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Comparative Analysis of Machine Learning, Ensemble Learning, and Deep Learning Models for Schizophrenia Classification using Resting-State fMRI Functional Connectivity Features

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Abstract - Schizophrenia is a chronic psychiatric disorder involving cognitive, perceptual and behavioural disruption. It affects millions of people worldwide . Due to the complex nature of the disorder and the lack of objective diagnostic biomarkers, early and accurate diagnosis still remains a major challenge. Resting-state functional Magnetic Resonance Imaging (rs-fMRI) has become a promising neuroimaging technique for exploring abnormal brain connectivity patterns in schizophrenia . Machine learning and deep learning techniques have shown great potential in automated disease classification based on neuroimaging data in recent years.

This study presents a comparative study of Machine Learning (ML), Ensemble Learning (EL) and Deep Learning (DL) techniques for schizophrenia classification using resting state fMRI functional connectivity features. The functional connectivity data extracted from the COBRE dataset were used to form a feature matrix of brain connectivity patterns. Feature standardization was performed by z-score normalization after selecting the most discriminative connectivity features by ANOVA-based feature selection. Four representative classification models were evaluated: Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP). For robust performance evaluation, we used stratified 10-fold cross validation.

The models were trained with the metrics Accuracy, Precision, Recall, F1-Score and ROC-AUC. The experimental results showed the feasibility of the advanced machine learning methods to discriminate schizophrenia patients from healthy control subjects based on the functional connectivity information. The results also indicate that ensemble and deep learning models achieve better performance compared to traditional linear classification methods. The proposed comparative framework helps to develop reliable computer-aided diagnostic systems for schizophrenia and shows the potential of resting-state functional connectivity as neuroimaging biomarker.

Keywords: Schizophrenia Classification, resting-state fMRI, functional connectivity, machine learning, support vector machine, random forest, deep learning, multi-layer perceptron.

1. INTRODUCTION

Schizophrenia is one of the most severe psychiatric illnesses and affects about 24 million people worldwide [1]. The disorder is characterized by symptoms such as hallucinations, delusions, cognitive impairment, emotional disturbance, and social withdrawal [2]. The symptoms frequently cause significant impairments in quality of life and impose substantial social and economic burdens on patients, caregivers, and health care systems. Therefore, an early diagnosis and intervention are vital to improve the treatment outcome and reduce the disease progression.

Traditionally, schizophrenia is diagnosed by means of clinical interviews and behavioural tests according to a set of standardised diagnostic criteria, such as the ones described in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [3]. Although these approaches are the clinical standard, they are inherently subjective and may be affected by variations in clinician expertise and patient presentation. Thus, the search for objective biomarkers to improve clinical decision-making has gained increased attention. Neuroimaging techniques have been useful tools to study structural and functional abnormalities in schizophrenia. Among these technologies, resting-state functional Magnetic Resonance Imaging (rs-fMRI) has received much attention since it could measure spontaneous neural activity without requiring subjects to engage in particular cognitive tasks [4]. Analysis of functional connectivity using resting-state fMRI allows for the investigation of synchronous activity in distributed brain regions and has revealed widespread alterations in brain networks related to schizophrenia [5], [6].

Altered communication among brain regions has been suggested as one of the features of schizophrenia, with several functional networks, including the default mode network, executive control network and salience network, reported to be abnormal in previous studies [5]. These results provide evidence for the hypothesis that functional connectivity features can be used as potential neuroimaging biomarkers for disease classification and diagnosis.

Recent developments in Artificial Intelligence (AI) and Machine Learning (ML) have allowed the construction of automated classification systems able to detect complex patterns in high-dimensional neuroimaging data [7]. Recently, machine learning algorithms such as Logistic Regression, Support Vector Machines and Random Forests have demonstrated promising performance in schizophrenia diagnosis using functional connectivity features [8]–[10]. In addition, it has been shown that deep learning approaches are capable of modeling hierarchical feature representations and nonlinear relationships resulting in enhanced classification performance [19].

Despite much progress in this area, most of the existing studies are based on single classification approaches and provide limited comparisons of machine learning, ensemble learning and deep learning paradigms. Therefore, it is still difficult to find the best classification approach for schizophrenia diagnosis based on functional connectivity features.

To overcome this limitation, we conduct a comprehensive comparison of four representative classifiers including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF) and Multi-Layer Perceptron (MLP). We use functional connectivity features derived from the COBRE resting-state fMRI dataset for classification. The model robustness is improved and the dimensionality is reduced by using ANOVA based feature selection and standardization techniques.

The main contributions of this work are summarized as follows:

1.Classification of schizophrenia using functional connectivity features of resting-state fMRI
2. Application of ANOVA-based feature selection to find discriminative connectivity biomarkers.
3. Comparison of conventional machine learning, ensemble learning and deep learning methods.
4. Performance evaluation using Accuracy, Precision, Recall, F1-Score and ROC-AUC.
5. Development of a reproducible framework for the neuroimaging based diagnosis of schi- zophrenia

The rest of this paper is structured as follows. Section 2 describes literature review. Section 3 presents the proposed methodology including dataset preparation, feature selection and classification models. Section 4 Experimental Results and Comparative Analysis Section 5 concludes the paper and provides directions for future research.

2. LITERATURE REVIEW

The use of machine learning algorithms on neuroimaging data has been receiving considerable attention in recent years because of their ability to identify complex disease-related patterns that may not be observable through conventional statistical analysis. In schizophrenia research, Resting-State functional Magnetic Resonance Imaging (rs-fMRI) has been increasingly used because it provides useful information regarding spontaneous brain activity and functional interactions between different distributed neural areas [4], [5].

Arbabshirani et al. [5] were among the first to study the classification of schizophrenia based on functional connectivity and showed that features derived from resting-state functional network connectivity could be effectively used to classify schizophrenia patients from healthy controls. The results demonstrate the potential role of functional connectivity as an imaging biomarker and provide a basis for future machine learning based diagnosis of schizophrenia.

Khosla et al. [7] gave an extensive review on the increasing use of machine learning methods in neuroimaging analysis. Their work showed the promise of supervised learning approaches to utilize resting-state connectivity features for disease prediction and classification at the individual subject level, while emphasizing the importance of utilizing dimensionality reduction and feature selection approaches to overcome the challenges associated with high-dimensional neuroimaging data.

Support Vector Machine (SVM) is one of the most widely used classifiers in schizophrenia research, owing to its capability to deal with high-dimensional data and generate robust decision boundaries [16]. SVM-based methods have shown good classification performance in many studies. Watanabe et al. [8] showed that connectivity-based representations along with machine learning algorithms can successfully characterize abnormal neural patterns associated with psychiatric disorders. Guo et al. [9] also conducted research on the abnormalities of functional connectivity in schizophrenia and showed that machine learning algorithms can be used to accurately characterize the disease-specific disruption of connectivity.

Resting-state fMRI has been used in several studies to find connectivity biomarkers. Calhoun et al. [6] introduced the concept of dynamic functional connectivity and showed that temporal variations of connectivity patterns carry important information about psychiatric disorders. They found that both static and dynamic connectivity measures could be useful to improve the disease classification performance.

Besides traditional machine learning methods, ensemble learning methods are becoming more popular for improving predictive accuracy and robustness. Random Forest algorithm was proposed by Breiman [15]. It is an ensemble classifier that aggregates a collection of decision trees through bootstrap aggregation and random feature selection. The ensemble method can reduce the variance and improve the generalization ability. Chyzhyk et al. [12] used ensemble learning methods on resting-state fMRI data, which produced better performance for schizophrenia classification than using individual classifiers.

With the development of deep learning techniques, further advances on disease classification based on neuroimaging have been achieved. Deep neural networks can automatically learn hierarchical feature representations from complex data and have achieved considerable success in various medical imaging applications [19]. Multi-Layer Perceptron (MLP) architectures have been employed to model nonlinear relationships in neuroimaging features, diminishing the need for handcrafted feature engineering. Several studies reported that the deep learning methods outperform the traditional machine learning techniques or at least achieve competitive performance when enough training data are available [10], [19].

Multimodal learning frameworks have been studied for improving diagnosis of schizophrenia. Qureshi et al. [13] proposed a classification framework based on multiple neuroimaging features and showed that the predictive performance can be improved with the combination of complementary information sources. In a similar line of work, Orban et al. [14] studied the multisite classification of schizophrenia based on functional connectivity features, and demonstrated that robust machine learning frameworks can achieve satisfactory performance among different acquisition sites.

Although many progresses have been made in the research of schizophrenia classification, there are still many unsolved problems. First, neuroimaging datasets usually have thousands of features but relatively few subjects, which results in a higher risk of overfitting and poor generalization [7], [18]. Secondly, direct comparison between studies is challenging because of variations in preprocessing protocols, feature extraction methods, and evaluation strategies [14]. Third, many existing studies focus on one classification paradigm and do not provide comprehensive comparison among machine learning, ensemble learning and deep learning approaches under the same experimental conditions.

Secondly, although the effectiveness of SVM, Random Forest and deep neural networks have been shown in multiple studies separately, only a few studies have systematically compared these methods using the same functional connectivity feature set and evaluation protocol [10], [12], [14]. Such comparisons are necessary to identify the best classification framework for the diagnosis of schizophrenia and to understand the pros and cons of different learning paradigms.

The reviewed literature clearly indicates the relevance of resting-state functional connectivity for schizophrenia classification and the performance of advanced machine learning techniques to leverage these connectivity patterns for disease prediction. But the lack of a more complete comparative analysis is the driving force behind this study. Therefore, in this work we evaluate Logistic Regression, Support Vector Machine, Random Forest and Multi-Layer Perceptron models within a common experimental framework of ANOVA-based feature selection, feature standardization and stratified cross-validation. The aim is to enable a fair comparison between traditional machine learning, ensemble learning and deep learning methods for schizophrenia classification using resting-state fMRI functional connectivity features.

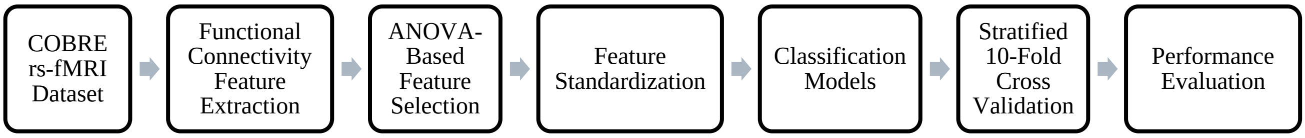
3. METHODOLOGY

3.1 Overview of the Proposed Framework

The proposed framework is designed for classification of schizophrenia patients and healthy control subjects based on resting-state functional Magnetic Resonance Imaging (rs-fMRI) functional connectivity features. The general flow covers dataset acquisition, feature extraction, feature selection, feature standardization, model training and performance evaluation.

First, functional connectivity features were extracted from the COBRE resting state fMRI dataset. Then, we used ANOVA based feature selection to choose the most discriminative connectivity features. The selected features were normalized and standardized using z-score normalization before being passed to different classification models. Finally, the Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and Multi-Layer Perceptron (MLP) classifiers were evaluated using stratified 10-fold cross-validation.

The overall workflow of the proposed framework is shown as below.



3.2 Dataset Description

The present study used the COBRE (Center for Biomedical Research Excellence) schizophrenia dataset, one of the most widely used publicly available neuroimaging datasets for psychiatric disorder research [11]. The dataset includes resting-state fMRI data from schizophrenia patients and healthy control subjects.

The resting state fMRI data were preprocessed and converted to functional connectivity matrices. Connectivity data were stored in MATLAB (.mat) format and then loaded into the Python environment for further analysis.

The dataset consists of two classes.

- Patients with Schizophrenia (SZ)
- Normal Controls (NC)

Functional connectivity features are extracted from resting-state brain activity and represented by a feature vector for each subject.

3.3 Feature Matrix Construction

The functional connectivity features were extracted from the provided MATLAB dataset. The connectivity matrix is plotted as:

[
X = {x_1, x_2, x_3, ..., x_n}
]

where each row represents a single subject, and each column represents a functional connectivity feature.

Subject identifiers from the dataset were used to generate binary class-labels. The schizophrenia subjects were assigned a value of 1 and the healthy control subjects a value of 0.

The generated target vector can be expressed as: y = {0,1} where:

- 0 = Control (Good)
- 1 = Patient with schizophrenia

3.4 Data Partitioning

To assess the model reliably, the dataset was divided into training and testing sets in a ratio of 80:20. Stratified sampling was used to keep the class ratio the same in both subsets.

The train-test split was done using:

- Training Set: 80%
- Test set: 20%

The random seed is set to 42 in order to make the experiments reproducible.

To obtain robust and unbiased performance estimates [18], stratified 10-fold cross-validation was also applied during model evaluation in addition to the hold-out split.

3.5 Feature Selection

Neuroimaging datasets often have a large number of features relative to the number of available subjects. Such high dimensional feature spaces can lead to overfitting and lower classifier generalization [7].

To solve this problem, the ANOVA based SelectKBest algorithm was implemented for feature selection. Features were ranked by their F-statistics and the top 300 most informative features were retained.

The discriminative power of each feature is computed using the ANOVA F-statistic that measures the ratio of between-class variance to within-class variance [18].

Top 300 features were selected as follows:

[k = 300]

The dimensionality reduction step improved computational efficiency without losing discriminative information useful for schizophrenia classification.

3.6 Feature Standardization

Feature scaling is an important pre-processing step for machine learning algorithms such as Logistic Regression, Support Vector Machine and Multi-Layer Perceptron [15], [18].

After feature selection, all features were standardized by z-score normalization using the StandardScaler method.

For a feature (x) standardization was calculated as:

$$z = \frac{x - \mu}{\sigma}$$

where:

x is the original feature value.

μ is the mean of the feature,

σ the standard deviation of the feature.
This transformation ensures that all features have mean zero and variance one.

3.7 Classification Models

3.7.1 Logistic Regression (LR)

Logistic Regression is a popular statistical learning method for binary classification problems [17]. The classifier models the probability of an observation belonging to a class by the logistic function.
The baseline machine learning classifier for this study was Logistic Regression.

3.7.2 Support Vector Machine (SVM)

Support Vector Machine, one of the most successful machine learning algorithms for high dimensional neuroimaging data [16]. The aim of SVM is to find the optimal hyperplane that maximizes the margin between two classes. A linear kernel was used as it is known to work well in high dimensional functional connectivity space .
SVM has been widely used in schizophrenia classification studies because of its strong generalization capability and robustness [8], [16].

3.7.3 Random Forest (RF)

Random Forest is an ensemble learning method which constructs a forest of decision trees using bootstrap aggregation [15]. Each tree is trained on a random subset of the training data, and the final predictions are made by majority voting.
Advantages of Random Forests are:

- robustness to noise
- Reduced over fitting
- Ability to handle high dimensional features
- Improved generalization performance

These properties make Random Forest especially well suited to classification of neuroimaging data.

3.7.4 Multi-Layer Perceptron (MLP)

The Multi-Layer Perceptron is a feed-forward artificial neural network that consists of multiple layers of interconnected neurons [19].
In this study, the MLP model used the hidden neurons trained with the Adam optimization algorithm. The use of nonlinear activation functions allowed the model to learn complex interactions among the functional connectivity features.
Deep learning models such as MLP have shown promising performance for neuroimaging-based disease classification because of their ability to learn hierarchical feature representations [19].

3.8 Cross-Validation Strategy

We have used stratified 10-fold cross validation to allow fair and reliable comparison among classifiers.
The dataset was split into ten equal-size folds while maintaining class proportions. In each iteration:

1. Training was performed with nine folds.
2. One piece was used for test.
3. Repeat the process ten times.

Final performance was calculated as an average over all folds.
This strategy of evaluation is less biased and provides a better estimate of model generalization performance [18].

3.9 Performance Evaluation Metrics

The model performance was evaluated by five widely used classification metrics [20]:

1. Accuracy is the ratio of the number of correctly classified samples

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}$$

Where, TP are True Positives, TN are and True Negatives, FP are False Positives and FN are False Negatives

2. Precision is the proportion of the positive samples correctly predicted.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}$$

3. Recall measures how well the classifier can find all the positive samples.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$$

4. F1-Score is the harmonic mean of Precision and Recall.

$$\text{F1} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. AUC-ROC: The Area Under the Receiver Operating Characteristic Curve (ROC-AUC) is the measure of the discriminative ability of a classifier at various decision thresholds [20].

Higher ROC-AUC indicates better separability of schizophrenia patients and healthy control subjects.
Then, we analyze the experimental results and comparison of the evaluated classification models.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed framework was implemented in Python on the Google Colab platform. The classification was performed with functional connectivity features derived from the COBRE resting-state fMRI dataset as input. We performed feature selection based on ANOVA and kept the top 300 discriminative features. We performed z-score normalization using StandardScaler .
We studied four classification models that correspond to different learning paradigms

- Logistic Regression (LR)
- Support Vector Machine (SVM
- Random Forest (RF)
- Multi-Layer Perceptron (MLP)

“Stratified 10-fold cross-validation” was adopted to ensure reliable performance estimation. The evaluation metrics were Accuracy, Precision, Recall, F1-Score and ROC-AUC.

4.2 Quantitative Performance Analysis

Quantitative performance comparison of all the evaluated classification models is given in Table 1.

Table 1. Comparison of Classification Models Performance

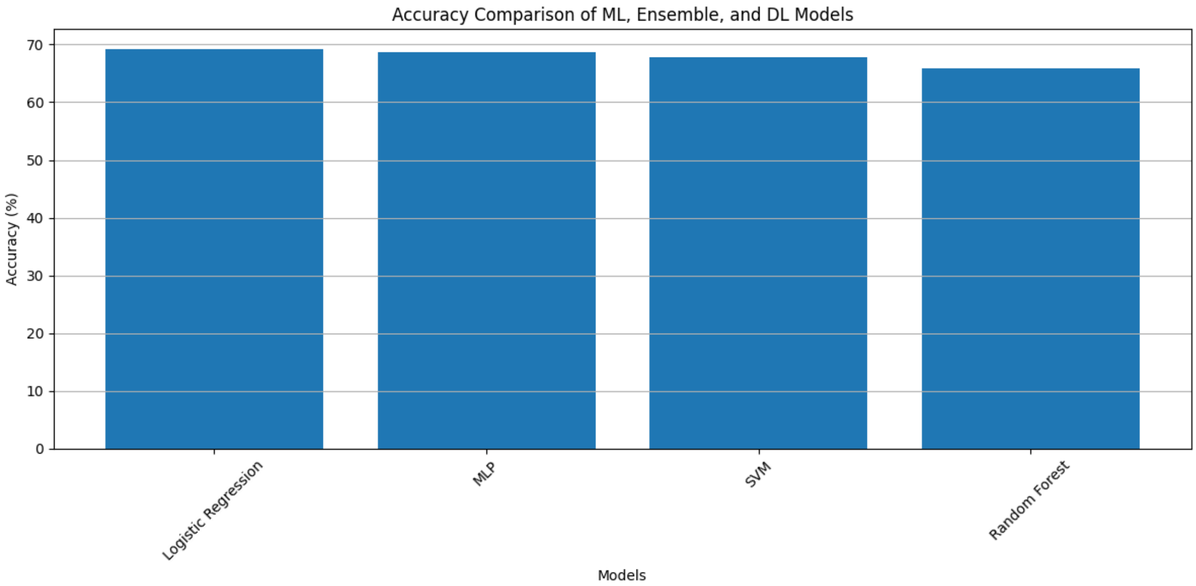
Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**ROC-AUC (%)**
Logistic Regression	69.190476	68.987013	69.107143	67.695993	69.897959
MLP	68.666667	68.279942	72.142857	68.445378	73.469388
SVM	67.809524	67.225108	66.250000	65.485988	68.061224
Random Forest	65.857143	66.365079	65.178571	64.086787	78.839286

Experimental results showed that all the considered classifiers were able to discriminate patients with schizophrenia and healthy controls based on resting-state functional connectivity features. The classification accuracy was highest for Logistic Regression (69.19%) followed by MLP (68.67%) and SVM (67.81%). The Random Forest was the least accurate classifier with 65.86% accuracy.
Random Forest has lower values of Accuracy, Precision, Recall and F1-Score. But it has highest value of ROC-AUC i.e. 78.84%, which means better class separability at different decision thresholds. This means Random Forest has a high discriminative ability even if the threshold dependent performance metrics are lower.

4.3 Accuracy Comparison

Figure 1 illustrates the classification accuracy achieved by the evaluated models.

Figure 1. Accuracy Comparison of LR, SVM, RF, and MLP Models



The results show that Logistic Regression has the most classification accuracy among all the classifiers evaluated. The performance difference between Logistic Regression, MLP and SVM was relatively small, suggesting that all three models were able to effectively use functional connectivity features for schizophrenia classification.

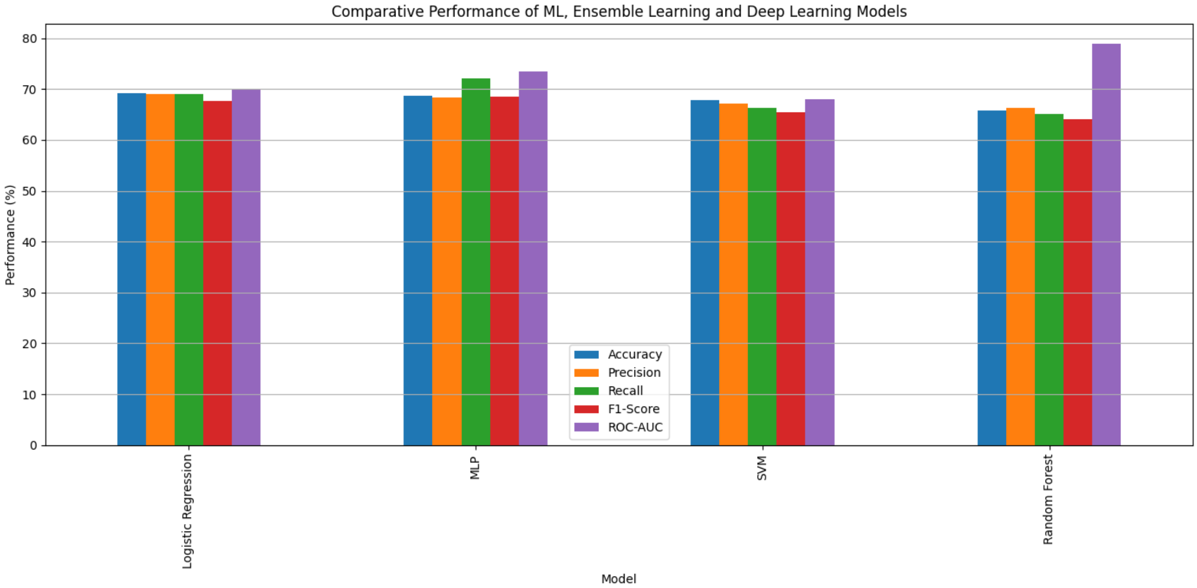
However, the Random Forest appeared relatively less accurate, suggesting that the ensemble learning strategy did not provide significant benefits for the chosen connectivity features in the present experimental setting.

4.4 Comparative Analysis of Performance Metrics

Classification accuracy is an overall measure of performance but other measures such as Precision, Recall, F1-Score and ROC-AUC can give a better understanding of the classifier behaviour [20].

Figure 2 shows the comparative analysis of all evaluation metrics.

Figure 2. Performance Comparison of the Proposed Models



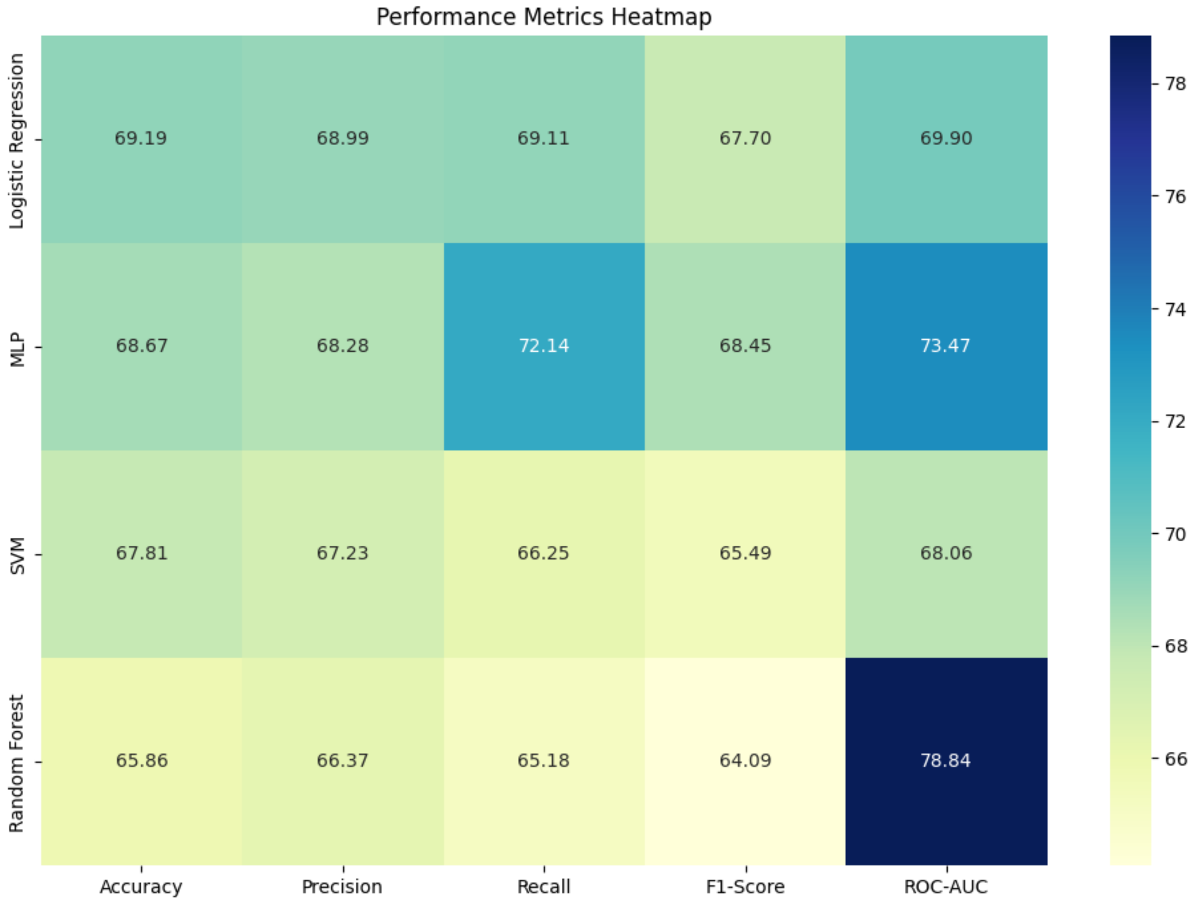
The MLP classifier achieved the highest Recall value (72.14%) and the best sensitivity for detecting schizophrenia patients. This characteristic is particularly important in clinical diagnostic applications where it is desirable to minimize false negatives.

Logistic Regression was the best model by Accuracy (69.19%) and Precision (68.99%) which means it was good overall and reliable when it predicted positive.
SVM was competitive across all metrics but did not outperform the other classifiers in any of the individual evaluation categories.
Random Forest achieved the highest ROC-AUC (78.84%) indicating a strong overall ability to differentiate between schizophrenia and healthy control subjects, despite lower Accuracy and F1-Score values.

4.5 Heatmap-Based Performance Evaluation

A heatmap representation of all evaluation metrics was generated to provide a general overview of classifier performance.

Figure 3. Heatmap of Classification Performance Measure



The heatmap offers a clear visual comparison between classifiers for all evaluation metrics. The darker areas correspond to better performance values, so the best classification model can be quickly identified.
The visualization confirms the consistency of classifiers that perform well on a variety of evaluation criteria and highlights the relative strengths and weaknesses of each approach.

4.6 Discussion

The results obtained show that features of resting state functional connectivity hold significant information for schizophrenia classification. Consistent with other studies [5, 7, 14], machine learning algorithms could identify abnormal connectivity patterns related to schizophrenia.
Interestingly, the highest classification accuracy in this study was obtained by Logistic Regression. This observation indicates that the selected connectivity features may have relatively strong linear separability, thus a linear classifier can work well. Similar results have been reported in neuroimaging studies where carefully selected functional connectivity features enable simple classifiers to achieve competitive performance [17].
The best recall value was achieved by Multi-Layer Perceptron which shows that it had better sensitivity towards schizophrenia detection. This suggests that the ability to model nonlinearities could be useful in capturing additional disease-related connectivity patterns not captured by linear classifiers [19].

Support Vector Machine is frequently reported to be a strong performer in classification tasks in the neuroimaging domain [16], however in the current study it performed slightly below both Logistic Regression and MLP. This can be explained by the properties of the selected feature subset and the linear kernel used during model training.

The Random Forest model yielded the highest ROC-AUC value, demonstrating good class discrimination performance. However, the lower Accuracy and F1-Score indicate that the classification decisions at the selected threshold may not be optimal. However, the high ROC-AUC indicates that ensemble learning strategies might be helpful for schizophrenia classification [15].

The overall results indicate that different classifiers are better on different evaluation metrics. Logistic Regression gave the best overall classification accuracy, MLP had higher sensitivity and Random Forest achieved the best discriminative ability using ROC-AUC

5. CONCLUSION AND FUTURE WORK

5.1 Conclusion

This paper presents a comparative analysis of Machine Learning, Ensemble Learning, and Deep Learning models for schizophrenia classification using resting-state fMRI functional connectivity features extracted from the COBRE dataset. We selected the top 300 most discriminative features using ANOVA, and then conducted the feature standardization and classifier evaluation with stratified 10-fold cross-validation.

The experimental results indicated that all the evaluated classifiers could discriminate between patients with schizophrenia and healthy controls. Logistic Regression got the best accuracy for classification among the evaluated models with 69.19% while Multi-Layer Perceptron got the best Recall value of 72.14%. Furthermore, Random Forest also obtained the highest ROC-AUC value of 78.84% which means good discriminative ability at all classification thresholds.

Our results suggest that features of functional connectivity extracted from resting-state fMRI can provide useful diagnostic information for classification of schizophrenia. While advanced models like MLP and Random Forest showed their power on certain evaluation metrics, Logistic Regression was the most balanced overall in terms of classification accuracy.

Overall, the study confirms the effectiveness of machine learning based analysis of resting state functional connectivity and shows its potential to support objective computer aided schizophrenia diagnosis.

5.2 Future Work

The results obtained are encouraging but there are several opportunities for extending the present work.

Future work may investigate the use of larger and multi-site neuroimaging datasets to improve the generalization and robustness of the model across different populations [14]. Data from multiple acquisition centers may further improve the reliability of machine learning models in a real-world clinical setting.

Second, we can investigate other feature extraction methods that can capture more complex properties of brain connectivity. Dynamic functional connectivity measures and graph-theoretical network features can give more information compared to conventional connectivity representations [6].

Third, the application of advanced deep learning architectures such as Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based models [19] for the classification of schizophrenia can be explored. Such architectures can facilitate more effective learning of complex spatio-temporal connectivity patterns.

Fourth, multimodal neuroimaging approaches integrating functional MRI, structural MRI, diffusion tensor imaging, electroencephalography and genetic information might yield richer representations of schizophrenia-related abnormalities [13]. Such multimodal frameworks can improve the accuracy and robustness of diagnosis significantly.

Fifth, we can incorporate explainable artificial intelligence (XAI) techniques to increase the interpretability of models and discover clinically relevant biomarkers. The translation of machine learning models into clinical practice can be facilitated and clinician trust improved by interpreting the contribution of individual connectivity features.

Finally, future research may focus on the development of real-time and personalized diagnostic systems able to support psychiatrists during clinical assessment. The integration of artificial intelligence and neuroimaging analytics could revolutionize the diagnosis of schizophrenia and build the foundation for precision medicine approaches to its treatment.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this research work.

DATA AVAILABILITY

The dataset used in this study is publicly available through the Center for Biomedical Research Excellence (COBRE) neuroimaging repository and can be accessed for research purposes subject to the repository guidelines.

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