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Psychotic Motivation for Improving Student Performance Based On Pattern Learner Features Using Deep Neural Classifier for Bipolar Disorder Students

S. PEERBASHA[1*], M. MOHAMED SURPUTHEEN[2*]

Research Scholar[1], Associate Professor[2] , P.G & Research Department of Computer Science – Jamal Mohamed College (Autonomous),Affiliated to Bharathidasan University, Tiruchirappalli, Tamilnadu, India.
Email: [1]bashapeer2003@gmail.com, [2]msurfudeen@yahoo.com

Abstract: Bipolar disorder is a depressive fact that makes manic illness pressures in young ages due to the non-intensive nature of brain functions, energy levels, mood-outs, and health disorders. These abnormalities may affect student performance under the learning strategies of students. Improvement of bipolar disorder affected student performance needs more data analysis forums that lead to high dimensional nature of features. The problem is that non-relation feature analysis depends on the nature of student fitness that creates low prediction during classifications for students' motivation. To resolve this problem, a Psychotic motivation is proposed for improving student performance based on Pattern Learner Features (PLF) using Intra Segment Recurrent Deep Neural Network (ISRDNN) for bipolar disorder students. The proposed system makes student academic data's with physical fitness data collection progressive approach to predict important features to classify the result. Bipolar Disorder Influence Rate (BDIR) is usedto spill the progressive student defectives and the learning capabilities for classification result. With Intra Segment Activation Function (ISAF), the recurrent neural network is optimized to classify the result. This classifier improved the student's academic performance based on psychological motivation recommendations. Results prove that the accuracy of the proposed system produces high results compared to the previous system.

Keywords: Behavioral analysis, Deep learning, Features Selection, Neural network, Pattern prediction.

INTRODUCTION

The student performance depends on the capability of the learning activities i.e. the activities be differ from normal learning students and bipolar disorder students. So the teacher may defect of learning capabilities to reach the student to improve the performance. The analysis of disorder student be important to intent a learning based on the behavior of the student. The bipolar disorder is a disease influence affected mentally to create a burden of the understanding nature. So many disorder classification techniques and future selection are predict the performance of the student capability to improve the student.

The teaching, learning, disease classification, behavioral findings, performance grading are the facts which is collected from student datasets from academic institutions also with fitness evaluated healthcare results. These data processed with deep learning based feature selection and classification techniques to make predictive model.

Bipolar disorder Predictive model performance relies on selecting the most relevant features from the list of features used in the student database. This database can be achieved by using various feature selection methods. In practice, the accuracy percentage is usually not chosen for the classification that the exact value is applied to the classes' base rate very differently. Besides, many factors affect the success of a given task of data processing algorithm. The data's value is defined as if the information analysis parameters are inappropriate or superfluous, or it is very difficult to detect cognition during training if the data noise is unreliable.

In general, selecting a subset of attributes is a process of identifying and eliminating as many of the difficult, irrelevant, and unwanted features as possible. Learning approaches vary as they emphasize attribute selection. Disorder state of progress can easily access such neighborhood learning as nearby. It is used to categorize new events using all presentation features of remote assessment.

On the other hand, most of the classifier algorithms select the unrelated features of the endeavor and do not focus on all related aspects. Despite the learner's effort to choose or ignore the problem attributes, pre-learning attribute selection can improve accuracy. Technologies that reduce data components can significantly reduce hypothetical space and work significantly faster and higher.

RELATED WORKS

Student Performance Analysis System (SPAS) is to ensure that student results are monitored based on the features selection and classification [1]. The early prediction depends the performance and the data analysis, which can define the function of students who are predicted to be poor andprovides a predictive system that can predict performance analysis and design [2].

The main challenges are analyses the performance for increasing feature that does not produce clustering [3]. During this period, the two most important data collection processes and analysis are likely to come under criticism. University ranking depends on academic performance and student status verified by MOOC principle based analyses [4]. In addition to academic performance prediction the student performance is analyzed through data mining algorithms but most of algorithms doesn't produce accuracy on classification [5], many other factors help understand the student's overall performance.

Classification techniques are described based on the predication performance and used in educational data mining [6]. The classification process is based on an artificial neural network algorithm with poor classification accuracy. Because curriculum and other factor consider taking academic performancethese techniques help assess the academic performance of learners, as well as teachers [7].They serve as an early warning system for students to improve their academic performance.

Educational data mining process designs are not well for low redundant based feature selection and classification, such as using data processing algorithms for educational data produce poor accuracy [8]. It theoretically seeks to intellectual data related to a student's graduate educationaffects the nature of relation feature selection by multiple hybrid algorithms [9]. Attempts have been made to find and predict a data mining modelusing Support Vector Machine (SVM) to classify best student performance based on these correlations.

Similarly the social activities doesn't improve the student performance, but they consider other equally important personality factors such as life and interests, traits and perceptions to predict student performance and achievement is done by MPG (Multifactor physiology Generalization) model [10]. It uses machine learning and in-depth variety to learn predictive techniques for data analysis to explore the basics of different relationships derived from student performance [11] and psychological characteristics are evaluated.

The feature selection and classification presented in some techniques but they consideration is not well for understanding importance of features and their relationship. After that Student Performance Assessment [12], the use of large-scale student performance forecasting over survey results using Heuristic Feature Selection model to make [13].Analysis are undertaken to identify the significance feature prediction and impact of student background, learning capabilities under poor performance activities and student coursework achievement in predicting student academic performance [14].The feature selection algorithm that calls opinion mining from differential evolution is used from the student database to predict the student performance. Some other feature selection algorithms are used in formula techniques and student performance that have never been used on a data Hybrid Regression and Multi-Label Classification [15]. Besides, the techniques of classification such as Naïve Bayes (NB), Decision Tree (DT), K-Nearest Neighbor (KNN) and Discriminant Analysis (DA) are evaluated. The Differential Evolution (DE), another aspect that evaluates students' academic performance [16], which gives them more accuracy than selection, is the feature selection algorithm used.

Educational Data Mining (EDM) is a growing research discipline that helps educational institutions improves student performance [17]. Feature Selection (FS) algorithm thereby enhances the classifier's performance used by EDM technology and removes inappropriate data from educational databases.

This convolution based classification model shows very high classification performance, and the C5.0 classification is known for its precision and accuracy [18]. Besides, the importance of variables for each taxonomic model is analyzedto predict based on Support Vector machine [19].Moreover deep learning features are intent to improve the performance accuracy, success as an instructor is based on students 'perceptions, mainly on students' course of interest study [20]. The models analyses the iterative performance on different level but the non-relevant information leads feature selection and classification inaccuracy

The rest of the section follows by proposed implementation in section 3, result and discussion in section 4 and the performance concluded in section 5.

3.PATTERN LEARNER FEATURES BASED DEEP NEURAL CLASSIFIER

This paper analyses the student behavior to identify the best pattern for Psychological recommendation for improving the student activities using Bipolar disorder student characteristics. To resolve this problem, a Psychological motivation is proposed for improving student performance based on Pattern Learner Features (PLF) using Intra Segment Recurrent Deep Neural Network (ISDN) for bipolar disorder students. Following a basic presentation of student academic characteristics, the bipolar behavioral characteristics are examined in detail, including key technologies to classify and detect for the recommendation of motivating student.

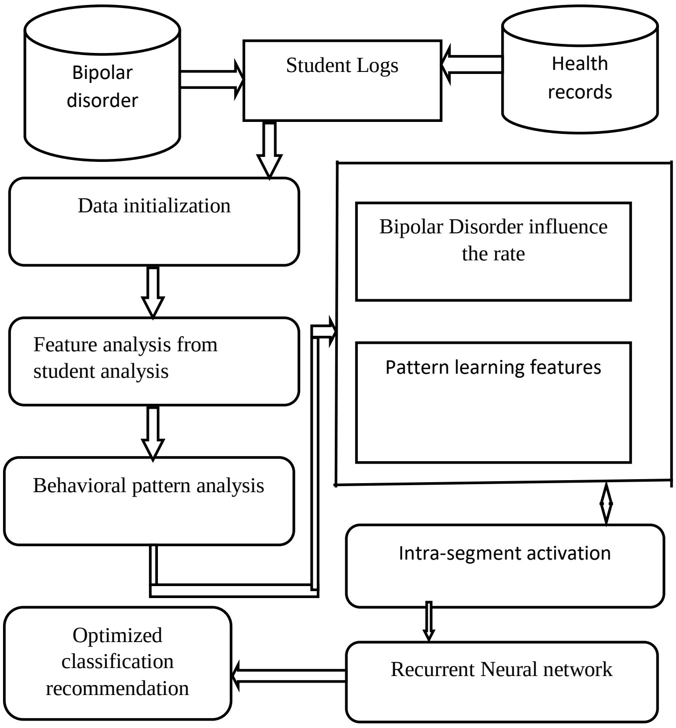

Figure1. Architecture diagram PLF-ISRDNN

The above Figure 1: shows the architecture diagram for a proposed PLF-ISRDNN system based on feature selection and classification, which is predicted from frequents pattern mining weights observed from patterns. The contribution begins with student feature selection and classification approach to develop a pattern prediction system that can extract large amounts of bipolar disorder states to the most appropriate low dimensionalfeatures.Further detection of the proposed active method can reduce adverse effects and noise and defect data. Various drive shapes to classify and predict are associated with high road risk in terms of unattended pre-training

3.1 Data preliminaries

Initially, the bipolar disorder collective data and student academic data process are observed to reduce the non-related data's empty data. This selects the relevance identified portion to predict the features on varying weights to make a single cluster. First, a pair of related features has been selected for the most stable student profile to identify the set interactions of attention obtained by finding comparisons of properties between all single-member values to minimize high-dimensional datasets.

Algorithm
Input: Disorder data, student data Ds, output Featured data,
Step1: Preliminaried Ds = {Dsl1,Dsl2….Dsln}
Compute for all ds to check !=null
Step2: Read List of featureLs→Student list {Dsl1….}
For (choose list query count!=Null as repeat data access)
Unique access list→Ls ++;
Step 3 computes all the equivalent access to the Feature value.

$$Ls= \sum_{ls}^{ln} \frac{total\ number\ of\ disorder\ (Qt) + Student\ log\ (Cq)}{total\ query\ term\ (Tq)} \quad ....(1)$$

Step 4 Extract the corresponding score to the order of feature relevance.
FLs={Qls1,qls2..}
Step 5 Sort the score vector in decreasing order to rank the features Rls.
Step 6 Return the Feature set QTs=Rls(T).

The above algorithm considers the student progressed feature set query term and data, which is the dimensional reduction on adaptable feature records values.

3.2 Behavioral Pattern Analysis

Student performance is analyzed based on different time windows, and performance is being measured according to activities and understanding of patterns being generated. It was created based on learning capabilities, disorder disease level of activates using the mentioned behavioral features, and the method creates different class performance methods. Similarly, the system estimates the neural activation by assert Performance Aspect Ratio (PAS), is rated with different class available formats

Algorithm

Input: Rls student logs

Step 1: For each Feature Si→compute user behavioral analyses A(i)

Compute frequency of Feature access

SL Freq = $\frac{\sum Al(i).Disorder==Si\ behavioural\ analysis}{Total\ services\ accesse+dterm\ repeated\ query}$ …. (2)

Step 2 Compute student computed access weight.

Scm = $\frac{\sum Al(i).service==Si}{total\ services\ accessed} * Sl(computed\ access\ weightage)$ …(3)

Step 3 compute relevance weightage score

If Scm> SC-Then rank list (service+ behavioral interest of user)

Service interest score {Sc1,Sc2…}

Step 4 Return term of student featured rank list →R(T)

End

End for

The above algorithm performs the student assessment for different performance pattern prediction classes depending on the featured behavioral activities.

3.3 Bipolar Disorder Influence Rate (BDIR)

The method uses the student activities occurrence at the event, measured according to the candidate most affected influence which is calculated by mean rate disease depression. Also, the mean rate is referred to as features present in each event class of disease. According to Event Support's value, a specific event has been selected and produced as a result, referred to as disorder affected rate.

Algorithm

Input: Training set R(T), Input Data Point Dp student logs.

Output: R(Ts) value.

Start

Identify all the concrete dimensions that have compactness values.

CD = $\int_{i=1}^{size(Md)} \sum Md(i) \in (\forall Ts(k))$ …(4)

Identify all depression possible dimensions that have values.

PD = $\int_{i=1}^{size(Md)} \sum Md(i) \in (\forall \uparrow\downarrow Ts(k))$ …(5)

Compute similarity on mood-out depression rate.

CDSim = $\int_{i=1}^{size(CD)} \sum_{j=1}^{size(Ts)} Dist(Ts(j,i), Dp(i)) \downarrow DThreshold$ …(6)

Compute similarity on possible dimensions upset.

PDSim = $\int_{i=1}^{size(PD)} \sum_{j=1}^{size(Ts)} Dist(Ts(j,i), Dp(i)) \downarrow DThreshold$ …(7)

Compute Eccentric Measure Em. All CD, PD sum mean rate.

EM = $\frac{CDSim \times PDSim}{Size(Ts)}$ …(8)

Stop.

The event prediction process has presented the above pseudocode, and the method computes the event support for various event classes. Finally, a single event has been selected as a possible event to produce a result.

3.4 Pattern learning Features Selection

This stage considers the maximal region similarity measurement by covering the boundary limit of scaling values from behavioral activity of best pattern. This creates rough set groups to make the fuzzy rules set for the non-deterministic as lower features. The multi attributes have the same similarity, which is identical to nature, considered as unique features, as similar on another feature nature

Step1: Input PDs data initialization.
Step2: Perfect logs PDs For each Class Cl→Ts
Identify search term attribute for frequent query
Attribute For each Cl→A_i of Fv_i
Pattern compute data PCl = $\int_{i=1}^{N} \sum \left(Ai(Fvi) - Ai(Fv)\right)^2$
End
Ds(i) = $\sum Dsi + Cl$
End
End
Step3: identify each class Cl of data request set Ts
Ai →for each case attribute
Compute the Relational feature count SC = $\int_{i=1}^{N} \sum Dsi(Ai) \geq STh$
End
Measure relative pattern case Dm = $\frac{Sc}{size(Cli)} \times 100$ …(9)
End
Step4: read end

Every segment vector is then utilized as an input vector, while the normal of every attribute at maximal features. In the training phase, the network is trained by providing input and output based on selected features by constructing a neural network.

3.5 Intra Segment Recurrent Neural Network

In this stage, the recurrent neural network is optimized with decision statements with the logical representation of the activation function to find the recommendation for student motivation with classified classes. Initially, the neural activation function is performed based on intra segmented neuron layers to be activated with downsampling observed features. The features are input progressed into the pooling layer to downgrade the non-negative samples.

Non-linear input sample data is processed with input layerwhich is analyzed by selecting the part/sub from hidden layer which the maximum or mean value is derived activation nueral section. The hidden layer division is generally non-superficial and is one of the most common forms of training features for maximum closest pattern of behavioral student. The main purpose of pattern relates the max features given to input data below the step-by-step model so that the filter/kernel data can operate at different resolutions based on cumulative data points. Then the hidden layer aggregate the implementation processed independently.

Algorithm:
Input: Student Current Sample scs, Student Performance Trace Apt.
Output: optimized class pattern
Start: compute the behavioral patterns and occurrence of services

Read Apt. Data values and Scs. Data values.
For each pattern class Pc
Compute the hidden layer neurons weight to c as set = $\int_{i=1}^{size(Apt)} \sum Apt(i).class = c$
Closest pattern Pps = Closest pattern (Cset).
For each closest pattern on the relative link, each pattern p
By each similarity, features are classified as categories.

$$Pfs = \frac{\int_{i=1}^{size(p)} \sum P(i) == Scs(i)}{size(p)} \quad \ldots(10)$$

End
Compute cumulative PFS $= \frac{\sum_{i=1}^{size(pps)} Pfs}{size(pps)}$ …(11)
End
Optimized behavioral pattern Ps = PFs return set maximum values
Stop

The above algorithm classified the performance of bipolar disorder observed students, which is trained along the logical features evaluated trained set. The neural classifier predicts the disorder based recommendation following the student academic principles that are classified into class labels.

RESULT AND DISCUSSION

According to the proposed PLF-ISRDNN method, the collective student dataset is processed with feature selection and classification. The implementation algorithm is tested with the confusion matrix and comparison with TDP-HIF (Time Domain Psychotic Habitual Impact Factor), Behavioral Pattern Based Psychotic Analysis Model (BPPAM), GA (Genetic algorithm), Support Vector Machine (SVM). The performance evaluation comparisons of the proposed system and the conventional system are tabulated below. The feature selection and classification remains training and tested features. It contains a set of steps according to a common basic evaluation method. Sensitivity and accuracy, such as the relationship between system input and output variables, are understood using appropriate performance metrics.Table 1 shows the detailed parameters: the type definition dataset and the values used in the training dataset.

Table 1:details of the parameters and values processed.

Limits used	Variables processed
Program and framework	Python, Jupiter notebook
Disease status	Moderate, high, Low
Number of features	Less than 30
Dataset used	Physical fitness, student academic Log
Number of Class	Suggest and non-recommend

The performance evaluation is carried out by Intel i3 configuration on windows environment, which is Jupiter's intent. The classification results use Table 1 parameters to estimate the results produced by precision rate, recall rate, classification accuracy, time complexity to prove the resultant factor.

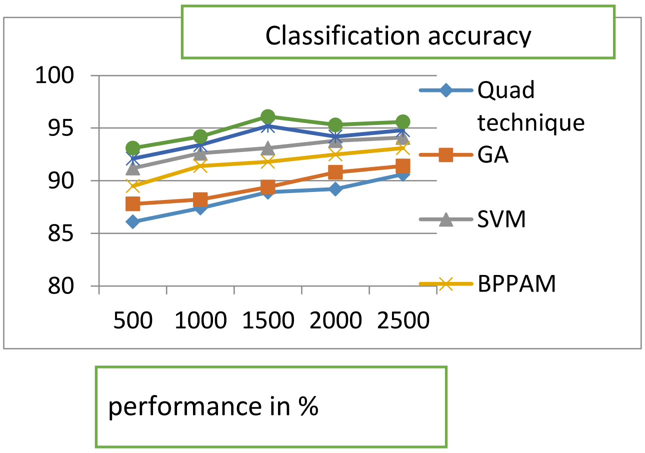

Fig.2: Performance of classification accuracy

The classification accuracy is done by evaluating the sensitivity and specificity analysis by testing the records produced by different methods. The Proposed system PLF-ISRDNN proves the best performance, as shown in figure 2. The estimation is based on the positive and negative values from the True /false optimized category.

Table 2 Performance of classification accuracy

The number of records/techniques used.	Impact of Classification Accuracy in %						
	MFPG	Quad technique	GA	SVM	BPPAM	TDP-HIF	PLF-ISRDNN
500	86.1	87.8	89.5	91.2	92.1	93.1	94.3
1000	87.4	88.2	91.4	92.6	93.4	94.2	95.2
1500	88.9	89.4	91.8	93.1	95.2	96.1	96.3
2000	89.2	90.8	92.5	93.8	94.2	95.3	96.4
2500	90.6	91.4	93.1	94.1	94.8	95.6	96.7

The classification produced by different methods likeGenetic Analysis (GA) technique which has shown 90.6 % accuracy, quad technique 91.4 %, and SVM produce 94.1 % lower accuracy is shown in Table 2. The proposedPLF-ISRDNN system produces high performance compared to the previous system which is up to 96.7%.

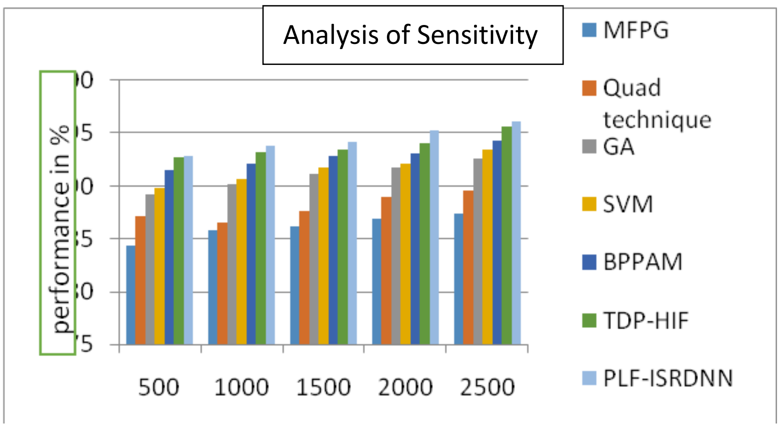

Fig.3:Performance of sensitivity analysis

The sensitivity analysis is shown in figure 3. The performance of the proposed system PLF-ISRDNNproduces higher results than any other method. The existing methodSVM producesas low level 93.4 %, and the proposed performance produces 96.1 % sensitivity rate.

Table 3 Performance of sensitivity analysis

The number of records/techniques used.	Impact of Sensitivity Analysis in %						
	MFPG	Quad technique	GA	SVM	BPPAM	TDP-HIF	PLF-ISRDNN
500	84.4	87.1	89.2	89.8	91.5	92.7	92.8
1000	85.8	86.5	90.2	90.6	92.1	93.2	93.8
1500	86.2	87.6	91.2	91.8	92.8	93.4	94.2
2000	86.9	88.9	91.7	92.1	93.1	94.1	95.3
2500	87.4	89.6	92.6	93.4	94.3	95.6	96.1

Table 3 shows the impact of sensitivity rate produced by different methods, inwhich the proposed system PLF-ISRDNNproduces a higher sensitivity rate than other methods.By definition, the false-positive values are correlated with confusion matrix defend with true negative divided with false-positive values to defend the classification. The Specificity is calculated by

$$\text{Specificity} = \frac{TN}{TN+FP} \ldots(12)$$

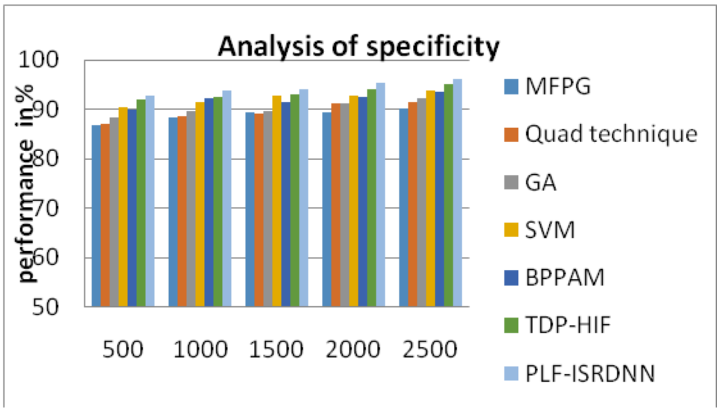

Fig.4: Performance of Specificity

Figure 4 demonstrates the contrast of Specificity formed by dissimilar approaches, and the projected PLF-ISRDNN method which has shaped higher performance than additional methods.

Table 4 Performance of Specificity

The number of records/techniques used.	Impact of Specificity in %						
	MFPG	Quad technique	GA	SVM	BPAM	TDP-HIF	PLF-ISRDNN
500	82.3	87.3	89.3	90.5	91.3	92.1	92.8
1000	83.8	87.6	91.2	91.6	91.8	92.6	93.8
1500	84.2	88.5	92.6	92.7	92.8	93.1	94.2
2000	85.3	88.9	92.8	92.9	93.2	94.2	95.3
2500	86.3	90.2	93.5	93.8	94.5	95.1	96.1

The harmonic representation of precision values depends on the Specificity of true positive average mean rate of true positive and false positive values. Table 4 shows the contrast of the specificity rate produced by different methods.

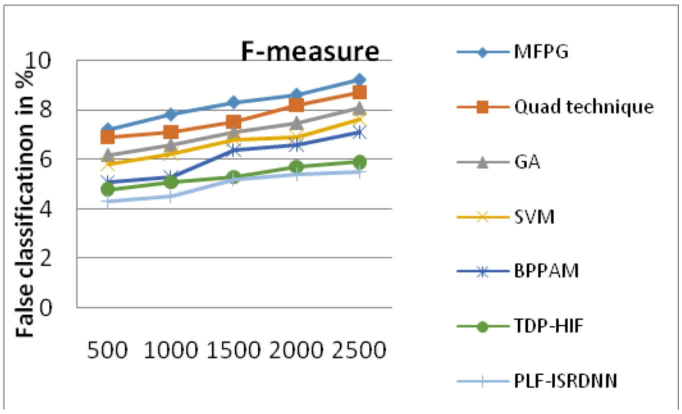

Fig.5:Performance of F-measure

The f-measure defines the sensibility and specificity rate at the mean rate of the absolute error value. The above figure 5 shows the proposed PLF-ISRDNN false rate as F-measure value, and the accuracy remains the false representation as well as the lower rate compared to the SVM and previous system.

Table 5 Performance of F-measure

The number of records/techniques used.	Comparison of F-measure in %						
	MFPG	Quad technique	GA	SVM	BPPAM	TDP-HIF	PLF-ISRDNN
500	7.2	6.9	6.2	5.8	5.1	4.8	4.3
1000	7.8	7.1	6.6	6.2	5.3	5.1	4.5
1500	8.3	7.5	7.1	6.8	6.4	5.3	5.2
2000	8.6	8.2	7.5	6.9	6.6	5.7	5.4
2500	9.2	8.7	8.1	7.6	7.1	5.9	5.5

Table 5 demonstrates the contrast of PLF-ISRDNN false classification ratio and its appearancesshow that the suggested process yields less F-measure.

Time complexity (Tc) $=\sum_{k=0}^{k=n} \times \frac{\text{Total Features Handeled to Process in Dataset}}{\text{Time Taken (Ts)}}$ …(13)

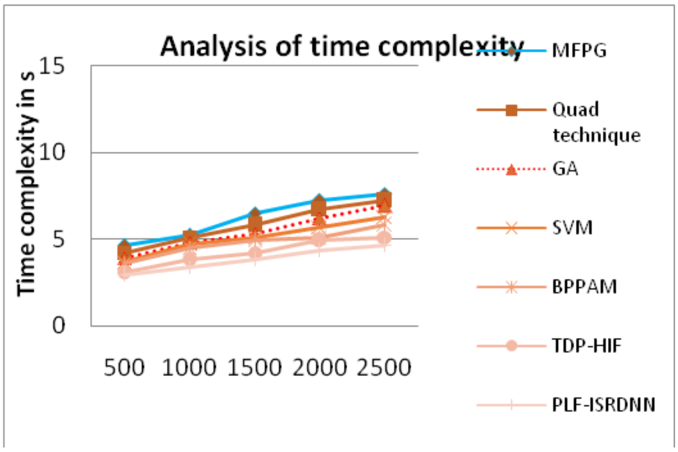

Fig.6:Performance of time complexity

The time complexity refers to O(n) 's execution rate at the meantime records to be classified at the recommended state. Figure 6 shows the performance of PLF-ISRDNNtime complexity in seconds to classify the result.

Table 6 Performance of time complexity

The number of records/techniques used.	Impact of Time Complexity in seconds						
	MPG	Quad technique	GA	SVM	BPPAM	TDP-HIF	PLF-ISRDNN

500	4.6	4.2	3.9	3.7	3.6	3.1	2.9
1000	5.2	5.1	4.8	4.7	4.5	3.8	3.4
1500	6.5	5.8	5.3	5.1	4.9	4.2	3.8
2000	7.2	6.7	6.2	5.7	5.1	4.9	4.3
2500	7.6	7.2	6.9	6.3	5.8	5.1	4.6

The above table 6 shows the time performance with execution utilized in different methods. Table 6 shows that the proposed PLF-ISRDNN method produces 4.6 seconds lower time complexity than other conventional methods SVM produce 6.3 Seconds.

CONCLUSION

To conclude, the proposed system has produced the best prediction performance at that rate of student academic performance.Steps of feature selection have been developed to effectively predict and implement sustainable and profitable information exchange among educational institutions. Psychotic motivation has been performed for improving student performance based on pattern Learner features using deep neural classifier for bipolar disorder students. The proposedPLF-ISRDNN feature selection method is used to classify the student performance. Removal of inappropriate features,as this technique has many advantages and the removal of exaggeration are found as relevant features as possible. This classification increases the result's accuracy up to 96.7 %, supporting bipolar student motivation for recommending features for performance improvement.

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