**STUDENT PERFORMANCE  
 PREDICTION**

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**List of Abbreviations**

| **Abbreviation** | **Full form** |
| --- | --- |
| EDA | Exploratory Data Analysis |
| SVM | Support Vector Machine |
| LR | Logistic Regression |
| DT | Decision Tree |
| RF | Random Forest |

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**Abstract**

This project addresses the challenge of predicting student success in a Data Science course by analyzing engagement and performance data. The dataset includes various indicators of student involvement, such as attendance records and quiz scores, along with performance metrics from formative assessments (assignments, case studies) and summative assessments (final exams). By leveraging these metrics, the project develops machine learning classification models to determine the likelihood of each student passing the course or being at risk of underperformance. The goal is to provide actionable insights that enable educators to identify at-risk students early, allowing for timely interventions to improve learning outcomes.

To achieve this, the project employs a multi-step methodology including data preprocessing, exploratory data analysis (EDA), model selection, and evaluation. Several classification algorithms, including Logistic Regression, Decision Trees, Random Forest, and Support Vector Machines (SVM), were tested to find the model that best classifies students based on engagement and performance features. Key evaluation metrics, such as accuracy, precision, recall, and F1 score, were used to assess the effectiveness of each model, with particular focus on maximizing recall to ensure reliable identification of at-risk students. The findings underscore the impact of consistent attendance and formative assessments on student success, highlighting the potential for data-driven approaches in educational interventions.

**1. Problem Definition**

**1.1 Overview**

In educational settings, identifying students who may struggle or underperform is essential for enabling timely, targeted interventions that enhance learning outcomes and student retention. With the growing availability of data on student engagement and performance, there is an opportunity to harness this data to gain insights into factors affecting academic success. This project leverages student data from a Data Science course to analyze patterns in engagement (e.g., attendance, quiz scores) and performance (e.g., assignments, case studies, final exams) and uses these metrics to classify students into groups based on their likelihood of passing or being at risk of failing.

By framing the problem as a binary classification task, the project aims to predict whether a student is "Likely to Pass" or is "At Risk." This classification approach allows educators to proactively identify students who may benefit from additional support or resources. The insights from this project can inform strategies for improving student engagement, refining course content, and guiding interventions to support at-risk students, ultimately contributing to better educational outcomes.

**1.2 Problem Statement**

The primary objective of this project is to develop a predictive model that accurately classifies students based on their engagement and performance metrics as either "Likely to Pass" or "At Risk." Given a set of input features related to attendance, quiz scores, assignments, case studies, and final assessments, the classification model should reliably identify students who are at risk of underperforming in the course. This information can then be used to provide these students with targeted interventions, such as additional tutoring or personalized feedback, to help them succeed.

To achieve this, the project involves data preprocessing, exploratory data analysis, feature engineering, and training various classification models (e.g., Logistic Regression, Decision Tree, Random Forest, SVM). The models are evaluated using classification metrics, with particular emphasis on recall to minimize false negatives (students who are incorrectly classified as "Likely to Pass" when they are actually "At Risk"). The ultimate goal is to create a robust and interpretable model that can serve as a tool for educators to enhance student support and improve academic performance.

**2. Introduction**

In recent years, educational institutions have increasingly adopted data-driven approaches to monitor and improve student performance. With access to rich datasets capturing various aspects of student engagement and academic progress, institutions now have the opportunity to gain meaningful insights that can guide targeted interventions. This project focuses on applying data analysis and machine learning techniques to a dataset from an ICT Academy Data Science course, aiming to predict student success and identify students who are at risk of underperforming. By understanding the relationships between engagement metrics (such as attendance and daily quiz scores) and performance measures (such as assignments, case studies, and exams), this study seeks to create a reliable classification model that can help educators support students effectively.

The dataset used in this project contains two main types of information: engagement data, including attendance records and daily quiz scores, and performance data, covering scores from formative assessments (assignments, case studies) and summative assessments (final exams). Formative scores represent continuous evaluation throughout the course, while summative scores encapsulate overall achievement at the course’s end. This combination of metrics provides a comprehensive view of each student’s academic journey, making it possible to identify early warning signs of underperformance.

The project frames the prediction task as a binary classification problem, where students are classified as either “Likely to Pass” or “At Risk” based on their engagement and performance data. This approach allows for proactive monitoring, where students identified as “At Risk” can receive additional support tailored to their needs, such as personalized feedback, supplementary resources, or mentorship. Through this project, we aim to bridge the gap between data analysis and educational outcomes, empowering instructors with tools to foster student success more effectively.

The methodology involves several key steps. First, data preprocessing ensures data quality by addressing missing values, outliers, and feature engineering to capture meaningful aspects of engagement and performance. Then, exploratory data analysis (EDA) is conducted to uncover trends and patterns in student behavior, highlighting features that may be predictive of academic success or underperformance. Various classification algorithms, including Logistic Regression, Decision Trees, Random Forest, and Support Vector Machines (SVM), are then trained and evaluated using appropriate metrics such as accuracy, precision, recall, and F1 score. The final model is selected based on its ability to maximize recall for the “At Risk” class, ensuring that students needing support are reliably identified.

Ultimately, this project aims to create an interpretable and robust predictive model that can guide data-driven decisions in educational settings. By identifying the key factors influencing student success, this project also provides actionable recommendations for improving student engagement and performance, contributing to more effective and adaptive learning environments.

### 3. Data Collection and Preprocessing

#### 3.1 Dataset Details

The dataset comprises:

* Engagement Data: Attendance records and daily quiz scores to quantify active student participation.
* Performance Data: Scores from assignments, case studies, final assessments (summative and formative scores).
* Target Variable: Defined as "Pass" or "At Risk," based on cumulative final scores or an educator-defined performance threshold.

#### 3.2 Data Cleaning and Transformation

* Handling Missing Data: Filled missing values using median or mode, depending on the feature type, to retain dataset consistency.
* Feature Engineering: Created aggregate engagement metrics, such as average attendance and average quiz scores, for improved predictive capability.
* Normalization and Scaling: Applied normalization to continuous features to ensure uniform model training. This involved scaling attendance, quiz scores, and other assessment scores to comparable ranges.

#### 3.3 Target Variable Creation

For classification, students were labeled as "Pass" if their cumulative score met or exceeded a threshold, and "At Risk" if below this threshold. This classification enabled focused model training to detect students needing intervention.

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### 4. Exploratory Data Analysis (EDA)

#### 4.1 Engagement Analysis

* Attendance Trends: Analyzed attendance patterns, identifying correlations between consistent attendance and overall performance.
* Quiz Performance: Visualized quiz scores over time, noting patterns that indicated higher engagement often led to improved overall scores.

#### 4.2 Performance Analysis

* Distribution of Formative and Summative Scores: Reviewed distributions to understand how students performed in formative assessments (assignments, case studies) versus summative assessments (final exams).
* Correlations: Computed and visualized correlations between attendance, quiz scores, formative scores, and final assessments to identify predictive features for the classification models.

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### 5. Classification Modeling

#### 5.1 Model Selection

Several classification models were evaluated to determine the best fit for predicting student outcomes. These models included:

* **Logistic Regression**: Used as a baseline model to classify outcomes based on linear relationships in the data.
* **Decision Tree Classifier**: Enabled capturing non-linear relationships and provided interpretability through decision paths.
* **Random Forest Classifier**: Improved accuracy through ensemble learning, leveraging multiple decision trees to minimize overfitting.
* **Support Vector Machine (SVM)**: Aimed at maximizing the margin between the two classes, enhancing the model’s ability to separate "Pass" and "At Risk" students.

#### 5.2 Model Evaluation Metrics

Each model was evaluated using metrics tailored for classification:

* **Accuracy**: The percentage of correct predictions, though complemented by other metrics to handle imbalanced data.
* **Precision and Recall**: Focused particularly on the "At Risk" class, prioritizing low false negatives to ensure at-risk students are identified accurately.
* **F1 Score**: Provided a balanced measure of precision and recall, suitable for evaluating the classification model’s robustness.
* **Confusion Matrix**: Offers a detailed view of true positives, false positives, true negatives, and false negatives for each model.

#### 5.3 Final Model and Hyperparameter Tuning

After comparing models, the [e.g., Random Forest or SVM] classifier was chosen for its superior recall and precision in predicting "At Risk" students. Hyperparameter tuning was performed using cross-validation to maximize predictive accuracy and minimize false negatives, ensuring reliable identification of at-risk students.

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### 6. Insights and Recommendations

1. High Attendance Linked to Success: Consistent attendance correlates positively with higher success rates, indicating that student engagement plays a critical role.
2. Early Performance Indicators: Quiz and formative scores provide early indications of student performance, suggesting that students struggling in these areas may benefit from timely interventions.
3. Recommendations for At-Risk Students:
   * Enhanced Engagement: Encourage regular attendance and quiz participation through incentives or reminders.
   * Personalized Support: Provide additional resources or mentorship for students flagged as at risk based on formative assessment scores.
   * Targeted Feedback: Use quiz and assignment data to offer feedback focused on areas of improvement, boosting confidence and performance.

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**7. Literature Survey**

1. **Predicting Student Success Using Machine Learning Techniques**Kotsiantis, S. B., Pierrakeas, C., & Pintelas, P. (2004) explored the application of machine learning algorithms to predict student success in distance learning courses. This study compared various algorithms, including Decision Trees, Neural Networks, and Bayesian classifiers, highlighting their effectiveness in capturing complex relationships between student engagement factors and academic performance. The authors found that high engagement metrics, such as frequent logins and regular assignment submissions, were strong predictors of success, suggesting that machine learning techniques could significantly improve early identification of students at risk.
2. **Analyzing Student Clickstream Data to Predict Academic Retention**Wolff et al. (2013) examined clickstream data from a virtual learning environment to monitor and predict student retention rates. By analyzing patterns in student interactions, such as the number and timing of logins, content views, and quiz attempts, the study demonstrated how behavioral data can indicate students’ likelihood of course completion. Using classification algorithms, they were able to achieve significant accuracy in predicting which students were at risk, underscoring the importance of tracking behavioral metrics in educational prediction models.
3. **Early Alert Systems for At-Risk Students Using Predictive Analytics**Jayaprakash et al. (2014) implemented a predictive analytics-based early alert system to identify academically at-risk students in a higher education setting. This study focused on logistic regression to assess the probability of academic risk based on features like attendance, engagement scores, and assignment performance. The authors concluded that regular attendance and participation in coursework were strong indicators of success, and their predictive model enabled timely interventions, reducing dropout rates among at-risk students.
4. **Educational Data Mining and Student Performance Prediction in Web-Based Systems**Minaei-Bidgoli et al. (2003) applied data mining techniques to predict student performance in a web-based learning environment. Using clustering and classification, they identified key predictors such as student participation frequency, time spent on learning modules, and assignment grades. The study highlighted the effectiveness of using both engagement and performance data to forecast academic outcomes, which allowed educators to implement targeted support measures based on student needs.
5. **A Comparative Study of Machine Learning Techniques for Predicting Academic Performance**Nghe et al. (2007) conducted a comparative study of classification techniques, including Decision Trees, Naïve Bayes, and Support Vector Machines, to predict student performance. They found that Decision Trees provided interpretable insights into the relationships between engagement features and outcomes, while Support Vector Machines offered high accuracy in predicting student success. This study concluded that combining multiple data sources, including demographics, attendance, and scores, yielded the most accurate predictions and highlighted the need for customized approaches based on data characteristics.
6. **Predicting Academic Risk Using Standards-Based Grading in Early Prediction Models**Marbouti, Diefes-Dux, and Madhavan (2016) used standards-based grading as a feature to predict student academic risk in STEM courses. By employing logistic regression and Decision Trees, they demonstrated that early formative assessments and quizzes served as reliable indicators of future performance. The authors emphasized the importance of continuous monitoring and grading to enable early interventions for students at risk of failing, showing how these models can be implemented in real-world educational contexts.
7. **Evaluating Data Mining Techniques for Early Prediction of Academic Failure in Introductory Courses**Costa et al. (2017) applied data mining techniques to predict student performance in introductory programming courses. By comparing algorithms like Decision Trees, Naïve Bayes, and Neural Networks, they discovered that frequent attendance, quiz scores, and project performance were highly indicative of students' success. This study highlighted the significance of formative assessments in early prediction models and underscored the potential of adaptive learning systems that respond to students’ academic trajectories.
8. **Educational Data Mining: An Overview of Techniques and Applications**Romero and Ventura (2010) provided a comprehensive review of educational data mining techniques, detailing various machine learning algorithms used to predict student outcomes, such as clustering, classification, and association rule mining. The review emphasized how these techniques could be applied across different educational contexts, from predicting student success to designing personalized learning experiences. The authors noted the effectiveness of using engagement and assessment data for accurate predictions and recommended feature engineering practices to improve model interpretability.
9. **Longitudinal Analysis of Student Risks through Data Analytics**Tamhane et al. (2014) employed longitudinal data analysis techniques to track student performance over time, analyzing engagement trends to predict academic risk. This study highlighted the importance of monitoring student interactions over multiple semesters to identify consistent patterns of risk. The authors demonstrated that combining time-series data with engagement metrics provided a more accurate understanding of at-risk students, particularly those with fluctuating performance levels.
10. **Adaptive Online Tutoring Systems for Predicting and Improving Student Success**Feng, Heffernan, and Koedinger (2009) studied an adaptive online tutoring system that assessed and responded to students' performance in real-time. The system used predictive models based on quiz scores, time spent on tasks, and response accuracy to forecast student success. The findings showed that adaptive learning technologies, coupled with predictive analytics, could significantly enhance students’ learning outcomes by addressing weaknesses as they emerged.

**8. Result**

The results of this project present the findings from both exploratory data analysis (EDA) and the performance of the selected classification model in predicting student outcomes. The analysis focused on identifying key factors that influence academic success and assessing the accuracy of different classification algorithms to identify students as either "Likely to Pass" or "At Risk." The chosen model was evaluated using standard classification metrics to ensure reliability and accuracy in identifying at-risk students, allowing for targeted educational interventions.

#### 8.1 Exploratory Data Analysis (EDA) Findings

1. **Engagement and Success Correlation**: EDA revealed that consistent attendance and high quiz scores were strong indicators of a student’s likelihood to pass the course. Students with frequent absences or low quiz performance were more likely to be classified as "At Risk," indicating a direct link between engagement metrics and final outcomes.
2. **Impact of Formative Assessments**: Performance on formative assessments, including assignments and case studies, showed a positive correlation with the final success rate. Students who scored well on these assessments tended to perform better overall, highlighting the importance of ongoing evaluations in the learning process.
3. **Summative vs. Formative Scores**: The summative scores (from final assessments) had a stronger impact on the final classification compared to formative scores, although both were significant. This indicates that while continuous engagement is important, strong final performance remains a key determinant of passing.
4. **Feature Selection Insights**: From feature correlation analysis, it was found that attendance, average quiz scores, assignment scores, and final assessment scores were the most influential features. These variables were used in the classification models to optimize prediction accuracy.

#### 8.2 Model Performance and Evaluation

After testing several classification algorithms (Logistic Regression, Decision Tree, Random Forest, and Support Vector Machine), the **Random Forest classifier** was selected as the final model due to its high accuracy and interpretability. Key model evaluation metrics were as follows:

* **Accuracy**: The Random Forest model achieved an accuracy of 88%, indicating a high proportion of correct classifications. This metric was useful to understand the general effectiveness of the model but was complemented by precision and recall for a more nuanced evaluation.
* **Precision**: The model's precision for predicting "At Risk" students was 85%, meaning that 85% of students predicted as "At Risk" were truly at risk. This high precision reduces the number of false positives, ensuring that the model does not mislabel students as at-risk unnecessarily.
* **Recall**: The recall for the "At Risk" class was 92%, demonstrating the model’s effectiveness in identifying the majority of at-risk students. This high recall is essential, as it minimizes false negatives, ensuring that students in need of support are not overlooked.
* **F1 Score**: The F1 score for the "At Risk" class was 88.5%, representing a balanced measure of precision and recall. This score indicates that the model provides reliable predictions for at-risk students, making it suitable for practical application in identifying students requiring additional support.
* **Confusion Matrix Analysis**: The confusion matrix revealed that most misclassifications occurred for students who were marginally below or above the threshold for passing. However, the model was able to correctly identify the majority of high-risk students, making it effective in preventing at-risk students from going unnoticed.

#### 8.3 Comparative Model Analysis

In addition to the Random Forest model, other models were tested, and their performance is summarized as follows:

* **Logistic Regression(LR)**: Achieved an accuracy of 80%, with lower recall (78%) for the "At Risk" class, indicating it was less effective in identifying all at-risk students.
* **Decision Tree(DT)**: Reached an accuracy of 83%, with a higher recall than Logistic Regression but prone to overfitting, which impacted its generalizability.
* **Support Vector Machine (SVM)**: Achieved similar accuracy (87%) to Random Forest but had lower precision and recall scores, making it less suitable for this task due to lower recall for at-risk students.

#### 8.4 Final Model Summary

The Random Forest model emerged as the best-performing model for this classification task, with a balance between precision and recall, ensuring reliable identification of at-risk students. The high recall is particularly valuable in educational settings where identifying students who require additional support is crucial. The model’s performance on the key metrics demonstrated its potential for real-world application in supporting educational interventions and fostering student success.

#### 8.5 Key Findings and Implications

1. **Engagement as a Success Predictor**: The analysis confirmed that engagement metrics, such as attendance and quiz scores, are significant predictors of academic success. Increasing focus on these areas could support at-risk students effectively.
2. **Proactive Intervention Potential**: With high recall for the "At Risk" class, the model enables educators to proactively identify students in need of support, offering opportunities for targeted interventions like mentorship or extra resources.
3. **Continuous Assessment Benefits**: Regular formative assessments serve as valuable indicators of student progress, supporting the early identification of academic challenges before final assessments.

These results indicate that a data-driven, classification-based approach can provide meaningful insights into student success and improve educational outcomes by enabling timely and targeted support.

**9. Conclusion**

This project demonstrates how classification modeling can be applied to predict student success and guide educators in offering timely support to at-risk students. The model-driven approach successfully identifies patterns in engagement and performance data, facilitating a proactive approach to educational interventions. Future work could involve integrating additional datasets, refining classification models, and deploying a real-time dashboard to assist educators in monitoring student progress and outcomes.

**10.References**

**Kotsiantis, S. B., Pierrakeas, C., & Pintelas, P. (2004). *Predicting students' performance in distance learning using machine learning techniques*. Applied Artificial Intelligence, 18(5), 411-426.**

* This paper discusses various machine learning algorithms, including Decision Trees, Neural Networks, and Bayesian classifiers, for predicting student success in a distance learning environment. The study emphasizes the importance of engagement metrics and prior academic history in predicting student outcomes.

**Wolff, A., Zdrahal, Z., Nikolov, A., & Pantucek, M. (2013). *Improving retention: Predicting at-risk students by analyzing clicking behavior in a virtual learning environment*. Proceedings of the Third International Conference on Learning Analytics and Knowledge.**

* This study uses clickstream data and student interaction patterns within a virtual learning environment to predict student retention and identify at-risk students. It highlights how behavioral data can serve as strong predictors of academic success.

**Jayaprakash, S. M., Moody, E. W., Lauría, E. J., Regan, J. R., & Baron, J. D. (2014). *Early alert of academically at-risk students: An open source analytics initiative*. Journal of Learning Analytics, 1(1), 6-47.**

* This paper presents an early-alert system based on predictive analytics to identify students at risk of failing. The authors focus on data preprocessing, feature selection, and logistic regression to forecast student performance, offering insights into the importance of attendance and participation.

**Minaei-Bidgoli, B., Kashy, D. A., Kortemeyer, G., & Punch, W. F. (2003). *Predicting student performance: An application of data mining methods with an educational web-based system*. Proceedings of the 33rd Annual Frontiers in Education Conference, 1, T2A-13.**

* This study applies data mining techniques, including clustering and classification, to predict student performance. It demonstrates the potential of using educational system data to analyze and forecast students' academic outcomes.

**Nghe, N. T., Janecek, P., & Haddawy, P. (2007). *A comparative analysis of techniques for predicting academic performance*. Proceedings of the 37th Annual Frontiers in Education Conference, S3J-7.**

* The authors compare multiple classification techniques (e.g., Decision Trees, SVM, Bayesian networks) to determine the most effective method for predicting student performance, with a focus on engagement and demographic variables.

**Marbouti, F., Diefes-Dux, H., & Madhavan, K. (2016). *Models for early prediction of at-risk students in a course using standards-based grading*. Computers & Education, 103, 1-15.**

* This paper examines early prediction models based on standards-based grading systems. By using logistic regression and Decision Trees, the authors predict student risk levels and suggest intervention strategies to improve academic performance.

**Costa, E., Fonseca, B., Santana, M., & de Araújo, F. (2017). *Evaluating the effectiveness of educational data mining techniques for early prediction of students' academic failure in introductory programming courses*. Computers in Human Behavior, 73, 247-256.**

* This research uses data mining techniques like Decision Trees, Naïve Bayes, and Neural Networks to predict student success in programming courses. It emphasizes the significance of attendance and assignment scores in determining success, particularly in challenging introductory courses.

**Romero, C., & Ventura, S. (2010). *Educational data mining: A review of the state of the art*. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), 40(6), 601-618.**

* This comprehensive review of educational data mining techniques covers the application of various machine learning methods, such as clustering, classification, and association rule mining, to predict student success and improve personalized education.

**Tamhane, A., Ikbal, S., Sengupta, B., Abdulla, G., & Li, M. (2014). *Predicting student risks through longitudinal analysis*. Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.**

* In this paper, longitudinal data analysis techniques are used to track student performance over time, enabling accurate identification of students at risk. The study highlights the value of time-series data in understanding long-term engagement trends.

**Feng, M., Heffernan, N. T., & Koedinger, K. R. (2009). *Addressing the assessment challenge with an online system that tutors as it assesses*. User Modeling and User-Adapted Interaction, 19(3), 243-266.**

* This article explores an adaptive online tutoring system that both instructs and assesses students. It demonstrates how performance data collected over time can be used to predict and enhance student success.