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Bipolar Diseased Student Performance Prediction using Machine Learning-Multi Tier Tier Performance Analysis Approach

Vadrevu A M Jyothi [1], Prof.P.Suresh Varma [2]

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Abstract: Severe mood swings and extreme highs and lows characterize a mental health condition termed bipolar disorder. This is probably the most common abnormality in connection with mental health, and people of every age fail to recognize it. In general, bipolar disorder occurs in families, though not all siblings will be impacted by it or have the same genetics and risks factors. Here, we combine the information gathered from Magnetic Resonance Imaging (MRI) with the random forests method. These discrepancies are useful in differentiating particular bipolar disorder patients from individuals with psychological issues that are under medical control. A closer look into majority of the existing schemes using machine learning shows dataset is directly applied to machine learning algorithm without much emphasis towards working on features. The complications of determining an exact state of bipolar disorder is quite challenging and demands deeper insights towards understand the trend of behavior. Unfortunately, there are few reported studies in existing scheme where machine learning has been introduced with more emphasis towards feature management process. Majority of the existing machine learning-based framework towards mental illness are not assessed over benchmarked test environment. Due to this absence, the claims of accuracy reported in existing system cannot be justified to be working on real-time environments too. Hence, lack of benchmarking doesn't only reduce the applicability but also acts as an impediment towards further optimization.

Keywords: *Machine learning, bipolar disorder, Confusion matrix, Long Short-Term Memory (LSTM)*

1. Introduction

In recent decade, there is an increasing interest and demand for models detecting the influencing factors of student performances in education, specifically incorporating Machine learning models. The Machine learningin educational domain and research is termed as Educational Machine learning in Bakhshinategh et al. (2018). The main motive of Educational Machine learning is to help for identifying the poor performing students earlier and improving their learning skills, which makes the institution to provide higher educational standards. Moreover, Educational Machine learning is the fast growing research domain because of its capability to obtain information from large amount of student data worked by Wook et al. (2017). In recent times, Machine learning and student information systems are effectively integrated for evaluating the student performances accurately in Salloum et al. (2018). Additionally, the Educational Institutions use this for digitalizing the student data and transactions in Yukselturk et al. (2010). The huge amount of student information, presented in Student Information System, includes the following factors Course Data, Tutor Data Student Personal Data, Student Demographics, Student's Grade, Attendance Data In EDM, the applications and services of Machine learning operations, machine learning and analytics to the data are observed from educational data 2 bases from universities.

Department of Computer Science & Engineering University college of Engineering Adikavi Nannaya University Andhra Pradesh 1,2

At the top level, the domain searches to frame and enhances the techniques for data exploration that applies in hierarchical operations in multiple levels. Based on that, the EDM techniques has provided two methods of learning analytics by the research people in the learning psychology of students. EDM is concerned with application and development of mining techniques for pattern recognition from large educational dataset and for better student and environmental analysis done by Crist´obal Romero & Sebasti´an Ventura (2010). Educational Machine learning incorporates various techniques of Machine learning and data analytics carried out by Siemens & Baker (2014) for processing. The frequently used prediction methods are classification, regression and latent feature derivation methods. Unsupervised learning methods such as clustering, factor evaluations and network computations are used for determining the efficient structure in several domains of educational data.

In the proposed research, an approach for diagnosing bipolar disorder (BD), which is characterized by two extreme mood asserts—mania, or high mood disorder, and depression, or low mood disorder—is presented. A person with BD may have a number of symptoms all through time, from moderate to serious situations. The challenging component of this emotional condition is that each person with BD might experience its symptoms different; a single individual may be very manic or very depressed. Bipolar disorder includes a wide range of symptoms, however in order to fully understand the severity of this mental illness, it is crucial to understand some of the specific symptoms as well as their root causes.

According to psychiatric theories now in use, bipolar illness frequently affects teenagers, who develop an assortment of symptoms over time. Any individual may develop depression due to a variety of the environment, psychological, and biological variables . When more adverse events occur in real life, such as the death of a loved one, abuse, violence, financial crisis, unstable circumstances in life, etc., this severity can be further affected. Furthermore, evidence indicates that depressive disorders can run in the family. Nevertheless, the heightened emotional state, including hypomania or a state of confirms the presence of BD and is a potential indicator. The state of the BD is carefully evaluated as part of a diagnosis of BD using an assortment of diagnostic techniques. It also seeks to identify multiple factors that could cause up BD symptoms. For the sake of assessing the degree of severity, the medical professional will ask the individual several inquiries regarding their daily activities and events that are connected to their emotions, sleeping habits, etc. To help to better understand the root causes of the trigger points of BD, the psychologist analyses a person's emotions, feelings, and concepts while also discussing the patient's family. While conducting a psychiatric evaluation, a psychiatrist communicates with the patient in speech to comprehend the patient's mental state . A disorder of mood questionnaire is given to the individual's doctor as a screening tool, and once it has been filled out by the patient, the psychiatrist gets an excellent idea of the patient's mental state including the severity of the mental issue. adopted an approach of diagnosis that asks the patient to keep a record every month of their symptoms, behaviors, and other relevant factors to help diagnose bipolar disorder . Maintaining a record of your emotions may assist you understand why bipolar illness prefers to show itself as severe. The information obtained from mood charts comprises facts on medications, hours of rest prior to the attack, the presence of anger and anxiety, and psychotic symptoms, amongst other factors.

2. Literature Review

Cooper et al.'s study model make use of artificially generated neural networks to foresee the exact moment of diagnosis needed to treat BD. The research's major point is that more accurate prediction modeling that take temporal aspects into consideration will eventually enable detailed investigation of BD incidence in the future. The main drawback of this framework is that it focuses little focus on processing incoming data, which is usually large and contains a lot of redundant information. Without an objective function, depression data cannot be filtrated, which additionally acts as an indication that better data gathering is possible if data processing is prioritized before installing a learning model. The latest study by Highland and Zhou has outlined some of the key state-of-the-art techniques for diagnosing bipolar illness. Some conventional and some unconventional ways of detection have been briefly discussed in the discussion. The authors' description of unconventional detection techniques included information on data gleaned from social networks, sensor technology, and the global positioning system. In the research they conducted, Arribas et al. Used a classification-based approach to differentiate bipolar disorder from other types of mental disease, which include schizophrenia. The suggested method performs out the classification issue using the stochastic gradient scheme for rule-based learning. Functional Magnetic Resonance Image data is used as the analysis's input. This data is then subjected to a dimensional reduction procedure utilizing a statistical evaluation method and singular value decomposition. The study's findings show that the Bayesian classification method is more effective in achieving convergence. As identified in the work of AbeiKoupaei and Osman, the existing categorization scheme additionally includes the use of many modalities. Based on the circumstances of the individuals with this mental disorder, classification occurs. The same author, AbeiKoupaei and Osman, carried out research on multi-modalities, where they categorized multi-modal features using multi-layer perceptron’s and convolution neural networks. In addition, reinforcement learning is utilized in order to help optimize. In an experiment including a classification challenge, the same authors AbeiKoupaei and Osman introduced Long Short Term Memory (LSTM) to the retrieved sequence of characteristics in order to comprehend the state of bipolar disorder. Convolution neural networks are utilised as well in this study to extract admit data from the subject's input video. where the diagnosis of depression is improved by making use of a neural network. In the present scheme, the feature is obtained using a neural network, and the assessment is carried out through altering the substance while using machine learning to look at the data gathered at every stage of the medication. The study's overall contribution is that it offers immediate consequences for various antipsychotic doses and different types of exclusive inhibitors in regards to suppressing bipolar illness. In addition, it has been noted that a combined approach of applying several machine learning techniques has been found to provide favorable findings when performing the identification of a discrete state of bipolar disorder. Such research has been presented by Pan et al.and asserts to be capable to identify a patient's manic state through the analysis of speech signals.

3. DATASET

In the dataset , we used these mentioned parameters

- school : student's school (binary: "GP" or "MS")
- sex : student's sex (binary: "F" - female or "M" - male)

- age : student's age (numeric: from 15 to 22)
- address : student's home address type (binary: "U" - urban or "R" - rural)
- famsize : family size (binary: "LE3" - less or equal to 3 or "GT3" - greater than 3)
- Pstatus : parent's cohabitation status (binary: "T" - living together or "A" - apart)
- Medu : mother's education (numeric: 0 - none, 1 - primary education (4th grade), 2 - 5th to 9th grade, 3 - secondary education or 4 - higher education)
- Fedu : father's education (numeric: 0 - none, 1 - primary education (4th grade), 2 - 5th to 9th grade, 3 - secondary education or 4 - higher education)
- Mjob : mother's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
- Fjob : father's job (nominal: "teacher", "health" care related, civil "services" (e.g. administrative or police), "at_home" or "other")
- reason : reason to choose this school (nominal: close to "home", school "reputation", "course" preference or "other")
- guardian : student's guardian (nominal: "mother", "father" or "other")
- traveltime : home to school travel time (numeric: 1 - <15 min., 2 - 15 to 30 min., 3 - 30 min. to 1 hour, or 4 - >1 hour)
- studytime : weekly study time (numeric: 1 - <2 hours, 2 - 2 to 5 hours, 3 - 5 to 10 hours, or 4 - >10 hours)
- failures : number of past class failures (numeric: n if 1<=n<3, else 4)
- schoolsup : extra educational support (binary: yes or no)
- famsup : family educational support (binary: yes or no)
- paid : extra paid classes within the course subject (Math or Portuguese) (binary: yes or no)
- activities : extra-curricular activities (binary: yes or no)
- nursery : attended nursery school (binary: yes or no)
- higher : wants to take higher education (binary: yes or no)
- internet : Internet access at home (binary: yes or no)
- romantic : with a romantic relationship (binary: yes or no)
- famrel : quality of family relationships (numeric: from 1 - very bad to 5 - excellent)
- freetime : free time after school (numeric: from 1 - very low to 5 - very high)
- goout : going out with friends (numeric: from 1 - very low to 5 - very high)
- Dalc : workday alcohol consumption (numeric: from 1 - very low to 5 - very high)
- Walc : weekend alcohol consumption (numeric: from 1 - very low to 5 - very high)
- health : current health status (numeric: from 1 - very bad to 5 - very good)
- absences : number of school absences (numeric: from 0 to 93)

4. Proposed Methodology

In Educational Data Mining, the process of knowledge discovery is determined with the student data from the institutions. The main purpose of this work is to present the evaluation results of student performance that supports in framing the education quality and to enhance the student pass percentage and the overall results of the institution. Here, the large data samples which are in databases of educational institutions are obtained from the student log. The obtained student's records are provided in different forms that include the data of student's personal data and academic logs. The institution can provide better results with enhanced accuracy with the efficient student classification model. For deriving the results, the student features are derived based on the obtained knowledge patterns and afforded to the academicians to take appropriate decision. Based on their decisions, the teaching methods are modified. Moreover, the advanced management methods and educational data model of student requirements are listed Describing and considering the distinctive factors of academic and personal student data. Developing efficient EDM model for student data classification.

4.1. Predictive Framework for BD State Confirmation

The finished system's modelling is carried out using a phase-wise approach. In order to fully understand the characteristics of the data set and the demands associated with proper preprocessing, exploratory analysis is first performed. The analysis suggests the collection is chronological data since it has both time-series and distinct characteristics. It has also been stated that the dataset contains details about 55 people, 23 of which received a bipolar illness diagnoses. In addition, preliminary processing activities are performed to treat missing data. It is apparent from the suggested method described in the preceding section that the proposed system utilizes a simplified identification a position based on a standard scale and psychometric attributes. It was established that the selected method provides better internal consistency, assuring the dependability of this scale and improving being adopted. The suggested structure assures that they must be strongly connected with the basic notion of depression according to the performance of the trust element of the contents. The suggested approach utilizes one of a number of different statistical characteristics of MADRS, which have been extensively utilized to assess the efficacy of depressive drug studies. For an effective analysis of this score with regards to granularity, a descriptive evaluation of the score needs to be performed, where the efficacy of the score may be evaluated with regard to several types of error detection. The proposed computational model is assessed using this inference as the back end logic in order to assess the severity of bipolar illness in a patient. The third level that operates on top of the second implementation module associated with classification is the final module. This structure develops a more flexible framework that may allow deeper research with greater precision towards confirming true state of BD using deep learning, so resolving the problems related to symptomatic scale of BD subject diagnosis. Before learning operations are applied, the input of the BD dataset is subjected to a multi-stage cleaning operation, which is followed by a fine-tuning process. To determine the rating score of the level linked with Bipolar Disease, a standard scale is employed. The study in addition utilizes feature engineering to optimize feature management and process. Correlation analysis follows in order to provide comprehensive contextual information for the established statistical score. The model that is suggested has been subjected to a predictive analysis utilizing recurrent decisions trees. In a consequence, the three implementation modules collaborate in order to achieve the overall goals and objectives of the research. In addition, all work implementation is done with mathematical modelling, with variables generated based on the behavioral elements of the work's objectives. The scripting for the work suggested is executed in Python environment using a conventional bipolar dataset. The dataset includes multiple samples that have been organized in both categorical and integer form. In addition, the programming model over parallel computing through Graphical Processing Unit constitutes a component of the implementation environment. The proposed system's results from the study have been evaluated in relation to various performance metrics for processing speed and accuracy. The suggested approach can be implemented in the Python programming language while taking into account a typical Windows PC. The depressive dataset is utilised for implementation purposes. The dataset comprises of a metadata file, two types of data (controlled and conditional), and a metadata file. The initial one is a time-series data data of an individual who received an optimistic diagnosis of bipolar disorder from a medical professional, while the subsequent one is a time-series data of a patient who has received a negative diagnostic of bipolar disorder.

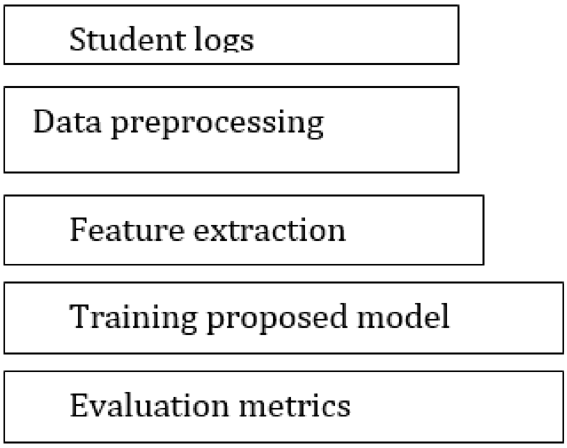

Fig. 1. Generalized Architecture

4.2. Algorithm for Prediction

This algorithm's primary objective is to make prediction about the next phase of bipolar illness. This algorithm's basic idea is that it might be challenge to determine that an individual suffers bipolar illness due to their unpredictable mood. The majority of extant theories list depression as an indication of bipolar illness, yet there is minimal proof to back up this claim. The reason for this is that sadness may also be a condition of inactivity, consequently it is difficult to prove that depression is an actual symptom of bipolar disease. As a consequence, by providing an Actigraph-based monitoring system, the suggested method helps to provide a solution to this problem. That might prove useful for detecting diverse motor activity variances in a single individual.

Bipolar Disorder State Prediction Algorithm

Input: n (elements of Dataset)

Output: Pred(predicted Outcome)

1. *For i=1:n*
2. *If n==error*
3. $N \leftarrow s_{val}$
4. $M=f_1(n)$
5. $C_{val} = f_2(M)$
6. $Pred = f_3(C_{val})$
7. *End*

In the proposed work, the meta classifiers such as AdaBoosting, Stacking and RF operations are incorporated with base classifier for further classifying the student data from the aforementioned four classes with more precision and accuracy. Moreover, the advantages in performing multi-tier classification in the proposed model are provided below,

i. Providing better classification results than using base or single classifier.

ii. Achieving good generalization with ensemble based classification techniques.

Multi-Tier Performance Evaluation Model is developed from student sample of 300 and it was compared with the Algorithms such as ANN, SVM and the proposed method. Further, Ensemble Student Performance Evaluation Models are developed namely KNN-ANN, DT-KNN, ANN-DT, DT-SVM, NB-SVM and DT NB from student sample of 500 and It were compared with both MTSPEM model and traditional classification techniques such as, K-Nearest Neighbour (K-NN), Artificial Neural Networks (ANN), Support Vector Machine (SVM), Decision Tree (DT), Naive Bayes (NB).MTSPEM model is derived for student performance evaluation and categorization for providing additional efforts to the students for providing better results. Here, the classification is processed with two levels as,

1. Primary Level-Classification
2. Secondary Level-Classification

In the primary level classification, traditional classification method are used and in secondary classification, meta-classifiers are used for categorizing the students under four labels, as follows,

i. Outstanding

ii. Good

iii. Average

iv. Poor

5. Results and Discussions

To successfully assess machine learning and deep learning algorithms, appropriate performance criteria must be chosen. For the objective of this analysis, we used mainly the performance measures precision (P), accuracy (A), recall (R), and F1-score (F1).

True Positive: The data point that predicted belongs to a positive class as exact as the actual positive class. Such kind of collection of data points obtained under this scenario is called True Positives.

True Negatives: The data point that predicted belongs to a negative class as exact as the actual negative class. Such kind of collection of data points obtained under this scenario is called True Negatives.

False Positives: The data point that predicted belongs to a positive class which is different from the actual negative class. Such kind of collection of data points obtained under this scenario is called False Positives.

False Negatives: The data point that predicted belongs to a negative class which is different from the actual positive class. Such kind of collection of data points obtained under this scenario is called True Positives.

These metrics value lies between 0 and 1 and to obtain in percentage the value is multiplied by 100. In the equation, TN indicates True Negatives, TP indicates True Positives, FN indicates False Negatives, and FP indicates False Positives

Confusion Matrix: It is a table-like structure that provides information that the size of data points that belong to various classes. From the confusion matrix, the number of true positives, true negatives, false positives, and false negatives may be derived.

Accuracy: It is a metric utilized for identification of the framework trained well or not using the training dataset and thereby using the testing dataset and confusion matrix, accuracy will be calculated as mentioned in Eq. (1). It represents the number of accurately classified data points over the total number of data points.

$$Accuracy = \frac{Tp+TN}{Tp+TN+FP+FN} \tag{1}$$

Precision: It is a metric utilized for identification of the framework trained well or not using the training dataset and thereby using the testing dataset and confusion matrix, precision will be calculated as mentioned in Eq. (2).

$$precision = \frac{True\ positive(Tp)}{True\ positive(Tp)+False\ positive\ (Fp)} \tag{2}$$

Recall: It is a metric utilized for identification of the framework trained well or not using the training dataset and thereby using the testing dataset and confusion matrix, precision will be calculated as mentioned in Eq. (3).

$$Recall = \frac{True\ positive(Tp)}{True\ positive(Tp)+False\ Negative\ (Fn)} \tag{3}$$

F1-Score: It is a metric utilized for the identification of the framework trained well or not using the training dataset and thereby using the testing dataset and confusion matrix, precision will be calculated as mentioned in Eq. (4). It is the mean value of precision and recall and is more accurate than accuracy.

$$F1\ score = 2 * \frac{Recall*precision}{Recall+precision} \tag{4}$$

5.1. Comparison of different algorithms with proposed multi-tier algorithm

In the comparison of classification methods, including k-Nearest Neighbors (KNN), Naive Bayes, and a proposed method, precision, accuracy, F1 score, and recall were evaluated. While Naive Bayes demonstrated the highest precision and accuracy among the three methods, achieving 0.7243 and 0.707 respectively, the proposed method surpassed both Naive Bayes and KNN in precision (0.91), indicating its potential superiority in correctly identifying positive instances. However, Naive Bayes and the proposed method shared the same F1 score of 0.69, while the proposed method showed the highest F1 score (0.82), suggesting better balance between precision and recall compared to KNN and Naive Bayes. The proposed method also exhibited a high recall of 0.89, indicating its capability to identify most positive instances among all actual positive instances, further highlighting its effectiveness in classification tasks. These findings suggest that the proposed method outperforms both KNN and Naive Bayes across multiple metrics, making it a promising approach for the given classification task.

Table 1. Comparison of different algorithms with proposed multi-tier algorithm

Metric	KNN	Navie Bayes	Multi-tier Algorithm (Proposed Method)
Precision	0.6957	0.7243	0.91
accuracy	0.6800	0.707	0.90
f1 score	0.69	0.69	0.82
Recall	0.639	0.67	0.89

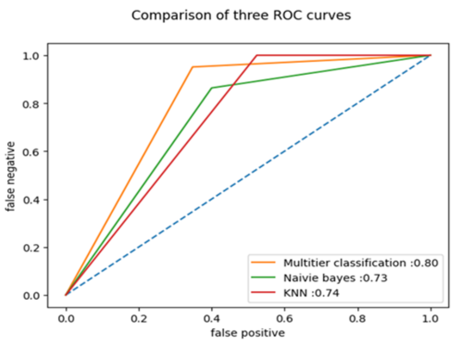

Fig. 2. Comparison of ROC Curves

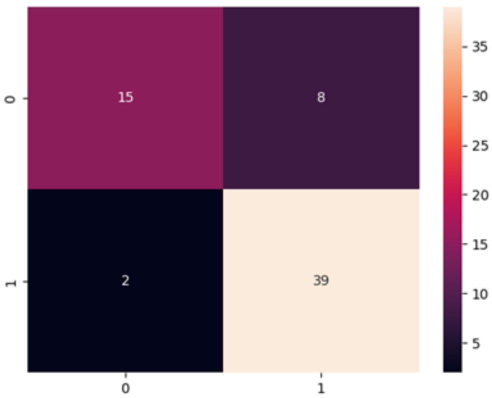

Fig. 3. Confusion matrix of Multi-tier classification

Now, based on extracted factors, let's give some advices for students, parents and school administration :

- People should get educated especially men so that they help their children in their studies.
- The government should help students whose parents are not rich that much so they get access to internet or looking forward taking higher education.
- Administration should send warnings to parents when students reach the maximum acceptable number of absences before exam period begin.
- When students are having a lot of failures, the administration, teachers should search for the problems faced by this students and also get contact with the parents for more information.
- Student should find, at home, a suitable space to study, they need desks or just a small area when they can focus on their studies. Imagine how you would tell this student not to go out with his friends and spend a lot of time and yet their parents shout all the time in front of him. Parents should keep their problems for themselves. These students need love and peace at home. Students will then spend many hours studying at home.

6. Conclusion

Improving the education system is a big problem, Machine learning can help achieve this goal by using technologies and study resources like machine learning materials, to come up with an innovative solution to help the students in need, especially students who live in difficult conditions. conditions (demographic, social, and educational issues). In this paper, we came up with the idea of creating a model that predicts the status of students based on different functionalities. Our main challenges were to define the best classification algorithm and identify the most influential factors for the academic status of students to provide them with a summary or valedictorian of the best conditions for students to achieve high academic status and avoid failures.

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