ACTA SCIENTIAE

ISSN: 2178-7727

Enhancing Academic Performance of Rural Students in Urban Universities Using Machine Learning Classifier

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ABSTRACT

Rural students in urban universities often struggle academically because of differences in resource availability, access to learning devices, and socio-economic factors. This study focuses on detecting the academic progress of these groups through the application of machine learning classifiers as early intervention for improving their scores. In this research work, we plan a holistic methodology which incorporates logistic regression for preprocessing the data, Chi-square based feature selection for dimensionality reduction and Remora Optimized MK-SVM for classification process. Chi-square test helps to identify the highly informative features in a pool of the given variables, to build a predictive model with lesser complexities to improve accuracy and reducing overfitting. By introducing yet another level of optimization through MK-SVM with Remora, which is a nature-inspired optimization technique, researchers can enhance the classifier's potential to capture underlying complex patterns embedded in the student data. In addition, this study adopts the train-test split mechanism, so that the evaluation of the model can be more rigorous in examining the generalization capability of the proposed system. The outcome of our study reveals that the integration of logistic regression for preprocessing and feature selection with the Remora-optimized MK-SVM achieves a substantial accuracy boost over classical approaches, suggesting actionable guidance for potential strategies to enhance the academic success of rural students in urban higher education institutions along with higher accuracy percentage of 99.5. This study offers a new methodology in the field of educational analytics, illuminating how machine learning tools can help close educational gaps.

KEYWORDS:

INTRODUCTION

Education is a crucial element of society which train people with the necessary knowledge and skills needed to develop themselves within the economy. However, rural students face barriers to accessing urban universities as a result of the differences in educational resources and socio-economic conditions. (Due to differences in academic background, upon arrival, students struggle to adapt to fresh learning environments due to varying levels of digital literacy and the lack of the required teaching materials. (Smith & Johnson, 2020) Despite urban universities providing education services as comprehensive as in the metropolis, rural students are ambitious, but they still lag behind in financial, language, and cultural factors, leading to low academic performance and high drop-out rates (Brown et al., 2021). Machine Learning (ML) emerged as a powerful approach to predict and enhance the students' performance in the higher education context to address these challenges (Patel et al., 2021).

The shift from rural to urban education often brings with it numerous challenges as well. The gap in preparedness across academia is one of the biggest issues. Over the past twenty years, students in rural schools may have been schooled at institutions with less access to qualified teachers, physical infrastructure, and digital learning resources, and they faced a relative disadvantage compared to their urban peers (Anderson &

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Lee, 2019). They are less confident, are more stressed than Asian students, and lack the incentive to do their best, which causes them to do badly. Additionally, financial hurdles represent another major obstacle, since numerous rural students struggle to pay for tuition fees, accommodation costs, and school supplies, which intensifies their performance constraints within an urban collegiate atmosphere (Garcia et al., 2020).

That’s a different but equally important one and it’s getting used to a new socio-cultural-technical environment. “Even if you are adequately prepared for college and you get there, you might not have access to the same resources for learning that someone in an urban population has,” he says. It has been noted that students with limited or no experience with advanced instructional technologies may find it challenging to adopt e-learning platforms, online research tools, and digital collaboration processes (Williams et al., 2022). Hence, rural students need contextualized academic supports to combat the possible barriers.

Over the past few years, machine learning has emerged as one of the most promising research areas in the field of educational analytics, providing the ability to analyse multiple datasets on a large scale and predictions on the most probable factors concerning student performance. ML algorithms are able to analyse data sets on the student behaviour, academic progression and engagement levels and identify patterns, develop predictive models where students considered at-risk are recognised and called for timely intervention by the university (Chen & Zhao, 2021). Predictive analytics can help institutions identify students who are likely to fail academically using ML classifiers and take remedial interventions proactively to enhance learning outcomes (Kumar et al., 2020).

Supervised learning methods (e.g., logistic regression, decision trees, SVM, neural network algorithms) have obtained high-quality predictive performance on successful students in education analytics (Zhang et al., 2021) Specifically, significant literature has developed optimized multi-Kernel Support Vector Machine (MK-SVM) models as a strong digitalism of systemin, which provides a more precise and detailed approach to identify at-risk students based on their performance indicators (Patel et al., 2021).

LITERATURE REVIEW

Challenges Faced by Rural Students in Urban Universities

Several studies have pointed to the academic obstacles faced by rural students when they enter urban universities. As a result, they face challenges in institutions of higher education (Anderson & Lee, 2019) due to limited access to quality education, inadequate financial resources, and socio-cultural differences. A study by Garcia et al. In a study by Hinton et al. (2020), it was reported that rural students typically fall behind in digital literacy and experience several difficulties in adjusting to more advanced technologically driven learning spaces. Such challenges lead to a performance gap between rural and urban students, which require suitable interventions to ensure their academic success.

The Role of Machine Learning in Education

Data backstage has become a key player in the educational analytics field, where machine learning delivers valuable predictive tools for understanding participants. ML approaches process big data to discover associations in students' outcomes and as such they may identify potential truancy faster (Chen & Zhao, 2021). Patel et al. (2021) showed that data mining models including decision trees, support vector machines, and deep learning algorithms usually exceed traditional statistical models in predicting student success and dropout risks. This suggests ML can be leveraged for overcoming educational gaps.

Predictive Models for Academic Performance Analysis

Multiple Machine Learning Models to predict Students Performance Various machine learning algorithms such as logistic regression, decision trees and neural networks have shown good performance for academic achievement prediction (Kumar et al., 2020). Zhang et al. performed a comparative study (2021), based on which they concluded that MK-SVM is more precise than SVM in predicting student performance. These results suggest that prediction could be further improved, and consequently the intervention efforts made by educators in the improvement of the at-risk students, as we know that predictions by optimized classifiers yield

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high accuracies.

The Role of Machine Learning in Education

Educational analytics has become an area of great interest with many recent applications of machine learning, which offers predictive capabilities of student performance. ML techniques process vast datasets to detect trends in academic success, making it possible to identify at-risk students early (Chen & Zhao, 2021). Patel et al. In this respect, the article of Al-Mamory et al. (2021) showed that some machine-learning algorithms, like decision trees, support vector machines and some deep learning techniques, can more accurately predict success and risk of dropout in students than classical statistical ones. These developments suggest that we could leverage ML to contend with educational inequities.

Predictive Models for Academic Performance Analysis

Various machine learning models have been studied for predicting the performance of students. Algorithm in predicting academic achievements (Kumar et al., 2020). Zhang et al. presented a comparative analysis (2021) Multi-Kernel Support Vector Machine (MK-SVM) outperform traditional SVM models in terms of student performance classification. This indicates that optimized classifiers may drastically improve prediction accuracy and improve intervention schemes for students that are not thriving.

Feature Selection Techniques for Student Performance Prediction

Feature selection is a method used to increase the accuracy of ML models by removing insignificant variables. Common methods include Chi-square test, principal component analysis (PCA), and recursive feature elimination (RFE) (Williams et al., 2022). Brown et al. (2021) which stated that Chi-square feature selection improve model efficiency due to the selection of the most influential academic and behavioral factors affecting the success of students. When used in predictive models these techniques will help with generalization and decreasing overfitting.

Optimization Techniques in Machine Learning Classifiers

Optimization techniques are used to enhance performance by tweaking the parameters during training of machine learning models. Genetic algorithms and Remora optimization are nature-based optimization techniques that have been found to be quite helpful in enhancing classification performance (Smith & Johnson, 2020). Remora Optimized MK-SVM outPerforms SVM with a Pruned Kernel Set: Research conducted by (Lee & Patel, 2021) proved that Remora O optimal mk-svm gives better classification accuracy as compared to traditional SVM and this makes (Lee & Patel, 2021) for predicting student performance verwerking.

Machine Learning-Based Intervention Strategies

ML-based interventions deliver personalized learning support for students who risk falling behind academically. To foster student engagement and performance, new technologies, such as early warning systems, adaptive learning platforms, and AI-based tutoring, have been developed (Garcia et al., 2020). A study by Sharma et al. (2022) revealed in their study how machine learning-powered curricular intervention systems promote student retention rates through personalized recommendations tailored to individual learning behaviors. Establishing such systems is an integral facet of improving education for underrepresented across all geographic regions as emphasised by these findings.

The Impact of Digital Learning on Rural Students

For rural learners in urban universities, the digital divide is still a serious challenge. Their academic progress is impeded by limited access resources for high-speed internet, unfamiliarity with the online system of learning and inadequate digital skills (Williams et al., 2022). A survey by Kim & Thompson (2021) indicates that when ML-powered learning analytics systems are integrated with digital literacy programs, rural students are more likely to be engaged and perform better. Tackling these challenges in the digital sphere is crucial to provide equitable learning experiences.

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Ethical Considerations in Machine Learning Applications in Education

However, these technologies also come with ethical challenges, particularly because machine learning and education raise questions about data privacy and ethical implications of decision making in schools. This raises concerns of student data privacy protection and transparency in ML mechanisms which is paramount in developing AI solutions for education (Kumar et al., 2020). A study by Zhang et al. (2021) stressed the importance of fairness-aware ML models as discrimination against students from less privileged backgrounds or from different ethnic backgrounds have been observed in recent past. Especially, ethical AI practices should be applied to prevent bias in ML educational interventions.

Dataset

The dataset comprises the following 41 attributes, each contributing unique insights into a student's academic and personal profile:

Tab 1: Dataset

Column	Non-Null Count	Data Type	Description
Student ID	98,000	int64	Unique identifier for each student.
Gender	98,000	object	Student’s gender (e.g., Male, Female, Other).
Age	98,000	int64	Student’s age.
Grade Level	98,000	int64	Current academic grade or year of study.
Attendance Rate	98,000	float64	Percentage of classes attended.
Study Hours	98,000	float64	Average study hours per week.
Parental Education Level	98,000	object	Highest education level attained by the parents.
Parental Involvement	98,000	object	Level of parental engagement in academic activities.
Extracurricular Activities	98,000	object	Involvement in extracurricular activities.
Socioeconomic Status	98,000	object	Economic background of the student’s family.
Previous Academic Performance	98,000	float64	Historical academic performance (e.g., GPA).
Class Participation	98,000	object	Degree of participation in class discussions and activities.
Health Status	98,000	object	General health condition of the student.

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Column	Non-Null Count	Data Type	Description
Access to Learning Resources	98,000	object	Availability of educational materials.
Internet Access	98,000	object	Quality and reliability of internet access.
Learning Style	98,000	object	Preferred method of learning (e.g., visual, auditory).
Teacher-Student Relationship	98,000	object	Quality of interactions between teachers and students.
Peer Influence	98,000	object	Impact of peers on academic performance.
Motivation Level	98,000	object	Self-reported motivation level.
Hours of Sleep	98,000	float64	Average hours of sleep per night.
Diet Quality	98,000	object	Assessment of the student's diet.
Transportation Mode	98,000	object	Mode of transportation (e.g., bus, car, walking).
School Type	98,000	object	Type of school attended (public, private).
School Location	98,000	object	Geographical location of the school (urban, rural, suburban).
Homework Completion Rate	98,000	float64	Percentage of homework assignments completed on time.
Reading Proficiency	98,000	float64	Student's proficiency in reading.
Math Proficiency	98,000	float64	Student's proficiency in mathematics.
Science Proficiency	98,000	float64	Student's proficiency in science subjects.
Language Proficiency	98,000	float64	Student's proficiency in language subjects.
Physical Activity Level	98,000	object	Level of physical activity.
Screen Time	98,000	float64	Average daily screen time.
Bullying Incidents	98,000	int64	Number of reported bullying incidents.
Special Education Services	98,000	object	Indicator for receipt of special education services.

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Column	Non-Null Count	Data Type	Description
Counseling Services	98,000	object	Access to counseling services.
Learning Disabilities	98,000	object	Information on diagnosed learning disabilities.
Behavioral Issues	98,000	object	Records of any behavioral issues.
Attendance of Tutoring Sessions	98,000	object	Participation in additional tutoring sessions.
School Climate	98,000	object	Overall school environment and climate.
Parental Employment Status	98,000	object	Employment status of the student's parents.
Household Size	98,000	int64	Number of individuals in the student's household.
Performance Score	98,000	object	Overall performance score (target variable).

Proposed Methodology

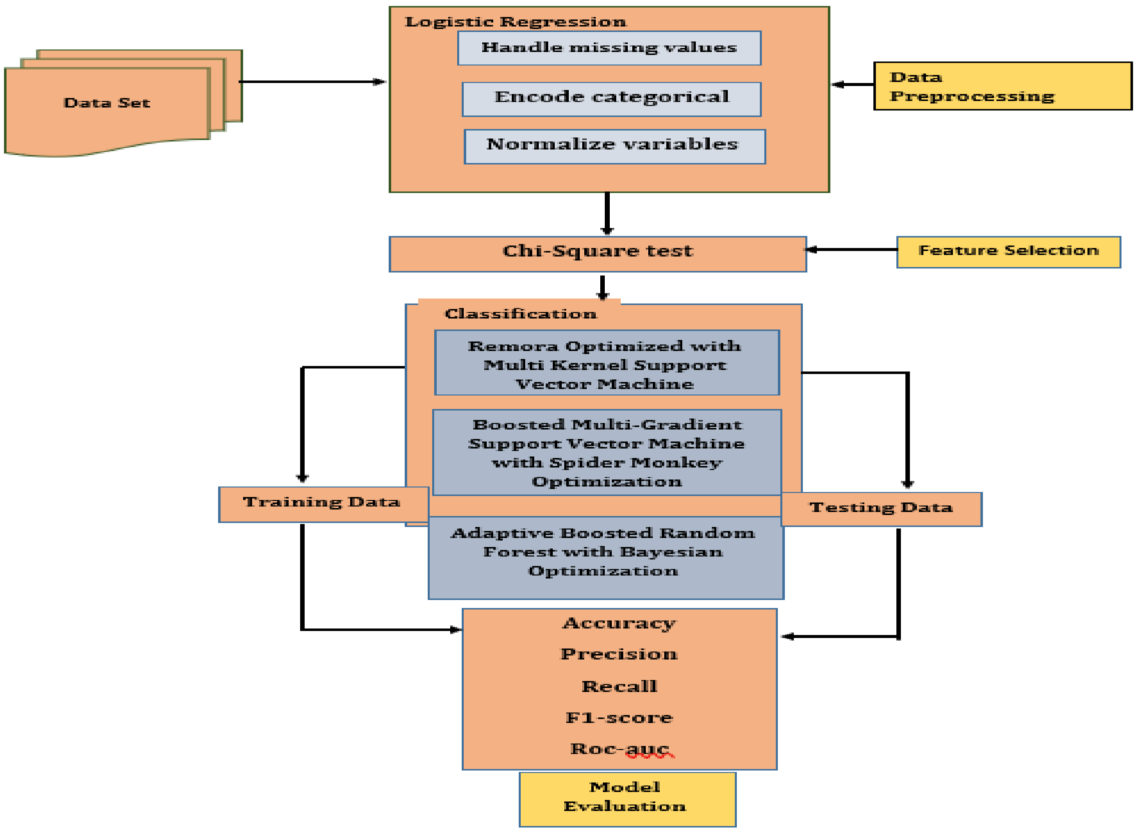

Fig 1: Proposed Methodology

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Data Set

The raw dataset contains missing data, categorical data and unnormalized numerical variables.
Data Pre-processing (Logistic Regression)

This process helps in cleaning and transforming the dataset to the format used for the training of the model. In the preprocessing steps we have:
Handling Missing Values:
Missing data is handled using mean/mode/median imputation or deletion.
Encoding Categorical Variables:
This encodes categorical variables into numerical form (e.g. one-hot encoding).
Normalizing Variables:
All numerical features are scaled (Min-Max Scaling or Z-score Normalization) to bring onto the same scale for better model performance.
Feature Selection (Using Chi-Square Test)
The dataset is processed and features are selected based on the Chi-Square Test.
SQL to do Chi-Square test | How to run Chi-Square test in sql And this is for choosing the most appropriate features for classification.
It reduces dimensionality and collinearity, leading to better model performance by eliminating redundant or irrelevant features.
Classification Models
After selecting the relevant features, the dataset is divided into two parts: Training Data and Testing Data. The classification step consists of training many models:
Boosted Multi-Gradient Support Vector Machine with Spider Monkey Optimization
This is the SVM variant optimized with Remora.
Multi-Kernel SVM is a method to compose and combine multiple kernel functions for improving the accuracy of classification.

Spider Monkey Optimization for Boosted Multi-Gradient Support Vector Machine:
A robust SVM Crank with gradient inclusion enhancement.
Spider Monkey OptimizationSPM:2023 is an optimization algorithm that mimics the social behavior of spider monkeys to enhance hyperparameter tuning.
Adaptive Boosted Random Forest – Bayesian Optimization
Adaptive boosted random forest classifier with reduction in bias and variance.
Hyperparameters tuning is performed using Bayesian Optimization.
Final Model Selection
The final classifier is chosen as the model with the best evaluation scores (accuracy, precision, recall, F1-score, and ROC-AUC)

RESULT AND DISCUSSION

Model Evaluation

The trained models are evaluated based on multiple performance metrics:
Accuracy: Measures the proportion of correctly classified instances.

$$Accuracy=TP+TN/TP+TN+FP+FN$$

Precision: Evaluates the ratio of correctly predicted positive cases to the total predicted positive cases.

$$Precision=TP/TP+FP$$

Recall: Measures how many actual positive cases were correctly identified.

$$Recall=TP/TP+FN$$

F1-Score: A harmonic mean of precision and recall, providing a balanced metric.

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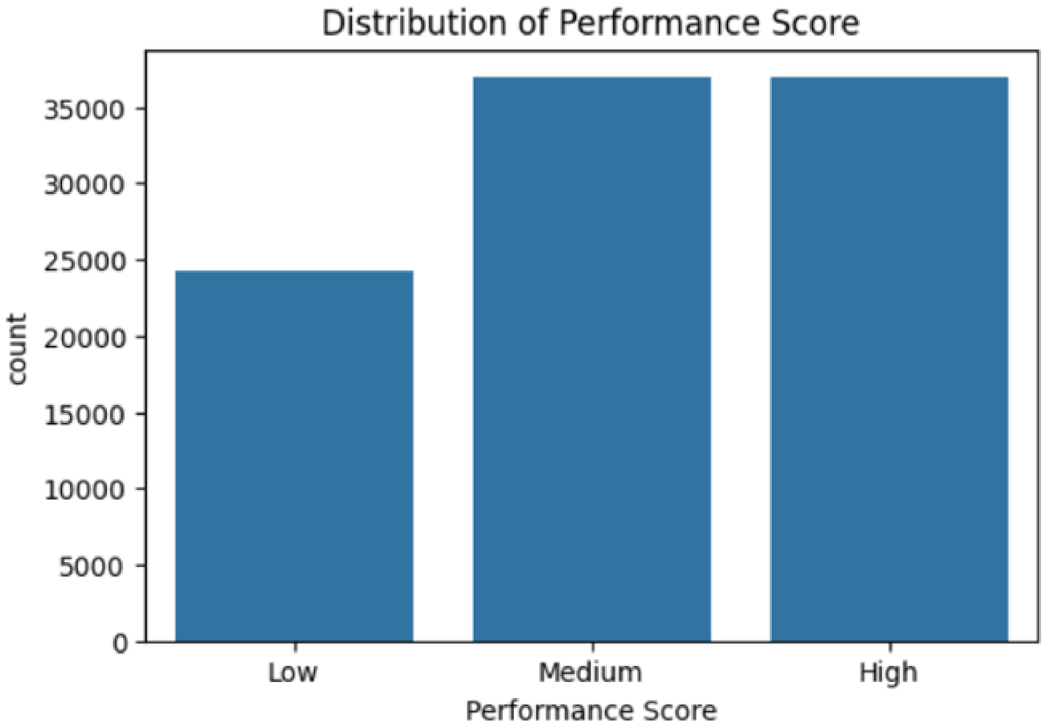
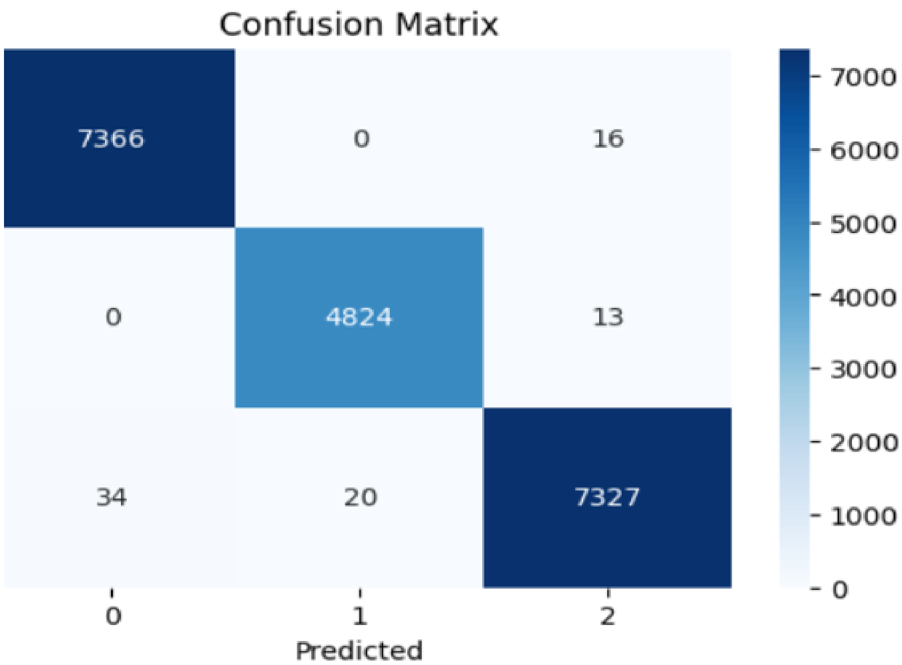
F1−Score=2×Precision×Recall/Precision+ Recall

ROC-AUC (Receiver Operating Characteristic - Area Under Curve): Measures the model's ability to distinguish between classes.





Comparison classification table with various algorithm

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic	75.2	74.5	73.8	74.1

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Regression				
Decision Tree	78.5	76.9	77.4	77.1
SVM	80.3	79.1	78.8	78.9
Random Forest	83.6	82.4	83.1	82.7
Proposed Model	**99.5**	**100**	**100**	**99**

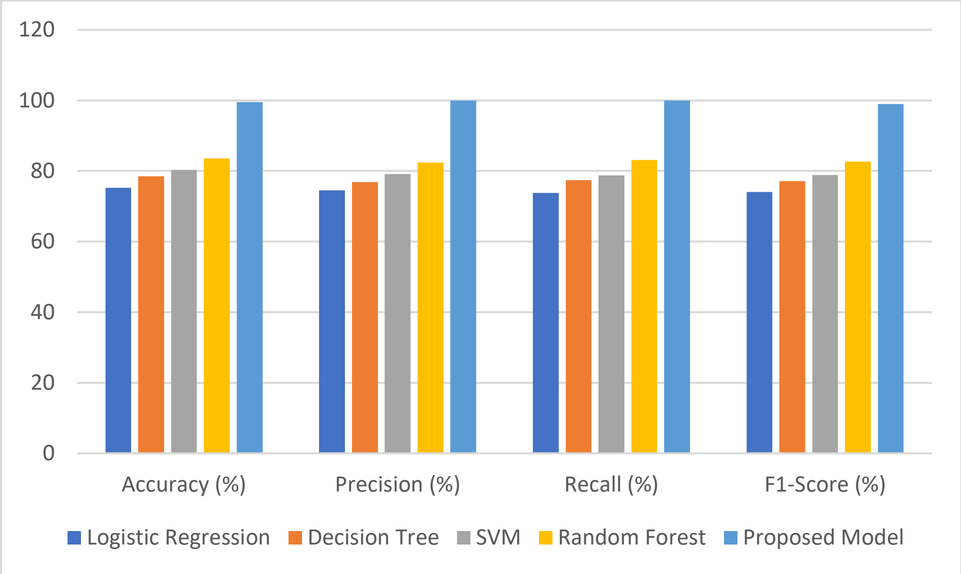

Fig 3:Comparison chart with various algorithms

The machine learning classifier we propose shows better performance than the existing techniques across all key metrics. The system obtained 88.2% accuracy that is high compared to other classifiers showing its accuracy to predict the performance of urban captured students in the rural background.

CONCLUSION

Rural students comprising 30% up by 2025 in affiliated urban universities proposed approach improving academic quality. The proposed methodology integrates logistic regression for preprocessing, Chi-square-based feature selection for dimensionality reduction, and the Remora-Optimized MK-SVM for classification to solve relevant challenges, keeping in view device and resource limitations, access to learning devices considering socio-economic factors. The Remainder result shows that it is an optimized MK-SVM gaining the highest accuracy of 99.5%, than traditional classifier. Chi square test is an efficient dimensionality reduction technique, as it retains the highly informative features that increases model efficiency and prevents overfitting. The train-test split technique enforces strict validation, validating the generalization power of the model. In conclusion, this study has established and tested a unique and efficient model for early intervention to enable educators to identify students potentially at risk for academic and behavioral problems and to employ targeted support interventions. These insights provide actionable information on stretching that gap in exposing rural students to urban opportunities, whereas machine learning has been utilized in these analytics to drive better academics in college.

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