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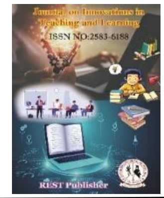

Student Success Performance Prediction Using Artificial Intelligence Approach

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Abstract: Prediction of student success is one of the numerous Artificial Intelligence (AI) applications that assist instructors in identifying students that need individualized support. Due to this factor, student behavior in institute may affect the learning results less scores in their academic performances. Intelligent algorithms have utilized this task considered for several factors for making accurate decisions. However, the traditional models have generated decisions are inefficient because of lacking in trust and explainability. The dataset collected with 33 attributes of personal details of students which include academic as well as student's behavior associated inside and outside campus of institute. However, finding of behavioral factors that affects the APS is essential to avoid and improve the student attitude and behavior in a better manner using Machine Learning (ML) methods but determines less accuracy. The research revealed that these models deemed certain sensitive features to be significant raising concerns about trust and fairness in their use. Hence, this paper have implement hyperparameter tuning of ML using Randomized Search optimizer has efficient in providing better balanced accuracy in determining the high classification prediction in ML method which determine the interest in academic as well as attitude of students in the university.

Keywords: Student behavior, machine learning, hyperparmaneter tuning, optimizer, classification prediction

1. INTRODUCTION

At present, schools and colleges have subsequent technology of web-based learning through succeeding in applicable learning platforms and resources. There are various learning mode access have been provided through higher studies universities for accomplishing student scores that enhance the policies as well as performances in teaching and learning [1]. In this educational process, the student performance has been characterized exactly in all activities which result from altering student's behavior and experiences the results. Thus, the resulting learning performs the student's capability or potential accomplishment [2]. In addition to comprehending knowledge, thinking skills, or physical skills, the results of students' learning can also be seen in their conduct as a result of the process of altering their behavior following attended sessions [3].Students' actual performance can be shown in their understanding of the content being studied, their proficiency in interpreting data, as well as their capability in making decisions based on particular concepts or physical prowess. After a series of classes, performance of students can be assessed and quantified based on their comprehension in the areas of information, attitudes, and skills. However, the student's performance has addressed these problems, obstruction until enduring to certain students. Hence, the access focused in developing school and classroom environments includes minimizing the negative distraction effects behavior that improves the modification through efficient learning and teaching which occur both students exhibiting problematic behavior as well as for their classmates. There is a need for novel approaches to removing learning barriers because an estimated one-third of students do not learn due to psychosocial issues that limit their capacity to fully devote themselves to and participate in educational activities. Hence, this is influenced by the instruction and learning processes individuals experience in learning effects are utilized for improving the standard of instruction [4]. However, there has been a corresponding increase in the students' number who are struggling and dropping out of such programmes. To overcome this concern, automation prediction systems perform an important role in anticipating student performance, allowing teachers to respond efficiently and avoid academic troubles [5]. Recent AI advancements in education have demonstrated the potential for making educated decisions. Success among students is major key measures used to assess the performance of educational service providers. Furthermore, by forecasting student achievement, instructors can develop practical strategies ahead of time. Ultimately, this might help to improve

the complete student success. ML algorithms are proved effective at prediction of student progress. In general, ML algorithms use data from multiple sources to predict student success at various academic careers stages [6, 7].
Concerns are being expressed regarding the use of sensitive predictors in automatic decision making as AI-based techniques that become more prevalent. It could affect making disproportionate conclusions about student succeed. [8, 9].The primary causes of the problem are the lack of explainability in the deployed models that eventually leads to trust concerns among the system's users. As a result, AI systems must be transparent, as well as users have to comprehend how much faith they may have in the results of fundamental ML technology [10].
Modern educational institutions have obstacles in measuring performance, offering high quality education, developing systems for assessing student achievement, and recognizing future requirements. Student intervention strategies are executed at the outset and over time, assisting universities in developing and evolving successful strategies for intervention. E-learning is a fast evolving and sophisticated kind of education in which students enroll through online courses.

Platforms such as intelligent tutoring systems (ITS), Massive Open Online Courses (MOOC) and Learning Management Systems (LMS) are used as EDM to create automated evaluation systems, recommenders, and adaptive systems. Although being an economical and more accessible type of education, e-learning remains recognized as a challenging environment for learning because of the lacking in direct communication among students as well as course instructors. The primary obstacles connected with e-learning systems are a lack of standardized evaluation methods, a high rate of dropout, and difficulty forecasting students' particular requirements owing to a lack of direct relationship. Log data of Long-term from e-learning systems has been utilized to analyze students and courses [11].
This study makes an important contribution to the EDM field by improving the student performance diagnosis by ML approaches. To tackle the issues, institutions have encounter modern learning as well as utilizing recent methods and the study has provided beneficial insights towards improving academic outcomes. The study investigates the ML algorithms integration towards conventional methods of teaching, revealing the way they might enhance student performance analysis as well as educational results. This employs K-means cluster as well as Davies' Bouldin approach for identifying clusters as well as major features impacting student’s performance, resulting in a better knowledge of succeeding student’s factors. The research even compared various ML algorithms involves Support Vector Machine (SVM), Decision Tree (DT) , Naive Bayes, and K-Nearest Neighbors (KNN) in evaluating their performance prediction in student success. The study addresses the technical shortcomings in forecasting student performance by concentrating on different alternatives to Artificial Neural Networks (ANNs). The research applies rigorous approaches, including recurring k-fold cross validation as well as hyperparameter tuning for ensuring accurate and trustworthy prediction results.

2. LITERATURE REVIEW

This literature is focused on addressing the student's performance and predicting the timely intervention earlier which is the significant aspects for intelligent tutoring systems. Researcher are pursued with various objective in these studies involves predicting dropout students earlier, detecting failing students, predict student success and forecasting student's academic performances. Jamjoom et al. have utilized bagging techniques model like SVM and DT for classifying the enrolled students into two target classes are pass and fail with respect to features namely midterm exam scores as well as quizzes that assist in detecting early intervention with risk students [12]. Pereira et al. have predicted student earlier performance in basic programming caourse by Extreme Gradient Boosting (XGBoost) method with feature includes grade of imdterm exam, time of procrastination and correctness [13]. Llanos et al. have predicted the student performances earlier in specific semester with respect to amount of programming attempts, grade of interim exam and students delivery time [14]. Liu et al. have predicted the student's final exam grade by analyzing 3 week programming events of this semester by distinct programming features namely inactive time, correct programs, program attempt counts as well as demographic data such as age, gender of the students [15].

Instead of previous studies efficiency, there are various issues are endured. Stable methods are failed in capturing the behavior of student dynamics at learning process. Approaches of data driven may cause lacking in generalizability over distinct programming courses because of variation over course structure as well as intermediate assessments. Moreover, Y.Mao et al. have discusses the introductory programming courses that may lack in interim exams as identified in the dataset utilized contains only programming assignments. Thus, this study introduced Deep Learning (DL) method to obtain familiarity in accomplishing optimal performance with small classroom sized dataset that remain challenging [16]. K.Aulakh et al. have explored Data Mining (DM) technique in involving multidisciplinary method to its success. The perfect value as well as intellectual insights have generate from raw data into meaningful pattern for improving student's knowledge as well as academic institutions [17]. J.M. Helm et al. have obtained information, which is processed and analyzed using various ML approaches to increases usage and construct connective tools on the learning platform. ML is a subset of AI in which system has learned from data, evaluate patterns, as well as predicting outcomes. The Growing data volumes with less storage, and resilient computer systems have resulted in the resurgence of ML from pattern recognition algorithms to DL methods [18]. Somiya College Mumbai created an approach in forecasting student performance that precisely reflected relationships with previous academic outcome. As the dataset grew, NN output enhanced, achieving 70.48% accuracy. Talwar et al. employed artificial neural networks (ANNs) to forecast student exam results, with a high precision of 85% [19].

B. A. Sani and H. Badamasi studied a dataset of university students employing several algorithms and evaluating accuracy as well as scores for recall. The DT design produced the most correct results. The Minho University in Portugal tested the DT, RF, SVM, and ANN accuracies in assessing students' performance in arithmetic and Portuguese language courses. Different study about predicting student achievement at beginning of academic cycle by academic records as accuracy is 85.09% [20]. E.S.Bhutto et al. have described a method in prediction of students' academic achievement employing supervised ML methods such as SVM and logistic regression. The sequential minimum optimization approach has higher accuracy than logistic regression [21]. The study intends to assist educational institutions in predicting future student behavior and identifying impactful aspects such as instructor performance and student motivation, with the goal of lowering overall dropout rates.

L.H. Alamri et al. highlighted how student performance on the final exam might be influenced by a variety of circumstances. The investigation employs SVM and RF methods to forecast final grades in the classes of mathematics and Portuguese language. The outcomes demonstrate binary classification has a 93% of accuracy, whilst regression involves RMSE as 1.13 with the lowest value in RF. Early prediction may assist educational organization in providing remedies for low performing pupils, thereby improving its academic outcomes. The review seeks in improving the performance of educational organizations [22]. B.Albreiki et al. have discussed modern academic institutions with difficulty assessing student success, providing high-quality instruction, and examining results [23]. The complete review of the literature on EDM from 2009 to 2021 found that ML techniques have used in anticipating student risk as well as dropout rates. The research majority relies on data from the environment of online learning as well as student’s databases. ML techniques are critical for improving student performance as well as prediction of risk as well as dropout rates. The researchers suggested that future study should focus on establishing efficient dynamic and ensemble algorithms to predict student performance as well as offering automated correction procedures. This will help educators build suitable approaches and achieve precise learning goals.

As a result, despite the aforementioned research findings, much more effort is needed to forecast student achievement. Because of existing efforts, it involves technical shortcomings, such as inaccurate projections and undiscovered characteristics. EDM researchers prefer DT, KNN, Naive Bayes and SVM over ANNs to predict student results because of their availability and simplicity of usage. Although ANNs have great accuracy in predicting their application has been limited due to specific technical skills necessary in their implementation. The finding discusses high accessible methods are commonly utilized for educational situations, leaving ANNs underutilized. This work seeks to improve prediction accuracy while compared as well as refined the SVM, KNN, DT, and Naive Bayes performances are usually used and easy in implementation in EDM operations. As a result, this study proposes a SVM that has seen certain performance improvements. Additionally, it compares DT, KNN, SVM and Naive Bayes. When comparing with traditional method, the suggested platform is based on highly reliable predictor of student performance. Furthermore, the approach demonstrates finding with less accurate as well as previously found features by hyperparameter adjustment with improved performance.

3. RESEARCH METHODOLOGY

The purpose of this proposed model is employed for determining the student performance by monitoring several features have provided as input from users. The dataset have been collected consists of 649 records and 33 attributes which discusses the address (Rural and Urban), parents status, family size, study time, free time, absences, Grade1, etc. shown in figure 1.These features are available to the respective ML model and based on how these features it is considered in a parameters that may considered as a features affect the label in providing improved accuracy over predicting the student overall performances. This may assist in search of an appropriate dataset which meet the requirements of the students and staff of the university. Figure 2 illustrates the family relationship status of the student which have been collected from their parents based on certain questionnaires. The rating from 0 to 5 represent the relationship among their student and their family in which table 1 mentioned the target status of student behavior. Based on the Exploratory Data Analysis (EDA), the status of family relationship is recognized but the other attributes are required to identify the exact spoiling of students. This can be done through the proposed architecture of hyperparameter tuning using randomizedsearchCV optimizer for better APS accomplishment.

Table 1 Family relationship status of their students

Family relationship status	**Representation based on coding**
Poor	1
Not Satisfactory	2
Satisfactory	3
Good	4
Excellent	5

school	sex	age	addres	famsiz	Pstatu	Medu	Fedu	Mjob	Fjob	reason	guardia	travelti	studyti	failures	school	famsup	paid	activiti	nursery	higher	interne	romant	famrel	freetim	goout	Dalc	Walc	health	absenc	G1	G2	G3
GP	F	18	U	GT3	A	4	4	at_home	teacher	course	mother	2	2	0	yes	no	no	no	yes	yes	no	no	4	3	4	1	1	3	4	0	11	11
GP	F	17	U	GT3	T	1	1	at_home	other	course	father	1	2	0	no	yes	no	no	no	yes	yes	no	5	3	3	1	1	3	2	9	11	11
GP	F	15	U	LE3	T	1	1	at_home	other	other	mother	1	2	0	yes	no	no	no	yes	yes	yes	no	4	3	2	2	3	3	6	12	13	12
GP	F	15	U	GT3	T	4	2	health	services	home	mother	1	3	0	no	yes	no	yes	yes	yes	yes	yes	3	2	2	1	1	5	0	14	14	14
GP	F	16	U	GT3	T	3	3	other	other	home	father	1	2	0	no	yes	no	no	yes	yes	no	no	4	3	2	1	2	5	0	11	13	13
GP	M	16	U	LE3	T	4	3	services	other	reputatio	mother	1	2	0	no	yes	no	yes	yes	yes	yes	no	5	4	2	1	2	5	6	12	12	13
GP	M	16	U	LE3	T	2	2	other	other	home	mother	1	2	0	no	no	no	no	yes	yes	yes	no	4	4	4	1	1	3	0	13	12	13
GP	F	17	U	GT3	A	4	4	other	teacher	home	mother	2	2	0	yes	yes	no	no	yes	yes	no	no	4	1	4	1	1	1	2	10	13	13
GP	M	15	U	LE3	A	3	2	services	other	home	mother	1	2	0	no	yes	no	no	yes	yes	yes	no	4	2	2	1	1	1	0	15	16	17
GP	M	15	U	GT3	T	3	4	other	other	home	mother	1	2	0	no	yes	no	yes	yes	yes	yes	no	5	5	1	1	1	5	0	12	12	13
GP	F	15	U	GT3	T	4	4	teacher	health	reputatio	mother	1	2	0	no	yes	no	no	yes	yes	yes	no	3	3	3	1	2	2	2	14	14	14
GP	F	15	U	GT3	T	2	1	services	other	reputatio	father	3	3	0	no	yes	no	yes	yes	yes	yes	no	5	2	2	1	1	4	0	10	12	13
GP	M	15	U	LE3	T	4	4	health	services	course	father	1	1	0	no	yes	no	yes	yes	yes	yes	no	4	3	3	1	3	5	0	12	13	12
GP	M	15	U	GT3	T	4	3	teacher	other	course	mother	2	2	0	no	yes	no	no	yes	yes	yes	no	5	4	3	1	2	3	0	12	12	13
GP	M	15	U	GT3	A	2	2	other	other	home	other	1	3	0	no	yes	no	no	yes	yes	yes	yes	4	5	2	1	1	3	0	14	14	15
GP	F	16	U	GT3	T	4	4	health	other	home	mother	1	1	0	no	yes	no	no	yes	yes	yes	no	4	4	4	1	2	2	6	17	17	17
GP	F	16	U	GT3	T	4	4	services	services	reputatio	mother	1	3	0	no	yes	no	yes	yes	yes	yes	no	3	2	3	1	2	2	10	13	13	14
GP	F	16	U	GT3	T	3	3	other	other	reputatio	mother	3	2	0	yes	yes	no	yes	yes	yes	no	no	5	3	2	1	1	4	2	13	14	14
GP	M	17	U	GT3	T	3	2	services	services	course	mother	1	1	3	no	yes	yes	yes	yes	yes	yes	no	5	5	5	2	4	5	2	8	8	7
GP	M	16	U	LE3	T	4	3	health	other	home	father	1	1	0	no	no	no	yes	yes	yes	yes	no	3	1	3	1	3	5	6	12	12	12
GP	M	15	U	GT3	T	4	3	teacher	other	reputatio	mother	1	2	0	no	no	no	no	yes	yes	yes	no	4	4	1	1	1	1	0	12	13	14
GP	M	15	U	GT3	T	4	4	health	health	other	father	1	1	0	no	yes	yes	no	yes	yes	yes	no	5	4	2	1	1	5	0	11	12	12
GP	M	16	U	LE3	T	4	2	teacher	other	course	mother	1	2	0	no	no	no	yes	yes	yes	yes	no	4	5	1	1	3	5	0	12	13	14
GP	M	16	U	LE3	T	2	2	other	other	reputatio	mother	2	2	0	no	yes	no	yes	yes	yes	yes	no	5	4	4	2	4	5	2	10	10	10
GP	F	15	R	GT3	T	2	4	services	health	course	mother	1	3	0	yes	yes	no	yes	yes	yes	yes	no	4	3	2	1	1	5	2	10	11	10
GP	F	16	U	GT3	T	2	2	services	services	home	mother	1	1	0	no	yes	no	no	no	yes	yes	no	1	2	2	1	3	5	6	10	11	12
GP	M	15	U	GT3	T	2	2	other	other	home	mother	1	1	0	no	yes	no	no	yes	yes	yes	no	4	2	2	1	2	5	8	11	12	12
GP	M	15	U	GT3	T	4	2	health	services	other	mother	1	1	0	no	no	no	no	yes	yes	yes	no	2	2	4	2	4	1	0	11	11	11
GP	M	16	U	LE3	A	3	4	services	other	home	mother	1	2	0	yes	yes	yes	yes	yes	yes	yes	no	5	3	3	1	1	5	2	12	12	13
GP	M	16	U	GT3	T	4	4	teacher	teacher	home	mother	1	2	0	no	yes	yes	yes	yes	yes	yes	yes	4	4	5	5	5	5	4	12	11	12
GP	M	15	U	GT3	T	4	4	health	services	home	mother	1	2	0	no	yes	yes	no	no	yes	yes	no	5	4	2	3	4	5	0	10	11	11
GP	M	15	U	GT3	T	4	4	services	services	reputatio	mother	2	2	0	no	yes	no	yes	yes	yes	yes	no	4	3	1	1	1	5	2	15	15	15
GP	M	15	R	GT3	T	4	3	teacher	at_home	course	mother	1	2	0	no	yes	no	yes	yes	yes	yes	yes	4	5	2	1	1	5	0	13	14	15

FIGURE 1. Student academic and personal database

However, the information is gathered together with an evaluation for values that are missing, which is done by imputing the missing value. The data gets preprocessed utilizing a label encoder as well as standardscaler in scaling any variable units as unique has been maintained when the missing imputation gets complete. Therefore, it has undergone data transformation as well as data get split towards 70% of train dataset and 30% of test dataset. The dataset has split with respect to models as well as predictions in term of train and test dataset.

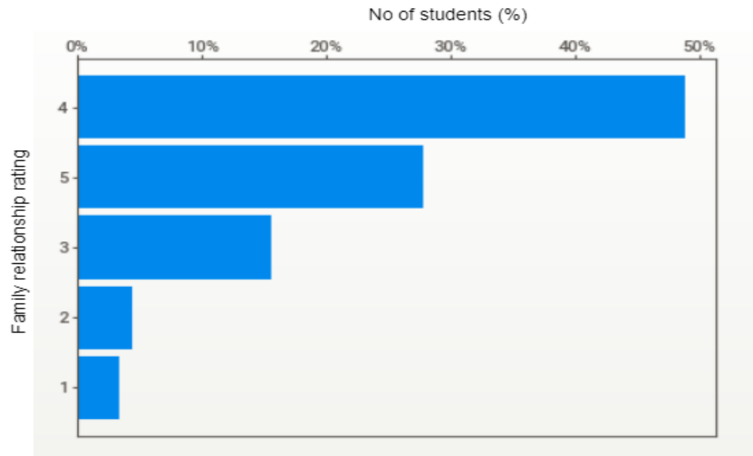

FIGURE 2. Family relationship rating from student dataset

The regression method is evaluated by lazypredict.supervised library. From the top best ML model performance is consider with untunned ML method and the top model can be improved its accuracy, the regression parameter is improved by proposed randomsearchCV hyperparameter tuning. Figure 3 illustrated the architecture of randomsearchCV hyperparameter in tunning the parameters to improve the ML model accuracy. The experimental research is initiated with data preprocessing using missing imputation by is.null() functions, label encoder for generating categorical value into individual column by binary value representations and normalizing by scaling all variable into similar scaling. Lazy predict library is used for various classifier to train the regression model in which the overfitting and imbalanced output from Nearest Centroid classifier. Hence, the improvised nearest centroid is generated through best optimizer RandomizedSearchCV as hyperparameter tuning. Thus, the high accuracy in generating prediction of student behavior assist the university management to avoid APS by providing counselling to the respective student in changing their bad attitude.

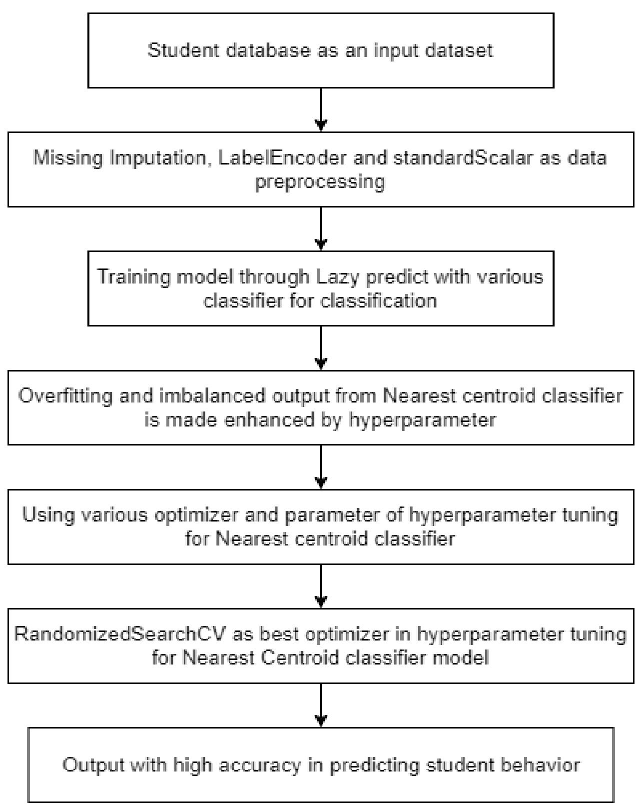

FIGURE 3. Architecture of hyperparameter in predicting student behavior

Working principle OF Hyperparmeter tuning

Let sample dataset assumed gets segmented towards S for m observations, as well as feature's variable has defined as X, target variable as Y, and joint distribution D(X,Y) has unidentifiable. Accomplished data with ML method uses function relationship between X and Y by predicting method generation as $\hat{F}(X,\ \theta)$ has maintained through hyperparameter configuration of n-dimensional $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ from the search spacing hyperparamater$\ominus = (\ominus_1,\ \ominus_2, \ldots, \ominus_n)$. Performance of prediction is evaluated by point-wise relationship among prediction function $\hat{F}(X,\ \theta)$ as well as true label Y. Loss function represented as $L\left(Y, \hat{F}(X,\ \theta)\right)$ and typically the predictable risk in the present algorithm have been computed with respect to current data and even sampled respectively $D: R(\theta) = E\left(L\left(Y, \hat{F}(X,\ \theta)\right)\middle|D\right)$. The specific data distributions have been provide through mapping encoder through influenced learning model as well as to specific performance cumputation. The defined parameter to all hyperparameter configuration is θ and the divine intervention of k using various datasets in data distributions is considered to be $D_1, D_2, \ldots, D_k$. Thus, it considered for k hyperparameter risk mapping as shown in equation 1.

$$R^{(i)}(\theta) := E\left(L\left(Y, \hat{F}(X,\ \theta)\right)\middle|D_i\right) \quad i = 1, 2, \ldots, k \qquad (1)$$

Configuration setup for optimal hyperparamer

Initially, the best hyperparameter configuration get considered to i dataset expressed over equation 2.

$$\theta^{(i)*} \coloneqq \underset{\theta \epsilon \ominus}{\overset{Arg}{}}\min R^{(i)}\,(\theta) \qquad (2)$$

However, the fundamental settings are recognized for endeavoring adequately in different divergent datasets and usually recognized by software packages by heuristic method or frequent ad hoc. Therefore, the configuration of optimal hyperparameter gets accomplished based on complete empirical experiments in term of dataset with k dissimilar benchmark has expressed over equation 3.

$$\theta^* \coloneqq \underset{\theta \epsilon \ominus}{\overset{Arg}{}}\min g\left(R^{(1)}(\theta), R^{(2)}(\theta) \ldots, R^{(k)}(\theta)\right) \qquad (3)$$

Where,
$R^{(i)}(\theta)$ = Mapping the hyperparameter for expected risk
g = Summarized specified function

Moreover, the $R^{(i)}(\theta)$ estimation is probable in scaling correctly before make it extremely proportional between datasets assisted for scaling all $R^{(i)}(\theta)$ to [0,1] through elimination of results with reference for dummy predictor as well as segregating it through absolute difference between the most excellent possible predictor or premeditated using Z-score. The appropriate scaling is considered depending upon performance of measuring.
The Random Search sample takes into account both the search space as well as the set's probability distribution. This is a strategy that uses random hyperparameter permutations to determine the best solution for the methods under consideration.

Randomized Search Algorithm for improving prediction

Step 1 – Initialize the actual point as $X_0 \subset S$, method parameters as Θ_0, and the iterations index with k = 0.

Step 2 – Generate the candidate point's collection as $V_{k+1} \subset S$ depend upon the specific generator as well as the relative sampling distribution.

Step 3 – Based on candidate points V_{k+1}, X_{k+1} get updated related to prior iterations as well as algorithmic parameters and even update algorithm parameters as Θ_{k+1}.

Step 4 - If a stopping criterion get mapped then stop else proceed with incremental in k and return to Step 2.

Step 5 – The random search principle based on two basic procedures such as the generator in Step 2which generates candidate points, and the updated procedure in Step 3

Step 6 – Returns: Therefore, the learning rate of training and testing dataset get improved through randomizedsearchCV as hyperparameter tuning in nearest centroid classifier for predicting student behavior based on APS.

4. RESULT AND DISCUSSION

Google Colab and Jupiter IDE are used in this experiment to collaborate and produce documents that may be explained using text, live code, and visualizations. The dataset for each student is compiled and divided into a 70% train dataset and a 30% test dataset. The various tools employed by the tunabilityhyperparameter had been Scipy, Seaborn, and Pandas. Utilizing the aforementioned tools, all of the regression procedures discussed above are put into practice. In order to find out the efficient untuned regression technique for prediction.NC Classifier is identified as best untuned ML model and the parameters of NC Classifier is represented with range of parameters and RandomizedsearchCV parameter distribution is listed and iterated with hyperparameter tuning. The untunedRFClassifieris the top most model from lazy predict library and top five model is evaluated through ERR metrics like RMSE, R2 and Adjusted R2 shown in table 2.

TABLE 2. Top 5 Classifier model from lazy predict classifier

MODEL	**Accuracy Score** $= \frac{TN+TP}{(TN+FP+TN+FN)}$	**Precision** $= \frac{TP}{(FP+TP)}$	**Recall** $= \frac{TP}{(TP+FP)}$	**F1 - Score** $F1 = 2\,x\,\frac{PPVxTPR}{PPV+TPR}$
NC Classifier	0.88	0.87	0.88	0.88
LGBM	0.87	0.87	0.87	0.87
Extra Tree Classifier	0.87	0.86	0.87	0.87
Random Forest Classifier	0.86	0.86	0.86	0.86
XGB Classifier	0.85	0.86	0.85	0.86

Table 2 illustrates the top 5 classifier model from lazy predict classifier model in which NC classifier has high R-Square and adjusted R-Square scores while compared to other classifier and these classifier method is the untuned results that evaluated through error rate metrics.

Figure 4 illustrates the accuracy of top 5 classifier model in the lazy predict classifier in which NC classifieraccuracy score is high as 0.88 while compared to other classifierwhich is 0.87 and 0.86 respectively. This determines the efficiency of model trained using lazy predict classifier library and which is said to be untuned classifier model which execute through default parameter in the ML classifier model.

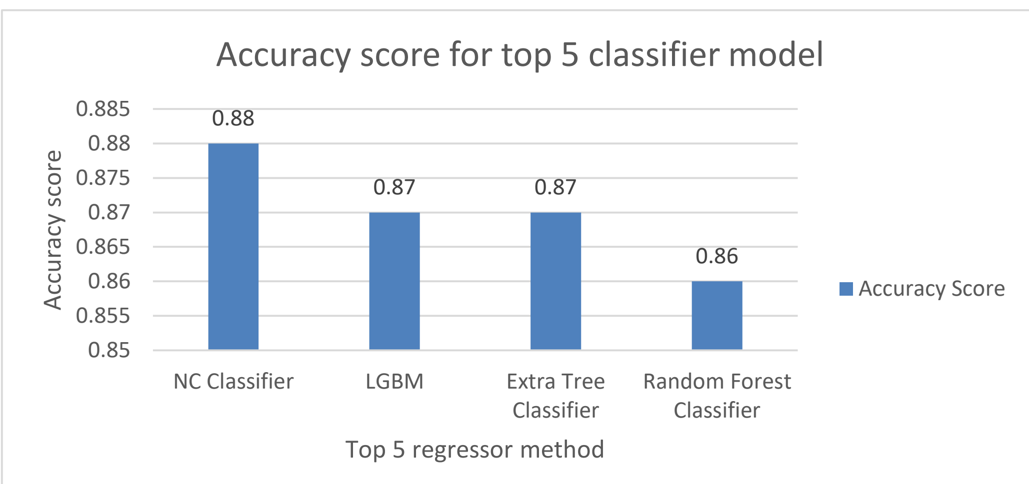

FIGURE 4. Comparison of accuracy score for top 5 classifier model

Nearest centroid is determined as best ML method as untuned ML model as well as the parameters of nearest centroid has represent with parameters range and RandomizedsearchCV parameters distribution has scheduled as well as iterated with hyperparameter tuning. Figure 5 has illustrated five different classification of family relationship from student in predicting the classification of their behavior for untuned NC classifier.

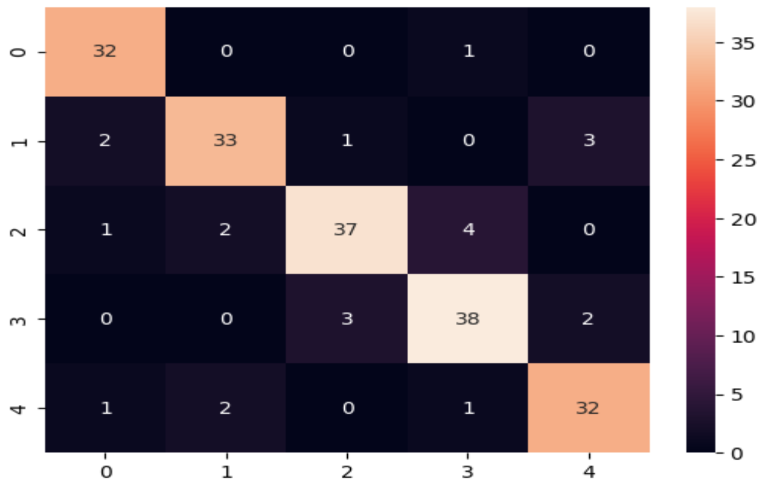

FIGURE 5. Confusion matrix for Untuned nearest centroid

Figure 6 has illustrated five different classification of family relationship from student in predicting the classification of their behavior for tuned NC classifier.

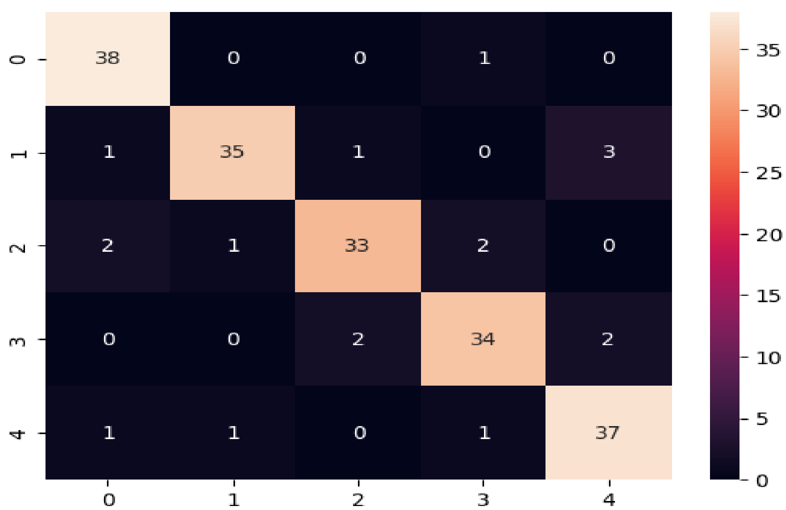

FIGURE 6. Confusion matrix for tuned nearest centroid

TABLE 3. Family relationship status with confusion matrix values

Family relationship status	Untuned Nearest centroid classifier				Tuned Nearest centroid classifier			
	TP	TN	FP	FN	TP	TN	FP	FN
1	32	158	4	1	38	152	4	1
2	33	152	4	7	35	153	2	6
3	37	147	4	7	33	154	3	5
4	38	146	6	5	34	153	4	5
5	32	154	5	4	37	150	5	3

Table 3 illustrates the family relationship status for five different classes for the students considered in the student database. This assist in identifying the status of student success with parents, guardian and their related family member as well as friends. This analysis helps in identifying the states of student mentality and concentration diversion behavior with their presence with family relationship. The confusion matrix value classified with True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

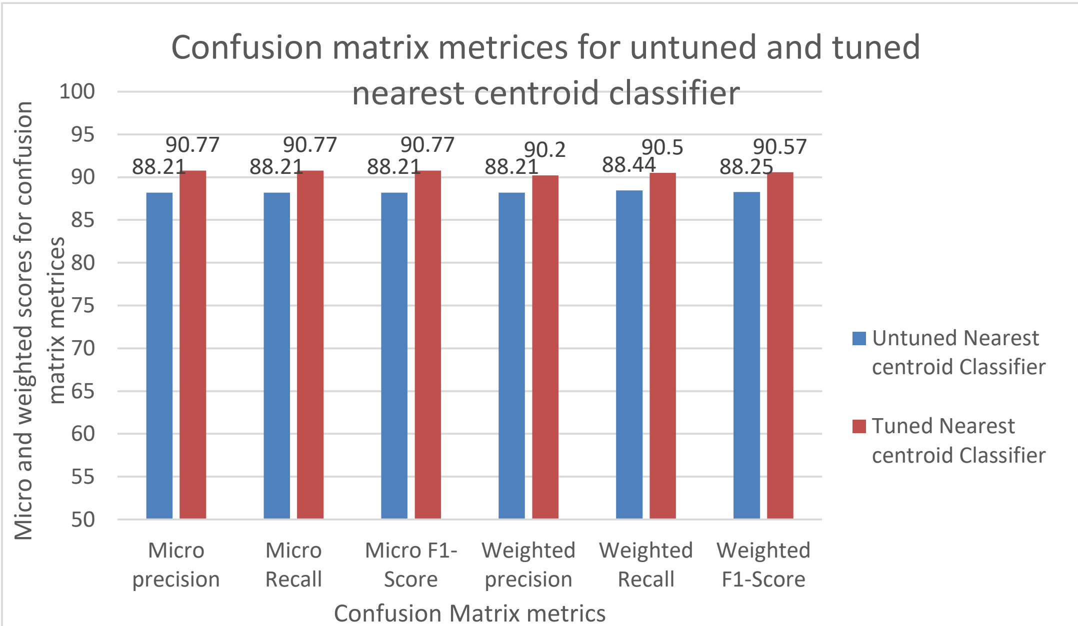

FIGURE 7. Confusion Matrix for Tuned and untuned nearest centroid classifier

Figure 7 illustrates the Micro accuracy through Micro F1-Score which can be determined through average of micro precision and micro recall whereas the accuracy of tuned Nearest centroid classifier is 90.77% which is higher than untuned nearest centroid classifier as 88.21%. Similarly the weighted precision, recall and F1-Score is high for tuned nearest centroid classifier as 90.2%, 90.5% and 90.57% while compared to untuned nearest centroid classifier as 88.21%, 88.44% and 88.25%. Thus the proposed hypertuning parameters enhanced the model accuracy by modifying the parameters as well as the optimizer. In this research RandomizedSerchCV generate better tuned result than other optimizer and nearest centroid classifier model performs high accuracy than other classifier ML model.

5. CONCLUSION

This research analyzes how model outcomes predict student achievement in terms of final exam score. The RF regressor has performed highly with WAM as age, gender, snapchat usage duration, and time spent requesting friends for help as the top five characteristics influencing the method outcome. The sensitive consideration factors like age, gender and parent’s details are an obvious cause to doubt the fairness as well as trustworthiness of the implemented model. The accuracy of the prediction models is subsequently enhanced by tuning parameter or optimizing hyperparameter. The results indicated that accuracy gets increased in after change in parameter. This study proved how DM technologies, especially combined with an effective methodology, can forecast students' grades. Moreover, this study investigates the effectiveness ML algorithms in predicting student success in higher education. Hence, the student success through family relationship with students is identified through nearest centroid classifier in which tuned nearest centroid classifier is 90.77% while compared with untuned nearest centroid classifier as 88.21%. Hence, the accuracy of ML classifier and regression model gets improved through hyperparameter optimizer as RandomizedSearchCV. This analysis identify the student success precisely which assist the management to take necessary action to improve the APS of their university by providing mentors or giving counseling to their students as well as parents of the respective students.

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