Detection of Major Depressive Disorder Using Genetic Algorithm for Features from EEG Signals

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KEYWORDS
Major depressive disorder; Feature selection; genetic algorithm; support vector machine; EEG.

ABSTRACT
Introduction: Depression is a widespread mental disorder that significantly impacts individuals' well-being and quality of life. In the previous few years, researchers have looked into the potential of electroencephalogram signals in detecting and diagnosing depression. The present study investigates an approach for depression detection using a genetic algorithm to optimize the selection of discrete wavelet transform features from EEG signals. The proposed method involves decomposing EEG data into seven sub-bands using the DWT, extracting relevant statistical, geometric, and physiological features, and then employing a genetic algorithm to identify the most informative features for depression recognition. The SVM classifier achieved the highest overall accuracy of 91.73%, a sensitivity of 91.01%, a recall of 92.18%, and an F1-score of 91.45%, outperforming the other models. Experimental results indicate that the proposed approach outperforms hand-engineered methods and highlighting its potential as a complementary tool for depression diagnosis.

1. Introduction

The severe depressive disease known as Major Depressive Disorder (MDD) has a detrimental effect on a person's emotional state, thinks and behaves, which can lead to significant impairment in day-today life quality. Depression is a common mental disorder, affecting over 280 million people worldwide (The World Health Organization) [1]. By 2030, MDD is anticipated to become the primary the reason behind the weight of illness, having ranked as the third most prevalent reason of disability in 2018. The COVID-19 pandemic worsened the occurrence of depression due to various factors such as social isolation, health issues, stress, and money related anxieties. Some studies reported the increment in the occurrence of symptoms during the pandemic period [2]. The influence on the strain and prevalence of MDD and anxious illnesses are significant between women and youth. Surveys on mental health are required to determine the length of time and intensity of this effect. Even prior to the pandemic, MDD and anxiety disorders are the leading causes around the globe, and most countries did not have mental health-care systems. The factors that are related to mental health may be different for different environments or geographic regions. Countries in war zone may have different factors compared to other regions. A person's mental health state may be affected by different factors, such as place of residence, living conditions, exposure to war or conflict, lifestyle, family history, and socioeconomic factors [3]. Conventionally, mental health professionals depend on interviews, self-assessment reports, and questionnaires for the assessment of mental health status. However, these approaches are subjective in nature, and erroneous due to self-reporting bias. So there is a need for robust and objective methods to detect and monitor mental health conditions [4]. Recent advancements in neuroscience and signal processing techniques made electroencephalogram (EEG) as prominent technique for the detection and assessment of mental health disorders like depression. It provides a non-invasive and economical approach for measuring the brain's electrical activity that can expose patterns and abnormalities associated with depression and other mental illnesses [5]. A useful technique for removing characteristics from biological signals is the discrete wavelet transform [6]. Previous studies have demonstrated the time-domain, frequency-domain, and wavelet based features [6-7]. The raw, unprocessed features may useful for accurate classification for depression. In addition, even though a lot of study has been done on analysing EEG signals to determine depression, less focus has been assigned to accurately detecting and diagnosing individuals with severe depressive illness [7]. Enhancing the classification accuracy for MDD is an important challenge that requires effective feature engineering strategy to unveil the discriminative patterns in the EEG data. The attributes gleaned from EEG recordings could not be perfectly suited for classification. Some features may be redundant (overlapping information), and others may be irrelevant for the specific task [8-9]. To address these challenges and obtain the most informative features, it's imperative to employ feature selection algorithms. The genetic algorithm is a promising technique that can be employed to optimize the selection of features from the EEG signals [10]. By utilizing the capacity of the genetic algorithm to examine the most discriminating subset by effectively utilizing the feature space, the classification accuracy can be increased significantly [11]. While recent studies have investigated the application of EEG signals for depression diagnosis, the systematic utilization of genetic approaches to evaluating features in this context has not been extensively investigated. We propose a comprehensive approach to detect depression using genetic algorithm-based feature selection of discrete wavelet transform features extracted from EEG signals. The research's fundamental objectives are:

1.To extract a comprehensive set of informative features from the discrete wavelet transform of EEG signals.

2. Using a genetic algorithm to maximize the process of choosing the most discriminating subset of DWT attributes

3. To assess and contrast how well five distinct machine learning classifiers performed in identifying MDD using the chosen features.

By addressing these key objectives, this paper presents a comprehensive and robust framework for reliable depression detection using neurophysiological biomarkers from EEG signals, with the potential to serve as a complementary tool for mental health assessment and diagnosis.

2. Materials and Methods

Data Acquisition and Pre-processing

The study included 60 healthy control subjects, 39 of whom were female and 21 of whom were male, as well as 34 persons with major depressive illness, 17 of whom were female and 17 of whom were male. The machine learning technique in this experiment was estimated using the EEG database generated in [12]. Approved by Hospital University Sains Malaysia's ethics committee, this study guarantees that the research is conducted ethically.

To reduce the possibility of confounding variables, the donors were carefully chosen based on their lack of past medical background, past incidents of head trauma and usage of prescription drug. Before the investigation the participants were asked to fast for at least two hours, which is a common practice to optimize the quality of physiological measurements. Every member completed an informed consent form and was paid an honorarium of RM 40 for their involvement, indicating their voluntary involvement in the study. The Hospital University Sains Malaysia's ethics council, Malaysia, was thoroughly reviewed and endorsed the design of the study to ensure the protection of the participants' rights and well-being.

Feature Extraction and Selection

EEG signals are a rich and multifaceted source of information that can provide invaluable insights into the neurophysiological characteristics of major depressive illness and other neurological and mental conditions. To effectively leverage this data for diagnostic and clinical applications, it is crucial to extract a comprehensive set of relevant features that can capture the underlying patterns and intricate dynamics in the EEG data.

In this research, we employed a diverse array of feature extraction techniques, including statistical, spectral, and wavelet-based methods, to comprehensively characterize the EEG data. The statistical features, such as mean, variance, skewness, and kurtosis, offer insights into the distributional properties and variability of the EEG signals, which can be indicative of underlying neurophysiological changes associated with depression [13]. The spectral features, including peak and median frequencies, provide valuable information about the frequency domain attributes of the EEG readings, which have been previously considered to be useful biomarkers for the detection of major depressive disorder [14-15].

Furthermore, we leveraged the power of wavelet analysis, a renowned technique for extracting time frequency information from non-stationary signals like EEG [8]. By decomposing the EEG signals into multiple sub-bands using a six-level discrete wavelet transform with the coif5 mother wavelet, the researchers were able to capture the intricate temporal and spectral dynamics of the signals. The wavelet-derived features, such as energy, variance, wavelength, entropy, and standard deviation, served as rich and informative descriptors of the EEG data, which could potentially aid in the accurate detection and the identification of severe depression.

The genetic algorithm is a randomized optimization technique used in data mining to find an optimal solution by mimicking the process of natural selection [16]. This method involves creating "chromosomes" at random to represent the data's features as genes, and then assigning a value of 0 or 1 to each gene to signal whether the associated feature is selected or not.

As the process of searching space, a point is represented by each genome, and a collection of these chromosomes is called a population. The genetic algorithm evaluates the "fitness" of each chromosome in solving the problem, and chromosomes with higher fitness assessments have a higher probability of selected as parents to produce new, potentially better, offspring. For the purpose of this study, the fitness function is the mutual information between features and labels, which indicates whether or not the features are dependent on their class labels. [17]. The fitness function is designed to prioritize chromosomes with fewer selected features while still providing a high detection rate. The selection process involves comparing the fitness of randomly selected chromosomes and retaining the one with the better fitness to be included in the next generation.

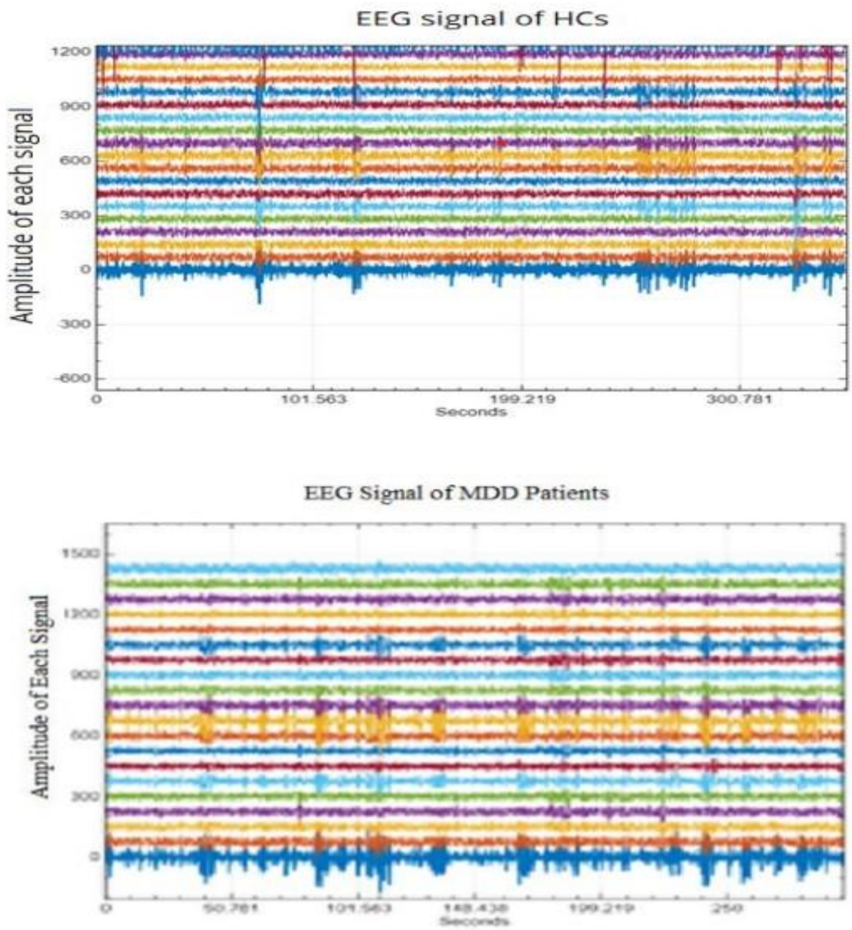


Figure 1: 19-channel EEG signals of healthy individuals (HC) and subjects with severe depression illness

Additionally, the genetic algorithm employs crossover and mutation operators to create new chromosomes. Crossover combines the features of two parent chromosomes to produce two offspring, while mutation randomly flips bits in a chromosome to maintain diversity and prevent premature convergence.

By integrating the genetic algorithm into the feature extraction and selection mechanism, it is possible to optimize the set of features used for depression detection from EEG signals. This approach allowed to identify the most outstanding discriminative and informative qualities, ultimately strengthening the overall productivity and accuracy of the depression detection system [11].

Classification

A flexible, nonlinear decision boundary is created via the supervised classification method known as quadratic discriminant analysis (QDA). It assumes Gaussian-distributed features with distinct means and covariance for each class, allowing it to better capture complex data structures and potentially achieve higher accuracy compared to linear discriminant analysis [18]. Naive Bayes is a simple yet effective probabilistic classifier that assumes independence between features. It is based on the Bayes theorem and can be quite useful for some classification problems, especially those that include textual input. Despite its simplicity, Naive Bayes classifiers have been used for categorization of various biomedical signals, including electro-cardiograms and electro-encephalograms [19]. Artificial neural networks are inspired by the human brain and can learn from data by adjusting the strengths of associated nodes or "neurons." They are useful for classifying major depressive disorder from EEG data because of their capacity for intricate learning, Nonlinear trends in data with high dimensions [20]. The performance of the neural network's classification can be enhanced by optimizing its parameters using the Levenberg, Marquardt backpropagation technique.

K-neighbours is a type of straightforward, learning by machine without constraints method that groups samples according to how close they are to the K closest neighbours within the feature space. By finding the k closest data samples and assigning the new sample to the most common class among them, KNN can effectively capture complex, nonlinear connections within the information, making it a useful technique for classifying major depressive disorder from EEG signals [21]. Support vector machines are effective for classifying complex biomedical signals like EEG data. To function, they search the high-dimensional feature space for the best hyperplane to divide various classes, increasing the margin of difference between the classes to improve the classifier's performance. SVMs are capable of handling large-scale data and identifying nonlinear correlations, making them useful for detecting and diagnosing neurological disorders like major depressive disorder from EEG signals. [22].

The paper explored the use of various machine learning techniques for the classification of EEG signals to detect MDD; each of these methods has unique strengths and weaknesses that were carefully considered in the context of this application. The evaluation used a 30% test set and 70% training set to assess the performance of the different classifiers in accurately detecting major depressive disorder from the EEG signals.

3. Results and Discussions

Throughout this section, we provide the comprehensive experimentation findings for assessing the models KNN, ANN, SVM, NB, and QDA that are recommended classification performance utilizing the characteristics chosen by the Genetic algorithm. Rigorous ablation experiments were conducted to thoroughly evaluate the feasibility and effectiveness of the proposed model design. The EEG data from 34 individuals diagnosed with Major Depressive Disorder and 60 healthy control subjects were utilized in this comprehensive investigation to distinguish between those with the mental health condition and their neuro typical counterparts. The five categorization

techniques and the suggested methodology were meticulously evaluated using a 70% train and 30% test data split. Four key performance metrics were employed in this study to provide an extensive examination of the categorization achievement: Accuracy, Sensitivity, Precision, and F1_Score.

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

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

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

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

The counts of the related sample categories are denoted by the words true positive (TP), false negative (FN), true negative (TN), and false positive (FP).

The classification outcomes obtained from the different classifiers are displayed in Table 1. The original feature set used in this study consisted of 42 attributes extracted from the EEG data. However, through the application of the genetic algorithm, the researchers were able to select a group of 30 features that were found to be the most informative and discriminative for the task of depression detection. This feature selection process using the genetic algorithm was a crucial step in optimizing the performance of the classification models, as it allowed the models to focus on the most relevant and meaningful characteristics of the EEG data, thereby enhancing their ability to accurately distinguish between individuals with normal boundaries and serious depression.

The results demonstrate that the SVM classifier, when applied to the optimized feature subset selected by the Genetic Algorithm, obtained the best overall performance in the division. The SVM model attained an impressive accuracy of 91.72%, indicating that it was able to correctly classify the majority of individuals as either having major depressive disorder or being healthy controls. Additionally, the model exhibited a sensitivity of 91.01%, suggesting a strong ability to accurately identify individuals with depression, and a recall of 92.18%, showcasing its effectiveness in detecting positive cases. The F1-score of 91.45% further underscores the model's balanced and robust performance, combining both precision and recall into a single metric. These exceptional results highlight the power of the Genetic Algorithm in determining the most illuminating and distinctive characteristics from the EEG data, which, when coupled with the inherent capabilities of the SVM classifier, led to a highly accurate and reliable system for the purpose of identifying serious depression.

The KNN classifier also exhibited excellent performance, reaching an impressive accuracy of 90.60%, a sensitivity of 91.12% indicating a strong ability to correctly identify individuals with depression, a recall of 90.36% showcasing its effectiveness in detecting positive cases, and an F1score of 90.52% further underscoring the model's balanced and robust performance, combining both precision and recall into a single metric. These exceptional results for the KNN classifier highlight the power of the Genetic Algorithm in determining the most illuminating and distinctive characteristics from the EEG data, which, when coupled with the inherent capabilities of the KNN model, led to a highly accurate and reliable system in order to identify serious depressive illness. The ANN, Naïve-Bayes, and QDA classifiers, while also demonstrating promising results, did not achieve the same level of performance as the SVM and KNN models. The ANN model achieved an accuracy of 78.57%, a sensitivity of 79.82%, a recall of 79.46%, and an F1-score of 78.56%. The Naïve Bayes model attained an accuracy of 72.93%, a sensitivity of 70.94%, a recall of 73.89%, and an F1score of 71.27%. The QDA model reached an accuracy of 70.68%, a sensitivity of 71.60%, a recall of 71.26%, and an F1-score of 70.64%. These findings are consistent with the results reported in [23], which showed that the GA-based feature selection approach can effectively identify the most discriminant EEG features, leading to a significant improvement in the classification accuracy for depression detection.

Table 1. Classification results (%) after feature selection by Genetic Algorithm

Classifier	Accuracy	Sensitivity	Recall	F_Score
KNN	90.6015	91.1184	90.3614	90.5177
ANN	78.5714	79.8246	79.4557	78.5566
NB	72.9323	70.9430	73.8883	71.2691
QDA	70.6767	71.6009	71.2574	70.6352
SVM	91.7293	91.0088	92.1771	91.4509

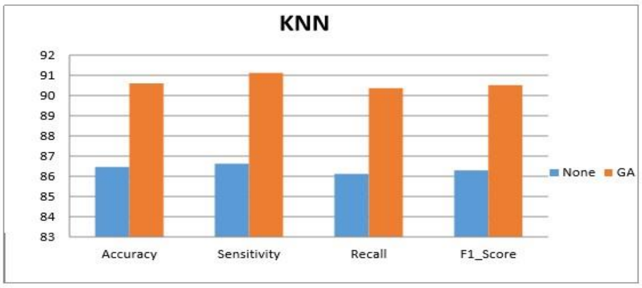
Table 2. Comparison of metrics for GA selection and without feature selection

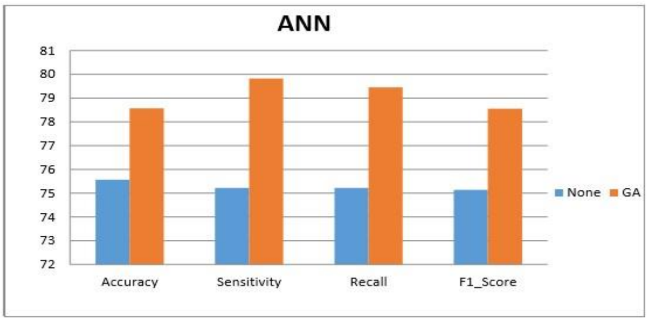
Classifier	Feature Selection	Accuracy	Sensitivity	Recall	F1_Score
KNN	None	86.4662	86.6228	86.1225	86.2918
	GA	90.6015	91.1184	90.3614	90.5177
ANN	None	75.5639	75.2193	75.2193	75.1334
	GA	78.5714	79.8246	79.4557	78.5566
NB	None	71.0526	70.2851	72.3164	70.3482
	GA	72.9323	70.943	73.8883	71.2691
QDA	None	68.4211	69.2982	68.9914	68.3764
	GA	70.6767	71.6009	71.2574	70.6352
SVM	None	87.594	86.0746	89.2527	86.9053
	GA	91.7293	91.0088	92.1771	91.4509

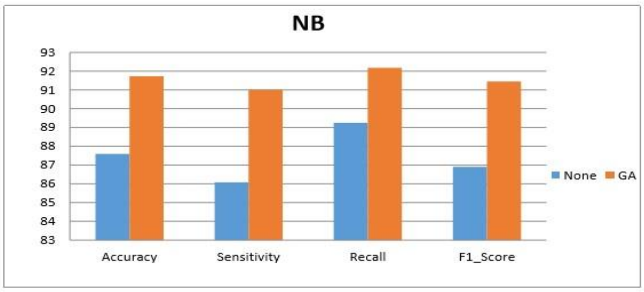
Furthermore, it is prudent to contrast the outcome of the classification algorithms using the complete feature set to highlight the superiority of the genetic algorithm in feature selection. In our previous work, we implemented a similar approach without utilizing the feature selection technique [24]. When compared to the results achieved by employing the genetic algorithm-based feature selection, as reported in Table 1, the performance metrics, including accuracy, sensitivity, recall, and F1-score, have revealed significant improvements. Table 2 reports the comparison of these two approaches where none means without feature selection.

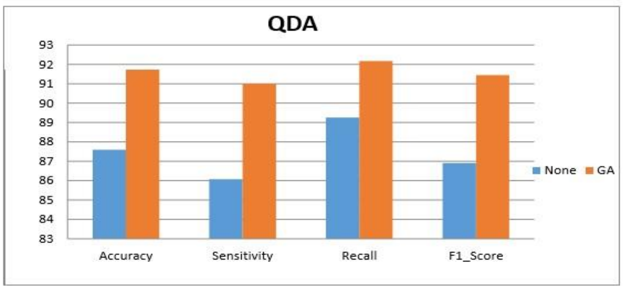
It is evident from the results in Table 2 that using a genetic algorithm for feature selection has greatly enhanced each and every one of the classification models compared to using the full set of 42 features. Across the board, we can see marked enhancements in the key metrics of accuracy, sensitivity, recall, and F1-score.

Specifically, the Accuracy of the KNN classifier increased from 86.47% to an impressive 90.60%, a gain of over 4 percentage points. The SVM model, which already exhibited strong performance, saw its Accuracy further improve to 91.73%, cementing its position as the top-performing classifier in this study. The improvements in Sensitivity were also noteworthy, with the KNN model achieving a slightly higher Sensitivity of 91.12% compared to the SVM's 91.01%. However, when examining the Recall and F1-Score metrics, the SVM demonstrated clear superiority, outperforming the KNN and all other classifiers. The ANN, Naïve Bayes, and QDA classifiers also benefited significantly from the GA-based feature selection, with their Accuracy increasing by over 2 percentage points in the case of ANN and QDA, and around 1 percentage point for Naïve-Bayes. Figure 2-6 reiterate the improvement in classifiers performance with GA.









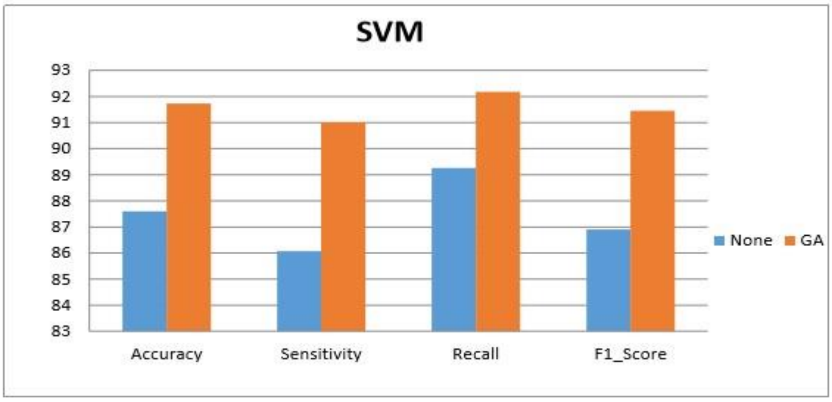


Figure 2-6: Improvement in performance metrics of KNN, ANN, NB, QDA and SVM.

These findings highlight the power of the Genetic Algorithm in determining the most illuminating and distinctive characteristics from the EEG data, which in turn enabled the classification models to focus on the most relevant characteristics, resulting in a substantial enhancement in their overall performance for the task of depression detection.

Future directions for research could involve analysing the impact of various EEG electrode placements, utilizing deep learning algorithms for feature extraction and classification, and monitoring the long-term effectiveness by applying these models for surveillance of the course of Major Depressive illness. Furthermore, adding other modalities like behavioural and demographic information might improve classification performance and provide a more thorough understanding of the disease. As a result, the study concludes that machine learning methods, including SVM and KNN, have a bright future in the categorization of MDD using EEG data.

4. Conclusion

In this research, we have demonstrated the effectiveness of using a Genetic Algorithm for feature choice in the context of depression detection using EEG signals. The GA-based approach was able to identify the most informative and discriminative features from the initial set of 42 features, leading to a significant improvement in the classification performance of various models, including SVM, KNN, ANN, Naïve-Bayes, and QDA.

The SVM classifier, in particular, achieved the highest overall accuracy of 91.73%, a sensitivity of 91.01%, a recall of 92.18%, and an F1-score of 91.45%, outperforming the other models. These results highlight the potential of the proposed GA based feature selection method in developing a robust and accurate system for the detection of serious mood disorder with electroencephalogram signals.

The KNN classifier also exhibited excellent performance, reaching an impressive accuracy of 90.60%, a sensitivity of 91.12% indicating a strong ability to correctly identify individuals with depression, a recall of 90.36% showcasing its effectiveness in detecting positive cases, and an F1score of 90.52% further underscoring the model's balanced and robust performance, combining both precision and recall into a single metric. The results of this investigation add to the expanding corpus of research on the application of machine learning methodologies, specifically feature selection algorithms, in the field of depression detection using EEG signals.

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