Original Article

A Detailed Analysis & Parametric Comparison Of Eeg Processing Models

Shawetangi Kala[1]*, Dr. Pankaj Kumar Mishra[2], Dr. S. P. Dubey[3]

*[1,2] Rungta College of Engineering & Technology, Bhilai, CG, India, [1]Email: shawetangikala@gmail.com,
[2]Email: pankaj.mishra@rungta.ac.in .
[3]Vice-Chancellor, The ICFAI University, Raipur, CG, India, Email: spdubeyfee@gmail.com

***Corresponding Author:** Shawetangi Kala

*[1]Rungta College of Engineering & Technology, Bhilai, CG, India, Email: shawetangikala@gmail.com,
DOI: 10.47750/pnr.2022.13.S02.44

Abstract

Electroencephalograms (EEGs) are capable of representing brain signals in terms of numerical vector sets. These signals are used to estimate a wide variety of neurological disorders including Dementias, Epilepsy, Parkinson, Stroke, Transient Ischemic Attack, etc. A wide variety of machine learning based methods are proposed for processing these signals, and each of these are variant in terms of the qualitative nuances, function advantages, application-specific characteristics, qualitative limitations, and deployment-specific future scopes. Thus, it is difficult for researchers to identify optimal EEG processing models for their clinical use cases. These models vary in terms of their performance metrics, which further complicates the process of model selection for clinical use cases. To overcome these issues, this paper initially provides a detailed discussion about existing EEG processing techniques, in terms of their functional details. This will allow readers to identify optimal machine learning techniques, which are suited for the functional use cases. Continuing this discussion, a comparative analysis of these models is done on the basis of their clinical accuracy, precision, computational complexity, delay and scalability metrics, which will assist readers to identify models for their performance-specific use cases. Thus, this text will allow readers to identify optimally performing models for different EEG processing scenarios.

Keyword: EEG, Machine, Learning, Bioinspired, computing, Brain, Disease, Clinical, Complexity, cases

1. INTRODUCTION

Recurrent seizure activity is one of the hallmarks of epilepsy as well as a number of other neurological conditions. The sufferers of these seizures, which are brought on by an aberrant release of neurons in the brain, may experience a great deal of bodily as well as mental anguish as a result of their condition. Epilepsy is one of the neurological illnesses that affects a disproportionately high number of individuals throughout the globe and poses a significant risk to their health. It is estimated that fifty million people throughout the globe are afflicted with the disease. When the brain is actively processing information, a large number of neurons collaborate to produce a synaptic postsynaptic potential that is often referred to as a brain wave. It is possible that it will portray the electrophysiological processes that are taking place in the cerebral cortex or on the surface of neurons in the scalp, in addition to oscillations in brain waves that take place while the brain is actively working [1]. As a result of this, the research of brain waves has evolved into a technique that is not only significant but also advantageous for the investigation of epilepsy. Researchers have been studying epilepsy since the 1980s using electroencephalography as their primary tool (EEG). One of the key areas of focus for study is the examination of electroencephalogram (EEG) data with the intention of diagnosing epilepsy [2]. Research of this kind has been carried out continuously since the 1980s. Using a computer classification model, a number of research have focused on the task of identifying characteristics that were collected from EEG signals [3, 4]. The progress that has been achieved in computer science and technology has made it such that this is now possible. When carrying out this sort of research, the following processes are often carried out: data collection and pre-processing using EEG equipment; feature extraction; the training of a classification model; and data prediction. The process of extracting features from the EEG data is one of the processes in the technique that is considered to be one of the most significant steps. The extraction of EEG characteristics may be accomplished via the use of a wide variety of methodologies, such as time-domain, frequency-domain, and time-frequency analyses, in addition to chaotic features [5-7]. In addition, a number of research have integrated or reconstructed these approaches in order to get additional characteristics, which has ultimately provided remarkable classification findings [8–10]. The accuracy of medical EEG collection equipment has seen significant improvements as a result of the expansion of scientific knowledge and the increased power of technology. In addition, it is now possible to get your hands on some portable EEG acquisition gear. For example, emotive has seen significant use in the field of brain-computer interface [11–13] due to its low cost, mobility, and performance that is comparable to those of medical devices. However, despite the fact that a great deal of medical gear and portable EEG collecting devices generate the EEG data, which can be used for research on epilepsy, there are no standard data formats because there are so many different sources of data. This is a limitation of the current state of the field. A few instances of the non-uniform data formats include sample frequencies that differ from one another, signal durations that vary, and sampling channels that vary as well. There is a possibility that inconsistencies in the data requirements will have an effect on the features that are produced via the use of traditional feature extraction techniques. Because of this circumstance, the issue arises as to how the flexibility of classification systems may possibly be strengthened in order to include new data. As a direct result of this, it is essential to make certain that EEG data can be detected and recognized in a more effective manner while simultaneously expanding the scope of the application of classification algorithms. Research into the development of technologies that facilitate more in-depth learning is becoming more popular. This technology can directly avoid the manual design features and extraction process that are required by conventional methods. This eliminates the challenges that are associated with manual design features in conventional methods as well as the difficulties associated with manually adjusting a large number of parameters.

This is attainable due to the fact that this technology is capable of independently gaining knowledge from data. In-depth learning technologies make it possible to do a great number of tasks that would be difficult to carry out using more conventional approaches. [14]. In the study of EEG, several researchers have used the utilization of a deep neural network [15]. Using a short-time Fourier transform, in [16] researchers were able to convert one-dimensional brain waves into two-dimensional visual data. After that, they utilized a deep neural network to classify the data they had collected. The frequency bands that were recovered from brain waves were converted into topographical maps in [17], who employed spectral power to do so (two-dimensional images). Following that, depth networks were applied to each of the photographs. Work in [18] developed a therapy for the prevention and treatment of epilepsy by using a solution that was based on an in-depth learning technique that was constructed on a cloud platform. A deep network-based coding technique was developed for the analysis of epileptic EEG data by both [19] and [20]. While the bulk of these studies have concentrated on regular data. For instance, they have kept the frequency and duration of the sample data samples the same across all of their research scenarios.

In the next portion of this paper, researchers will go through a review of other machine learning based approaches that are comparable to one another in terms of their quantitative performance measurements as well as their qualitative features. The next step is to conduct a parametric analysis of the models that have been assessed, as well as their comparative assessment, which will help in determining which models are the most suited for the various clinical use cases. In the conclusion, this piece of writing will come to a close with some context-specific remarks about the models that have been examined, as well as some recommendations for approaches to further improve its performance levels under various usage circumstances.

2. IN DEPTH REVIEW OF EXISTING EEG PROCESSING MODELS

There are many different machine learning-based models that have been suggested for processing EEG data, and each one has different qualitative and quantitative performance indicators. EEG is a useful method for diagnosing epilepsy since it is affordable, accessible, and noninvasive [1]. Long-term EEG recordings are a hardship for neurologists and other professions. Automatic EEG classification may help doctors recognize and treat individuals with epilepsy more effectively. We describe a Wavelet Convolution Neural Network that categorizes EEG data by attention in this research. The input EEGs are first decomposed into frequency band components using a Wavelet Convolution Neural Network trained on the Attention Mechanism. An attention method is used to classify and extract features from a convolutional neural network (CNN) utilizing decomposed multi-scale EEGs. Using the Bern-Barcelona EEG database, the suggested method obtains a binary classification accuracy of 99.70%. Experimental results have shown that the proposed approach Delivers state-of-the-art EEG classification results.

The topic was also looked at in [2]. Classification of EEG data to forecast human intention and behavior is a hot topic in BCI research. Recent studies have shown that CNN is more effective at categorizing EEG data. EEG data is being categorized using convolutional neural networks (CNNs), although these techniques are not particularly precise. A convolutional neural network (CNNlast)'s layer of feature maps, which lacks the local and granular data necessary for successful classification, is utilized by the bulk of presently used algorithms to merely detect EEG signals. This article describes how to classify multi-scale EEG data using a convolutional neural network. In this case, time-frequency images are produced by first processing EEG data using STFT. To classify EEG data, the changed time-frequency image is fed into a multi-scale convolutional neural network (CNN) model. The multi-scale CNN model takes into account both the local and global environments. The effectiveness of the recommended method is evaluated using the BCI contest IV benchmark data set 2b. The recommended approach improves classification accuracy over prior techniques by 10.4, 5.5, And 16.2 percent for support vector machines, stacked auto- encoders, and artificial neural networks, respectively.

EEG data's non-linearity and non-stationarity provide a significant challenge when attempting emotion identification [3]. (ER). Deeply buried EEG signal qualities at various levels cannot be recovered using existing feature extraction algorithms for effective categorization. Finding precise and practical feature extraction techniques for various EEG data formats could be challenging. The objective of this study is to provide a method for deep feature extraction that may be used to determine people's attitudes. Reliable deep features are discovered using networks like AlexNet, VGG16, ResNet50, Squeeze Net, and MobilNetv2. In order to do this, we first preprocess EEG rhythm images using Wavelet Transform (WT) and Continuous Wavelet Transform, and then we run those images through five well-known pretrained CNN models (CWT). The qualities are then classified into valence and arousal groups using DEAP data-based simulations and the suggested method's use of SVM. AlexNet features with Alpha rhythm had the best accuracy results (91.07% in channel Oz), whereas MobilNetv2 features with Delta rhythm (with channel C3) have the highest accuracy scores (98.93% in valence discrimination).

The classification of EEG signals provides a number of applications, as demonstrated in [4]. Two-stage techniques are used for this sorting. Examples of this include sorting and pre-processing. Attributes are created to classify signals during the pre-processing phase. It has been shown that this alteration may remove crucial information and provide dubious classification characteristics. This data loss could be compensated by using fuzzy classification features and fuzzy classifiers. It takes an extra step to pre-process the raw EEG data into fuzzy features. Fuzzification. The classification of EEG data using fuzzy classifiers is discussed in this article. Both fuzzy decision trees and fuzzy random forests are utilized to evaluate the strategy's efficacy. The fuzzy decision tree's and fuzzy random forest's accuracy levels are fairly high (up to 99.5%). Because they are more accurate, fuzzy classifiers perform better at classifying EEG data than non-fuzzy ones.

The development of BCI systems and technologies, according to [5,] depends on the P300 electroencephalogram (EEG) signal classification methods. A support vector neural network (SVNN) is proposed and constructed in this research to enhance the categorization of EEG data. This paper employs linear variational inequality to tackle classification problems for the first time using primal-dual neural networks and support vector machines. To demonstrate its global convergence and parallelism, SVNN iterates parameters as matrices until a convex optimization problem obtains an optimal solution. SVNN is used to categorize P300 EEG data. Dataset II from the BCI competition III and dataset IIb from the BCI competition II both provide perfect results when employing the proposed SVNN method. Both recognition accuracy and data transfer rate are at their highest with SVNN.

A block design, in which all stimuli from a single class are shown at once, is necessary for reliable EEG classification findings, while a rapid-event strategy, in which stimuli from many classes are presented in a random order, is unhelpful, according to researchers in [6]. Instead than using correlations in how people respond to stimuli, the block design uses temporal interactions between blocks to describe how the brain is functioning. Since many training trials and all test trials come from the same block, the block architecture of test trials detects illogical temporal artifacts rather than stimulus-related activity. The validity of any conclusions drawn from a later study of this data in other research is therefore called into doubt. The fact that a new item classifier generated using a random codebook outperforms one made using EEG data demonstrates this. Their research shows that temporal autocorrelations in neuroimaging data have the potential to have significant classification effects. Their study has improved our ability to understand the complexity at work and prevent us from generating too gloomy yet incorrect predictions.

To reduce the need for costly processing, the authors of [7] suggest using a hybrid neural network feature selection technique for identifying people's emotions. With the introduction of neural networks as machine learning tools for Edge Computing in the Internet of Things, the importance of EEG-based emotion classification is growing. Emotion classification is challenging due to the non-linear nature and weak temporal bounds of EEG data. For non-linear feature extraction, researchers advise using a hierarchical Semi-skipping Layered Gated Unit (SLGU). Recurrent neural networks' Gated Recurrent Units (GRU) use a semi-skipping layer to speed up processing (RNN). While being taught, the network ignores the divergence at the entry layer. Deep characteristics are derived from pre-processed EEG inputs using the hybrid SLGU-ENet model. Computing expenses might be decreased by using the Bag of Visualized Characteristics (BoVC). The capability allows for the comparison of two different public datasets. The proposed approach improves classification accuracy and speeds up processing while falling short of state-of-the-art techniques. The recommended method might be used for real-time IoT since it was quick (between 1.2 and 5 seconds).

The authors claim that recent advances in EEG signal classification have shown a reliance on domain-specific strategies that limit algorithm adaption. In this study, we propose CABLES, a computer-aided EEG approach for progressively categorizing six EEG domains. This research provides three distinctive components: Sample reduction using t-distributed stochastic neighbour embedding, feature selection using ensemble optimization, and complex variational mode decomposition (CVMD) (tSNE-SR) Using neural network, extreme learning machine, and machine learning classifiers with 10-fold cross-validation, we perform extensive experiments on seven distinct datasets. Motor imaging (datasets A and B), cortical potential amplitude (SCP), epilepsy, alcoholism, and schizophrenia databases The classification precision for EEG datasets ranges from 99.1% to 97.8%, 94.3 to 91.5%, and 99.9 to 95.3 to 92.2 percent. The suggested CABLES framework is a superior automated brain rehabilitation system, exceeding existing domain-specific strategies in terms of classification accuracy and multirole flexibility, according to the empirical investigation.

According to [9], electroencephalography (EEG) may be used to identify neurological problems and mental diseases. The classification and analysis of EEG data might help with more precise illness and anomaly diagnosis. We enhance EEG classification abilities by using a novel data encoding strategy that benefits from the physical layout of EEG sensors. The recommended technique of data representation frequently outperforms one that ignores sensor design in terms of classification accuracy. The recommended two-dimensional image-like representation of the EEG channel locations is in contrast to a one-dimensional concatenation of the frequency band channels. Machine learning uses models as a tool. The classification of social anxiety disorders and the detection of emotions using the DEAP dataset for physiological emotion analysis are the two tasks used to evaluate the models. The results show that the two-dimensional model performs better than the one-dimensional model. In terms of accuracy, our model typically outperforms rival machine learning techniques by 5-8%. SVM and k-Nearest Neighbors are significantly outperformed by convolutional neural networks in terms of performance.

In order to categorize task-state EEG data before and after spatial cognitive training, researchers in [10] proposed a multi-scale high-density convolutional neural network (MHCNN) classification approach for assessing spatial cognitive abilities. The properties of the EEG frequency band were discovered utilizing multidimensional conditional mutual information. Combining properties from many frequency bands led to the creation of multispectral images. Densenet was developed to improve the multi-scale convolutional neural network. Using multispectral image data, two-scale convolution kernels were initially trained on crucial channel and frequency band feature data. With the goal of reducing the number of parameters and maximizing feature propagation, the dense network was connected after the multi-scale convolutional network, and the stochastic gradient descent algorithm's learning rate change function was enhanced to allow for an objective evaluation of the training's efficacy. According to the test findings, the recommended MHCNN was able to recognize in six different combinations of frequency bands with a greater accuracy of 98%: theta-alpha2-gamma, alpha-beta2-gamma, beta-beta2-gamma, and theta-alpha1-gamma. Out of the six possible pairings, the theta-beta-gamma triple of frequency bands had the strongest classification impact. The MHCNN classification method that was used in this study has the potential to be used as a biomarker of the effects of training on spatial cognitions as well as a generalizable tool for evaluating brain processes.

Using brain-computer interfaces, the categorization of motor imagery electroencephalogram (MI-EEG) tasks is notoriously challenging [11]. (BCIs). Due to the nonstationary, time-variable, and individual variance of EEG data, an SSD-SE convolutional neural network (CNN) is offered for MI-EEG classification. The three divisions are as follows: Channel-wise characteristics are adaptively recalibrated using squeeze-and-excitation (SE) blocks, which performs better than traditional classification techniques in terms of accuracy and kappa value. We first suggest the sparse septotemporal decomposition (SSD) feature extraction approach. A convolutional neural network (CNN) is then constructed in order to fully use the time-frequency data. When compared to cutting-edge methods, the proposed framework delivers better classification quality and durability. The accuracy, efficiency, and durability of SSD-SE-excellent CNN throughout trials and sessions are advantageous for long-term MI-EEG applications.

Studies mentioned in [12] suggest that EEG scans may reveal the electrical activity of the brain. Only a few neurological diseases, such as epilepsy, schizophrenia, sleep issues, and Parkinson's disease, may be diagnosed and evaluated with the use of EEG signals. The authors recommend using two deep learning methods when examining EEG data to look for indications of epilepsy and schizophrenia. Procedures: Deep learning algorithms have the ability to autonomously do feature engineering, unlike traditional machine learning algorithms. The complicated, non-linear problems that occur in real life are immune to swarm intelligence. The Bat Algorithm (BA), Cuckoo Search Optimization (CSO), and Particle Swarm Optimization are used in the first technique, which combines a sparse autoencoder (SAE) with a swarm-based deep learning approach (SASDL) (PSO). The second technique involves reinforcement learning, which incorporates Q learning, an Attention Mechanism, Tree Long-Short Memory (LSTM), Bidirectional Long-Short Term Memory (BiLSTM), and an Attention Mechanism (RBLSTM). Finally, we draw the conclusion that both of these cutting-edge deep learning systems obtain a classification accuracy of over 93% when tested on epileptic and schizophrenia EEG datasets.

According to [13], brain-computer interfaces might be helpful for tetraplegic people. (BCIs). Few studies have focused on right/left hand/foot motions in place of tongue movements while creating a multiclass BCI. In this study, features and classifiers were used to decode the four tongue movement directions (left, right, up, and down) from pre-movement EEG recorded from a single session. For detection and classification in an offline investigation, researchers examined temporal, spectral, entropy, and template characteristics (10 able-bodied participants). Investigations were conducted utilizing the most recognizable kind of motion in both the 3-class and 2-class situations. The accuracy of motion detection and classification was greatly increased by the application of linear discriminant analysis. The up-and-down tongue movements had the highest detection accuracy, whereas the right-to-left tongue motions had the worst. While the 3-class and 2-class categories' accuracy rates were 75.68.4% and 87.78.0%, respectively, the 4-class classification's accuracy was 62.67.2%. The accuracy of categorization was increased by combining temporal and template features. This is most likely caused by the movement-related cortical potentials' bilateral asymmetries. This study emphasizes the need of cortical tongue representations for BCIs that can recognize various kinds of movement.

The researchers in [14] highlighted that, like other machine learning-based methods used for alcoholism detection, their method was unable to extract deep EEG data layers. This research presents a deep learning-based approach for detecting intoxicated EEG data. It also investigates if a certain feature extraction technique may improve deep learning's capacity to classify alcoholism. This study examines two classification schemes for alcoholics based on deep learning and EEG data. Principal component analysis (PCA) is used to extract features in the first method, which are then fed into an artificial neural network (ANN) for classification. Using inputs of unprocessed EEG data, the second approach use LSTM to detect alcoholism. utilized a public EEG dataset made available by UCI to try it out and evaluate the impacts of alcohol consumption. According to our experiments, Algorithm 2 is more accurate than Algorithm 1 in terms of categorization, with an average accuracy of 93%. The second algorithm performs better than the best ones already in use in the sector. Deep learning applied to raw data may provide better results than deep learning combined with hand-crafted features. Their strategy makes it easy to monitor treatment progress and spot EEG abnormalities caused by alcohol use.

[15] claims that it is unclear what length an EEG signal sequence should be at in order to improve emotion detection and retention rates. As far as is known, the impact of an EEG signal's duration on classifier accuracy hasn't been thoroughly studied. Obtaining high-quality EEG data is difficult due to human factors including attention deterioration and weariness. In this study, we investigate the short, medium, and long signal durations in the DEAP, MAHNOB, and STEED EEG datasets. For an EEG dataset to be helpful for emotion identification, it must satisfy two key requirements: (1) it must include publically available emotion stimulus data, and (2) it must be lengthy enough to have an impact on individuals. At least for the datasets under examination, longer signals provide better categorisation. This research did not look at how long-term exposure to stimulating media affects individuals.

As described in [16], advances in emotion recognition may result in greater human-computer interaction. One of the difficulties of identification tasks is the acquisition of reliable EEG representations. In this study, we provide a deep learning framework for EEG-based emotion recognition. Prior to that, the temporal context elements of the EEG data are weighted using a 1-D convolution layer. Next, spatial electrode correlations are recorded using 1-D dense structures. The proposed technique efficiently extracts features from noisy EEG data by taking into account electrode correlations and temporal dependencies. Finally, two well-known EEG emotion datasets are examined for validity. They achieve accuracy rates that are, on average, greater than competing studies (90.63% and 92.58% on the SEED and DEAP datasets, respectively). This cutting-edge method provides a clear result for EEG categorization issues.

In [17], a method based on signaling games is used to evaluate the best EEG electrode selection for noise reduction in spatial filtering of brain responses. Using the typical CSP filter as an input, this method generates the ideal electrode configuration for identifying mental processes as an output. When there is noise in the EEG data, the typical CSP algorithms are more likely to choose electrodes or signal sources that are unneeded for a certain cognitive activity, which lowers classification accuracy. The regularization term has received a lot of attention in this study since it may be used to the traditional CSP approach. These methods do not account for the differences in subjective brain response that occur both within and between sessions. The intra- and inter-session variation in scalp EEG data is captured by the fuzzy set that was used to construct the fuzzy signaling game-based strategy to optimize electrode selection in this study. Experimental results on a variety of categorization issues in cognitive tasks show that the recommended method increases electrode selection accuracy. Statistics from a Friedman test show how successful the proposed tactic is.

We have a method for identifying emotions that is user-independent and makes use of EEG data as well as the vast learning system, based on research from [18]. (BLS). For our objectives, we use DEAP and MAHNOB-HCI. Just one EEG electrode channel is employed for feature extraction. The GSI feature, a time-frequency representation of brain activity as captured by EEG, is extracted using continuous wavelet transform (CWT). Improved EEG-based emotion categorization accuracy is one of the ground-breaking BLS for emotion classification's key benefits. Results of the experiments show that the proposed work provides a trustworthy system with a high average accuracy of 94.4% and a training time of 0.6 s for the MAHNOB-HCI database.

The Transformer's feature correlation extraction and display method uses long-sequence data [19]. For precise classification, EEG data across time points and channels must exhibit spatial and temporal correlations. Transformer-based techniques for categorizing and visualizing motor-imagery EEG have not garnered much attention in the literature, especially without cross-individual validation. Using the PhysioNet dataset, researchers developed Transformer-based algorithms to categorize motor imagery EEG. In cross-individual validation using three samples of EEG data, their models outperformed prior state-of-the-art models on two-, three-, and four-class motor-imagery tasks by 0.88, 2.11, and 1.06%, respectively. Positional embedding modules in Transformer may improve EEG classification. The functioning of Transformer-based networks in motor imagery tasks was shown by examining attention weights. Analysis of the spectral distribution of Mu and beta rhythms revealed event-related desynchronization (ERD) and the geography of attention weights across sensorimotor areas. Their deep learning methodologies equip them with cutting-edge, effective tools for analyzing EEG data, which has ramifications for BCI technology.

Electroencephalogram (EEG) signal data classification is essential for epilepsy diagnosis, according to [20]. The automatic identification of EEG data has recently seen substantial improvements because to sparse representation-based classification (SRC) methods. In order to classify EEG signals according to reconstruction requirements, only a small number of active coefficients are used in the dictionary. The fact that the majority of SRC only learn a linear dictionary for encoding precludes them from adequately extracting nonlinear features for classification. An HD-SRC model for EEG signal identification is proposed to overcome this problem. HD-SRC may employ neural networks to learn hierarchical nonlinear transformations and convert signal data into nonlinear space. HD-SRC seeks to minimize classification, reconstruction, and discriminative sparse-code errors by using a dictionary-based discriminative representation. Improved data discrimination is made possible by concurrently studying a hierarchical feature mapping and a discriminative lexicon.

Experimental results from the Bonn EEG database sets show that the proposed model has a high degree of classification performance across a wide variety of EEG signal identification activities.

According to [21], classifying brain activity from EEG data is crucial for developing BCI applications. The interconnectedness of the brain during cognition is downplayed by the majority of existing approaches, which treat each channel separately. With the use of this study, multi-channel EEG data from various people may be categorized using a graph signal structure (MTMC-EEG). Each channel's EEG time series serves as a node in a task-based network. A smoothness constraint may be used in Graph Signal Processing (GSP) to identify the functional connection between brain nodes. We show the graph spectral properties of the two-norm total variation of eigen vector (TNTV) and the Laplacian energy (GLE), which employ the eigenvalues of the Laplacian matrix (JTVE). The suggested method is evaluated and compared to the state of the art using benchmark classifiers and two publically available datasets of MTMC EEG signals. In order to further verify the proposed measure, its accuracy, F-Score, and information transfer rate are compared to those of Gaussian RBF-based functional connectivity and Pearson correlation on smoothed graphs (ITR). The proposed method is verified by adding white Gaussian noise (AWGN) to EEG data at different signal-to-noise ratios.

According to [22], depression affects people's mental health on a global scale. Different neurophysiological reactions to both positive and negative stimuli are seen in healthy vs. depressed individuals. It was shown how to use spatial EEG to identify depression. Sixteen people with depression and fourteen controls took part in a face-in-the-crowd test with neutral and happy feelings. The evolutionary approach and differential entropy were used to select prospective traits for further study. TCSP was created before feature extraction to better accurately identify spatial differences. Classification outcomes for positive and negative stimuli using leave-one-subject-out cross-validation were 84% and 85.7% with TCSP and 81.7% and 83.2% without it, respectively (p 0.05). It has been shown that the gamma frequency range is best for categorization precision. Numerous classifiers, including logistic regression and k-nearest neighbour, showed improvements in classification using TCSP. Conclusion: It is feasible to identify depressed persons more precisely by taking location into account.

For the classification of EEG sleep phases in preterm babies, Sinc is a specific variant of the Convolutional Neural Network Inception (iCNN) block [23]. (EEG). At some facilities, just one or two EEG channels may be recorded. When there are fewer channels, multi-channel EEG automated systems now in use perform poorly. In order to reduce reliance on particular EEG channels, Sinc does a number of scale analysis on temporal EEG data. To prevent overfitting and reduce the number of trainable parameters, the researchers at Sinc employ Inception to enhance receptive fields and switch out equivalent filters. We train and assess this model using longitudinal EEG data from 26 preterm neonates. Modern techniques for identifying new-born calm sleep are outperformed by a sinc-based model, which has an accuracy of 0.77 (using 8-channel EEG) and 0.75. (with a single bipolar channel EEG). We are aware of no other effort that employs filter sharing and Inception-based networks for EEG analysis. The suggested network may be utilized in hospitals to detect calm sleep times using a single EEG channel as they often monitor patients' brain activity.

The findings in [24] indicate that it is difficult to diagnose heroin addiction using EEG data. Healthy brain microstates and mental well-being are related. How heroin affects the microstates of the brain is unclear. Researchers suggest a hybrid classifier that effectively distinguishes between AHAIs and controls using resting-state EEG microstate features (HCs). In addition to the original length, occurrence, and change, three additional criteria have been introduced. With a 73% accuracy rate, support vector machine (SVM) is the most reliable classifier for identifying AHAIs and HCs. When the weights were altered, GA's accuracy rose to 81%. The hybrid categorization presents empirical evidence that microstate characteristics may be employed as biomarkers for diagnosing AHAIs and suggests a strategy for differentiating between the brain states of addicts and non-addicts. Additionally, it shows that AHAIs may be discriminated from HCs based on EEG microstate characteristics. They might provide electrophysiological insight into the impacts of heroin withdrawal treatment thanks to their methods and personalities.

According to [25], alcoholism is associated with deficits in emotional regulation and behavior. Alcoholism may be recognized using EEG patterns. Prior machine learning and deep learning projects were largely concerned on alcoholism diagnosis. Sliding single spectrum analysis was used to decompose and denoize the EEG data in this investigation (S-SSA). The EEG components of drinkers and non-alcoholics were separated using independent component analysis (ICA). Then, using these elements, SVM, KNN, ANN, GBoost, AdaBoost, and XGBoost were trained to differentiate between drunk and sober EEG data. Model complexity and calculation time are decreased by sliding SSA-ICA. They compared the ICA's calculation time and accuracy to those of linear discriminant analysis and principal component analysis in order to evaluate the ICA's performance (LDA). The technique is examined utilizing University of California, Irvine, inebriated EEG data. Researchers use the F1 score, accuracy, precision, and recall to evaluate machine learning models. XGBoost is a very trustworthy classifier with a 98.97% accuracy rate. The recommended approach is shown by comparing classification metrics to the most productive recent research.

Another technological revolution in human-computer connection will begin once it is known how to classify EEG data for use in brain computer interfaces (BCIs). Since the EEG output is irregular and nonstationary, feature extraction and data mining are crucial for effective BCI EEG categorization. Improved BCI EEG classification and ELM techniques are suggested in this work using novel bionic whale optimization algorithms (WOA) [26]. The arbitrary weight initialization of the standard ELM is handled by two improved WOA-ELM algorithms. To avoid selecting the wrong candidate, we begin by selecting and voting for the best candidates. Then, using the bubble-net attacking strategy (BNAS) and a shrinking encircling mechanism, WOA optimizes the weights and bias of the initial connections between the nodes in the input layer and the nodes in the hidden layer (SEM). To enhance the generalization performance of the strategy, we use a variety of regularization methods across layers to produce a weight matrix that is properly sparse. The results of the comparison show that, on average, the proposed method outperforms state-of-the-art BCI methods.

Because it may be possible to monitor neurological patients with ALS, ASD, or Alzheimer's disease in real-time, interest in EEG-based wearable emotion classifiers has lately surged. The use of wearable emotion classifiers may improve patient socialization and medical results. Despite the importance of emotion classification to neuromedicine, hardware solutions for emotion categorization [27] have limitations in how they classify emotions in a medical setting. The theoretical foundations, computational architectures, and feature extraction methods of wearable emotion classifiers based on EEG data are examined by the authors of this work. This paper presents a neuroscience-based analysis of the state-of-the-art hardware emotion classifier accelerators and makes use of this analysis to outline potential future research areas, such as multi-modal hardware platforms, accelerators with closely coupled cores operating in the near/supra-threshold region, and pre-processing libraries for popular EEG-based datasets.

According to [28], manually staging EEG sleep data is a time-consuming, expensive, and error-prone process. The creation of an automated approach for identifying EEG sleep phases is of interest to researchers and medical professionals. In this study, a technique for classifying single-channel EEG data automatically into several sleep patterns is presented. Researchers replicate the intended study with noise using Lorenz and Rossler time series. Studies using the Rechtschaffen and Kales scale and the American Academy of Sleep Medicine sleep phases show that the proposed technique works better than the alternatives.

The method used in [29] to extract pain-related variables from EEG data was one way to objectively assess suffering. This study suggests a unique classification approach for assessing pain on a range of one to five, as well as quick EEG processing steps. 24 healthy individuals who were doing the cold pressor test had their EEGs captured. The first step was to remove EEG artifacts using independent component analysis. We looked for useful guidelines to apply while selecting sources in order to relieve discomfort. Electroencephalograms (EEGs) were reconstructed once sources were selected. Grand average brain maps were then calculated for each pain intensity in the Alpha(8–12 Hz) and Delta(0.5–4 Hz) frequency ranges. The observed alterations in brain mapping as pain intensity increased led to the creation of the recommended decision tree. To complete the data set, the researchers uncovered various other EEG features. For each node in the chain of options, a constrained subset of characteristics was picked in a forward-only fashion. The classification accuracy for the three pain levels and the five pain levels, using k-nearest neighbor (KNN) as the decision marker, was 80.5 and 60.5%, respectively. The outcomes improved to 83.5 and 62.6 percent after applying a support vector machine (SVM).

Broad adoption of such systems is difficult due to the need for a high number of channels in EEG-based brain-computer interfaces (BCIs), which may sometimes reduce classification performance. Despite multiple tries, it is still challenging to find the optimal subject-specific channel selection without losing classification performance. The authors of this paper propose a unique method for automatically finding a set of discriminative EEG channels called spatiotemporal-filtering-based channel selection (STECS) [30]. The channel selection problem in STECS is handled as a spatiotemporal filter optimization subject to group sparsity constraints using a computationally efficient approach. The evaluation of STECS makes use of three different motor imagery EEG datasets. When evaluating contemporary spatiotemporal filtering methods using full EEG channels, STECS achieves classification performance on par with the best of these systems. STECS outperforms other well-known channel-selection algorithms by a wide margin. These results imply that this strategy could make BCI deployments simpler and more useful.

Using EEG data to predict the beginning of an epileptic episode is a difficult area of study [31]. This article describes the development of a new algorithm for classifying epileptic situations. It makes use of bespoke features for multichannel EEGs, feature fusion and transfer learning (TL) with many deep neural networks (DNNs) that have already been trained, and discriminative feature extraction and epileptic state classification using a hierarchical neural network (HNN). In order to display multichannel EEGs, a MAS, MPSD, and WPF are first created, and then all of those features are combined into a single picture. The next step uses five common pre-trained DNNs to extract features from fused images. Make use of a 7-layer fully-connected (FC) HNN that classifies epileptic situations using discriminative traits. Effectiveness has been shown in experiments utilizing the CHB-MIT and iNeuro epileptic EEG datasets.

Both patients and technicians may experience discomfort as a result of the intensive use of electrodes during multichannel EEG. Wearable and point-of-care EEG devices cannot be developed because of the large number of electrodes required. To address this problem, the single-channel electroencephalogram (SCEEG) [32] was created. SCEEG is simple to use, inexpensive, widely available, and even wearable, despite having a lower spatial resolution than multichannel devices. SCEEG was utilized in this study to distinguish between major depressive disorder patients who reacted to rTMS and those who did not (MDD). To forecast a patient's reaction against repeated transcranial magnetic stimulation, researchers compared single-channel EEG to multichannel EEG (rTMS). Before receiving rTMS, 46 individuals with MDD had 19-

electrode EEGs. After undergoing treatment, 23 of the patients saw improvements. The testing (with 36 participants) and training datasets are distinct (10 subjects). Linear and nonlinear analyses were performed on EEG channels. mRMR was used to select pertinent attributes during training. Use of KNN with leave-one-out cross-validation allowed for the classification of the relevant features. The classification technique is applied to the validation set. F8 has an 80% success rate in differentiating between respondents and non-respondents. Both SCEEG and multichannel EEG have the ability to forecast how MDD therapy with rTMS will turn out. Their method of using SCEEG to predict how well rTMS would work to treat MDD patients offers exciting possibilities.

Researchers in [33] looked at the impact of recovering lost EEG data on tensor-based hand movement classification. Prosthetics must be properly classified in order for them to work properly. Accuracy of categorization is impacted by data quality. Data seen may be less trustworthy due to artifacts like disconnected electrodes. In this work, missing EEG data is recovered and hand movements are identified using tensor-based imputation techniques such as canonical/polyadic decomposition (CPD), weighted optimization version of CPD (CP-WOPT), and Nonnegative Matrix Factorization (NMF). Since data loss occurs in the actual world in a planned manner, this was examined. The rate rose to 50% when there was a 10% data omission. Several different types of data, including whole, partial, and recovered data, are used to evaluate a classifier's performance. Their system's effectiveness was shown by a mean classification accuracy of 71%, 53%, and 64% on complete, missing, and recovered data, respectively.

A tensor-based MTL classification method is examined in [34]. Training samples are often tiny and may be grouped into multidimensional arrays in real-world applications (tensors). The idea that using structural knowledge that is shared across related activities may enhance generalization performance has researchers interested in MTL. It is advised to use regularized MTL to combine feature selection with classification. Researchers choose discriminating characteristics and manage within-class nonstationarity using the Fisher discriminant criterion. Both general and task-specific structural data are used for categorisation. Each task's regression tensor consists of two components: a shared component and an individual component. The scaled latent trace norm and the l1-norm are used to regularize the shared tensor. To address the issues of combined learning of discriminative features and multitask classification, the authors provide an effective optimization strategy based on ADMMs. They provide evidence from genuine EEG datasets to support the efficacy of their strategy.

According to [35], EEG-based brain-computer interface (BCI) devices are extensively used in the medical field. Researchers have concentrated on raising the classification accuracy of EEG data in order to enhance BCI functionality. In this article, we provide a novel method for investigating BCIs using visual evoked potentials (VEPs). First, standardized visual evoked potential (VEP)-based brain exams like SSVEP and SSVEP are utilized to gather EEG data (SSMVEP). Initial attributes are collected using LPVG and its degree sequence. These details are supplied to a BLS for the purpose of categorizing SSVEP and SSMVEP signals. The classification results show that their LPVG-based BLS can correctly categorize VEP-based EEG signals since it has a sensitivity of 96.22% for SSVEP and a specificity of 74.54% for SSMVEP. These results significantly outperform those of conventional CCA-based methods. By using network science and BLS, these technologies open up new options for researching EEG-based BCI systems.

While the spatial architecture of the electrode channels is ignored, the common group sparse optimization technique enables simultaneous channel selection and classification for motor imagery EEG inputs. In order to create a unique classification model, the group sparsity and spatial smoothness of the EEG data are merged (LASSO) [36]. The disputing group is known as LASSO. In order to account for the group sparsity of EEG signals, the first step is to assign features of the same channel the same weight in group LASSO. The group LASSO-based regularizer total variation norm (TV-norm) ensures that the weights of neighboring channels are equal or the same. This enables the spatial smoothness of EEG signals to be mimicked. The primal-dual theory is used to optimize the new model. The new model was tested using three data sets: two from a public BCI competition and one from the researcher's own trials. The recommended approach improves physiological interpretability by an average of 81.09%, 86.64%, and 79.24%, as well as classification accuracy. Comparing the proposed method to spatial filtering methods with smooth restrictions, it produced an average classification accuracy of 84.96% across two competition data sets. According to experimental findings, the proposed technique enhances BCI performance.

[37] asserts that knowledge of human dishonesty is essential for law enforcement and national security. Using the subcomponent of electroencephalography (EEGP300), a hidden information test has been developed (CIT). Memory-related stimuli cause the P300 subcomponent to be activated. Using the P300 feature, test participants are shown pictures of both known and unidentified people. When a person is exposed to a visual display, EEG data is recorded. Processing, interpretation, and classification of raw EEG data. This is how CIT EEGs are categorized. The extraction of spatial components from EEG data is made possible by identifying a common spatial pattern (0.5-30 Hz). A potent fuzzy integrator is developed using data acquired from classifier performance assessments. For defuzzification, the generalized mean of maxima (GMoM) function has been recommended. The experimental results demonstrate a greater degree of classification accuracy for the fuzzy-based CIT.

Also looked at by [38]. The efficiency of any nuclear power plant depends on how efficiently it is managed. Those who will be in charge of a reactor must obtain medical clearance before they are allowed to run the controls. To categorize an operator's FFD, the authors of this study use deep learning techniques based on EEG data. Using EEG data collected during normal cognitive tasks, the mental state of employees in the nuclear business was evaluated. An operator's level of intoxication, stress, and weariness may be promptly and economically identified using the FFD classification approach, which is based on EEG monitoring. The goal of this study was to examine the implementation of the EEG-based FFD status classification system with information security that complies with ISO/IEC standards. The capacity of various data security techniques to safeguard anonymity, data integrity, and privacy was investigated. The resulting technique increases classification performance without sacrificing near-real-time safety for FFD databases and sensitive user data.

Researchers may more precisely identify and grasp sleep EEG events by analyzing sleep EEG signals [39]. The objective of this work is to use time-frequency analysis to classify EEG sleep stages. The spectral estimate of a signal is calculated using controlled wavelets and the multitier network with convolution (MT&C) approach. In this study, MT&C is used to examine one sleep EEG channel. There are two ways to group the different stages of sleep. The first method uses EEG wave classifications of various sleep stages to categorize each 30 second EEG segment following feature extraction (Rules-based strategy). The second method employs an SVM-Q classifier that has been trained using information acquired from the insights of domain experts. The results of the experiment show that the SVM-Q classifier has an overall accuracy of 90% when applied on healthy individuals, whereas the Rules-based approach has an accuracy of 87.6%. In contrast to the Rules-based technique, which had an accuracy rate of 73.4%, the SVM-Q classifier had a rate of 78.1% for data from aberrant sleep EEG.

[40] contains research that is relevant. Recently, deep architectures and neural networks have attracted a lot of attention for the purpose of deciphering EEG data in brain-computer interfaces (BCIs). In comparison to earlier methods that required signal amplification before classification, end-to-end models are more effective. They might replace specialized training and personal qualities. Numerous deep learning algorithms have been proposed, and they have shown astounding efficacy in recognizing kinetic or cognitive processes. The neuroscience community, however, disapproves of them since they are hard to understand. One possible contributing aspect is the high parameter density of deep neural networks, which makes them too sensitive to the detection of seemingly unrelated signals. The EEG-ITNet was proposed by the researchers as a complete deep learning architecture and a method to visually monitor network activities. In comparison to EEG-Inception and EEG-TCNet, their model uses inception modules and causal convolutions with dilation to extract rich spectral, spatial, and temporal information from multi-channel EEG data with fewer trainable parameters. In a variety of circumstances, the OpenBMI motor imaging dataset and dataset 2a from the fourth BCI competition enable EEG-ITNet increase classification accuracy by up to 5.9%. Neuroscientists provide evidence for and an explanation of network representations.

The present study focuses on understanding the brain state for brain-computer interface (BCI) and motor imaginary explorations [41]. The brain's health has an effect on intelligence and cognitive ability. A three-part categorization scheme for EEG findings is proposed in this study. We provide feature extraction, feature selection, and categorization. Using partial directed coherence, a sparse MVAR model is transformed into a new sparse parametric feature matrix (PDC). In the gLASSO technique, the MVAR is sparse. The sparse MVAR model's coefficient matrix serves as the foundation for the sparse PDC (sPDC). The mutual information (MI) approach is then used to prioritize the extracted energy, relative energy, entropy, and conditional entropy values from the sPDC. Third, we use the characteristics inferred from sPDCs to categorize the control and reflective brain states. Classification was done using a polynomial kernel support vector machine (k-SVM). The recommended method consistently and solidly divides participants into two groups.

According to studies [42], EEG screening is required for precisely identifying the regions of focal seizures prior to surgery. The authors of this paper provide an algorithm for identifying and categorizing intense EEG signals. Time-varying brain oscillations were discovered by collecting EEG data from persons with temporal lobe epilepsy and dividing it into focal and non-focal EEG components. To examine the relationship between the EEG rhythms in terms of time scale and time-frequency frame, researchers performed cross wavelet transform (XWT) on the remaining EEG rhythms with their respective reference rhythms after selecting one EEG signal at random from each rhythm to serve as a reference. For automatic EEG feature extraction and classification, cross-rhythm spectrum time-frequency image plots with a tailored CNN model were made accessible. The benchmarks for the proposed CNN model were VGGNet16 and AlexNet. In comparison to existing CNN algorithms, the suggested framework required much less time to identify EEG data and was 100% correct for the delta () rhythm. One particular EEG rhythm's maximal detection rate was discovered, pointing to its possible use in real-time monitoring of focal epilepsy.

The study of and use of quantum algorithms, or quantum machine learning (QML) [43], may enhance the performance of machine learning on quantum computers relative to conventional ones. Here, we examine a method for collecting and classifying EEG properties that is hierarchically organized and based on quantum physics. First, the collected classical EEG signals are transformed into a quantum form while retaining their original sign. The wavelet packet energy entropy (WPEE) characteristic of the quantum classifier is identified, and it is used to convert the wavelet packets into the quantum state (QWPT). The researchers propose to anticipate the label assigned to an electroencephalogram (EEG) signal by using a quantum support vector machine with a nonlinear kernel. The proposed framework is shown to be ten times faster than its structured classical counterpart by a complexity study. Measurements derived from actual experiments are used to establish the feasibility and validity of these claims.

This was also looked at in [44]. When it comes to conveying emotion, aBCIs may make use of a wide variety of EEG features from a number of frequency bands and channels. Given the limited and uneven nature of EEG data, it is crucial to examine emotional activation patterns for use in cross-session emotion detection. A self-weighted semi-supervised classification (SWSC) model for cross-session emotion detection and emotional activation patterns mining is proposed in order to overcome these difficulties. The following are some benefits of doing so: There are three methods offered: Three strategies are used to increase data collection: 1) mixing labelled and unlabelled samples from several sessions; 2) learning the value of EEG characteristics quantitatively and adaptively using a self-weighted variable; and 3) combining labelled and unlabelled samples. When tested across many sessions, SWSC performed well, with average accuracy levels of 77.40%, 79.55%, and 81.52%. In addition to the prefrontal, left/right temporal, and (central) parietal EEG channels, SWSC shows that the Gamma frequency band is the most crucial for cross-session emotion recognition.

For popular epileptic EEG signal recognition methods, labeled training data is required [45]. Additionally, these methods perform poorly when used to train and analyze EEG signal samples from different distributions, such as patient groups or data collection devices. This article describes the CDC-KUM model, a cross-domain categorization technique that makes the most of currently accessible data. It makes use of labelled and unlabelled samples from the current and related domains. The source domain labelled data's expected differences are combined into a single term using the pairwise constraint regularization. The target domain's unlabelled data distribution is exploited via a soft clustering regularization with quadratic weights and Gini-Simpson diversity. For classifying epileptic EEG data, CDC-KUM outperformed both non-transfer and transfer classification algorithms.

EEG-based emotion recognition is another area where ML-based systems have shown potential [46]. Five EML algorithms and five CML algorithms' abilities to recognize human emotions from EEG data are examined in this study. An ML-based system is built utilizing the publicly available DREAMER collection of emotions, and it is then tested using the SEED, INTERFACES, and MUSEC benchmarks. Using a discrete wavelet transform, theta, alpha, beta, and gamma bands from EEG signals are separated into their own intrinsic mode functions using empirical mode decomposition (IMFs). Then, a machine learning (ML)-based system is built using bagging, random forest, rotation random forest, extreme gradient boost, and adaptive boosting to recover 31 statistical characteristics from IMFs. Ten-fold cross-validation is used to compare five EML algorithms with five CML algorithms in terms of accuracy, F1-score, kappa-score, and area-under-the-curve (AUC). For arousal (88.95% vs. 83.08%) and valence (88.90% vs. 82.81%), five EML algorithms' mean accuracy is 5.87% and 6.08% higher than five CML algorithms'. For arousal and valence, the EML-based bagging approach achieved the highest accuracy, F1-score, kappa-score, and area under the curve (AUC). The pattern is consistent across three different validation datasets, according to the evidence. EML algorithms are superior then CML ones in identifying emotions.

Work was discovered in [47]. Recent advances in deep learning have made it feasible to develop EEG decoding systems that can understand motor images. Classification loss is currently only used by a small percentage of deep learning-based systems, which is hindering improvements in EEG decoding accuracy. In order to improve feature discrimination, this work suggests a discriminative feature learning technique based on central distance loss (CD-loss), central vector shift, and central vector update. It is suggested that samples first converge to the central vector using CD-loss. To improve the separation between the various sample classes in the feature space, the central vector shift method is applied. The central vector update method makes it possible to reduce beginning value effects and get rid of CD-loss non-convergence. Another issue with deep learning-based EEG decoding is overfitting. To increase experimental data sets without introducing noise or losing information, a circular translation-based data augmentation approach is created. Two publicly downloadable motor imaging EEG datasets were used by researchers to evaluate the approach (BCI competition IV 2a and 2b dataset). On both experimental datasets, their method consistently and typically has the greatest accuracy.

Big data analytics may aid in the identification and management of severe neurological illnesses, claims a research published in [48]. Popular supervised machine learning algorithms were tested for their ability to distinguish between individuals with traumatic brain injury (TBI) and those who have a stroke or an electroencephalogram that is otherwise normal (EEG). Methods: For the two-class classification of TBI patients from healthy persons and the three-class classification of TBI, stroke, and healthy individuals, SVM and KNN models were constructed utilizing a large feature set from the Temple EEG Corpus. At 10-fold CV, the accuracy for two-class classification was 0.94; at independent validation, it was 0.76. (IV). The three-class categorization exercise yielded scores of 0.85 for both CV and IV. CV, IV, and two- and three-class classification using LDA feature selection and SVM models were effective. Increased alpha, mu, beta, and gamma power was seen in patients with stroke or traumatic brain injury, along with decreased coherence and relative PSD in the delta frequency range. The theta power change was more noticeable in stroke patients. Finally, machine learning that is given EEG data may aid in categorizing TBI. Their research suggests that EEG ML might one day be utilized to distinguish between various neurological diseases.

Researchers in academia and industry who have focused on developing methods for accurately categorizing people's emotional states based on electroencephalogram (EEG) data have established the groundwork for more natural and intuitive machine-human interactions. The bulk of recent studies have either employed "feature transformation with classification" to identify emotions or have identified the most significant EEG properties directly. However, the latter often fails to function well and violates feature transformation and recognition. The authors of this paper propose combining discriminative subspace identification with emotion detection using semi-supervised sparse low-rank regression (S3LRR) [49]. By breaking down the projection matrix in LSR into two component matrices, S3LRR is created, which allows thorough discriminative subspace identification and establishes a connection between the representation of subspace EEG data and associated emotional states. We find that SEED V's cooperative learning model for S3LRR enhances emotion recognition. S3LRR also chooses EEG parameters and examines emotional activation patterns.

Both medical rehabilitation and cognitive research may benefit from the BCI technology, which employs electroencephalogram (EEG) impulses to establish direct communication between the human body and its surroundings. The introduction of deep learning technologies, notably the recognition and processing of motor imagery signals using CNN frameworks, has considerably enhanced the BCI system in recent years [50]. Due to the complexity of the required data representation, the end-to-end method lowers recognition. Because brain electrical capacitance is susceptible to interference from noise and other signal sources, EEG classifiers may be challenging to train and generalize. This article proposes a novel method for classifying EEG motor imagery data, which removes unwanted background noise using a variational autoencoder and then integrates a deep autoencoder (DAE) with a convolutional neural network (CNN) architecture. This setup may tell a deep neural network to precisely repeat its input and output via a series of encoding and decoding procedures. The proposed system for categorizing motor images performed well in testing. The performance of CNN-based and traditional machine learning methods was inferior to that of EEG data sets. Thus, the intrinsic performance characteristics of each of these approaches vary. The process of choosing the best model for EEG-based classification methods is further made simple in the next section, which compares the examined approaches in terms of several performance indicators and aids in the discovery of the best models for various use cases.

3. STATISTICAL ANALYSIS

Based on the extensive review of existing EEG processing models, it can be observed that these models vary largely in terms of their internal characteristics, and various performance levels. Thus, to simplify the process of model selection for different use cases, this section compares the reviewed models in terms of classification accuracy (A), precision (P), computational complexity (CC), classification delay (D), and scalability (S) levels. While values of accuracy & precision are directly available with the reviewed models, computational complexity, delay and scalability were estimated in terms of their approximate ranges, which were decided as Low Level (L=1), Medium Level (M=2), High Level (H=3), and Very High Level (VH=4), based on their internal characteristics. Using this strategy, the models were compared in table 1 as follows,

Model	A	P	CC	D	S
WCNN [1]	99.70	92.84	VH	H	M
STFT CNN [2]	98.50	92.78	VH	H	VH
CWT [3]	98.90	91.47	H	H	H
Fuzzy [4]	99.50	89.16	M	L	H
SVNN [5]	94.30	84.75	H	M	H
RC [6]	91.50	86.25	M	M	H
SLGU [7]	85.40	87.63	H	H	H
CVMD [8]	99.10	91.56	H	M	H
CNN [9]	95.90	91.63	H	M	H
Dense Net [10]	98.00	90.72	VH	VH	VH
SSD CNN [11]	99.30	87.50	VH	H	H
SAE SAS DL [12]	93.00	85.53	VH	H	VH
LDA [13]	87.70	76.78	M	L	H
PCA LSTM [14]	93.00	78.28	VH	H	M
Linear [15]	65.00	75.31	M	L	L
1D CNN [16]	92.50	84.50	H	H	H
Fuzzy CSP [17]	83.50	86.16	M	H	M
HLS CWT [18]	94.40	83.78	H	H	H
Xmer [19]	97.80	84.41	H	M	M
HD SRC [20]	75.90	80.63	H	H	M
JTVE [21]	96.40	81.13	M	H	H
TCSP [22]	85.70	76.31	H	H	M
iCNN [23]	77.50	80.44	H	M	H
GA SVM [24]	81.00	86.59	L	L	VH
ICA [25]	98.90	90.59	L	M	H
WOA ELM [26]	97.20	82.97	H	M	H
LRTS [28]	93.80	78.59	H	H	H
KNN [29]	74.50	79.84	M	H	M
STECS [30]	83.20	84.81	H	H	H
HNN [31]	97.80	88.03	H	H	H

Hybrid KNN [32]	90.40	84.16	H	VH	M
CP WOPT [33]	93.50	85.97	M	H	H
MTL [34]	85.40	83.81	H	H	H
CCA [35]	96.20	83.34	H	M	H
LASSO [36]	86.60	81.16	M	H	M
Fuzzy [37]	83.90	83.50	L	M	M
MT&C [39]	89.20	85.88	H	H	H
ITNet [40]	94.10	89.09	H	VH	VH
gLAS SO [41]	91.50	89.72	H	VH	H
XWT [42]	99.50	86.59	VH	H	L
QML [43]	96.10	85.66	H	VH	H
SWSC [44]	81.50	83.41	H	H	M
CDC KUM [45]	96.50	86.66	H	VH	H
CML [46]	88.90	85.34	VH	H	H
CTDA [47]	91.90	86.75	H	M	H
LDA SVM [48]	92.30	89.03	L	M	M
S3LRR [49]	93.40	90.33	VH	H	H
DAE CNN [50]	99.20	91.52	VH	H	H

Table1. Comparative evaluation of different EEG processing models

Based on this comparison, it can be observed that WCNN [1], Fuzzy [4], XWT [42], SSD CNN[11], DAE CNN [50], and CVMD [8] showcase high accuracy, while WCNN [1], STFT CNN [2], CNN [9], CVMD [8], DAE CNN [50], and CWT [3] showcase high precision, thus they can be used for a wide variety of high-performance EEG use cases.

In terms of complexity GA SVM [24], ICA [25], Fuzzy [37], and LDA SVM [48] are preferred, while in terms of high-speed operations LDA [13], Linear [15], and GA SVM [24] must be used so that EEG signals can be quickly classified into different categories. In terms of scalability, XWT [42], and Linear [15] showcase better performance, thus can be used for a wide variety of clinical scenarios. Thus, based on this comparison, researchers will be able to identify optimal models for different use cases.

4. CONCLUSION AND FUTURE SCOPE

After conducting a comprehensive analysis of the numerous EEG processing models that are now in use, it has been shown that these models exhibit a great deal of diversity in terms of the intrinsic properties that they possess as well as the different performance levels that they can achieve. As a result, the first section of this study presents a comprehensive analysis of the EEG processing approaches that are currently in use, focusing on the operational specifics of these methods. In continuation of this conversation, a comparative analysis of these models is done on the basis of their clinical accuracy, precision, computational complexity, delay, and scalability parameters. This study will aid readers in identifying models for their own performance-specific use cases. On the basis of which, it can be observed that WCNN [1], Fuzzy [4], XWT [42], SSD CNN [11], DAE CNN [50], and CVMD [8] showcase high accuracy, while WCNN [1], STFT CNN [2], CNN [9], CVMD [8], and DAE CNN [50] showcase high precision, and as a result, they can be utilized for a wide variety of high-performance EEG use cases. CWT [3] In terms of complexity, the GA SVM [24], the ICA SVM [25], the Fuzzy SVM [37], and the LDA SVM [48] are favored, while in terms of high-speed operations, the LDA [13], the Linear [15], and the GA SVM [24] must be employed so that EEG data may be swiftly sorted into distinct categories. XWT [42] and Linear [15] both provide higher performance in terms of scalability, and as a result, they are suitable for a broad range of clinical applications. Therefore, on the basis of this comparison, the researchers will be able to determine which models are the most effective for various use cases. In the future, researchers will be able to increase the performance of the model in a variety of contexts by using techniques like as deep learning and other transformer-based approaches.

REFERENCES

1. Q. Xin, S. Hu, S. Liu, L. Zhao and Y. -D. Zhang, "An Attention-Based Wavelet Convolution Neural Network for Epilepsy EEG Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 957-966, 2022, doi: 10.1109/TNSRE.2022.3166181.
2. C. Huang, Y. Xiao and G. Xu, "Predicting Human Intention-Behavior Through EEG Signal Analysis Using Multi-Scale CNN," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 18, no. 5, pp. 1722-1729, 1 Sept.-Oct. 2021, doi: 10.1109/TCBB.2020.3039834.
3. F. Demir, N. Sobahi, S. Siuly and A. Sengur, "Exploring Deep Learning Features for Automatic Classification of Human Emotion Using EEG Rhythms," in IEEE Sensors Journal, vol. 21, no. 13, pp. 14923-14930, 1 July1, 2021, doi: 10.1109/JSEN.2021.3070373.
4. J. Rabcan, V. Levashenko, E. Zaitseva and M. Kvassay, "EEG Signal Classification Based On Fuzzy Classifiers," in IEEE Transactions on Industrial Informatics, vol. 18, no. 2, pp. 757-766, Feb. 2022, doi: 10.1109/TII.2021.3084352.
5. Z. Zhang, G. Chen and S. Chen, "A Support Vector Neural Network for P300 EEG Signal Classification," in IEEE Transactions on Artificial Intelligence, vol. 3, no. 2, pp. 309-321, April 2022, doi: 10.1109/TAI.2021.3105493.
6. R. Li et al., "The Perils and Pitfalls of Block Design for EEG Classification Experiments," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 43, no. 1, pp. 316-333, 1 Jan. 2021, doi: 10.1109/TPAMI.2020.2973153.
7. M. A. Asghar, M. J. Khan, H. Shahid, M. Shorfuzzaman, N. N. Xiong and R. M. Mehmood, "Semi-Skipping Layered Gated Unit and Efficient Network: Hybrid Deep Feature Selection Method for Edge Computing in EEG-Based Emotion Classification," in IEEE Access, vol. 9, pp. 13378-13389, 2021, doi: 10.1109/ACCESS.2021.3051808.
8. X. Yu, M. Z. Aziz, M. T. Sadiq, K. Jia, Z. Fan and G. Xiao, "Computerized Multidomain EEG Classification System: A New Paradigm," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 8, pp. 3626-3637, Aug. 2022, doi: 10.1109/JBHI.2022.3151570.

9. L. S. Mokatren et al., "EEG Classification by Factoring in Sensor Spatial Configuration," in IEEE Access, vol. 9, pp. 19053-19065, 2021, doi: 10.1109/ACCESS.2021.3054670.
10. D. Wen et al., "Task-State EEG Signal Classification for Spatial Cognitive Evaluation Based on Multiscale High-Density Convolutional Neural Network," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 1041-1051, 2022, doi: 10.1109/TNSRE.2022.3166224.
11. B. Sun, X. Zhao, H. Zhang, R. Bai and T. Li, "EEG Motor Imagery Classification With Sparse Spectrotemporal Decomposition and Deep Learning," in IEEE Transactions on Automation Science and Engineering, vol. 18, no. 2, pp. 541-551, April 2021, doi: 10.1109/TASE.2020.3021456.
12. S. K. Prabhakar and S. -W. Lee, "SASDL and RBATQ: Sparse Autoencoder With Swarm Based Deep Learning and Reinforcement Based Q-Learning for EEG Classification," in IEEE Open Journal of Engineering in Medicine and Biology, vol. 3, pp. 58-68, 2022, doi: 10.1109/OJEMB.2022.3161837.
13. R. L. Kæseler, T. W. Johansson, L. N. S. A. Struijk and M. Jochumsen, "Feature and Classification Analysis for Detection and Classification of Tongue Movements From Single-Trial Pre-Movement EEG," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 678-687, 2022, doi: 10.1109/TNSRE.2022.3157959.
14. L. Farsi, S. Siuly, E. Kabir and H. Wang, "Classification of Alcoholic EEG Signals Using a Deep Learning Method," in IEEE Sensors Journal, vol. 21, no. 3, pp. 3552-3560, 1 Feb.1, 2021, doi: 10.1109/JSEN.2020.3026830.
15. E. T. Pereira, H. M. Gomes, L. R. Veloso and M. R. A. Mota, "Empirical Evidence Relating EEG Signal Duration to Emotion Classification Performance," in IEEE Transactions on Affective Computing, vol. 12, no. 1, pp. 154-164, 1 Jan.-March 2021, doi: 10.1109/TAFFC.2018.2854168.
16. Z. Gao, X. Wang, Y. Yang, Y. Li, K. Ma and G. Chen, "A Channel-Fused Dense Convolutional Network for EEG-Based Emotion Recognition," in IEEE Transactions on Cognitive and Developmental Systems, vol. 13, no. 4, pp. 945-954, Dec. 2021, doi: 10.1109/TCDS.2020.2976112.
17. B. Chakraborty, L. Ghosh and A. Konar, "Optimal Selection of EEG Electrodes Using Interval Type-2 Fuzzy-Logic-Based Semiseparating Signaling Game," in IEEE Transactions on Cybernetics, vol. 51, no. 12, pp. 6200-6212, Dec. 2021, doi: 10.1109/TCYB.2020.2968625.
18. S. Issa, Q. Peng and X. You, "Emotion Classification Using EEG Brain Signals and the Broad Learning System," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 51, no. 12, pp. 7382-7391, Dec. 2021, doi: 10.1109/TSMC.2020.2969686.
19. J. Xie et al., "A Transformer-Based Approach Combining Deep Learning Network and Spatial-Temporal Information for Raw EEG Classification," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 30, pp. 2126-2136, 2022, doi: 10.1109/TNSRE.2022.3194600.
20. X. Gu, C. Zhang and T. Ni, "A Hierarchical Discriminative Sparse Representation Classifier for EEG Signal Detection," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 18, no. 5, pp. 1679-1687, 1 Sept.-Oct. 2021, doi: 10.1109/TCBB.2020.3006699.
21. P. Mathur and V. K. Chakka, "Graph Signal Processing Based Cross-Subject Mental Task Classification Using Multi-Channel EEG Signals," in IEEE Sensors Journal, vol. 22, no. 8, pp. 7971-7978, 15 April15, 2022, doi: 10.1109/JSEN.2022.3156152.
22. C. Jiang, Y. Li, Y. Tang and C. Guan, "Enhancing EEG-Based Classification of Depression Patients Using Spatial Information," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 566-575, 2021, doi: 10.1109/TNSRE.2021.3059429.
23. H. Ansari et al., "A Deep Shared Multi-Scale Inception Network Enables Accurate Neonatal Quiet Sleep Detection With Limited EEG Channels," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 1023-1033, March 2022, doi: 10.1109/JBHI.2021.3101117.
24. J. Wang, R. Peng, Q. Liu and H. Peng, "A Hybrid Classification to Detect Abstinent Heroin-Addicted Individuals Using EEG Microstates," in IEEE Transactions on Computational Social Systems, vol. 9, no. 3, pp. 700-709, June 2022, doi: 10.1109/TCSS.2021.3135425.
25. S. Agarwal and M. Zubair, "Classification of Alcoholic and Non-Alcoholic EEG Signals Based on Sliding-SSA and Independent Component Analysis," in IEEE Sensors Journal, vol. 21, no. 23, pp. 26198-26206, 1 Dec.1, 2021, doi: 10.1109/JSEN.2021.3120885.
26. Z. Lian, L. Duan, Y. Qiao, J. Chen, J. Miao and M. Li, "The Improved ELM Algorithms Optimized by Bionic WOA for EEG Classification of Brain Computer Interface," in IEEE Access, vol. 9, pp. 67405-67416, 2021, doi: 10.1109/ACCESS.2021.3076347.
27. H. A. Gonzalez et al., "Hardware Acceleration of EEG-Based Emotion Classification Systems: A Comprehensive Survey," in IEEE Transactions on Biomedical Circuits and Systems, vol. 15, no. 3, pp. 412-442, June 2021, doi: 10.1109/TBCAS.2021.3089132.
28. S. Supriya, S. Siuly, H. Wang and Y. Zhang, "EEG Sleep Stages Analysis and Classification Based on Weighed Complex Network Features," in IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 5, no. 2, pp. 236-246, April 2021, doi: 10.1109/TETCI.2018.2876529.
29. T. Nezam, R. Boostani, V. Abootalebi and K. Rastegar, "A Novel Classification Strategy to Distinguish Five Levels of Pain Using the EEG Signal Features," in IEEE Transactions on Affective Computing, vol. 12, no. 1, pp. 131-140, 1 Jan.-March 2021, doi: 10.1109/TAFFC.2018.2851236.
30. F. Qi et al., "Spatiotemporal-Filtering-Based Channel Selection for Single-Trial EEG Classification," in IEEE Transactions on Cybernetics, vol. 51, no. 2, pp. 558-567, Feb. 2021, doi: 10.1109/TCYB.2019.2963709.
31. D. Hu, J. Cao, X. Lai, Y. Wang, S. Wang and Y. Ding, "Epileptic State Classification by Fusing Hand-Crafted and Deep Learning EEG Features," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 68, no. 4, pp. 1542-1546, April 2021, doi: 10.1109/TCSII.2020.3031399.
32. F. Hasanzadeh, M. Mohebbi and R. Rostami, "Single Channel EEG Classification: A Case Study on Prediction of Major Depressive Disorder Treatment Outcome," in IEEE Access, vol. 9, pp. 3417-3427, 2021, doi: 10.1109/ACCESS.2020.3046993.
33. M. Akmal, S. Zubair and H. Alquhayz, "Classification Analysis of Tensor-Based Recovered Missing EEG Data," in IEEE Access, vol. 9, pp. 41745-41756, 2021, doi: 10.1109/ACCESS.2021.3063382.
34. Q. Zheng, Y. Wang and P. A. Heng, "Multitask Feature Learning Meets Robust Tensor Decomposition for EEG Classification," in IEEE Transactions on Cybernetics, vol. 51, no. 4, pp. 2242-2252, April 2021, doi: 10.1109/TCYB.2019.2946914.
35. Z. Gao, W. Dang, M. Liu, W. Guo, K. Ma and G. Chen, "Classification of EEG Signals on VEP-Based BCI Systems With Broad Learning," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 51, no. 11, pp. 7143-7151, Nov. 2021, doi: 10.1109/TSMC.2020.2964684.
36. S. Zhang, Z. Zhu, B. Zhang, B. Feng, T. Yu and Z. Li, "Fused Group Lasso: A New EEG Classification Model With Spatial Smooth Constraint for Motor Imagery-Based Brain–Computer Interface," in IEEE Sensors Journal, vol. 21, no. 2, pp. 1764-1778, 15 Jan.15, 2021, doi: 10.1109/JSEN.2020.3016402.
37. Bablani, D. R. Edla, V. Kupilli and R. Dharavath, "Lie Detection Using Fuzzy Ensemble Approach With Novel Defuzzification Method for Classification of EEG Signals," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-13, 2021, Art no. 2509413, doi: 10.1109/TIM.2021.3082985.
38. J. H. Kim, Y. Cho, Y. -A. Suh and M. -S. Yim, "Development of an Information Security-Enforced EEG-Based Nuclear Operators' Fitness for Duty Classification System," in IEEE Access, vol. 9, pp. 72535-72546, 2021, doi: 10.1109/ACCESS.2021.3078470.
39. Zapata, Y. Li and P. Wen, "Rules-Based and SVM-Q Methods With Multitapers and Convolution for Sleep EEG Stages Classification," in IEEE Access, vol. 10, pp. 71299-71310, 2022, doi: 10.1109/ACCESS.2022.3188286.
40. Salami, J. Andreu-Perez and H. Gillmeister, "EEG-ITNet: An Explainable Inception Temporal Convolutional Network for Motor Imagery Classification," in IEEE Access, vol. 10, pp. 36672-36685, 2022, doi: 10.1109/ACCESS.2022.3161489.
41. L. Shaw and A. Routray, "Brain State Classification With Group l1 – norm Sparse PDC as Novel Features for EEG," in IEEE Sensors Journal, vol. 21, no. 12, pp. 13506-13513, 15 June15, 2021, doi: 10.1109/JSEN.2021.3068125.
42. S. Modak, S. Singha Roy, R. Bose and S. Chatterjee, "Focal Epileptic Area Recognition Employing Cross EEG Rhythm Spectrum Images and Convolutional Neural Network," in IEEE Sensors Journal, vol. 21, no. 20, pp. 23335-23343, 15 Oct.15, 2021, doi: 10.1109/JSEN.2021.3111102.

43. Y. Li, R. -G. Zhou, R. Xu, J. Luo and S. -X. Jiang, "A Quantum Mechanics-Based Framework for EEG Signal Feature Extraction and Classification," in IEEE Transactions on Emerging Topics in Computing, vol. 10, no. 1, pp. 211-222, 1 Jan.-March 2022, doi: 10.1109/TETC.2020.3000734.
44. Y. Peng et al., "Self-Weighted Semi-Supervised Classification for Joint EEG-Based Emotion Recognition and Affective Activation Patterns Mining," in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-11, 2021, Art no. 2517111, doi: 10.1109/TIM.2021.3124056.
45. K. Xia, T. Ni, H. Yin and B. Chen, "Cross-Domain Classification Model With Knowledge Utilization Maximization for Recognition of Epileptic EEG Signals," in IEEE/ACM Transactions on Computational Biology and Bioinformatics, vol. 18, no. 1, pp. 53-61, 1 Jan.-Feb. 2021, doi: 10.1109/TCBB.2020.2973978.
46. S. Kamble and J. Sengupta, "Ensemble Machine Learning-Based Affective Computing for Emotion Recognition Using Dual-Decomposed EEG Signals," in IEEE Sensors Journal, vol. 22, no. 3, pp. 2496-2507, 1 Feb.1, 2022, doi: 10.1109/JSEN.2021.3135953.
47. Yang, Y. Song, K. Ma and L. Xie, "Motor Imagery EEG Decoding Method Based on a Discriminative Feature Learning Strategy," in IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 29, pp. 368-379, 2021, doi: 10.1109/TNSRE.2021.3051958.
48. N. Vivaldi, M. Caiola, K. Solarana and M. Ye, "Evaluating Performance of EEG Data-Driven Machine Learning for Traumatic Brain Injury Classification," in IEEE Transactions on Biomedical Engineering, vol. 68, no. 11, pp. 3205-3216, Nov. 2021, doi: 10.1109/TBME.2021.3062502.
49. Y. Peng, Y. Zhang, W. Kong, F. Nie, B. -L. Lu and A. Cichocki, "S3LRR: A Unified Model for Joint Discriminative Subspace Identification and Semisupervised EEG Emotion Recognition," in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-13, 2022, Art no. 2507313, doi: 10.1109/TIM.2022.3165741.
50. J. F. Hwaidi and T. M. Chen, "Classification of Motor Imagery EEG Signals Based on Deep Autoencoder and Convolutional Neural Network Approach," in IEEE Access, vol. 10, pp. 48071-48081, 2022, doi: 10.1109/ACCESS.2022.3171906.