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MACHINE LEARNING TECHNIQUES FOR ASSESSING STUDENTS' ENVIRONMENTS' IMPACT FACTORS ON THEIR ACADEMIC PERFORMANCE

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Abstract: Performance factors analysis has recently gained popularity as a method for assessing how students' environments affect their academic performance. However, most of the progress has been made in analyzing student behaviour during the learning process. Machine Learning provides many powerful methods that could improve student performance prediction. Our aim is to examine all features of students' environmental life using the machine learning paradigm to assess how students' environment affects their grades. These features are divided into three categories (personality, family, and education) and their impact factors are calculated. To improve predictive accuracy, different models (Random Forest, AdaBoost, Decision Tree, Naive Bayes, and Multi-Layer perceptron) are used to score the features in each group according to their contribution to the solution. Results show that personality features are a minor effect on students' academic performance with 53%. Concerning the educational factors, outcomes offer the average impact was 60%. Regarding family factors, results indicate that students' family life significantly affects academic achievement with 64%.

Keywords: Machine Learning; Performance; academic performance; students' environment; assessing; educational factors

I. INTRODUCTION

Higher education is an essential pillar in building and developing societies. Annually, vast amounts of money are spent to support educational institutions to provide all the necessary supplies, starting with the infrastructure and ending with the educational staff. Despite that, many factors directly affect students' academic level, some of which are related to personal characteristics and others to the student's family life and the student's scientific interests. Several studies have dealt with the methods and methods that can follow to evaluate students' academic performance according to the students' academic results and the external factors surrounding the students. Many researchers have used artificial intelligence techniques to obtain an accurate assessment of students' academic performance.[1]

It is vital to investigate the interaction between all components to reach a standard view of how physical and social factors in learning settings influence the progress of the academic educational process. Teaching and learning cannot occur in a vacuum, separate from the student's surroundings. As a result, higher education institutions develop and implement intervention measures to address this issue. As a result, considerable emphasis has been placed on identifying susceptible students who are inclined to dropping their courses as early as feasible. [2,3].

II. LITERATURE REVIEW

Forecasting has recently used machine learning to aid in business decision-making. Machine learning techniques have been used to uncover behavior of students that have a significant impact on their performance, dropout rate, participation, and interactivity with online learning sources. Machine learning is increasingly being applied in higher education administration. More precisely, there has been a surge in interest in using Machine Learning to forecast student results and develop at-risk pupils. Automated Machine Learning could be used to improve the accuracy of forecasting academic achievement based on data available before the start of the academic program. “AutoML” is used to find the best classification model and its hyper-parameters. “Auto-Weka and Auto-sklearn” are two of the most well-known tools that are used to determine the model with adequate precision.[4]

[5] This research applies autonomous learning methods, including tree-based models and ANNs (ANNs). The dataset highlighted students' access to "VLE platforms" as a significant factor using these methodologies. One hundred twenty students earning a master's degree on a "VLE platform " studied this factor.

Giannakas, F., et al [6] examine and suggest a “Deep Neural Network” (DNN) paradigm for binary classification with two hidden layers. The approach is tested with several activation functions, also utilizes the "SHAP" approach to understand the architecture and identify the essential variables influencing the final forecast.

[7] employ ensemble learning as a powerful machine learning paradigm to produce sophisticated solutions in various industries. They present a new method combining "Random Forest, AdaBoost, and XGBoost" to improve student performance prediction accuracy. The scalable XGBoost beat the other models tested in the experiments and significantly enhanced system performance.

[8] clarify the impression of extreme precision in identifying at-risk students is created by the grading scheme. Twelve blended courses were organized into three grading policies: discrimination, stringency, and leniency. The "Grading-on-Leniency" policy has the greatest impact on risk assessment efficiency. "Data resampling" is a reliable way for assessing the efficacy of grading policies. Learning

analytics would be aided by critical aspects linked with learning activities in narrowing down the potential group.

Adnan, Muhammad, et al. study [9] proposed a predictive model that looks at the difficulties that at-risk students have, which then allows teachers to intervene at the right time to get students to increase their study engagement and improve their study performance. Different machine learning and deep learning algorithms are used to build the predictive model, which is then tested to see how students learn based on their study characteristics. The predictive model can help teachers find students who might not be able to keep up with the class early on, preventing them from dropping out. The results of the experiments show that the predictive model trained with Random Forest (RF) is the best.

[10] shows how different things affect how well students do. It didn't matter how many hours of sleep you had or how much energy you had. Mood and the time of day had an effect on how well students did in class. Students with different cognitive abilities can be taught in a way that is tailored to their needs, thanks to analysis.

[4] used machine learning tools to investigate the initial assessment of student achievement. For appropriate forecasting, the study looks at different variables such as education, job, gender, status, burden, course variables, etc. The crucial parameters affecting the pupils' achievement are identified using machine learning techniques for selecting features. The study's most noteworthy finding was that ethnicity, academic program, and semester bundle significantly impact students' academic achievement.

[11] presented a technique for predicting student outcomes called "the combinational incremental ensemble of classifiers". Three classifiers are merged in the proposed technique, with each classifier calculating the prediction output. The final prediction is chosen using a voting mechanism. The three methods utilized to create the system incrementally are “Naïve Bayes” (NB), “Neural Network” (NN), and “WINDOW”. When new cases happen, the values are predicted by all three classifiers, automatically the most correct is chosen.

To help establish the effectiveness of the "Student Evaluation of Teaching Effectiveness" (SETE) test, [12] used statistical techniques, NN, and Bayesian dimension reduction strategies. SETE is a broad metric of the quality factors or formative assessments on the online platform that does not appear to be supported by the findings.

[13] presented a tutor decision-making system for predicting student achievement. "Student demographic data, e-learning system logs, academic data, and entrance information" are all considered in this analysis. The dataset contains the data of 354 individuals, each with 17 features. Set of machine learning techniques called ["Model Tree (MT), NN, Linear Regression (LR), Locally Weighted Linear Regression, and Support Vector Machine (SVM)"].

[14] proposed three machine learning techniques, "Naive Bayes” (NB), “Decision Tree” (DT), and “Multilayer Perception” (MLP), for predicting student achievement. The collection has 257 examples with 12 features in total. As assistance was provided, they chose Weka software. Accuracy, learning time, and error rate evaluate the classifiers. With a training process under one second and significant errors, the NB achieves a high average precision of 76.65%.

[15] analyzed the activity logs of students who took the first programming class in the course to see how well they did. According to this study, instead of using a direct method to determine how students' performance varies over time, it should employ a predictor based on automatically measured parameters. They devised a scoring algorithm known as "WATWIN," which assigns points to various aspects of student programming. The methodology considers both the student's capacity for dealing with programming errors and the time required to rectify them. Gave a WATWIN score is assigned to each student's activity, which may then be utilized in linear regression to determine how well they performed. With a 76 percent accuracy rate, the WATWIN score is employed in linear regression.

[16] shed light on the imbalanced dataset that can be used to predict how students will do. This study has matched the ten standard classification algorithms built into Weka "Jrip NNge OneR Prison Ridor ADTree Random Tree REPTree Simple CART" with three different genetic algorithms. The three types of the genetic algorithm: "ICRM v1, ICRM v2, and ICRM v3". The ICRM v2 performs better with balanced data.

Our research work relies on ML techniques to help increase the accuracy of predicting student performance using the data available based on Influence of the learning environment on student success. It makes sense that pupils do better in happy learning environments. Since most individuals would agree that some surroundings are better for academic success than others. But just because something makes sense doesn't mean educators and politicians have the knowledge, they need to help kids achieve their goals. Now that researchers know how specific elements affect pupils, educators may start improving learning settings.

Diet, exercise, and social support all play a role in students' It found that pupils in positive learning contexts get a month and a half more math instruction than those in negative learning situations. The study found that good learning settings can save 25%. Schools that provide better settings, in other words, may be more successful while spending less.

III. METHODOLOGY

The purpose of the study is to identify and compare the influence of students' performance based on three sets of related features (Personal, Family, and education) using various machine learning techniques. This section explains our proposed approach which is composed of three stages: data collection, and preprocessing, Data clustering, and a classification and evaluation stage, as shown in Fig. 1.

A. Dataset Collection and Coding

We analyze a dataset introduced by UCI machine learning repository[17]. The dataset comprises 145 instances of students for 30 features. The data set features were divided into three categories: Family (10 features), personals (6 features), and educational (14 features) as shown in Table 1.

We coding the values of all features and converting to integer. The individuals were labeled in a binary format: "1" for the pass and "0" for fail, as demonstrated in Table 2.

B. Methods

Classification is a fundamental job in machine learning. It is the recognition of the category labels associated with occurrences in a dataset that are typically characterized by a set of properties (features). Classification aims to effectively estimate the actual labels of examples whose feature values are known but whose class labels are undetermined. In the realm of machine learning, classification tasks are binary, multi-class, multi-labeled, and hierarchical. Numerous machine learning methods have been effectively applied to pattern recognition and classification issues [18].

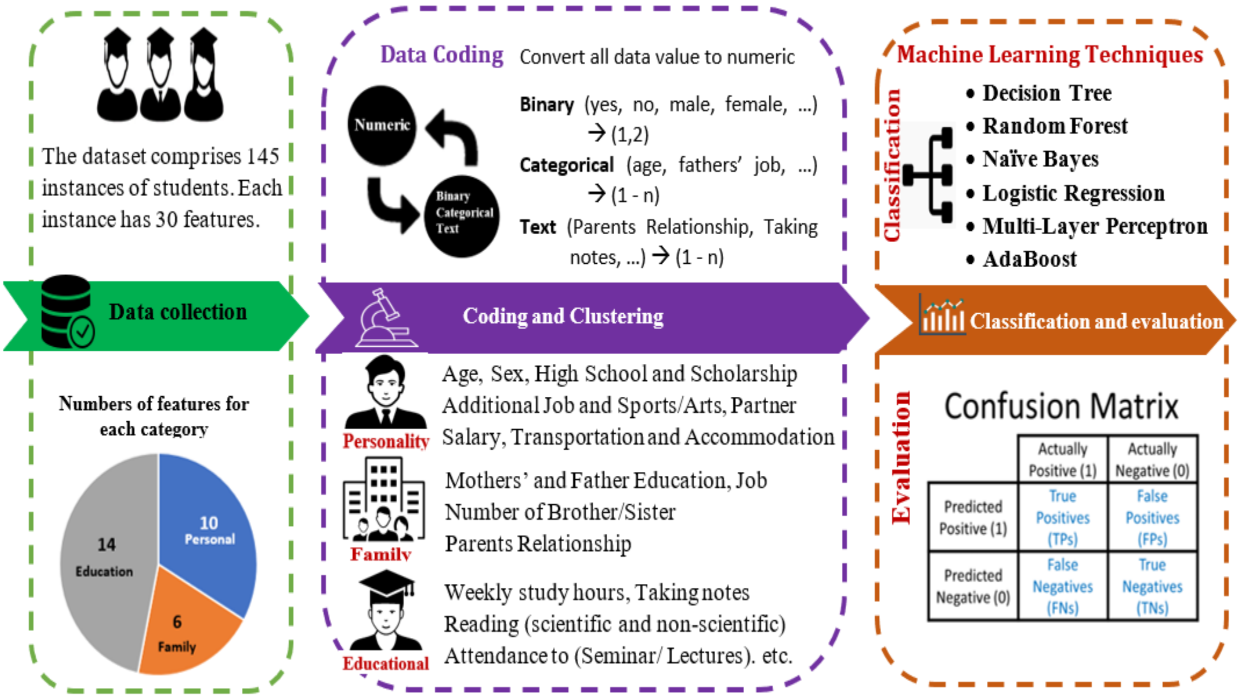

Figure 1. The block diagram of the proposed approach.

Table 1. Dataset's features characteristic

Category	Features' name	Type	Category	Features' name	Type
personal	Age	int	education	Weekly study hours	int
personal	Sex	text	education	Reading (non-scientific)	text
personal	High School Type	text	education	Reading (scientific)	text
personal	Scholarship Type	real	education	Attendance to Seminar/Conference	text
personal	Additional Job	text	education	Effect of Projects and Activities	text
personal	Sports/Arts	text	education	Lectures attendance	text
personal	Partner	text	education	Study type I (Group/Alone)	text
personal	Salary	int	education	Study type II (Regular/Last week)	text
personal	Transportation	text	education	Taking notes	text
personal	Accommodation	text	education	Writing/Listening	text
family	Mothers' Education	text	education	Effect of in-class Discussions	text
family	Fathers' Education	text	education	Effect of Flip Classroom	text
family	Number of Brother/Sister	int	education	GPA of Last semester	real
family	Parents Relationship	text	education	Expected CGPA at graduation	real
family	Mothers' Job	text			
family	Fathers' Job	text			

Table 2. Dataset's features coding

Feature's name	**values range and coding**					
Age	18–21→1	22-25→2	above 25→3			
Gender	female→1	male→2				
High School Type	Private→1	Public→2	Other→3			
Scholarship Type	None→1	0.25→2	0.50→3	0.75→4	Full→5	
Additional Job	Yes→1	No→2				
Sports/Arts	Yes→1	No→2				
Partner	Yes→1	No→2				
Salary	135-200→1	201-270→2	271-340→3	341-410→ 4	> 410→5	
Transportation	Bus→1	Private car→2	Bicycle→3	Other→4		
Accommodation	rental→1	dormitory→2	family→3	Other→4		
Mothers' Education	primary school→1	secondary school→2	high school→3	university→4	master→5	Ph.D.→6
Fathers' Education	primary school→1	secondary school→2	high school→3	university→4	master→5	Ph.D.→6
Number of Brother/Sister	1→1	2→2	3→3	4→4	>= 4→5	
Parents Relationship	married→1	divorced→2	died→3			
Mothers' Job	retired→1	housewife→2	government→3	private→4	self-employ→5	
Fathers' Job	retired→1	government→	private→4	self-employ→5		
Weekly study hours	None→1	5 hours→2	6-10 hours→3	11-20 hours→4	above 20 →5	
Reading (non-scientific)	None→1	Sometimes-->2	Often→3			
Reading (scientific)	None→1	Sometimes→2	Often→3			
Attendance to Seminar/Conference	Yes→1	No→2				
Effect of Projects and Activities	positive→1	negative→2	neutral→3			
Attendance to Lectures	always→1	sometimes→2	never→3			
Study type I (Group/Alone)	alone→1	with friends→2	not applicable→3			
Study type II (Regular/Last week)	closest date exam→1	regularly→2	never→3			
Taking notes	always→1	sometimes→2	never→13			
Writing/Listening	always→1	sometimes→2	never→13			
Effect of in-class Discussions	always→1	sometimes→2	never→13			
Effect of Flip Classroom	not useful→1	useful→2	not applicable→3			
GPA of Last semester	2.00→1	2.00-2.49→2	2.50-2.99→3	3.00-3.49→4	above→5	
Expected CGPA at graduation	2.00 →1	2.00-2.49 →2	2.50-2.99 →3	3.00-3.49 →4	above→5	

1.DECISION TREE

The decision tree uses a binary tree to solve the problem, where each node represents a class label and features are represented on internal nodes. Problem solved utilizing tree representation where each leaf node represents a target class and each inside node represents a characteristic. A decision tree is an excellent approach to represent data since it considers all possible paths leading to the ultimate choice through a hierarchical tree form. The one of the most well-known data categorization methods is the decision tree classifier [19],[20]. The most important aspect of DT is its ability to simplify complex decision-making situations, resulting in a solution that is more clear and easier to grasp. A decision tree is a graph that depicts the numerous possibilities available to make a decision. It displays the many outcomes of a set of decisions. The graph starts with a box (or root) from which several solutions sprout. Decision trees are useful for a variety of reasons. They're useful not only because they're basic diagrams that assist us, but they can also serve as a framework for calculating all possible alternatives.[21] For classification and regression issues, DT is an effective non-parametric approach. They're hierarchical data structures that use supervised learning to predict or classify other response variable by splitting input space into several local areas. [22], [23].

2.RANDOM FOREST

Random Forest is a well-known machine learning technique that is effective for various classification problems. A Random Forest is a collection of classifiers with a tree-structured topology [24]. Each tree in the forest casts a unit vote, allocating each input to the class label with the highest probability. It is a quick approach that is resistant to noise and a successful ensemble capable of identifying non-linear patterns in data. It is equally adept at handling quantitative and qualitative criteria [25]. One of the critical advantages of Random Forest is that it is resistant to overfitting, even as the forest grows larger.
The Random Forest method gives an unbiased calculation of the generalization error, therefore there is no need to deploy a separate test subset or apply cross-validation. To avoid overfitting, Random Forests use only two user-defined parameters: the number of trees and the number of random split variables. As the classifier's performance improves, so does the number of trees, until the generalization error falls to 10% or less. Using Random Forests almost blindly is possible if the classifier's error has converged and the number of random variables has been minimized. Due to the various decision tree formed by resampling the same dataset, the main downside of Random Forests was that it could be challenging to grasp the rules employed to produce the final categorization.[26]

3. Naïve Byes (DT)

The Naive Bayes approach is a subclassification problem-solving technique based on the Bayes theorem. The Naive Bayes Classifier is a straightforward and effective classification approach that enables the rapid building of accurate machine learning models.[27]
By assuming that attributes are class-independent, the naive Bayes classifier drastically simplifies learning. Although independence is a poor assumption in general, naive Bayes frequently beats more sophisticated classifiers. The Naive Bayes model is straightforward to build and particularly useful when dealing with huge data sets. Along with its simplicity, it has been demonstrated that Naive Bayes outperforms even the most sophisticated classification systems [28]. Machine learning approaches that take advantage of statistical independence are called Naive Bayes classifiers. In comparison to more complex Bayes algorithms, these methods are easy to construct and perform well. [28]

4. Multi-Layer Perceptron (MLP)

A multilayer perceptron (MLP) is a feedforward artificial neural network that produces a set of outputs based on a set of inputs. Between the input and output layers, a directed network with multiple layers of input nodes is connected. Backpropagation is used by MLP to train the network [29], [30].
A multilayer perceptron is a sort of neural network in which multiple layers are connected in a directed graph by a unidirectional signal route through the nodes. Each node, with the exception of the input nodes, has a nonlinear activation function. MLP is a deep learning technique due to the several layers of neurons. A backpropagation-based technique to supervised learning is referred to as an MLP [31]. MLP is frequently used to address supervised learning challenges as well as computational neuroscience and parallel distributed processing research. [32]

5. The AdaBoost

The AdaBoost algorithm, shortened for Adaptive Boosting, is a method for ensemble learning in machine learning. An AdaBoost [33] classifier begins by fitting a classifier to the full dataset, and then maintains numerous copies of that classifier on the same dataset, with the weights of misclassification cases altered so that subsequent classifiers focus on a more sophisticated instance.
The weights are redistributed to each instance, with greater weights applied to cases that were incorrectly detected. With a few modifications, the AdaBoost approach is similar to boosting. Boosting is used to eliminate bias and variation in supervised learning. It is based on the sequential learning idea. With the exception of the first, each subsequent student is formed from previously cultivated learners. In other words, weak students develop into strong students [34]. The data training phase results in the creation of a predetermined number of decision trees. As the first decision tree/model is formed, the poorly classified data in the first model is given weight. Only these records are supplied as input to the second model. The technique is repeated until the desired number of base learners is specified. Bear in mind that all boosting procedures permit unlimited repetition. [35]

Stage 1: A weak classifier is built using weighted samples on top of the training data. The weights of each sample show the importance of being correctly categorized. For the first stump, give equal weight to all of the samples.
Stage 2: For each parameter, design a decision stump and test how well it classifies data into its intended classes. Look at how many examples are rightly or erroneously labeled as fit or Unfit for every particular stump.
Stage 3: The incorrectly classified samples are given additional weight in order to be properly identified in the subsequent decision stump. Additionally, each classifier is assigned a weight based on its accuracy, with higher accuracy equaling a higher weight.
Stage 4: Repeat Stages 2–4 until all data points are correctly categorized, or the highest iteration level is reached.

6. Model Evaluation

In order to assess the consistency of the machine learning model, performance measures are used. For any model, evaluating machine learning techniques is essential. there are several multiple kinds of assessment metrics available for evaluating a model. These include accuracy of classification, logarithmic loss, confusion matrix, Area Under the Curve, and others.

6.1 Confusion matrix

A confusion matrix is a strategy for outlining classification algorithm results. The percentage of positive and negative predictions is summarized and decomposed by each class by counting values. A Confusion matrix is used to assess the output of a classification algorithm by providing a comprehensive view of how well the identification model works and what sorts of mistakes it makes [36].
All confusion matrix calculation metrics are based on the four basic parameters: “True Positives, False Positives, True Negatives, and False Negatives” are directly compared. Other classification metrics, such as "Accuracy," on the other hand, provide fewer valuable details, as accuracy is simply the distinction between correct forecasting separated by the overall number of forecasting.[37], [38]

IV. RESULTS

The purpose of the study is to identify and compare the influence of students' performance using various machine learning techniques. a dataset introduced by UCI machine learning repository. The dataset comprises 145 instances of students for 30 features. The study used two approaches. First approach, divided the features into three categories (Personal, Family, and education). Each category is tested using various machine learning techniques. , Random Forest, naïve Bayes MLP, and AdaBoost). The outcomes proved that the family and educational features are the more affected students’ academic achievement than personality characteristic. The results show that the Random Forest has gain the highest accuracy about (72.4%) base on family features, while AdaBoost technique has gain about (63.4) based on education fetures as shown in Figure 2.

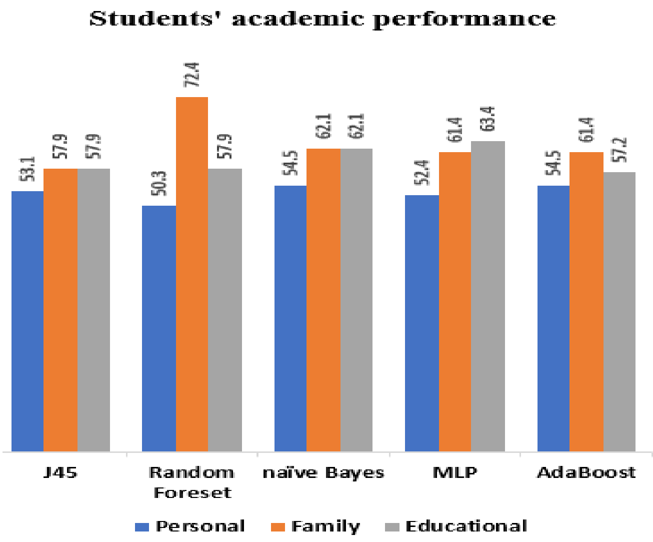

Figure 2. Students' academic performance based on three kinds features using five machine learning techniques

In the second approach we test Students' academic performance based on all features as one package. Five machine learning techniques are used to calculate the best academic achievement. The results state that AdaBoost technique has the best scoring about (84.8), while Random Forest achieved second best scoring about (78.6). On the other hand, Naïve Bayes recorded the worst scoring about (66.2) as shown in Figure 3.

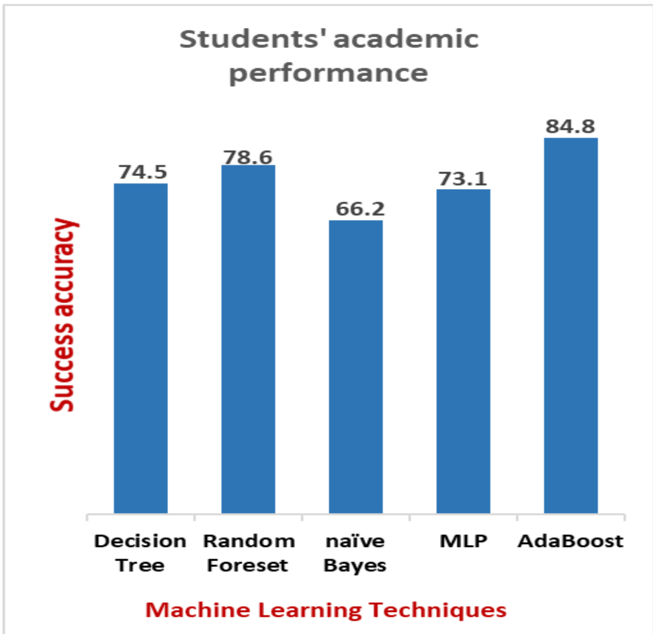

Figure 2. Students' academic performance based on three kinds features using five machine learning techniques

The confusion matrix was used as evaluation metric to explain the scoring of each machine learning techniques. TP, FP, TN and FN are the basic metric using to calculate the accuracy of each techniques as shown in Table .

Table 3. Confusion Matrix Scales for Five ML Techniques for the two approaches (features combined and separated as categories)

Features' categories	ML	TP	FP	TN	FN	F-Measure	Accuracy
Personal	DT	69	49	8	19	0.670	53.103
	RF	55	39	18	33	0.604	50.345
	Naïve Bayes	75	53	4	13	0.694	54.473
	MLP	57	38	19	31	0.623	52.414
	AdaBoost	71	49	8	17	0.683	**54.483**
Family	DT	60	33	24	28	0.663	57.931
	RF	73	25	32	15	0.785	**72.414**
	Naïve Bayes	59	26	31	29	0.682	62.069
	MLP	59	27	30	29	0.678	61.379
	AdaBoost	63	31	26	25	0.692	61.379
Educational	DT	57	30	27	31	0.651	57.931
	RF	62	35	22	26	0.670	57.931
	Naïve Bayes	54	21	36	34	0.663	62.069
	MLP	64	29	28	24	0.707	**63.448**
	AdaBoost	60	34	23	28	0.659	57.241
All features	DT	71	20	37	17	0.793	74.483
	RF	79	22	35	9	0.836	78.621
	Naïve Bayes	59	20	37	29	0.707	66.207
	MLP	67	18	39	21	0.775	73.103
	AdaBoost	82	16	41	6	0.882	**84.828**

V. CONCLUSION

In this paper, we utilized machine learning techniques for assessing students' environments impact factors on their academic performance. We focused on the features of students' environments that could be further translated into axioms and rules.

These features are divided into three categories (personality, family, and education) and calculated as impact factors. Different models (Random Forest, AdaBoost, Decision Tree, Naive Bayes, and Multi-Layer perceptron) are used to score the features in each group according to their contribution to the solution. The UCI machine learning repository introduced a dataset. The dataset comprises 145 instances of students for 30 features. The results show that the Random Forest has gained the highest accuracy (72.4%) based on family features, while the AdaBoost technique has gained about (63.4) based on education features.

Finally, assessing academic accomplishment is one of the most challenging problems to solve globally, as data suggests that it is intimately linked to economic growth, jobs, and a country's overall well-being. The learning environment is a significant a footnote factor in students' success. Learning ability can be affected by many things, including personal, family, and educational aspects. A positive learning environment makes students more motivated, excited, and better at learning. It will be much harder for students to learn and stay interested in class if the environment is unpleasant, noisy, or full of distractions. Here, let's think about how students' surroundings affect how they study and think about how to make a good comprehensive curriculum.

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