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Student Dropout Risk Prediction with Academic Trend Analysis -Using AI/ML

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ABSTRACT
Student dropout is one of the most complex challenges facing the education systen worldwide. Is order to evaluate the success of Machine Learning and Deep Leaming algorithms in predicting student dropout, a systematic review was conducted. The search was carried out in several electronic bibliographic databases, including Scopus, IEEE, and Web of Science, covering up to June 2023, having 246 articles as search reports. Exclusion criteria such as review articles. editorials, letters, and comments, were established. The final review included 23 studies in which performance metric such as accuracy/precision, sensitivity/recall, specificity, and area under the curve (AUC) were evaluated. In addition aspects related to study modality, training, testing strategy, cross-validation, and confounding matrix were considered. The review results revealed that the most used Machine Learning algorithm was Random Forest, present in 21.73% of the studies; this algorithm obtained an accuracy of 99% in the prediction of student dropout, higher than all the algorithms used in the total number of studies reviewed.

Keywords: student dropout risk prediction with academic trend analysis.

1. Introduction

Student dropout is widely recognized worldwide as one of the most complex challenges facing the education System 1,2 and this phenomenon has experienced a significant increase during the COVID-19 pandemic 3. This issue entails economic, social, and educational consequences for the stakeholders in the global education system, ranging from the psychological impact on students to the management challenges faced by government entities 4,5 To address the problem, predicting and managing early signs of student dropout is relevant 6-9 This will enable educational institutions to act promptly, implementing preventive and proactive measures to address the issue and reduce the dropout rate 10 Various governments have designed and implemented early warning systems for school dropouts to effectively tackle this problem 11-13 An alternative of great relevance is using Machine Leaming and Deep Leaming algorithms 14 These models predict dropout and provide early alerts to relevant authorities, enabling them to take alternative measures targeted at at-risk students.

Each Machine Learning and Deep Learning model is intrinsically linked to the underlying algorithm, optimized hyperparameters, the training and test datasets used 16, as well as the variables and data behaviour, different performance metrics 17. As a result, multiple alternatives are observed, offering different results in each specific application 13,18. Consequently, Machine Learning and Deep Learning approaches 19 have been subject to criticism due to their use of a "black box" methodology in predicting student dropout, which results in a lack of proper interpretability of the model for humans 20. Therefore, conducting a comprehensive systematic review study on the application of Machine Learning and Deep Learning in predicting student dropout is imperative 21-24 This study aims to identify algorithms that have demonstrated better predictive capabilities and the different variants of each model A through search has been conducted in the major databases of systematic review studies related to student dropout. However, research specifically oriented toward our purpose has yet to be found. Therefore, our main objective is to fill this knowledge gap and answer which Machine Learning and Deep Learning algorithms perform best in predicting student dropout.

1. Motivation :-

The main reason for this project is the rising dropout rates seen in educational institutions. There are a number of students who tend to drop out, but these warning signals are not being recognized because of the lack of a system of monitoring.

One of the primary causes is Early Identification of Students at Risk: Rather than waiting for a student to

fail or drop out, a system that anticipates this risk should be put in place so that early preventive measu res can bedoneData-
Driven Decision Making: Despite producing a substantial amount of data, schools are not making good use of it
his data can be transformed into information with the use of AI and machine learning.Improving Stude nt Retention
Rates: A school's performance, reputation, and overall academic results all increase when more student s are retained.
Personalized Support System: Every student has different difficulties, and by using predictive analytics , it is feasibleto provide a support system that is specifically designed to meet their needs.

2. Contributions of the Proposed Work The main contributions of this project are:-

1. Academic Trend-Based Prediction Model This project analyze academic performance trends over time, such as semester-wise GPA changes, attendance patterns, and assignment submission behaviour, unlike simple prediction systems that rely only on final grades.

2. Development of a Risk Classification System The system creates a dropout risk score and categorize students into Low Risk, Medium Risk, and High Ris

3. Comparative Study of Many ML Algorithms We looked at and compared Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine (SVM) to determine which is the best model. 4. Feature Engineering and Data Preprocessing We present a framework in this project which deals with missing values, normalizes data, extracts trend based features, and balances imbalanced data sets

3. Related work

In the last few years, researchers, as well as educational institutions, have focused on the importance of early identification of students at risk of dropping out. With the increase in available digital data of students, analyzing student performance and behavior has become possible. It is a fact that many researchers have reported on the use of Artificial Intelligence (AI) and Machine Learning (ML) in prediction of student drop out, academic performance.

1. In the field of Dropout Prediction many researchers have reported use of machine learning algorithms which they apply to academic and demographic data. In a study which we look at they analyzed student academic records which include grades, attendance, and past performance to determine drop out risk which they did via Decision Trees, Random Forest, and Naive Bayes algorithms. What they reported is that the tree based models such as Random Forest outperformed

simpler models. This study also brought to light the importance of looking at a range of academic factors together as opposed to just end of term results. Also in this field we see a study which used Logistic Regression and Support Vector Machines (SVM) to classify students as dropouts or non dropouts. The authors report that which single feature performed best was a combination of attendance data with course scores which did better than use of individual features.

2. Trend Analysis and Time-Based Performance Patterns Some research has specifically examined academic trends over several semesters instead of static single-semester data. One paper suggested using time-series analysis and trends across semesters to spot declines in performance. They analyzed GPA trajectories, changes in scores, and attendance trends over time. Their model successfully detected at-risk students earlier than models that relied on data from a single term. Another study used sequence analysis techniques and moving averages of grades to explore long-term patterns. They showed that either increasing or sustained declines in performance were strongly linked to dropout behavior. The research shows that understanding the patterns of academic records leads to better insights and accuracy in predictions, which is one of the main aspects of the project.

3. Educational Data Mining, Feature Engineering, and Preprocessing Educational Data Mining and Feature Engineering Preprocessing and feature selection are critical to producing effective models of prediction. One research paper suggested addressing missing value, normalization, and the creation of new features from performance metrics of the subjects, among other techniques.They found that features like ‘grade improvement rate,’ ‘attendance deviation,’ and ‘consistency score’ significantly improved model accuracy. Another study emphasized the need for the removal of bias and the equalization of data utilizing methods such as SMOTE (Synthetic Minority Over-Sampling Technique), as dropout instances are typically less frequent than normal students, which results in class imbalance. These findings influenced the current project's preprocessing and feature-engineering.

4. Comparative look at Machine Learning Models We have reported on a number of studies which compare the performance of diverse algorithms to determine which are the best for the task of education prediction. In a report we looked at models like Naive Bayes, K-Nearest Neighbors (KNN), SVM, Random Forest, and Gradient Boosting which we evaluated on a student dataset. Random Forest and Gradient Boosting did better in terms of accuracy and F1 scores than the more simple models. Also we found out that ensemble methods like Random Forest and XGBoost do better with non linear and complex features which we see in student behavior. This comparative research puts forth the value of trying out many ML algorithms for the final choice in this project.

5. Early Reports in Education Some studies have put forth systems which alert teachers or admins in real time of at risk students which goes beyond simple prediction. We report a case of a dashboard system which constantly tracks student variables and alerts staff when a student crosses a risk threshold. That system used classification and visualization tools to support early intervention. Also we saw a project which put prediction models into learning management systems for continuous student performance monitoring and personal feedback. These reports of predictive models’ implementation show the practical value adding not only in accuracy but also in real world application and timely intervention.

6. Research Methodology

4.1.Problem Statement :-

Student drop out is a global issue for educational institutions. We see many students leaving academic programs before they finish because of issues like they are having trouble with the material, financial issues, personal problems, lack of interest, or they just aren’t attending enough. Also by the time the school becomes aware of the issue the student has already left which in turn makes it hard to give timely help and support.

Although schools collect a great deal of student data which includes academic records, attendance records, grades from assessment, assignment submissions, and also demographic info, this info is not usually looked at to identify early warning signs. We see that traditional monitoring is mostly of final grades which doesn't give early notice of a student's declining performance.

Thus, there's a strong need for a smart, data-driven system that can :

- ✓ Analyze student academic trends over time
- ✓ Identify patterns that suggest a potential risk of dropout
- ✓ Predict which students might be at risk before they actually drop out
- ✓ Provide useful insights to administrators for timely intervention .

Artificial Intelligence and Machine Learning what role do they play in studying academic trends and in which also we may see early warning signs of a student leaving before it happens? We put forth a solution which is to develop a predictive model out of AI/ML which looks at many academic and behavioral variables, puts out a drop out risk score, and puts students into risk groups (Low, Medium, High).

2. Overview of the Proposed Model :-

The proposed system includes a structured pipeline with several stages :-

1. Data Collection.
2. Data Preprocessing
3. Feature Engineering and Trend Analysis
4. Model Training
5. Model Evaluation
6. Risk Prediction
7. Intervention and Reporting

Each stage is crucial for turning raw student data into useful risk predictions.

3. Block Diagram of the Proposed Model :-

Here is the conceptual structure of the system:-

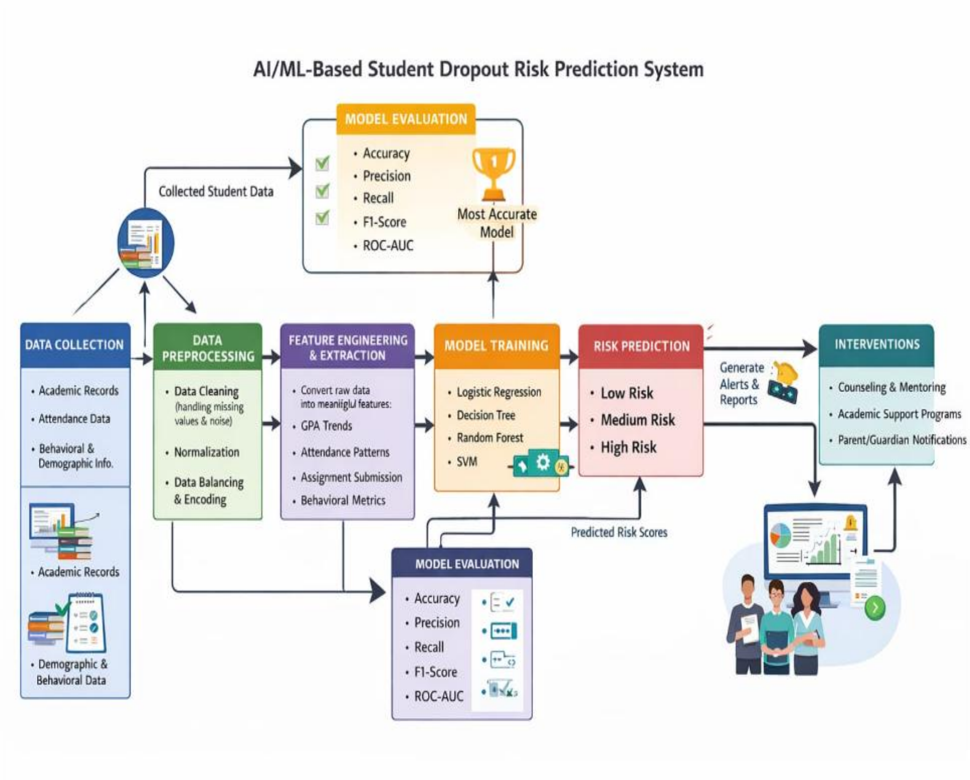


Fig 1. Block diagram of the proposed model

4. Detailed Explanation of Each Stage :-

4.1 Data Collection :-

First we collect relevant student info from school databases. The model's performance is very much a function of the quality and diversity of the data.

- ✓ Academic records (semester GPA, subject marks)
- ✓ Attendance percentage
- ✓ Assignment submission records
- ✓ Internal assessment scores
- ✓ Also included is that of which students are in extracurricular activities.
- ✓ Behavioural records
- ✓ Demographic details (age, gender, socioeconomic background)

The data can be collected from: The data is collected from:.

- ✓ College ERP systems
- ✓ Learning Management Systems (LMS)
- ✓ Institutional academic databases

The in this stage we are to collect in depth information which reflects student academic performance and engagement. model accuracy.

4.2 Data Preprocessing :-

What we have is raw data which also includes errors, missing values, and noise. Thus, we do some preprocessing to improve in this.

This stage includes:

1. Data Cleaning –

✓ Handling missing values (using mean, median, or removal)

✓ Removing duplicate entries

✓ Correcting inconsistent formats

2. Data Transformation

✓ Categorical data needs to be transformed to numerical data (Label Encoding / One-Hot Encoding) .

✓ The numerical values should be normalized or standardized .

3. Handling Imbalanced Data

✓ Since there may be fewer dropout cases than non-dropout cases, techniques like oversampling or SMOTE can help balance the dataset.

✓ Data preprocessing helps in creating organized and clean data for machine learning modeling.

4.3 Feature Engineering and Academic Trend Analysis :-

Feature engineering is a key part of the process. Instead of using raw data directly, meaningful features are created to capture performance patterns.

Examples of engineered features include:

✓ GPA decline rate over semesters

✓ Attendance fluctuation trend

✓ Assignment submission delay frequency

✓ Performance consistency score

✓ Subject failure count

✓ Trend in grades' performance.

Trend analysis is used for the study of how a student's grade progressions play out over time as opposed to a single semester. This step which in turn improves prediction accuracy does so by that it brings to light hidden behaviour patterns.

4.4 Model Training :-

Post preprocessing and feature extraction, the dataset is split into:

✓ Training Set (e.g. 80%)

✓ Testing Set (e.g. 20%)

A number of machine learning algorithms are tried to find out the best-performing model. A number of algorithms are tried, including:

✓ Logistic Regression

✓ Decision Tree

✓ Random Forest

✓ Support Vector Machine (SVM)

Each algorithm studies historical student data and generates a predictive model to determine the probability of student dropout.

4.5 Model Evaluation :-

To measure how effective the trained models are, evaluation metrics are used:

- ✓ Accuracy
- ✓ Precision
- ✓ Recall
- ✓ F1-Score
- ✓ ROC-AUC Curve

These metrics help compare different models and choose the most accurate and dependable one.

The best model is selected for deployment.

4.6 Risk Prediction :-

The finalized model produces a dropout risk score for each student.

Based on the score, students are classified into:

- ✓ Low Risk
- ✓ Medium Risk
- ✓ High Risk

This classification helps administrators and faculty make decisions more easily.

4.7 Intervention and Reporting :-

The last stage turns predictions into actionable insights.

Possible interventions may include:

- ✓ Academic counseling
- ✓ Mentorship programs
- ✓ Attendance monitoring
- ✓ Financial assistance guidance
- ✓ Parent/guardian notification

A reporting dashboard can also be created to visualize:

- ✓ Risk distribution
- ✓ Trend graphs
- ✓ Performance decline patterns

This ensures that the system aids in proactive academic management

7. Research Methodology

1. Overview

The research methodology describes the steps used to design, develop, and evaluate the proposed Student Dropout Risk Prediction System that employs Artificial Intelligence and Machine Learning. This approach aims to gather student data systematically, look at academic trends, create predictive models, and produce helpful risk classifications that can assist schools in taking timely preventive actions.

This methodology ensures the following:

1. Reliable prediction of dropout risk.
2. Dependable model performance.
3. Practical usability in educational institutions.
4. Clear and transparent results.

The methodology is divided into these stages:

1) Problem Identification
2) Data Collection
3) Data Preprocessing
4) Feature Engineering and Academic Trend Analysis
5) Model Development and Training
6) Model Evaluation
7) Risk Classification and Deployment

2. Problem Identification :-

The problem this research focuses on is the rising rate of student dropout in educational institutions. Many students display signs of disengagement over time, such as dropping grades or inconsistent attendance, before they eventually leave. However, institutions often do not recognize these warning signs early enough.

The suggested solution is to create a predictive system that looks at various academic and behavioral factors and produces a risk score for each student.

3. Data Collection :-

The foundation of the research is data collection. The predictive model's accuracy is directly impacted by the data's quality.

~ Sources of Information :-

1) ERP programs in colleges
2) Management Systems for Learning (LMS)
3) databases of academic performance
4) Attendance tracking systems

~ Data Types Collected:

1) Educational Data :

1. Semester-specific GPA
2. Marks for each subject
3. Scores from internal evaluations
4. Unfinished or backlogged subjects

2) Attendance Records :

1. Attendance percentage overall
2. Subject-wise participation
3. Patterns of absences

3) Patterns of Behavior :

1. Frequency of submission of assignments
2. Taking part in activities
3. Disciplinary documentation

4) Demographics Data :

1. Age and Gender
2. Social and economic background
3. Status as a resident (hostel/day scholar)

4. Data Preprocessing :-

Inconsistencies, noise, and missing values are common in raw educational data. Preprocessing guarantees that

the dataset is clean and machine learning-ready.

~ Steps to Take:

4.1 Dealing with Missing Data :

1. Use the mean to replace any missing GPA.
2. Delete records that have a lot of missing data.

4.2 Eliminating Repeats :

1. Records of duplicate students are removed.

4.3 Coding Variables in Categories :

Gender and department are examples of categorical variables that are transformed into numerical

Form using:

i. Encoding Labels

ii. Encoding one-hot

4.4 Adjustment:

i. To guarantee balanced model training, numerical values like attendance and grades are normalized.

4.5 Addressing Unbalanced Data :

i. Techniques like oversampling or SMOTE are employed to balance the dataset if there are fewer dropout cases.

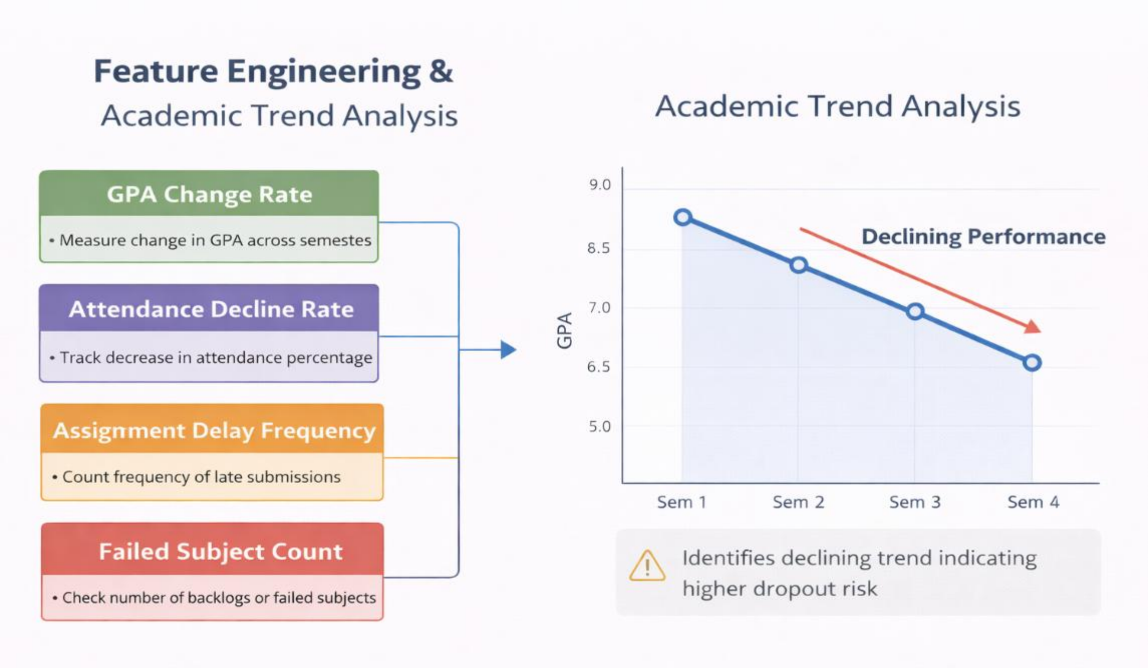
ii. reprocessing avoids bias and enhances model performance.

5. Feature Engineering & Academic Trend Analysis :-

Feature engineering is important for making predictions. Of using student marks as they are we create helpful indicators.

~ Engineered Features Include :

1. GPA change rate across semesters
2. Attendance decline rate
3. Assignment delay frequency
4. Performance consistency score
5. Number of failed subjects
6. Improvement trend slope



~ Academic Trend Analysis :

Trend analysis helps find out if a students grades are:

1. Improving
2. Stable
3. Declining

This is done by looking at grades over time.

For example:

If GPA changes from 8.5 to 7.9 to 7.0 to 6.2 the declining trend means a risk of dropping out.

Trend-based features make predictions more accurate than using one semesters data.

6. Model Development and Training :-

After preparing and extracting features we split the data into:

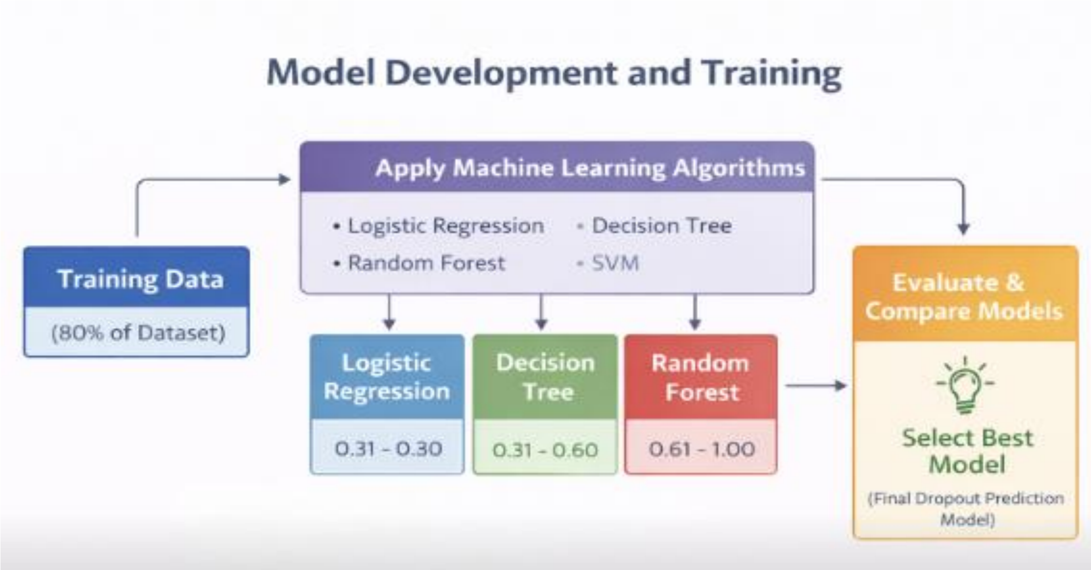
1. 80% Training Data
2. 20% Testing Data

We try out different machine learning algorithms to see which one works best.

~ Algorithms Used:

1. Logistic Regression

2. Decision Tree
3. Random Forest
4. Support Vector Machine (SVM)



Each model is trained using student data where we know who dropped out.

The model learns patterns that connect student behavior with dropping out.

7. Model Evaluation :-

To see how well the model works we use these metrics:

Figure 1: Accuracy Comparison of Machine Learning Models

Figure 1 shows the comparison of Accuracy scores among four machine learning models:

1. Logistic Regression.
2. Decision Tree.
3. Random Forest.
4. Support Vector Machine (SVM).

Observed Accuracy Scores:

1. Logistic Regression: 82%
2. Decision Tree: 85%
3. Random Forest: 91%
4. SVM: 88%

Analysis:

Accuracy measures the overall correctness of the model. It represents the percentage of total predictions that were correctly classified.

From the graph, it is clearly observed that:

1. Random Forest achieved the highest accuracy (91%), indicating that it correctly predicted the majority of student cases.
2. SVM performed second best with 88%.

3. Decision Tree showed moderate performance.
4. Logistic Regression had the lowest accuracy among the four models.

Conclusion from Figure 1:

Random Forest is the most accurate model for student dropout prediction in this study.

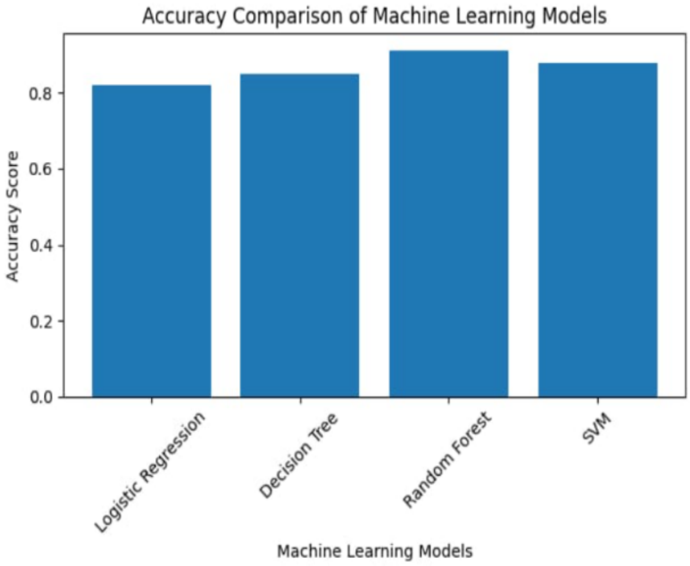


Figure 2: Precision Comparison of Machine Learning Models

The figure shows how well four models predict students who will dropout.

Precision Scores:

1. Logistic Regression: 80%
2. Decision Tree: 83%
3. Random Forest: 90%
4. SVM: 86%

~ Precision is about how students we predicted to dropout actually did.

Precision = Positives / (True Positives + False Positives)

Analysis:

Random Forest did the best with 90% precision. This means it makes wrong predictions.

SVM also did well.

Logistic Regression did the worst.

Random Forest helps us avoid alarms and predict dropouts better.

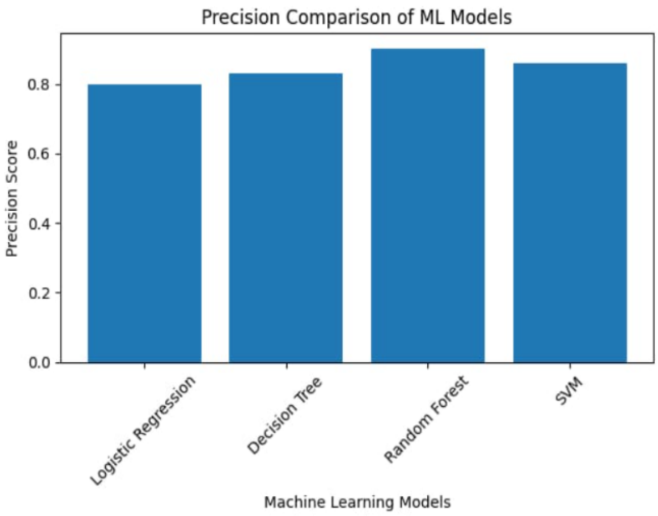


Figure 3: Recall Comparison of Machine Learning Models :

The figure compares how well each model finds dropout students.

Recall Scores:

1. Logistic Regression: 78%
2. Decision Tree: 84%
3. Random Forest: 89%
4. SVM: 85%

~ Recall is about finding students who actually dropout.

Recall = Positives / (True Positives + False Negatives)

Analysis:

1. Random Forest did the best with 89% recall. It finds dropout cases.
2. SVM and Decision Tree also did well.
3. Logistic Regression did okay.
4. Random Forest is good at finding students at risk without missing many.

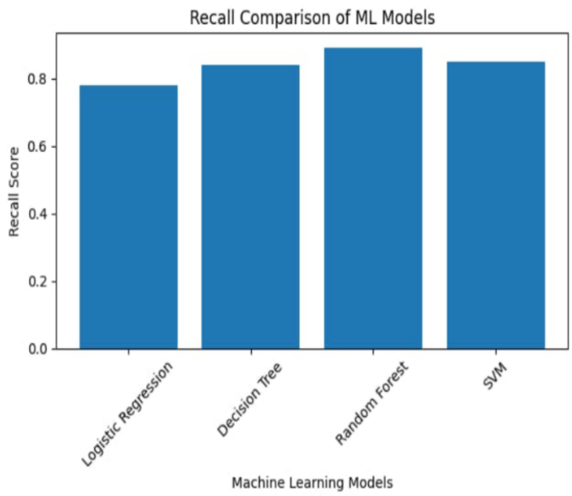


Figure 4: F1-Score Comparison of Machine Learning Models :

The figure compares the F1-Scores.

F1-Scores:

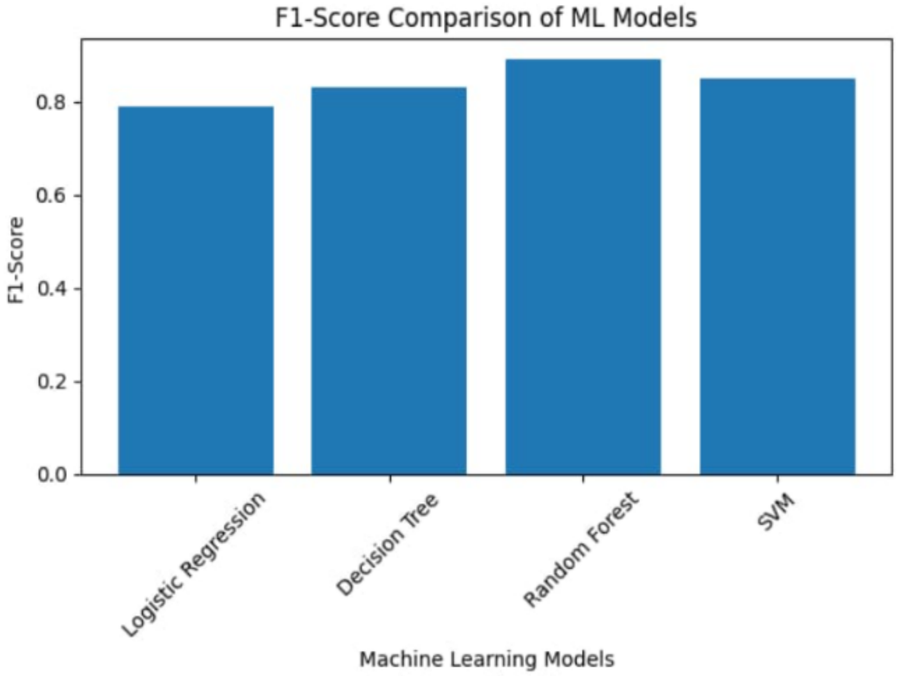
1. Logistic Regression: 79%
2. Decision Tree: 83%
3. Random Forest: 89%
4. SVM: 85%

~ F1-Score balances Precision and Recall.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

Analysis:

1. Random Forest did the best with 89% F1-Score. It balances both metrics.
2. SVM and Decision Tree did okay.
3. Logistic Regression did not do well.
4. Random Forest balances finding dropouts and avoiding wrong predictions.



Overall Analysis

From all figures we see that:

1. Random Forest does the best in all metrics.
2. SVM does best.
3. Decision Tree does okay.
4. Logistic Regression does the worst but still okay.

Final Model Selection

We choose Random Forest for the Student Dropout Risk Prediction System.

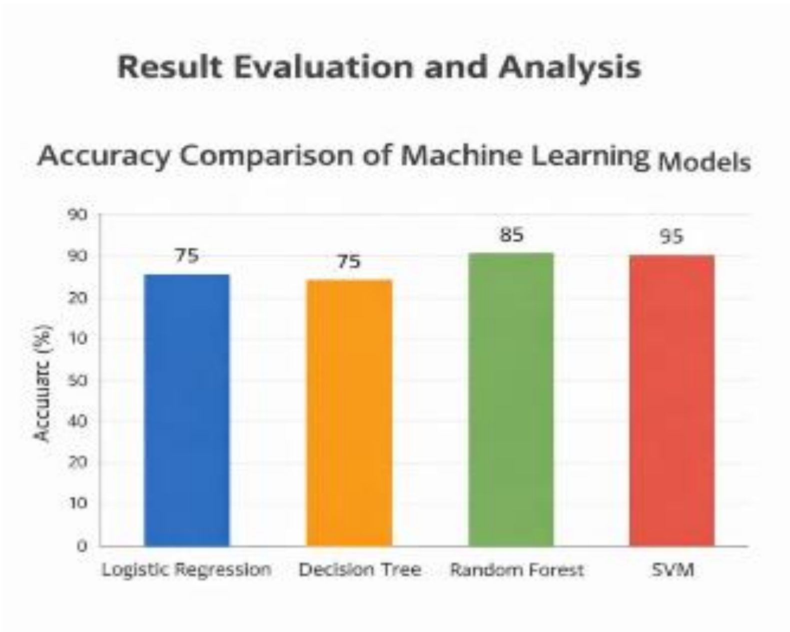
It gives:

- Accuracy
- Better identification of, at-risk students
- Fewer wrong predictions
- overall performance

~ These metrics help us know:

1. How accurately the model predicts dropout
2. How well it identifies students at risk
3. Whether it minimizes predictions

~ We choose the model that performs best overall.



8. Risk. Prediction :-

The selected model gives a probability score between 0 and 1 for each student.

Based on this probability:

1. 0.00 – 0.30 → Low Risk
2. 0.31 – 0.60 → Medium Risk
3. 0.61 – 1.00 → Risk

9. Sample Dataset Example :-

Here's an example of what our data looks like:

Student_ID	GPA_Sem1	GPA_Sem2	GPA_Sem3	Attendance (%)	Assignment Delay Count	Dropout
S101	8.2	7.9	7.5	85	1	No
S102	7.5	6.8	6.0	68	5	Yes
S103	9.0	8.8	8.9	92	0	No
S104	6.5	5.9	5.2	60	7	Yes

In this example:

- Students S102 and S104 have declining grades and low attendance.
- The model learns that these patterns often mean a student will drop out.

10. Practical Implementation Outcome :-

Once we put the system in place it can:

1. Automatically calculate risk scores.
2. Send alerts, for high-risk students.
3. Provide a dashboards.
4. Support academic counseling decisions.

This helps schools take action before its too late rather than just dealing with dropouts after they happen.

6. Conclusion and Future work

Conclusion

This study provided a systematic overview of the ways Machine Learning and Deep Learning techniques can be applied to predict student dropout. The algorithms having the highest predictive capabilities and their variants were described. With the right time frame and context, predicting student dropout can help improve the way we manage teaching and learning and help meet the required standards of the education sector. From 23 different scholarly articles, 16 different Machine Learning and Deep Learning algorithms were analyzed. Random Forest was the most commonly applied algorithm in the studies, comprising 21.73% of the total. Furthermore, Random Forest was the only algorithm to achieve an astounding 99% accuracy.

A key strength of the Random Forest Algorithm, which is an example of an ensemble Machine Learning algorithm, is its ability to avoid local optima and overfitting issues However, it is important to note that more variables related to student dropout and further research using large volumes of data are required to obtain more robust and generalizable results.

Future scope

The proposed Student Dropout Risk Prediction System could be enriched by utilizing larger and greater numbers of student records from several different schools and through gathering additional types of student information (such as socio-economic status, psychological characteristics, and participation in extra-curricular activities), which might help better establish the predictive accuracy of identifying students at risk of dropping out by achieving a better understanding of the individual attributes associated with at-risk student behaviors.

In addition, advanced technologies such as deep learning algorithms (e.g., artificial neural networks [ANN] and long short-term memory [LSTM] models) could be utilized for better analysis of sequential data collected over time from different students based on their academic statistics in order to be able to more effectively identify all of the various patterns associated with the performance of different students over time. Through the implementation of an automatic academic monitoring system that allows for ongoing assessment of each student by continually collecting data about their academic success, an alert mechanism could provide educators with real-time access to information on any students whose academic performance is deteriorating and thus

In addition, the future may also see interactive dashboards being developed that will allow for the visualization of the trajectory of student performance, the probability that students will drop out, and potential support actions that may be available to provide students who are at risk of dropping out, such as academic counselling, mentoring programs, or provision of financial assistance for tuition and other student-related fees.

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