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PREDICTING STUDENTS' ACADEMIC SUCCESS USING HYPER PARAMETERIZED MACHINE LEARNING TECHNIQUES

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Abstract: The definitive goal of any educational institute is to provide students with the best possible educational knowledge and practice. Categorizing students who need additional backing and taking proper steps to improve student performance plays a key role in attaining this goal. A student's academic performance is a significant aspect for educational success at all stages. Academic background is very important for students who want to continue their studies and secure their future. Several studies have uncovered factors related with personal responses such as: For example, in relation to family's communication, understanding and anticipating student perspectives on campus to improve student performance. A regressor that can forecast student success in the academic's status from the student dataset collected from online repositories. The main goal of this research work focus on the academic performance of the students through their behavior using five different Machine Learning techniques such as Random Forest Regressor (RFR), Extra Trees Regressor (ETR), Gradient Boosting Regressor (GBR), Bagging and ElasticNet. The comparative analysis of these models shows that RFR model best fit model through the predictors lazy regressor and standard scalar methods. A proposed model is developed by hyperparameter tuning the best fit model using random search. The performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R Squared, Adjusted R Squared shows that proposed method is better than the existing models.
Keywords: Hyperparameter tuning, Machine Learning, Random Forest, student performance, lazy regressor, random search

INTRODUCTION

The classroom plays an important role for students to learn wisdom and become educated. With the continuous development of social skills and the firming up of education restructuring, the need for data and intelligent investigation to improve the eminence of teaching in the classroom is increasing. The training of face-to-face classes is a pillar of educational research. Education data mining (EDM) is an emerging field concerned with creating and evolving improved approaches of mining knowledge from education-generated data. Over the past decade, numerous researchers have focused on student behavior analysis. Student behavior is examined through entropy measures to help determine behavioral traits of industry and tidiness. This examination aims to establish a correlation between the regularity of campus life and academic performance [1].

A method for predicting preschool children's performance associated with multiple instances of multiplication learning. This technology idea is used in student behavior at the end of a course to anticipate the complexity of learning current trending courses. The results of this work are therefore suitable for teachers to track and understand the learning progress of individual students [2]. These are the main differences between rural students who do not enter tertiary education and urban students who do enter tertiary education [3]. Some rural students have made it through to higher education, but in most cases, it has not been a smooth transition [4]. Much research exists in the field of equality and access to education, but certain studies have translated through the mediation effects of rural areas [5] on higher education [6]. The main learning commotion organ for discerning student behavior is clearly manifested in classroom teaching activities. Students' attitudes towards learning are reflected in their behavior and effective learning in the classroom and are largely related to the eminence of classroom teaching. Research focused mainly on over-all education, general social sciences, and secondary professional education [7].

Some students have not been able to adapt to the technical requirements set by the university. This is because the rural students who acquired the technical requirements during their school days are not familiar with the technology. However, for some students, lack of technical knowledge is a major hurdle and impedes their learning. As a result, some students discuss their challenges, move away from their families (homesick), and adjust to social life at university. As a result, students from rural areas face various hurdles in the course of their education. Rural students are found to face several barriers in transitioning to higher education due to rural-urban inequalities within the country. Earlier studies cast-off outdated statistical approaches to determine these variables. Traditional statistical techniques used in this area include regression analysis, cluster analysis, and discriminant analysis. The EDM research work used data mining (DM) techniques to collect data from numerous educational institutions to improve the quality of education. DM is therefore very important as it permits teachers to intervene as needed to optimize student performance.

EDM is used to measure student learning performance to improve the learning process and motivate students in terms of learning efficiency. This allows universities to provide feedback and suggest learning recommendations depending on student behavior, helping shape the learning process and identifying aberrant learning behaviors and problems. help. Seeking a deeper understanding of educational phenomena and various factors can cause students to distance themselves from various researchers. Therefore, focusing primarily on geographic regions can have a significant impact on student academic performance. In general, there is an image that rural students are good at studying but have low presentation skills, while urban students are good or bad at studying but have excellent presentation skills. This student status allows students to pursue their studies in a mixed or unified environment and influence the educational structure. There is also a lack of research on individual courses [8]. Most of the studies mentioned use ML approaches to perform a complete analysis of student behavior [9].

Currently, there are certain well-known ML approaches related to traditional ML approaches [10] and certain advanced ML approaches [11]. These prevailing ML systems are used in a variety of real-world applications spanning medical, industrial, and basic hypothetical research [12]. Analyzing student behavior using ML is more accurate based on performance, but has higher computational complexity and hardware performance requirements. The time complexity and behavioral analysis associated with ML is relatively low and the methods are very easy to implement. Therefore, this study emphases on examining student academic performance using hyperparameter-based ML technique. The purpose of this research is to focus on a predictive model to help universities determine student performance in both rural and urban areas. The main objective of this research paper are as follows,

- Identify deep observations in your dataset and set better student performance based on the factors obtained.
- To achieve high accuracy and low error rate, the optimizer is considered as a hyperparameter protocol for ML methods to predict student's family relationship performance.
- Hyperparameter tuning with the ML method for determining rural and urban student academic achievement from student academic achievement and personal datasets improves the accuracy of student academic achievement prediction models.

The rest of the research work organized as follows. Section 2 discusses about related works to this research work; Section 3 tells about the research methodology used for this research work to find accuracy. The experimental results are illustrated in the section 4. Finally, this work concludes with its innovative information in section 5.

Related Works

A lot of research has been done in the field of data mining in education due to the use of predictive models. This work is designed to predict student performance and recognize risk at students. This is considered a difficult problem since performance hang on numerous relevant student characteristics. These traits can be broken down into a student's GPA [13] and grades, demographics, psychological profile, values, academic progress and educational attainment. Student. GPA is the utmost significant attribute for predicting performance. A GPA indicates that: Bring real value to the future education, career opportunities and progress. Moreover, academic potential can be assessed using grade point averages. In addition to family circumstantial, gender, disability and age are also emphasized attribute. This work presents two new features that focus on the use of eloquent features. In connection with the use of the Internet and social networks and their impact on performance.

On the one hand, numerous ML and DM methods have been cast-off to predict student ability. Some of them are RFR, ETR, boosting, GBR and ElasticNet. Student performance are examined and assessed in terms of student academic performance, and automated assessments were suggested. In this case, the literature review includes various regression techniques to accurately predict student behavior and academic performance. EDM is used for regression techniques in the proposed system. Before addressing these issues, students discussed their understanding of the concept of rurality, which is consistent with guideline theory, which emphasizes place and space when considering rurality [14].

This was necessary to allow students to focus on the places and spaces that underpin their educational courses. This description is found to be consistent with the rural conceptualization used in this study. For example, researchers define rural areas as geographic locations, particularly those far from cities and towns, where few facilities are available[15]. P. Liasitinski et al. argued that most previous research on hyperparameter optimization has focused exclusively on investigating grid search (GS) and random search, or comparing the two techniques [16]. P. Probst et al. presented a detailed investigation of tunability and formulated the tuning problem in statistical terms proposing a quantification of hyperparameter tuning [17].

Research Methodology

Machine Learning Algorithms

3.1.1 Random Forest (RF): RF is an ensemble learning technique for classification and regression that works by making several decisions trees for training. Random Forest Fixes Decisions Trees have a tendency to overfit the training set with accidental training. Forests smears the common method of bagging to tree learners [18].

3.1.2 Gradient Boosting (GB): GB is a weak data transformation technique turn students into robust learners by growing their weights properties that are hard to categorize. After producing the first one, weights are transformed in the tree and subtrees are formed from them. Each tree is an improved version of the novel dataset. These tree outcomes are used to get more precise results. It is intended for regression and prognosis [19].

3.1.3 Deep learning (DL): DL [20] is a group of connected I/O units, each connections have weight of their own. These networks learn through adaptation. We do the weighting by training with a model that knows the outcome. This network can handle continuous I/O. It is used to find value and describe patterns. It is useful for predictions and regression.

3.1.4 Extra Tree Regressor: Extremely Randomized Trees Regressor [21], also known as ETR, is a form of ensemble learning technique that combines the findings of various de-correlated decision trees gathered in a "forest" to produce its regression outcome.

3.1.5 Bagging: Bagging [22] is a machine learning ensemble approach that integrates forecasts from several decision trees. It is also simple to implement because it just has a few crucial hyperparameters and practical heuristics for setting those hyperparameters. The quantity of decision trees employed in the ensemble is a crucial hyperparameter of the bagging technique. Until the model performance stabilizes, the number of trees is frequently increased. Contrary to what one may initially assume, adding more trees does not result in overfitting.

3.1.6 ElasticNet CV: A regularization penalty is added to the loss function during training in the Elastic Net extension to linear regression [23]. Utilizing coordinate descent, determine the elastic network path. Make a prediction using a linear model. a prediction's coefficient of determination is returned. Provide the estimator's parameters. Coordinate descent was used to fit the model.

Proposed Architecture

Before a university or institution's students can implement learning techniques, the institution or university needs to understand the student's learning outcomes and behavior. Most students prefer a comfortable life of learning and understanding education-related data. This study focused primarily on the happiness of rural students compared to urban students with respect to learning concepts and behaviors at university, and parents' understanding of their interest in changing the way they make a living at university. I'm here. Various factors are available to measure student academic performance, but student behavior is important in understanding interests and stress in order to avoid dropout and suicide among rural students.

The study finds that the ease of access to technology in schools has made it possible to use and adopt emerging technologies, boosting their self-confidence [24], as well as urban students who are aware of the latest trends. focused on helping you. Although there are several factors that influence student participation in class, certain factors are internal or external in nature. Some students are active and proactive, while others are shy and passive. Factors that identify both academic performance and student behavior are considered in this work. But this notion justifies whether rural students are as normal as urban ones. As the environment changes, rural students have the opportunity to adapt their livelihoods to current and latest available trends. Additionally, the collected student database can be analyzed using automated ML techniques to identify rural and urban student status in terms of academic performance and student behavior. Therefore, overfitting of the data in the ML model can affect model accuracy, and tuning the hyperparameters of a specific ML by changing the parameters and optimizers used in the hyperparameters of the ML model. We can avoid this by doing Therefore, the more accurate the ML model, the more accurate it will be in predicting and identifying student academic performance, as well as analyzing each student's familial behavior. Figure 1 shows the architecture for student improvement using ML technology as EDM.

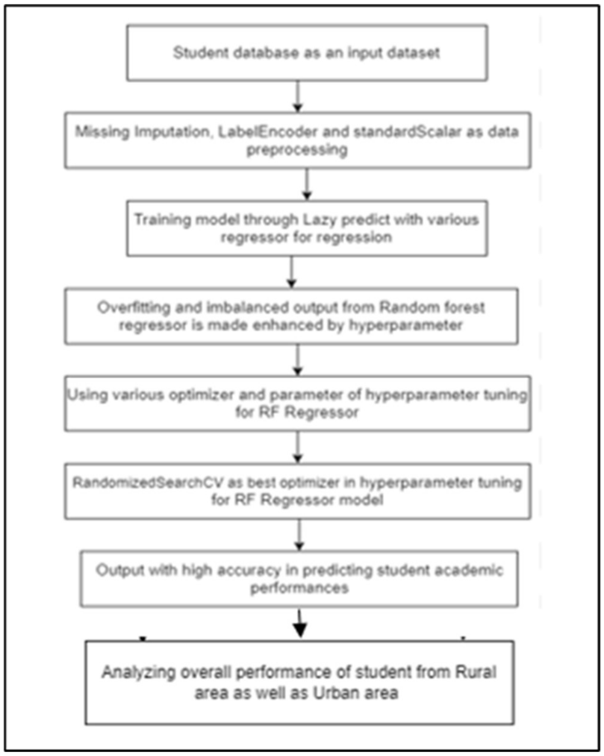

Figure 1: Proposed architecture of student performances

The purpose of this proposed model is to determine student performance by monitoring multiple features provided by the user as input. The retrieved dataset consists of 649 records and 33 attributes covering address (rural and urban), parental status, family size, study time, free time, absence, grade 1, etc. shown figure 2. These features are available in specific ML models and are based on how these features are described by the parameters, providing greater accuracy than predicting a student's overall performance. Features can be viewed as influencing labeling. This helps us find the right datasets to meet the needs of university students [25] and staff.

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GP	F	18	U	GT3	A	4	4	at_hom	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_hom	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_hom	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	reputati	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
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GP	F	15	U	GT3	T	4	4	teacher	health	reputati	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	reputati	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	reputati	mother	1	3	0	no	yes	no	yes	yes	yes	yes	no	3	2	3	1	2	2	10	13	13	14
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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
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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	reputati	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
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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	reputati	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_hom	course	mother	1	2	0	no	yes	no	yes	yes	yes	yes	yes	4	5	2	1	1	5	0	13	14	15

Figure 2: Student Academic and Personal Database

However, the data are collected and checked for missing values. This is done by imputing missing values. Once missing imputations are complete, the data are preprocessed using a label encoder and standard scalers to scale unity of all variables and unambiguously handle them. Therefore, a data transformation may be performed to split the data into 70% of the training data set and 30% of the test data set. The data set is split in terms of models and predictions related to training and testing data sets. Regression models [26] are evaluated using the lazypredict.supervised library. By using the top ML model with the best performance, the unparalleled ML model can be considered and the accuracy of the top model can be improved. The regression parameters can be improved by the proposed randomsearchCV hyperparameter optimization. RandomsearchCV hyperparameters for tuning parameters to improve the accuracy of the ML model.

3.3 Hyperparameter Tuning Working Principle

Consider the feature variable as X, the target variable as Y, and the unidentified joint distribution as D(X,Y). The sample dataset is segregated [27] as S with m observations. ML models can search data using the functional relationship between search distances ⊖ = (⊖_1,⊖_2,…,⊖_n). Predictive performance was calculated by the pointwise relationship between the prediction function F̃(X,θ) and the true notation Y. The loss function is defined as L(Y,F̃(X,θ)) and the associated algorithm's expected risk is usually measured based on real data, also sampled from D.

R(θ)=E(L(Y,F̃(X,θ))|D). Each data distribution uses a persuaded learning model and is provided by a mapping encoder for a specific performance measure. where the defined number for all hyperparameter configurations is θ. The provision of k different data sets with their data distributions is denoted as D_1, D_2, ..., D_k. This is illustrated by the k hyperparameter risk assignment in Equation 1.

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

Setting of optimal hyperparameter configuration

First, consider the optimal hyperparameter configuration for the i-data set represented by Equation 2.

θ^((i)*)≔ (_θ∊⊖^Arg)min 〚R^((i)) 〛 (θ) (2)

However, common configurations are believed to be appropriate for a variety of different datasets and are typically determined using software packages in an ad-hoc or heuristic manner. Therefore, the optimal hyperparameter configuration is obtained by extensive empirical experiments on k different benchmark data sets and is expressed in Equation 3.

θ^*≔(_θ∊⊖^Arg)min g(R^((1)) (θ),R^((2)) (θ)…,R^((k)) (θ)) (3)

where,

g = summary of the specified function

R^((i)) (θ) = expected risk of hyperparameter assignment

Moreover, the R^((i)) (θ) estimates are well scaled before being highly proportional to the dataset which helps in scaling R^((i)) (θ) to [0,1]. may have been Either look at the dummy predictors and divide the result by the absolute difference between the best potential predictors, or use the Z-score to compute it. Proper scaling is fundamentally based on power measurements.

Algorithm for Randomized Search

Step 1: Initialize the origin as X0 ⊂ S, the algorithm parameters as Θ0, and the iteration index as k = 0.

Step 2: Generate a collection of candidate points as Vk+1 ⊂ S with respect to the specified generator and relative sampling distribution.

Step 3: Based on candidate points Vk+1, Xk+1, they are updated with respect to previous iterations and algorithm parameters, even algorithm parameters are updated as Θk+1.

Step 4: Stop if Stop Criterion is assigned. Otherwise, continue increasing k and return to step 2.

Step 5: The Random Search principle is based on two basic processes such as the generator in step 2 generating candidate points and the update process in step 3.

Step 6: Return

Results and Discussion

The data is preprocessed and checked for missing values. Several factors involving the performance of the Proposed Algorithm. Regarding the accuracy of prediction, the period of training. Here are the predictions and how each feature affects the results to be considered. The methodology and its phases used in this study are:

Shown below: 1. First: Gradient Reinforcement with Machine Learning Algorithm such as RFR, ETR, Elastic Net CV and bagging are trained using an educational dataset.

2. The trained model obtained in the first stage is: Applied to the test data splitting the dataset

70% training group, 30% test group [28].

The results of each algorithm are analyzed and compared in terms of accuracy, prediction time and error rate. Various models were selected in this paper and a comparative analysis of their performance was performed using phython. Educational dataset is pre-prepared and later provided for GBR, RFR, ETR, boosting and Elastic Net CV. These algorithms were trained and tested and the final results are as shown in the following table 1.

Table 1: Final results of Five ML models with Metrics

Model	Adjusted R-Squared	R-Squared	RMSE	Time Taken
Random Forest Regressor	0.87	0.90	0.95	0.23
Extra Trees Regressor	0.86	0.89	1.00	0.19
Gradient Boosting Regressor	0.85	0.89	1.02	0.08
Bagging Regressor	0.85	0.89	1.03	0.03
Elastic Net CV	0.84	0.88	1.05	0.03

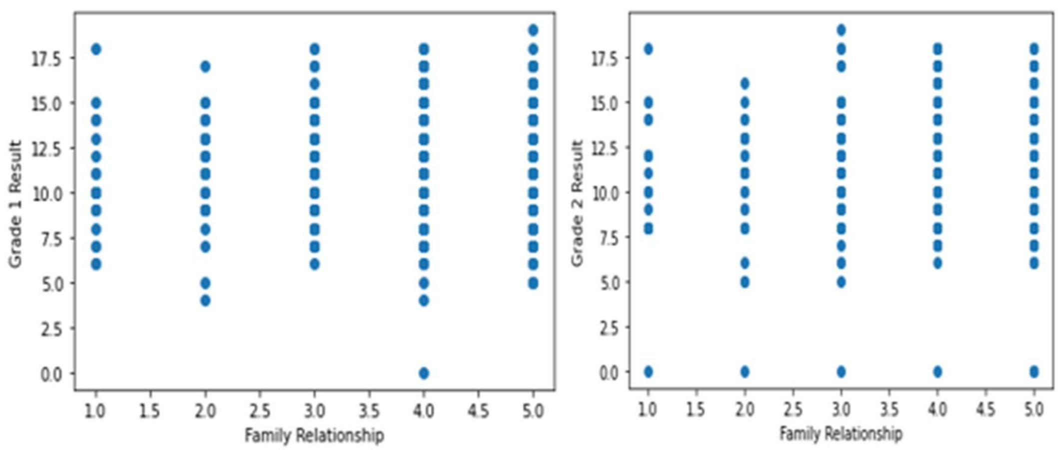

Figure 3: Results of prediction plot for grade 1 and 2 results with family relationship

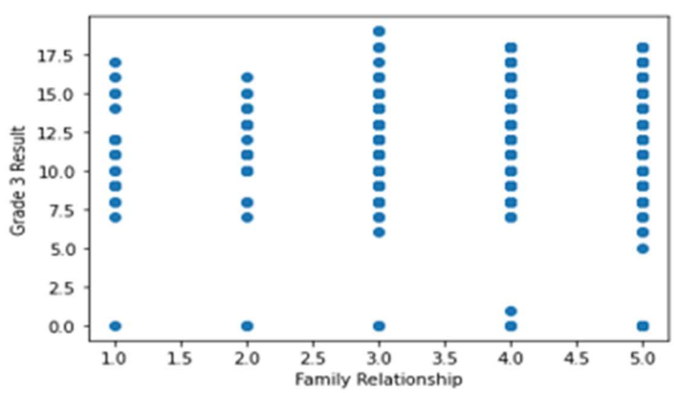

Figure 4: Results of prediction plot for grade 3 results with family relationship

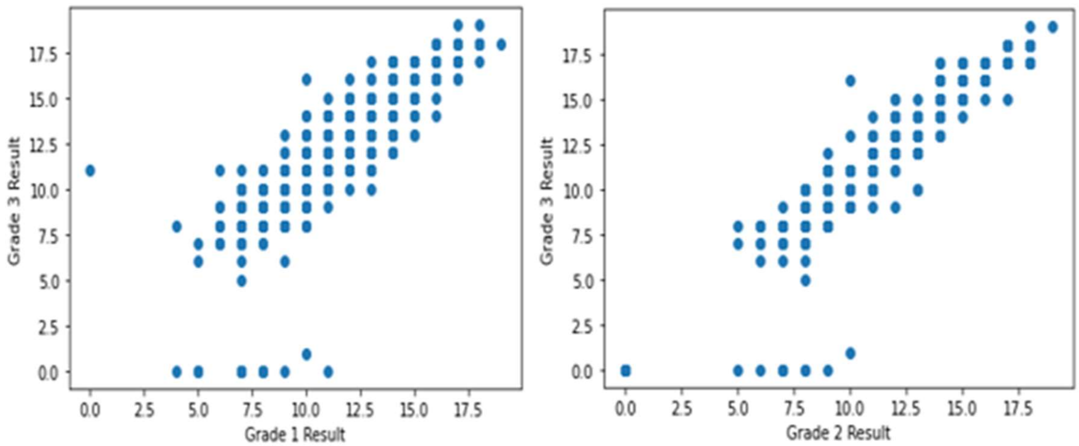

Figure 5: Results of prediction plot for grade1 vs grade3 and grade2 vs grade2 results with family relationship

Figure 3, 4 and 5 shows the comparative predictions of grade1, 2 and 3 with 1 vs2, 2vs3 results with respect to family relationships. The RFR model exhibited that not all attributes influence grades of Students, for better or worse. There are five main attributes that influence regression. These are grades - course 1, accommodation, interest in learning, satisfied with educational environment, family relationship and housing. Therefore, to strengthen the weak, faculty and administrative associates must pay special consideration to student performance and make decisions based on those attributes. Providing additional sessions, behavioral changes and lab work may improve student performance. Moreover, to make the subject more interesting to the student, or to the student. A better educational environment could also help them improve their performance.

Performance Analysis

This work uses Google Collab with the Jupiter IDE to support the sharing and creation of documents that can be annotated with text, live code, and visualizations. The student's personal database is recorded as records, divided into 70% training records and 30% test records. Other tools such as Scipy, Seaborn, and Pandas were used for tuning hyperparameters. All of the above regression techniques are implemented using the tools mentioned above.

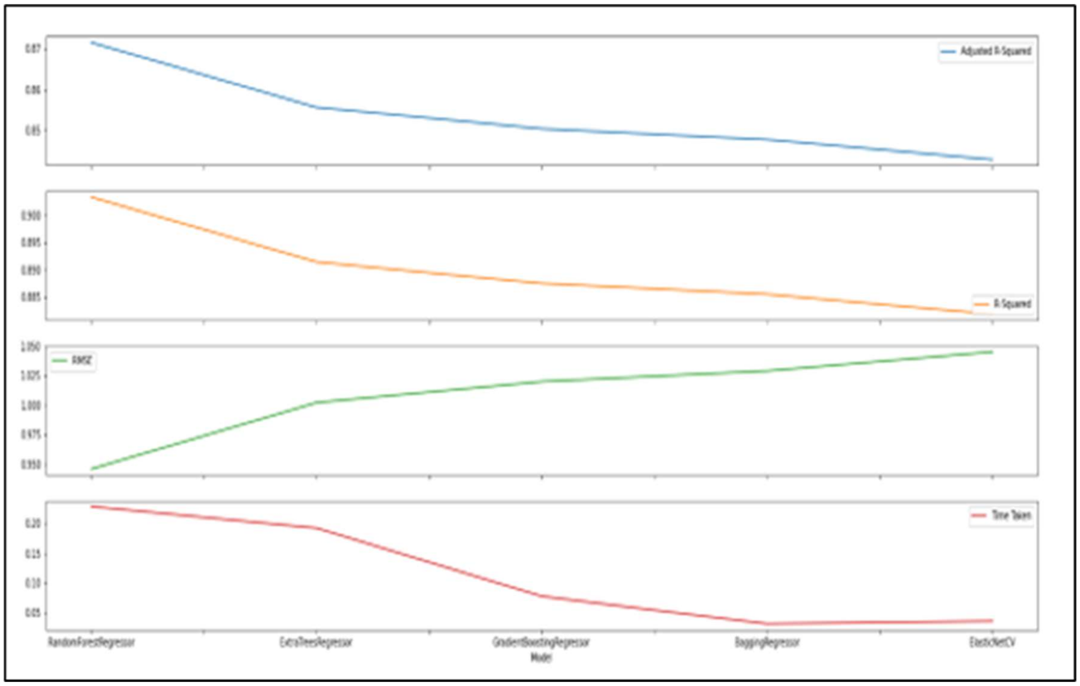

Figure 6: Performance metrics of existing ML algorithms

To find efficient unadjusted regression methods for forecasting. RFRegressor is identified as the best untuned ML model, RFRegressor's parameters are represented by a set of parameters, RandomizedsearchCV parameter distributions are enumerated and iterated with hyperparameter tuning. The optimized XGBRegressor is evaluated against the unoptimized RFRegressor using ERR metrics such as RMSE, R2, and R2 adjusted. Figure 6 shows the performance metrics of the existing model using the student data set.

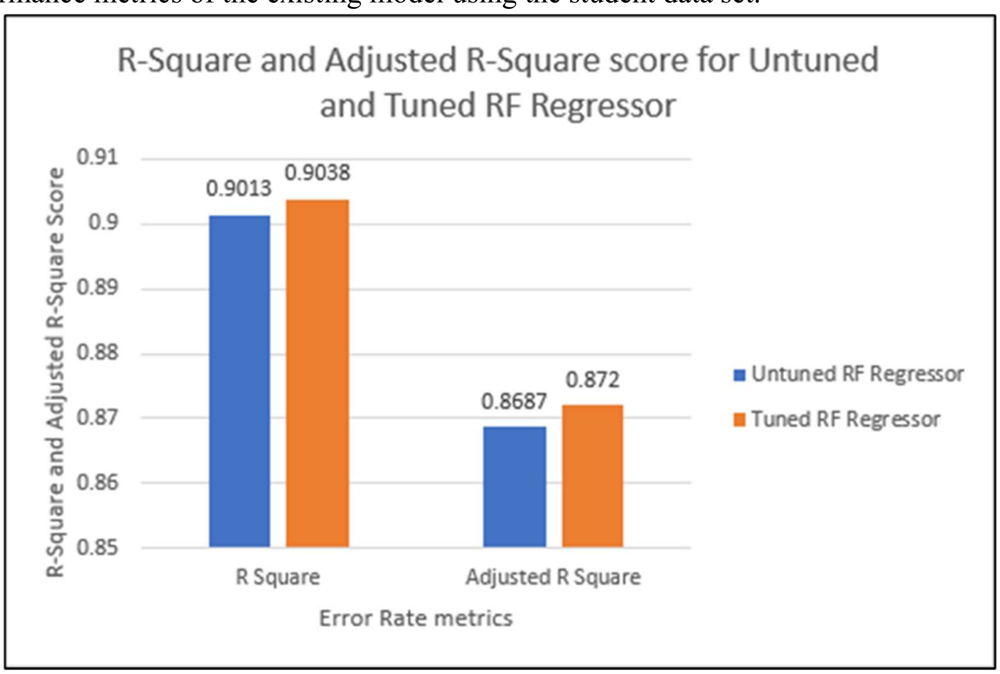

Figure 7: Results of R-Square and Adjusted R-Square score for Untuned and tuned RF Regressor

Figure 7 shows the R-squared and tuned R-squared for untuned and tuned RF regressors. The tuned RF regressor's R-squared and tuned R-squared are 0.9434 and 0.872 higher than 0.9013 and 08687 for the untuned RFR regressor indicating that the model accuracy of the tuned RF regressor model is high. Thus, student academic performance was better observed and understood with the matched RF regressor model than with the other ML models.

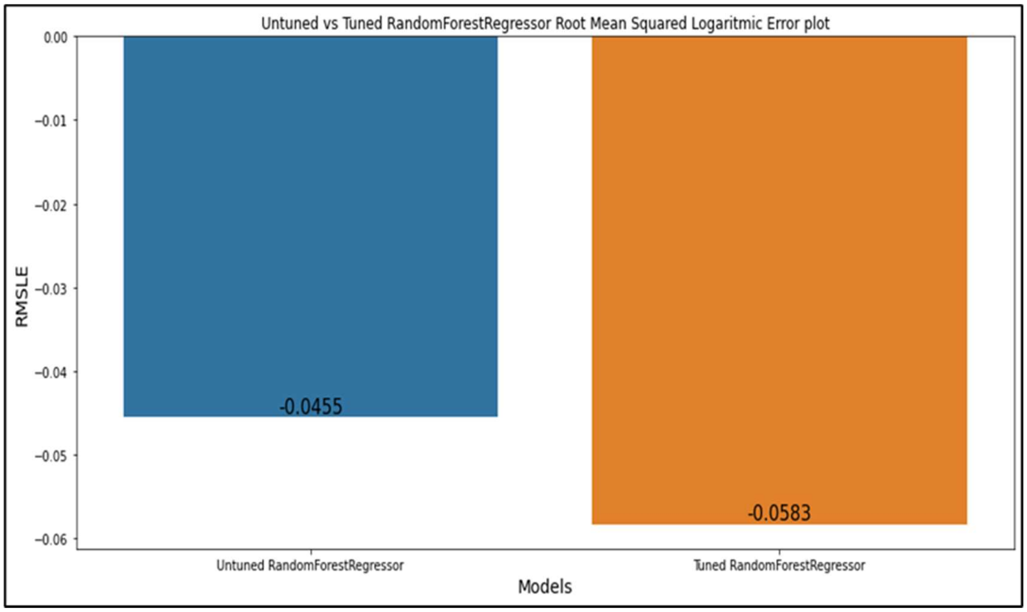

Figure 8: Comparison of RMSE for untuned and tuned RFR algorithms

Figure 8 shows the comparison of RMSE for untuned and tuned RFR algorithms. The untuned value of -0.045 is less than the tuned value of -0.058 of RFR algorithm.

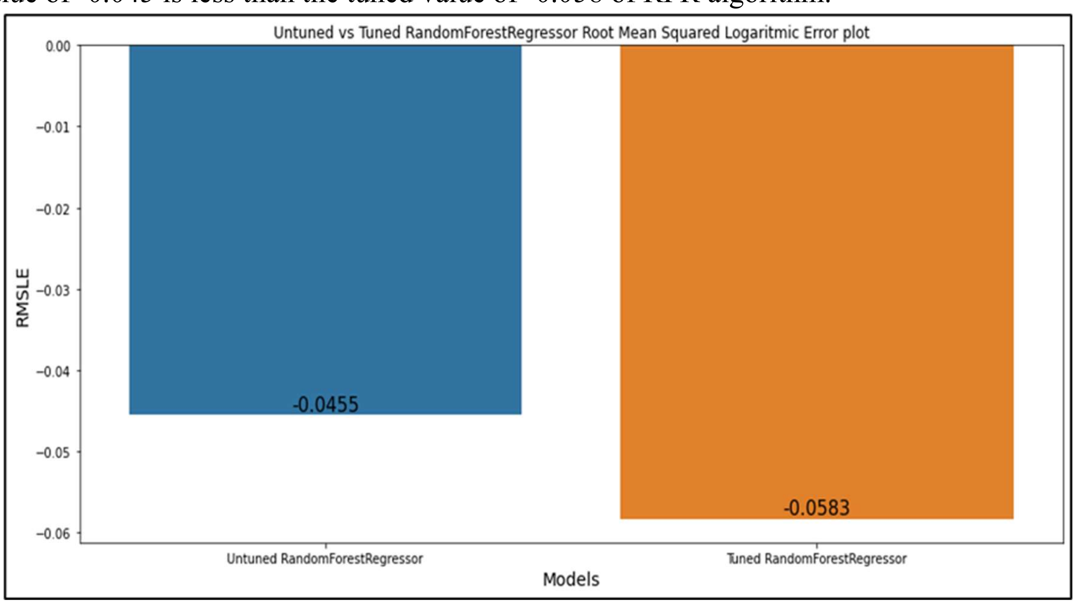

Figure 9: Comparison of RMSLE for untuned and tuned RFR algorithms

Figure 9 demonstrates that untuned RMSLE of -0.045 is less than -0.058 of RFR algorithms. Thus, RFR algorithm outperforms the untuned RFR when compared with tuned RFR.

Conclusion

Data mining in educational systems is very important for analyzing and predicting student academic performance based on various performance factors. This research provides a solution for pre-assessment of student performance, thereby helping to improve student performance and guide them in the right direction in a timely manner. This main survey question was split into three question sets. The results of this paper show that the adjusted RF regressor performs a better analysis of students' academic performance and through Error metrics such as R-squared and adjusted R-squared with accuracies of 94.34% and 87.2%, It shows that you get better results. Regional academic performance patterns along rural-urban gradients derived from impermeable surfaces are discussed by introducing model results as frequency-domain and surface properties. Future applications of this approach may provide new opportunities to try to interpret ML models for complex social expressions from a single location. Equally important, university teachers represent educational practice and engage students from low-income rural areas. In my opinion, "spatial blindness" is a serious problem that needs to be addressed, especially in higher education. Therefore, interventions and institutional changes are needed to facilitate the transition and transition of rural students to higher education. This includes the major modernization of rural schools and rural-wide facilities, the provision of career guidance, the introduction of comprehensive instructional programs, and the evaluation of higher education teaching and learning approaches.

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