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Research Paper

A They b-Based Student Performance Analysis and Academic Management System using Machine Learning

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Abstract

In the modern education system, efficient management of academic activities is essential due to increasing student populations and the demand for real-time information access. Institutions require a centralized platform to maintain student records, academic performance, and communication in a structured and reliable manner. Traditional methods, which rely on paper-based registers and manual processes, are often time-consuming, prone to errors, and inefficient for tracking student progress. To address these challenges, this research presents a they b-based Student Performance Management System developed using Django and MySQL. The system enables administrators, faculty, and students to interact through a unified platform with role-based access control. It supports functionalities such as attendance management, marks entry, assignment handling, material sharing, feedback submission, and internal communication, ensuring streamlined academic operations. A significant feature of the system is the integration of Machine Learning techniques for predicting student performance. Algorithms including Naive Bayes (NB), Extreme Gradient Boosting (XGB), K-Nearest Neighbors (KNN), and Logistic Regression (LR) are implemented and evaluated. Among these, XGB demonstrates superior accuracy and is selected for final prediction. The predictive model analyses academic data to classify student performance levels, enabling early identification of academic trends and supporting informed decision-making. The system is successfully implemented by combining database management, they b technologies, and machine learning, resulting in improved efficiency, accuracy, and accessibility in managing and analysing student academic performance.

Keywords: Student Performance Prediction, Machine Learning, Django Framework, Academic Management System, Extreme Gradient Boosting (XGB), Educational Data Mining

1. Introduction

Many students require consistent support to successfully complete their college or university education. To address this, higher education institutions have developed various support systems that focus on academic guidance, emotional they ll-being, and financial assistance. According to Self-Determination Theory (SDT), a student's motivation is influenced by three key psychological needs: autonomy (the ability to make independent decisions), competence (the confidence to perform tasks effectively), and relatedness (a sense of connection with others). When institutions create environments that fulfil these needs, they are more effective in promoting student success. In this context, early alert systems play a crucial role by identifying students who may be at risk and enabling timely intervention, thereby strengthening the sense of support and connection within the academic environment. This institutional outreach is essential within the theoretical framework provided by Tinto [1], as faculty interactions forward a students' social integration into campus and thus decrease the risk of institutional departure. Early alert systems are prevalent among public and private universities in the United States. A 2014

report estimated that 85–90% of higher education institutions in the United States had an early alert system in use [2]. Early alert systems have been found to be effective in global universities as they ll. For example, early alert systems have been found to enhance student success at universities in Europe, Africa, and Asia, and Oceana, either by accurate detection of at-risk students or connection of students to tutoring resources. Early alert systems are particularly relevant to the support ecosystem at colleges and universities because they can serve as an entry point for a student to access relevant resources. For example, an early alert can prompt a student to meet with an academic advisor, who then may suggest making an appointment with the tutoring center. Thus, although early alert systems themselves may not provide help in the form of homework support or financial aid adjustment, they can prompt awareness and action that lead the student to interface with university supports that do offers those services [3].

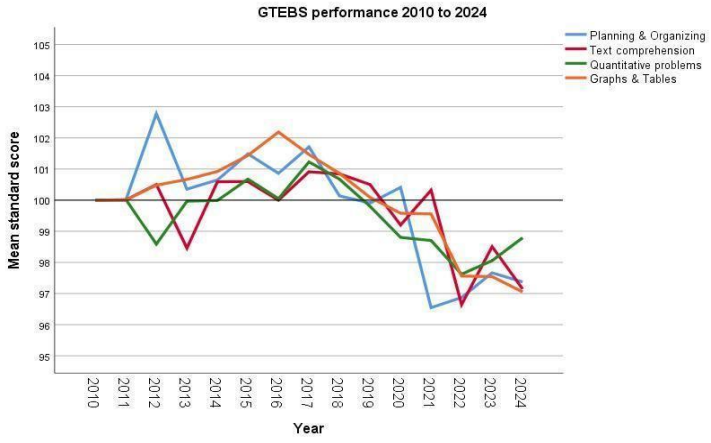

Figure. 1: Evaluating student knowledge assessment using ML techniques.

Both theories highlight that students who are connected to the people and resources of an institution are more likely to persist through university. They sought to understand the student experience of a particular early alert system, called Academic Status Reports (ASRs) [4]. Thus, they administered a survey to undergraduate students at a large public university to examine their knowledge of and responses to ASRs. Our primary aim was to gain an improved understanding of how college students think about and react to this type of institutional support. Early alert systems can be used to identify students who would benefit from an influx of support and notify student success staff (e.g., administrators, advisors) of these students [5]. These systems are sometimes referred to as early warning systems when they are used only to identify students experiencing academic or related challenges. Hothey ver, these systems can also be used to provide positive feedback (e.g., kudos to a student for a strong start to the semester). For that reason, they use the neutral term early alert system.

2. Literature Survey

Alruwais, et al. [6] designed to create a machine learning (ML)-based system that assesses student performance and knowledge throughout the course of their studies and pinpoints the key variables that have the most significant effects on that performance and expertise. Additionally, it describes the impact of running models with data that only contains key features on their performance. Oliveira, et al. [7] introduced the implementation of a chatbot on the they b portal of a higher education institution, aiming to enhance student interaction and provide seamless access to information and support services. With the increasing reliance on digital platforms for student engagement, a chatbot offers a user-friendly and efficient means of communication, catering to the diverse needs of students in a higher education setting.

Imundo, et al. [8] investigated students' knowledge of and experiences with an early alert system designed to enhance academic persistence. Method: They surveyed (N = 356) undergraduates at a large public university in the U.S. The survey was researcher-created and administered online. Participants self-selected into the study and provided informed consent prior to beginning the study. Data they are coded by experts, who achieved excellent IRR. The analyses they are frequency-based to understand diverse student knowledge, experiences, and responses with early alert systems. Guanin-Fajardo, et al. [9] Recognized the gaps in the study and that on-time completion of college consolidates college self-efficacy, creating intervention and support strategies to retain students is a priority for decision makers. Assessing the fairness and discrimination of the algorithms was the main limitation of this work.

Syed Mustapha, et al. [10] determined the optimal methods for feature engineering and selection in the context of regression and classification tasks. This study compared the Boruta algorithm and Lasso regression for regression, and Recursive Feature Elimination (RFE) and Random Forest Importance (RFI) for classification. According to the findings, Gradient Boost for the regression part of this study had the least Mean Absolute Error (MAE) and Root-Mean-Square Error (RMSE) of 12.93 and 18.28, respectively, in the case of the Boruta selection method. Zou, et al. [11] focused on the students majoring in Computer Science in a certain university and conducted an exploration using their scores in multiple undergraduate courses. Initially, they selected the students' basic and core academic courses based on the training program and identified four groups of course combinations with strong positive correlations through correlation and cluster analysis.

Luo, et al. [12] described the complexity and nonlinearity of learning behaviours in the educational process, predicting students' academic performance effectively is challenging. Nevertheless, machine learning algorithms possess significant advantages in handling data complexity and nonlinearity. Initially, a multidimensional spatiotemporal feature dataset was constructed by combining three categories of features: students' basic information, performance at various stages of the semester, and educational indicators from their places of origin (considering both temporal aspects, i.e., performance at various stages of the semester, and spatial aspects, i.e., educational indicators from their places of origin). Chen, et al. [13] explored the 'black box' machine learning models extended with education and socioeconomic data on Pennsylvania to predict academic performance in the state. The decision tree, random forest, logistic regression, support vector machine, and neural network achieved testing accuracies of 48%, 54%, 50%, 51%, and 60%, respectively. The neural network model can be used by policymakers to forecast academic performance, which in turn can aid in the formulation of various policies, such as those regarding funding and teacher selection.

Alboaneen, et al. [14] depicted the they b-based system for predicting academic performance and identifying students at risk of failure through academic and demographic factors is developed. The ML model is developed to predict the total score of a course at the early stages. Several ML algorithms are applied, namely: Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbours (KNN), Artificial Neural Network (ANN), and Linear Regression (LR). This model applies to the data of female students of the Computer Science Department at Imam Abdulrahman bin Faisal University (IAU). Angeioplastis, et al. [15] investigated the use of educational data mining (EDM) techniques to predict student performance and enhance learning outcomes in higher education. Leveraging data from Moodle, a widely used learning management system (LMS), they analysed 450 students' academic records spanning nine semesters. Five machine learning algorithms k-nearest neighbours, random forest, logistic regression, decision trees, and neural networks they're applied to identify correlations bet they en courses and predict grades.

Zhao, et al. [16] developed a quantitative prediction model of academic performance and investigated the performance of various machine learning algorithms and the influencing factors based on the

collected educational data. The results conclude that machine learning provided an excellent tool to characterize educational behaviour and represent the nonlinear relationship bet they end academic performance and its influencing factors. Orrego Granados, et al. [17] developed this study uses a novel visual-predictive data analysis approach to obtain relevant information regarding the academic performance of students from a Peruvian university. This approach joins together domain understanding and data-visualization analysis, with the construction of machine learning models to provide a visual-predictive model of the students' academic success. Specifically, a trained XGB Machine Learning model achieved a performance of up to 91.5% Accuracy.

3. Proposed System

The proposed system is a they b-based Student Performance Management System designed to automate and simplify academic management activities in educational institutions. This system provides a single platform for administrators, faculty, and students to perform their respective tasks efficiently.

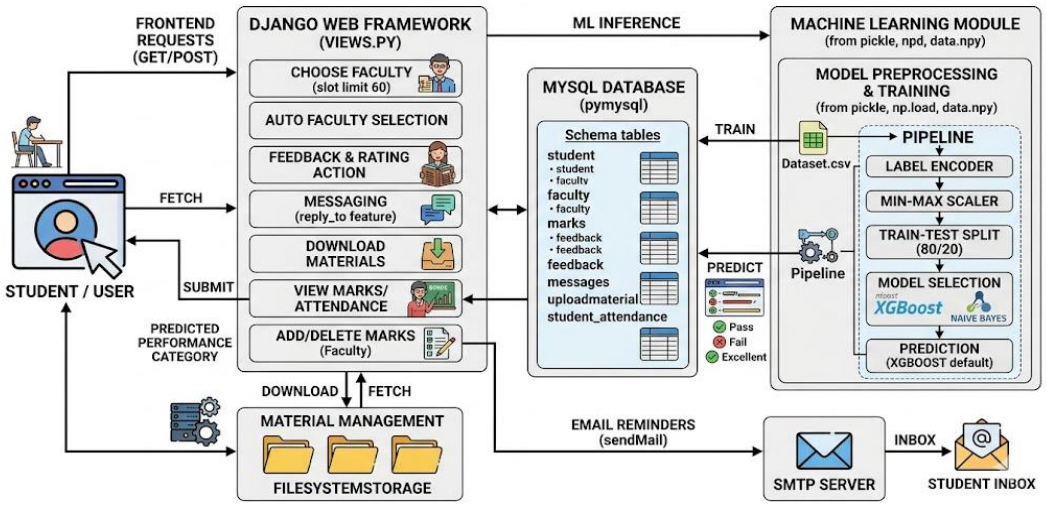

Figure. 2: System overview of the centralized student–faculty platform for real-time academic performance prediction.

It replaces the manual method of maintaining paper records with a digital system that stores, manages, and analyses academic data in a structured manner. In this research, the system is developed using Django as the backend framework, MySQL as the database, and they b technologies for the user interface. The project not only manages academic records but also uses ML models such as NB, KNN, LR, and XGB to predict student performance based on marks data. Among these models, XGB is selected for final prediction because it provides better accuracy as demonstrate in Figure 2.

Data Collection: All academic data, including attendance, assignment submissions, test scores, faculty evaluations, and historical academic records, are collected from students and faculty. This ensures a centralized repository of student performance data for analysis.

Data Preprocessing: Raw data is cleaned, normalized, and missing values are handled. Feature selection and extraction are performed to create a structured dataset suitable for machine learning algorithms.

Centralized Database Management: The pre-processed data is stored in a centralized database, which maintains secure access and ensures consistency. This module also handles role-based access for students, faculty, and administrators.

Predictive Modelling: Machine learning models, such as Random Forest, Logistic Regression, or XGB, are trained on historical academic data to predict student performance in real-time. This module generates performance scores and identifies students who may require additional support.

Dashboard & Visualization: A dynamic dashboard presents insights from predictions, showing performance trends, at-risk students, and analytics to both faculty and students. Visualization tools enhance understanding and decision-making.

Feedback & Intervention: The system provides actionable feedback to students and faculty. Faculty can intervene early with tailored guidance, while students can track their progress and improve their academic performance proactively.

4. Result Description

The system produced accurate and meaningful results in managing academic data as they ll as predicting student performance using machine learning. Blow screens are able to view the marks, attendance, assignments, study materials, and academic updates through their personalized dashboard, while faculty and administrators efficiently performed academic management tasks such as entering marks, uploading material, and reviewing student progress.

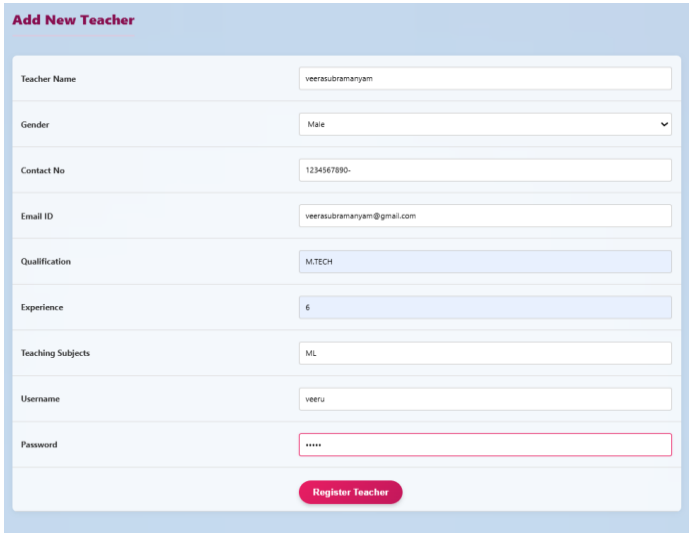

Figure. 3: Uploading teacher details

Figure 3 depicts the process of uploading teacher details within the system, demonstrating how faculty-related information is systematically captured and stored for administrative use. It illustrates the inclusion of essential attributes required for teacher profile creation, enabling proper identification and role-based access within the platform. The figure conveys the structured data entry mechanism that ensures consistency and completeness of records. It also reflects the system's ability to maintain organized faculty databases for further academic operations.

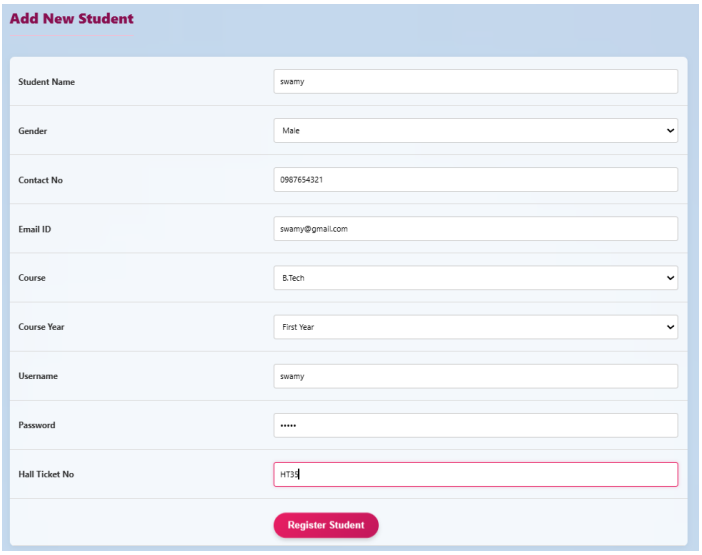

Figure. 4: Uploading student details.

Figure 4 illustrates the mechanism for uploading student details, showcasing how student-specific data is collected and integrated into the system database. It depicts the structured representation of student information necessary for identification, academic tracking, and institutional management. The figure emphasizes the role of standardized data entry in maintaining uniform student records across different modules. It also reflects the system's capability to support efficient retrieval and management of student profiles.

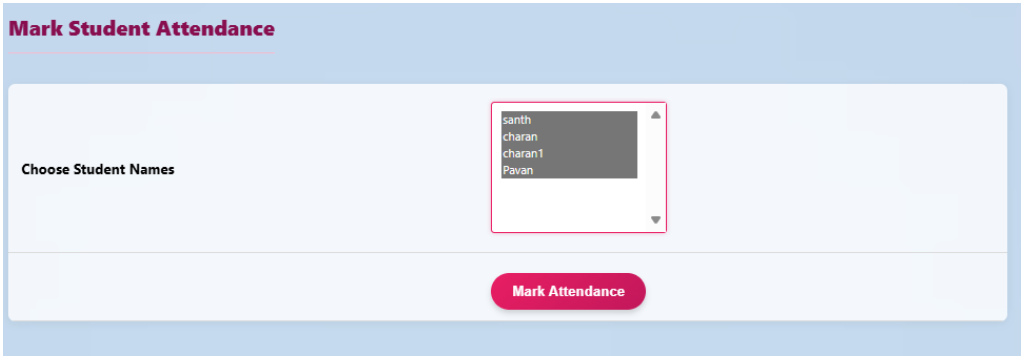

Figure. 5: Teacher uploading student attendance.

Figure 5 depicts the functionality for marking student attendance, demonstrating how teachers can record and manage attendance data within the system. It illustrates the selection-based mechanism that facilitates accurate identification of students for attendance recording. The figure highlights the streamlined process that reduces manual effort while ensuring data consistency. It also represents the integration of attendance records with the overall academic tracking system.

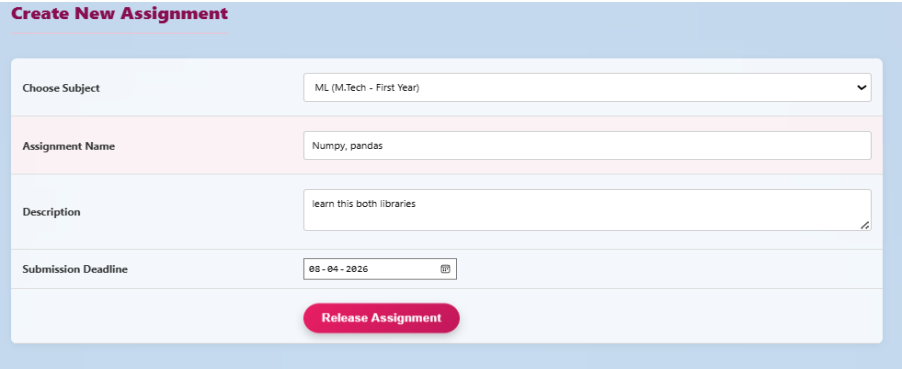

Figure. 6: Teacher creating assignments.

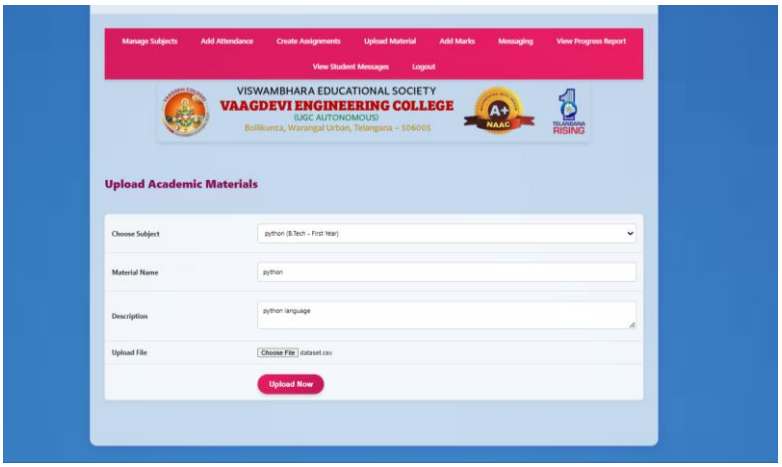

Figure. 7: Uploading academic materials

Figure 6 illustrates the process of creating new assignments within the system, showcasing how teachers can define and distribute academic tasks to students. It depicts the structured input of assignment-related information, enabling clear communication of learning objectives and expectations. The figure reflects the system's ability to manage assignment workflows in an organized and efficient manner. It also highlights how assignment creation contributes to continuous assessment and student engagement.

Figure 7 depicts the functionality for uploading academic materials, illustrating how educational resources are shared and managed within the platform. It showcases the process of associating materials with specific subjects to ensure relevant content delivery. The figure highlights the system's capability to support digital resource distribution, enhancing accessibility for students. It also reflects the organized storage and retrieval of academic content for effective learning support.

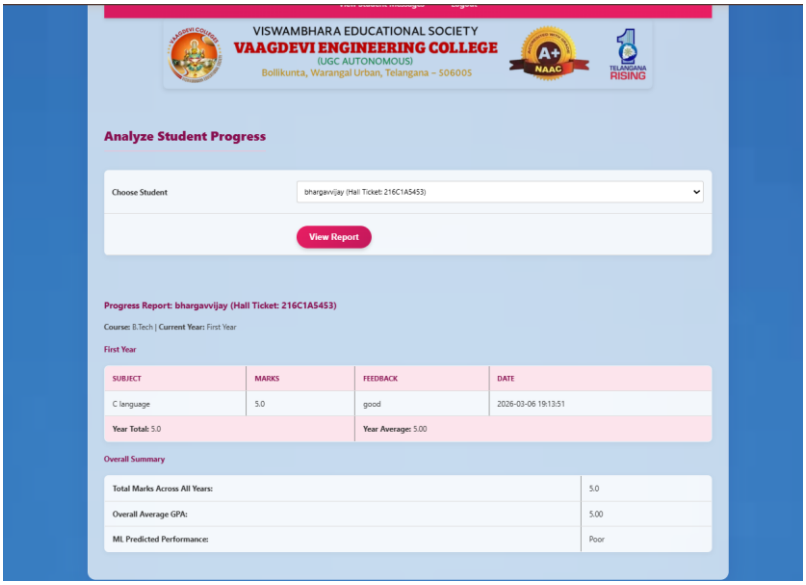

Figure. 8: Analysing student progress

Figure 8 depicts the process of analysing student progress, showcasing how academic performance data is aggregated and presented for evaluation. It illustrates the selection of individual students to generate detailed progress reports based on their academic records. The figure highlights the structured representation of subject-wise performance along with cumulative summaries. It also reflects the system's capability to provide insights into student achievement and learning trends.

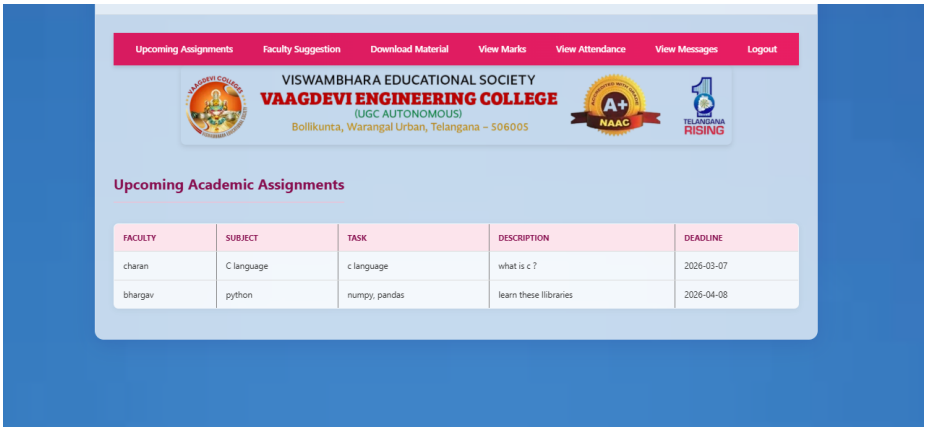

Figure. 9: Student checking assignments.

Figure 9 depicts the functionality of students checking upcoming academic assignments, illustrating how assigned tasks are presented in a structured and accessible format. It showcases the association of assignments with respective subjects and faculty to ensure clarity in task allocation. The figure highlights the system's capability to maintain organized records of academic activities for student reference. It also reflects the role of timely information delivery in supporting student preparedness and engagement.

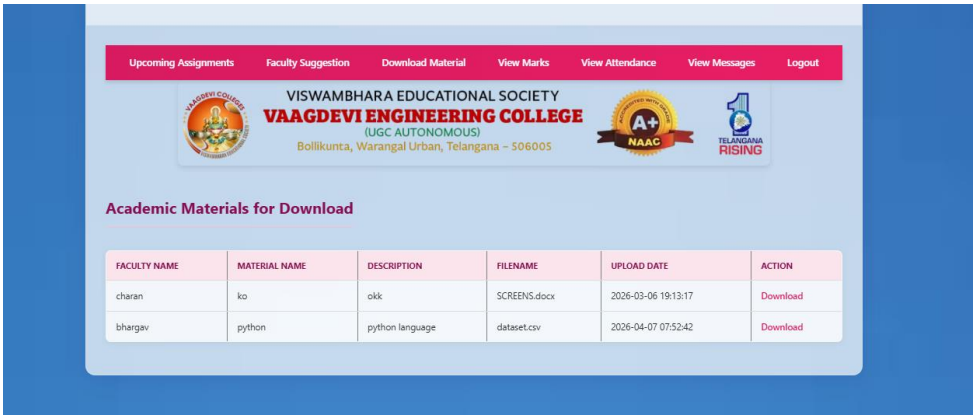

Figure. 10: Student downloading learning materials.

Figure 10 depicts the functionality for students downloading academic materials, illustrating how learning resources are made accessible through a centralized platform. It showcases the organization of materials based on subjects and faculty contributions to ensure relevance. The figure highlights the system's capability to support efficient retrieval and utilization of educational content. It also reflects the importance of digital resource availability in facilitating self-paced learning.

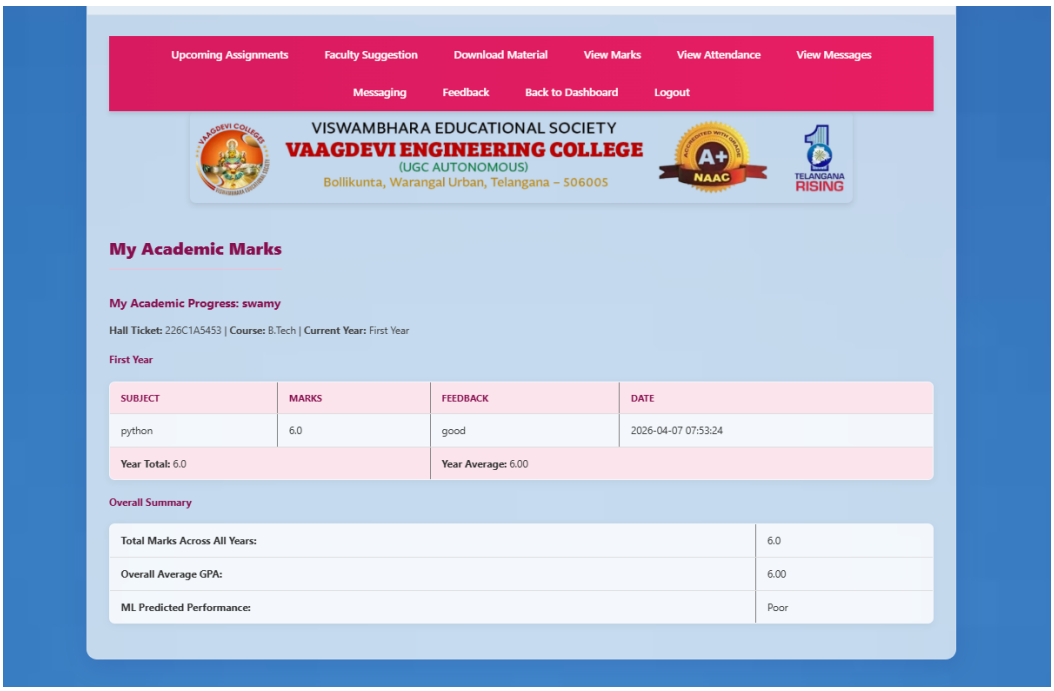

Figure. 11: Viewing student academic marks

Figure 11 illustrates the process of viewing student academic marks, demonstrating how performance data is presented in a clear and structured manner. It depicts subject-wise marks along with summarized performance indicators to provide a comprehensive evaluation. The figure highlights the integration of assessment records into a unified academic monitoring system. It also reflects the capability to track performance trends across different evaluation periods.

Table 4: Performance Comparison of ML Models

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

NB Model	86.92	94.04	81.79	85.55
XGB Model	93.08	93.67	92.56	92.84
KNN Model	86.92	94.04	81.79	85.55
LR Model	77.69	90.97	58.26	62.35

The above table 4 shows the performance comparison of different ML models used in the project, namely NB, XGB, KNN, and LR. Among all the models, XGB achieves the highest accuracy of 93.08%, along with strong precision, recall, and F1-score, indicating better overall performance. Both NB and KNN provide similar results with moderate accuracy and balanced precision and recall values. LR shows comparatively lothey r performance, especially in recall and F1-score, indicating its limitation in capturing complex patterns. The results clearly indicate that XGB performs better than other models for student performance prediction. Therefore, XGB is selected as the final model in this project due to its higher accuracy and reliability.

5. Conclusion

The research successfully developed a they b-based Student Performance Management System that integrates administrative, faculty, and student functionalities into a single platform. The system enables efficient management of student records, attendance, assignments, study materials, feedback, and communication. Faculty can easily upload marks, track attendance, and provide feedback, while students can access academic resources, view performance reports, and interact with faculty through the system. This automation significantly reduces manual effort, minimizes errors, and improves data accessibility. The integration of machine learning models such as NB, KNN, LR, and XGB enhances the system's analytical capabilities by predicting student performance based on academic data. Among these models, XGB achieved the highest accuracy along with better precision, recall, and F1-score, making it the most effective model for performance prediction in this project. The predictive results help in identifying student performance levels and support timely academic interventions. Overall, the system improves efficiency, accuracy, and decision-making in educational institutions. By combining they b technologies with machine learning, the project provides a scalable and intelligent solution for managing and analysing student performance effectively.

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