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Analysis of Machine Learning Methods for the Prediction of Major Depressive Disorder

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Abstract: Major depressive disorder is a widespread and debilitating mental health issue with substantial economic and social impact. Accurate diagnostic techniques are essential for effective treatment. Various time domain and wavelet features are extracted from publicly available database. This research examines the performance of machine learning classifiers, including K-Nearest Neighbors, Naive Bayes, Quadratic Discriminant Analysis, Artificial Neural Networks, and Support Vector Machines, in categorizing MDD patients based on relevant features. The selection of these classifiers was based on their respective strengths in handling high-dimensional data, identifying optimal decision boundaries, and modelling complex non-linear relationships. The metrics for performance used were accuracy, sensitivity, recall, and F1-score. The experimental results proved that the KNN, SVM classifiers demonstrated the highest overall predictive accuracy. This suggests that machine learning models can aid in the precise identification of MDD, potentially leading to improved treatment outcomes.

Keywords: *Major deressive disorder, support vector machine, Electroencephalography, machine learning methods.*

I. INTRODUCTION

Major Depressive Disorder (MDD) is a prevailing and weakening psychological well-being condition that significantly impacts individuals, communities, and healthcare systems globally [1-2]. Conventional diagnosis and assessment methods such as clinical interviews can be subjective and influenced by cognitive biases, which underscores the need for more objective and reliable techniques [2]. Recent advances in machine learning have revealed great promise in the automatic detection and classification of mental health disorders, including MDD [1, 3].

A study evaluates the superiority of research supporting the estimates from the 2017 Global Burden of Disease of MDD, examining factors such as representativeness, research approach, sample, and diagnostic standards [4]. Another research has analyzed sleep EEG data to understand the disrupted sleep architecture in depression, revealing a sensitive dependence on initial conditions in chaotic systems [5]. A survey highlights a significant treatment gap among the Indian population underscoring the need for community-based mental health services and culturally sensitive research to address the issue [6]. The study [7] indicates that a considerable proportion of persons with MDD did not decrease after pharmaceutical treatments based on polygenic scores. Furthermore, a prediction model has been developed that categorizes anxiety into preclinical stages using data from Kashmir, India [8].

This model demonstrates good prediction and recommendation accuracy, suggesting its potential usefulness in forecasting anxiety stages and providing appropriate psychiatric assistance based on disorder risk and probability.

An electroencephalography (EEG)-based approach for the prediction of MDD, utilizes the Multi-modal Open Dataset for Analysis of Mental Disorders [9]. The proposed method outperforms current approaches concerning electrode usage, classification accuracy, and feature vector length. The machine learning models to diagnose depression in its early stages comparing user-level linguistic metadata and convolutional neural networks [10]. The results demonstrate advanced performance with the examination of the ERDE score. Furthermore, the researchers developed a one-dimensional convolutional neural network to enhance EEG-based depression detection, incorporating gender and age factors marking it as the first study to do so [11-12]. Another study [13] utilizes user-generated data from social media to categorize posts into depressive and non-depressive groups and employs the Random Forest classifier to determine the severity of depression, converting LIWC data into predictive outputs.

Utilizing Support Vector Machines (SVM) and Logistic Regression and Linear Regression implemented to enhance the detection and evaluation of MDD using ratio features extracted from Electroencephalography (EEG) signals. The study combines Principal Component Correlation (PCC)

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and Recursive Feature Elimination (RFE) to enable interpretable diagnosis and severity assessment [14]. Language processing strategies and neural network models can be used for the early classification of depressive symptoms in written texts, examining assessment measures and user-based metadata features [15]. Furthermore, the study [16] presents K-Nearest Neighbors (KNN) approach to evaluate the geographical variability of k values and identify the optimal k for Potential Vegetation Cover (PVC) mapping in the Duolun and Kangbao regions of China.

An automated segmentation approach employed to analyze subcortical volumetric differences among healthy individuals and patients with MDD during remission or depressive episodes [17]. Despite challenges in encoding discriminative information, obtaining and labeling data, and addressing facial changes and noise, the research endeavored to assess depression severity using facial video recordings [18]. A study [19] utilized an ensemble learning system with Convolutional Neural Networks, incorporating text, image, and audio data, to evaluate whether a speaker has been diagnosed with depression. Furthermore, a deep learning-based method for diagnosing depression using video data, employing a two-stream framework for facial images and flows, as well as joint tuning layers, demonstrated equivalent performance to contemporary techniques in the AVEC competition [20].

Discrete wavelet transform (DWT) is an effective method for extracting features from biomedical signals [21]. While the time, frequency, and wavelet-based representations of the original features have been explored, it is important to also consider the original features themselves [22]. Features are the primary drivers of classification outcomes. Additionally, while substantial research has focused on identifying depression using EEG signals, less attention has been given to individuals with severe depressive illness and the accuracy of this identification still requires improvement [23]. Effective feature engineering is crucial to enhance the classification accuracy for detecting major depressive disorder [24].

This paper introduces several machine learning algorithms that are highly effective and extensively used in several domains such as data mining, pattern recognition, and artificial neural networks. These algorithms, including KNN, ANN, and SVM, are characterized by their straightforward structure, ease of implementation, quick convergence and excellent robustness [25-30]. These algorithms can be utilized for extracting relevant features from the EEG, which then provide a solid foundation for the subsequent classification step. The experimental results presented in this work demonstrate that the suggested technique can considerably enhance the performance of categorization in comparison to alternative techniques, highlighting the potential of these algorithms in enhancing the identification of major depressive disorder.

The balance of document is organized as such. In the Second portion, the experimental design and techniques are thoroughly explained, including details on the data collection, preprocessing, and analysis techniques employed. The outcomes of the experiment are examined and discussed in depth in Section 3, with a focus on the key findings and their implications for the field. The article is concluded in Section 4 with recommendations for further research topics that can build upon the insights gained from this study.

II. Materials and Methods:

A. Data acquisition and preprocessing

The study utilized EEG data from 34 individuals diagnosed with MDD, comprising 17 females and 17 males, as well as 30 healthy control participants, including 9 females and 21 males. Mumtaz et al. [31] compiled an EEG database which is available freely was used to estimate the machine learning technique in this investigation.

The study was authorized by Hospital's ethics committee University Sains Malaysia. The contributors were selected based on the absence of any prior medical history, history of head injuries, and medication use. Prior to the experiment, each participant was required to fast for a minimum of two hours. Each participant received an honorarium of RM 40 for their participation and signed an informed consent form. The ethics committee of Hospital University Sains Malaysia, had approved the study design. Figure 1 represents the 19-channel EEG signals of major depressive disorder subjects and healthy persons (HC).

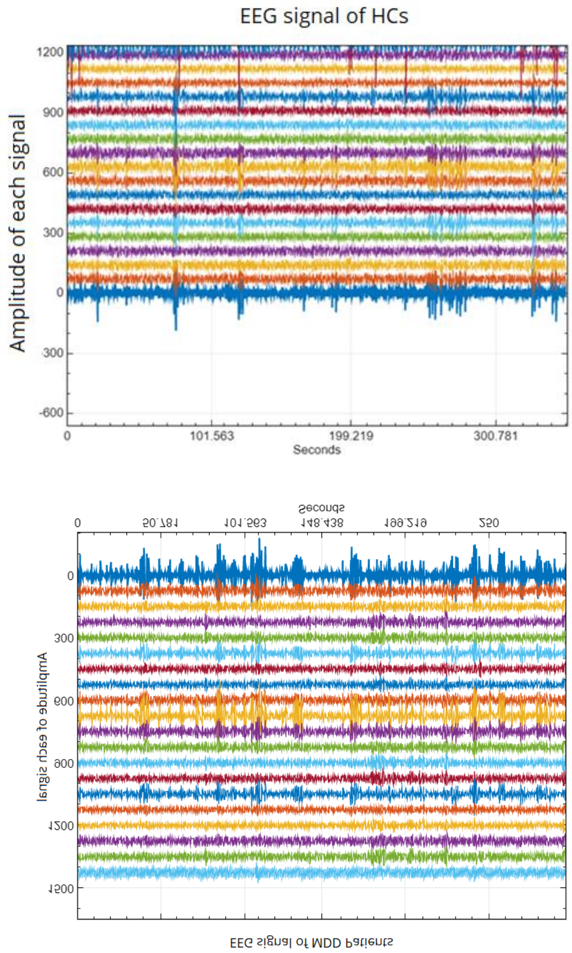

Fig 1: 19-channel EEG signals of major depressive disorder subjects and healthy persons (HC).

The dataset included 5-minute resting-state EEG recordings with eyes closed for each participant. Following the 10-20 international system, 19 electrodes distributed across various brain areas are used to obtain the EEG recordings, which were sampled at 256 Hz. A band reject filter is used for removing 50 Hz power connection noise with 0.5 to 70 Hz band-pass filter is used for artefacts elimination. The raw EEG signals were segmented into multiple non-overlapping 5-second samples, each containing 1,280 data points. Samples with amplitudes fewer than -100 uV or better than 100 uV were excluded. Thereafter, the Z-score transformation and re-referencing to the average reference were performed on the remaining samples. Finally, the proposed preprocessing procedure was validated using 57 patients and a total of 3,163 samples.

B. Proposed Method

The proposed framework with the purpose of finding MDD using electroencephalography (EEG) data is depicted in Figure 2. The 10-20 international EEG framework was deloyed to acquire the EEG recordings from both MDD subjects and healthy controls (HC) [31]. For the suggested procedure, a bandpass filter was applied to the signals to eliminate artifacts, and the data was then sampled at a frequency of 50 Hz [32]. Various feature extraction methods can be employed to obtain characteristics related to the time and wavelet properties of the EEG signals. Finally, a confusion matrix was produced to display the classification results.

The key stages in the proposed methodology were: 1) Data acquisition and preprocessing, 2) Feature extraction, and 3) Classification. During feature extraction phase, the preprocessed EEG data signals are decomposed using the DWT and the wavelet coefficients at different frequency bands along utilizing temporal domain characteristics and peak frequency are used as features for the classification. These extracted features along with time domain features were then utilized to train several well-known machine learning models to differentiate individuals with MDD from HCs.

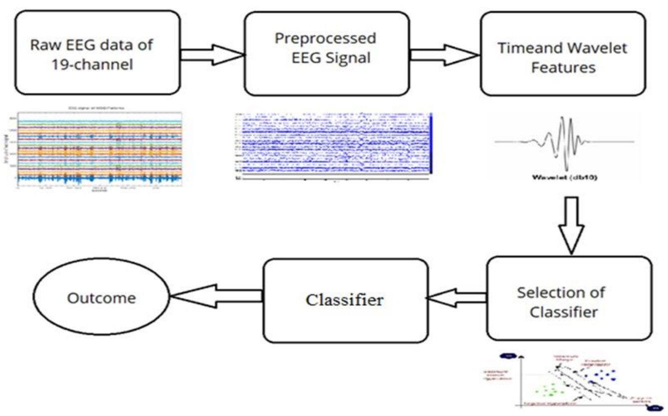

Fig 2: The proposed frame work for classification of MDD patients

C. Machine Learning Techniques

A probabilistic classifier is called Naive Bayes (NB), which supposes that each attribute is independent of the others. It is a simple yet effective machine learning algorithm for fast prediction on high-dimensional datasets. Based on the premise of independence between each pair of features, the Bayes theorem forms the basis of the NB classifier. Despite its simplicity, Naive Bayes can be highly effective for certain classification tasks, particularly those involving text data. The "naive" assumption is that features are independent given the label of the class. Naive Bayes classifiers are used to classify different types of biomedical signals, such as electrocardiograms or electroencephalograms [33]. Quadratic discriminant analysis is a supervised classification method that constructs a quadratic decision boundary. This approach can be advantageous when the classes exhibit nonlinear separability. The algorithm assumes the feature variables adhere to a Gaussian distribution with distinct mean vectors and covariance matrices for each class [34]. Compared to the more commonly used linear discriminant analysis, quadratic discriminant analysis allows for a more flexible and difficult decision-making limits that can better snatch up the underlying information structure, potentially leading to higher classification accuracy.

Artificial neural network (ANN) is motivated through the anatomy between the human brain and its function. They are made up of networked nodes, or "neurons," that can transmit signals to other neurons, as well as the potency or "weight" the associations can be modified based on experience, making neural networks capable of learning from data. For the classification of MDD based on EEG data, artificial neural networks can be particularly useful because of their ability in learning complex, nonlinear patterns in high-dimensional data [35]. Levenberg-Marquardt backpropagation, a popular training algorithm for feedforward neural networks, can be employed to optimize the network parameters and improve classification performance.

The k-nearest neighbors (KNN) is a simple, nonparametric machine learning technique which discerns sample points based on their proximity to their k nearest neighbors in the feature space. The algorithm works by finding the k data samples closest in distance to the new sample point and then assigning the new point to the class that is most common among its k neighbors. KNN can be a useful technique to classify signals in the context of major depressive disorder, can capture complex, nonlinear relationships in the data [36]. Using high-dimensional feature space, the Support Vector Machine (SVM) is a potent machine learning technique that creates the best hyperplane to divide data categories. SVMs are recognized for their expertise in handling high dimensional data and can be highly effective in the classification of intricate biomedical signals, including EEG data [37].

The EEG signal classification challenges involved techniques like Naive Bayes, Quadratic Discriminant Analysis, Artificial Neural Networks, K-Nearest Neighbors and Support Vector Machines, each with distinct advantages [38-39]. Factors such as data size, complexity, computing power, interpretability, and preprocessing methods like feature extraction and filtering were important considerations. The evaluation used 30% of the EEG signals as the test results and the residual 70% for training data.

III. Results and Discussions

In this area, we offer the experimental outcome for evaluating the classification performance of the suggested KNN, ANN, SVM, NB, and QDA models. Ablation studies were carried out to confirm the viability and effectiveness of the suggested framework design. The EEG information from 34 MDD and 30 HC subjects are utilized in this investigation to distinguish between individuals and healthy controls (HCs) who suffer from Major Depressive Disorder (MDD). The proposed approach and the five classification techniques were assessed using a 70% train and 30% test data split. The classification results were evaluated using four performance metrics.

Four performance metrics are used in this study for evaluation of classification performance.

Accuracy: This measure shows the percentage of appropriately classified instances with relation to the overall quantity of occurrences.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

The sensitivity metric calculates the percentage of real positive cases that the model successfully recognized.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Precision: The percentage of successfully anticipated positive cases among all positively predicted instances is represented by this metric. It is computed by dividing the total number of false positives and true positives by the number of true positives.

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

F1_Score: This metric is the harmonic mean of precision and recall, offering a balanced measure of the model's performance. It is computed by taking the precision and recall products twice and dividing the result by the total of the products.

$$\text{F1\_Score} = 2 * \frac{Precision * Recall}{Precision + Recall} \quad (4)$$

The terms true positive (TP), false negative (FN), true negative (TN), and false positive (FP) refer to the counts of the corresponding sample types.

The detailed classification results, encompassing various performance metrics such as accuracy, sensitivity, precision, and F1-score, are presented in Table 1. Values displayed for the metrics are in percentage (%).

Table 1: Classification results of five classifiers (in %)

Classifier	Accuracy	Sensitivity	Recall	F1_Score
QDA	68.4211	69.2982	68.9912	68.3764
NB	71.0526	70.2851	72.3164	70.3482
ANN	75.5639	75.2193	75.2193	75.1334
KNN	86.4662	86.6228	86.1225	86.2918
SVM	87.5940	86.0746	89.2527	86.9053

According to Table 1, the Naive Bayes (NB) model demonstrated classification performance metrics of 71.0526% accuracy, 70.2851% sensitivity, 72.3164% precision, and 70.3482% F1_score. The Artificial Neural Network (ANN) model exhibited classification performance metrics of 75.5639% accuracy, 75.2193% sensitivity, 75.2193% precision, and 75.1334% F1_score. The Quadratic Discriminant Analysis (QDA) model achieved classification performance metrics of 68.4211% accuracy, 69.2982% sensitivity, 68.9912% precision, and 68.3764% F1-score, signifying its performance.

The k-nearest neighbors (KNN) model demonstrated impressive classification performance metrics, achieving an accuracy of 86.4662%, sensitivity of 86.6228%, precision of 86.1225%, and F1-score of 86.2918%. The SVM model displayed exceptional classification performance metrics, achieving an accuracy of 87.5940%, sensitivity of 86.0746%, precision of 89.2527%, and an F1-score of 86.9053%. These experimental outcomes show the SVM model's strong capability in accurately classifying individuals with both healthy controls (HCs) and major depressive disorder based on EEG signals, outperforming the other models evaluated in this study.

Figures 3 through 7 present the confusion matrices obtained for the five classifiers evaluated in this study: Naive Bayes, Artificial Neural Network, Quadratic Discriminant Analysis, k-nearest neighbors, and Support Vector Machine. These confusion matrices offer detailed insights into the performance of each model, highlighting the true positive, false positive, true negative, and false negative rates for the classification of individuals with MDD and HCs.

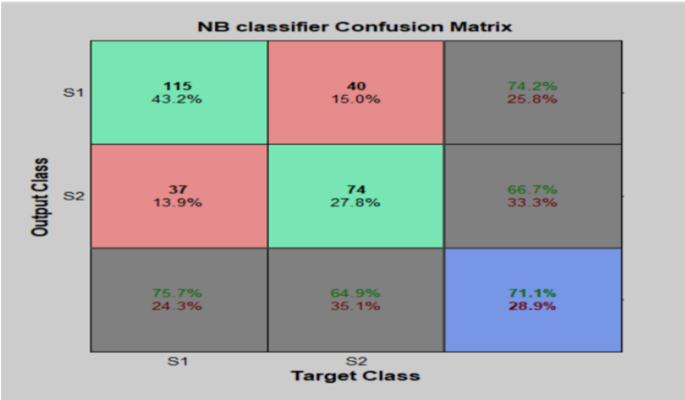

Fig 3: Confusion matrix for NB classifier

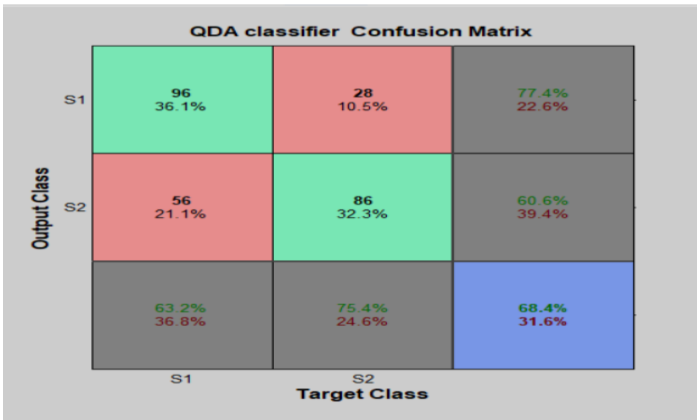

Fig 4: Confusion matrix for QDA classifier

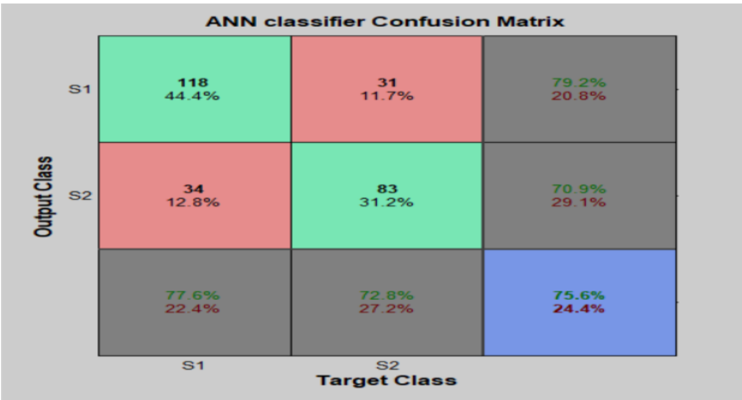

Fig 5: Confusion matrix for ANN classifier

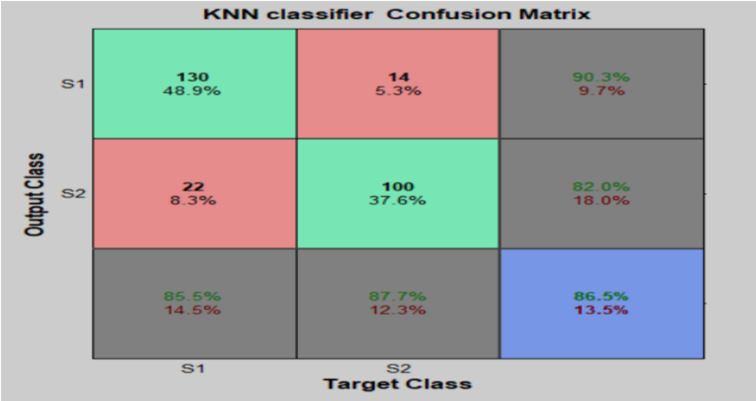

Fig 6: Confusion matrix for KNN classifier

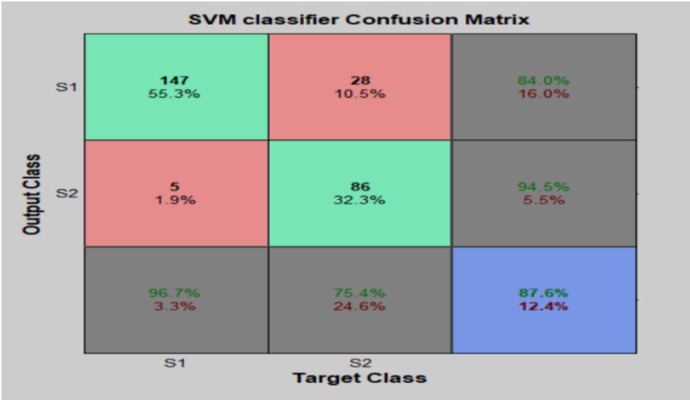

Fig 7: Confusion matrix for SVM classifier

The confusion matrix of the Naive Bayes (NB) Classifier, which was used for classifying individuals with both healthy controls (HCs) and major depressive disorder, is displayed in Figure 3. Naive Bayes may have performed relatively worse due to its assumption of feature independence, which might not accurately reflect the complex relationships present in EEG signals. The Artificial Neural Network (ANN) Classifier's confusion matrix for the classification of healthy controls individuals with Major Depressive Disorder (MDD) is displayed in Figure 4. The ANN model's performance is dependent on the harmony between recall and precision achieved during the training process. The results show that the ANN model exhibited strong performance metrics, with high F1-score, sensitivity, recall, and overall accuracy. This suggests that the ANN model is able to effectively capture complex nonlinear patterns present in EEG signals, outperforming the Naive Bayes (NB) classifier. Figure 5 presents the confusion matrix for the Quadratic Discriminant Analysis (QDA) classifier. The QDA model was able to outperform the other classification techniques evaluated in this study, likely due to its ability to effectively capture the nonlinear relationships present within the complex EEG data. Unlike linear discriminant analysis, QDA does not require the assumption of equal covariance matrices across the classes, which may be a more appropriate assumption for the sophisticated patterns observed in the EEG signals associated with Major Depressive Disorder and healthy controls. This flexibility in modeling the underlying data structure appears to have contributed to the superior performance of the QDA classifier in this application.

The confusion matrices in Figures 6 and 7 illustrate how the KNN and SVM classifiers performed in detecting Major Depressive Disorder (MDD). For the KNN classifier, the accuracy determined with the choice of the K-value primarily. K-value represents the number of nearest neighbors used for the classification. Similarly, the performance of the SVM classifier is influenced by the selection of the appropriate kernel function, which can capture the nonlinear relationships in the EEG data. The K-value for KNN and the kernel function for SVM also have a significant impact on the F1-score, recall, and the ability to handle imbalanced datasets, where the number of data samples for each type of data (MDD and healthy controls) may differ.

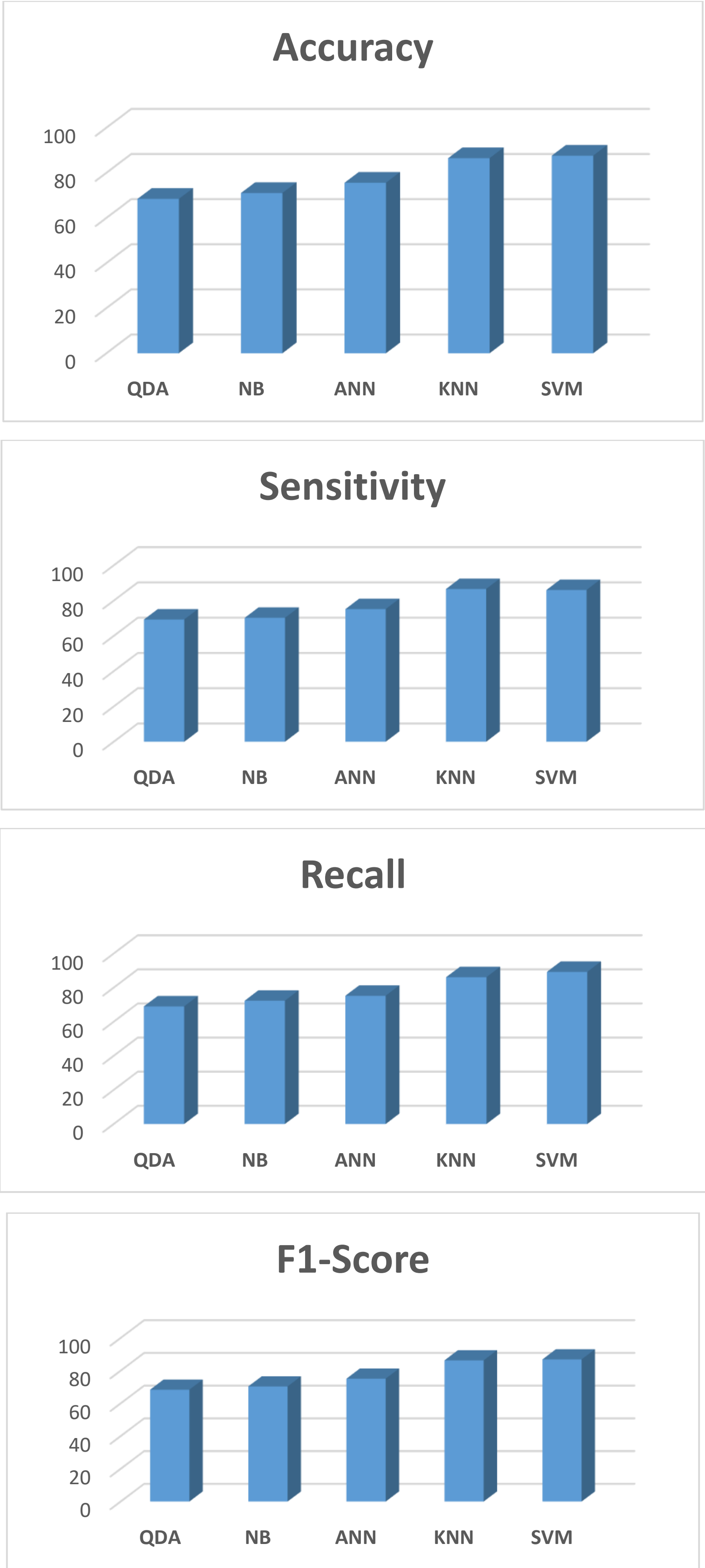

Fig 8: Results comparison of different classifiers

The paper proposes the use of five different machine learning classifiers - Naive Bayes, Artificial Neural Network, Quadratic Discriminant Analysis, k-nearest neighbors, and Support Vector Machine - to classify individuals with MDD from HCs using EEG signals. The results indicate that the k-nearest neighbors (KNN) and Support Vector Machine (SVM) classifiers demonstrate the best performance, achieving classification accuracies exceeding 85%. These findings suggest that the EEG-based features developed in this study can significantly enhance the detection of MDD using the SVM classifier. The proposed method allows doctors to accurately distinguish between MDD subjects and healthy individuals based on their EEG data, as shown in the Table 1 and the bar graphs in Figure 8. This highlights the potential of these machines learning methods to serve as valuable clinical decision support tools in the early diagnosis and monitoring of MDD.

Overall, the findings of this study underscore the potential of machine learning techniques, especially SVM and KNN, in effectively classifying individuals with Major Depressive Disorder using EEG data. Further research is warranted to assess the generalizability of these results and to explore the integration of these techniques into clinical decision support systems for diagnosing and monitoring Major Depressive Disorder.

IV. CONCLUSION

In this study, we have investigated the application of various machine learning algorithms, including SVM, KNN, ANN, NB, and QDA, for the classification of Major Depressive Disorder using EEG data. The results indicate that the SVM and KNN models demonstrate superior classification performance, achieving accuracies exceeding 85%. These findings recommend that machine learning approaches can be effective in the diagnosis and monitoring of Major Depressive Disorder, potentially serving as valuable tools for clinicians in the early detection and intervention of this disorder. However, additional research is desirable to confirm these results on extensive and diverse databases, as well as to investigate the integration of these techniques into clinical decision support systems.

Future research directions may include exploring the use of deep learning algorithms in order to extract features and classify them, investigating the impact of different EEG electrode placements, and examining the longitudinal performance of these models in tracking the progression of Major Depressive Disorder. Additionally, the incorporation of other modalities, for instance, behavioural and demographic information, could potentially enhance the classification performance and offer a more comprehensive knowledge of the disorder. In conclusion, the study highlights the promising potential of machine learning techniques, particularly SVM and KNN, in the classification of MDD using EEG data.

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