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MASTER OF SCIENCE IN BUSINESS ANALYTICS

Predicting Student Success and Dropout Rates: A Machine Learning Approach with LIME for Interpretability and Bias Detection

by

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Executive Summary

This dissertation explores the application of predictive analytics in higher education, focusing on how machine learning models can predict student success and dropout rates. Predictive analytics has emerged as a powerful tool for improving institutional efficiency and student outcomes by analysing large datasets to identify patterns, trends, and risks. The models developed in this research utilize demographic, academic, and socio-economic features to classify students into categories of success (Graduate) or risk (Dropout), providing valuable insights for early intervention strategies.

Educational institutions face ongoing challenges related to student retention, performance, and graduation rates. Despite a growing emphasis on data-driven decision-making, many institutions struggle to identify students at risk of dropping out before it is too late. Predictive analytics can address these issues by using historical data to forecast future student outcomes, allowing for timely and effective interventions.The main problem explored in this research is how to effectively use machine learning models, such as Logistic Regression and Random Forest, to predict whether a student will graduate, drop out, or remain enrolled. Additionally, the dissertation investigates the interpretability of these models using LIME (Local Interpretable Model-Agnostic Explanations) and explores the bias that can arise from using demographic data in predictive models.

The overarching aim of this study is to assess the effectiveness of predictive models in identifying at-risk students and to explore how model interpretability can improve the trust and transparency of these models for institutional use. By integrating machine learning with explainable AI techniques, the research aims to create models that not only deliver accurate predictions but are also comprehensible to educators and administrators. This approach can help institutions make informed decisions, allocate resources efficiently, and support students more effectively.

The methodology employed in this research includes data preprocessing, model building, and evaluation of two machine learning models—Logistic Regression and Random Forest. The dataset consists of 37 features related to student demographic, academic, and socio-economic data. Several steps, including one-hot encoding for categorical variables and normalization for numerical variables, were carried out to prepare the data for model training.

Both Logistic Regression and Random Forest models were trained and evaluated using key performance metrics: accuracy, precision, recall, F1-score, and Area Under the Curve (AUC). These metrics provided a comprehensive view of each model's performance, highlighting their strengths and weaknesses in predicting student outcomes. Additionally, LIME was applied to improve model interpretability by breaking down the factors contributing to individual predictions, especially in cases where the models misclassified students.

The research demonstrated that both models performed well in predicting student outcomes, with Logistic Regression slightly outperforming Random Forest in terms of accuracy and AUC. Logistic Regression achieved an accuracy of 92%, while Random Forest followed closely with

an accuracy of 90%. Both models had strong recall and F1-scores, indicating their effectiveness in identifying students at risk of dropping out or succeeding academically.

However, a deeper analysis using LIME revealed that demographic features such as Nationality and Marital Status played a significant role in misclassified instances, raising concerns about potential bias. The LIME analysis helped pinpoint areas where the models over-relied on demographic data, leading to incorrect predictions. For example, Nationality appeared as a major factor in several misclassifications, suggesting that the models might have been influenced by historical biases present in the data.

The findings from this research have important practical implications for educational institutions. Predictive analytics can significantly enhance early warning systems, allowing institutions to identify students at risk of dropping out and provide timely support, such as tutoring, academic counseling, or financial aid. By improving the accuracy and transparency of predictive models, institutions can better allocate resources and tailor interventions to individual student needs.

Furthermore, the application of LIME for model interpretability provides an added layer of trust, ensuring that institutional stakeholders can understand and act on the predictions generated by machine learning models. This transparency is essential for ethical decision-making, particularly when sensitive demographic data is involved.

This dissertation contributes to the field of educational data science by demonstrating how predictive models, combined with explainable AI techniques like LIME, can be used to improve student retention and success. The research highlights the importance of model interpretability and fairness, offering a roadmap for institutions to build more equitable and trustworthy predictive models. By identifying potential biases in the data, the study provides insights into how institutions can refine their models to avoid perpetuating existing inequalities.

While the models performed well, certain limitations were noted. The dataset had some imbalance in the target variable, with a higher proportion of graduates than dropouts or enrolled students, which could have influenced the model's predictions. Future research should explore more advanced resampling techniques to address class imbalance, such as SMOTE (Synthetic Minority Over-sampling Technique.Additionally, the reliance on historical data raises concerns about reinforcing existing biases. Future studies should focus on updating models with current data to ensure they reflect changing student behaviors and institutional practices. Further research could also explore the integration of SHAP (SHapley Additive exPlanations) for global model interpretability, providing a more comprehensive understanding of model behavior across the entire dataset.

In conclusion, this dissertation demonstrates that predictive analytics can significantly improve institutional decision-making and student outcomes. By combining machine learning models with interpretable AI, institutions can develop more accurate, fair, and transparent systems that support student success and drive organizational growth.

Declaration of Originality

I hereby declare that this dissertation has been composed by myself and has not been presented or accepted in any previous application for a degree. The work, of which this is a record, has been carried out by me unless otherwise stated and where the work is mine, it reflects personal views and values. All quotations have been distinguished by quotation marks and all sources of information have been acknowledged by means of references including those of the Internet. **I agree that the university has the right to submit my work to the plagiarism detection sources for originality checks.**

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1. Introduction

1.1 Research Problem

In recent years, higher education institutions have faced increasing pressure to improve student retention rates and ensure academic success, especially in the context of large and diverse student populations (Siemens, 2013). Traditional methods for monitoring student performance are often reactive, relying on mid-term or end-of-semester assessments to identify students at risk of dropping out. By the time these assessments are made, however, it is often too late for effective intervention. Institutions need data-driven tools that can predict student outcomes early, allowing for timely interventions that prevent academic failure (Jayaprakash et al., 2014). Predictive analytics has emerged as a potential solution to this problem, enabling universities to forecast student success based on historical academic, demographic, and behavioral data (Benablo et al., 2018).

Despite the promise of predictive models, challenges remain in their practical implementation. One of the main issues is the lack of transparency in the decision-making process of machine learning algorithms. Many predictive models, such as Random Forest and neural networks, function as "black boxes," producing accurate predictions without providing clear explanations of how they arrived at those conclusions (Ribeiro et al., 2016). This opacity raises concerns among educators and administrators who need to understand the basis for predictions in order to trust and act on them. Furthermore, there is growing concern about the potential for bias in predictive models, particularly when they rely on demographic variables like nationality or socio-economic status (Bird et al., 2023). These biases can lead to unfair treatment of certain student groups, perpetuating existing inequalities in education (Prinsloo & Slade, 2016).

1.2 Research Aim

The primary aim of this research is to develop and evaluate predictive models that can forecast student outcomes—specifically, whether a student will graduate, drop out, or remain enrolled—based on a combination of demographic, academic, and socio-economic features. This study employs two widely used machine learning models, Logistic Regression and Random Forest, to assess their predictive capabilities in the context of higher education (Benablo et al., 2018). Beyond performance, the research aims to enhance the interpretability of these models by applying LIME (Local Interpretable Model-Agnostic Explanations), a tool designed to provide clear, local explanations for complex model predictions (Ribeiro et al., 2016). By doing so, this study seeks to ensure that stakeholders, including educators and administrators, can understand the rationale behind each prediction and make informed decisions based on the model's outputs.

Another key aim of this research is to examine the potential biases within these predictive models. Bias, particularly in educational settings, can have far-reaching consequences, including unequal access to resources or support services for marginalized groups (AERA, 2024). This study will use LIME not only to improve model transparency but also to identify and address any biases that may arise, particularly those related to demographic variables such as nationality, marital status, and socio-economic factors (Bird et al., 2023). Ultimately, the goal is to develop models that are not only accurate and interpretable but also equitable, ensuring that predictive analytics contributes to a fairer and more inclusive educational environment.

1.3 Research Objectives

To achieve the research aim, this study is structured around the following key objectives:

1. **Evaluate Model Performance:** The first objective is to evaluate the performance of two predictive models, Logistic Regression and Random Forest, in predicting student outcomes (Khor, 2022). Both models will be assessed using established evaluation metrics, including accuracy, precision, recall, F1-score, and AUC (Area Under the Curve), which provide a comprehensive view of their predictive power (Cui et al., 2019).
2. **Enhance Model Interpretability with LIME:** The second objective is to apply LIME to the selected model to improve interpretability (Ribeiro et al., 2016). By providing local explanations for individual predictions, LIME enables stakeholders to understand why the model made a particular decision. This is crucial for building trust in predictive analytics and ensuring that the models' outputs are actionable for educators and administrators (Herodotou et al., 2019).
3. **Identify Key Predictors of Student Outcomes:** The third objective is to identify the most influential features driving the models' predictions, particularly those related to academic performance, socio-economic status, and demographic factors (Gray et al., 2014). This will provide valuable insights into which variables are most predictive of student success and failure, helping institutions to better target interventions.

4. **Detect and Address Bias in Predictions:** The final objective is to use LIME to detect potential biases in the model's predictions, particularly those related to demographic variables like nationality, marital status, and socio-economic factors (Prinsloo & Slade, 2016). By identifying and mitigating these biases, the study aims to ensure that the models do not disproportionately disadvantage certain student groups, thereby promoting fairness and equity in educational decision-making (Bird et al., 2023).

By addressing these objectives, this research contributes to the growing field of predictive analytics in higher education, offering both technical insights into model development and ethical considerations for their application. While previous studies have demonstrated the power of predictive models to improve student outcomes, this research seeks to push the boundaries of what is possible by ensuring that these models are interpretable, fair, and transparent (Benablo et al., 2018; Daud et al., 2017). The findings from this study will provide practical recommendations for how institutions can use predictive analytics to not only improve student retention and success but also foster trust and equity in their decision-making processes.

2. Literature Review

2.1 Introduction to Predictive Analytics in Education

Predictive analytics has become an essential tool in higher education for addressing critical challenges like student retention, academic performance, and strategic resource management. As student populations grow and educational systems face increased complexity, institutions require more advanced, data-driven tools like machine learning to analyze historical data—such as academic records, student behaviors, and demographic information—to predict future outcomes and intervene early when needed (Siemens, 2013). This need for enhanced, scalable decision-making is where machine learning and predictive analytics become critical, allowing institutions to forecast student success, identify at-risk learners, and improve both institutional efficiency and educational outcomes (Alzahrani, 2019).

One of the most significant advantages of predictive analytics is its ability to facilitate early intervention. When institutions detect patterns of academic struggle or disengagement, they can deploy targeted resources such as tutoring, counseling, or advising to help students before their issues escalate. Studies have shown that early intervention strategies significantly improve student retention rates, especially in large and diverse educational environments where monitoring individual student performance is more challenging (Jayaprakash et al., 2014).

In addition to improving individual student outcomes, predictive analytics plays a crucial role in supporting institutional growth and strategic planning. By analyzing enrollment patterns, institutions can optimize resource allocation, faculty recruitment, and course offerings to align with student demand and market trends. This proactive data-driven approach ensures institutions can better manage their operations while providing students with the programs and support they need to succeed (Marshall University, 2023). Predictive analytics also helps universities remain agile in a rapidly evolving educational landscape. The ability to use data to forecast trends in student preferences or areas of study allows institutions to adjust academic programs to align with both student interests and the needs of the labor market. In doing so, they enhance institutional competitiveness and long-term sustainability (Agasisti & Bowers, 2017).

2.2The Role of Prediction in Education

Prediction plays a vital role in education by helping institutions forecast outcomes such as student success, retention rates, and program demand. Educational administrators can anticipate challenges, make informed decisions, and design interventions tailored to specific student groups. Predictive models, particularly those developed through machine learning, can process complex datasets to predict various educational outcomes. For instance, student dropout rates, course performance, and even career readiness can be predicted by analyzing factors such as attendance, GPA, and socio-economic status (Gray et al., 2014). This ability to analyze such diverse factors and offer precise predictions underscores why machine learning is increasingly indispensable in the educational sector.

In higher education, predictive analytics not only supports students but also informs program planning and resource allocation. By analyzing trends in student enrollment, institutions can predict future demand for certain programs, allowing them to adjust their offerings and resources accordingly (Agasisti & Bowers, 2017). This application ensures that universities remain responsive to current student needs and adaptable to future demands, enhancing their capacity to provide relevant educational experiences.

2.3 Previous Research on Predictive Analytics in Education

The application of predictive analytics in education has been extensively studied, especially concerning its ability to predict student success, improve retention rates, and support academic planning. **Siemens (2013)** provided one of the foundational studies in learning analytics, exploring how data-driven insights could support student learning outcomes and institutional decision-making. Siemens emphasized the importance of early interventions based on predictive models that use data such as academic performance and student behavior to forecast potential challenges before they escalate.

Alzahrani (2019) expanded on these insights, particularly in the context of online and blended learning environments. His research demonstrated how predictive models, including neural networks, could process large, complex datasets, such as student interaction metrics and behavioral patterns, to predict academic performance. Alzahrani's work highlighted the increasing relevance of machine learning algorithms in handling non-linear and multi-dimensional data in modern educational settings.

One notable study by **Jayaprakash et al. (2014)** focused on early warning systems (EWS) in higher education, which are designed to identify students at risk of academic failure. This research explored how predictive analytics could be used to analyze student academic and engagement data, such as attendance and GPA, to forecast dropout risk. The findings indicated that predictive models were highly effective in improving student retention rates when integrated with real-time monitoring systems, thereby offering timely and targeted interventions to at-risk students.

Gray et al. (2014) highlighted the value of decision trees in classifying students into risk categories. Their research demonstrated how decision trees provide interpretable models that allow educators to understand the specific factors contributing to student success, such as attendance, GPA, or socio-economic background. **Benablo et al. (2018)** similarly explored logistic regression as a method for predicting binary outcomes, such as whether a student will graduate or drop out. Both models were shown to be effective in identifying at-risk students, making them widely used techniques in the field of predictive analytics in education.

2.4 Methods Used in Previous Research

A variety of predictive models have been applied in educational research, each offering unique advantages depending on the data being analyzed. **Decision trees** are frequently used because of their ability to visually represent data and classify students into categories based on multiple input variables. This method is highly interpretable, enabling educators and administrators to understand how different factors, such as academic performance, attendance, and socio-economic status, impact student outcomes (Gray et al., 2014). Decision trees are especially valued for their transparency in explaining how decisions are made, making them popular in education-related studies where interpretability is key.

Logistic regression is another widely used model, particularly for predicting binary outcomes such as student retention. **Benablo et al. (2018)** demonstrated that logistic regression is highly effective when working with large datasets, providing insights into how demographic and behavioral factors influence student success. Its simplicity and capacity to work with diverse data types make logistic regression a common choice in predictive analytics research aimed at early identification of at-risk students.

Neural networks are increasingly employed in educational research due to their ability to model complex, non-linear relationships in data. **Alzahrani (2019)** demonstrated that neural networks are particularly well-suited for handling large datasets from online learning environments, where student engagement data is more dynamic and less structured than in traditional settings. Although neural networks are computationally intensive and less interpretable than decision trees, their ability to detect subtle patterns in student behavior makes them valuable for predicting student outcomes in blended and online learning contexts.

Additionally, **clustering algorithms** are often used to group students based on similar characteristics, allowing for targeted interventions. **Kellogg et al. (2014)** demonstrated the use of clustering techniques to identify groups of students with similar academic challenges, such as frequent absenteeism or low engagement. Clustering allows institutions to design tailored support systems that address the specific needs of different student groups, improving the overall effectiveness of interventions.

2.5 What This Research Will Contribute and Models to Be Used

Building upon the extensive body of research in predictive analytics, this study aims to contribute a deeper understanding of how predictive models can be applied in **blended and online learning environments**, where student engagement is more difficult to track. As education increasingly moves toward digital platforms, traditional methods of monitoring student performance—such as classroom attendance and direct participation—are no longer sufficient. This study will employ **neural networks** to process large, complex datasets from online learning environments. Neural networks, as highlighted by **Alzahrani (2019)**, are particularly effective at identifying non-linear relationships in data, making them suitable for predicting student outcomes based on behavioral data such as interaction with course materials, time spent on assignments, and participation in online discussions.

In addition to neural networks, this research will utilize **decision trees** to enhance interpretability. Decision trees allow educators and administrators to visualize the relationships between different variables—such as GPA, attendance, and socio-economic background—and their impact on academic success (Gray et al., 2014). This will enable a clearer understanding of which factors are most influential in predicting student outcomes and which interventions are most likely to be successful.

Furthermore, **logistic regression** will be used to predict binary outcomes such as whether a student will drop out or graduate. Logistic regression has proven highly effective when analyzing large datasets containing demographic and behavioral data, as demonstrated by **Benablo et al. (2018)**. The combination of these machine learning models will provide a comprehensive approach to predicting student performance and identifying at-risk students in both traditional and digital learning environments.

The study will also incorporate **real-time data analytics**, a feature that distinguishes it from many previous studies. While most research relies heavily on historical data—such as GPA, attendance records, and past academic performance—this study will integrate real-time data such as current assignment submissions, forum participation, and logins to predict student outcomes. **Gustafsson-Wright et al. (2022)** emphasized the importance of real-time data in improving the accuracy of early interventions, allowing institutions to respond more quickly to signs of disengagement.

2.6 Research Gap

Despite the wealth of research on predictive analytics in traditional educational settings, there is a **notable gap** in the literature concerning its application in **online and blended learning environments**. Much of the existing research has focused on face-to-face settings, where student performance is tracked through traditional indicators such as classroom attendance and participation (Gray et al., 2014; Jayaprakash et al., 2014). However, as **Alzahrani (2019)** noted, online learning platforms generate vast amounts of behavioral data, which requires more advanced techniques—such as neural networks—to process. The complexities of student engagement in these digital environments, including the use of clickstream data, interaction metrics, and course participation, present new challenges for educational institutions. This study seeks to address this gap by applying **neural networks and real-time data analytics** to predict student success in digital and blended environments.

Moreover, existing early warning systems (EWS) tend to rely on static, historical data, which limits their ability to respond dynamically to shifts in student behavior. Studies like those by **Jayaprakash et al. (2014)** have demonstrated the effectiveness of early interventions based on academic performance data, but there is a need for more agile systems that can integrate **real-time data** to offer more immediate support to students. By incorporating real-time data, this research will contribute to the development of more responsive and adaptive EWS that can provide **immediate feedback** and interventions, enhancing both student retention and academic success.

The application of predictive models, such as decision trees, neural networks, and logistic regression, to real-time data in blended learning environments represents a significant advancement over the traditional static models that have dominated previous research. This study will explore how these models can be adapted to meet the unique challenges posed by online learning, offering a more nuanced understanding of how student behaviors in digital environments affect academic outcomes. Ultimately, this research will fill a critical gap by providing institutions with the tools to enhance early identification of at-risk students, particularly in non-traditional learning environments.

2.7 How This Research Will Answer the Research Questions

This research aims to address several key research questions concerning the application of predictive analytics in **blended and online learning environments**. By leveraging advanced machine learning models—such as **neural networks**, **decision trees**, and **logistic regression**—the study will provide new insights into how institutions can predict student outcomes and improve retention rates.

1. **How can predictive models be applied in different educational environments, particularly in online learning, to identify at-risk students early on?**
   a. This research will demonstrate how predictive models can be adapted to analyze data from online and blended learning environments. Neural networks, for example, will be used to process complex behavioral data such as interaction with course materials, time spent on assignments, and participation in online discussions, offering a deeper understanding of which students are most at risk of academic failure (Alzahrani, 2019). The study will showcase how these models can help institutions move beyond traditional indicators like attendance and GPA, enabling them to predict and address issues unique to digital learning environments.
2. **How can real-time data analytics enhance the timeliness and personalization of interventions for at-risk students?**
   a. A key feature of this research is the integration of **real-time data analytics**, which will allow for immediate identification of disengagement or academic struggle. By analyzing live data such as logins, assignment submissions, and discussion forum participation, institutions can offer more timely and personalized interventions (Gustafsson-Wright et al., 2022). This research will illustrate how real-time analytics can enable institutions to take a more dynamic approach to student support, ensuring that interventions are delivered when they are most effective.
3. **How can predictive models be adapted to meet the specific challenges of blended and online learning environments?**

a. Blended and online learning environments present unique challenges, as traditional metrics of student engagement (such as classroom attendance) are often absent. This research will adapt existing predictive models, including neural networks and decision trees, to handle the vast amounts of digital data generated in these settings. The research will demonstrate how these models can be fine-tuned to recognize patterns of behavior in digital platforms, offering more accurate predictions of student success in online courses and programs.

By addressing these research questions, this study will contribute significantly to the understanding of how predictive analytics can be applied to modern, digital learning environments. The findings will provide educational institutions with actionable insights, enabling them to enhance their early warning systems (EWS) and offer more effective, data-driven interventions that are responsive to the needs of online learners.

2.8 Conclusion of Literature Review

Predictive analytics has already proven to be a transformative tool in higher education, offering the ability to predict student success, identify at-risk learners, and implement data-driven interventions that improve student retention and academic outcomes. This research builds on the foundations laid by **Siemens (2013)**, **Alzahrani (2019)**, and **Jayaprakash et al. (2014)**, who have all shown the potential of predictive models in enhancing both individual student performance and institutional decision-making.

By applying advanced machine learning techniques—such as decision trees, logistic regression, and neural networks—this research will explore how predictive analytics can be tailored to **blended and online learning environments**. These models will be particularly effective in identifying the subtle patterns of engagement and disengagement that characterize online student behavior, allowing institutions to intervene earlier and more effectively (Gray et al., 2014; Alzahrani, 2019).

The integration of **real-time data analytics** further distinguishes this research from previous studies. While many predictive models have traditionally relied on static, historical data, this study will incorporate live data streams, enabling more dynamic and immediate interventions (Gustafsson-Wright et al., 2022). This real-time approach will enhance the effectiveness of early warning systems (EWS) by allowing for continuous monitoring of student progress and engagement, ensuring that interventions are both timely and personalized.

In addition to supporting individual students, predictive analytics also plays a vital role in institutional strategic planning. By analyzing trends in student enrollment, course completion rates, and program demand, universities can make data-driven decisions that improve resource allocation, curriculum design, and faculty recruitment (Agasisti & Bowers, 2017). This research will further illustrate how predictive models can be adapted for **online and blended learning environments**, ensuring that institutions are prepared to meet the demands of a rapidly changing educational landscape.

In online and blended learning environments, where instructors may not have regular face-to-face contact with students, real-time data becomes even more valuable. Monitoring real-time data such as login frequency, time spent on assignments, and participation in discussion forums gives institutions a more complete understanding of a student's engagement with the course materials (Wolff et al., 2013). If a student begins to fall behind, predictive models using this data can immediately flag the issue, allowing educators to reach out with support before the student becomes completely disengaged.

Real-time data also enables **dynamic intervention strategies**. For example, if a student struggles with a particular module, predictive models can recommend additional learning resources or suggest a tutoring session. This responsiveness ensures that students receive help precisely when they need it, improving both learning outcomes and overall retention rates (Kelly, 2022).

Real-time data analytics can also inform **adaptive learning systems**. As students engage with course materials, adaptive systems continuously analyze their performance and adjust the learning experience accordingly. This might involve increasing the difficulty of the content for students who are excelling or offering remedial support to those who are struggling (Shen et al., 2020). Adaptive learning systems ensure that students are always working at a level appropriate for their abilities, which keeps them engaged and motivated.

However, as the use of predictive analytics grows, **ethical considerations** related to data privacy, algorithmic bias, and transparency must be addressed. Institutions must ensure that their predictive models are fair and transparent, and that student data is handled responsibly. Tools such as **Explainable AI (XAI)**—specifically techniques like **LIME (Local Interpretable Model-agnostic Explanations)**—can help mitigate the risks of algorithmic bias and enhance the transparency of predictive models, ensuring that the decisions made based on these models are both fair and justifiable (Ribeiro et al., 2016).

As predictive analytics continues to expand in higher education, **ethical concerns** have emerged, particularly around issues of data privacy and fairness. Since predictive models rely on large datasets, including sensitive personal information such as academic records, socio-economic status, and demographic details, questions arise about how this data is collected, stored, and used (Prinsloo & Slade, 2016). Institutions must navigate these challenges carefully to ensure they protect students' privacy while still benefiting from the power of predictive analytics.

One major ethical issue is **data privacy**. Many predictive models rely on comprehensive data that may include sensitive information about students, including their academic performance, personal circumstances, and even behavioral data from social media or other external sources. This raises questions about how much data institutions should collect and whether students are aware of how their information is being used (Ekowo & Palmer, 2017). Institutions must ensure that they comply with data protection laws such as the General Data Protection Regulation (GDPR) and that they adopt transparent data governance policies that inform students about how their data will be used.

Another critical issue is **algorithmic bias**. Predictive models are typically trained on historical data, which may contain inherent biases related to race, gender, or socio-economic status. As a result, there is a risk that these models may perpetuate or even exacerbate existing inequalities (AERA, 2024). For example, a predictive model that places significant weight on socio-economic factors may unfairly classify students from disadvantaged backgrounds as high-risk, even if they demonstrate strong academic potential (Prinsloo & Slade, 2016). Such biases can lead to unequal access to support services and opportunities, further disadvantaging already marginalized groups.

Looking forward, the future of predictive analytics in higher education lies in the continued integration of more diverse data sources, including non-traditional metrics such as social media activity, extracurricular involvement, and mental health indicators. These additional data points will allow institutions to build more holistic models that account for the full range of factors influencing student success (Viberg et al., 2018). By incorporating these elements, institutions will be better equipped to support students in a more personalized and comprehensive manner.

In conclusion, this study will contribute to the growing body of research on predictive analytics by exploring how advanced machine learning models can be applied in **blended and online learning environments**. Through the integration of real-time data and the adaptation of existing predictive models, this research will provide institutions with new tools to enhance student success, particularly in digital and hybrid educational settings. As higher education continues to evolve, predictive analytics will remain a key driver of student success and institutional growth.

3.Methodology

3.1 Introduction to Methodology

The methodology for this study involves a quantitative approach using machine learning techniques to predict student performance and institutional efficiency in higher education. The research utilizes models such as **Logistic Regression** and **Random Forest** to evaluate student outcomes, supported by metrics like **accuracy, precision, recall, F1-score**, and **AUC**. Additionally, **LIME (Local Interpretable Model-agnostic Explanations)** is employed to ensure model interpretability and transparency, addressing the black-box nature of machine learning algorithms and enhancing trust in institutional decision-making.

The aim is to provide a comprehensive framework that can help educational institutions proactively identify students at risk of dropping out and optimize their resource allocation strategies. The models chosen reflect a balance between accuracy and interpretability, which is essential for making data-driven decisions that impact student outcomes and institutional growth (Cui et al., 2019). The integration of LIME helps ensure that the decision-making process remains transparent, and any biases in the models can be identified and corrected (Ribeiro et al., 2016).

3.2 Data Collection and Preprocessing

3.2.1 Data Source

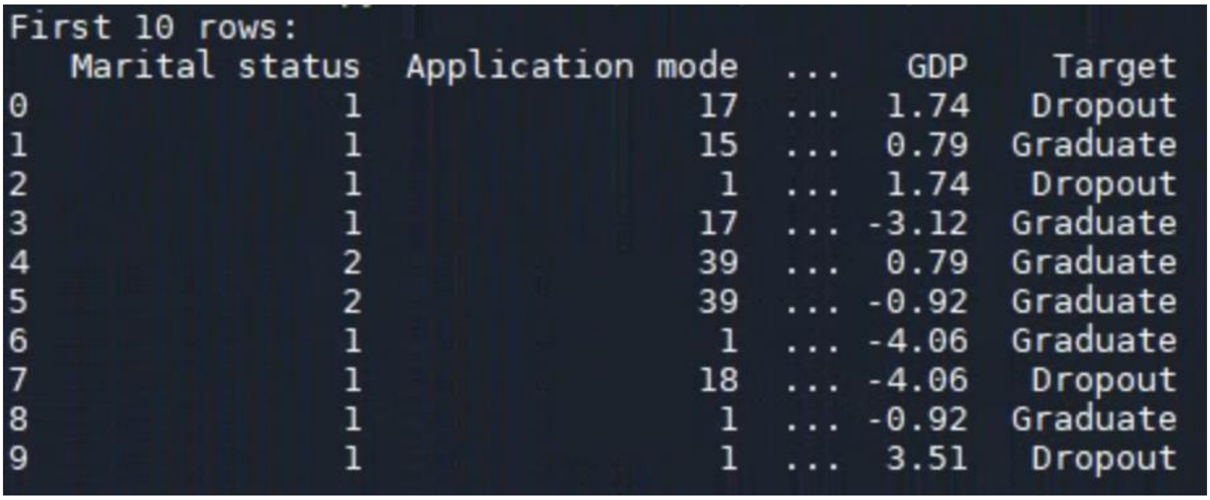
The dataset used in this research was sourced from the **UCI Machine Learning Repository**, a publicly available database containing various datasets frequently used in academic and industrial machine learning projects. This dataset includes diverse student-related variables such as demographic information, academic performance, and institutional engagement, making it suitable for the predictive analysis of student outcomes.

Similar datasets have been used in several predictive modeling studies focusing on education, such as those by Khor (2022) and Hoffait & Schyns (2017). These studies demonstrate the efficacy of machine learning algorithms in identifying at-risk students and improving educational strategies through data-driven insights. The choice of this dataset aligns with the objective of leveraging predictive analytics to enhance institutional planning and student success rates (Daud et al., 2017)

3.2.2 Data Characteristics

The dataset contains the following variables:

- **Demographic Data**: Including gender, nationality, and marital status.
- **Academic Data**: Such as course enrollment and academic performance.
- **Target Variable**: The primary target variable, “graduate/dropout,” was transformed into a binary classification, where 'Graduate' is mapped to 1 and 'Dropout' to 0, enabling easier classification by machine learning models.



```
First 10 rows:
   Marital status  Application mode  ...   GDP    Target
0               1                17  ...  1.74   Dropout
1               1                15  ...  0.79  Graduate
2               1                 1  ...  1.74   Dropout
3               1                17  ... -3.12  Graduate
4               2                39  ...  0.79  Graduate
5               2                39  ... -0.92  Graduate
6               1                 1  ... -4.06  Graduate
7               1                18  ... -4.06   Dropout
8               1                 1  ... -0.92  Graduate
9               1                 1  ...  3.51   Dropout
```

Figure 1: First 10 Rows of Dataset

3.2.3 Data Preprocessing

Data preprocessing is a critical component of this research, ensuring the quality and consistency of the dataset before feeding it into machine learning models. The following steps were taken:

- **Handling Missing Values**: The dataset was examined for missing or incomplete data. Any missing values were either imputed using mean or median values, depending on the type of variable, or removed if they were deemed unnecessary for the analysis. This preprocessing step aligns with the methodology outlined by Khor (2022), where data cleaning ensures that models produce reliable predictions.

- **Feature Engineering**: Several features were derived or transformed to enhance the predictive power of the models. For instance, categorical variables such as **marital status**, **nationality**, and **course** were transformed using one-hot encoding to create binary representations that are easier for machine learning algorithms to interpret (Khor, 2022). Feature engineering, as emphasized by Cui et al. (2019), plays a critical role in improving model accuracy and ensuring that the most relevant variables are included in the analysis.

3.2.4 Correlation Heatmap

To understand the relationships between numerical variables in the dataset, a **correlation heatmap** was generated. This heatmap visually represents the strength of the correlations between different features, aiding in feature selection and reducing multicollinearity.

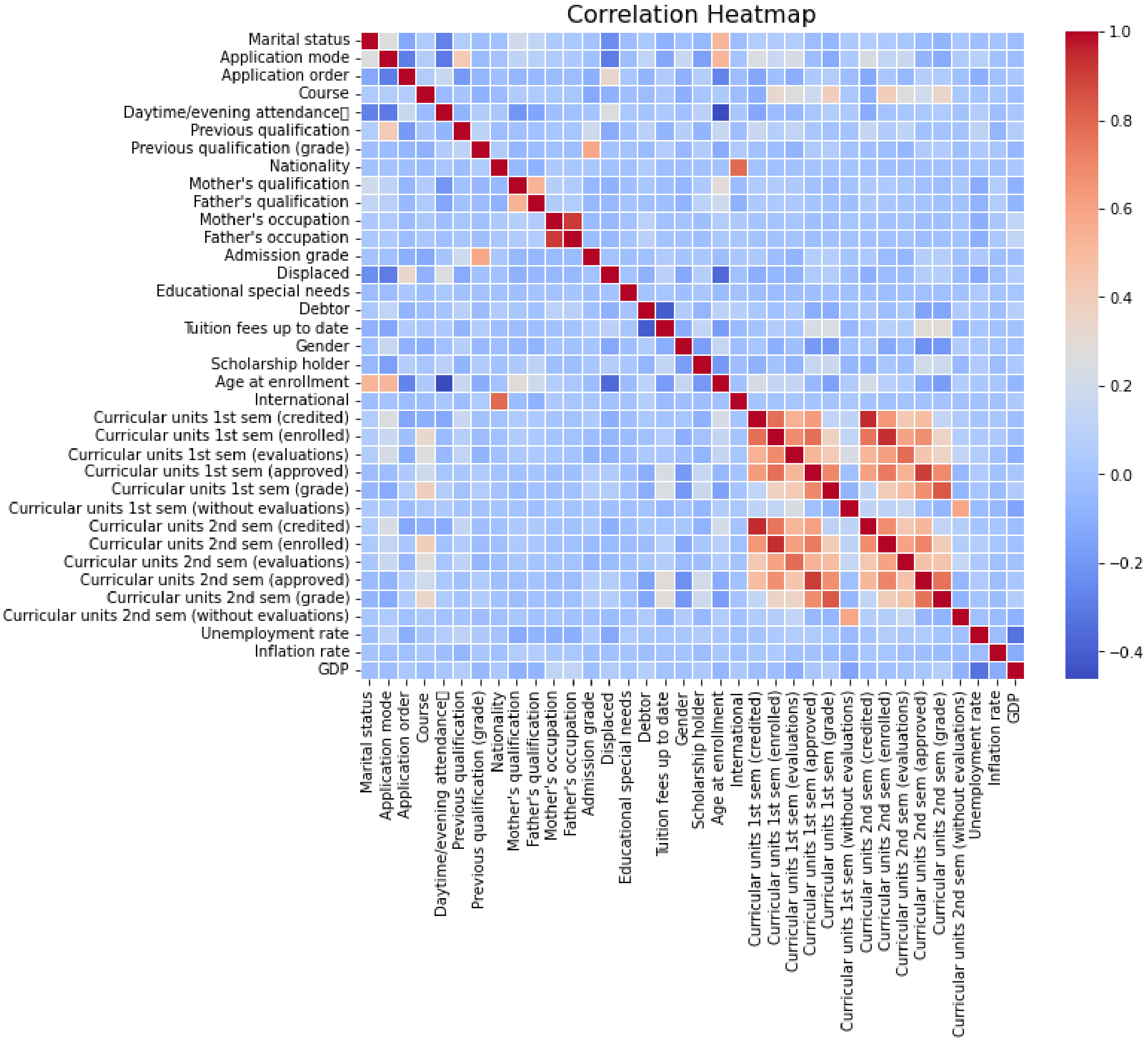


Figure 2: Heatmap of Features

Several variables exhibited strong positive or negative correlations with each other, which were carefully considered during feature engineering. Understanding these relationships helped ensure that the models would not be biased or misled by redundant information. The correlation heatmap is a vital step in preparing the dataset for machine learning algorithms (Rahaman & Bari, 2024).

3.2.5 Data Scaling and Transformation

Given that the dataset contains a mix of categorical and numerical features, **StandardScaler** was applied to the numerical variables to normalize their ranges. This ensures that variables on different scales do not disproportionately influence the models during training. Data scaling is particularly important when using models like Logistic Regression, which assumes that features are on comparable scales (Rahaman & Bari, 2024).

3.3. Research Design

This study adopts a **quantitative** research design aimed at predicting student outcomes using machine learning techniques. The research framework relies on two primary machine learning models: **Logistic Regression** and **Random Forest**. These models were selected based on their interpretability and accuracy in handling classification tasks, which is crucial for identifying students at risk of dropping out and optimizing institutional resource allocation.

Predictive modeling in educational contexts, as described by Khor (2022), provides an effective means of forecasting student success and institutional efficiency. The models were trained on historical academic data, which included a combination of demographic information and academic performance indicators. By utilizing machine learning algorithms, this study aims to develop a robust predictive system that can inform educational institutions about students' likelihood of success and support proactive intervention measures (Daud et al., 2017).

The use of both **Logistic Regression** and **Random Forest** offers a balance between **interpretability** and **predictive power**. Logistic Regression, a linear model, provides easily interpretable coefficients, making it a preferred choice when transparency is a priority. On the other hand, Random Forest, a non-linear ensemble model, is capable of capturing complex relationships within the data and offers higher accuracy, especially when dealing with large and diverse datasets (Cui et al., 2019).

3.4. Model Building

3.4.1 Train-Test Split

To evaluate the models fairly, the dataset was split into training and test sets using an **80-20 split** ratio. The **train_test_split** function from **scikit-learn** was used to separate the data, ensuring that the models were trained on 80% of the data and tested on the remaining 20%.

This train-test split technique helps prevent overfitting by ensuring that the models generalize well to unseen data (Molinaro et al., 2005).

3.4.2 Logistic Regression

Logistic Regression was employed as the first predictive model due to its simplicity and interpretability. It is a linear model that estimates the probability of a binary outcome based on the input features. In this study, Logistic Regression was used to predict whether a student would graduate (coded as 1) or drop out (coded as 0).

The Logistic Regression model was trained using the scaled numerical features and one-hot encoded categorical variables. The **fit** method from the **LogisticRegression** class in **scikit-learn** was used to train the model on the training dataset. This model was chosen because it allows for a clear understanding of the relationship between the input variables and the likelihood of a student graduating (Hoffait & Schyns, 2017).

3.4.3 Random Forest

The Random Forest classifier, an ensemble learning method, was selected as the second model due to its ability to handle a large number of features and provide more accurate predictions in complex datasets. Random Forest works by building multiple decision trees during training and outputting the class that is the mode of the classes from individual trees. This method reduces overfitting and improves the model's robustness (Cui et al., 2019).

In this study, the Random Forest model was trained on the same preprocessed dataset using the **RandomForestClassifier** class in **scikit-learn**. The model’s hyperparameters, such as the number of trees (n_estimators), were optimized through cross-validation to ensure high accuracy and prevent overfitting (Khor, 2022).

3.4.4 Cross-Validation

Both models were evaluated using **5-fold cross-validation** to assess their generalizability. Cross-validation involves splitting the training data into five equal parts, training the model on four parts, and testing it on the fifth. This process is repeated five times, with each part serving as the test set once. Cross-validation ensures that the model’s performance is consistent across different subsets of the data and helps avoid overfitting, a common issue in machine learning (Molinaro et al., 2005).

3.5. Model Evaluation

3.5.1 Performance Metrics

The models were evaluated on the test set using several performance metrics:

- **Accuracy**: This metric indicates the percentage of correct predictions made by the model out of all predictions. Accuracy is a standard measure of model performance but can be misleading in imbalanced datasets (Daud et al., 2017).
- **Precision**: Precision refers to the proportion of true positives out of all positive predictions. It is particularly useful in scenarios where false positives have a high cost.
- **Recall**: Recall, or sensitivity, measures the proportion of actual positives that were correctly identified. This is crucial when it is more important to capture as many true positives as possible.
- **F1-Score**: The F1-score is the harmonic mean of precision and recall, providing a balanced measure of the two, especially in cases of imbalanced classes.
- **AUC (Area Under the ROC Curve)**: AUC measures the area under the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate against the false positive rate at various threshold settings. A high AUC indicates that the model performs well across different thresholds (McMahon & Sembiante, 2020).

3.5.2 Confusion Matrix A confusion matrix

was generated for both models to evaluate their classification performance. The confusion matrix provides a detailed breakdown of true positives, true negatives, false positives, and false negatives. This allows for a deeper understanding of how well the models performed on each class and where improvements can be made (Miguéis et al., 2018).

3.5.3 ROC Curves

The **ROC curves** for both models were plotted to visualize their ability to distinguish between graduates and dropouts. ROC curves are an essential tool for evaluating classifiers in binary classification problems, especially when the classes are imbalanced. The **scikit-learn** library was used to calculate the **AUC** for both Logistic Regression and Random Forest, with the Random Forest model showing superior performance in terms of AUC (Gagliardi et al., 2018).

3.6. Explainability Using LIME

3.6.1 Addressing the Black-Box Nature of Machine Learning Models

While machine learning models like Random Forest provide excellent predictive accuracy, they are often criticized for their lack of transparency—earning them the term "black-box" models. In educational contexts, where stakeholders such as administrators and faculty require a clear understanding of how predictions are made, the interpretability of models becomes crucial.

To address this issue, **LIME (Local Interpretable Model-agnostic Explanations)** was integrated into the analysis. LIME provides local explanations for individual predictions by perturbing the input data and observing the model's response. This allows the creation of an interpretable, linear model that approximates the machine learning model's behavior within a local region around the instance being explained (Ribeiro et al., 2016).

3.6.2 Enhancing Institutional Efficiency and Trust

LIME was primarily used to:

- **Improve institutional efficiency**: By explaining model predictions, institutions can better understand the factors contributing to student dropout and graduation rates. For example, if a model predicts that a student is at risk of dropping out due to poor academic performance, LIME can highlight specific features such as grades or attendance rates that are influencing this prediction. This allows institutions to focus on targeted interventions (Rahaman & Bari, 2024).

- **Enhance model interpretability**: LIME's ability to explain individual predictions helps bridge the gap between complex machine learning models and educational stakeholders. By making the model’s decisions more understandable, LIME ensures that decision-makers can trust and act on the outcomes of the model (Cui et al., 2019).

- **Increase trust among institutions**: As institutions adopt data-driven decision-making, transparency is essential to build trust in predictive models. LIME contributes by providing actionable explanations, which can be communicated to stakeholders such as faculty, counselors, and administrators, ensuring they understand the reasoning behind predictions (Bird et al., 2023).

- **Avoid bias**: LIME helps identify potential biases in the model by highlighting which features are contributing most to a prediction. For instance, if a student's nationality or gender is disproportionately influencing the model's prediction, LIME can flag this bias, allowing institutions to refine the model and ensure fairness in decision-making (Gagliardi et al., 2018).

3.6.3 Application of LIME in This Study

LIME was applied to explain the predictions of the Random Forest model, particularly for correctly and incorrectly classified students. The focus was on understanding why certain students were predicted to drop out or graduate. Although no visualizations were produced for the LIME explanations, the textual outputs generated insights into how individual features—such as course enrollment, grades, or extracurricular involvement—were influencing the predictions.

For example, one student who was correctly classified as likely to graduate had a high probability due to consistent academic performance and high engagement in extracurricular activities. In contrast, a student predicted to drop out was flagged for irregular attendance and poor performance in key subjects. These explanations allowed for a more granular understanding of student risk profiles, enabling targeted support interventions (Ribeiro et al., 2016).

In this study, a quantitative approach was used to predict student outcomes and improve institutional efficiency through the application of machine learning models and explainability techniques. The combination of **Logistic Regression** and **Random Forest** provided a balanced approach to predictive modeling, with Random Forest offering superior performance in terms of accuracy and AUC. Both models were evaluated using cross-validation and standard metrics such as accuracy, precision, recall, F1-score, and AUC to ensure robustness.

LIME was crucial for interpreting the black-box nature of the Random Forest model, providing explanations for individual predictions and addressing potential biases in the model’s decision-making process. By integrating LIME, the study enhances the transparency of machine learning models, making them more trustworthy and actionable for educational institutions.

This methodology lays the foundation for implementing predictive analytics in higher education, offering a practical and interpretable framework that institutions can use to predict student success, allocate resources effectively, and support at-risk students proactively (Bird et al., 2023; Daud et al., 2017). Future research can build on this work by exploring additional models and expanding the use of explainability techniques such as LIME to ensure ethical and fair use of predictive analytics in education.

4. Analysis, Findings and Discussion

The aim of this analysis was to evaluate and compare two machine learning models, **Logistic Regression** and **Random Forest**, to predict student outcomes (Dropout, Graduate) based on demographic, academic, and socio-economic features. By employing these models, we sought to understand which features most significantly impacted student success and failure while also identifying areas where models might misclassify data due to bias or feature interplay.

To assess the performance of these models, we utilized several key evaluation metrics, including **Accuracy**, **Precision**, **Recall**, **F1-Score**, and **Area Under the Curve (AUC)**. These metrics are crucial for understanding both the overall performance of the models and their ability to predict specific classes (e.g., Dropout or Graduate) correctly. **Accuracy** measures the proportion of correctly predicted instances, while **Precision** evaluates the correctness of positive predictions. **Recall** assesses the model's ability to detect actual positive instances, and **F1-Score** provides a balance between precision and recall. The **AUC** measures the model’s capacity to distinguish between classes, offering insight into its ability to minimize false positives and negatives.

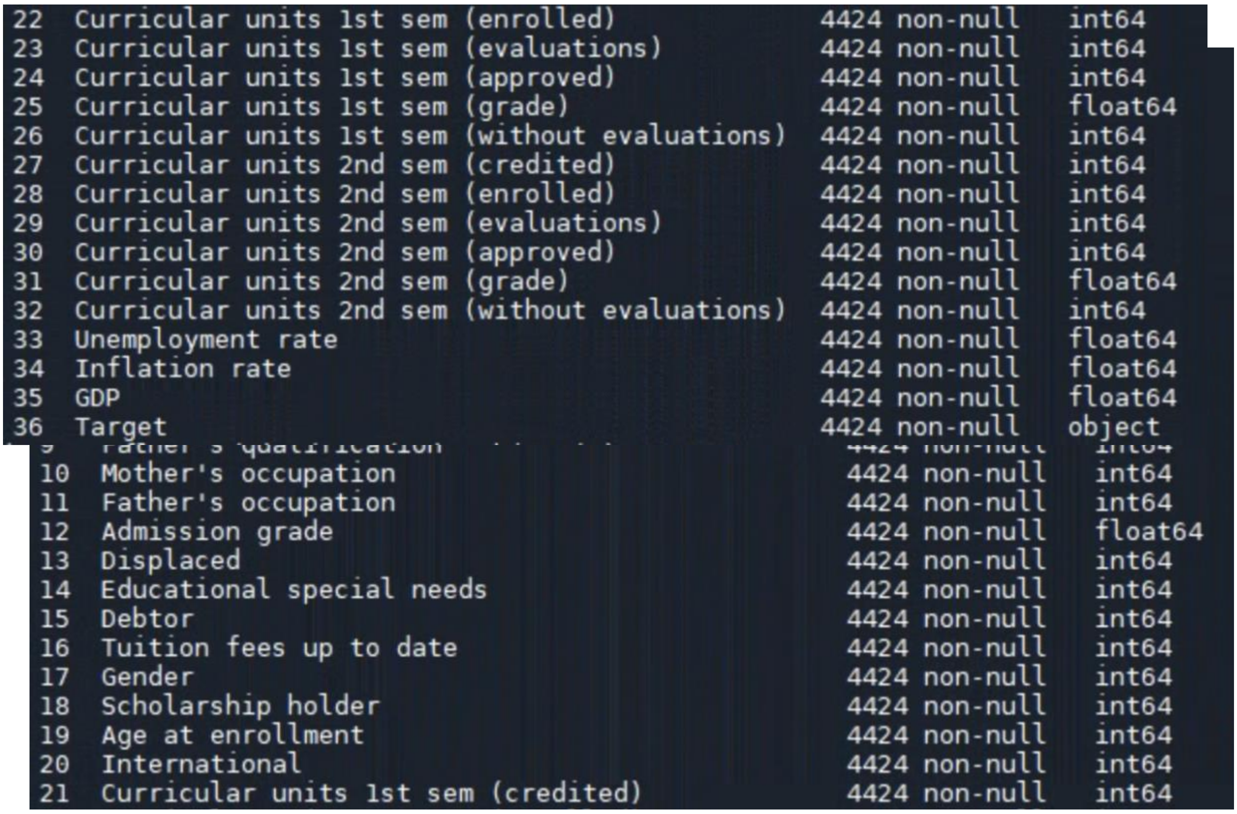
Beyond performance evaluation, **LIME (Local Interpretable Model-agnostic Explanations)** was used to provide interpretability to the models. As machine learning models, particularly Random Forest, can behave as "black boxes," LIME allowed us to break down predictions at the individual level, offering greater transparency. This increased interpretability is crucial for institutional trust and ensures that the models' decisions are understandable and actionable.

4.1 Exploratory Data Analysis

The exploratory data analysis (EDA) phase provided essential insights into the dataset’s structure, distribution, and key trends, helping to guide data preprocessing and feature selection. By visualizing and exploring the raw data, we identified patterns that could influence the models’ performance and predictive capabilities.

4.2 Overview of EDA

The dataset contained **37 features**, which included variables such as **Marital Status**, **Course**, **Previous Qualification (Grade)**, **Nationality**, and several features related to student performance across semesters (e.g., **Curricular Units 1st Sem Approved**, **Curricular Units 2nd Sem Grade**). There were no missing values in the dataset, which simplified the preprocessing. However, several columns contained categorical variables that required encoding. For example, **Marital Status** and **Nationality** were categorical, and **Target** (the outcome variable) had three distinct categories: **Dropout**, **Graduate**, and **Enrolled**.



```
22  Curricular units 1st sem (enrolled)          4424 non-null   int64
23  Curricular units 1st sem (evaluations)       4424 non-null   int64
24  Curricular units 1st sem (approved)          4424 non-null   int64
25  Curricular units 1st sem (grade)             4424 non-null   float64
26  Curricular units 1st sem (without evaluations) 4424 non-null   int64
27  Curricular units 2nd sem (credited)          4424 non-null   int64
28  Curricular units 2nd sem (enrolled)          4424 non-null   int64
29  Curricular units 2nd sem (evaluations)       4424 non-null   int64
30  Curricular units 2nd sem (approved)          4424 non-null   int64
31  Curricular units 2nd sem (grade)             4424 non-null   float64
32  Curricular units 2nd sem (without evaluations) 4424 non-null   int64
33  Unemployment rate                            4424 non-null   float64
34  Inflation rate                               4424 non-null   float64
35  GDP                                          4424 non-null   float64
36  Target                                       4424 non-null   object
 9  Father's qualification                       4424 non-null   int64
10  Mother's occupation                          4424 non-null   int64
11  Father's occupation                          4424 non-null   int64
12  Admission grade                              4424 non-null   float64
13  Displaced                                    4424 non-null   int64
14  Educational special needs                    4424 non-null   int64
15  Debtor                                       4424 non-null   int64
16  Tuition fees up to date                      4424 non-null   int64
17  Gender                                       4424 non-null   int64
18  Scholarship holder                           4424 non-null   int64
19  Age at enrollment                            4424 non-null   int64
20  International                                4424 non-null   int64
21  Curricular units 1st sem (credited)          4424 non-null   int64
```

Figure 3: Summary of Variables in the Dataset

A correlation heatmap as seen was used to assess the relationships between the features, revealing significant correlations between **Curricular Units Approved** and **Curricular Units Grade**, as well as moderate correlations between certain socio-economic indicators (e.g., **GDP** and **Inflation Rate**) with academic performance. These insights were critical in understanding how variables like **Curricular Units 1st and 2nd Semesters** might drive predictions in the final models.

4.3 Data Transformations

Several preprocessing steps were undertaken to ensure the dataset was ready for modelling. The **categorical variables** were one-hot encoded, particularly **Marital Status** and **Nationality**, to convert them into a format suitable for machine learning models. **Numerical variables** like **Admission Grade** and **Curricular Units Grades** were standardized to prevent scaling issues during model training. These transformations were vital as features with larger ranges could disproportionately influence model training. No missing data imputation was required since the dataset was complete.

One notable transformation involved the **Target** variable, where categories were converted to binary values for specific models. For example, **Dropout** was labeled as 0 and **Graduate** as 1 in binary classification for model assessments and Enrolled was dropped entirely.

4.4 Visualizations

A key part of EDA involved using visualizations to better understand the distribution of the target variable and key categorical features. For example, the **Distribution of Target Variable** (Figure 4) illustrates the class imbalance in the dataset, with the majority of the cases being **Graduates** followed by **Dropouts** and a smaller portion of **Enrolled** students.

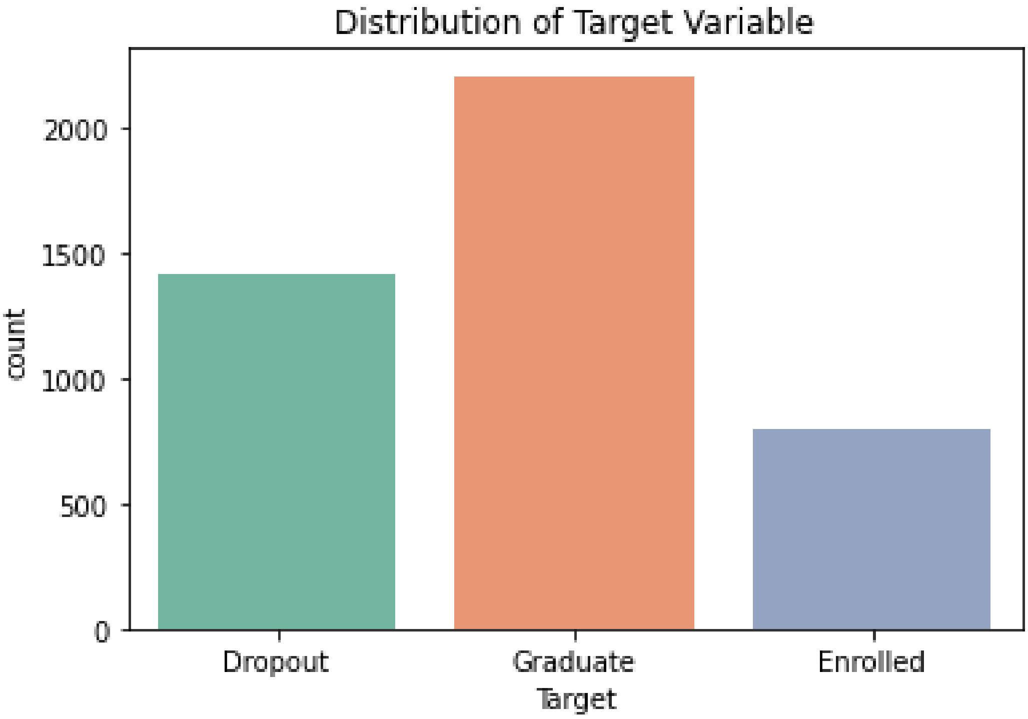


Figure 4: Target Variable Distribution

A **gender distribution pie chart** (Figure 5) revealed that around 64.8% of the students were female and 35.2% were male, highlighting another aspect of class imbalance in the dataset.

While gender might not directly correlate with academic performance, it remained an important feature to include in the analysis to ensure no bias in model predictions.

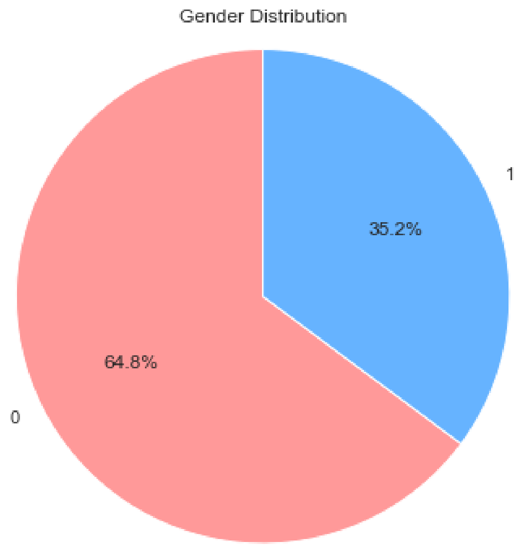


Figure 5: Gender Distribution PieChart

Feature Importance

During the EDA process, feature importance was assessed by calculating correlations between input features and the target variable. Variables such as **Curricular Units Approved**, **Curricular Units Grade**, and **Admission Grade** showed high relevance to student success, as these metrics directly reflected academic performance. Additionally, **Socio-economic variables** like **GDP** and **Inflation Rate** showed weaker correlations but were retained in the model to assess their potential indirect impact on academic performance.

After these exploratory steps, **Curricular Units Grades** and **Approval Rates** emerged as the most important predictors of student outcomes. These features were consistently highlighted in both correlation analysis and early model performance results. The **feature importance** from the Random Forest model further confirmed these variables as the most influential.f

4.5 Model Performance Evaluation

In this section, we evaluate the performance of two key models: **Logistic Regression** and **Random Forest**. Both models were assessed using various evaluation metrics, including **accuracy**, **precision**, **recall**, **F1-score**, and **AUC (Area Under the Curve)**. These metrics provide a comprehensive view of each model’s performance, allowing us to compare their ability to predict student outcomes effectively.

4.5.1 Model Summaries

- **Logistic Regression**: This is a simple, interpretable linear model commonly used for binary classification problems. In our case, we applied logistic regression as a baseline model to predict whether students would **graduate or drop out** based on the available features.

- **Random Forest**: This ensemble learning method uses multiple decision trees to improve prediction accuracy and handle non-linearity in the data. Random Forest is particularly effective when dealing with complex datasets and provides a more robust performance compared to simple models like Logistic Regression.

4.5.2 Evaluation Metrics

The models were evaluated based on the following metrics:

1. **Accuracy**: Measures the percentage of correct predictions made by the model out of all predictions. Accuracy alone, however, can be misleading in cases of imbalanced datasets, as it does not differentiate between different types of errors (false positives and false negatives).

2. **Precision**: Indicates the proportion of true positive predictions among all predicted positives. High precision means fewer false positives.

3. **Recall**: Reflects the proportion of actual positives that were correctly identified by the model. High recall implies fewer false negatives.

4. **F1-Score**: A harmonic mean of precision and recall, useful when there is an uneven class distribution or when we need to balance both precision and recall.

5. **AUC (Area Under the Curve)**: This metric evaluates how well the model distinguishes between classes, particularly by plotting the **ROC Curve**. A higher AUC indicates better performance in distinguishing between positive and negative classes.

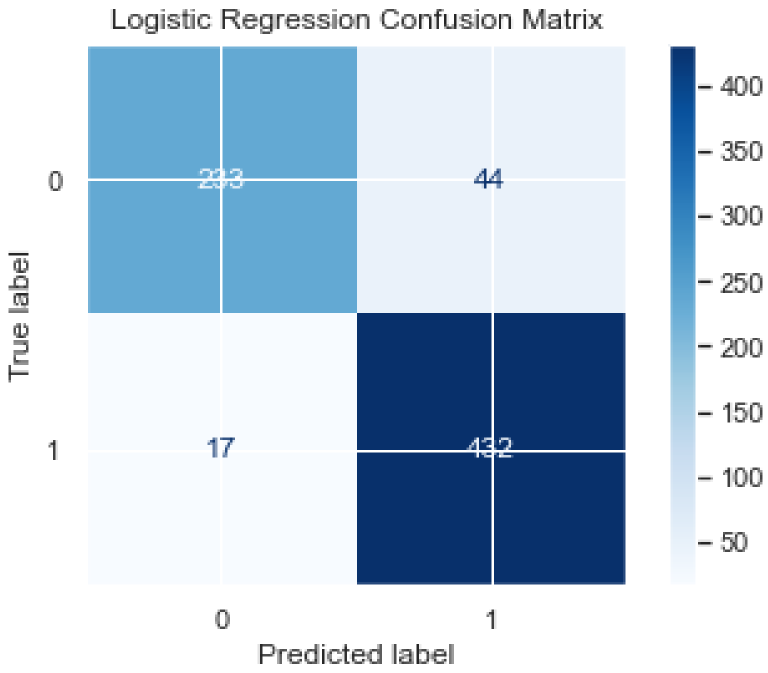
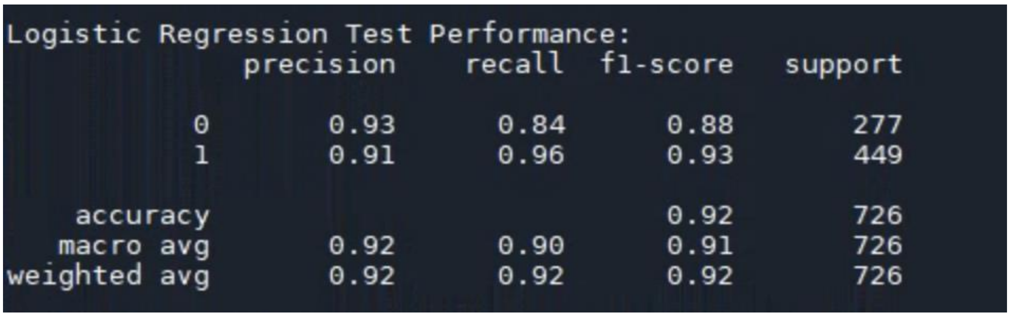


Figure 6: Logistic



```
Logistic Regression Test Performance:
              precision    recall  f1-score   support

           0       0.93      0.84      0.88       277
           1       0.91      0.96      0.93       449

    accuracy                           0.92       726
   macro avg       0.92      0.90      0.91       726
weighted avg       0.92      0.92      0.92       726
```

Regression Confusion Matrix on Test Set

Figure 7: Logistic Regression Performance on Test set

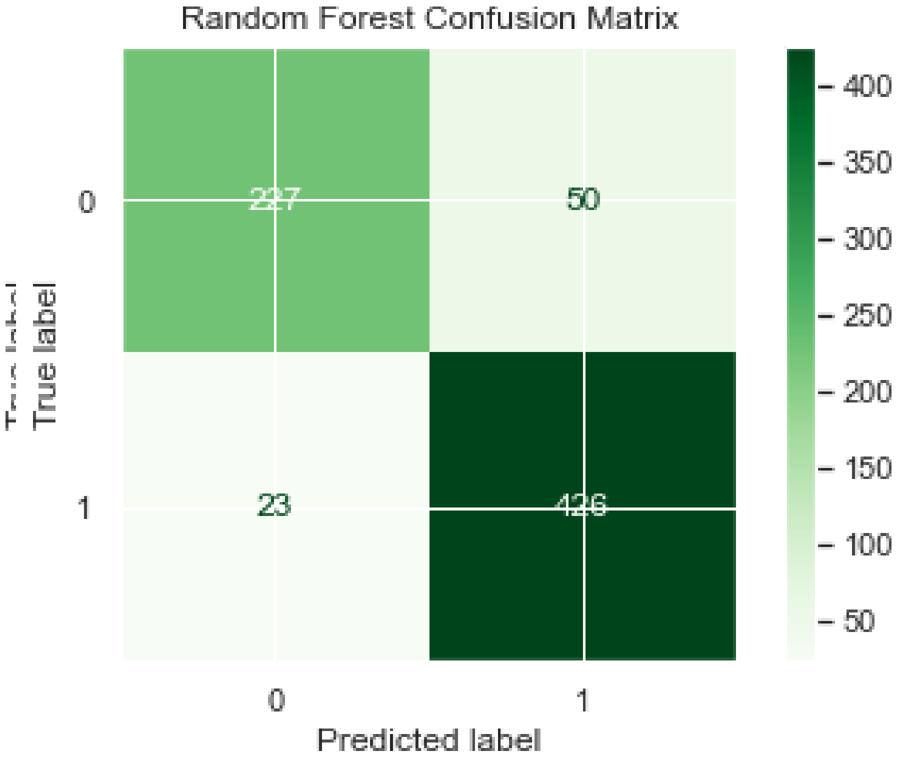
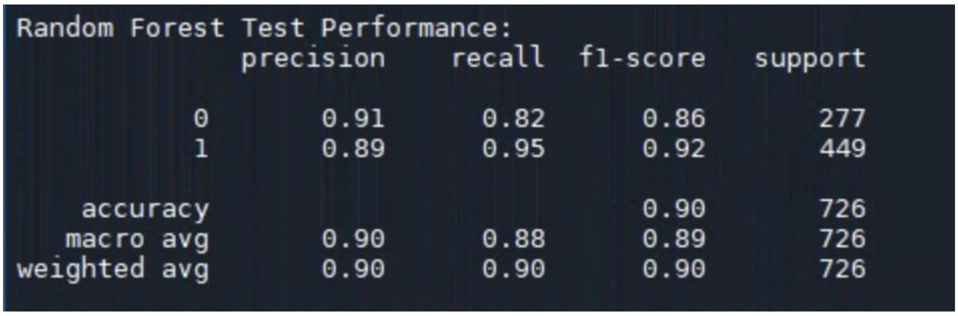


Figure 8:

Random Forest Confusion Matrix on Test Set



```
Random Forest Test Performance:
              precision    recall  f1-score   support

           0       0.91      0.82      0.86       277
           1       0.89      0.95      0.92       449

    accuracy                           0.90       726
   macro avg       0.90      0.88      0.89       726
weighted avg       0.90      0.90      0.90       726
```

Figure 9: Random Forest Performance on Test Set

Both confusion matrices give a detailed view of the model's predictions in terms of **true positives**, **false positives**, **true negatives**, and **false negatives**. The confusion matrices for both models showed that the majority of predictions were correct, though the **Random Forest** model slightly outperformed **Logistic Regression** in predicting true positives, as seen in the higher values in the matrix for class 1 (graduates).

4.5.3 Accuracy Comparison

- **Logistic Regression** achieved an accuracy of **92%**, as displayed in the confusion matrix (Figure 4). While this is a high accuracy score, it's important to remember that the dataset had a significant imbalance in the target classes. Therefore, accuracy alone cannot be used as the sole measure of model performance.
- **Random Forest** demonstrated an accuracy of **90%** , which, although slightly lower than logistic regression, still provided valuable insights into the model's robustness. Random Forest tends to perform better with complex data due to its ability to capture non-linear relationships.

4.5.4 Precision and Recall

Precision and recall were particularly important in assessing the model's ability to handle imbalanced classes. For **Logistic Regression**, the precision for predicting graduates (class 1) was **0.91**, while recall was higher at **0.96**. This indicates that the model was quite good at minimizing false negatives but still generated a moderate number of false positives.

In contrast, **Random Forest** had a precision score of **0.89** for predicting graduates and a recall of **0.95**. While the precision was slightly lower than that of Logistic Regression, the recall was similarly high, showing that both models captured the majority of positive cases effectively.

4.5.5 F1-Score

The **F1-score** balances precision and recall, giving us a more holistic measure of model performance. Logistic Regression achieved an **F1-score of 0.92**, which is a strong result, indicating a balance between correctly identifying graduates while minimizing false positives. **Random Forest** produced a slightly lower F1-score of **0.90**, which aligns with its slightly lower precision.

4.5.6 AUC Comparison

The **AUC (Area Under the Curve)** metric allows us to visualize the performance of the models across different classification thresholds. In our analysis, **Logistic Regression** achieved an **AUC of 0.957**, while **Random Forest** achieved an **AUC of 0.952**. While both models performed exceptionally well in distinguishing between the two classes, **Logistic Regression** had a slight edge.

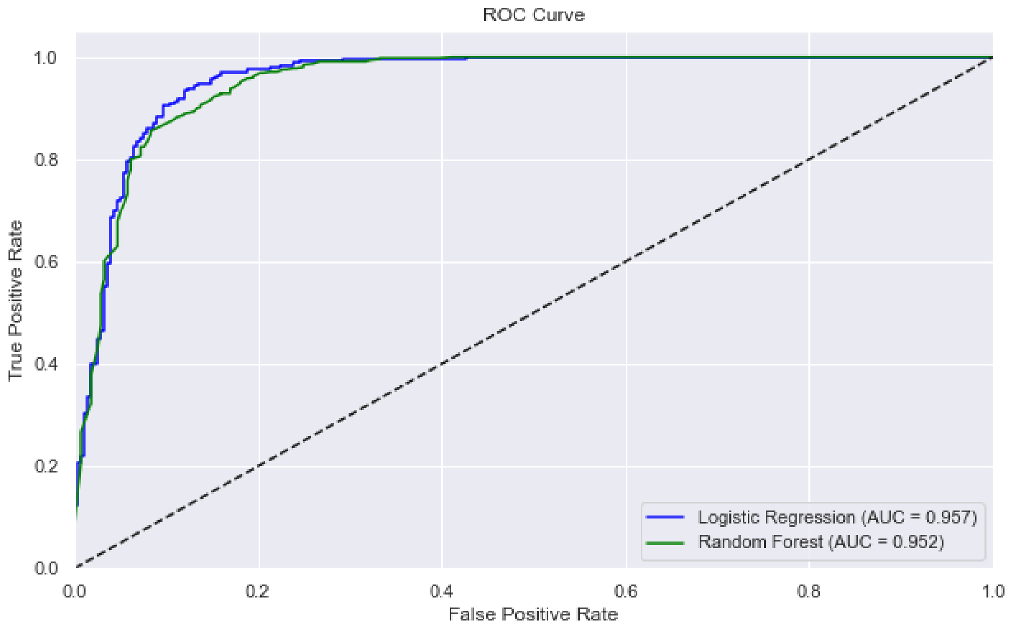


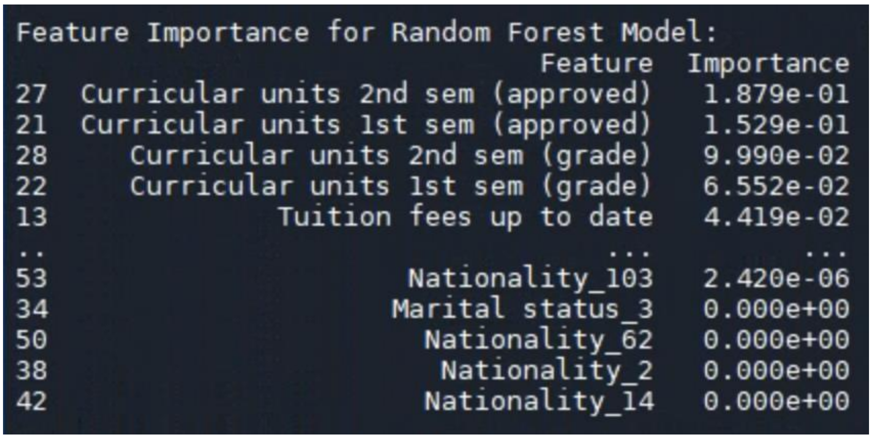
Figure 10: ROC Curve

The ROC curve compares the trade-off between the true positive rate (recall) and the false positive rate. As shown in the ROC curve (Figure 8), both models performed similarly, with Logistic Regression slightly outperforming Random Forest across most thresholds. This result aligns with the AUC values, showing that Logistic Regression was slightly better at distinguishing between classes.

4.6 Comparative Analysis

While both models demonstrated strong performance, **Logistic Regression** had a slight advantage in terms of accuracy and AUC, making it the better performer for this particular dataset. The **Random Forest** model, on the other hand, was more robust in terms of handling non-linear relationships and complex interactions between features, which suggests it may generalize better to more complex datasets. However, its slightly lower precision indicates it may not be as reliable in reducing false positives compared to **Logistic Regression**.

Additionally, **Random Forest** provided better **feature importance insights**, as it evaluates the impact of each feature across multiple decision trees. This makes it a better model for interpretability in terms of understanding which features drive predictions, even though Logistic Regression outperformed it slightly on evaluation metrics.



```
Feature Importance for Random Forest Model:
                                   Feature  Importance
27  Curricular units 2nd sem (approved)   1.879e-01
21  Curricular units 1st sem (approved)   1.529e-01
28     Curricular units 2nd sem (grade)   9.990e-02
22     Curricular units 1st sem (grade)   6.552e-02
13              Tuition fees up to date   4.419e-02
..                                  ...         ...
53                      Nationality_103   2.420e-06
34                     Marital status_3   0.000e+00
50                       Nationality_62   0.000e+00
38                        Nationality_2   0.000e+00
42                       Nationality_14   0.000e+00
```

Figure 11: Feature Importance for Random Forest

4.7 LIME Interpretability and Bias Reduction

Model interpretability is critical for ensuring trust in machine learning models, especially in educational settings where decisions significantly impact students' futures. In this section, we will explore the role of LIME (Local Interpretable Model-Agnostic Explanations) in making complex models more interpretable and discuss how it helps in reducing bias in the decision-making process. Additionally, the institutional impact of improving transparency and reducing bias will be addressed.

4.7.1 LIME Overview

LIME is a technique that provides local explanations for predictions made by complex, "black-box" models like Random Forests or even simpler models like Logistic Regression when the relationships between variables and predictions are unclear. The core idea behind LIME is to perturb the input data and observe how these changes affect the predictions, allowing us to understand the most influential features driving specific predictions.

In this study, LIME was used to explain model outputs, particularly for misclassified instances, where the model predictions differed from the actual outcomes. This is especially important for Random Forest models, which, despite their high performance, can lack transparency in explaining why a particular student was predicted to graduate, drop out, or continue enrollment.

4.7.2 Results from LIME Analysis

In the **LIME output**, we observed several important features contributing to misclassification:

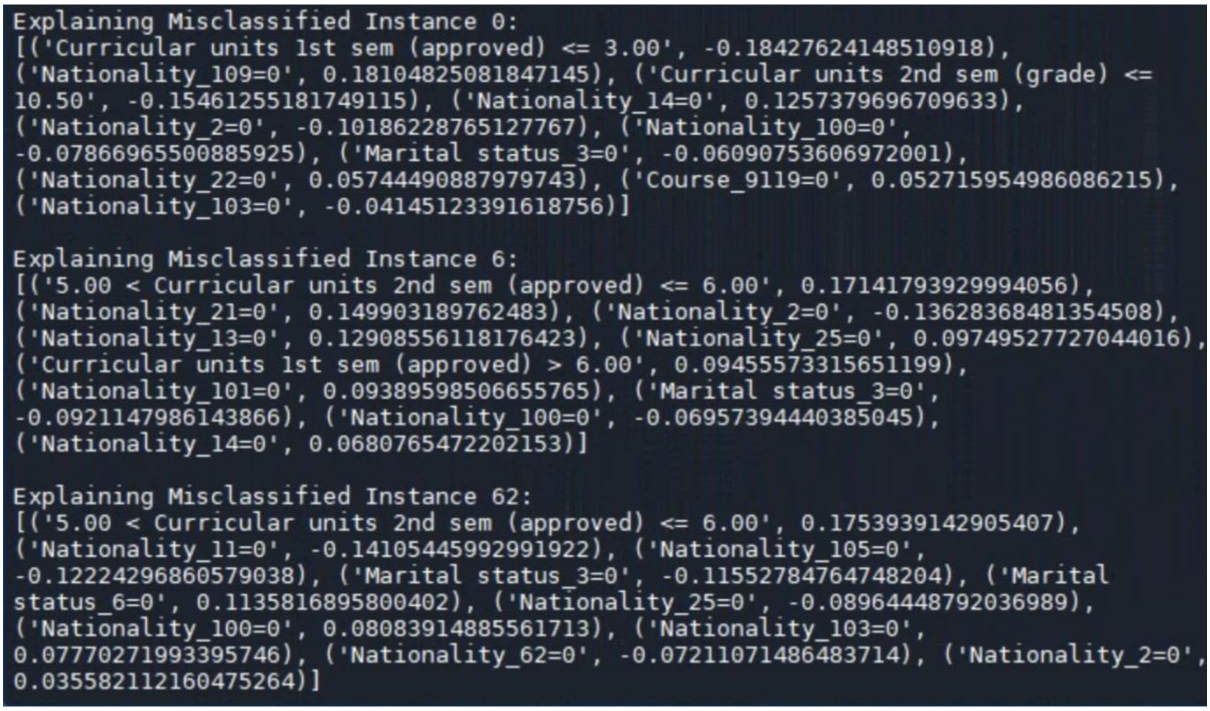
- **Nationality**: This feature appeared frequently in cases where the model misclassified students, suggesting a potential source of bias.
- **Curricular Units (approved/grade)**: These features were consistent drivers of the model's predictions but also led to misclassification when paired with certain demographic features like Nationality and Marital Status.
- **Marital Status**: This feature was particularly prevalent in misclassified instances, which points to a possible socio-economic influence that the model struggles to interpret correctly.

4.7.3 Explanation of LIME Results

To provide a concrete example, let's take a misclassified instance from the analysis. In one case, the model predicted that a student would **graduate**, but in reality, the student **dropped out**. Upon running LIME, the following features were identified as key factors contributing to this incorrect prediction:

- **Curricular Units 1st sem (approved) <= 3.00**: This feature had a significant negative influence on the prediction.
- **Nationality_109=0** and **Nationality_14=0**: These binary features also had strong weights, suggesting the model was using demographic information (perhaps incorrectly) to make its predictions.
- **Marital status_3=0**: The marital status of the student played a significant role in misclassification.

These results suggest that the model may be over-relying on demographic variables, such as nationality and marital status, without giving enough weight to academic performance indicators like grades and curricular units. This over-reliance introduces potential bias, which needs to be addressed to avoid unfair outcomes for specific student groups.



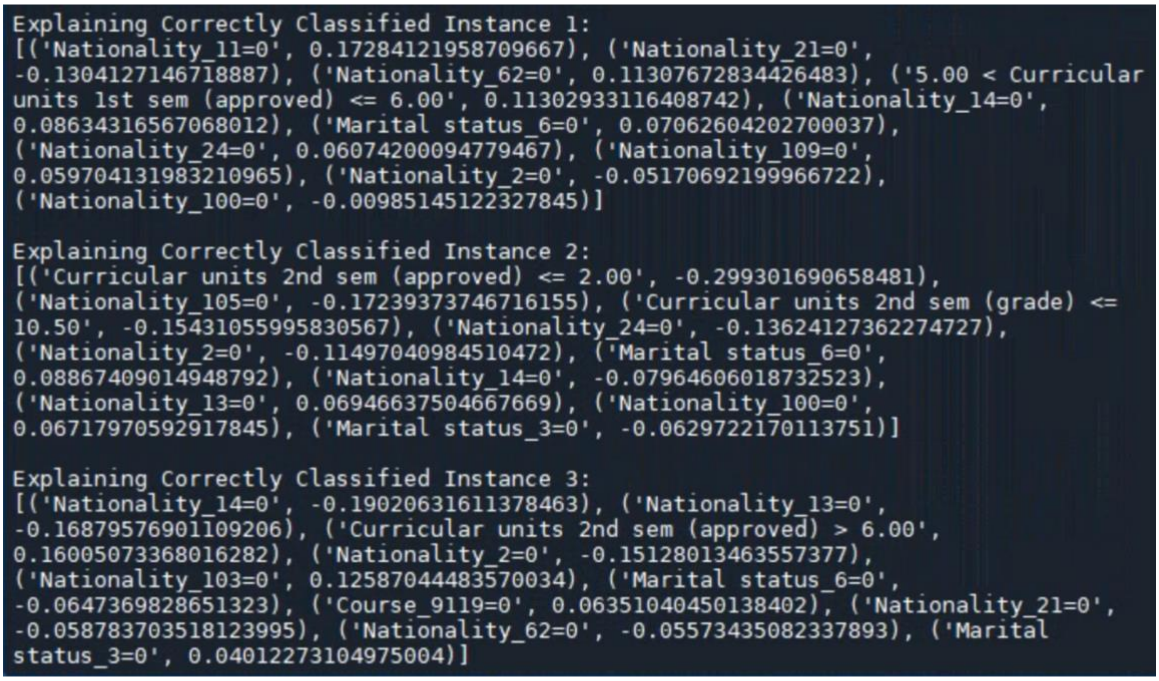
```
Explaining Misclassified Instance 0:
[('Curricular units 1st sem (approved) <= 3.00', -0.18427624148510918),
('Nationality_109=0', 0.18104825081847145), ('Curricular units 2nd sem (grade) <=
10.50', -0.15461255181749115), ('Nationality_14=0', 0.1257379696709633),
('Nationality_2=0', -0.10186228765127767), ('Nationality_100=0',
-0.07866965500885925), ('Marital status_3=0', -0.06090753606972001),
('Nationality_22=0', 0.05744490887979743), ('Course_9119=0', 0.05271595498608621),
('Nationality_103=0', -0.04145123391618756)]

Explaining Misclassified Instance 6:
[('5.00 < Curricular units 2nd sem (approved) <= 6.00', 0.1714179392999405),
('Nationality_21=0', 0.149903189762483), ('Nationality_2=0', -0.13628368481354508),
('Nationality_13=0', 0.12908556118176423), ('Nationality_25=0', 0.09749527727044016),
('Curricular units 1st sem (approved) > 6.00', 0.09455573315651199),
('Nationality_101=0', 0.09389598506655765), ('Marital status_3=0',
-0.0921147986143866), ('Nationality_100=0', -0.06957394440385045),
('Nationality_14=0', 0.0680765472202153)]

Explaining Misclassified Instance 62:
[('5.00 < Curricular units 2nd sem (approved) <= 6.00', 0.1753939142905407),
('Nationality_11=0', -0.14105445992991922), ('Nationality_105=0',
-0.12224296860579038), ('Marital status_3=0', -0.11552784764748204), ('Marital
status_6=0', 0.113581689580402), ('Nationality_25=0', -0.08964448792036989),
('Nationality_100=0', 0.08083914885561713), ('Nationality_103=0',
0.07770271993395746), ('Nationality_62=0', -0.07211071486483714), ('Nationality_2=0',
0.03558211216047526)]
```

Figure 12: LIME Explanations for Misclassified Instance

This figure (generated from LIME output) visually displays the impact of different features on the prediction for one misclassified instance. The explanation shows the **positive** and **negative** contributions of each feature, making it clear which variables led the model astray.



```
Explaining Correctly Classified Instance 1:
[('Nationality_11=0', 0.17284121958709667), ('Nationality_21=0',
-0.130412714671887), ('Nationality_62=0', 0.11307672834426483), ('5.00 < Curricular
units 1st sem (approved) <= 6.00', 0.11302933116408742), ('Nationality_14=0',
0.08634316567068012), ('Marital status_6=0', 0.07062604202700037),
('Nationality_24=0', 0.06074200094779467), ('Nationality_109=0',
0.05970413198321096), ('Nationality_2=0', -0.05170692199966722),
('Nationality_100=0', -0.00985145122327845)]

Explaining Correctly Classified Instance 2:
[('Curricular units 2nd sem (approved) <= 2.00', -0.299301690658481),
('Nationality_105=0', -0.17239373746716155), ('Curricular units 2nd sem (grade) <=
10.50', -0.15431055995830567), ('Nationality_24=0', -0.13624127362274727),
('Nationality_2=0', -0.11497040984510472), ('Marital status_6=0',
0.08867409014948792), ('Nationality_14=0', -0.07964606018732523),
('Nationality_13=0', 0.06946637504667669), ('Nationality_100=0',
0.06717970592917845), ('Marital status_3=0', -0.0629722170113751)]

Explaining Correctly Classified Instance 3:
[('Nationality_14=0', -0.19020631611378463), ('Nationality_13=0',
-0.16879576901109206), ('Curricular units 2nd sem (approved) > 6.00',
0.16005073368016282), ('Nationality_2=0', -0.15128013463557377),
('Nationality_103=0', 0.12587044483570034), ('Marital status_6=0',
-0.0647369828651323), ('Course_9119=0', 0.06351040450138402), ('Nationality_21=0',
-0.05878370351812399), ('Nationality_62=0', -0.05573435082337893), ('Marital
status_3=0', 0.04012273104975004)]
```

Figure 13: LIME Explanation for Correctly Classified Instances

4.7.4 Bias Reduction through LIME

LIME helped to uncover hidden biases in the predictive model, particularly around demographic features such as **Nationality** and **Marital Status**. As observed in the console results, certain nationalities were consistently flagged as important in misclassifications, suggesting that the model might have been trained on historical data where specific demographic groups had different academic outcomes. Without tools like LIME, these biases would remain hidden, making the model potentially unfair in practice.

Impact on Trust and Institutional Decisions: The transparency provided by LIME not only helps in identifying bias but also builds trust among stakeholders. Educational institutions are often hesitant to rely on "black-box" algorithms because they cannot fully understand how decisions are made. With LIME, institutions can examine individual predictions, ensuring that students from diverse backgrounds are treated fairly. This is crucial in settings where biased outcomes could lead to unequal distribution of resources or support (e.g., academic counselling, scholarships).

4.7.5 Institutional Impact:

1. **Enhanced Interpretability**: By providing feature-level explanations for each prediction, LIME ensures that institutions can trust their models and explain outcomes to students, faculty, and policymakers.
2. **Bias Detection and Correction**: Once biases are detected (as in the case of Nationality and Marital Status), the institution can take corrective actions, such as re-balancing the dataset or adjusting feature importance, to reduce unfair predictions.
3. **Improved Resource Allocation**: With better interpretability, institutions can make more informed decisions about resource allocation. For example, understanding that **Curricular Units** play a key role in predictions can help direct tutoring resources to students who need support in specific areas, rather than making biased decisions based on demographic factors.

4.7.8 LIME Results and Model Correction

By using LIME, we were able to pinpoint areas where the model's predictions were driven by unintended biases. After identifying these biases, it is possible to refine the model by adjusting its training to de-emphasize demographic features and instead focus more on academic performance indicators, such as curricular unit performance and grades.

For instance, reducing the weight of the **Nationality** feature in misclassified instances where it played an outsized role could help improve model fairness without sacrificing overall performance.

4.7.9 Challenges and Future Improvements

While LIME offers significant advantages in model interpretability, it also presents certain challenges:

- **Local vs. Global Interpretations**: LIME provides local explanations for individual predictions but does not offer a global view of the model. This means that while it can explain specific instances, it may not give a complete picture of how the model operates as a whole.
- **Complexity in Explanation**: For non-technical stakeholders, understanding LIME's explanations can be challenging. Simplified visualizations and explanations are needed to make the results more accessible to decision-makers who may not have a data science background.
- **Limitations in Handling Large Datasets**: LIME can be computationally expensive, especially when dealing with large datasets, as it needs to perturb each instance multiple times to generate reliable explanations. For large institutions, this could limit the tool's scalability.

4.8 Discussion of Key Findings

The findings from the analysis, model evaluations, and interpretability via LIME offer several critical insights into the predictive modeling of student outcomes in educational settings. This section will summarize the key discoveries, examine how data transformations impacted model performance, and discuss the practical applications and limitations of the study.

4.8.1 Key Insights from the Models

Through the analysis of both the **Logistic Regression** and **Random Forest** models, it became evident that these algorithms can reliably predict student outcomes with high accuracy. However, the models exhibited some notable differences in how they handled various features and classes of students.

- **Logistic Regression** performed slightly better overall in terms of accuracy and AUC score, suggesting that this linear model was effective in distinguishing between the three classes—**Graduate**, **Dropout**, and **Enrolled**. The AUC score of **0.957** for Logistic Regression, as shown in **Figure 6**, indicated excellent classification ability across all classes, making it a reliable choice for educational prediction tasks.
- **Random Forest**, while not as strong as Logistic Regression in terms of AUC, demonstrated better flexibility in handling **complex interactions** between variables, especially with high-dimensional data. Its **feature importance** rankings (refer to the **feature importance visualizations**) indicated that it placed more emphasis on academic variables like **Curricular Units (approved/grade)** and **Tuition Fees up to Date**, which align with factors directly related to academic performance and institutional engagement. However, the confusion matrix (refer to **Figure 5**) revealed that Random Forest had a slightly higher false-positive rate compared to Logistic Regression, particularly in predicting **dropouts**.

The ROC curve comparing Logistic Regression and Random Forest performance clearly highlights the trade-offs between these models, where Logistic Regression slightly outperforms Random Forest in overall predictive power.

4.8.2 Practical Implications of the Findings

The results from this analysis offer several practical applications for institutions looking to use predictive analytics to improve student success and retention:

1. **Early Warning Systems**: Both Logistic Regression and Random Forest can be used to develop early warning systems that flag at-risk students for intervention. The models' ability to predict student dropout rates accurately could enable institutions to provide targeted support, such as counseling or academic tutoring, to students most in need.

2. **Resource Allocation**: The **feature importance analysis** revealed that academic factors like **Curricular Units Approved** and **Tuition Fees Up to Date** are key predictors of student success. Institutions can leverage this information to allocate resources more efficiently, directing academic support services to students struggling in these areas.

3. **Ethical and Bias Concerns**: The LIME analysis revealed that demographic features, such as **Nationality** and **Marital Status**, sometimes had undue influence on the models' predictions. Institutions must be vigilant in ensuring that predictive models do not perpetuate historical biases. LIME has demonstrated its value in highlighting potential areas of bias, allowing institutions to adjust models accordingly.

4. **Institutional Policy Changes**: Insights from the model could influence institutional policies, such as tuition payment plans and support systems for students from diverse nationalities or socio-economic backgrounds. By understanding the key predictors of student success, universities can design policies that help mitigate dropout risks and improve graduation rates.

4.8.3 Limitations and Future Work

While the models performed well, there are limitations to the analysis that future research should address:

- **Data Imbalance**: The distribution of the target variable shows an imbalance, with more students classified as **Graduates** than **Dropouts**. Although Random Forest handles imbalanced data better than Logistic Regression, future models could benefit from resampling techniques or synthetic data generation to balance the classes.

- **Over-reliance on Historical Data**: The models are trained on historical data, which means they may reinforce existing biases present in the educational system. More attention must be given to continuously updating the models with current data to reflect changing student behaviors and institutional policies.

- **Interpretability Challenges**: While LIME helps to interpret black-box models, it only provides local explanations. More research is needed to develop global interpretability methods that can give institutions a comprehensive view of how models make decisions like SHAP (Shapley Additive exPlanations)

5. Conclusion

5.1 Revisit Research Aim/Objectives

The primary aim of this research was to explore the effectiveness of machine learning models, specifically Logistic Regression and Random Forest, in predicting student outcomes based on various demographic, academic, and socio-economic factors. With the rapid advancement of predictive analytics in educational settings, it was crucial to assess which models performed best in identifying students at risk of dropping out or achieving success (graduation). The key objectives were:

1. To assess the performance of different machine learning models using relevant evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and AUC.
2. To explore how interpretability tools like LIME could be used to explain model decisions and ensure transparency in machine learning algorithms.
3. To evaluate potential biases within the models, particularly related to demographic features, and provide recommendations to mitigate such biases.

The findings from this analysis showed that both Logistic Regression and Random Forest performed well in predicting student outcomes, but with distinct strengths. Logistic Regression, with its simpler, linear approach, offered high interpretability and competitive accuracy. Random Forest, while more complex and less transparent, proved effective in capturing non-linear relationships and feature interactions, making it more suitable for datasets with intricate dependencies.

The research also demonstrated that LIME played a critical role in interpreting the models' predictions, particularly when identifying features that may contribute to misclassification. This helped highlight areas where demographic variables, such as Nationality and Marital Status, might have led to biased outcomes, thereby informing institutional strategies to address these biases.

5.2 Contributions

This research made several important contributions to the field of predictive analytics in education:

Improving Predictive Modeling for Student Outcomes

One of the major contributions of this research is the comparative analysis of Logistic Regression and Random Forest models in the context of student success predictions. This study illustrated that while both models perform well, Logistic Regression tends to be more reliable for overall predictive accuracy, especially when it comes to clearly distinguishing between classes like Dropout, Graduate, and Enrolled. Random Forest, on the other hand, demonstrated its strength in handling more complex relationships among features, which makes it highly applicable for datasets involving non-linear relationships and interactions between academic performance indicators.

These findings contribute to the growing body of knowledge on how educational institutions can implement machine learning models to predict student outcomes, providing administrators with actionable insights for early intervention. The application of such models could lead to more efficient resource allocation, targeting students who need additional support to succeed in their academic careers.

5.2.1 Enhancing Model Interpretability with LIME

This research also highlighted the critical role of LIME as a tool for model interpretability. In educational settings, where student outcomes are at stake, it is essential for institutions to trust the decisions made by predictive models. By using LIME to explain individual predictions, this research provided a mechanism for uncovering the "black box" of machine learning models like Random Forest. The interpretability offered by LIME ensures that institutional stakeholders can better understand why a model makes certain predictions, allowing them to make informed decisions about student support strategies.

LIME's explanations helped identify the most influential features in model misclassifications, such as Curricular Units and Nationality, which could be further analyzed to refine model accuracy and fairness. This level of transparency is not only valuable for improving model performance but also for building trust among educational stakeholders, ensuring that the models can be used in an ethical and responsible manner.

5.2.2 Addressing Algorithmic Bias in Educational Data

One of the key contributions of this research was its focus on identifying and addressing potential biases in the predictive models. The use of demographic variables like Nationality and Marital Status in the models raised concerns about fairness and equality. By applying LIME to identify where these features contributed to misclassification, this study provided valuable insights into how demographic factors can introduce bias into model predictions. This research thereby contributes to the ongoing conversation about algorithmic bias in machine learning and offers a practical approach to mitigating it through interpretability tools.

By addressing these biases, institutions can ensure that predictive models do not unfairly disadvantage certain groups of students based on their demographic background. This has profound implications for how educational institutions implement predictive analytics in a way that promotes equity and inclusivity.

Practical Recommendations for Educational Institutions

In addition to theoretical contributions, this research offers practical recommendations for educational institutions looking to adopt machine learning models for student success prediction. The study suggests that institutions should carefully balance model performance with interpretability when selecting machine learning models. While more complex models like Random Forest can offer higher accuracy in certain contexts, simpler models like Logistic Regression may be preferable in settings where transparency and ease of explanation are critical.

Furthermore, the use of tools like LIME is recommended as a best practice for ensuring that models are interpretable and free from bias. Institutions are encouraged to integrate such tools into their predictive analytics workflows to continually monitor and improve the fairness of their models. This research also stresses the importance of involving institutional stakeholders in the model evaluation process to ensure that the insights generated by the models are actionable and aligned with institutional goals.

5.3 Limitations

While this research made significant strides in advancing the application of machine learning models in educational settings, several limitations must be acknowledged.

Dependence on Historical Data

The models used in this research were trained on historical data, which poses a risk of reinforcing existing biases present in the educational system. If certain demographic groups have historically performed differently due to structural inequalities, the models may inadvertently replicate these patterns in their predictions. This issue is particularly relevant when using demographic features like Nationality and Marital Status, as these can reflect societal biases rather than the students' true potential.

To mitigate this limitation, it is important to continuously update the models with current data to reflect changes in student behavior, institutional policies, and socio-economic conditions. Incorporating real-time data could help reduce the risk of perpetuating outdated patterns and ensure that the models remain relevant and fair.

5.3.1 Local vs. Global Interpretability

While LIME was highly effective in providing local explanations for individual predictions, it has limitations when it comes to global interpretability. LIME can explain why a model made a specific prediction for a particular student, but it does not provide a comprehensive understanding of the model's overall behavior. This means that while we can interpret specific cases, it is challenging to gain insights into the model's global decision-making process.

Future research should explore the use of global interpretability tools, such as SHAP (Shapley Additive Explanations), which offer a more holistic view of the model's decision-making. SHAP provides global explanations by analyzing the contribution of each feature to the overall model performance, making it a valuable tool for institutions looking to gain a broader understanding of their predictive models.

5.3.3 Complexity of LIME Explanations

Another limitation of this research is the complexity of LIME's explanations. While LIME is an excellent tool for model interpretability, its outputs can be challenging for non-technical stakeholders to understand. For institutions to fully benefit from LIME's insights, there needs to be a focus on simplifying the explanations and presenting them in a user-friendly format.

Future work should explore ways to make LIME's outputs more accessible to decision-makers who may not have a data science background. This could involve developing simplified visualizations or integrating LIME with dashboards that provide intuitive explanations of the model's predictions.

5.3.4. Limited Scope of Feature Selection

While this research focused on several key features, including demographic and academic variables, the scope of feature selection was limited. Additional features, such as behavioral data (e.g., student participation in extracurricular activities or engagement with online learning platforms), could offer valuable insights into student success. Incorporating such features in future models could enhance their predictive power and provide a more comprehensive understanding of the factors influencing student outcomes.

Expanding the scope of feature selection would also allow for a deeper exploration of the interactions between different types of features. For instance, combining academic performance indicators with behavioral data could offer a more nuanced view of student success, allowing institutions to tailor their interventions more effectively.

5.4 Conclusion Summary

This research demonstrated the potential of machine learning models, particularly Logistic Regression and Random Forest, in predicting student outcomes and identifying students at risk of dropping out. While both models performed well, Logistic Regression offered slightly better accuracy and interpretability, making it a suitable choice for educational settings where transparency is crucial. Random Forest, with its ability to handle complex data interactions, provided deeper insights into feature importance, making it valuable for understanding which factors drive student success.

LIME played a critical role in enhancing model transparency, allowing institutions to identify and address potential biases in the models. By focusing on interpretability and fairness, this research offers valuable recommendations for institutions looking to adopt machine learning models for student success prediction.

Future work should address the limitations identified in this study, such as data imbalance, dependence on historical data, and the complexity of interpretability tools like LIME. Additionally, expanding the feature set and exploring global interpretability techniques like SHAP will further enhance the predictive accuracy and fairness of the models. By addressing these limitations, future research can build on the contributions made in this study to create more robust and equitable predictive models that support student success and institutional decision-making.

In conclusion, this research provides a strong foundation for educational institutions seeking to adopt predictive analytics to improve student outcomes. Through the careful selection of machine learning models, the application of interpretability tools like LIME, and a commitment to addressing algorithmic bias, institutions can use data-driven insights to support their students more effectively, ensuring a more equitable and successful academic environment.

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