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An Interpretable Classical Machine Learning Framework for EEG-Based Brain Abnormality Detection

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ABSTRACT

Although electroencephalography (EEG) provides an excellent, non-invasive method for monitoring brain activity, the complexity and density of these signals present a significant challenge for automated analysis. Therefore, this paper proposes an intelligent, machine learning-based framework that is both understandable and computationally efficient for classifying these signals and detecting Brain Abnormalities. The study adopted traditional machine learning techniques as a practical alternative to deep learning models, which typically consume enormous amounts of data and computing resources. It started with TUH recordings being processed with frequency filtering and subdivision into overlapping windows in order to deal with signal instability. The research then meticulously extracted the time and frequency domain features manually with emphasis on statistics and power density and used PCA to simplify the data and still maintain its central features. To improve the accuracy of the results and improve the data analysis process, the study used a number of machine learning algorithms. Such algorithms are Support Vector machine (SVM), random forest (RF), k-Nearest neighbors and extreme gradient boosting (XGboost). With experiments on these algorithms, the Supporting Vector Machine (SVM) proved to be the most successful with a fine balance between performance and an accuracy of 88.6 per cent. This shows that the traditional approaches, where they are backed by effective feature extraction, are still very competitive in the area, particularly because the suggested system focuses on clarity, modifiability, and low complexity, thus suit best the intelligent software and decision-making systems.

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1. Introduction

Brain tumors are classified as serious diseases, which can cause severe damage to the brain, posing a threat to life if the treatment is not sought [1, 2]. Thus, detecting this disease at an early stage plays a significant role in accelerating the recovery process and ensuring a smooth treatment response. Historically, traditional techniques... have been utilized of magnetic resonance imaging (MRI) and computed tomography (CT) scans, which have shown efficiency and accuracy in detecting the position of brain tumors [3, 4]. The methods, however, are costly and can endanger an individual's health, considering that they use radiation [5, 6].

Recently, electroencephalography (EEG) is used as a complementary neurodiagnostic tool due to its efficiency with no side effects, low cost, and high resolution[1, 2]. Physicians and scientists have widely used EEG to detect neurological disorders and to study brain functions[3, 4]. Investigating the electrical activity of the brain using EEG records is considered the most significant tool to diagnose neurological diseases such as sleep disorders, epilepsy, and dementia [5, 7]. Therefore, adopting this technique to detect brain tumors seems to be a very promising trend,

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but given the huge amount of data produced by EEG recordings, the use of advanced techniques - such as computer-aided analysis systems - has become essential for classifying abnormal signals and supporting the diagnosis of brain diseases, as this classification helps us sort through parts of the EEG and determine whether the patient is healthy [12, 14].

The remarkable development in machine learning techniques have enabled reliable analysis of EEG signals. This development has led to improve diagnostic consistency and reduce reliance on manual inspection[8, 9]. Previous studies emphasized that using classical machine learning techniques with signals processing and feature extraction provide reliable solutions for decision makers in medical systems [10, 12]. The classical model also requires low training samples and is more suitable to adopt in clinical systems. Another advantage is that the model requires fewer training samples and are more suitable for deployment in clinical environments where transparency and reproducibility are essential[13, 15].

The recent studies using EEG-based Brain Abnormalities have increased. However, using this approach faces several challenges. Many previous studies employed one specific dataset which affect the generalization of the findings[16, 17]. Moreover, some of these datasets did not provide specific information for brain tumor, resulting in a lack of ability to develop robust detection models. Therefore, there is a need to use a systematic evaluation of classical machine learning approaches employing large scale of real-world EEG datasets[18, 19].

This study proposed a framework of an automated EEG-based Brain Abnormalities using classical machine learning techniques that evaluated on the Temple University Hospital (TUH) EEG Abnormal dataset. The study involves several steps, including preprocessing, multi-domain feature extraction, feature selection, and supervised classification. The study employed several traditional machine learning approaches, such as Support Vector Machine (SVM) with a radial basis function (RBF) kernel, Random Forest (RF) classifier, Extreme Gradient Boosting (XGBoost), and k-Nearest Neighbors (kNN). The study developed a standardized EEG analysis process using a large clinical dataset and tested by many classical machine learning for Brain Abnormalities. The study is also using quantitative performance comparison of classical machine learning methods using clinically relevant evaluation metrics.

The main contributions of this study as follows:

- Proposes an interpretable and low-complexity classical machine learning framework for automated EEG signal classification, suitable for software-oriented and resource-constrained environments.
- Designs a compact feature engineering pipeline combining time-domain statistics and frequency-domain band power features for effective EEG representation.
- Provides a subject-independent comparative evaluation of classical classifiers on a large-scale EEG dataset.

2. Related work

As highlighted in the following studies, analyzing the brain's electrical activity through EEG has become essential for detecting neurological abnormalities, including brain tumors.

1. Complexity of the Human Brain

The human brain is an extraordinarily complex organ, containing approximately one hundred billion nerve cells, or neurons [20, 21]. These neurons form extensive networks along with the spinal cord, enabling intricate communication within the nervous system [22]. The electrochemical activity of neurons generates electrical signals, which are essential for normal brain functions [23]. Disruptions in these electrical activities may lead to abnormal brain functioning, affecting various physiological and cognitive processes [24].

2. Electroencephalography (EEG) as a Diagnostic Tool

Electroencephalograms (EEG) give a non-invasive technique to monitor the electrical activity of the brain, and are extensively utilized in clinical and research practice [31]. EEG is recorded through electrodes on the scalp using the 1020 international system and amplified using high gain circuits. EEG analysis is essential in the diagnosis of neural disorders, such as sleep disorders, strokes, Parkinson disease, and brain tumors[32] due to the large amount of data it provides. The complexity and volume of the available EEG data require more advanced methods of analysis, classification, and interpretation of the signal [5, 33].

3. Traditional Feature-Based Analysis

Initial research in EEG analysis was aimed at deriving statistics and spectral information, including measures of amplitude, band power and entropy. The common methods of classification of these features were based on classical machine learning algorithms, such as k-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Linear Discriminant Analysis (LDA). Despite good outcomes, such methods tended to be constrained by small datasets and non-standardized protocols of acquisition [34, 35].

4. Time-Frequency Analysis Techniques

The modes of analysis of the non-stationary EEG signals that were to be followed included the time-frequency analysis techniques, namely, Wavelet Packet Decomposition (WPD) and Discrete Wavelet Transform (DWT). These techniques were applied in combination with ensemble classifiers like the Random Forest and Gradient Boosting to describe the activity in transient brain signals and enhance the performance of the system classification [36, 37].

5. Deep Learning Approaches

As the growth in the usage of the deep-learning frameworks was identified, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures have been applied to the electroencephalographic data classification in the scenario of brain-tumour detection [38]. The methods are good in classification, but constrained by uninterpretability and high cost in terms of large annotated corpora. Comparatively, the traditional machine-learning algorithms are competitive because they are cheaper to compute, are easier to understand, and predictable in reference to performance as they are trained on relatively large datasets[39, 40].

Ali [41] investigated the potential use of AI in the diagnosis of neurological conditions such as Alzeheimer and epilepsy to identify the type of brain disorder in another study. To reach this objective, the author has used a number of algorithms, such as, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Support Vector Trade-offs (SVM), and the Random Forest classifiers. The datasets were of three types, including ADNI, PPMI, and TUH EEG. The outcome has demonstrated CNN to have the best accuracy of 92%.

6. Use of the TUH EEG Corpus

Many studies have used this dataset, primarily focusing on epilepsy detection rather than general brain abnormalities. Moreover, systematic benchmarking of multiple classical machine learning models using standardized feature extraction and evaluation protocols remains limited. For instance, Albaqami, Hassan [42] used TUH abnormal EEG Corpus V.2.0.0. (TUAB) dataset for detecting abnormal raw EEG data. They employed different algorithms, including WaveNet–Long Short-Term Memory (LSTM) and LSTM, the study has achieved a high classification accuracy of 88.76%. In the same vein, Lopez, Suarez [43] adopted baseline classification algorithms, such as " k-Nearest Neighbor (kNN) and Random Forest Ensemble Learning (RF). A subset of the TUH EEG Corpus was used to evaluate performance. Principal Components Analysis (PCA) was used to reduce the dimensionality of the data".

7. Research Gaps and Motivation

Despite these advancements, certain gaps remain in the development of automated systems for detecting EEG-based brain abnormalities. The absence of standardised assessment measures, repeatability and inter-observer confirmation was a characteristic feature of earlier studies. To surmount these shortcomings, the present study uses classical machine-learning classifiers of the TUH EEG data, that concentrates on understandable feature presentations, consistency in research, and whether the models derived can be put into feasible clinical applications.

3. Methodology

This section describes the proposed methodology for EEG-based classification of normal and abnormal brain activity. The overall workflow of the proposed framework is illustrated in Figure (1):

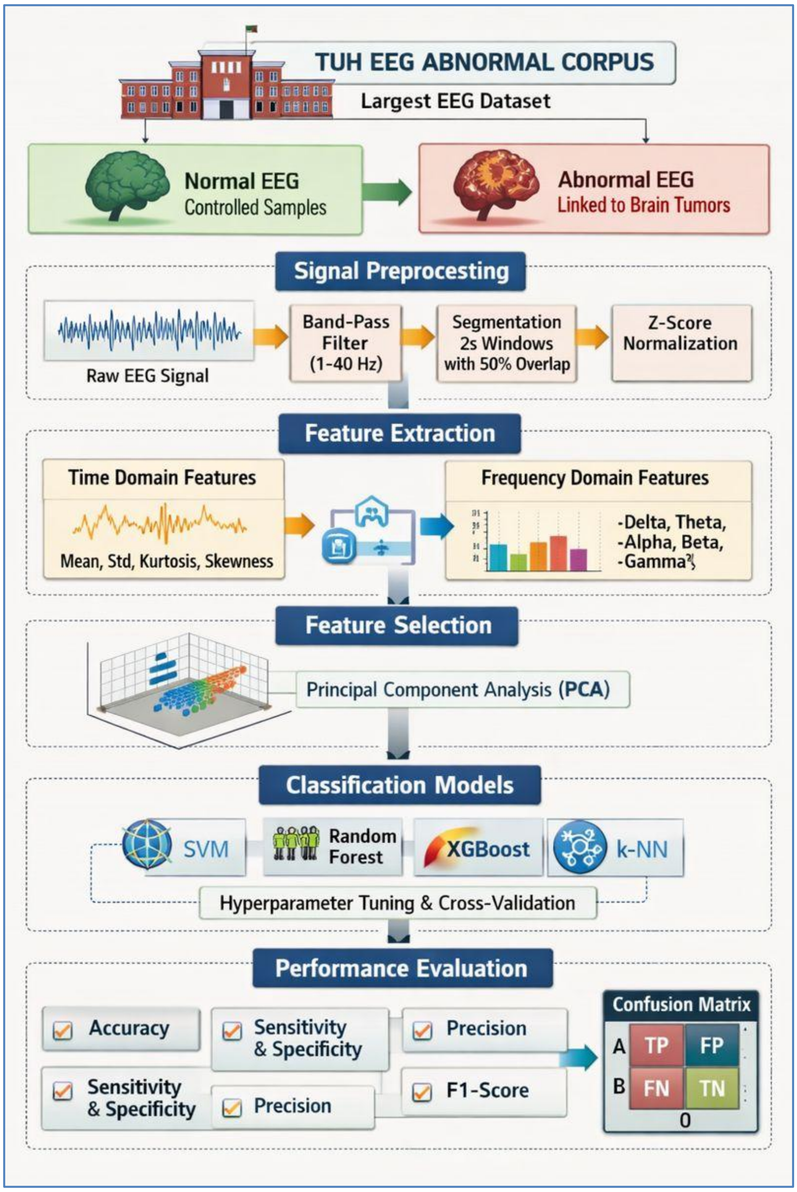

Fig 1: Proposed Methodological Pipeline for EEG-Based Brain Tumor Classification

3.1 Dataset Description

We have used the Temple University Hospital EEG Abnormal Corpus (TUH EEG Abnormal v2.0.0) which can be regarded as one of the largest publicly available EEG datasets. It holds massive EEG recordings both normal and abnormal EEG recordings as collected by patients belonging to different population groups. The frequencies of sampling are usually 250 to 256 Hz. It also follows international standardization which entails 10 to 20 system electrode placements and 19 and 21 channels of scalp use. Normal-labeled recordings were taken as controlled samples in this study. With regard to the abnormal class, covers a broad range of neurological abnormalities as opposed to particular disorders that include brain tumours. This feature renders the dataset suitable to the generalized abnormality detection, but with clinical relevance. We have also added sessions with the adequate recording time and the whole channel data to promote reliability and stability of the analysis.

3.2 Signal Preprocessing

Raw EEG signals were preprocessed to eliminate noise and artifacts. This is necessary to enhance the signal quality and to prepare to feature extraction. A band -pass filter (1-40 Hz) was used to remove high frequency artifacts, and low frequency drift. Such frequencies do not apply to neurophysiology activity. Also, EEG data were divided into 2 seconds fixed length windows and slightly overlapped (50%). The reason why this process is needed is to decrease the effect of non-stationary as well as help extract features. In EEG based classification, the segmentation method is extensively used to ensure a tradeoff between time localization and computational efficiency. We also normalized using Z-score, per segment, to normalize subject-to-subject variation and differences in amplitude across datasets.

3.3 Feature Extraction

To achieve the strictly stable and efficient classifying of the classical machine learning algorithms, the model was learnt to generate time-domain and frequency dependent features. It is a significant step towards finding small spectral features in EEG signals in abnormal activity. Eventually, our approach will calculate a series of statistical descriptors of each segment; mean, standard deviation, variance, skewness and kurtosis of the signal describing its character of distribution and its asymmetry that distinguishes between normal and pathological recordings. Meanwhile spectral power density (PSD) estimation using Welch method was used to obtain frequency domain characteristics. At the same time, we estimated spectral power density (PSD) using the Welch method in order to obtain frequency domain properties. The reason is that we have computed power values of typical domains (delta, theta, alpha, beta, and gamma), which are the most sensitive areas to the activity of any neurological disorder since they represent the energy distribution.

3.4 Feature Selection

PCA was adopted to help the efficiency and precision of classification. This approach has contributed to the reduction of feature redundancy. Moreover, PCA transformed the original features into a number of orthogonal components that were reduced without extracting a significant amount of the variance in the EEG data. We used the number of components retained to account for 95% of total variance. The method improves the computational efficiency and helps to prevent over-fitting during the model training.

3.5 Classification and Performance Evaluation Models

To accurately assess the efficiency of the proposed models, we adopted a set of standard criteria used in medical diagnosis: accuracy, sensitivity (recall), specificity, precision, and F1 score. To thoroughly examine areas of error and correctness, we analyzed confusion matrices that illustrate positive and negative (true and false) states. To ensure the integrity of the results and prevent any data leakage, we adhered to strict separation between training and testing data, with subject-wise splitting based on participant identity rather than simply random image shuffling.

4. Experimental Results

Experimental Setup

The TUH EEG Abnormal dataset served as the basis for all experimental procedures, adhering to the preprocessing and feature extraction protocols outlined in Section 4. To reduce the data leakage and provide an opportunity to evaluate data without bias, the dataset was divided into training and test data and a subject-independent methodology was used. The training phase had five-fold cross-validation to optimize the hyperparameters. In addition, the imbalance in the classes was alleviated by adopting class-weight adjustments during the model training process. The experiments were repeated a number of times and the performance measures recorded are the average of the results.

1- Classification Performance

Table 1 summarizes the classification performance of the evaluated classical machine learning models, including kNN, Random Forest (RF), XGBoost, and SVM with an RBF kernel.

Performance comparison of classical ML classifiers on the TUH EEG dataset

Table 1 - Performance comparison of classical ML classifiers on the TUH EEG dataset

Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
kNN	78.6	76.9	80.1	77.5	77.2
R F	84.1	83.4	84.8	83.9	83.6
XGBoost	87.2	86.5	87.8	86.9	86.7
SVM (RBF)	**88.6**	**89.2**	**88.0**	**88.4**	**88.8**

The Support Vector Machine (SVM) model which relies on a Radial Basis Function (RBF) kernel showed the best overall performance with the best accuracy rate at 88.6 and an F1-score at 88.8. It implies a strong ability to distinguish between normal and abnormal electroencephalogram (EEG) signal. SVM performed best due to its ability to handle high-dimensional data and model non-linear EEG patterns. It also offers a good balance between accuracy and computational efficiency compared to other methods.

2- Confusion Matrix Analysis

A confusion matrix evaluates classification performance by comparing predicted and actual labels using four metrics: TP, TN, FP, and FN. Table 2 shows the results for the SVM (RBF) model, which achieved balanced performance with high correct classifications. The low number of false negatives is especially important in medical applications, as it indicates reliable detection of abnormal EEG signals. The confusion matrix of the best-performing classifier (SVM with RBF kernel) is presented in Table 2.

Table 2 - Confusion matrix for SVM (RBF) classifier

Actual \ Predicted	Normal	Abnormal
Normal	412	56
Abnormal	49	432

The confusion matrix demonstrates that the classification is well balanced, and there are not so many false negatives and false positives. Notably, the fact that the number of misclassified abnormal samples is small means that the suggested system is efficient in recognizing abnormal EEG patterns.

Comparative Discussion

The results indicate that the classical machine learning techniques are useful in the process of identifying abnormal electroencephalographic signals in brain tumors, and it relies on the incorporation of appropriate preprocessing and feature extraction steps. Ensemble-based models, namely, Random Forest and XGBoost, were more efficient compared to k-nearest neighbors, which prove their appropriateness to non-linear decision boundaries and feature interactions. The fact that the support vector machine (SVM) classifier has capabilities of traveling in high dimensional feature space as well as maximizing the distance between classes can explain its enhanced effectiveness. Similar to the previous studies in the field of EEG-based brain tumour detection, the accuracy obtained is not the highest, but the computing load is less as compared to deep learning paradigms. The specified characteristic, in its turn, renders the suggested framework particularly useful in terms of its practical implementation in the resource-constrained clinical environment.

Limitations

The results are positive; however, there are a few limitations, which should be considered. First, even though the TUH EEG data is large in specificity, the labels provided can be described as generic descriptions of abnormalities as opposed to being specific about tumor types. Moreover, the traditional methods of features extraction might not be adequate to sense the complex spatiotemporal dynamics of EEG records. Therefore, the research activities in the future should involve investigation of hybrid methodology, which would integrate the classical elements with simplified deep learning models and multimodal data integration.

5. Conclusion

This study presented an automated and interpretable EEG-based framework for Brain Abnormalities using classical machine learning techniques evaluated on the large-scale TUH EEG Abnormal dataset. The proposed methodology incorporated standardized preprocessing, multi-domain feature extraction, dimensionality reduction using PCA, and a subject-independent evaluation protocol to ensure robustness and generalizability of the results. Experimental findings demonstrated that classical machine learning models, particularly the SVM with an RBF kernel, achieved competitive classification performance in distinguishing normal from abnormal EEG signals, with an accuracy of 88.6% and a balanced sensitivity–specificity trade-off. The results confirm that carefully designed time- and frequency-domain characteristics, combined with appropriate classification algorithms, could identify EEG abnormalities related to cerebral neoplasms without having to use computationally intensive deep-learning structures. Relative to the extant literature on EEG-based tumor detection, the methodology proposed strikes a desirable trade-off of predictive accuracy, interpretability, and computational parsimony, therefore, making it applicable to implementation in resource-limited clinical environments. Despite the limitation of the study by the coarse labels of the abnormalities in the dataset, the results obtained point to the efficacy of the conventional machine-learning pipelines as reliable decision-support tools in the EEG-based neurodiagnostic practice. Future studies will strive to add in granular clinical annotations, test hybrid learning paradigms and generalize the framework to include multimodal diagnostic platforms.

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