Predictive Analytics for Identifying Academic Risks in Students with Disabilities

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ABSTRACT:

The innovative approach to risk identification in the academic performance of students with disabilities is the concept of predictive analytics because it enables the possibility to detect possible risks early in their development and offer individual help. The complete machine learning model is created that incorporates the scholarly, behavioral and disability specific characteristics to boost the accuracy of prediction. Various algorithms, such as Decision Trees, Random Forest, Support Vector Machines, and Gradient Boosting are analyzed, and ensemble algorithms prove to be more effective. The framework also uses explainable AI techniques to promote transparency and enable informed decision-making. Experiment findings suggest that the presence of contextual and accessibility-related features greatly enhance risk prediction ability. It is also responsible in

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terms of ethical considerations of fairness, data privacy, and inclusiveness. The suggested system offers a viable and scalable approach to enhancing the academic performance and decreasing the chances of dropping out of school in students with disabilities.

Keywords: Predictive Analytics, Academic Risk Prediction, Students with Disabilities, Machine Learning, Inclusive Education, Explainable AI.

I. Introduction

Inclusive education has become one of the urgent concerns of the contemporary academic system, with an accent on the equal learning opportunities to be offered to students with varying abilities. Students with disabilities usually face complex issues that impact their performance at school, such as cognitive, sensory, socio-emotional, and absence of individualized instructional support. These problems make them vulnerable to academic risks including low grades, retardation and increase their dropout rates. The old system of assessment that is predominantly based on periodic assessment fails to detect any early warning signs of academic problems, hence restricting the possibility of intervening in time. With recent innovations in predictive analytics and decision-making based on data, there are new opportunities to transform educational support systems. Predictive analytics uses both past and current data to determine patterns and predict the future, allowing educators and administrators to achieve proactive actions to mitigate the risk of academics to occur (Albreiki et al., 2021; Buenaño-Fernández et al., 2019). When applied to the student with disabilities, these approaches have a great potential, as they can be used to monitor the student personally and identify the obstacles to their learning early. With the help of combining machine learning algorithms and educational datasets, one will be able to create smart systems that are capable of predicting academic performance and detecting at-risk students with a higher level of precision (Aggarwal et al., 2021; Kanetaki et al., 2022; Kittur et al., 2022).

Although the importance of educational data mining and learning analytics has been increasing, the current models tend to be not inclusive and consider the factors unique to disabilities. Most of the predictive systems are created using generic datasets which fail to address the individual learning patterns and the support requirements of students with disabilities. This restriction implies the necessity to use special frameworks that may include both academic and non-academic measures, including the use of assistive technologies, behavioral trends, attendance record, and individualized education plans (IEPs) (Karabatak et al., 2024). The significance of psychological, social, and experiential variables in the educational outcomes has been highlighted by previous research as well, which also proves the necessity of inclusive predictive models (Hübner et al., 2021). The current study concentrates on creating a predictive analytics platform to be specific to the detection of academic risks of students with disabilities. The proposed solution combines various data sources, most modern machine learning tools, and explainable AI processes to guarantee accuracy and interpretability. The research will fill the gap between the theoretical progress of predictive modeling and practice in the inclusive school setting.

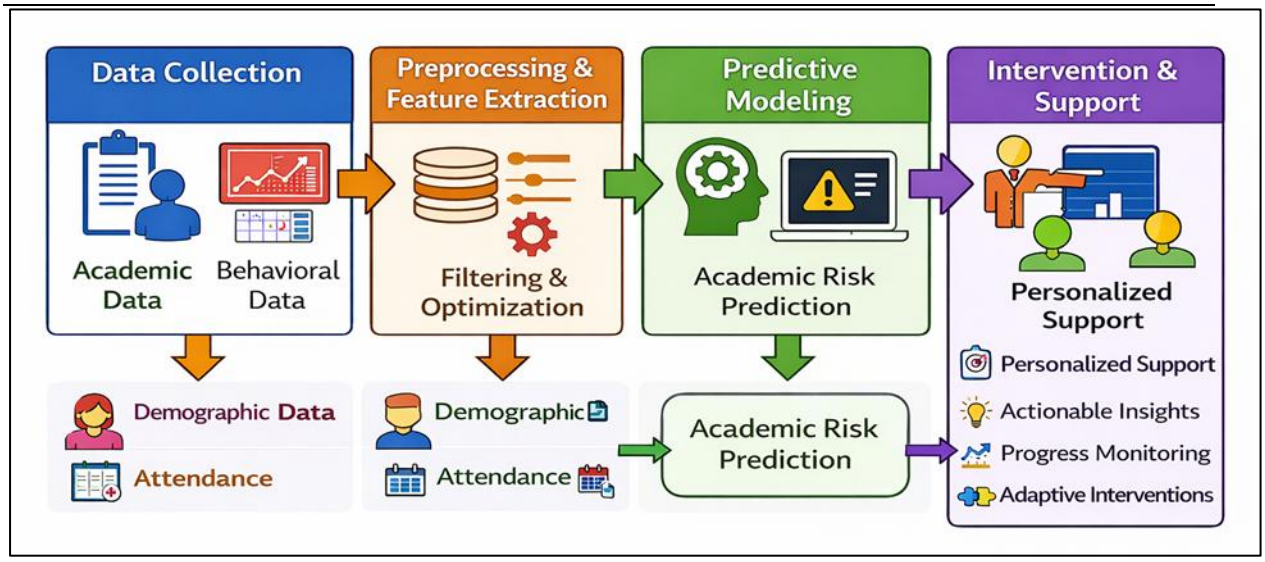

Figure 1. Predictive Analytics Framework for Academic Risk Identification in Students with Disabilities

Inclusive education has become one of the urgent concerns of the contemporary academic system, with an accent on the equal learning opportunities to be offered to students with varying abilities. Students with disabilities usually face complex issues that influence their performance in school, such as cognitive, sensory, socio-emotional and inadequate instructional support. These problems make them vulnerable to academic risks including low grades, retardation and increase their dropout rates. Conventional evaluation systems that are largely based on an infrequent evaluation system can hardly detect initial indicators of academic challenges thus crippling the ability to act in time. New possibilities to reform the system of educational support have appeared with the recent development of predictive analytics and decisions made based on the data. Predictive analytics is based on past and present data to identify trends and forecast the future to enable educators and administrators to take actions beforehand to avert any academic perils that might arise. The effectiveness of such strategies regarding students with disabilities is rather high because it will be possible to individually track each of them and spot learning barriers at an early stage. Combining machine learning algorithms with the educational data, it is possible to develop intelligent systems that will be more accurate predictors of academic performance and will help identify at-risk students. Though the significance of educational data mining and learning analytics has been on the rise, the existing models are rather trendy and not all-inclusive, taking into account the factors peculiar to disabilities. The majority of the predictive systems are developed based on general data sets that do not support the individual learning profiles and the students with disabilities support needs. The specified constraint underscores the need of implementing special frameworks that would incorporate the application of both academic and non-academic measures, such as the application of assistive technology, behavioral trends, attendance levels, and individualized education plans (IEPs). The present research paper focuses on the design of a predictive analytics platform that will be specific to the identification of academic risks of students with disabilities (White et al, 2025). The suggested approach will combine several sources of data, the most recent machine learning algorithms, and interpretable AI processes to achieve the accuracy and interpretability goals. school environment.

II. Literature Review and Gap Identification

The major statistical techniques that were used in early studies were regression analysis to determine the correlation between academic performance and other variables including attendance, grades and demographic variables. As machine learning methods have evolved, more advanced models such as decision trees, random forests, support vectors

machine and neural networks have been used to improve the predictive accuracy. Learning analytics studies have shown that behavioral data, including learning management system (LMS) usage, assignment submission frequency, and frequency of interaction can be powerful predictors of academic achievement. These methods have been extensively embraced in institutions of higher learning in order to come up with early warning systems to help in curbing the number of dropouts. Nevertheless, the majority of these systems are aimed at the general population of students and fail to specifically refer to the needs of students with disabilities.

Table I: Summary of Existing Studies and Research Gaps

Study Focus	**Method Used**	**Key Findings**	**Identified Gap**
Student Performance Prediction	Regression Models	Identified correlation between grades and attendance	Lacks disability-specific features
Dropout Prediction Systems	Decision Trees, SVM	Early warning systems improve retention	Limited personalization for diverse learners
Learning Analytics (LMS Data)	Data Mining Techniques	Engagement metrics predict academic success	Ignores accessibility and assistive technology factors
Special Education Studies	Qualitative Analysis	Focus on individualized learning strategies	Minimal use of predictive analytics
AI-Based Education Systems	Neural Networks, ML	High prediction accuracy achieved	Lack of explainability and transparency

Research on special education has been mostly on qualitative measurements, individualized teaching methods and assistive technologies. Although such contributions are worthy, predictive analytics are not integrated much in this field. The current literature does not pay much attention to such key factors like cognitive diversity, accessibility needs, and adaptive learning behaviors. In addition, predictive modeling datasets rarely include disability specific attributes, resulting in biased or incomplete predictions. The other weakness that is noteworthy is that predictive models lack the ability to be explained. Black-box algorithms are also correct but do not have a lot of information on the factors influencing the predictions. This is particularly a weakness as far as education is concerned and where transparency and accountability play an important role in decision making. Teachers must have models, which are interpretable and can be used to come up with predictions and interventions.

III. Problem Formulation and Research Objectives

The issue of identifying academic risks of students with disabilities is a multidimensional and multifaceted question and demands to integrate various types of data and analysis methods. The disability and learning pattern heterogeneity and the need to be supported presents extreme challenges in generalizing the predictive models. The conventional approaches fail to necessarily capture these complexities, and thereby cause the

misidentification or delayed identification of students at risk. In its turn, a systematic problem statement is a prerequisite to come up with a useful predictive analytics framework that is inclusive education-specific. The issue can be defined as the challenge of establishing the risk of a student with disabilities to be in academic danger using the past and current educational history. Academic risk in this context is the risk of poor academic performance, lack of engagement with learning or even dropout. The predictive model should take into account a large set of the input variables such as academic history, attendance history, and indications of behavior, accessibility requirements, and the use of assistive technology. These inputs create a multidimensional feature space that is a reflection of cognitive and environmental factors that affect student performance. The idea is to come up with a monitored learning model in which the input characteristics are represented as a target variable of the academic risk levels (e.g., low, medium, high). The issue is that it is difficult to choose the most relevant features, missing or unbalanced data, and make sure that the model is robust among the various types of disability. Also, the model should be able to generate interpretable results that can guide teachers to make well-informed decisions.

IV. Proposed Predictive Framework

This proposed predictive model is customized to fully detect academic risks among students with disabilities through a combination of data gathering, pre-processing and modeling and decision support systems. The architecture adopts a multi-layered architecture that offers an effective flow of data and accurate prediction and at the same time is interpretable and scalable. Data acquisition layer is at the bottom level and collects data about various sources, including academic records and attendance logs, behavioral observations and assistive technology use. These data sources give a nutritious description of the performance and learning conditions of the students. The dataset is contextually suitable since it comprises disability-specific items, e.g., type of impairment, the needs of the accommodation, and individualized education plan. The cleaning, normalization and transformation of data is done by the preprocessing layer. The non-observed values will be handled through the aid of the imputation techniques, and the categorical variables will be coded so that they can support the machine learning applications. Both correlation analysis and principal component analysis are dimension reduction techniques taken to remove the dimensions and improve the efficiency of the model taken.

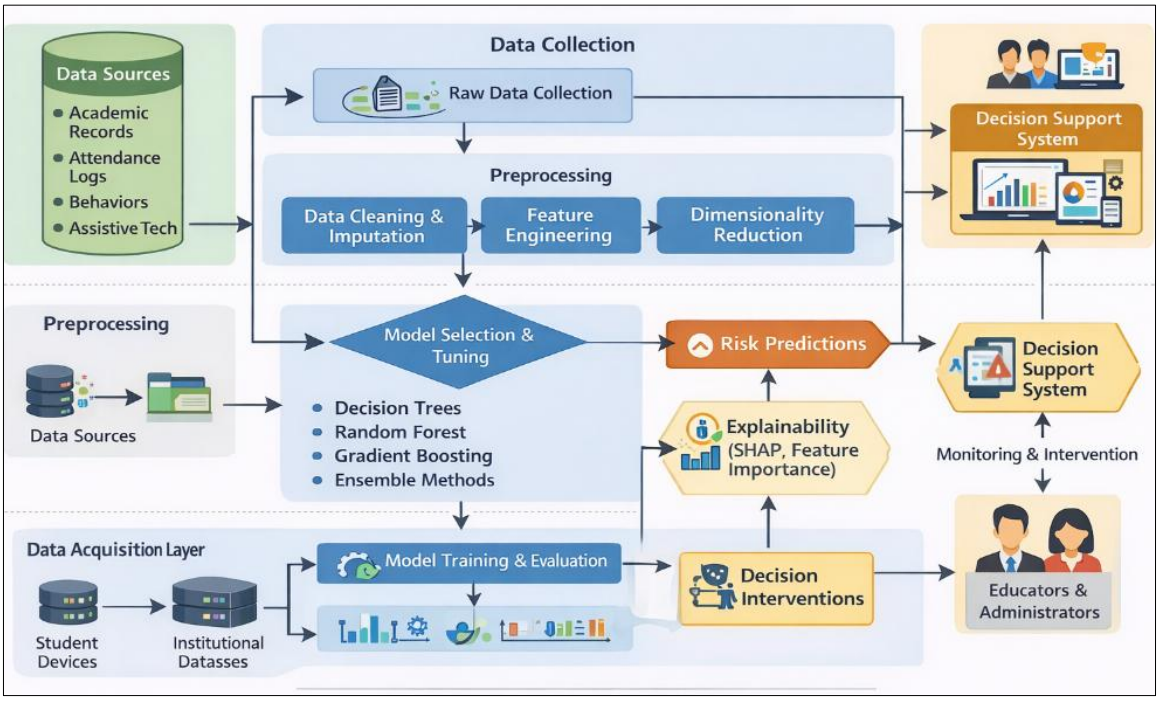

Figure 2. ML-Based Workflow for Academic Risk Prediction in Inclusive Education Systems

Predictive modeling layer is the main element of the structure and it involves the machine learning models to categorize the students according to the degree of academic risk. Different models are taken into consideration like decision trees, random forests and gradient boosting techniques to determine which one is the best. Ensemble techniques are also believed to increase predictive performance, and minimize overfitting. The framework has a module of explainability which provides insights into model predictions. The techniques such as feature importance analysis and SHAP (Shapley Additive Explanations) values, which are valuable to establish the critical factors influencing academic risk help to identify the features that are important. This kind of transparency assists teachers in gaining an understanding of the cause of the risk and creating the particular intervention. The last layer is the decision support system that develops insights and predictions in the form of convenient to use dashboards. This interface will assist the administrator and educator to track the performance of the students, know the students who are at risk and take intervention measures in time.

V. Machine Learning Model Development

It is activated by transforming ready educational data to an organized form that can be utilized with overseen education algorithms.

$$D = \{(xi, yi)\}i = 1N$$

As the data is heterogeneous (numerical variables, categorical variables, behavioral variables) it is encoded with appropriate encoding strategies such as one-hot encoding and label encoding in such a way that it can be used with other models. Data is also normalized and standardized to provide consistency and improve convergence, during model training.

$$f(xi) = y^i$$

Various machine learning algorithms are experimented with to find the most helpful predictive method to use. The initial reason why Decision Tree models are employed is that they are straightforward, easy to analyze and have the ability to model nonlinear relationships among the input features and the target outputs. These models provide a clear illustration of what decisions are made where, it is more beneficial in learning situations where transparency is a key factor. However, to overcome constraints such as overfitting and poor generalization, the ensemble-based approaches are used.

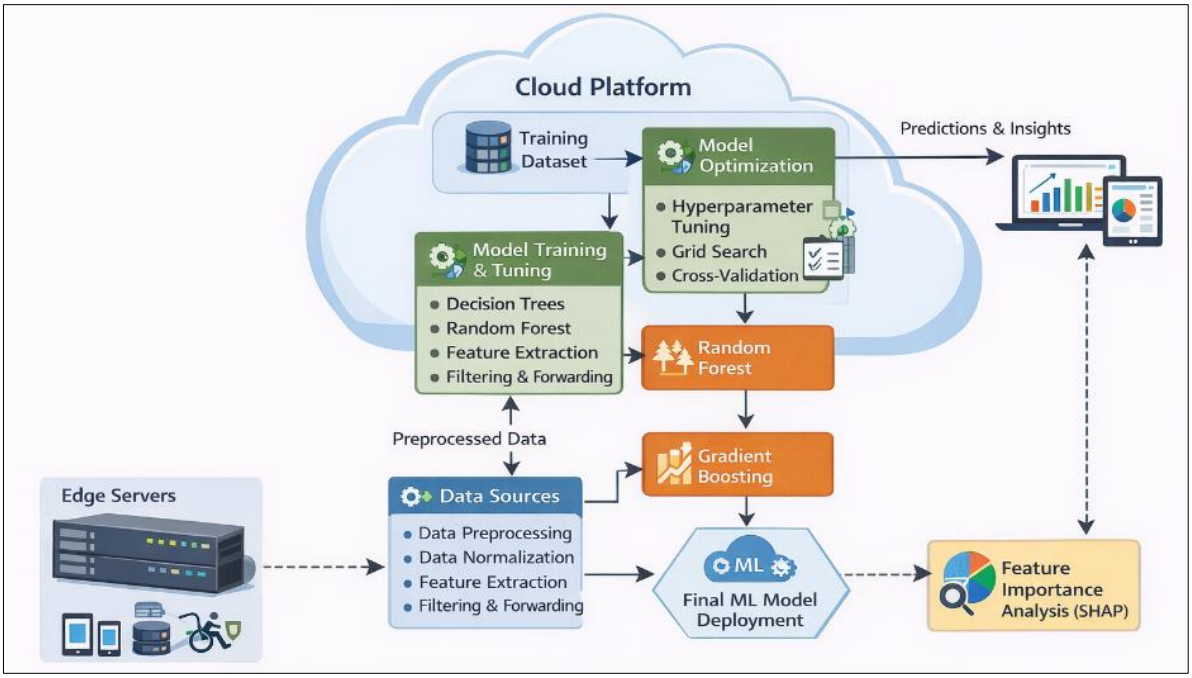

Figure 3. Deployment Diagram of Machine Learning Model Development Framework

The figure 3 displays the machine learning pipeline on end-to-end machine learning which is used to predict academic risk. The first stages of preprocessing data are encoding and features selection stages. The processed features are then fed to a number of machine learning models like Decision Trees, Random Forest and Gradient Boosting.

$$L = -i = 1\sum Nc1 = Cyic\log\sum\left(y^{ic}\right)$$

Hyper parameter optimization and cross-validation are useful in optimization of model performance. Ensemble methods are used to combine the outputs of individual models to give the final prediction of the level of academic risk.

$$y = T1t = 1\sum Tft(x)$$

Random Forest models enhance the accuracy of prediction, through the combination of a number of decision trees using bagging techniques. The technique reduces variance and improves robustness specifically in high dimensional data in the presence of noise. .

$$Fm(x) = Fm - 1(x) + \eta \cdot hm(x)$$

Gradient Boosting algorithms may also be employed to predictive performance, e.g., XGBoost. These models gradually correct the previous steps, and thus, are quite handy in learning rich interactions among features and learning imbalanced sets of data which are commonly posed in academic risk prediction problems. They are also optimized systematically, through systematic tuning of the hyperparameters of a model using grid search and cross-validation. All the most crucial parameters, such as the depth of the tree, the learning rate, the number of estimators and the minimum splits, are adjusted to find the most suitable ones. Stratified k-fold cross-validation is also employed to ensure that each fold is balanced in terms of at-risk and non-risk students and to increase the chances that the model will be able to generalize and reduce bias. It is important to analyze the importance of features which enhance the predictive model. The model identifies the variables that are of the greatest importance, the regularity of attendance, the proportion of assignments done, the involvement of assistive technologies and student engagement level. Not only does this process increase the computational efficiency by removing redundant features but also increases interpretability such that educators are able to see the factors behind academic risk. The last model is chosen to be based on a thorough analysis of performance metrics, such as accuracy, precision, recall, and F1-score, and interpretability aspects. In order to make sure that it can be practically implemented into the life of educational activities of the real world, the emphasis is placed on the fact that it is possible to strike a balance between predictive performance and explainability. A reliable and transparent tool of early intervention of academic risks would be the resulting model that would simplify timely and precise methods on the students with disabilities.

VI. Experimental Evaluation and Results

The proposed predictive framework is evaluated experimentally to determine the effectiveness of the proposed framework with real and simulated educational data. The data set is separated into training and testing sets, which usually are in the proportions of 80:20 to test the performance of the model on unseen data. The assessment is centered on the classification accuracy, and the capability to identify at-risk students. The dataset employed is this study has a wide range of features that reflect academic, behavioral and disability specific characteristics. These characteristics are well chosen to make sure that the student performance and learning conditions are fully represented. The predictive model is contextualized by including disability-related variables like the use of assistive technology and type of impairment.

Table 2: Dataset Description and Feature Distribution

Feature Category	**Feature Name**	**Type**	**Sample Value**	**Description**
Academic Performance	GPA	Numerical	6.8	Semester grade point average
Attendance	Attendance Rate (%)	Numerical	72%	Percentage of classes attended
Behavioral	LMS Login Frequency	Numerical	15/week	Number of logins per week
Assignment	Submission Completion Rate	Numerical	65%	Percentage of assignments submitted
Disability-Specific	Assistive Tech Usage	Categorical	High	Usage level of assistive tools
Disability Type	Disability Category	Categorical	Visual	Type of disability
Engagement	Class Participation Score	Numerical	5/10	Engagement in classroom activities
Socio-Emotional	Stress Indicator Level	Numerical	7/10	Self-reported stress level
Outcome Variable	Academic Risk Level	Categorical	High	Target variable (Low / Medium / High risk)

The assessment utilizes a set of performance measures to give a full evaluation such as accuracy, precision, recall and F1-score. Precision is the percentage of correctly identified at-risk students of all the predicted at-risk cases and recall is the power of the model to identify real at-risk students. The F1-score would be a more balanced score as it combines both precision and recall, thus it can be especially useful when the dataset is imbalanced (as in many datasets of at-risk students, there are many more non-risk students). Several machine learning models are executed and evaluated to find out which is the most suitable predictive method. They are Decision Trees, Random Forest, Support Vector Machines, Gradient Boosting and Logistic Regression. All the models are trained and tested on equal experimental terms in order to make a fair comparison.

Table 3: Model Performance Comparison

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC**
Decision Tree	78.5	75.2	72.8	74.0	0.79
Random Forest	86.3	84.5	82.7	83.6	0.88
Support Vector Machine	83.1	81.0	79.5	80.2	0.85
Gradient Boosting	89.2	87.6	86.4	87.0	0.91
Logistic Regression	80.4	78.9	76.3	77.6	0.82

The findings show that ensemble-based models, especially Gradient Boosting and random forest, outperform the traditional single model approaches in all the evaluation measures. The best predictive capability with the highest accuracy of 89.2% and AUC-ROC at 0.91 indicates that Gradient Boosting can predict the risk categories with high accuracy and a high degree of discrimination. Random Forest also exhibits strong results, as it has the advantage of being an ensemble and can deal with variation of features. Decision Trees have a lower degree of accuracy, but have good interpretability which is

useful in understanding both decision boundaries and feature contributions. The Support Vector Machines are not the fastest or the slowest and can be sensitive to parameter adjustment to give the best results. Although simpler, Logistic Regression can be an effective baseline model to make comparisons. The presence of disability-specific features plays a larger role in enhancing the accuracy of prediction, which demonstrates the value of modeling the context in inclusive education. The reliability of the proposed framework and its consistency is further confirmed using the visualization tools like confusion matrices and ROC curves. The results of the experiment confirm the usefulness of the predictive analytics method in determining academic risks in students with disabilities. The framework has strong capabilities of being applied in practice and helps educators to carry out timely interventions and enhance student performance.

VII. Explainability and Decision Support

To achieve transparency and trust in predictive analytics systems applied in education, explainable AI (XAI) techniques need to be incorporated. With students with disabilities, the issue of interpretability is even more important, because educators and other stakeholders need to have the knowledge of the underlying factors behind each prediction, to implement relevant interventions. As a main form of interpretability technique, feature importance analysis is used. The system prioritizes features, i.e., factors that contribute to model predictions, to emphasize important aspects of academic risk factors. Other variables like consistency of attendance, GPA, rate of doing assignments, and LMS activity are noted to be the most influential in prediction results followed by assistive technology use and level of engagement.

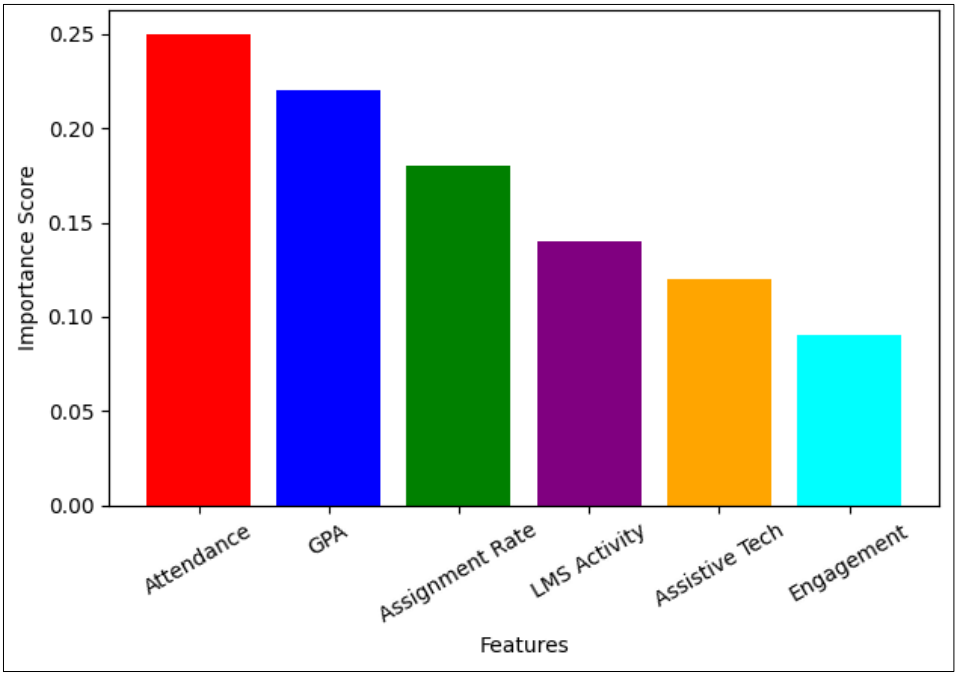

Figure 4. Illustrates the Feature Importance Distribution Derived from the Predictive Model

It is evident in the plot that the predictors of attendance and GPA are dominant and thus to show that the consistent participation and academic performance remains central even in disability-inclusive environments. But the fact that the use of assistive technology and interaction are important factors emphasize the significance of accessibility and adaptive learning support. State of the art explain ability methods like SHAP (Shapley Additive Explanations) values are included to give a detailed explanation of individual predictions. SHAP values are used to measure the influence of each feature on a particular prediction, and allow a finer insight into why a student is being labeled as high-risk.

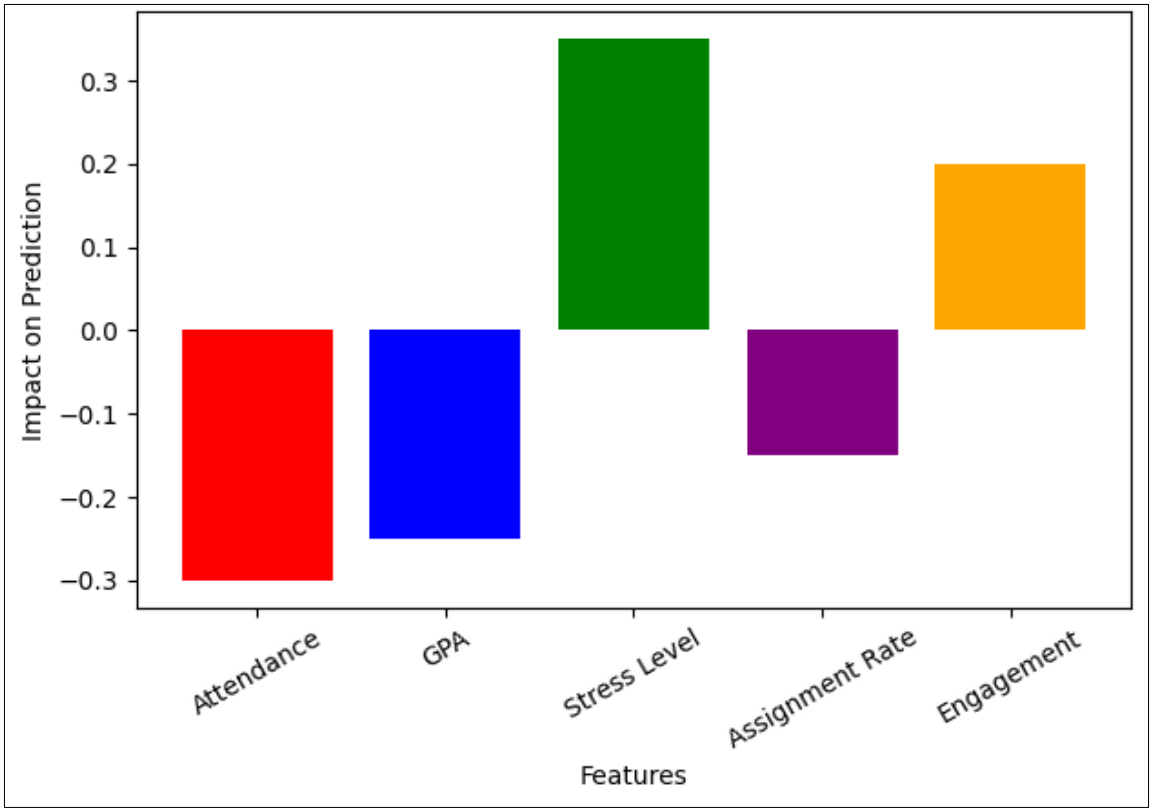

Figure 5. Presents a SHAP-Like Contribution Plot Demonstrating Positive & Negative Influences of Features

According to the plot, stress levels and lack of engagement are all aspects that positively influence academic risk, but good attendance and GPA have an adverse effect and decrease the risk probability. This two direction interpretation enables educators to be able to clearly identify the risk-inducing and risk-reducing factors.

VIII. Ethical, Social, and Accessibility Considerations

Predictive analytics implementation in education are greatly affected by ethical, social, and accessibility issues, especially when working with disabled students. The fairness, transparency and data privacy is crucial to avoid such unintended consequences as discrimination or bias.

The application of predictive analytics should be used socially towards the objective of helping students, instead of branding or stigmatizing them. The framework aims at helping teachers offer solutions in time, instead of punishment strategies in order to foster a student-friendly learning atmosphere.

IX. Conclusion and Future Directions

This paper demonstrates that predictive analytics could be useful in disclosing the academic risks of students with disabilities through an inclusive and data-driven model. The synergistic effect of the different traits (including academic performance, behavioral signs and disability-related traits) is very high, making risk prediction models more precise and applicable. The two solid and trustworthy ensemble learning methods are Gradient Boosting and Random Forest, although explainable AI methods are ensured to be non-opaque and transparent. The framework is not only concerned about predictive accuracy but also usefulness in the learning environment in terms of supporting early identification and intervention strategies. These ethical considerations of fairness, privacy, and accessibility are in the list, and it enables the system to adhere to the principles of inclusive education and responsible use of AI. The authors mention the opportunities of applying machine learning together with education data to create smart decision-support systems that could improve the outcomes

of students in the results. The subsequent set of enhancements can be focused on introduction of real time data flows, adaptive learning and further personalization capabilities to optimize the predictive ability. Developing inclusive, data-driven education systems that have the potential to empower teachers and learners can be based on the proposed strategy.

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