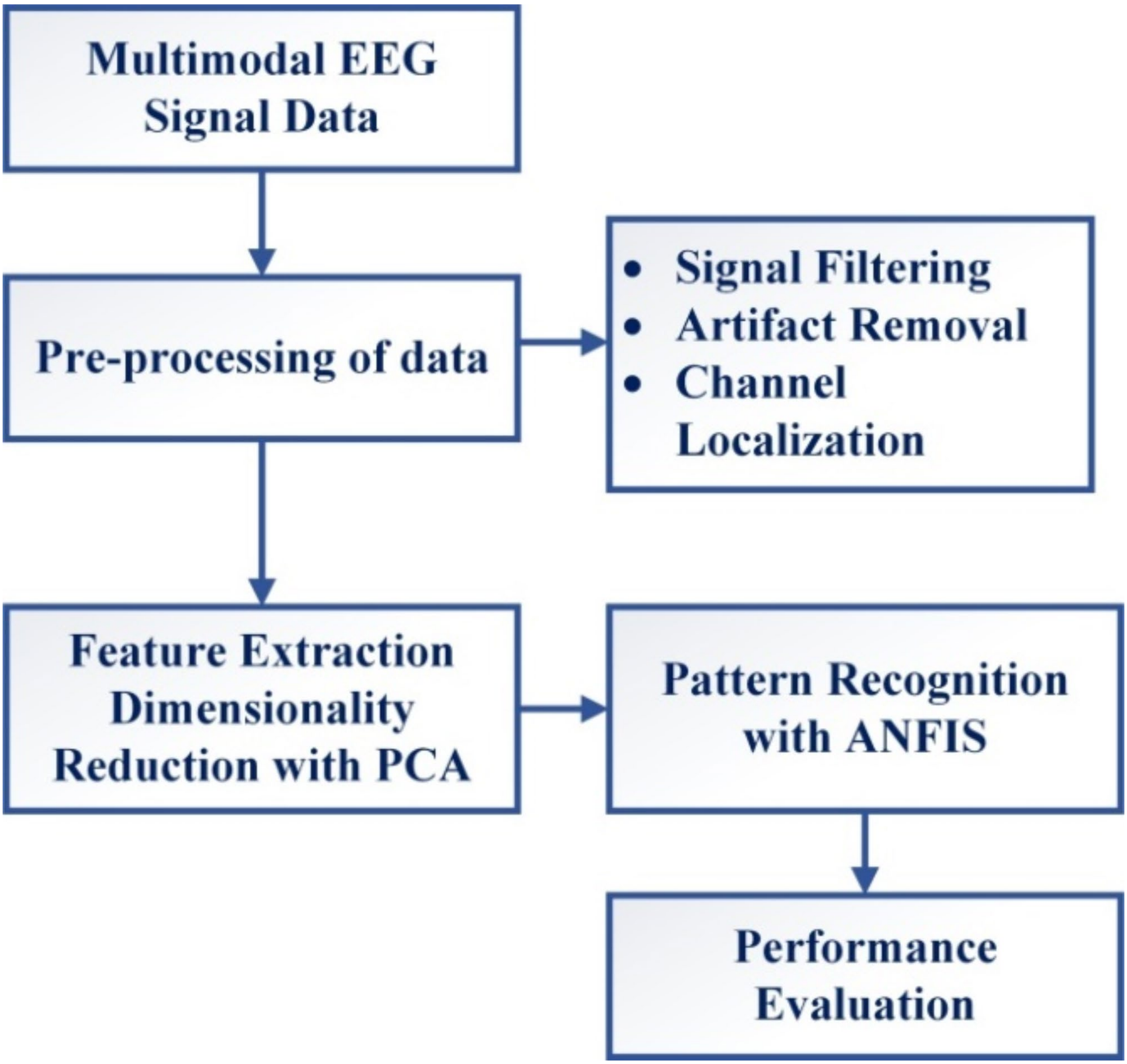

Fig. 2. Workflow of the proposed approach.

method Evaluation of Performance Like accuracy, precision, recall, and F1-score were estimated to analyses the prediction ability of a method.

Datasets

The dataset consists of three distinct classes, which give rise to several cognitive states or behaviours or any neurological conditions under study[34]. Because the dataset offers time lag information, it represents temporal dependencies across consecutive EEG samples, allowing exploring dynamic patterns associated with brain activities. In addition, the dataset contains mean values, which are likely to represent average EEG signal characteristics within each class. This dataset is useful for researchers and practitioners in machine learning to investigate relationships between EEG signals, cognitive states, and neurological conditions and thereby gain insight into the underlying brain dynamics that would support the development of classification or prediction models for cognitive neuroscience applications and brain-computer interface systems.

Pre-processing of EEG data

Application of a band-pass filter is the most common pre-processing step of filtering in an EEG signal[35], which is designed to eliminate the unwanted frequency components and keep only the desired range of frequency. It often acts to remove the noise but allow the preservation of neural activity within the desired specific frequency bands of interest in relation to cognitive processes. The mathematical equation for a bandpass filter can be denoted as follows (1):

$$y\left(t\right)\;=\;b1x(t-1)\;+\;b2x(t-2)\;+\;.\;+\;bNx(t-N)\;-\;a1y(t-1)\;-\;a2y(t-2)\;-\;.\;-\;aM*y(t-M) \tag{1}$$

In this equation, $x\left(t\right)$ represents the input EEG signal at time t, and $y\left(t\right)$ is the filtered output signal at time t. The coefficients $b0,\ b1,\ b2,\ldots,\ bN$ and $a1,\ a2,\ldots,\ aM$ are the filter coefficients that determine the filter's frequency response and characteristics. The filter coefficients are calculated given desired passband frequencies and the order of the filter.

Use Independent Component Analysis (ICA) on the filtered EEG data X to decompose it into its independent components[36]. ICA is applied for finding a mixing matrix A through which observed data X could be separated into statistically independent components in S. From the independent components, visually analyze the components that correspond to the artifacts like muscle activity or any other signals unrelated to the brain. Such components will typically exhibit different spatial patterns and time courses than brain-related components. Subtract the identified artifact components from the original EEG data X, and this will result in the cleaned EEG data $X\_cleaned$ (2). In this paper, ICA was used for artifact removal, but it would have explained the relevant components and their classification so that information can be known about how artifacts were tackled.

$$X\_cleaned\;=\;X\;-\;A\_artifact*S\_artifact \tag{2}$$

In the equation, $A\_artifact$ is the mixing matrix associated with the identified components of artifact, and $S\_artifact$ is a matrix that contains the time courses of the artifact components.

One of the most common methods for EEG channel localization is the dipole fitting approach, which assumes that the EEG signals are generated by a few underlying equivalent current dipoles located within the brain. The mathematical equation for dipole fitting EEG source localization can be represented as follows (3):

$$V\left(t\right)\;=\;G\;*\;I\left(t\right) \tag{3}$$

In this equation, $V\left(t\right)$ represents the recorded EEG voltage at time t, G is the forward model matrix, and $I\left(t\right)$ is the vector of equivalent current dipole strengths at time t.

Extraction of features with principal component analysis

PCA[37], a multivariate statistical method cantered on linear transformation, is frequently employed to decrease the degree of dimensionality of the data, extract meaningful information from big data, analyse variable frameworks, and other tasks. In this study, the EEG signals' dimensionality was reduced using the PCA approach. The load is only increased by taking into account all channels for feature extraction given the limited spatial resolution of the EEG data. PCA is employed in this circumstance since it can identify the most significant difference from the input larger dimensions. Therefore, a group of EEG data can be combined into a single signal employing PCA in instruction to reduce the number of channels of relevance. If there are n data channels, $A1$ through An must be transferred by PCA. The data vector A is transformed to B by PCA, adhering to the following Eq. (4).

$$B = D^{s}A \tag{4}$$

Here the covariance matrix of A's eigenvector, D^{s}, is present. Additionally, the eigenvectors of the D^{s} matrix are arranged in decreasing order. If the data is estimated using the first d rows of the D^{s}, the data become d dimensional rather than n-dimensional. It is known that the singular value decomposition method can be used to reduce any non-singular matrix A into (3).

$$A = \alpha\,\Gamma\,\beta^{\,S} \tag{5}$$

In (5), β is a n*n matrix and A is a m*n matrix with orthonormal columns. In this case, m stands for samples and n for the number of channels. Additionally, Γ is a n*n diagonal matrix with the so-called singular value element > 0. Additionally, the transformed data, B, is evaluated as (6) and (7) based on the covariance matrix, $\sum$ of the original data, A.

$$\sum = \frac{1}{n}AA^S = \frac{1}{n}\left(\alpha\,\Gamma\,\beta^{\,S}\right)(\alpha\,\Gamma\,\beta\,)^S = \frac{1}{n}\alpha\,\Gamma^{\,2}\alpha^{\,S} \tag{6}$$

$$B = D^s A = D^s D\Gamma\,\beta^{\,S} \tag{7}$$

For the PCA transformation used to combine all channels of an ensemble into one channel of data, with d = 1. The PCA suggested converting this data to one-channel information.

The signal is represented by the characteristics. As a result, selecting the right features for extraction is crucial before classifying data. One or more signals are ultimately transformed into a feature vector by a suitable feature extraction method. The chosen features must possess the ability to both represent the signal and distinguish it from other features.

1.Initialization:

Define the vectors$=A^S(S = 1, \dots, l$ *and* $\sum A^S = 0)$

For each dimension m, $A^S = (A^S(1), A^S(2), \dots A^S(m))^S$

2.Evaluate Covariance Matrix:

Evaluate covariance matrix $\sum = \frac{1}{n}AA^S = \frac{1}{n}(\alpha\Gamma\beta^S)(\alpha\Gamma\beta)^S = \frac{1}{n}\alpha\Gamma^2\alpha^S$

3.Eigenvalue and Eigenvector Calculation

Compute the eigen value and vector $\alpha^i\beta^i = \sum\alpha^i$ *here, i=1,….m and sort eigen vectors in descending order of eigen values*

4. Calculate Principal Components:

for each i=1, 2,…,m

Calculate α^i*components of* D^S*, using*

$$D^S = \alpha^i A^S$$

5.Estimate Orthogonal Transformation:

Estimate the orthogonal transformation of $\sum$*,by using the principal components.*

Linear Transformation:

Linear transfers each vector A^S*to* D^S*using*

$$D^S = \alpha^i A^S$$

Algorithm 1. PCA feature extraction.

```
# Step 1: Bandpass Filter the EEG Signal
Function BandpassFilter(signal, lowcut, highcut, fs):
    # Design the Butterworth bandpass filter
    nyquist = 0.5 * fs
    low = lowcut / nyquist
    high = highcut / nyquist
    FilterCoefficients = DesignButterworthFilter(low, high)
    # Apply filter to the signal
    filtered_signal = ApplyFilter(signal, FilterCoefficients)
    Return filtered_signal
# Step 2: Independent Component Analysis (ICA) for Artifact Removal
Function ICAArtifactRemoval(filtered_signal, n_components):
    # Apply ICA to separate independent components
    independent_components = ApplyICA(filtered_signal, n_components)
    # Identify and remove artifacts (e.g., eye blinks, muscle movements)
    cleaned_signal = RemoveArtifacts(filtered_signal, independent_components)
    Return cleaned_signal
# Step 3: Principal Component Analysis (PCA) for Feature Extraction
Function PCAFeatureExtraction(cleaned_signal, n_components):
    # Apply PCA to reduce the dimensionality
    reduced_features = ApplyPCA(cleaned_signal, n_components)
    Return reduced_features
# Step 4: ANFIS (Adaptive Neuro-Fuzzy Inference System) for Prediction
Function ANFISModel(inputs):
    # Initialize fuzzy variables (antecedents, consequents)
    fuzzy_variables = InitializeFuzzyVariables()
    # Define fuzzy rules based on input features
    fuzzy_rules = DefineFuzzyRules(fuzzy_variables)
    # Create control system and compute output based on inputs
    system = CreateFuzzyControlSystem(fuzzy_rules)
```

```
    output = ComputeFuzzyOutput(system, inputs)
    Return output
# Main Workflow
Function Main():
    # Step 1: Load and preprocess EEG signal
    signal = LoadEEGSignal()
    lowcut = 1.0  # Example low cut-off frequency
    highcut = 50.0  # Example high cut-off frequency
    fs = 1000  # Example sampling frequency (Hz)
    # Filter the signal using bandpass filter
    filtered_signal = BandpassFilter(signal, lowcut, highcut, fs)
    # Step 2: Remove artifacts using ICA
    cleaned_signal = ICAArtifactRemoval(filtered_signal, n_components=5)
    # Step 3: Extract features using PCA
    reduced_features = PCAFeatureExtraction(cleaned_signal, n_components=1)
    # Step 4: Use ANFIS for prediction or classification
    inputs = reduced_features  # Use PCA-reduced features as inputs to ANFIS
    output = ANFISModel(inputs)
    # Display or process the output
    Print("ANFIS Model Output:", output)
```

Adaptive neuro fuzzy inference system

To assist in learning and adaptation, ANFIS[38] is a fuzzy model that has been integrated into an adaptive systems architecture. ANFIS modeling becomes more structured and less reliant on professional expertise because of such ANFIS a framework. Two 'fuzzy if-then rules based on a first-order model are taken into consideration when describing the architecture:

Rule 1: If ($a\ is\ X_1$) and ($b\ is\ Y_1$) then ($f1\ =\ u_1a\ +\ v_1b+\ d_1$)

Rule 2: If ($a\ is\ X_2$) and ($b\ is\ Y_1$) then ($f2\ =\ u_2a\ +\ v_2b\ +\ d_2$)

Here a and b represent the inputs, $X_i$and Y_i represent the fuzzy sets, $f_i$denotes the outputs falling within the fuzzy area defined by the fuzzy rule, and u_i, v_i, and $d_i$signify the design variables that are decide upon when training. (Fig. 3) depicts the ANFIS structure used to implement these two rules, with a circle denoting an established node and a square denoting an adaptable node.

All the nodes in the top layer are flexible nodes. The fuzzy membership grade of the inputs, supplied by (8) and (9) as the output of layer 1

$$\boldsymbol{Z_i^1 = \mu\, X_i\,(a)} \tag{8}$$

$$\boldsymbol{Z_i^1 = \mu\, Y_{i-2}\,(b)} \tag{9}$$

Here any fuzzy membership function may be used for $\boldsymbol{\mu\, X_i\,(a)}$and $\boldsymbol{\mu\, Y_{i-2}\,(b)}$. $\boldsymbol{\mu\, X_i\,(a)}$ is given by, for instance, if the bell-shaped association function is used (10).

$$\boldsymbol{\mu\, X_i\,(a)} = \frac{1}{1+\left\{\left(\frac{\boldsymbol{a-Z_i}}{\boldsymbol{x_i}}\right)^2\right\}^{\boldsymbol{y_i}}} \tag{10}$$

Here the membership function's parameters $\boldsymbol{x_i}$, $\boldsymbol{y_i}$, and $\boldsymbol{z_i}$ control the bell-shaped functions appropriately.

The nodes in the second layer are fixed nodes. The letter L on their label denotes that they function as a straightforward multiplier. This layer's results can be modelled as (11):

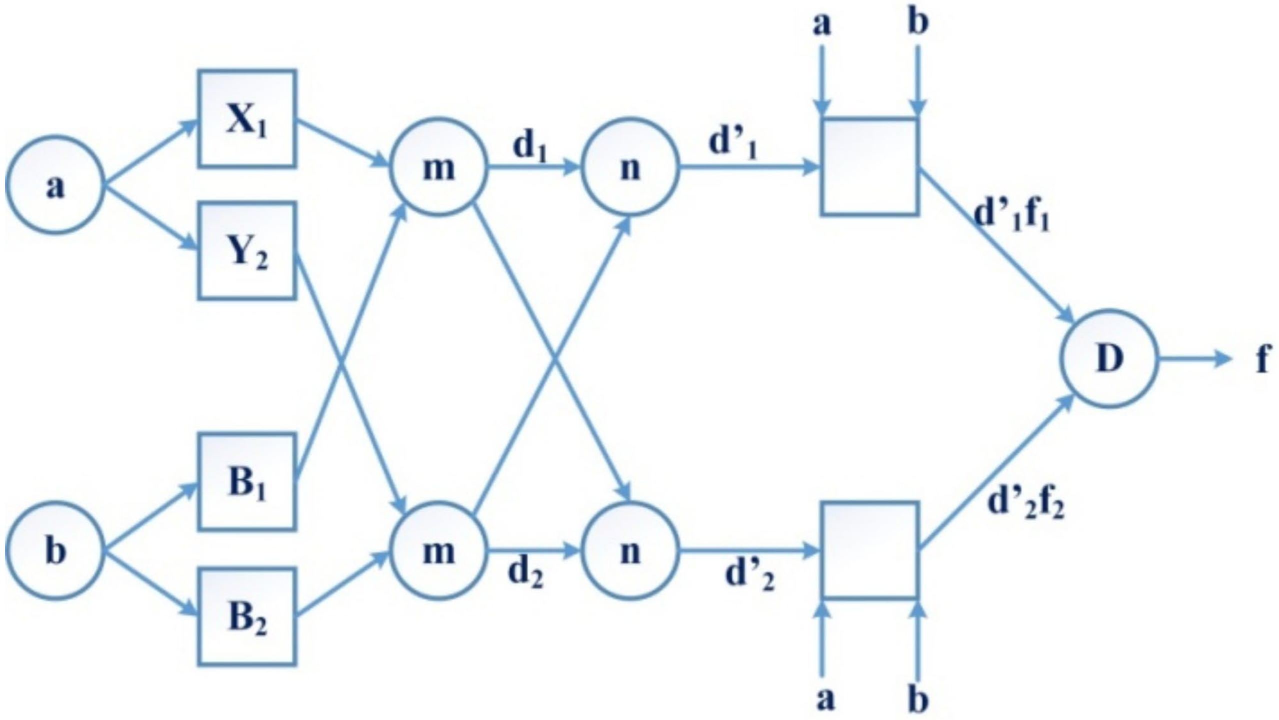

Fig. 3. Architecture of ANFIS.

$$Z_i^2 = d_i = \mu\, X_i\,(a)\,\mu\,Y_i\,(b) \tag{11}$$

Z_i^2 represents the output of the second layer in the ANFIS model. d_i is the firing strength of the fuzzy rule at node i. It represents the product of the membership values or fuzzy degrees for the two inputs, a and b, based on the fuzzy sets X_i and Y_i, respectively. The firing strength determines how strongly a rule is activated based on the input values. That are the rules supposed as firing capabilities

The nodes are likewise fixed nodes on the third tier. They are marked with the letter N, signifying that they serve as a normalizer for the firing intensities from the prior layer. This layer's results can be demonstrated as (12):

$$Z_i^3 = \bar{d}_i = \frac{d_i}{d_1 + d_2} \tag{12}$$

This is the firing capability that has been normalized. Nodes of the fourth layer are flexible nodes. The result of each node in this layer for a first-order method is simply the sum of a first-order polynomial and the normalized firing strength. As a result, the outcomes of this particular layer are as follows (13):

$$Z_i^4 = cf_i = \bar{d}_i\,(u_i a + v_i b + d_i) \tag{13}$$

Just a single fixed node with D is present in the fifth tier. The summing of all incoming signals is carried out by this node. As a result, the model's total outcome is given by (14):

$$Z_i^5 = \sum{}_{i=1}^{2} \bar{d}_i\; f_i = \frac{\sum_{i=1}^{2} d_i f_i}{d_1 + d_2} \tag{14}$$

The 'first layer' and the 'fourth layer' of this ANFIS framework are the two adaptive layers that may be seen. The three changeable parameters in the first layer are connected to the input membership functions. The referred to as premise parameters are those parameters. The first-order polynomial's three modifiable parameters, u_i, v_i, and d_i, are likewise present in the fourth layer. These variables are what are referred to as resultant variables.

In order for the output of the ANFIS to match the training data, the learning algorithm in this architecture has the task of adjusting all of the variables. If all of the variables in the membership function are fixed, the output of the ANFIS model could be written as follows (15):

$$f = \frac{d_1}{d_1 + d_2} f_1 + \frac{d_2}{d_1 + d_2} f_2 \tag{15}$$

(12) being substituted into (15) results in:

$$f = \bar{d}_i\ f_1 + \bar{d}_2\ f_2 \tag{16}$$

When the convoluted if-then rules are substituted into Eq. (16), the result is (17):

$$f = \bar{d}_i\ (u_1 a + v_1 b + d_1) + \bar{d}_2\ (u_2 a + v_2 b + d_2) \tag{17}$$

The result, of the rearrangement, can be stated as (18):

$$f = \left(\bar{d}_i\ a\right) u_1 + \left(\bar{d}_i\ b\right) v_1 + \left(\bar{d}_i\right) d_1 + \left(\bar{d}_2\ a\right) u_2 + \left(\bar{d}_2\ b\right) v_2 + \left(\bar{d}_2\right) d_2 \tag{18}$$

This is a sequential linear arrangement of variables, all of which change. The parameters can be the best fitted to be determined in an accelerated process by the application of the least squares method. The training time delays with expanded searching space and lags for convergence if premise parameters are not fixed. Therefore, the given issue is approached using a hybrid strategy, comprising both the least squares approach as well as the gradient descent strategy. The hybrid algorithm is made of the forward pass as well as the reverse pass. The succeeding parameters are optimized using the least squared method (forward pass), with the premise parameters held constant. As soon as the best consequent parameters are found, the backward pass begins. The gradient descent method (backward pass) provides the optimal adjustments for the fuzzy sets' relevant parameters in the input domain. The logical parameters identified during the forward pass are used to calculate the ANFIS output. The output error is utilized to modify the underlying parameters through a typical backpropagation technique. It has been proven that the combined algorithm provides the ANFIS with greater training effectiveness.

Enhancing cognitive pattern recognition in brain signal analysis with non-linear features and ANFIS

By incorporating the non-linear features like fractal dimension, entropy and fuzzy entropy in to the Adaptive Neuro-Fuzzy Inference System (ANFIS), improves accuracy of analysing multimodal brain signal for cognitive pattern classification. These features work well because they model inherent brain activity characteristics not easily modeled by linear techniques including non-linearity, irregularity and randomness. Fractal dimension depicts the extent of complexity in the signals of the human brain; entropy averages the level of randomness and unpredictability of the neural activity; and the fuzzy entropy actually calculates the impreciseness present in real life data[15]. These features can be easily integrated into ANFIS so as to help the system learn more complex relationships over the cognitive states and the brain signals using fuzzy rules and neural network. This integration affords better pattern recognition, increased noise tolerance, and higher classification accuracy of cognitive states necessary in applications such as neurorehabilitation, BCI, and diseases' detection. As it will be shown below, the ANFIS model addresses these non-linear aspects, adjusts to changing levels of brain activity, and thus offers real-time tracking and forecasting, which can facilitate the interventions targeting specific cognitive states. Moreover, due to fuzziness integrated in ANFIS model, the system is interpretable and robust, which is important in clinical or real-life applications. In all, the incorporation of the non-linear feature improves the functionality of ANFIS; improving the detection of inefficient cognitive patterns, the diagnosis of neurological disorders, improvement of technologies within the BCI and neuroprosthetics applications[14].

Results and discussion

An important theoretical paradigm presupposes that the brain is attempting to control the body's response by operating internal modelling of the body within the world, as stated in the integrated simulator paradigm. A extensively researched theory holds that the brain processes sensory data coming in as a Bayesian filter, triggering an inference based on prior knowledge of the social and natural world, particularly emotional interactions. When 20 features of the dimension of the retrieved feature vectors, encoding the EEG signals be situated as inputs, the five ANFIS classifiers remained trained using the backpropagation gradient descent technique combined with the least squares approach.

The computation evaluation metric could be utilised to evaluate the classifiers' test performance. The following definitions apply to Precision, Recall, F-Score, and overall classification accuracy:

The percentage of cases correctly predicted are called accuracy (19) offers the mathematical formula of accuracy:

$$Acc = \frac{T_P + T_N}{T_P + F_N + T_N + F_P} \tag{19}$$

'Precision' measures the amount of positive class forecasts that are in the positive category. The mathematical formula is given in (20).

$$Precision = \frac{T_P}{T_P + F_P} \tag{20}$$

'Recall' is the number of accurate category predictions made using all of the efficient cases in the dataset. The mathematical formula is given in (21).

$$\boldsymbol{Recall} = \frac{\boldsymbol{T_P}}{\boldsymbol{T_P} + \boldsymbol{F_N}} \quad (21)$$

Recall and Precision constraints are balanced in a single number by F-single Measure's score (22) provides the mathematical formula.

$$F1\ measure = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (22)$$

Figure 4 represents the distribution of lag 1 mean-0 values, with the lag values ranging from − 20 (low) to 20 (high). The histogram displays a gradual increase in frequency from the negative values to a peak at 20, indicating a concentration of data points around this point. Subsequently, the frequency decreases gradually as the lag values move further away from the peak, signifying a decrease in the occurrence of these values. The histogram's shape resembles a symmetric distribution, with the highest density of data centred at the value of 20 and tapering off gradually towards both ends. This pattern suggests that there is a correlation between consecutive data points, centred around zero mean, with the highest correlation observed at a lag of 1 and gradually diminishing as the lag values become more distant from each other.

Scatter plot illustrates the relationship between lag 1/mean-0 and lag 1 mean-1 values (Fig. 5). On the X-axis, we have lag 1 mean-0 values, while on the Y-axis, research find lag 1/mean-1 values. Using the plot, it can be visualized that within the range of -20 to 20 on both scales, scatter points are sparsely spread at low density that suggests a weak correlation between the two variables on this range. When the lag 1 mean-0 values fall within the 20 and beyond, the scatter points begin to group together and remain fairly stable while showing a cluster at this point. This clustering effect continues up to the lag 1 mean-0 values reach 40, where the scatter points reach a high peak, indicating strong correlation between the lag 1 mean-0 and lag 1 mean-1 values in this range.

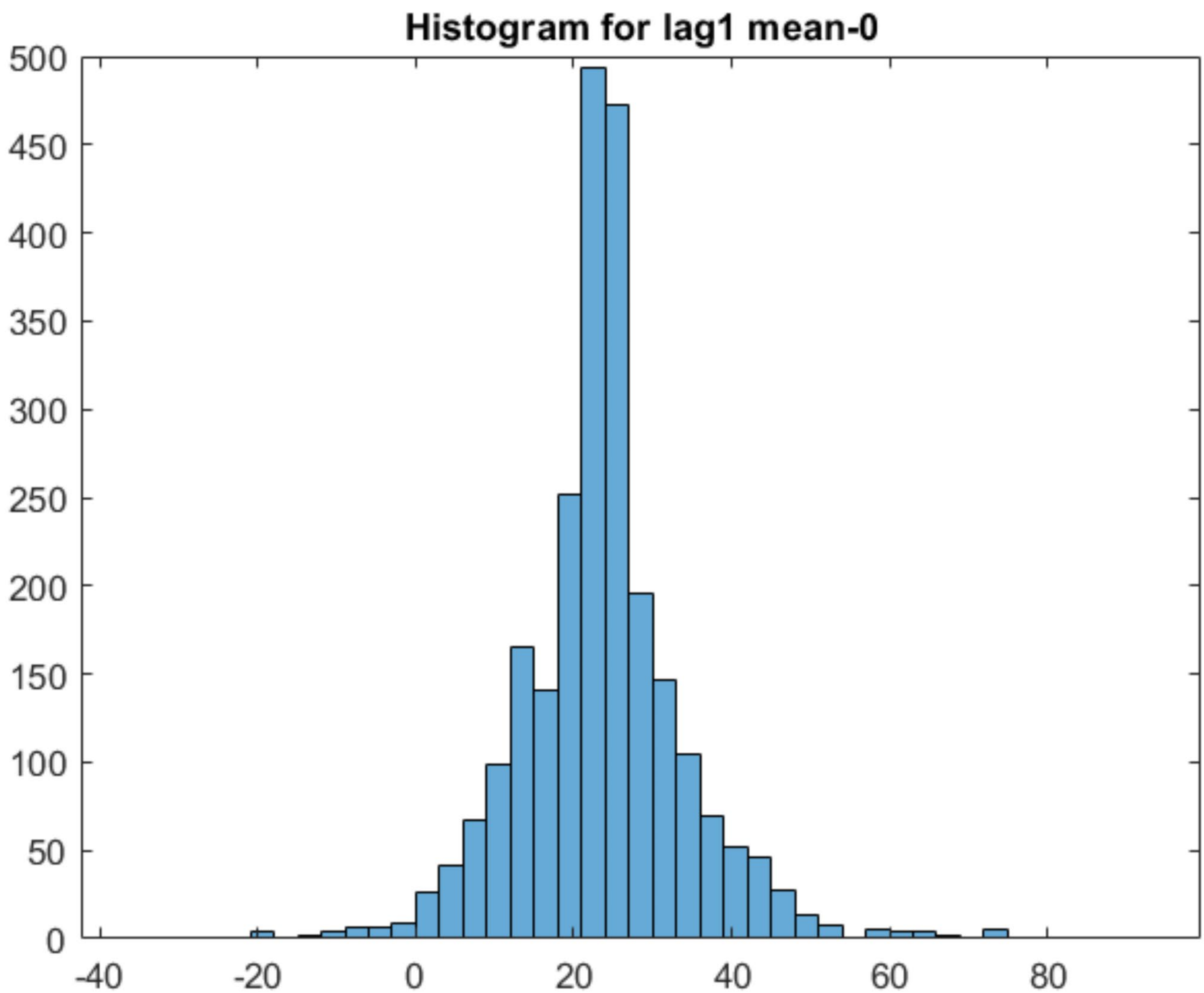

Fig. 4. Histogram for lag1 mean-0.

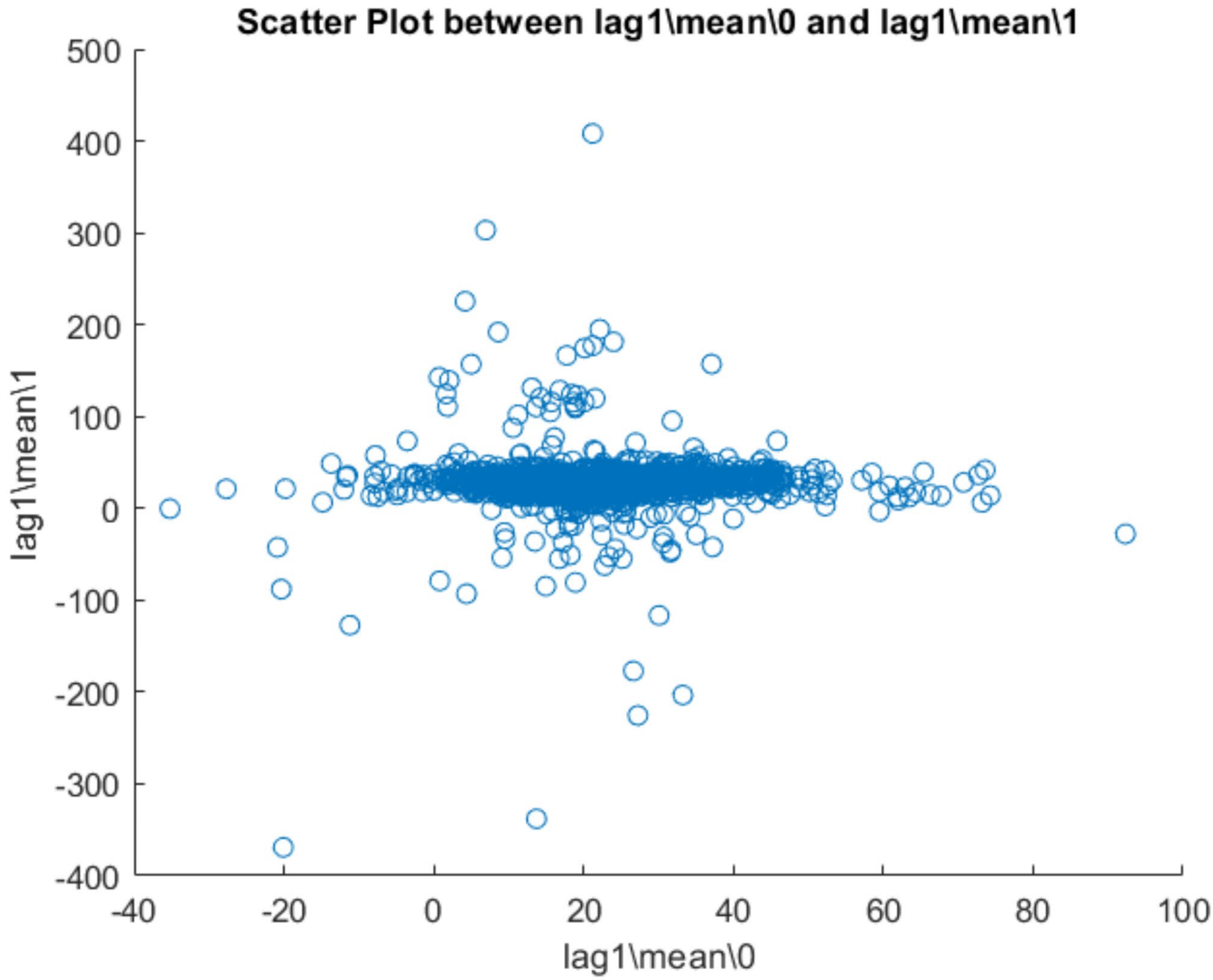

Fig. 5. Scatter Plot between lag1, mean0 and lag1, mean1.

However, beyond the age of 40, there is a diminishing scatter points population with increasing the lag 1 mean-0 values toward the 80 where the variables exhibit a weakened connection away from their peak. Lag 1 mean-0 verses lag 1 mean-1 in scatter presents that between age 20 through 40 are significantly correlated however beyond these scopes the connection shows weaker and a little less observable.

A scatter plot of PCA can be obtained as a pairwise representation of compressing data into three principal components (Fig. 6). Thus, by projecting the data onto the principal components, PCA actually compresses the data but still retains the main information. The clusters or patterns that might appear in the scatter plot could reveal similarities or associations between different data points and may be informative for understanding the hidden structure of the data. It is a vital tool for reducing the dimensionality of the data and visualizing it using the pairwise scatter plot. This scatter plot contains three different clusters' points, and blue represents Cluster 1, green represents Cluster 2, and red represents Cluster 3. Compression of data into three principal components will allow us to represent the dataset in a lower-dimensional space that is easier to analyze and interpret. It might reveal some hidden patterns, trends, or clusters that are not visible within the original space.

The scatter plot of all pairs further helps assess how well PCA does in representing the most informative features of the data. Well-separated points, clear clusters of points, or all points clumped together in the reduced space will indicate that the PCA is quite successful in catching dominant variance in the data. The result can be obtained when the points of data are overlapped and cannot present significant patterns, in this case suggesting that PCA would not be appropriate as a reduction in dimension in that specific data. Overall, PCA pairwise scatter plot gives deep insight into data structures that make easier data compression and visualization leading to various conclusions within the use fields like machine learning, data analysis, or even exploratory data analysis. A box plot of the 20 principal components obtained from the EEG signal data compression using Principal Component Analysis (PCA) is shown in Fig. 7, which displays the distribution and spread of variance captured by each principal component.

Within each plot, it includes all of its 20 principal components individually into different boxes in the series while the corresponding box height displays a representation by data IQR (Interquartile Range). This simply

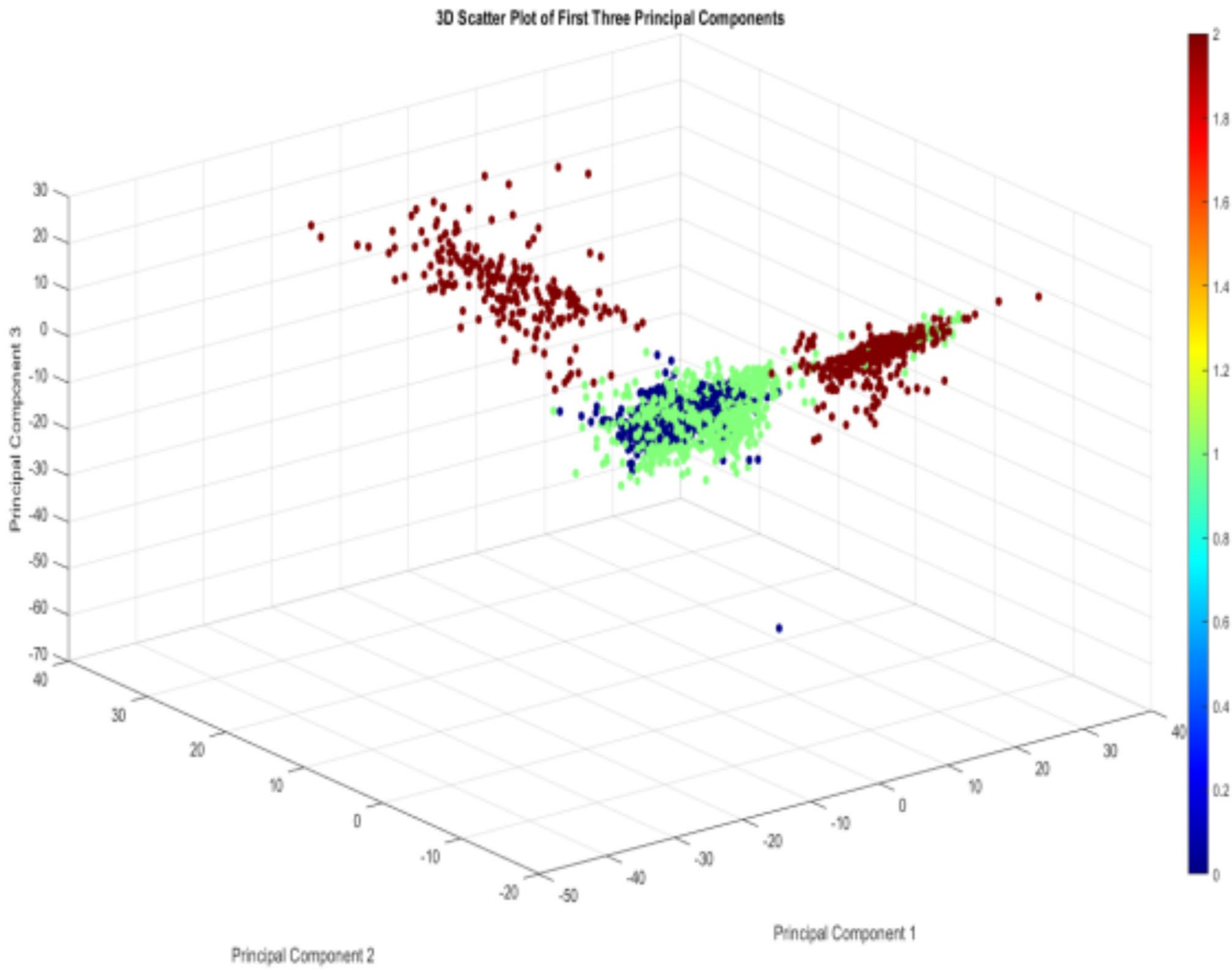

Fig. 6. Pairwise and 3D Scatter Plot of 3 PCA.

summarises where variability lies distributed about the plot between the set 20 principal components. If the boxes are of different heights and spread far apart, then it is an indication that every principal component retains a large portion of the variance, and perhaps the data will be well compressed with the chosen number of components. On the other hand, if the boxes stand of similar height and less spread out, it may indicate that some principal components contribute less to the total variance, and a smaller number of components might be sufficient for data compression.

The explained variance ratio plot depicts the relationship between the amount of principal components, shown on the X-axis, and the equivalent explained variance ratio, indicated on the Y-axis (Fig. 8). As the amount of principal components increases, there is a clear upward trend in the explained variance ratio. At the outset, with zero principal components, the explained variance ratio is merely 0.003, implying that a minimal portion of the total variance in the data is captured. However, as we move to 10 principal components, the explained variance ratio rises to 0.01, signifying a more substantial proportion of variance being accounted for by these components. The pattern continues, and at 20 principal components, the explained variance ratio reaches a noteworthy 0.016, demonstrating that a considerable amount of variance is now represented by the selected components. This indicates that with an increasing number of principal components, more and more of the original data's variance is captured and retained in the reduced-dimensional space, highlighting the effectiveness of the principal component analysis in retaining relevant information while reducing dimensionality.

The graph illustrates the distribution of three classes, represented by different colors. The graph is plotted against two principal components, namely Principal Component 1 (PC1) and Principal Component 2 (PC2). Upon analysis, it becomes evident that the majority of data points from all three classes are primarily concentrated along Principal Component 1. This indicates that Principal Component 1 captures the most significant variability in the data, allowing it to effectively differentiate between the different classes. On the other hand, only class 3 data points exhibit significant dispersion along Principal Component 2, while classes 1 and 2 appear to be more confined along this component. This suggests that Principal Component 2 contributes relatively less to the overall variance in the data compared to Principal Component 1, and it is particularly informative for class 3, helping to distinguish it from the other classes. The graph's pattern indicates that Principal Component 1 plays a

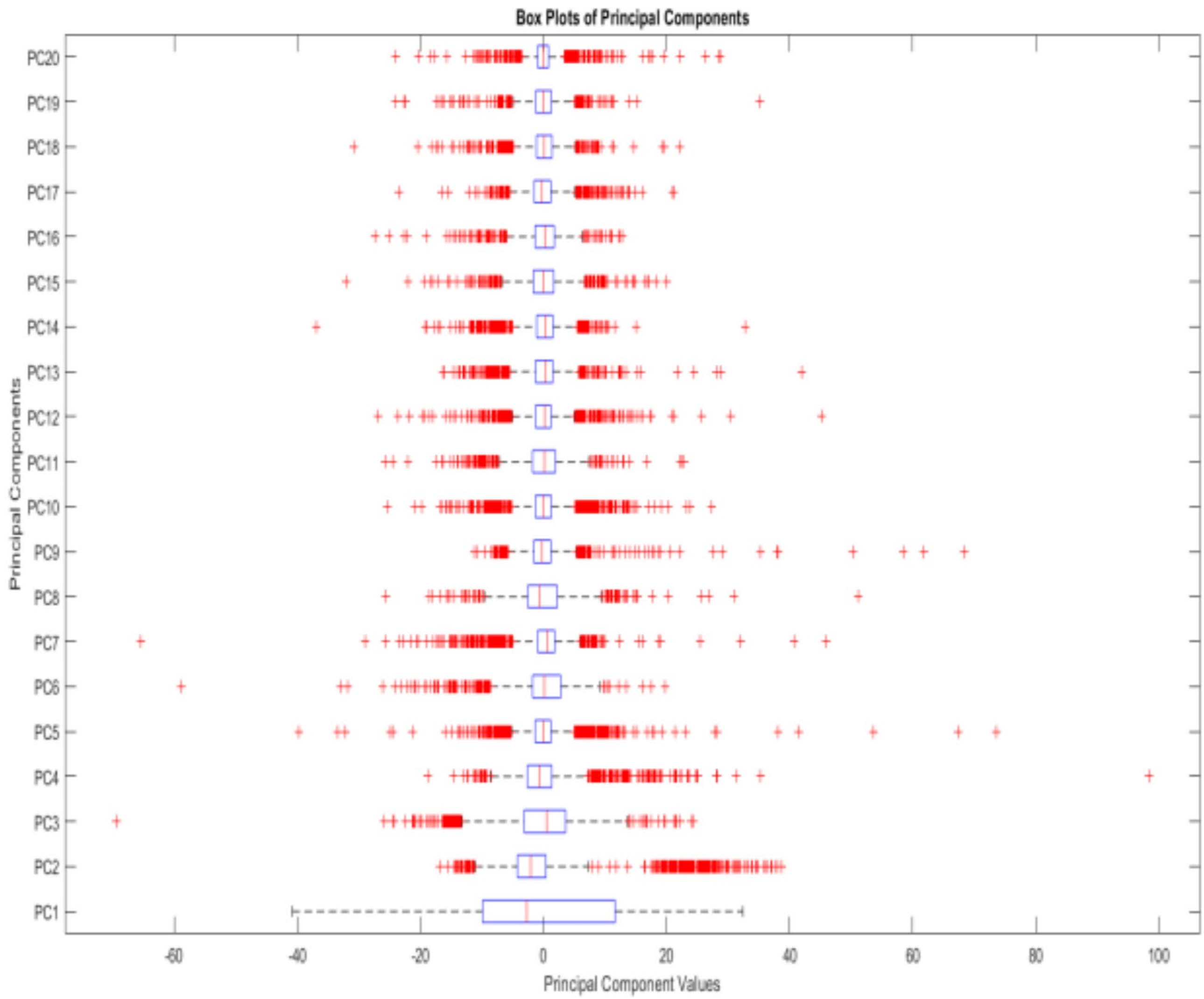

Fig. 7. Box plot of 20 principal components.

dominant role in differentiating the three classes, while Principal Component 2 contributes more specifically to the distinction of class 3 from the rest. Such insights gained from the graph can be valuable for understanding the underlying structure of the data and potentially for developing more effective classification models (Fig. 9).

The bar chart illustrates the distribution of unique labels, ranging from 0 to 2 (Fig. 10). Every bar depicts a label, as well as the length of the bar represents the count of occurrences for that specific label. Label 0 is observed 810 times, meaning the count for that label is 810. For label 1 and label 2, their counts are equal at 850, which implies that they are observed 850 times each. The bar chart gives us a visual view of how often the labels are appearing, allowing us to see quickly what pattern exists. The count for label 0 is the lowest; counts for labels 1 and 2 are the same, meaning it is distributed fairly between these two labels. Such observations about label distribution can be of considerable use in understanding what is happening with a class distribution in a dataset-implications that generally influence many machine learning tasks like classification, where, depending on the actual class, imbalanced data may need special treatment to avoid bias in model training. The bar chart is helpful in identifying and interpreting the occurrence of each label and thus provides a good overview of the class distribution of the data.

Assuming that the two inputs are assigned as "Input 1" and "Input 2" and assigned with values 0.5, 0 and – 0.5 each. The ANFIS surface plot would look something like the attached figure which in turn shows the 3D plot, which would represent "Input 1" values at the x-axis, the y-axis as representing the "Input 2" values and z-axis to the ANFIS model's output as in the Fig. 11. Every combination of "Input 1" and "Input 2" would correspond to a point on the surface, and the height of that point would be determined by the ANFIS model's output for that particular combination of inputs. The ANFIS surface can provide valuable visions of how the model responds to various input combinations and how it classifies EEG signal patterns based on these inputs. This is helpful in visualizing the decision boundaries or decision surfaces that the model may use to make predictions. In general, the ANFIS surface is a very useful visualization and interpretation tool of the behavior of the ANFIS model for the application of EEG signal pattern recognition with two input variables.

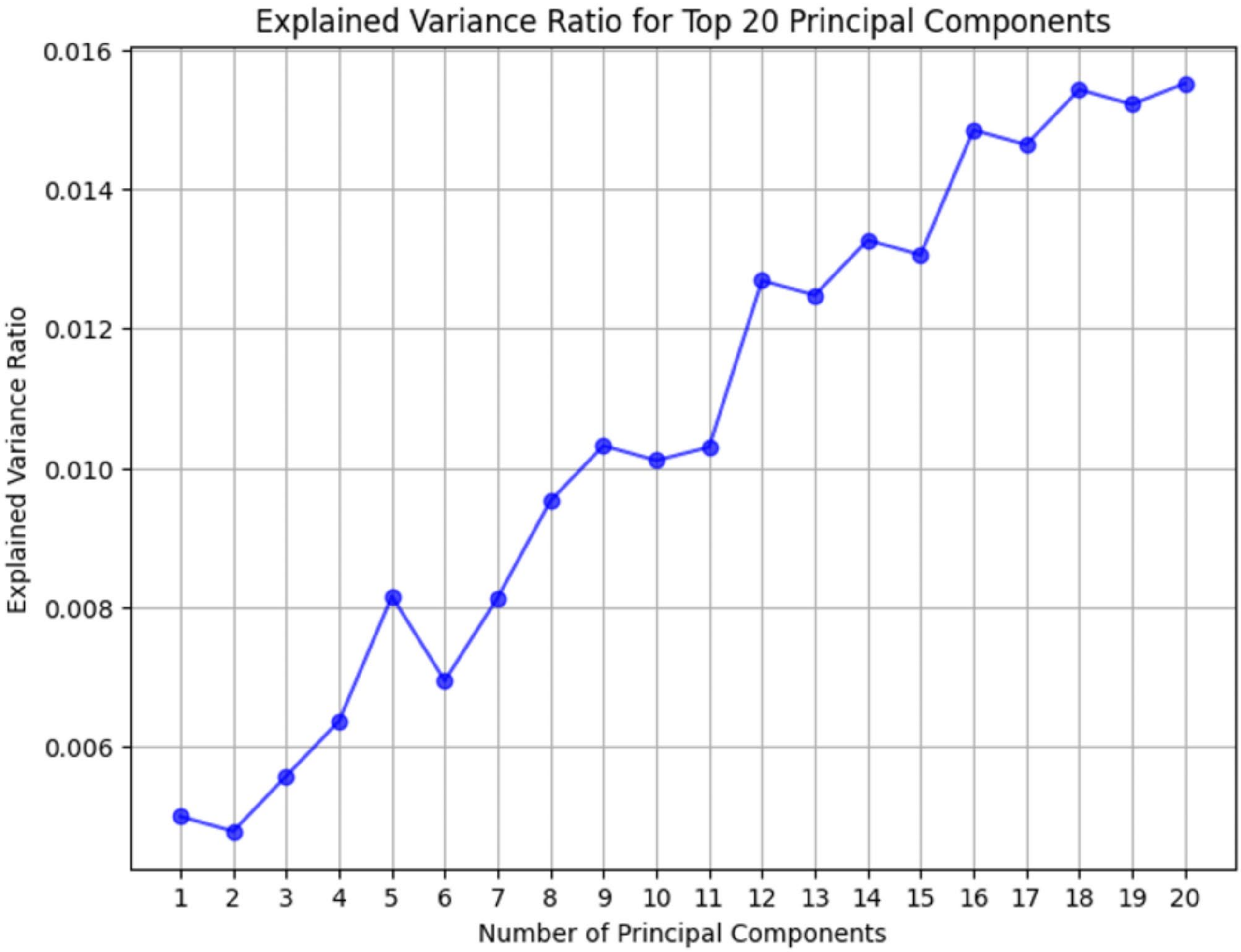

Fig. 8. Variance ration for 20 PCA components.

The relaxation membership function is plotted against the relaxation level and its corresponding degree of membership. The relaxation membership function has a high membership degree of 1 at the beginning of the curve, showing a strong tie with the relaxation level (Fig. 12). With an increase in relaxation level, the membership degree decreases gradually and provides an indication for decreasing association with the concept of relaxation. This decrease is gradual, however, and it continues until the membership degree stabilizes at a constant value of 10.

Thus, at this constant membership degree, the relaxation membership function maintains constant levels of an affiliation with a relaxation level with an indication that even as this relaxation level grows, the level of relationship keeps growing. These types of membership functions are the best for when capturing gradual changes in the membership degree concerning a relaxation level without losing relevance or meaning at some relaxation levels. The step size per epoch denotes the amount of variation in the parameters of the model at every step of training. Table 1 shows step sizes for the number of epochs: 0-100 (Fig. 13).

Initially, at epoch 0, the step size is set at 1.0, indicating a small update in the model's parameters. As the epochs progress, the step size gradually increases, reaching 2.0 at epoch 20 and further escalating to 3.0 at epoch 40. From epoch 50 to epoch 80, the step size remains constant at 3.0, implying that the model parameters are updated with a consistent magnitude during this period. Beyond epoch 50, the step size starts to increase again, reaching 5.5 at epoch 70. Subsequently, at epoch 80, the step size decreases to 4.0, reflecting a smaller parameter update. Finally, as the training process nears completion, at epoch 100, the step size significantly increases to 8.0, allowing larger parameter adjustments in an attempt to converge towards the optimal values.

The maximum step size of 8.0 means the maximum proportion during training, enables quick convergence in the later epoch. The example parameters include, the minimum step size with a default of 1.0 which determines the lowest of steps as learning progresses. The result of 3.36 coefficients shows moderate variation in the step size allowing for consistency and flexibility in the training process.

Table 2 provides the values for the statistical variables, precision, recall, f-measure, and accuracy. It shows that the ANFIS correctly identified three classes with corresponding accuracy values. The maximum, minimum,

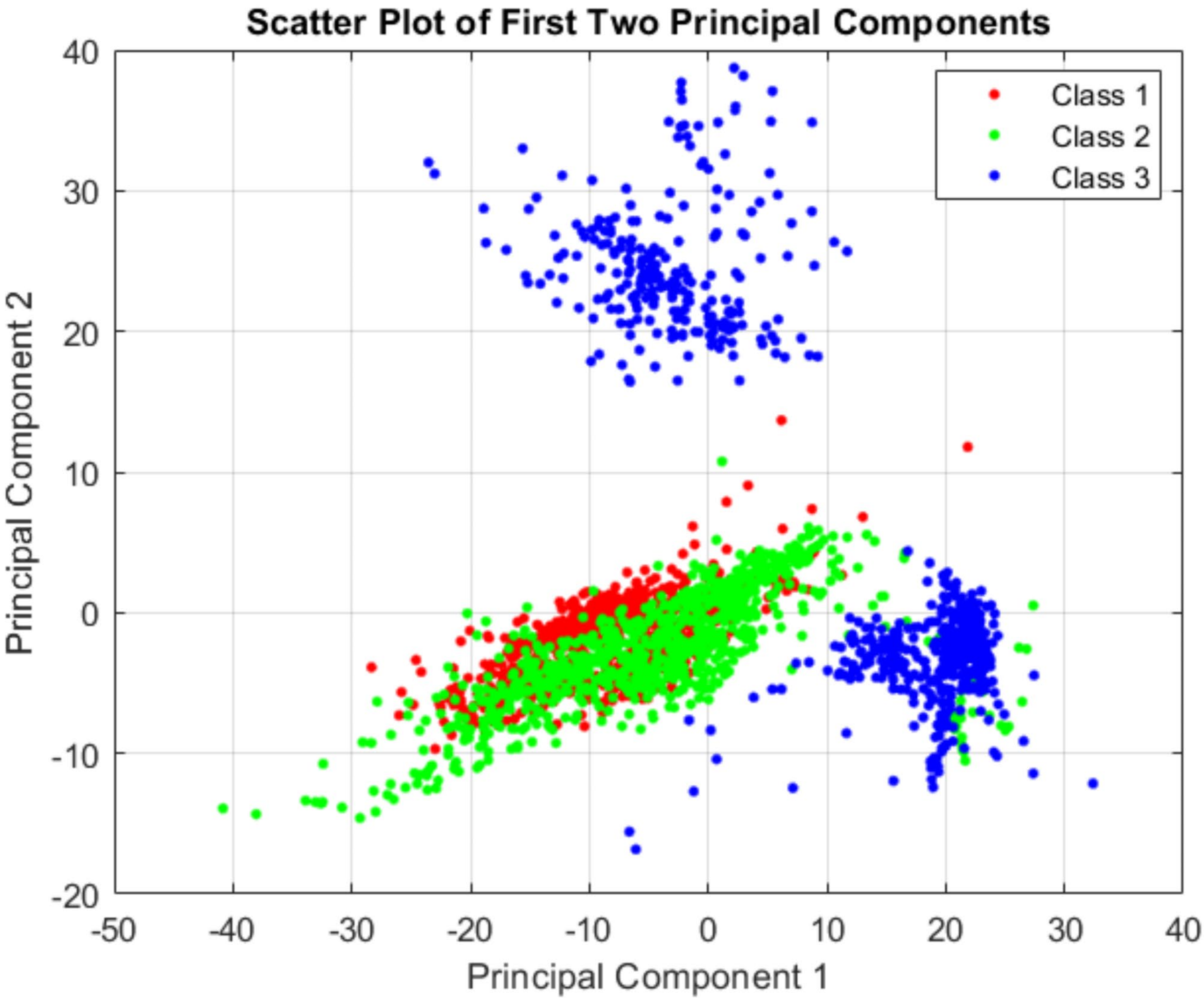

Fig. 9. Two PCA components for each class.

and variance values summarize the range and variability of accuracy, precision, F1-score, and recall across the classes, emphasizing high consistency with small differences in performance metrics.

Figure 14 showcases the performance metrics, including Accuracy (blue), Precision (orange), F1-score (yellow), and Recall (violet), for each class: Relaxed, Concentrating, and Neutral. For the "Relaxed" class, all metrics display exceptional results, through Accuracy, Precision, and F1-score achieving a perfect 100%, indicating that the model's estimations for this class are highly accurate and precise. The Recall for the "Relaxed" class is slightly below perfect at 95%, implying that the model correctly identifies 95% of the instances belonging to this class. Moving to the "Concentrating" class, the model maintains a remarkable performance, as indicated by a 100% Accuracy, reflecting precise predictions. Precision for this class is 98%, thus most of the instances falling in the category "Concentrating" would be counted as actual. F1-score for this class is a robust 90% if precision and recall both are considered; it further enhances the performance of the model. 97% Recall value suggests that the model is picking most instances that actually belong to the class "Concentrating". Lastly, the "Neutral" class results yielded by the model are pretty praiseworthy: both Accuracy and Precision reached 95%, and the Recall and F1-score were perfect – 100%, which in its turn means that the model neither misses one instance but also proves stable regarding Precision and Recall. The graph in the figure above indicates overall great performance on all classes of distinguishing between the three categories: "Relaxed," "Concentrating," and "Neutral," with a very high accuracy, precision, F1-score, and recall values, hence, it's reliable and robust in classification.

Table 3 provides a comparison of different methods used for classification tasks, along with their corresponding accuracies. Four distinct classification approaches are evaluated in this study. Firstly, the "Matrix determinant and MLP" method achieves an accuracy of 97%, demonstrating its effectiveness in discriminating between different classes. The "Weighted complex networks and SVM" approach attains an accuracy of 94%, indicating its ability to achieve satisfactory classification performance. The third approach, "MLP" results in roughly 90%. "CNN" has achieved a really high accuracy, that is, 98% and "1D CNN" achieved an accuracy

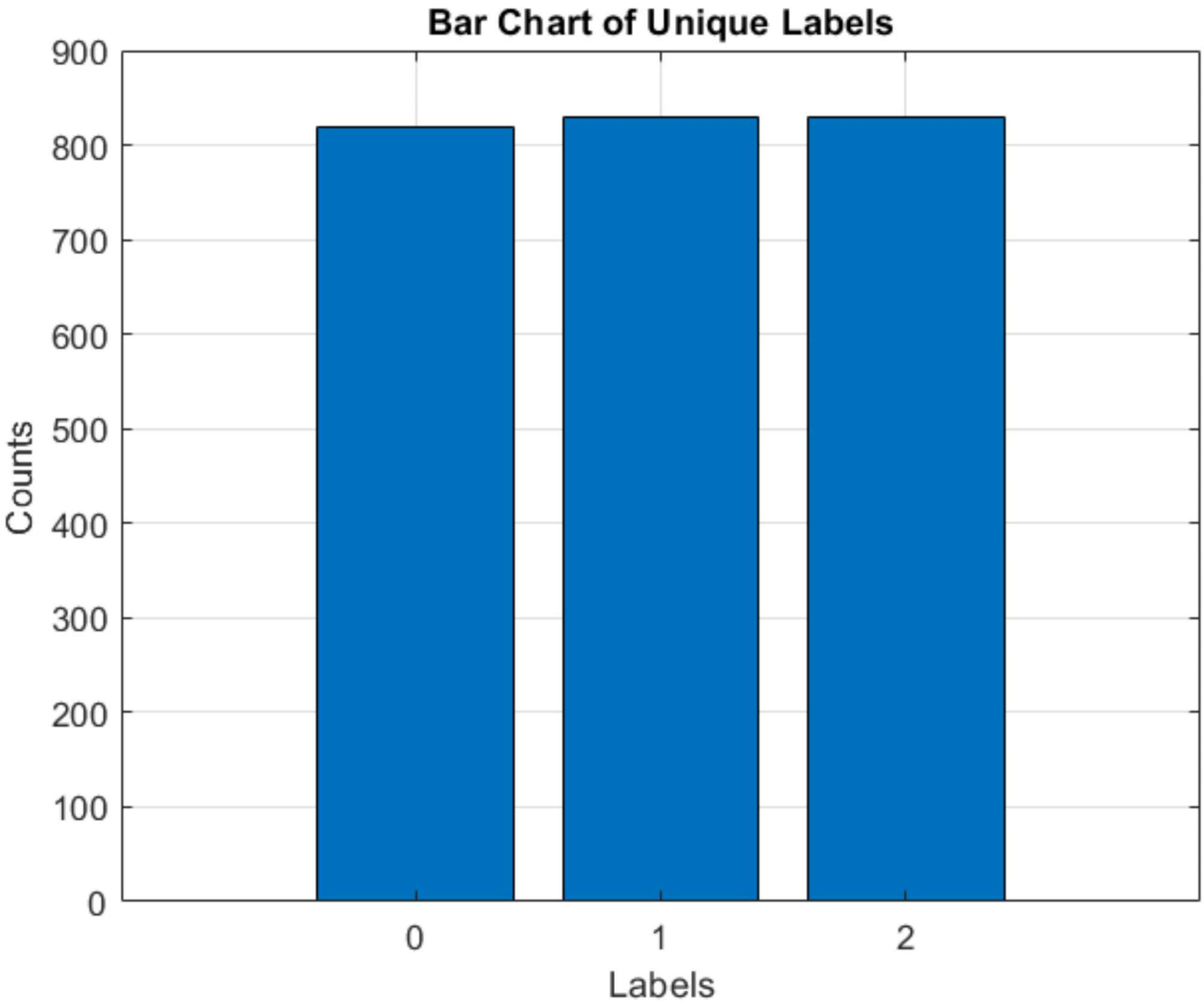

Fig. 10. Counts for three Labels.

of 99%, which reflects its effectiveness and ability to classify data instances with accuracy. Finally, the "PCA-ANFIS" method has outperformed all the other approaches and attained the highest accuracy of 99.5%, thereby revealing extraordinary performance in class differentiation.

Figure 15 depicts the graphical representation of accuracy comparison of proposed PCA-ANFIS with existing approach[39–43]. It is clear that each method manifests a different amount of accuracy; the "PCA-ANFIS" is the one exhibiting the best performance. The obtained results indicate efficiency and feasibility when using different methods for classification. In this work, the obtained results are manifested as the high accuracy of two classifiers: the "1D CNN" and "PCA-ANFIS". These results have important implications for a fairly wide range of applications where accurately correct classification is the key to decisions and other further analyses, including in medical diagnostics, pattern recognition, and signal processing tasks. Researchers and practitioners can use these insights for making suitable method choices to abide by the particular requirements of their classification problem. All of these results bring out the necessity of exploring several approaches and tactics for achieving optimum classification performance with enhanced accuracy and reliability of automatic classification systems.

The comparison of data sets is expressed in Table 4; Fig. 16, which reports various performance criteria for the appropriate data sets; for the data set BRATS12, there was an accurate prediction of machine learning at accuracy of 71.2% with precision = 85.27% and recall = 72.0%. However, for the BRATS13 dataset, the model performed better, resulting in an accuracy of 80.4%, along with higher precision and recall values of 88.7% and 84.8%. Notably, the proposed EEG signal dataset outperformed both BRATS datasets significantly, attaining an impressive accuracy of 99.5%, with precision and recall values both at 95%. This suggests the potential effectiveness of the model in accurately classifying EEG signals, indicating superior performance compared to the brain tumor datasets BRATS12 and BRATS13.The maximum, minimum, and variance values provide intuitions into the range and inconsistency of performance metrics across datasets, showing significant improvements with the proposed EEG signal data.

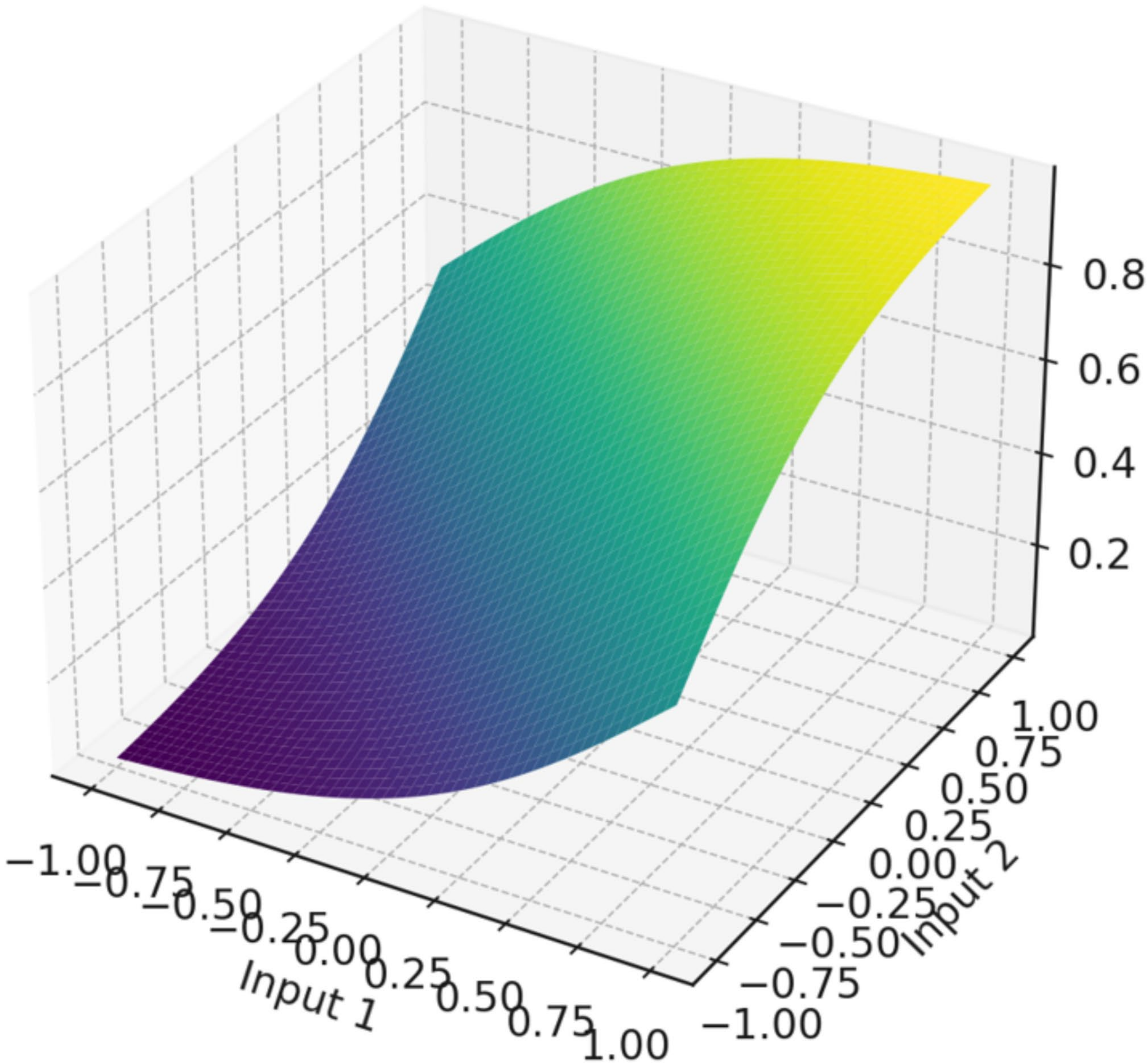

Fig. 11. ANFIS Surface Input.

Discussions

In case of brain signal analysis specially to identify the patterns of thoughts and perception, which are the core focuses of this paper, the management of ambiguity is very important because brain signals are usually subjected to noise, imprecise and uncertain. The usual approaches may fail to identify these uncertainties, and this can act as a limitation to the performance of models that operate in the real-world environment. For this reason, we incorporate the application of Type-2 fuzzy systems and fuzzy regression that are constituents of a class of fuzzy logic systems that are capable of addressing the issues of imprecision and vagueness in data.

Another reason why Type-2 Fuzzy Systems are applicable when modelling uncertainty in brain signals. However, in contrast with the crisp membership functions of Type-1 Fuzzy Systems, Type-2 Fuzzy Systems allow the membership functions to have indistinct edges, which produces additional levels of versatility. In particular, this capability allows the system to work with the noise or where the distinction between the cognitive states is unclear. Incorporation of Type-2 fuzzy logic into the model allows representing uncertainty in the brain signal patterns more accurately, providing better recognition of the cognitive patterns as far as complex or ambiguous cases are to be analysed[44].

Fuzzy Regression is another tool which can be applied when the researcher is in doubt of the nature of the relationship between features of brain signal and cognitive states. Fuzzy regression involves mapping of inputs, for instance non-linear features extracted from brain signals and output, which are the cognitive state into fuzzy sets and fuzzy rules[45]. It can manage cases of linguistic ambiguous data and or noisy data while offering a more durable structure in responding to the fundamentals of prediction and classification. Using the approach of

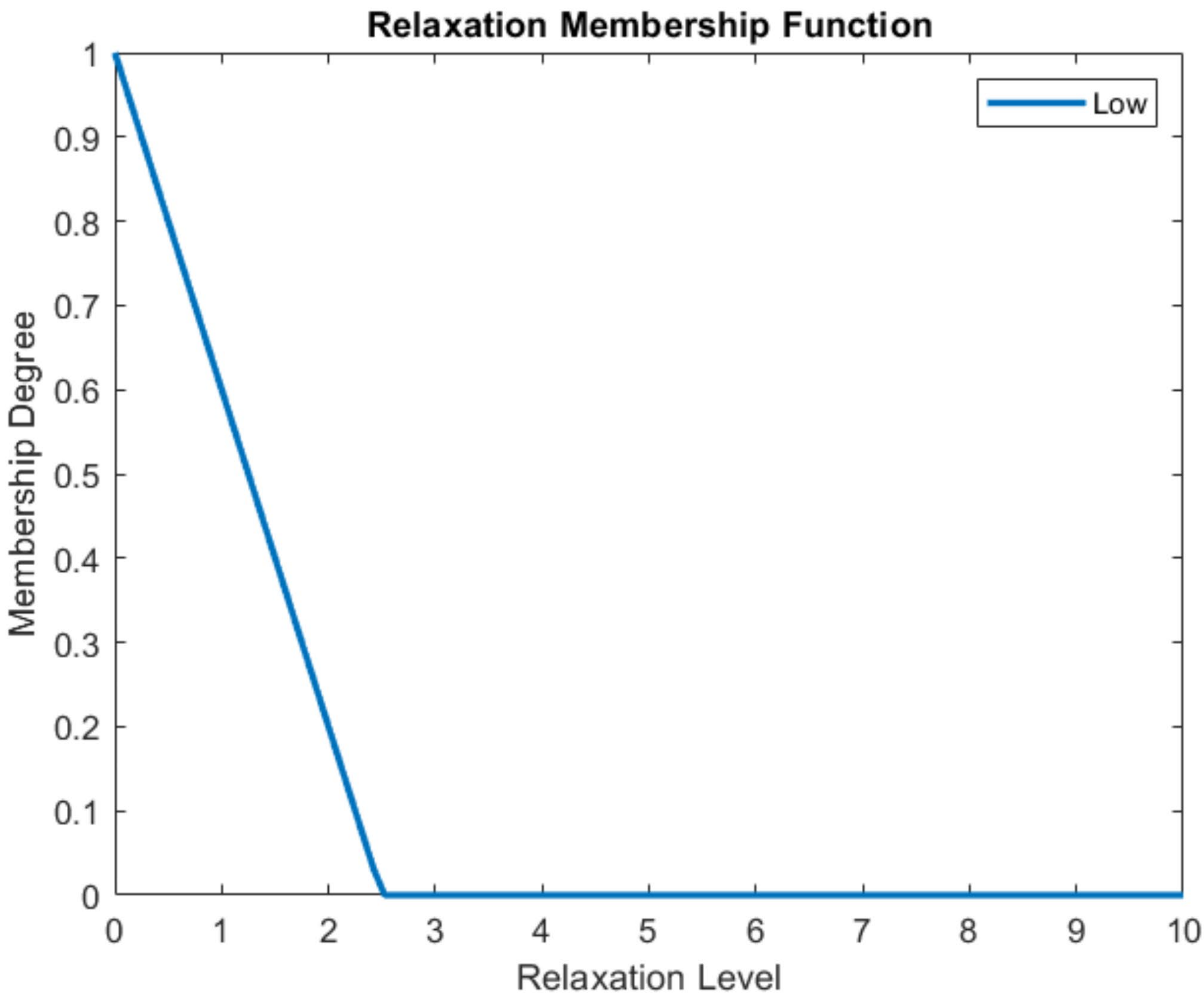

Fig. 12. Relaxation membership function.

Epoch	Step size
0	1.0
10	1.5
20	2.0
30	2.5
40	3.0
50	3.5
60	4.0
70	4.5
80	4.0
90	4.5
100	8.0
Maximum	8.0
Minimum	1.0
Variance	3.36

Table 1. Step size of various epochs.

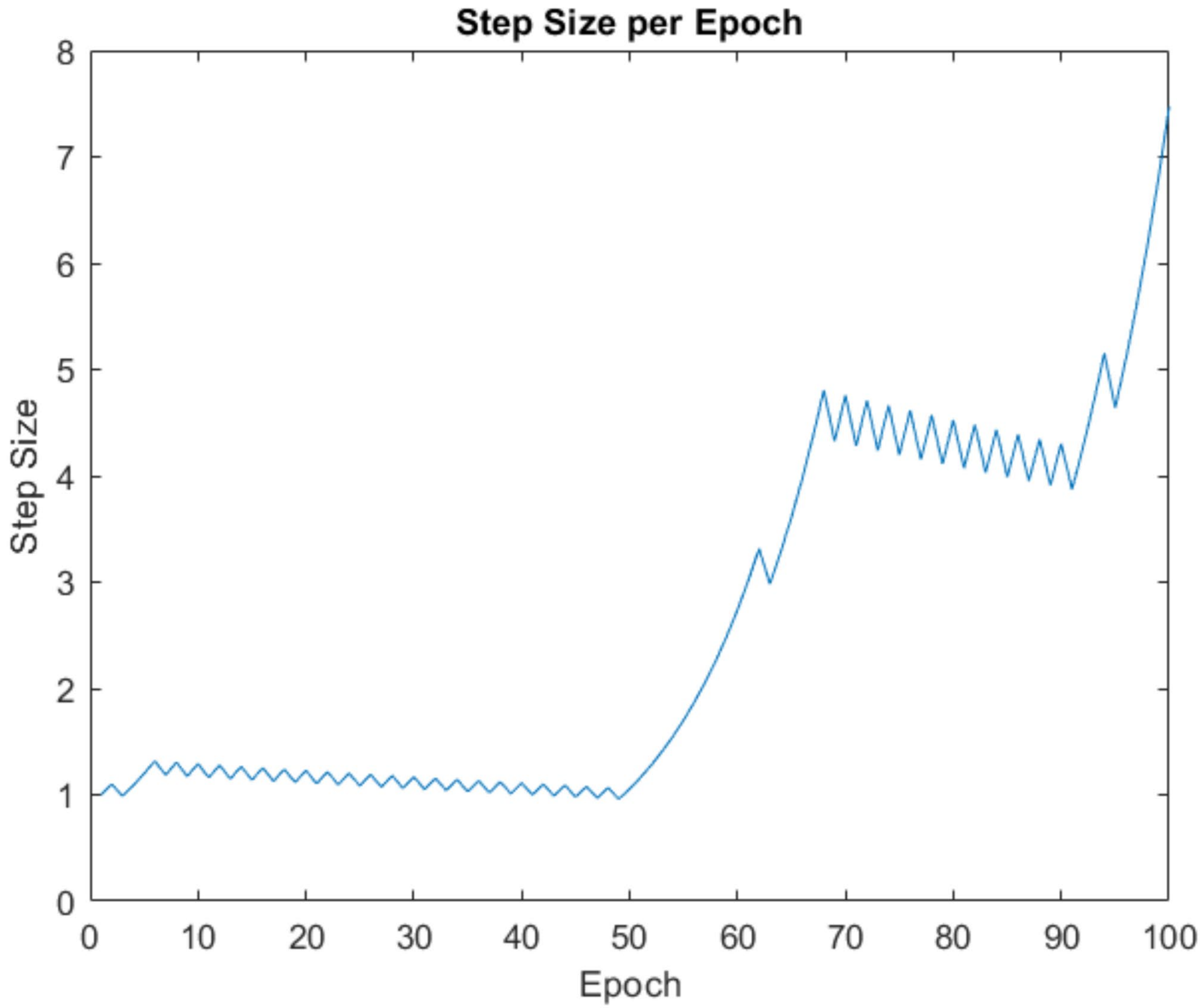

Fig. 13. Step size per each epoch.

Class	Accuracy	Precision	F1-Score	Recall
Relaxed	100%	100%	100%	95%
Concentrating	100%	98%	90%	97%
Neutral	95%	95%	100%	100%
Maximum	100	100	100	100
Minimum	95	95	90	95
Variance	5.00	4.67	16.67	5.33

Table 2. Accuracy, precision, recall and F-score of each class.

fuzzy regression, we can develop a model that not only describes the link between the activities in the brain and the related states of cognition, but also takes into consideration the level of vagueness in the given data Therefore, such a model increases the degree of credibility and accuracy of the predictions[46].

The incorporation of type 2 fuzzy systems and fuzzy regression into ANFIS improves means of dealing with uncertain and ill-defined features of the brain signals and thus improving cognitive pattern recognition. This is especially beneficial in tasks like neurone habitation or BCI and disease detection where accuracy is critical, yet variability is unavoidable. By applying these fuzzy techniques, our method has the ability to consider the inherent uncertainty of multimodal signals from the human brain and offers a more robust and explainable solution to the analysis of the cognitive state[47].

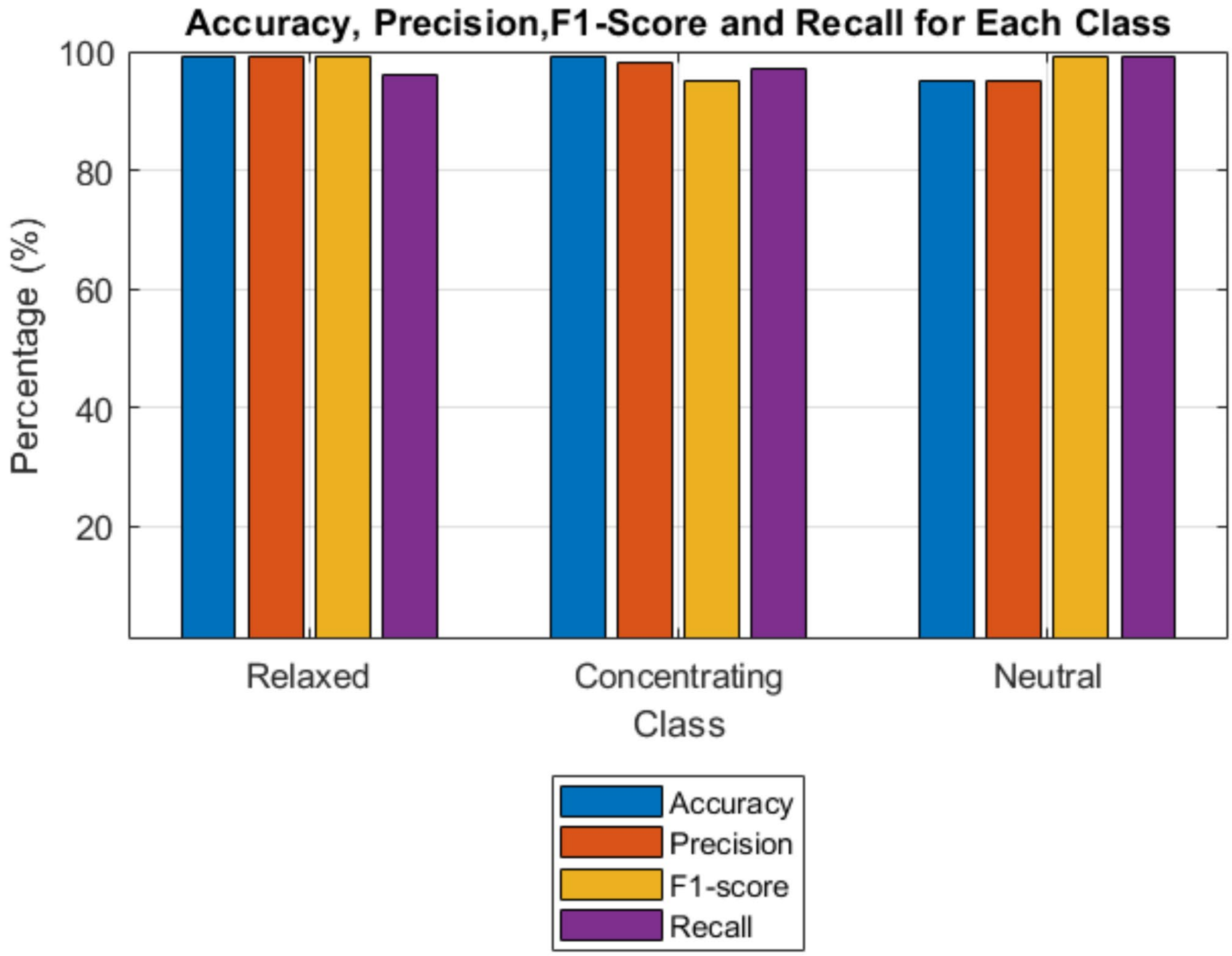

Fig. 14. Performance metrics of each class.

Methods	Accuracy
Matrix determinant and MLP[39]	97%
Weighted complex networks and SVM[40]	94%
MLP [41]	90%
CNN[42]	98%
1D CNN[43]	99%
PCA-ANFIS	99.5%
Max Accuracy	99.5%
Min Accuracy	90%
Variance	8.72

Table 3. Accuracy comparison of proposed PCA-ANFIS with existing approach.

Disease severity and clinical significance

Hence, if quantitative progression of the neurological diseases or the extent of the pathology in a patient is to be understood accurately for diagnosis or follow-up, the parameters of disease quantification become extremely relevant. To sum, the combination of the proposed procedurally theoretical ANFIS model supplemented by non-linear features such as the fractal dimension, entropy and fuzzy entropy has large potential to approach to disease severity and progression of cognitive deficits over time. Because of the utilized inherent functions of ANFIS and incorporation of fuzzy logic this method allows monitoring and analysing subtle shifts in the brain signal patterns that can help monitor the development of various diseases and their clinical meaning[48].

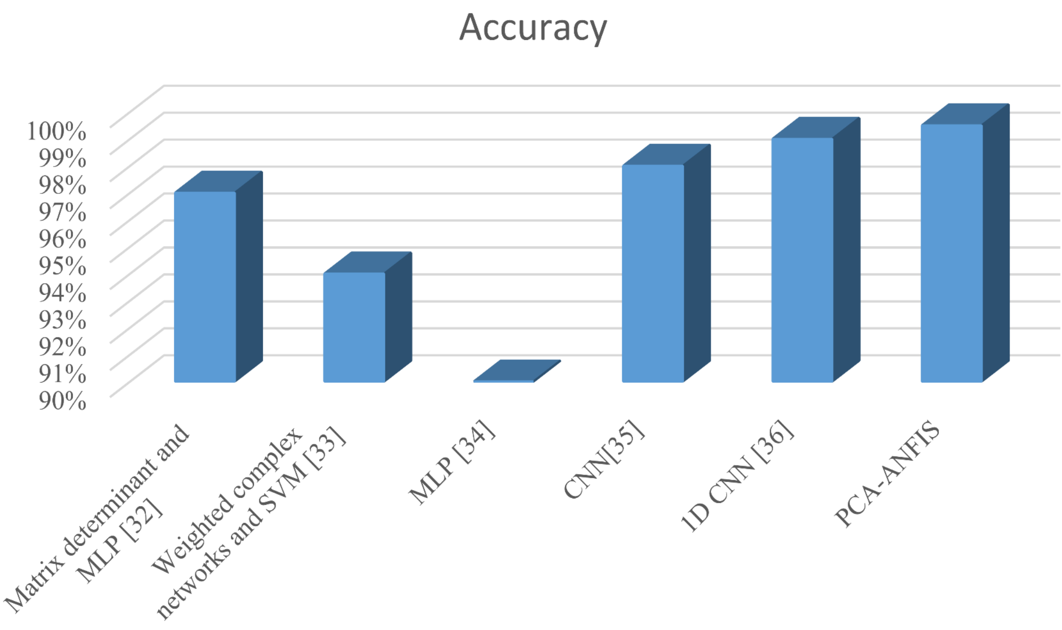

Fig. 15. Accuracy comparison of proposed PCA-ANFIS with existing approach.

Dataset	Accuracy	Precision	Recall
BRATS12	71.2%	85.27%	72.0%
BRATS 13	80.4%	88.7%	84.8%
Proposed EEG signal Data	99.5%	95%	95%
Maximum	99.5	95.0	95.0
Minimum	71.2	85.27	72.0
Variance	172.46	17.16	122.22

Table 4. Performance comparison.

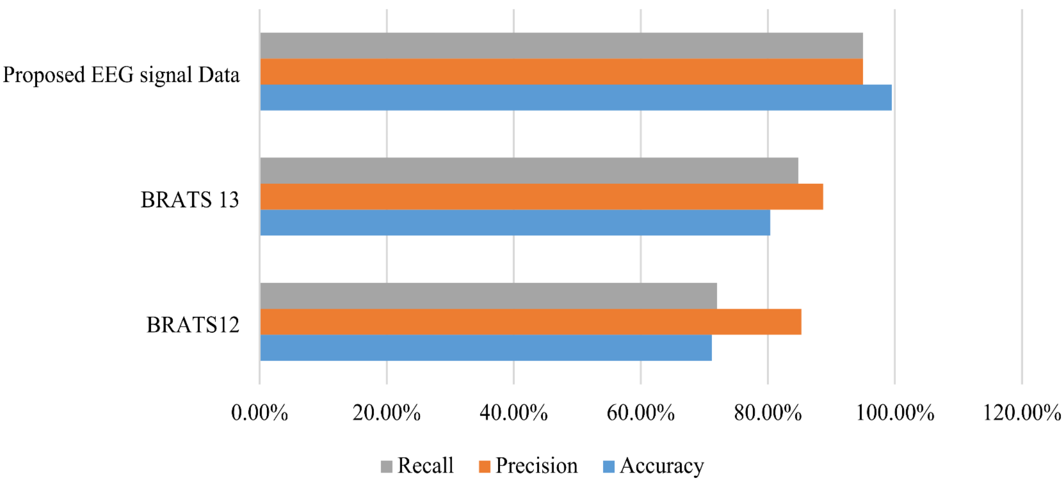

Fig. 16. Performance comparison.

Analysing disease progression
This is important as disease progression is defined in part by changes in brain function that may not always show up on standard examinations or imaging. In conditions like Alzheimer's disease (AD) or Parkinson's disease (PD) or schizophrenia, brain functions get progressively demoralized and movement disorders eventually become apparent. Since application of non-linear features such as fractal dimensions and entropy allow handling of these

changes in a dynamic manner on the proposed ANFIS model. These features involve many characteristics of brain signals, which are chaotic and can express emergent shifts prior to a clear identifiable change[48].

For instance, loss of connectivity between neurons, differences in power and frequency, and maintenance of co-herency in Alzheimer's disease can be computed as fractal dimension and entropy differences. Most of these features are useful in facilitating diagnosis of early cognitive abnormalities in the signal patterns of the brain. Using the above features with ANFIS, the system can quantify the advancement of the disease to the healthcare givers hence assisting in managing and planning patient treatment for disease severity and levels of cognitive impairment[49].

Highlighting clinical significance

The clinical implication of our approach is that it provides interpretable, real-time prediction of disease progression for developing tailored interventions. Thanks to the possibility of plotting temporal changes in the patterns of the recorded signals, the model can be used to assess the efficacy of the treatment measures and prognosis the disease's development. This is particularly important with disease such as Parkinson's disease which varies from patient to patient due to factors such as changes in medication regime, physical therapy and cognitive therapy regimes.

For instance, in Parkinson's disease, using ANFIS for assessment of motor feature and cognitive impairment, based on the multi-modal brain signal data recorded via EEG and other diagnostics. The system is able to identify even minor changes in the rates of brain activity to reflect motor and cognitive dysfunction, including tremors, bradykinesia and others, and offer recommendations on changes to treatment plans as needed. Likewise, in schizophrenia, the cognition and emotions impaired, ANFIS can separate medication influence from disease evolution continuously providing changes of brain signal[50].

Furthermore, the fuzzy logic incorporated in ANFIS can be interpreted easily for developing rules that will explain to human beings the interaction between it and the disease severity proportional to the brain signals that it produces. This can help clinicians make better decisions regarding patient diagnosis and care as well as offer information regarding the impact on different cognitive states or cerebral loci to aid the in overall process of diagnosing the disease.

Our approach provides a valuable framework for monitoring and modelling the course of the disease namely in neurological diseases, in which brain signals reflect changes in cognitive and motor functions[51]. The introduced non-linear features when embedded then in ANFIS model will be useful in enabling the clinician to have a more precise and immediate assessment of the severity of the respective disease so as to enable him or her to intervene appropriately and thus facilitate the drafting of individual patient's treatment plans. Besides it contributes to the field of neurorehabilitation and disease monitoring in general making the method a valuable addition to the clinical practice starting the detection of neurological conditions such as Alzheimer and Parkinson[52].

Here are five key limitations of the study:

- The application of the proposed method is largely a function of the quality of the available multimodal brain signal data. Some origins of variability include noise, artifacts or inconsistency of the signal collection and pre-processing such that their impact may be reflected in the accuracy/ precision of the cognitive PR.
- They further admitted that the method was primarily established with a specific type of data set and may not be readily applicable to other population or other neurological disorders. Demographics and other, coexisting cognitive abnormalities may impact signal differences on which the classification model would depend.
- As much as the ANFIS is a robust model, such a model interpretation might prove quite challenging, thus having implications when applied in clinical practice. The dynamic nature of the model may pose some challenges in that hcahs might not have an advisable grasp of the artificial intelligence techniques used to arrive at given prediction or decisions.
- The addition of non-linear components of fractal dimension, entropy, and fuzzy entropy in the ANFIS model enhances the model's computational intensity. This could prove cumbersome in real-time applications or in a system limited resourced environment such as the clinical setup and, therefore, restrict the practical applicability of the method in clinical practice.
- The collection and analysis of brain signal data are best described as privacy and ethical sensitive due to the nature of health data. Cognitive security of a person and privacy of their brain data is critical as well as ethical and legal norms to avoid misuse and the confidentiality of patients' information.

Conclusion and future work

Multimodal brain signal analysis is significantly impacted by EEG artefact contamination and non-stationarity. There are several challenges and obstacles that must be resolved in order to read and use brain signals to understand cognitive processes and neurological disorders. To recognize the EEG signals using the Adaptive Neuro-Fuzzy Inference System (ANFIS) model, the approach described in the research analyses the cognitive pattern of EEG signals with cognitive processes using variational pattern recognition using brain computation. The most important information is kept while the dimensionality of the EEG data is deducted using Principle Component Analysis (PCA). This process produced a smaller set of 20 primary components that struck a compromise between computational effectiveness and data complexity. The decision-making procedure was carried out by the ANFIS in two steps using the backpropagation method in conjunction with the least square technique. The results are improved since these cognitive signals that distinguish between tasks are congruent with spectral intensity measurement and visual EEG understandings. Task recognition makes it clear that EEG signals may distinguish between complex behaviour or performance-related elements linked to the cognitive components of the work and sensory-motivational and motivating factors. The PCA-ANFIS method outpaces all the other approaches, attaining the highest accuracy of 99.5%. Future work includes testing and enhancing the model's performance with larger, more diverse EEG datasets and exploring potential applications in various fields.

Some essential limitations deserve further attention and can be considered in the development of the further work regarding the proposed method in clinical practice. First, enhanced methods of data pre-processing that will be further discussed allow minimizing noise, artifacts, and inconsistencies within the data, and, as a result, increasing the accuracy. Improving coverage and range of the model to other ethnic groups and neurological disorders will further increase the practical applicability of the system. Introduced next, integrated approaches for model interpretability using explainable AI (XAI) will improve clinicians' understanding of the underlying decision-making process and increase their uptake as well. Measures such as using small models, and incorporating hardware accelerators into the model, should allow real-time operation in scenarios with reduced computing capacity. This calls for a much-needed emphasis on ethical and privacy issues raising adequate protection mechanisms for collected brain signal data to meet the required privacy standards. Possible future research directions are the incorporation of multi-modal data, following the evolution of diseases using longitudinal analyses, and implementing personalisation of cognitive models for better diagnostic and treatment of patients. Overcoming all these hurdles will improve the method's efficiency and expand its use in the diagnosis and management of neurological diseases.

Data availability
The datasets generated and/or analysed during the current study are available in the Kaggle repository, https://www.kaggle.com/datasets/birdy654/eeg-brainwave-dataset-feeling-emotions.

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Author contributions

T. Thamaraimanalan, Dhanalakshmi Gopal wrote the main manuscript text and S.Vignesh, Kishore kumar K prepared Figs. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15 and 16. All authors reviewed the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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