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Advancements in Machine Learning-based Predictive Models for Bipolar Disorder Episodes

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Abstract

Diagnosing bipolar disorder presents significant challenges due to the disorder's diverse mood patterns, which complicate the accurate identification of mood fluctuations. However, with systematic evaluation and comprehensive analysis, enhancing diagnostic precision and improving treatment outcomes is feasible. The unclear etiology is influenced by multiple factors, such as changes in brain structure, genetic predispositions, and environmental conditions. The current diagnostic challenges prompt the exploration of machine learning (ML). This study presents a novel computational framework that uses machine learning to help diagnose bipolar disorder, with a focus on mood swing patterns derived from behavioral stimulation. The proposed framework comprises three operational models: a dynamic mood transition model based on stochastic processes, a binary mood state classification model using a Bayesian neural network, with a predictive analysis model powered by Recurrent Neural Decision Trees. Performance comparisons with existing methods demonstrate the proposed framework's enhanced accuracy and reduced processing time, providing a refined approach to feature extraction, classification, and learning optimization for enhanced diagnostic accuracy in bipolar disorder. The proposed approach holds significant promise for enhancing bipolar disorder diagnosis.

Keywords: Bipolar Disorder, Machine Learning, Dynamic Mood Transition, Bayesian Neural Network.

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1. Introduction

In this research, a diagnostic model for Bipolar Disorder (BD) is proposed. Bipolar Disorder is characterized by significant mood fluctuations, encompassing episodes of mania or elevated mood states that alternate with episodes of depression or low mood. This model aims to enhance the understanding and identification of BD, facilitating improved therapeutic interventions and patient outcomes. [1]. A variety of symptoms can be displayed by BD patients over time, ranging from mild to severe. It is difficult to gauge the severity of this disorder due to the variability of symptoms among individuals, as some individuals may experience intense manic or depressive episodes between episodes whilst maintaining normal functioning between episodes. A range of negative emotions are associated with depression in BD, including lethargy, hopelessness, sadness, and suicidal thoughts [2]. A manic episode, on the other hand, can cause worsening of mood, insomnia, impulsivity, and irritability, as well as potentially life-threatening behavior. Datasets and environmental parameters that are essential to model development in BD research commonly use the term "depression.". Various environmental, psychological, and genetic factors influence depression, which leads to prolonged periods of low mood with significant impacts on daily functioning. Depression can be exacerbated by adverse life events such as loss, abuse, violence, financial crisis, and instability. In addition to feeling worthless, losing appetite, disinteresting in activities, persistent sadness, and mood fluctuations in social situations, these are noticeable symptoms of depression. Uncertainty surrounds reliable indicators of different BD modes, making understanding BD symptoms challenging [3-5].

It is challenging to diagnose bipolar disorder (BD) because mood episodes are diverse, making accurate identification of mood fluctuations necessary. In addition to genetic predispositions, changing brain structure, and environmental influences all contribute to the unclear cause of BD. People experiencing BD symptoms may exhibit mild, moderate, or severe symptoms over time, complicating diagnosis. Depressive episodes are characterized by prolonged periods of sadness, hopelessness, and lethargy, whereas manic episodes are marked by elevated mood, impulsivity, and potentially harmful behavior. Depressive disorders can be exacerbated by adverse life events, as well as by genetic predispositions. It remains difficult to distinguish between BD modes despite advancements. Machine learning (ML) has increasingly been used in the diagnosis of BD due to its diagnostic challenges. With the help of machine learning, complex datasets can be rendered more accurate and efficient. Based on behavioral stimulation patterns, an innovative computational framework is presented to help diagnose BD using ML. Three operational models are included in the framework: a stochastic mood transition model, a Bayesian neural network-based binary mood classification model, and a Recurrent Neural Decision Tree-based predictive analysis model. Performance comparisons with existing methods demonstrate how the framework raises accuracy while minimizing processing time, presenting a refined approach to feature extraction, classification, and learning optimization for better BD diagnosis [6-9]. The proposed model aims to provide an extensive understanding of BD by incorporating precision-based parameters. The model uses sequential statistical computations and machine learning techniques to extract important features from datasets encompassing BD cases, normal individuals, and people who experience unipolar depression. The approach aims to find relevant communication channels for accurate diagnosis by examining nonverbal signals and interpersonal sensitivity features. Furthermore, the model divides BD into various categories based on observable evidence such as facial expressions and body language, in order to enhance the classification accuracy.

Statistical evaluation and feature enrichment help to create an effective training strategy, ultimately boosting the accuracy of prediction models for BD classification. The computational aspects approach employed in the proposed model is intended to improve the classification process for BD diagnosis. The system improves diagnostic precision by iteratively assessing dataset properties, using conditional logic, and scaling up outcomes before employing machine learning techniques. The use of MiniPONs for standardized interpretation of nonverbal signals allows for broader study and classification of BD. The subsequent execution of statistical evaluation and machine learning algorithms improves the model's ability to foresee, giving rise to more accurate BD diagnosis [10-16].

2. Methodology

The overarching objective of the proposed approach is to gain an in-depth understanding of various types of bipolar disorder by applying precision-based traits. Figure 2.1 depicts the workflow of the proposed, which consists of consecutive statistical analyses such as general analysis, descriptive analysis, variable/domain analysis, and extensive research on the selected database.

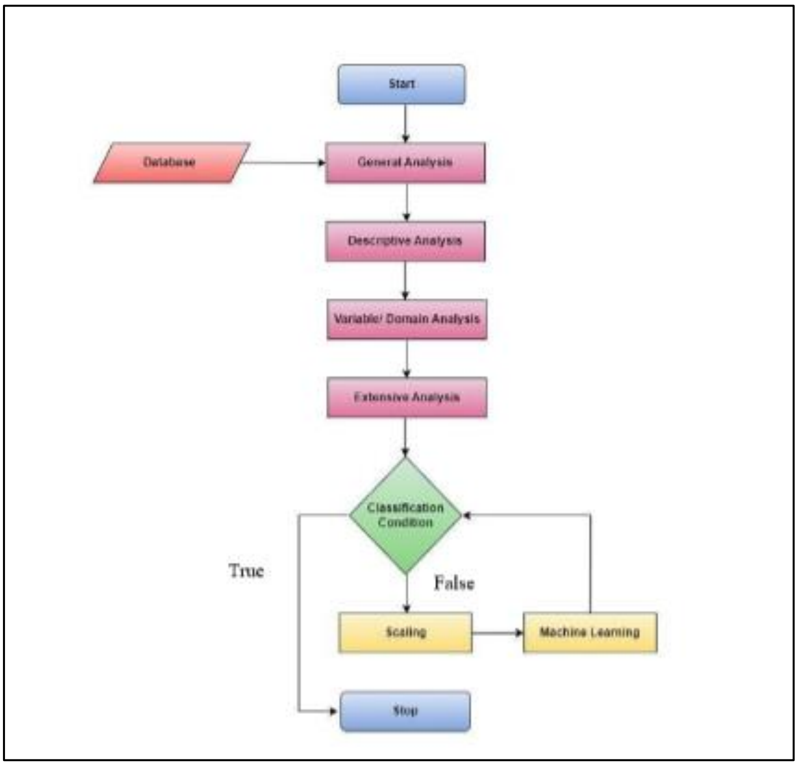


Figure 2.1. Process Flow of Proposed Scheme

Following that, a conditional logic for classification is developed, followed by upscaling and the setting up of a machine learning model based on Bayesian neural network algorithms. The dataset used contains information of an identifiable number of individuals diagnosed with bipolar disorder, including 70 classed as Type I and 49 as Type II. To better evaluate classification performance, the study uses data from a specific number of normal individuals (120) and subjects reporting to have unipolar depression (40), who serve as a control group. The entire process is carried simultaneously using MiniPONs to enable the decoding of nonverbal signals from multiple sources. The suggested model presents a comprehensive evaluation of individuals' specific interpersonal sensitivity characteristics, aiming to identify key channels of communication. Additionally, the model recognizes four distinct classifications of bipolar disorder, none of which demonstrate superior performance compared to the control group across various indicators, including facial gestures, body language, and tone of voice. To enhance its robustness, a range of machine learning techniques commonly employed in existing methodologies are also implemented. The objective of this study is to examine the significance of the accuracy achieved through the proposed methodology for diagnosing bipolar disorder, employing a Bayesian Neural Network. This analysis aims to enhance understanding of the implications of diagnostic precision in clinical settings and its potential influence on treatment approaches for individuals with bipolar disorder. Additionally, this investigation puts forth a hypothesis suggesting that there is no significant difference between unipolar depression and all groups within the bipolar groups.

The primary aim of this study is to evaluate the hypothesis presented. To achieve this, it is essential to conduct a thorough statistical analysis that will facilitate the generation of an expanded set of attributes. It is hypothesized that these additional features could enhance classification performance and contribute to a more accurate diagnosis of bipolar disorder. Furthermore, this approach is expected to indirectly support the development of an effective training plan. A comprehensive discussion of the proposed algorithm will be provided in the following section.

3. Algorithm Implementation

3.1 Strategy of Algorithm Design

This approach conducts a comprehensive evaluation of numerous examples featuring peak performance decoded signals from diverse channels, to refine the sorting process for bipolar disorder. For instance, the utilization of MiniPONs facilitates the ongoing interpretation of nonverbal signals. Furthermore, the proposed algorithm's ternary strategy offers an integrated operation for applying machine learning methodologies and recovering statistical characteristics. This approach involves the application of conditional logic subsequent to subjecting the database to multiple iterations of statistical and mathematical analyses. The conditional logic's outcome is then scaled up before machine learning techniques are employed. Together, these approaches seek to make the algorithmic process sequential, which will improve the statistically accomplished features over time. This increases the precision of the suggested prediction model for bipolar disorder classification.

3.2 Algorithm Execution

The program seeks to accomplish two different targets: (i) using machine learning for prognostic diagnosis of bipolar disorder, and (ii) statistical evaluation to extract more detailed features. The algorithm's steps are as follows:

3.2.1 Algorithm for Predictive Classification with Enriched Description

```
Input:
  n: Number of entities in dataset
Output:
  ipo: Predictive outcome
BEGIN
FOR i = 1 to n DO
Initialize iga, ida, iva using functions f1 (), f2(), and f3()
Evaluate if clcond is satisfied
IF clcond is true THEN
HALT
ELSE
Execute function f4() to apply machine learning techniques
Capture ipo as the predictive outcome
END IF
END FOR
END
```

Figure 3.1 Algorithm

The approach described (Figure 3.1) here introduces an advanced technique for predictive classification, intended specifically for detecting bipolar disorder in complicated datasets. The main objective is to use enriched descriptive data to boost diagnostic accuracy. The algorithm accepts as input the number of entities (n) in the dataset and returns prediction outcomes (ipo) that have been considered essential for bipolar disorder classification. The heart of the algorithm is a multi-step mechanism. Initially, it goes through a detailed initialization phase in which three separate types of analyses have been carried out for every component. These require creating General Analysis Insights (iga), recording Descriptive Analysis Consequences (IDA), and extracting Variable Analysis Information (IVA). These investigations, enabled by functions f1(), f2(), and f3(), respectively, provide the algorithm with a thorough comprehension of the dataset's details. The program evaluates a classification criterion (clcond) to determine whether further processing needs to be done. If the list of requirements is not met, the algorithm seamlessly moves on to the machine learning phase, which is the building block of its predictive powers. In this particular instance, multifaceted machine learning techniques are applied, among which is a Bayesian Neural Network with RNDT model is wrapped within function f4(). This model mixes the positive aspects of architectures of neural networks with Bayesian inference techniques, allowing for a more detailed classification of bipolar disorder within the dataset. Furthermore, the outcomes (ipo) provided during the machine learning phase contribute a significant increase in accuracy. They provide essential facts for health care practitioners and researchers, which enables more accurate and quick diagnosis of bipolar disorder.

The algorithm offers a paradigm change in mental health diagnosis by providing an extensive framework that effortlessly merges descriptive analysis and machine learning approaches. To prove its efficacy, the algorithm can be exposed to rigorous testing across various datasets, with its performance verified against known diagnostic methods. Such validation not only confirms its dependability, but also emphasizes its potential to transform bipolar disorder diagnosis in the digital age.

4. Result Analysis

The discussion includes details of the obtained results, taking note of the analysis practices used and the results' interpretation.

4.1 Evaluation Strategy

The initial step to carry out the proposed method is to present a test environment in which the model can be evaluated using the algorithm that has been suggested. For this purpose, the Anaconda environment is employed, providing access to numerous packages and libraries without dependency on administrative permissions or specific operating systems. With over a thousand packages available, Anaconda simplifies the installation and deployment of essential tools for AI and machine learning applications. Jupyter Notebook, a browser-based kernel system, is utilized alongs the Anaconda environment to perform data analysis and coding tasks for the proposed plan. Jupyter Notebook facilitates the visualization of graphical trends generated from code execution outputs and offers flexibility in utilizing various graphing libraries that leverage the Python kernel.

The second step of the analysis involves the use of MiniPONs, which are designed to read and effectively manage data related to depressive conditions. Input data is processed using semicolons as separators, while the output is retained in its raw format. The analysis is conducted on 0–276 samples organized into a matrix with 12 columns. Ten variables are numerical (integers), while two are categorical. Descriptive analysis is performed using statistical operations such as mean, standard deviation, minimum, maximum, and quantile.

Variable analysis identifies the domain associated with the processed outcomes from the input dataset, whereas domain-based evaluation provides insights into clinical trials and sample-specific data for unipolar and bipolar disorders. These include Type II bipolar disorder, the control group, and unipolar depression. Individual assessments for each group are conducted based on voice-based responses, facial video analysis, and mean body language patterns. Correlation analysis is performed on each variable and factor, considering four possible groupings. The findings indicate that unipolar depression does not differ significantly from Type I or Type II bipolar disorder in derived scores and is thus classified as abnormal. However, unipolar depression may, in some contexts, be considered closer to normal.

The third strategy involves duplicating the input dataset for use in machine learning approaches. Kernel Density Estimation (KDE) is applied to differentiate between normal and non-normal classes through density-based inference. To optimize computational efficiency, data preprocessing employs min-max scaling. Machine learning algorithms, including k-nearest neighbors (k-NN), Gaussian Naïve Bayes, and logistic regression, are utilized to enhance data encoding for inference. The dataset is split for training and testing, and the results are evaluated using performance metrics accuracy, precision, recall and f1 score.

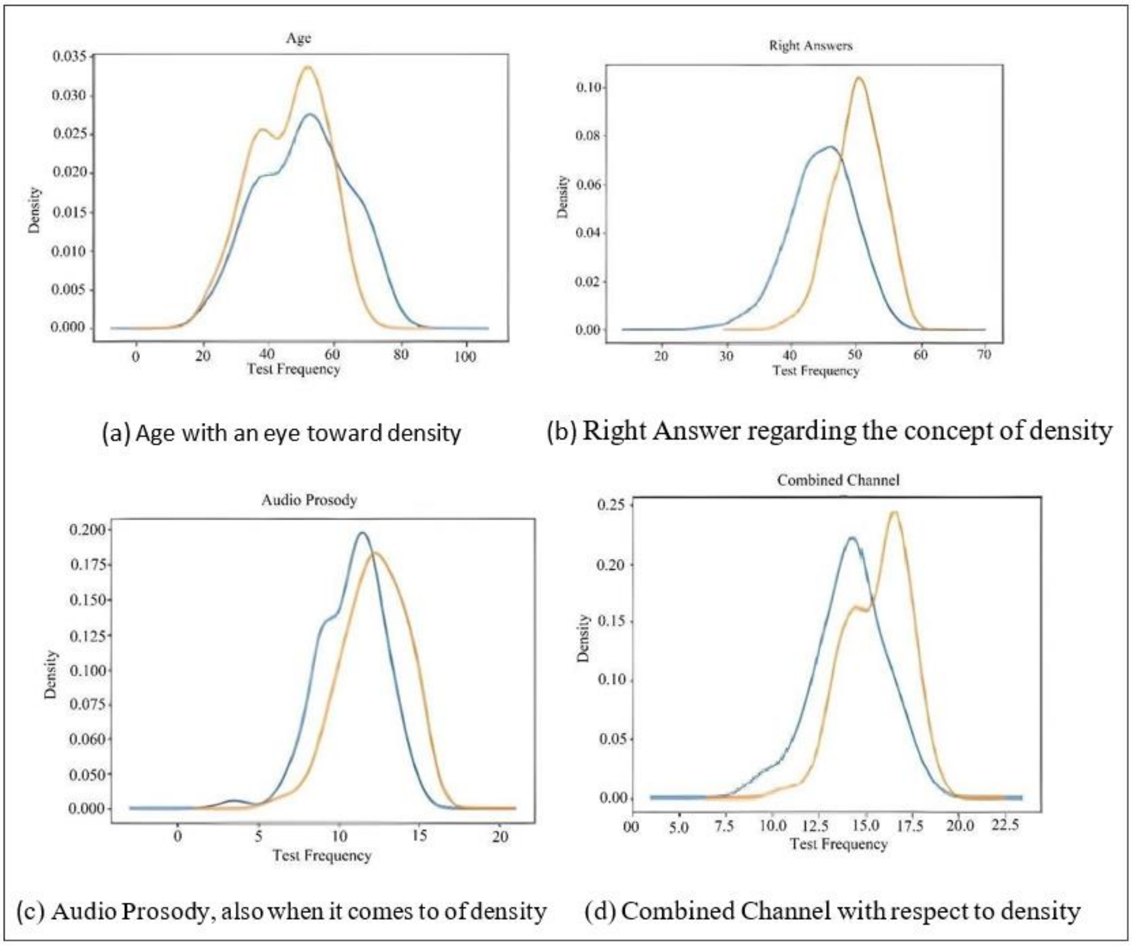
Given the challenges in developing effective probabilistic models for neural networks, a Bayesian Neural Network (BNN) is adopted [17]. This model incorporates a Gaussian process prior to sampling functions and combines non-parametric methods with deep learning techniques based on Bayesian frameworks with Recurrent Neural Decision Trees (RNDT).

4.2 Proposed Model Architecture

The architecture is designed with two input layers, effectively addressing both sequential and static features. The sequential data is initially processed by a GRU_1 layer, which comprises 128 units and utilizes a tanh activation function and returning sequences. Following this, a Dropout_1 layer is implemented to reduce the risk of overfitting, with a dropout rate of 0.2. The processed data is then directed to a second GRU_2 layer, featuring 64 units and employing tanh activation, which produces the final output without sequences. A subsequent Dropout_2 layer, configured with a dropout rate of 0.2, is applied. Simultaneously, the sequential features undergo processing through a Dense_Sequential layer to facilitate feature extraction, while a Dense_Static layer handles the static features. The outputs from both the sequential and static layers are combined through a concatenate layer, resulting in a cohesive feature set.This integrated feature set is then processed using a Decision Tree layer, which contributes to informed decision-making insights. Subsequently, the model incorporates a Bayesian Neural Network (BNN) framework, with a Dense_BNN_1 layer dedicated to uncertainty modeling. A Dropout_BNN_1 layer is applied next, utilizing Bayesian Dropout at a rate of 0.2, which feeds into an additional dense layer, Dense_BNN_2. This is followed by a second Dropout_BNN_2 layer to further quantify uncertainty. Finally, the Output_Layer employs a dense layer with a sigmoid activation function, yielding a binary classification of normal and bipolar disorder. This model effectively synthesizes sequential processing through GRU layers, feature extraction via dense layers, uncertainty estimation through Bayesian Dropout, and decision-making support through decision trees to accomplish binary classification objectives.

5. Result Analysis

The proposed methodology was completely executed by employing an established dataset of bipolar depression obtained from Kaggle [18]. The implementation processes involved examining 277 samples in columnar format, which included both integer and categorical data. The scripting for the suggested technique was done in Python within the Anaconda environment, which serves as an integrated development platform. In order to speed up computation, a parallel computing environment was used, which combined the Computed Aided Device Architecture (CUDA) programming model with a Graphical Processing Unit (GPU), notably the NVIDIA GEFORCE GTX. Using this test environment, the proposed technique sequentially allocated CPU resources. Furthermore, deep neural network libraries have been implemented for best GPU acceleration via cuDNN, fine-tuning layers such as activation, pooling, normalization, and convolution. TensorFlow, a versatile architecture, enabled intensive matrix manipulation to boost classification performance. TensorFlow's graphical support, architectural flexibility, efficient parallelism, and compatibility with Keras made it appropriate for bipolar disorder classifying analysis.



(a) Age with an eye toward density (b) Right Answer regarding the concept of density

(c) Audio Prosody, also when it comes to of density (d) Combined Channel with respect to density

Figure 5.1. TensorFlow's Graphical Support, Architectural Flexibility, Efficient Parallelism, and Compatibility with Kera’s.

The orange and blue curves in Figure 5.1 above illustrate normal and unconventional curves for the reviewed characters, respectively. Analysis of these graphical statistics reveals distinct a propensity between the two classes. Figures 5.1(a) and 5.1(b) show that normal values of age have higher scores than unconventional values, which is consistent with other qualities. Notably, Figure 5.1(c) shows lower performance for audio prosody attributes. The challenging task of distinguishing mixed signals from voices contributes to poor classification in audio prosody, but the wealth of information provided through body video attributes promotes classification accuracy.

For effective benchmarking, the outcomes of the proposed method were compared with K- Nearest Neighbor (KNN), Gaussian Naïve Bayes (GNB), and Logistic Regression (LR). These algorithms were selected due to their frequent utilization in classification problems. To ensure a fair comparison, all approaches were subjected to a similar evaluation environment. While K-Nearest Neighbor was initially considered theoretically suitable for classification, practical exploration revealed its infeasibility due to the dataset size. As the proposed dataset comprises 277 samples, probabilistic modeling similar to Naïve Bayes was considered to be more appropriate. Thus, preliminary assessment involved Gaussian Naïve Bayes and K-Nearest Neighbor, and logistic regression as a baseline algorithm. Further enhancement was conducted using min-max scaling to optimize computational resource utilization.

After scaling, grouping modeling had been done using both proposed (Bayesian Neural Network with RNDT) and existing methods (K-Nearest Neighbor, Gaussian naive Bayes, and logistic regression). Encoding operations were done for figuring out whether the inference system was normal (0) or not normal (1). Cumulative learning uses 70% of the data for training and 30% for testing. For evaluating outcomes, the analysis utilized accuracy as performance metrics. Table 5.1 depicts the quantitative findings of the analysis.

Table 5.1. The Comparative Evaluation

Metric	**Proposed**	**Exist1 (GNB)**	**Exist2 (LR)**	**Exist3 (KNN)**
F1-Score	0.882299	0.820499	0.85536	0.750891
Recall	0.882857	0.821429	0.85500	0.756429
Precision	0.884081	0.821711	0.86074	0.756925
Accuracy	0.8113	0.7075	0.7711	.6186

Table 5.1 reveals that the proposed system outperforms all the existing models on the four defined performance metrics. Precision, evaluated as the number of successfully predicted positive cases divided by the total true and false positives, is an important performance parameter, especially given the increased cost associated with false positives in bipolar disorder classification. Recall, measures the number of predicted positive occurrences divided by the actual positive instances in the dataset, could potentially assist you choose a model, especially when there is a higher cost associated with false negatives. Furthermore, accuracy, which is influenced by a substantial percentage of true negatives in bipolar disorder classification, is considered to be lesser significance than false negatives and false positives, which directly reflect the classification cost.

As an outcome, the study includes an investigation of another performance metric: the F1 score. This metric seeks to strike a compromise between precision and recall, offering a weighted metric that requires both precision and recall in order to maintain better scores and boost the F1 score. The numerical findings in Table 5.1 show that the approach suggested outperforms Gaussian Naïve Bayes and Logistic Regression. However, the K-Nearest Neighbors algorithm performs much more severe than other possible approaches, instead the numerical scores for Gaussian Naïve Bayes and Logistic Regression suggest no significant differences. The following graph in Figure 5.2 depicts the performance comparison of the proposed with the existing methods.

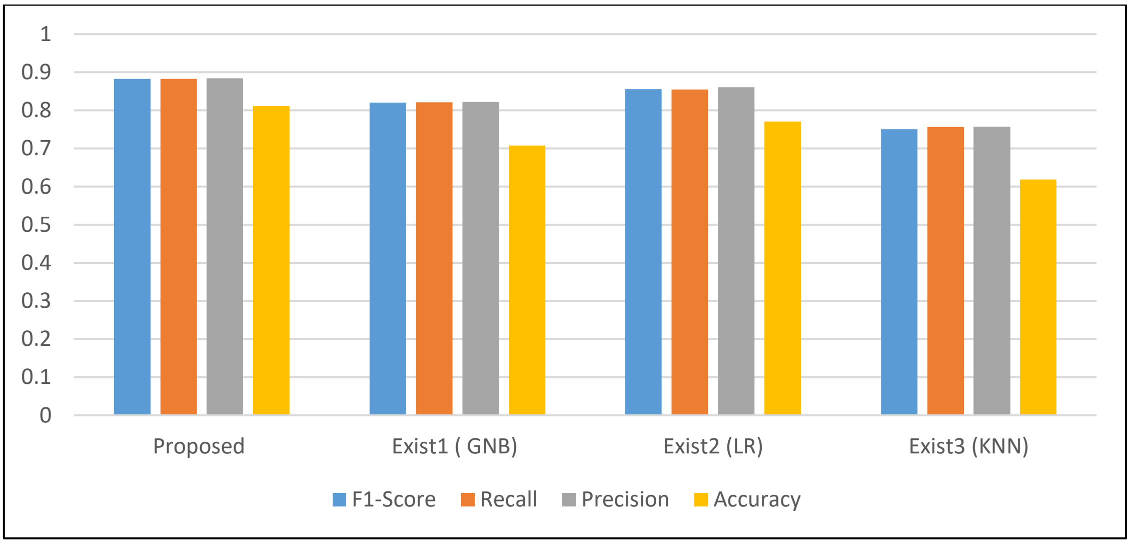


Figure 5.2. Comparison of Performance Metrics

It has shown how the proposed approach, outperforms other currently available methods in terms of accuracy. A more in-depth examination of this curve suggests that the K-Nearest Neighbors algorithm performs poorly, owing to its inability to handle vast data sets and excessive sensitivity to slight outliers. There are additionally issues with missing values, which reduce its performance. Logistic regression outdoes the K-Nearest Neighbors algorithm due to its efficient training process and simple implementation. However, as a consequence of the minimal number of features recovered from the bipolar disorder dataset under scrutiny, it is highly susceptible to overfitting. Gaussian Naïve Bayes is more scalable as well as requires less training dataThe findings presented may have limitations in their applicability to real-world scenarios, primarily due to the assumption regarding the validity of independent traits. Consequently, the proposed approach that employs Bayesian neural network with RNDT technology represents a robust and effective solution to the classification problem identified in the study.

6. Conclusion

This study presents a classification framework for distinguishing between typical and abnormal states of bipolar disorder. The proposed approach is compared with the traditional methods and other classifiers in an attempt to analyze their performance. Compared to other methods, the proposed framework has a significantly higher accuracy rate. Additionally, the study will concentrate on establishing the possibility of bipolar disorder in the subsequent research. To enhance diagnostic efficiency and precision between the different stages of bipolar disorder, this research will describe approaches used to enhance diagnostic efficiency and precision.

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