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Electroencephalogram (EEG) based automated detection of mental disorders using artificial intelligence processing pipelines

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Abstract: Bipolar disorder, major depressive disorder, and schizophrenia often have overlapping symptoms that lead to frequent misdiagnoses. To address the need for an objective, quantitative and accurate tool for diagnosing mental disorders, we developed an AI-based approach using electroencephalography (EEG) signals. Our study analysed data from Seoul National University, including EEG assessments and medical records of 383 subjects: bipolar disorder (*n*=67), major depressive disorder (*n*=199), and schizophrenia (*n*=117). Our method involved three steps: (1) balancing the dataset with SMOTE up-sampling, (2) extracting key features, and (3) employing machine learning and deep learning models for classification. The combination of Independent Component Analysis, ANOVA F-value, and Gradient Boosting yielded the highest accuracy of 96.67% and minimal misclassifications. These results suggest this approach could significantly improve the correct diagnosis of mental disorders, and it is feasible to quantify the EEG signals to obtain an objective computer-aided diagnosis system.

Keywords: Bipolar disorder; Schizophrenia; Major depressive disorder; Artificial intelligence; Electroencephalography.

1.0 INTRODUCTION

In 2022, the World Health Organization (WHO) reported that one in every eight people worldwide experienced mental health conditions (Mental Disorders, n.d.). In particular, approximately 40 million people are living with bipolar disorder, 280 million with major depressive disorder, and 24 million with schizophrenia. These conditions are accompanied by behavioral and cognitive changes that have a significant impact on individuals' personal lives, social interactions, and economic well-being.

The conventional diagnostic approach for mental illnesses typically relies on symptom-based assessments and self-report evaluations, following the criteria outlined in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) and the International Statistical Classification of Diseases and Health Problems, Tenth Revision (ICD-10) (Diagnostic and Statistical Manual of Mental Disorders, n.d.; ICD-11 for Mortality and Morbidity Statistics, n.d.). However, diagnosing bipolar disorder, major depressive disorder, and schizophrenia poses significant challenges due to subjectivity and overlapping symptoms (Crespi & Badcock, 2008). Laursen et al. (2009) have indicated that individuals with bipolar disorder may experience depressive episodes similar to those with major depressive disorder, while schizophrenia can sometimes be mistaken for other psychotic disorders (Tm et al., 2009). Alarmingly, a high rate of misdiagnosis has been reported, with 60% of individuals with bipolar disorder mistakenly receiving a diagnosis of schizophrenia, 56.25% of those with schizophrenia being misdiagnosed as having bipolar disorder, and 54.17% of those with major depressive disorder being incorrectly identified as having schizophrenia (Tm et al., 2009). Also, people with bipolar disorder were frequently given the wrong first diagnosis of schizophrenia or depression, instead caused an average of 6.46 years delay in accurate diagnosis (Ayano et al., 2021). This often led to severe consequences, including inadequate and delayed treatment plans, worsening symptoms, social and occupational difficulties of patients, and even suicidal ideation (Lublóy et al., 2020). These limitations underscore the need for more objective and quantitative diagnostic methods to improve diagnostic accuracy and minimize misdiagnosis rates of these disorders.

In this regard, the incorporation of quantitative tools, such as artificial intelligence (AI), into computer-aided diagnosis (CAD) systems holds promise in assisting clinicians with mental disorder diagnosis. One such tool is electroencephalography (EEG), a non-invasive and reliable method for measuring the brain's electrical activity (Nur et al., 2022; Derrick et al., 2019). By analysing these signals, we can provide real-time insights into patients' brain functioning, which is particularly helpful in cases with overlapping symptoms (Krishnan et al., 2020; Shah et al., 2023; Y. Lei et al., 2022). Currently, quantitative EEG (QEEG) has been used to detect clear signal abnormalities in diagnosing neurological disorders like seizures or epilepsy (Acharya et al., 2013; Binder & Haut, 2013). Following The American Clinical Neurophysiology Society (ACNS) and The American Academy of Neurology (AAN), QEEG can be used for epilepsy, encephalopathy, several neurodegenerative and neurodevelopmental diseases such as dementia, attention deficit hyperactivity disorder (ADHD), etc. (Kopanska et al., 2022; Turner, 2021). Since mental disorders like bipolar disorder, major depressive disorder, and schizophrenia also result from neuronal circuitry changes (Alamian et al., 2017; Benes, 2000). Diagnosing these disorders based on EEG assessments could provide a more objective and quantitative diagnostic method, one that does not rely on self-reporting. QEEG has also been proven to have evidence of abnormality patterns in functional connections of mental disorders such as depression (Popa et al., 2020; Kusuma et al., 2024), anxiety disorder (Kopanska et al., 2022). Furthermore, the integration of AI within CAD systems can improve diagnostic accuracy by analyzing quantitative EEG signals and considering existing diagnoses to identify subtle patterns that humans might miss (Acharya et al., 2015; Hébert et al., 2020; Mahato & Paul, 2019; Vellante et al., 2020).

Several studies have employed machine learning techniques to classify bipolar disorder, major depressive disorder, and schizophrenia and achieved promising results. Alimardani et al. (2018) introduced an approach that combines statistical measures and the K-nearest neighbours algorithm, achieving an accuracy of up to 91.30% in classifying bipolar disorder and schizophrenia. Luján et al. (2022) proposed a method based on a fuzzy-means algorithm and a radial basis function neural network that attained an accuracy rate of 96.78% in classification. Concurrently, Sanchez et al. (2022) and L. Lei et al. (2022) focused on classifying major depressive disorder and bipolar disorder, achieving accuracies of 84.90% and 96.88%, respectively, in their classification models. However, despite these efforts in binary classifications, a gap remains, with limited studies focusing on the simultaneous multi-class classification of these disorders.

In this study, we aimed to develop a multi-class classification approach based on EEG signals to diagnose bipolar disorder, major depressive disorder, and schizophrenia. We employed neural networks (NN) and a range of machine learning algorithms, including

K-Nearest Neighbor (KNN), Logistic Regression, Random Forest, and Gradient Boosting to perform the classification tasks. This comprehensive approach promises to improve the accurate diagnosis of these complex mental disorders.

2.0 MATERIALS AND METHODS

2.1 Dataset description

The retrospective data were collected from the Seoul Metropolitan Government-Seoul National University (SMG-SNU) Boramae Medical Center in South Korea between 2011 and 2018 (Park et al., 2021). This dataset included resting-state QEEG, medical records, and personal information, such as age, sex, education, and intelligence quotient (IQ; **Table 1**). Qualified psychiatrists made the diagnoses based on the DSM-5 criteria, and comprehensive psychological assessments were carried out using the Mini-International Neuropsychiatric Interview. This study focused on the analysis of 383 subjects from the dataset, categorizing them into three distinct groups: bipolar disorder (*n*=67), major depressive disorder (*n*=199), and schizophrenia (*n*=117). We aimed to conduct a multi-class classification study to classify these three groups.

Table 1. The metadata of participants, including the number of participants, age, sex, education, and IQ.

Specific disorder	Age	Sex	Education	IQ
Bipolar disorder (*n*=67)	29.71 ± 11.01	Male: 42 (62.7%) Female: 25 (37.3%)	14.11 ± 2.21	89.62 ± 17.51
Major depressive disorder (*n*=199)	31.26 ± 13.23	Male: 109 (54.8%) Female: 90 (45.2%)	13.05 ± 2.51	101.85 ± 15.28
Schizophrenia (*n*=117)	31.73 ± 12.10	Male: 65 (55.6%) Female: 52 (44.4%)	12.84 ± 2.95	100.81 ± 16.98

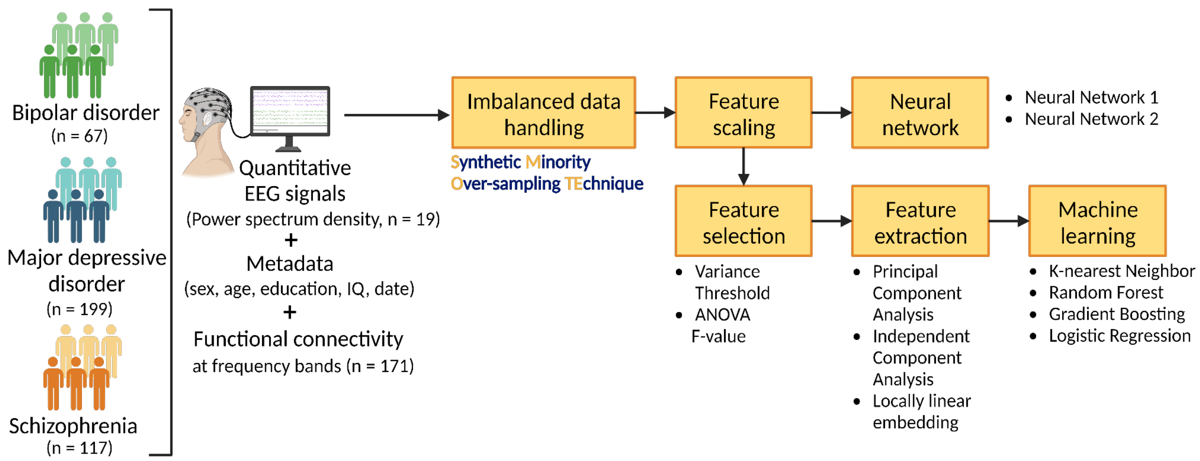

Figure 1. The flowchart of two approaches used in this study.

The EEG recordings were obtained during 5 minutes of eye-closed resting state from patients using a 19-channel setup, including electrodes placed at FP1, FP2, F7, F3, Fz, F4, F8, T7, C3, C4, T8, P7, P3, P4, P8, O1, and O2. To ensure signal quality, a ground channel was positioned between the FPz and Fz electrodes. In addition to the metadata (**Table 1**) and QEEG signals, the dataset comprised power spectrum density (PSD) with 19 features and functional connectivity (FC) at different frequency bands with 171 features. PSD represents the absolute power values of the EEG signal, reflecting spectral power at the sensor level, while FC characterizes the temporal correlations of neurophysiological events across spatially distant regions, indicated by coherence values between two signals based on phase consistency. In total, the study involved the analysis of 1,144 computed features, which include 190 features derived from the combination of PSD and FC QEEG parameters at each of the six frequency bands (delta, theta, alpha, beta, high beta, and gamma).

2.2 EEG-based mental disorder detection pipelines

Our proposed system comprised two main approaches (**Figure 1**). The first one employed two designated neural networks for classification, referred to as neural network 1 (NN1) and neural network 2 (NN2). Prior to this, pre-processing of input data was conducted to address data imbalance using Synthetic Minority Over-sampling Technique (SMOTE) and feature scaling techniques.

The second approach constituted a machine learning-based pipeline, which primarily involved a sequence of stages – SMOTE, feature scaling, feature selection, and feature extraction – to mitigate the presence of irrelevant features. Subsequently, classification was executed using a diverse set of algorithms, including K-Nearest Neighbor, Random Forest, Linear Regression, and Gradient Boosting.

2.2.1 Pre-processing data

The analyzed dataset showed an unequal distribution of its classes, with 67 samples for bipolar disorder, 199 for depression, and 117 for schizophrenia. This class imbalance posed a significant challenge in classification tasks, particularly when the minority class held greater importance and significance for the analysis (L. Lei et al., 2022), as exemplified by bipolar disorder in our context. To address this, we used the SMOTE technique (**Figure 2**). Unlike traditional oversampling techniques that simply replicate existing data, SMOTE systematically identifies the spatial coordinates of minority class data points within the feature space and subsequently generates synthetic samples that interpolate between neighboring data points (Park et al., 2021). Hence, SMOTE effectively supplements the minority class to rectify the data imbalance.

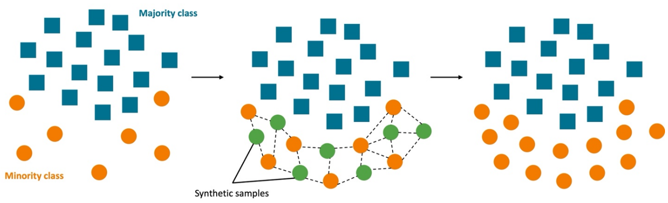

Figure 2. The Synthetic Minority Over-sampling Technique (SMOTE) synthesizing new data points for the minority class.

In addition, feature scaling ensured uniform scaling across all features by enhancing optimal algorithm performance and minimizing the impact of variable magnitudes on the results.

2.2.2 Mental disorder classification using neural network

A neural network is a set of mapping functions designed to recognize underlying data relationships by mimicking the function of the human brain (Elrahman & Abraham, 2013). It consists of node layers, including an input layer, one or more hidden layers, and an output layer, with each node or neuron interconnecting and having its weight and bias. Node activation occurs when the output surpasses a predefined threshold, enabling the transfer of data to the subsequent layer. In this context, neural networks excel at capturing intricate data relationships related to conditions that exhibit diverse manifestations across individuals, such as bipolar disorder, major depressive disorder and schizophrenia.

In NN1, the neural network architecture included an input layer, a flattening layer, two dropouts, one hidden, and an output layer (**Figure 3**). The hidden layers consisted of 10 units and Re-Lu activation. Moreover, NN1 features two dropout layers, each set with a rate of 0.2 before and after the hidden layer. To facilitate three-class classification tasks, the output layer incorporated three units and used the Soft-max function.

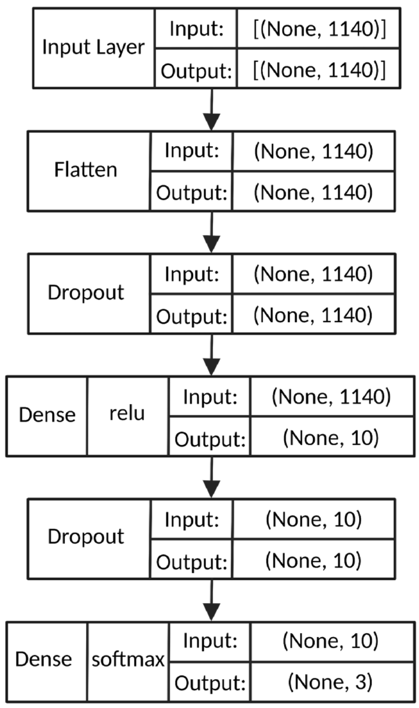

Figure 3. The Neural Network 1 architecture.

To compare its effectiveness with NN1 in classification, NN2 was designed with a deeper architecture incorporating more hidden and dropout layers (**Figure 4**). Specifically, NN2 comprised two hidden layers, each featuring 18 units with Re-Lu activation, and three dropout layers with rates of 0.1, 0.2, and 0.2, respectively. Similar to NN1, the output layer of NN2 used the Soft-max function to ensure uniformity in its three-class classification approach.

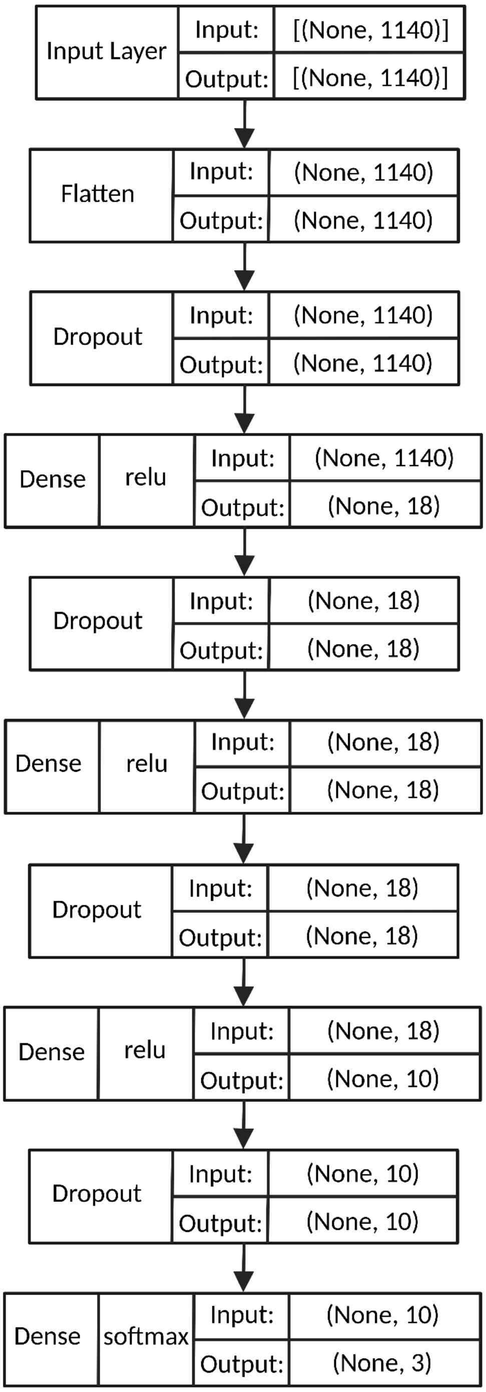

Figure 4. The Neural Network 2 architecture.

2.2.3 Mental disorder classification using machine learning

Feature extraction and feature selection

Feature extraction generates new features and representations from the original dataset while retaining essential information (Chawla et al., 2002). This process is particularly crucial when dealing with datasets characterized by numerous features, some of which may be redundant or noisy. Feature extraction enhances model performance, reduces computation time, and aids in uncovering relevant patterns. In this study, we used Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Locally Linear Embedding (LLE) as key techniques for feature extraction.

Complementing feature extraction, feature selection improves accuracy in classifying mental health conditions by strategically choosing a subset of relevant features. This targeted selection reduces dimensionality, enhances model interpretability and mitigates the risk of overfitting (Uhrig, 1995). Variance Threshold (VT) and ANOVA F-value were employed as feature selection techniques in this study.

Machine learning models for mental disorder classifications

We investigated the performance of several machine learning algorithms, including K-nearest neighbours (KNN), Random Forest (RF), Gradient Boosting (GB), and Logistic Regression (LR). In detail, KNN classifies data points based on the majority vote of its closest neighbors in the training data, which offers interpretable results due to clear decision boundaries (Peterson, 2009). Random Forest, on the other hand, leverages an ensemble of decision trees, each making individual classifications (Biau & Scornet, 2016). The final prediction of Random Forest algorithm is chosen by a majority vote to reduce the risk of overfitting. Gradient Boosting builds a more accurate model sequentially by focusing each new decision tree on correcting errors from previous one (Natekin & Knoll, 2013). Finally, Logistic Regression, though typically used for binary classification, can be adapted to multi-class problems through approaches like One-vs-Rest and Multinomial Logistic Regression (Boateng & Abaye, 2019). One-vs-Rest trains separate classifiers for each class versus all others, while Multinomial directly models probabilities for all classes simultaneously.

3.0 RESULTS

3.1 Results of neural network pipelines

Our model achieved its optimal performance using the hyper-parameter configurations listed in **Table 2**. Despite showing slightly lower precision for bipolar disorder and major depressive disorder classes compared to NN1, NN2 showed superior overall accuracy and recall rates. The effectiveness of NN2 was assessed via various metrics, including confusion matrix, receiver operating characteristic (ROC) curve, accuracy and loss (**Figure 5**).

Table 2. Results and hyper-parameters of the NN1 and the NN2.

	Neural Network 1			**Neural Network 2**		
	Precision (%)	Recall (%)	F1 score	Precision (%)	Recall (%)	F1 score
Bipolar disorder	88.89	100.0	94.12	83.33	86.75	81.51
Major depressive disorder	100.0	40.00	68.70	100.0	50.00	67.80
Schizophrenia	67.80	80.00	77.35	83.33	86.75	81.51
Macro average	85.86	80.00	77.35	83.33	86.75	81.51
Accuracy	80.00			**83.33**		
Hyper-parameter	Epochs = 150 Batch size = 256 Optimizer = Adam Learning rate = 0.1			Epochs = 300 Batch size = 256 Optimizer = SGD Learning rate = 0.1		

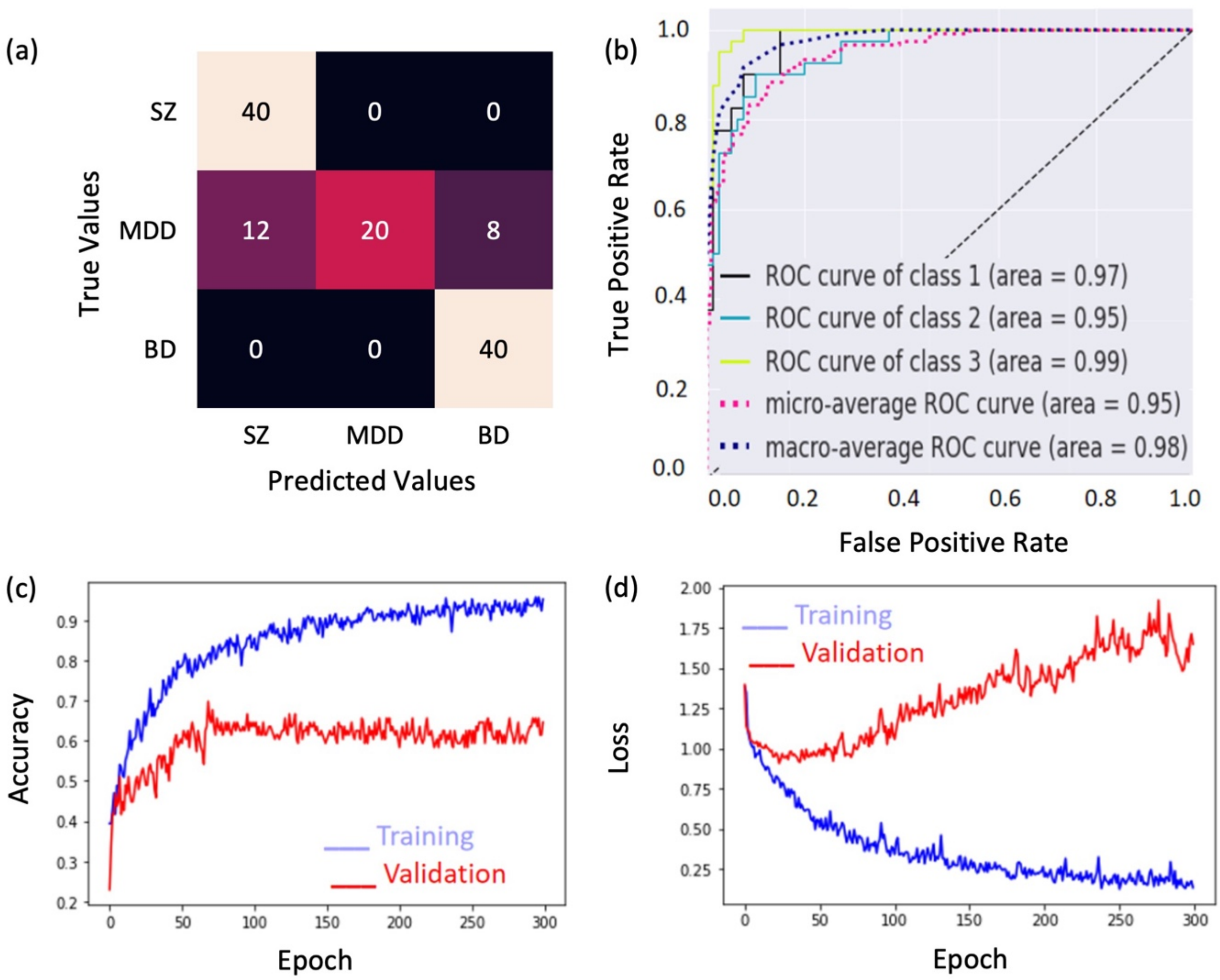

Figure 5. (a) Confusion matrix, (b) ROC, (c) accuracy, and (d) loss of the NN2.

3.2 Results of machine learning pipelines

Dimensionality reduction techniques significantly improved classifier performance, except for the KNN approach, which still exhibited low accuracy compared to the others (**Figure 6**). When fine-tuning and dimensionality reduction were combined, all classifiers obtained accuracy levels exceeding 70%. Performance evaluation metrics, such as the confusion matrix and ROC curves, were also employed. The performances of all machine learning pipelines were summarized in **Table 3**.

Among the classifiers, Gradient Boosting and Random Forest pipelines consistently outperformed others across all evaluation criteria (**Figure 6**). Specifically, the accuracy of ICA – VT – RT, ICA – ANOVA F value – RT, ICA – VT – GB, and ICA – ANOVA F value – GB were 90.83%, 92.50%, 95.00%, and 96.67%, respectively. The misdiagnosis rate between these four pipelines were slightly different (**Figure 7 – 10**).

Remarkably, the ICA – ANOVA F value – GB pipeline showed the highest performance across all metrics, with an accuracy of 96.67%, a precision of 96.86%, F1 score of 96.63% and a recall of 96.67% (**Figure 10**). This pipeline also had the lowest mislabeling in the confusion matrix, with only three major depressive disorder patients misdiagnosed as schizophrenia.

Table 3. Machine learning models without and with dimensional reduction.

	Feature Extraction	Feature Selection	Model	Accuracy (%)	F1 score	Precision (%)	Recall (%)
Non-dimensional reduction	-	-	LR	64.17	57.68	68.65	62.17
	-	-	KNN	58.33	55.09	59.34	58.33
	-	-	RF	80.00	78.55	81.11	78.33
	-	-	GB	76.47	76.47	81.17	78.33
Dimensional reduction	LLE	VT	KNN	78.33	72.13	82.73	76.67
	PCA	ANOVA F value	LR	76.67	74.74	83.94	78.33
	ICA	VT	RF	90.83	90.89	92.81	90.83
	ICA	ANOVA F value	RF	92.50	92.45	93.37	92.50
	ICA	VT	GB	95.00	95.03	95.65	95.00
	ICA	**ANOVA F value**	**GB**	**96.67**	**96.63**	**96.86**	**96.67**

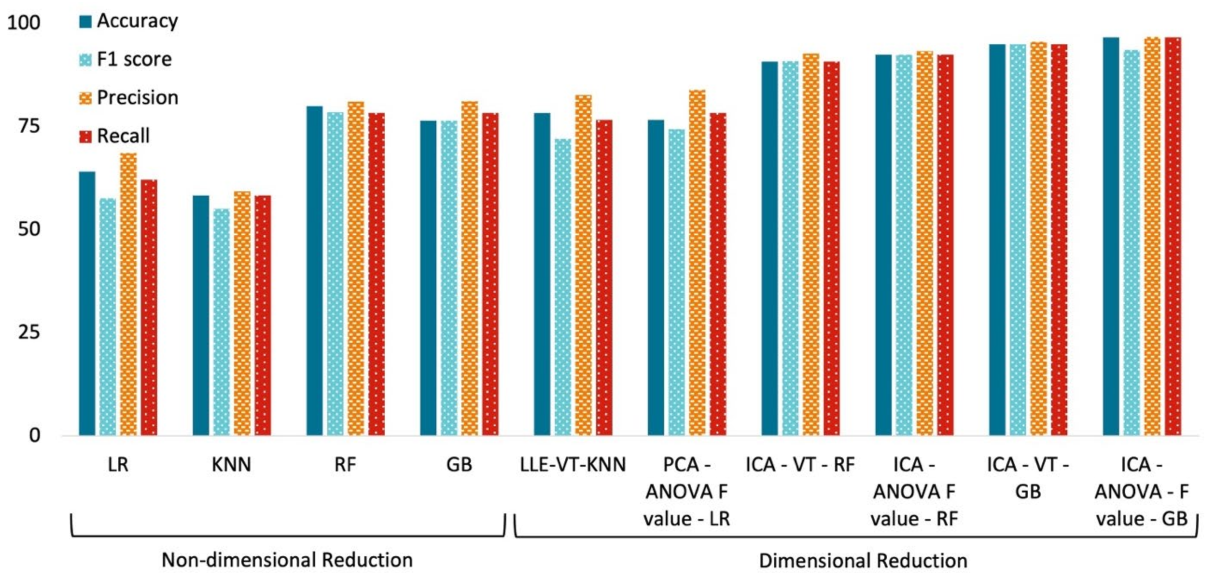

Figure 6. The comparison between different performance pipelines without and with dimensional reduction.

4.0 DISCUSSION

In this study, we address the global challenge of accurately diagnosing mental health disorders, particularly bipolar disorder, major depressive disorder, and schizophrenia. Traditional methods often lead to misdiagnosis due to subjectivity and symptom overlap, resulting in inadequate treatment and severe consequences. To improve diagnostic accuracy and aim to have a subjective and quantitative diagnostic aiding tool, we implemented a novel approach that incorporates EEG data and AI within a multi-classification framework.

Our findings highlighted that the performance of the ICA – ANOVA F value – GB pipeline achieved the remarkable accuracy rate of 96.67% in classifying bipolar disorder, major depressive disorder, and schizophrenia. In a prior study using the same dataset, Park et al. (2021) focused on binary classification, distinguishing each condition (bipolar disorder, major depressive disorder, and schizophrenia) from healthy controls. However, their accuracies were lower than our multi-class classification approach, with results of 92.13% for bipolar disorder, 87.92% for major depressive disorder, and 93.83% for schizophrenia (**Table 4**).

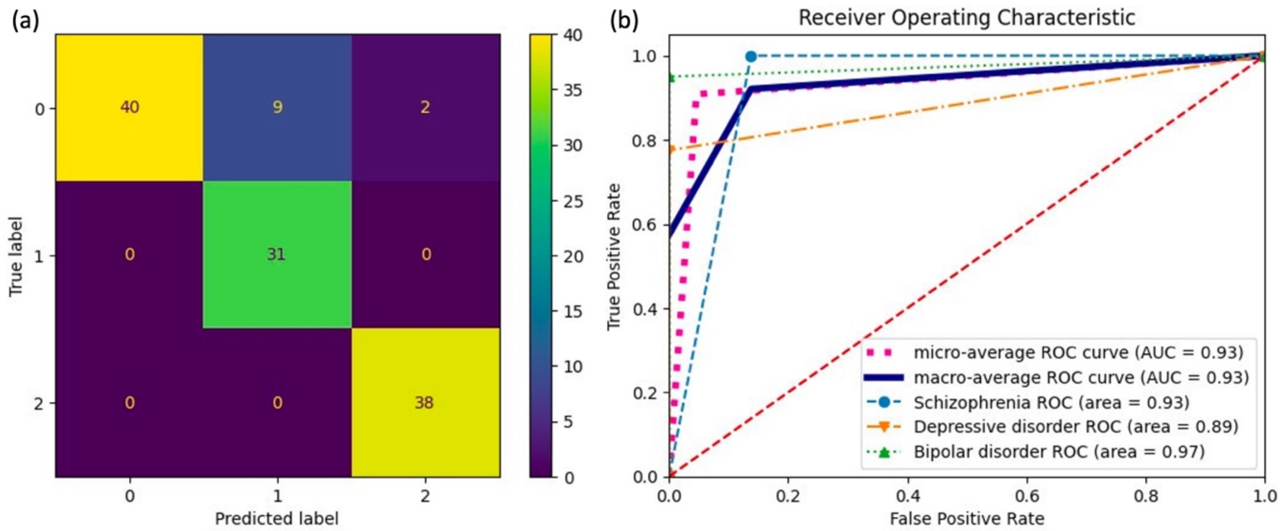

Figure 7. (a) Confusion matrix and (b) ROC of the ICA – VT– RF pipeline.

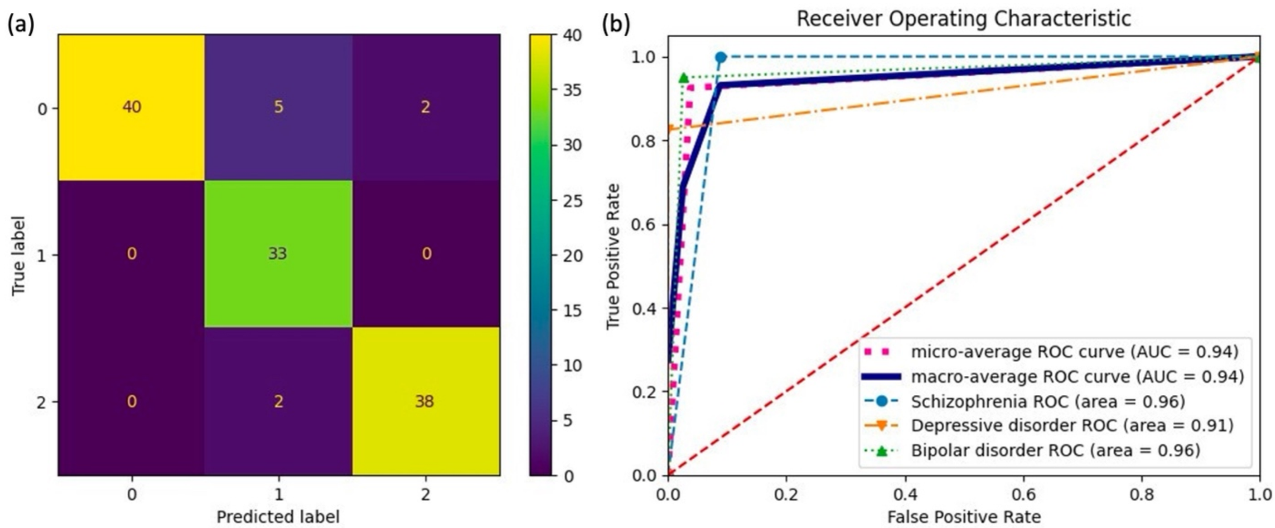

Figure 8. (a) Confusion matrix and (b) ROC of the ICA – ANOVA – RF pipeline.

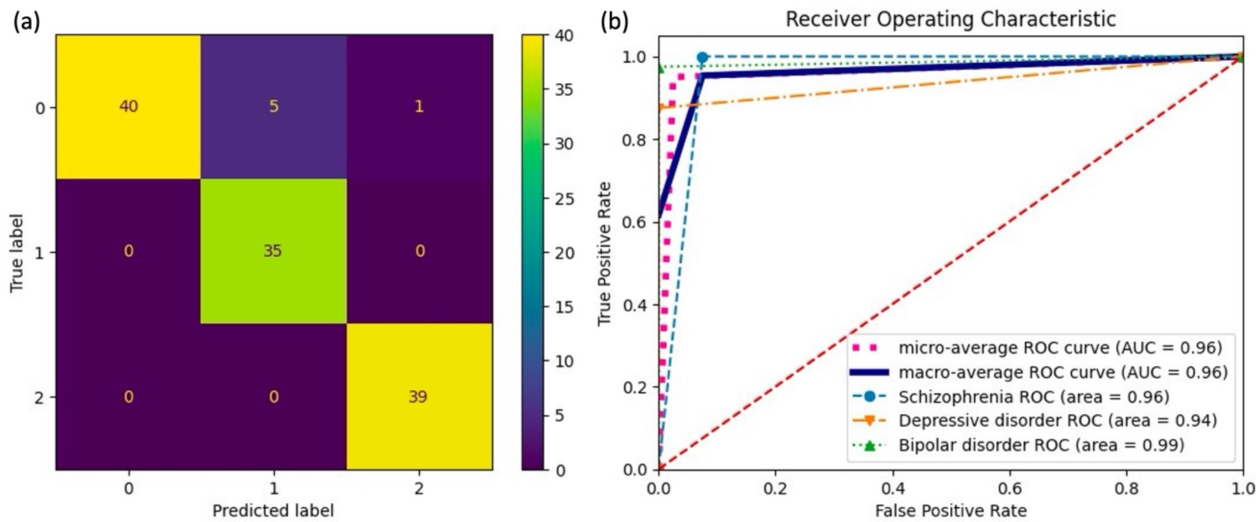

Figure 9. (a) Confusion matrix and (b) ROC of the ICA – VT – GB pipeline.

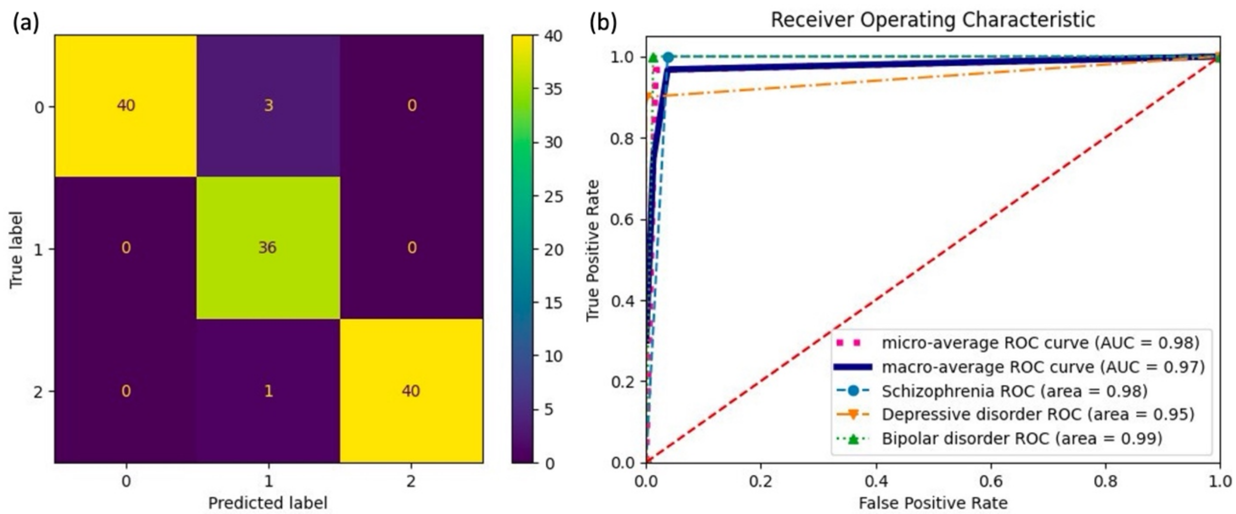

Figure 10. (a) Confusion matrix and (b) ROC of the ICA – ANOVA – GB pipeline.

Table 4. The comparison between Park et al. (2021) study and this study using the same dataset.

	Classification	Area under curve (AUC)	Recall (%)	Precision (%)	Accuracy (%)
Park et al. (2021)	Major depressive disorder vs. Healthy control	83.26	68.32	94.89	87.92
	Bipolar disorder vs. Healthy control	88.30	92.62	79.22	92.13
	Schizophrenia vs. Healthy control	87.08	85.11	85.30	93.83
This study	Major depressive disorder vs. Bipolar disorder vs. Schizophrenia	97.00	96.67	96.86	96.67

Previous studies also mainly used binary classification, which aimed to classify bipolar disorder from schizophrenia or major depressive disorder. For instance, Alimardani et al. (2018) conducted a study involving 27 patients diagnosed with bipolar disorder and 26 those with schizophrenia. They employed statistical features for feature selection and machine learning classifiers, resulting in an accuracy of 91.30%.

Likewise, Luján et al. (2022) carried out a study using feature extraction and machine learning classifier with a larger sample size of 105 individuals with bipolar disorder and 302 with schizophrenia, yielding a higher accuracy of 96.78%. Regarding the classification between bipolar disorder and major depressive disorder, Sanchez et al. (2022), L. Lei et al. (2022) and Zhao et al. (2023) reported accuracies of 84.90%, 96.88%, and 83.16% respectively for their studies. However, these approaches fell short in capturing the complexity of simultaneously distinguishing between multiple psychiatric disorders, especially when dealing with highly overlapping conditions, such as bipolar disorder, major depressive disorder, and schizophrenia.

In this context, the multi-class classification approach offers a more comprehensive understanding of these complex psychiatric disorders. In 2016, El Gohary et al. employed the multi-class classification approach and successfully classified 80 cases of bipolar disorder, 80 of schizophrenia, and 70 healthy controls, with an accuracy of up to 98.00% (El Gohary et al., 2016). Significantly, Khodayari-Rostamabad et al. (2010) conducted both binary and multi-class classifications to classify 12 cases of bipolar disorder, 64 of depressive disorder, 40 of schizophrenia, and 91 healthy controls. Their results showed accuracies of 92.70% for bipolar disorder versus depressive disorder, 88.30% for depressive disorder versus schizophrenia, and 87.10% for depressive disorder, schizophrenia, and healthy controls. When compared to the aforementioned studies, our research achieved a higher accuracy of 96.67% using the multi-class classification approach for bipolar disorder, major depressive disorder, and schizophrenia, coupled with a larger sample size. This expanded dataset capacity contributes to better generalization and a reduction in prediction errors. In addition, a combination of feature extraction, feature selection and imbalance handling prior to machine learning models for classification enhance our overall results.

However, our findings (**Figure 6**) illustrate that even within multi-class classification, variations in pipeline design can influence results. Specifically, the choice of feature extraction and feature selection techniques can significantly impact the data used to train the model. While ICA – VT captures overall variability in the data to highlight broader patterns, ICA – ANOVA F value focuses on features that show statistically significant differences between the three disorder groups. The latter could lead to features that are more discriminative but potentially miss some of the broader variability. Meanwhile, RF is less reliant on feature selection as it can handle a wider range of features, whereas GB might benefit more from feature selection as it prioritizes the most informative ones. In our case, the ICA – ANOVA F value – GB pipeline outperformed others, likely by identifying the most informative features and effectively combining them to classify bipolar disorder, major depressive disorder, and schizophrenia accurately.

While psychiatric disorders are prevalent across diverse cultures and societies, there exists a significant diversity in terms of the age, intensity, and nature of the presenting symptoms. These variations are influenced by many socioeconomic and cultural factors, which are particularly relevant to specific countries. It is worth noting that many of the existing datasets were derived from European sources, with only a few exceptions like the studies conducted by Alimardani et al., (2018) and L. Lei et al. (2022), which featured relatively limited data from Asian sources. In this regard, our study, replying on the data collected in Korea, is better suited for Asian countries. By utilizing this dataset, our research provides a more relevant perspective of psychiatric disorders in the Asian context.

Nevertheless, our study encountered several limitations. The dataset, while extensive, contains a relatively small number of cases for each class that potentially hinders the effective learning and performance of machine learning algorithms. Furthermore, the dataset's highly unbalanced distribution leads to skewness which we attempted to address with SMOTE. However, this method sometimes resulted in the over-generation of synthetic samples in certain classes as it may affect the overall model performance and introduce potential issues of noise and bias. Therefore, for generalization, it is necessary to verify the results with additional real samples that address imbalance issues. In the future, we are planning to collect more data to verify the algorithm in the clinical practice in Vietnam. A bigger dataset with age stratification should be considered for future study to obtain a more accurate CAD. If there is enough data for both young subjects and elders, the algorithms will not be biased by the age, even with elderly, who are at higher risk of mental disorders.

5.0 CONCLUSIONS

In summary, our study proves that machine learning and neural network techniques using EEG can effectively classify bipolar disorder, major depressive disorder, and schizophrenia in a multinomial classification, which induces that an objective and quantitative diagnostic support tool is feasible in detecting mental disorder using EEG signals. One of the proposed pipelines, ICA – ANOVA F value – GB, showed the best results obtained with accuracy, recall, precision, and F1 score better than 96.60% overall. This approach demonstrates the potential of the multi-class classification as a promising complementary tool in clinical contexts for diagnosing individuals with mental illnesses.

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Author Contributions:
LN and HH supervised the project; LN, AL, KH and HH conceptualized and designed the study; AL, KH and TL analyzed the data; AL and KH interpreted the data; LN and KH implemented the codes; LN and AL wrote the original draft of the manuscript; TL, NN, SN, and HH reviewed and edited the manuscript draft; All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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