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Firefly Algorithm-Based Feature Selection for Accurate Prediction of Major Depressive Disorder from EEG Signals

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Abstract:
Around the world, billions of people suffer from Major Depressive Disorder, a complex mental health issue. Most psychological assessments are subjective, and symptoms can fluctuate widely, making the diagnosis of Major Depressive Disorder challenging. Improved diagnostic accuracy can be achieved through innovative approaches like machine learning and optimization. In this study, we present the Firefly Algorithm, a nature-inspired metaheuristic, to enhance feature selection and classification for MDD diagnosis. Firefly-adapted artificial intelligence identifies the most relevant elements that lead to a correct diagnosis, adapting to the complexity of MDD datasets. Using real-world MDD datasets, we evaluate the FA's effectiveness compared to conventional machine learning methods. The results demonstrate that the Firefly Algorithm is a promising approach for improved MDD diagnosis, as it reduces computational complexity and boosts diagnostic accuracy. Specifically, the FA-optimized SVM model (96.24%) achieved the highest level of diagnostic accuracy, followed by KNN, ANN, QDA, and Naïve Bayes. These findings highlight how the FA can select the most suitable characteristics to yield more accurate and efficient models, potentially enhancing MDD diagnosis

Keywords: Major depressive disorder, Feature selection, Firefly algorithm, support vector machine, EEG.

1. Introduction

Major depressive disorder is a prevalent and debilitating mental health condition characterized by persistent low mood, loss of interest in daily activities, and a range of physical symptoms such as changes in appetite and sleep patterns. It is a complex disorder that affects more than 264 million people globally, according to the World Health Organization [1], making it a leading cause of disability worldwide. The profound impact of major depressive disorder on individuals, communities, and the community at large emphasizes the crucial need for correct diagnosis and successful therapy approaches to address this significant public health challenge.

Due to the diverse range of signs and symptoms that frequently co-occur with other mental disorders, accurately and promptly diagnosing Major Depressive Disorder is crucial for receiving effective treatment. Machine learning-based approaches have become invaluable tools in mental health diagnosis, as they can identify complex patterns in clinical trials and neuroimaging data [2-3].

The effectiveness of applying classical machine learning techniques, such as Support Vector Machines (SVM), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Quadratic Discriminant Analysis (QDA), and KNN, to MDD identification has been observed to varying degrees [4-6]. On the other hand, a lot of the way that those designs work is based on the caliber of the features that are utilized, and working with high-dimensional datasets might render them less accurate. In this scenario, feature selection methodologies that goal to lower the dimensionality of the data while preserving the most valuable qualities are the only ways to increase the performance of machine learning models [7].

Several industry sectors, including medical diagnostics, have successfully incorporated nature-inspired optimization algorithms for feature selection, involving Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Firefly Algorithm (FA) [8-9]. In particular, FA has shown a pledge because of its robustness in avoiding local optima and its capacity to strike a state of equilibrium between extraction and innovation [10]. In order to boost the performance of five prominent machine learning models—KNN, ANN, Naïve Bayes, QDA, and SVM—this work examines the use of FA to optimize feature selection for MDD diagnosis.

An increasing number of mental health diagnostics, including MDD, are employing machine learning techniques. KNN, a simple but effective algorithm, categorizes incidents based on the majority class of their nearest neighbors. It has been widely used in medical applications but is sensitive to irrelevant features and the selection of k [11-12]. ANN, which mimics the structure of the human brain, can model complex relationships between inputs and outputs but requires a large amount of data and can suffer from overfitting [13]. Naïve Bayes, despite being made computationally efficient, assumes feature independence, which is rarely the case in complex disorders as MDD [14-15]. The quadratic classifier, or QDA, can be sensitive to noisy data, but it is useful in differentiating among classes with various covariances [16]. The program has demonstrated that SVM performs well in mental diagnoses, such as MDD [17], and has been particularly successful in high-dimensional fields.

In order to reduce the dimensionality of data, methods for selecting features such as Recursive Feature Elimination (RFE) and Principal Component Analysis (PCA) are widely applied; yet they might be computationally more expensive and may fail to recognize minor interactions between features [18-19]. Different approaches to feature selection have been offered by metaheuristic algorithms such as PSO and GA. By choosing the most essential features, these techniques optimize model performance by exploring the solution space for the ideal feature subset [20-21]. FA is a fairly recent metaheuristic, modeled upon the flashing activity observed in fireflies. FA's greatest benefit is its ability to achieve a balance across local search and global exploration, thereby minimizing the likelihood of it becoming stuck in local optima [22].

2. Objectives

As discussed in Section 1, recent work has proven that FA may be helpful for improving feature selection in several kinds of classification applications, such as bioinformatics, medical diagnosis, and images being processed [23] [24]. Its usage for people with mental disorders, especially those characterized by major depression (MDD), has been prohibited. The present study fulfills this gap by optimizing feature selection for MDD diagnosis utilizing FA in KNN, ANN, Naïve Bayes, QDA, and

SVM models.

3. Materials & Methods

A. Data acquisition and pre-processing

In order to conduct the study, the researchers recruited 60 healthy control volunteers, which included 34 people with severe depressive disorder (17 women and 17 males). Of them, they consisted of 21 men and 39 women. In this experiment, the EEG database constructed in [25] is being utilized to figure out the machine learning techniques. The EEG recordings are displayed in Figure 1 for both MDD subjects & Healthy persons. With authorization from Malaysia's Hospital University ethics committee, the present investigation assures that the research is performed ethically.

The donors were specifically selected based on their lack of preceding medical education, history of head trauma, and prescription medication intake in order to greatly reduce the probability for confounding variables. In an effort to achieve the greatest accuracy of physiological measurements, the participants were advised to remain hydrated for a minimum of two hours before the experiment. Every participant deliberately agreed to participate in the research study by writing up an informed consent form to receive an honorarium of RM 40. To ascertain the protection of the participant's rights and social services, the study's design was meticulously reviewed and approved by the Hospital University Sains Malaysia's ethics council in Malaysia.

B. Feature extraction and selection

EEG recordings are a broad and varied resource of data that may provide a significant understanding of the neurophysiological features of serious depressive disorder in addition to related mental and neurological disorders. In order to use this data for clinical and diagnostic use, it is critical to extract an extensive variety of relevant traits that may determine the complicated interactions and underlying patterns in the EEG data.

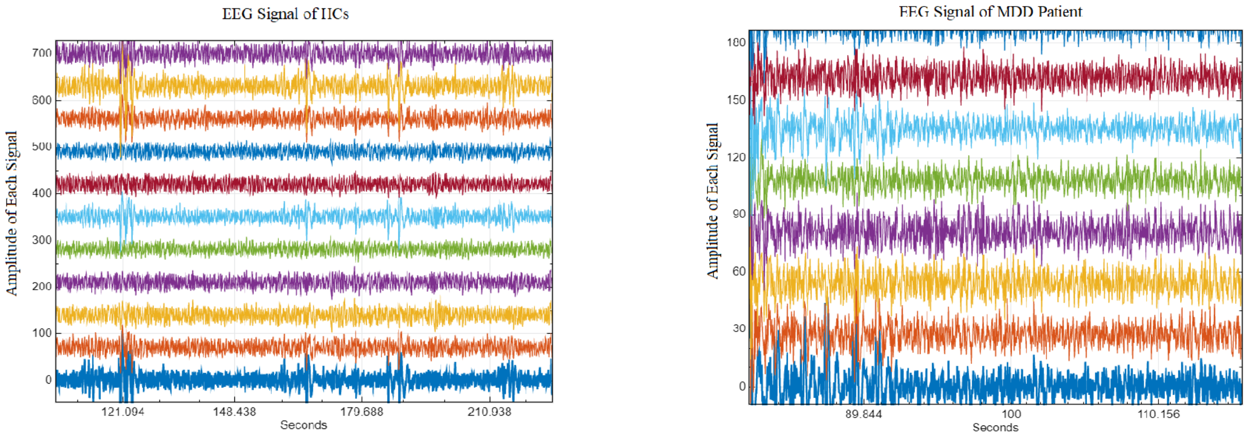

Figure 1: patients with major depressive illness and healthy people (HC) using 19-channel EEG signals.

A wide range of feature extraction methods, consisting of statistical, spectral, and wavelet-based methodologies, have been utilized in this investigation to accurately represent the EEG data. The EEG signals' variability and distributional properties are shown by statistical metrics which comprise the variance, mean, skewness, and kurtosis, which may be an indicator of underlying neurophysiological abnormalities linked to depression [26]. The spectral properties, such as peak and median frequencies, provide crucial information regarding the frequency-domain aspects of the EEG readings and were previously thought to be helpful biomarkers for the identification of major depressive illness [27–28].

Additionally, we made use of wavelet analysis, a well-known method for obtaining time-frequency data from non-stationary signals such as EEG [29]. The researchers were able to capture the complex temporal and spectral dynamics of the EEG data by breaking them down into several sub-bands using a six-level discrete wavelet transform with the coif5 mother wavelet. Energy, variance, wavelength, entropy, standard deviation, and other wavelet-derived characteristics were rich and relevant descriptors of the EEG data that may help with the precise diagnosis and identification of severe depression.

A form of metaheuristic effective optimization method called the "firefly algorithm" imitates the flashing patterns of firefly [30]. In 2009, Xin-She Yang created an unconventional optimization method called the Firefly Algorithm, which draws inspiration from the environment. It draws inspiration from the natural fireflies' flashing activity. The key principles underlying the Firefly Algorithm are:

All fireflies are attracted to one another, regardless of their sex. The attractiveness between two fireflies is proportional to their brightness, which represents the objective function value being optimized.

A firefly with lower brightness will be attracted towards a firefly with higher brightness. The attractiveness between fireflies decreases as the distance between them increases.

If a firefly cannot find a brighter neighbor, it will move randomly.

The brightness of a firefly is determined by the value of the objective function being optimized, which is the fitness function in the context of the algorithm.

The Firefly Algorithm is known for its strong exploration capabilities and ability to efficiently search complex, high-dimensional optimization spaces. It has been successfully applied to a wide range of optimization problems, including feature selection, which is a critical step in building accurate predictive models, such as for major depressive disorder diagnosis from EEG signals.

The results obtained from the Firefly Algorithm were compared against Genetic Algorithm and direct classification. The mutual information between the features and the class labels was used as the fitness function for the optimization algorithms. The maximum number of generations/iterations was set to 100 for this research. The GA implementation utilized a pressure parameter of 6 and an elite count of 2. The FFA was implemented with a fixed step size, a light absorption coefficient of 1, and the number of fireflies was set to 25. These parameter settings were chosen to leverage the inherent strengths of each algorithm and facilitate a comprehensive comparison of their performance in the context of feature selection for major depressive disorder diagnosis from EEG signals.

C. Classification

Another method for classification under supervision is a quadratic discriminant analysis that provides a versatile, limit for cubic decisions. Unlike linear discriminant analysis, it may better capture intricate data structures and potentially achieve higher accuracy when it assumes Gaussian-distributed features with distinct attributes and covariances for each class [31]. Naïve Bayes, a computationally efficient probabilistic classifier, is employed in our research for issues related to classifications that are binary and multi-class, with the Gaussian NB algorithm used to instantiate a classifier object [32]. K-Nearest Neighbor is a fundamental machine learning algorithm based on supervised learning, which stores all available data and uses similarity to classify new data points, instead of learning directly from the training set, and leverages the preserved dataset as needed [33].

Support Vector Machines are a supervised learning method for classification. They emphasize establishing the optimal decision boundary for data points [34]. Artificial neural networks, inspired by the human brain, can learn from data by modifying the strengths of connected nodes or "neurons." Their ability to learn complex information and detect nonlinear patterns in high-dimensional data makes them valuable for classifying major depressive disorder from EEG data [35]. The Levenberg-Marquardt backpropagation technique can enhance the neural network's classification performance.

This research reviewed that multiple methods of machine learning may be utilized for categorizing EEG recordings for MDD identification. The benefits and limitations of each algorithm were completely examined in the brightness of this application. They worked with a 30% test set and a 70% training set to determine every classifier's activity inappropriately decoding serious depressive conditions from the electroencephalogram (EEG) signals.

4. Results

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 carried out to thoroughly evaluate the feasibility and effectiveness of the proposed model design. The EEG data from 34 people with severe depressive disorder diagnosis and 60 health control subjects were utilized in this comprehensive investigation to distinguish between those with the mental health condition and their neurotypical 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, Recall, Precision, and F1_Score.

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

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

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

$$\text{F1\_Score} = \frac{2 * TP}{2 * TP + FP + FN} \quad (4)$$

For the appropriate sample categories, the number of samples is denoted by the words true positive (TP), false negative (FN), true negative (TN), and false positive (FP).

Table 1 presents the categorization outcomes derived from the various classifiers. 42 characteristics that were taken from the EEG data made up the initial feature set employed in this investigation. Nevertheless, by using the firefly method, the researchers were able to choose 30 features that were the most discriminative and instructive for the depression detection job. An essential stage to enhancing the performance of the classification models was the process of choosing features implementing the firefly algorithm, which allowed the models to specialize on the most critical features of the EEG data, strengthening their capacity to discriminate between people with normal boundaries and those suffering from severe depression.

When applied to the finest feature subset assigned by the Firefly Algorithm, the SVM classifier achieved the greatest overall score in the division, according to the results. As illustrated by the SVM model's incredible 96.23% accuracy, nearly all people were properly classified as either majorly depressed or healthy controls. A precision score of 95.94% proved the model's ability to find people with depression, and a recall of 96.39% proved it was successful in identifying instances of optimism. Further supporting the model's balanced and reliable outcome is its F1-score of 96.14%, which aggregates precision and recall into a single amount. These excellent findings point out the Firefly Algorithm's ability to extract the most exposing and unique features from the EEG data. When mixed with the SVM classifier's integrated capabilities, this approach developed a highly accurate and faithful system for noticing severe depression.

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

Classifier	Accuracy	Precision	Recall	F1_Score
KNN	94.7368	94.2982	94.9836	94.5888
ANN	75.9398	76.2061	75.7077	75.7424
NB	73.3083	72.9167	76.1523	72.8380
QDA	75.5639	75.7675	75.2932	75.3461
SVM	96.2406	95.9430	96.3928	96.1445

Additionally, the KNN classifier performed exceptionally well, achieving an impressive 94.73% accuracy, a precision of 94.29% that demonstrated a strong ability to correctly identify individuals with depression, a recall of 94.98% that demonstrated its effectiveness in detecting positive cases, and an F1-score of 94.58% that further highlighted the model's balanced and robust performance by combining precision and recall into a single metric. These amazing results for the KNN classifier, when teamed with the built-in abilities of the KNN model, suggest that the Firefly Algorithm may extract the most unique and explaining features from the EEG data, developing a highly reliable and accurate system for discovering serious mood disorders.

In addition, they presented good outcomes, the ANN, Naïve-Bayes, and QDA classifiers have not been as successful as the SVM and KNN models. 75.93% accuracy, 76.20% precision, 75.70% recall, and 75.74% F1-score were achieved by the ANN model. The accuracy, precision, recall, and F1-score of the Naïve-Bayes model reached 73.30%, 72.91%, and 76.15%, respectively. The QDA model achieved 75.56% accuracy, 75.76% precision, 75.29% recall, and 70.34% F1-score. The results shown in [36] demonstrate that the Firefly Algorithm-based feature selection method may successfully uncover the most discriminant EEG features, resulting in a notable increase in the classification accuracy for diagnosing melancholy.

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

Classifier	Feature Selection	Accuracy	Precision	Recall	F1_Score
KNN	None	86.4662	86.6228	86.1225	86.2918
	GA	90.6015	91.1184	90.3614	90.5177
	FA	94.7368	94.2982	94.9836	94.5888
ANN	None	75.5639	75.2193	75.2193	75.1334
	GA	78.5714	79.8246	79.4557	78.5566
	FA	75.9398	76.2061	75.7077	75.7424
NB	None	71.0526	70.2851	72.3164	70.3482
	GA	72.9323	70.9430	73.8883	71.2691
	FA	73.3083	72.9167	76.1523	72.8380
QDA	None	68.4211	69.2982	68.9914	68.3764
	GA	70.6767	71.6009	71.2574	70.6352
	FA	75.5639	75.7675	75.2932	75.3461
SVM	None	87.5940	86.0746	89.2527	86.9053
	GA	91.7293	91.0088	92.1771	91.4509
	FA	96.2406	95.9430	96.3928	96.1445

Table 2 reports the comparison of three approaches where none means without feature selection. The Firefly Algorithm (FA) significantly raised all algorithms' classification accuracy by picking the feature subsets with greater efficiency. The outcomes of every model are summarized in Table 1. SVM (96.24%) and KNN (94.74%) had the best diagnostic accuracy when applying FA-optimized feature selection. SVM (96.24%) and KNN (94.74%) have demonstrated the highest diagnostic accuracy when using FA-optimized feature selection.

An adequate level of performance was demonstrated by the QDA and ANN accuracy achievements, with scores of 75.56% and 75.94%, respectively. The Naïve Bayes algorithm produced the worst results, scoring 73.31%, since it heavily relies on the idea of feature independence. FA predicted the number of features required in each technique without sacrificing accuracy, leading to the development of smaller, more comprehensible models. The models' feature reduction rates varied, ranging from 30% to 40%. In medical diagnostics, computational efficiency and interpretability are crucial, and this reduction is particularly noteworthy [37-38].

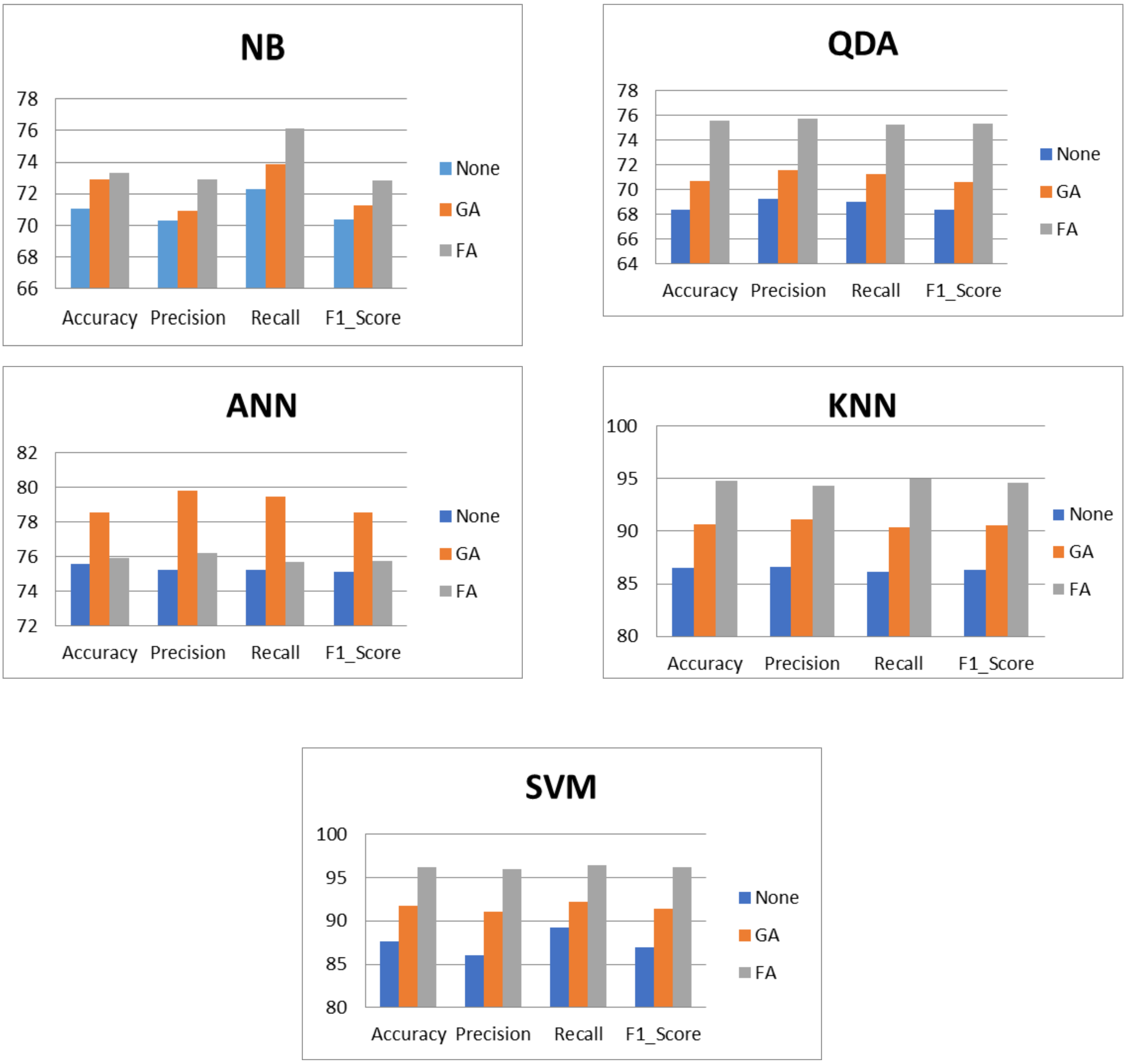

Figure 2-6: Improvement in performance metrics of KNN, ANN, NB, QDA, and SVM.

In particular, for SVM and KNN models, observations demonstrate that the Firefly Algorithm is highly flourishing at optimizing feature selection for MDD diagnosis. In addition to FA, medical diagnosis can be further improved by identifying the most pertinent characteristics, as evidenced by the notable improvement in classification accuracy. Another factor that suggests that FA is an adequate match for medical applications—where extremely dimensional data is more often encountered—is its capability to reduce dataset dimensionality without affecting accuracy [39-40].

Features augmentation (FA) presents a more flexible and successful feature optimization approach compared to previous feature selection techniques. It can avoid the traps of local optima, which may decrease the performance of other metaheuristics such as GA and PSO, owing to its dynamic balance between exploration and exploitation [41-42]. In particular, the FA-optimized SVM model exhibits promise for practical clinical applications where diagnostic precision is crucial [43].

The principal contributions to this work are as follows: We encourage a novel Firefly Algorithm-based feature selection method for accurately diagnosing major depressive disorder from EEG signals. The FA-based feature selection approach is shown to be more effective than conventional techniques like GA, as demonstrated by the higher classification accuracy, precision, recall, and F1 score achieved by SVM and KNN classifiers. The reduction in the number of features without sacrificing accuracy is particularly beneficial in medical applications where interpretability and computational efficiency are important.

Future work could explore using deep learning for feature extraction and classification, test different EEG electrode placements, and track how these models perform over time in detecting changes in Major Depressive Disorder. Incorporating other data types, like behavior and demographics, may also improve classification and provide more insights into the disorder. Using EEG data, this work demonstrates the potential of machine learning methods, particularly SVM and KNN, for the classification of major depressive disorder.

5. Discussion

This study demonstrates the effectiveness of the Firefly Algorithm in enhancing feature selection for the diagnosis of Major Depressive Disorder across multiple machine learning models. The results indicate that the Firefly Algorithm has great potential to improve the diagnostic capabilities of machine learning techniques in the field of psychiatry. The FA-optimized Support Vector Machine model achieved the greatest degree of accuracy, followed closely by the K-Nearest Neighbors model.

To further enhance patient outcomes and diagnostic accuracy, future research should focus on integrating the Firefly Algorithm with deep learning approaches. This integration could lead to even more powerful and robust models for the detection and management of MDD. Additionally, exploring the application of the Firefly Algorithm-based feature selection method to other psychiatric disorders could yield valuable insights and advancements in the field of mental health diagnostics and treatment.

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