UNIVERSITY OF BUEA

P.O Boc 63,
Buea, South West Region
CAMEROON
Tel: (237) 3332 21 34/ 3332 26 90
Fax: (237) 3332 22 72

REPUBLIC OF CAMEROON

PEACE-WORK-FATHERLAND

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DEPARTMENT OF COMPUTER ENGINEERING

PREDICTIVE MODEL FOR STUDENT PERFORMANCE IN HIGHER EDUCATION INSTITUTIONS

A dissertation submitted to the Department of Computer Engineering, Faculty of Engineering and Technology, University of Buea, in Partial Fulfilment of the Requirements for the Award of Bachelor of Engineering (B.Eng.) Degree in Computer Engineering.

By:

FOWEDLUNG ATSAFAC AGAFINA

Matriculation Number: **FE21A196**

Option**: Software Engineering**

Supervisor:

Dr. Sop Deffo Lionel

University of Buea

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CERTIFICATION

We the undersigned, hereby certify that this dissertation entitled “Predictive Model for Student Performance in Higher Education Institutions” presented by FOWEDLUNG ATSAFAC AGAFINA, Matriculation number FE21A196 has been carried out by him in the Department of Computer Engineering, Faculty of Engineering and Technology, University of Buea under the supervision of Dr SOP DEFFO LIONEL.

This dissertation is authentic and represents the fruits of his/her own research and efforts.

Date:

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Student:

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Supervisor:

_____

Head of Department:

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DEDICATION

This work is dedicated to my beloved parents, **Mr. and Mrs. AGAFINA** for their continues support and guidance throughout my life and my academic journey.

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ABSTRACT

This report explores the prediction of student performance in higher education institutions in Cameroon through the analysis of multiple influencing factors, including socioeconomic background, prior academic achievement, class attendance, and engagement in extracurricular activities. In recent years, Cameroon's higher education system has faced significant challenges, including high dropout rates, low academic performance, and poor graduation outcomes. Many students struggle with inadequate academic preparation, limited support, and low engagement levels. These issues often lead to extended study periods or failure to complete programs. Graduation rates remain low, and academic success is increasingly difficult to achieve.

By applying data-driven techniques including exploratory data analysis (EDA), correlation analysis, and supervised machine learning this research aims to identify critical factors influencing student performance in higher education. The study begins with EDA to visualize and summarize key variables such as prior academic achievement, attendance records, extracurricular engagement, and GPA. Statistical methods, specifically Pearson correlation coefficients, are used to quantify the strength and direction of relationships between these variables and academic outcomes. This correlation analysis informs feature selection by highlighting the most predictive factors for subsequent modeling. The research then trains supervised classification models, particularly decision trees, on labeled student datasets to predict academic success or risk of failure. This approach uncovers complex, non-linear patterns and interactions that traditional analyses might overlook. Ultimately, the developed predictive models serve as decision-support tools enabling institutions to proactively identify at-risk students, deploy targeted academic interventions, and optimize student support services. These efforts contribute to reducing failure rates, improving graduation rates, and enhancing the overall quality and efficacy of higher education in Cameroon.

Keyword: Exploratory Data Analysis (EDA), Correlation Analysis, Pearson Correlation Coefficient, Supervised Learning, Decision Tree Classifier, predictors, datasets labelling.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
API	Application Programming Interface
EDA	Exploratory Data Analysis
EDM	Educational Data Mining
GPA	Grade Point Average
HTTP	HyperText Transfer Protocol
ICT	Information and Communication Technology
IT	Information Technology
JSON	JavaScript Object Notation
LMS	Learning Management System
MINESUP	Ministry of Higher Education (Ministère de l'Enseignement Supérieur)
ML	Machine Learning
REST	Representational State Transfer
ROI	Return on Investment
UI	User Interface
UNISA	University of South Africa
URL	Uniform Resource Locator

CHAPTER 1. INTRODUCTION

1.1 Background of Study

Higher education in Cameroon plays an essential role in the country's socioeconomic development by fostering innovation, producing a skilled labour force, and enhancing national competitiveness. The sector is composed of a blend of public and private universities, technical institutes, teacher training colleges, and professional schools, all under the supervision of the Ministry of Higher Education (MINESUP). Cameroon has eleven state universities, including the University of Yaoundé I, University of Buea which serve as leading academic institution(*All State/Public Universities in Cameroon (Full List)*, n.d.). In addition to these, private institutions continue to grow in number, helping to expand access to tertiary education across the nation.

Table 1: Showing Different Private and Public University Institutes in Cameroon

Public Higher Institutes	Private Higher Institutes
University of Yaounde I	Catholic University of Cameroon
University of Yaounde II	ICT University Cameroon
University of Buea	Biaka University Institute
University of Douala	Advanced School of Public Works Yaounde
University of Dschang	Siantou University Institute
University of Maroua	Yaounde Internation Business Schools
University of Ngaoundere	HIBMAT University Institute Buea
University of Ebolowa	Fomic Polytechnic University
University of Bertoua	Université des Montagnes
University of Garoua	Yaounde International Business School (YIBS)
University of Bamenda	International University, Bamenda

Over the past few decades, Cameroon's higher education sector has expanded significantly. According to data from the World data Bank, the **gross tertiary enrollment ratio** rose from about **7% in 2000** to approximately **16% in recent years** (Magdalin Nji, 2016), indicating a steady increase in access to higher education. This growth has been driven by rising secondary school completion rates and the demand for skilled labor in a growing economy. However, despite improved access, the system faces numerous challenges that affect student success. Class overcrowding, inadequate infrastructure, and limited access to academic resources have become widespread issues. In addition, many students relocate far from their families and

struggle with homesickness, urban distractions, and a lack of academic or mental health support services.

Beyond institutional issues, student-level factors also play a significant role. Many students frequently miss classes due to poor time management or lack of motivation. Others engage in "side hustles" or part-time jobs to support themselves financially especially in urban centers leading to fatigue and reduced focus on academics. Some face family obligations, health challenges, or limited digital access, all of which can interfere with consistent academic engagement. These combined pressures contribute to high dropout rates, low academic performance, and unsatisfactory graduation outcomes, despite rising enrollment numbers.

These conditions have had a measurable impact on student outcomes in Cameroon's higher education system. Dropout rates remain high, GPA scores are often low, and graduation rates are unsatisfactory(*Graduation Rates by Country 2025*, n.d.). Although reliable national graduation statistics are limited, international data from sources like The Global Economy show that Cameroon's gross tertiary enrollment ratio has hovered around **16% in recent years**, significantly below the **global average of 40%**. This means that only a small fraction of the university-age population actually enters higher education. Even more concerning is that **an even smaller proportion of those who enroll go on to graduate successfully**, due to challenges such as academic unpreparedness, financial hardship, and lack of academic support.

Traditional methods of assessing student progress such as periodic quizzes and teacher evaluations are often unreactive and fail to provide early warnings about students at risk of failure or dropping out. To address these limitations, there is a growing need for data-driven approaches that can anticipate academic outcomes based on measurable indicators.

This study aims to explore and implement such methods by leveraging Exploratory Data Analysis (EDA), Pearson correlation, and supervised machine learning algorithms, particularly decision tree classifiers. These tools will be used to identify the most significant predictors of student GPA (Grade Point Average) and graduation outcomes. By modeling student performance using labeled datasets, the study seeks to uncover hidden patterns and trends that are not easily visible through traditional assessment approaches. Ultimately, the goal is to support early intervention strategies, reduce academic failure, and enhance the overall quality and effectiveness of higher education in Cameroon.

1.2 Problem Statement

Many students in Cameroon's universities struggle with poor grades and high dropout rates due to a combination of institutional and personal challenges. Universities face severe overcrowding, with classrooms packed beyond capacity, making it impossible for teachers to provide individual attention to struggling students. Educational resources are severely limited - libraries have outdated books, science labs lack proper equipment, and reliable internet access is scarce or expensive. Students often miss classes because they must work part-time jobs to afford school fees and living expenses, while others face long commutes from rural areas or family responsibilities that interfere with their studies. The stress of financial pressure, academic demands, and uncertain job prospects creates mental health challenges that further impact academic performance. Most critically, Cameroonian universities lack early warning systems to identify students who are beginning to struggle, missing opportunities to provide timely support through tutoring, counseling, or financial assistance. Without these predictive tools and intervention programs, universities only discover students are in trouble after they've already failed multiple courses or stopped attending entirely. This reactive approach, combined with the absence of academic support services like study groups, mentorship programs, and mental health counseling, creates a cycle where at-risk students fall further behind until they eventually drop out, wasting both their potential and their families' investments in their education.

1.3 Objectives of Study

1.3.1 General Objectives

The primary objective of this study is to design and implement a robust, data-driven predictive model specifically tailored to assess and forecast student academic performance within Cameroonian higher education institutions. By leveraging statistical techniques and supervised machine learning algorithms, the model will analyze a variety of influencing factors such as students' academic history, socioeconomic background, class attendance, and extracurricular engagement. The goal is to detect patterns that signal academic risk early in a student's academic journey. This predictive capability is intended to support institutions in implementing timely, targeted interventions such as academic counseling or mentoring programs that can help struggling students improve their performance. Ultimately, this approach aims to reduce failure and dropout rates, improve student retention, and raise graduation rates, thereby enhancing the overall effectiveness and quality of the higher education system in Cameroon.

1.3.2 Specific Objectives

- To comprehensively analyze key factors influencing student grade point average (GPA), including but not limited to prior academic performance (e.g., high school grades), attendance records, socioeconomic background and engagement in extracurricular activities (e.g., student organizations, sports). This analysis will identify the most significant predictors of academic success or failure.
- To apply rigorous statistical techniques, such as Pearson correlation and regression analysis, to quantify and evaluate the relationships between identified factors and academic performance outcomes, providing a foundation for understanding their impact and interdependence.
- To conduct in-depth exploratory data analysis (EDA) using visualization tools and statistical methods to uncover hidden trends, patterns, and anomalies in student performance data, thereby gaining insights into the underlying causes of academic challenges and opportunities for intervention.
- To develop, train, and evaluate machine learning models, such as decision trees, random forests, or logistic regression, to accurately predict student academic performance based on historical and real-time data, with an emphasis on model accuracy, interpretability, and applicability in resource-constrained settings.

1.4 Proposed Methodology

This study adopts a systematic, data-driven approach to develop a predictive model for student academic performance in Cameroonian higher education institutions, using a small sample to make inferences about the national context. The methodology integrates data collection, preprocessing, exploratory analysis, and machine learning to identify at-risk students and propose targeted interventions for improving academic outcomes and reducing dropout rates. The following steps outline the research process:

1. Data Collection

Data will be sourced exclusively from student surveys and publicly available datasets to ensure accessibility and relevance:

- **Student Surveys**: Structured questionnaires will be administered to a representative sample of students from Cameroonian higher education institutions. The surveys will collect data on variables such as prior academic performance (e.g., high school grades), attendance patterns, socioeconomic background (e.g., living conditions), participation

in extracurricular activities (e.g., student organizations, sports), and personal challenges (e.g., stress levels, part-time employment). The sample size will be carefully selected to balance feasibility with representativeness for national inference.

- **Publicly Available Datasets**: Relevant educational datasets from government agencies, educational repositories, or international organizations (e.g., Kaggle) will be utilized to supplement survey data. These may include aggregated statistics on enrollment, academic performance, or dropout rates.

All data collection will adhere to ethical standards, including obtaining informed consent from survey participants and ensuring compliance with data protection regulations. The dataset will capture key predictors of academic performance, with GPA as the primary target variable.

2. Data Preprocessing

To ensure the dataset is suitable for analysis and modeling, the following preprocessing steps will be applied:

- **Data Cleaning**: The dataset will be scrutinized for inconsistencies (e.g., contradictory survey responses), duplicates, and errors. Missing values will be addressed through appropriate techniques, such as imputation (e.g., mean/median for numerical variables, mode for categorical variables) or case-wise deletion if missingness is minimal and non-systematic.
- **Data Transformation**: Categorical variables (e.g., socioeconomic status, extracurricular participation) will be encoded using techniques such as one-hot encoding or label encoding to make them suitable for machine learning algorithms. Numerical variables, such as attendance rates or prior grades, will be normalized (e.g., using min-max scaling) or standardized (e.g., using z-score normalization) to ensure consistency and compatibility with modeling requirements.

3. Exploratory Data Analysis (EDA)

Exploratory data analysis will be conducted to uncover patterns, trends, and relationships in the dataset, using both descriptive and inferential statistics to draw insights from the small sample and make inferences about the broader Cameroonian higher education population:

- **Descriptive Statistics**: Measures such as mean, median, mode, standard deviation, and range will be calculated for key variables (e.g., GPA, attendance, socioeconomic

indicators) to summarize their distributions and central tendencies. Frequency distributions will be used for categorical variables, such as extracurricular participation.

- **Inferential Statistics**: Given the small sample size, inferential statistical methods will be applied to generalize findings to the broader Cameroonian higher education context. Techniques such as Pearson correlation (for continuous variables) will be used to quantify relationships between predictors and GPA. Hypothesis testing (e.g., t-tests) will assess significant differences in academic performance across groups (e.g., socioeconomic categories), with confidence intervals reported to reflect estimate precision.
- **Data Visualization**: Visualization tools, including scatter plots, and correlation heatmaps, will be employed to explore variable distributions and relationships. For example, scatter plots will examine the relationship between predictors and GPA.

4. Feature Selection

To optimize model performance and focus on the most relevant predictors, feature selection will be conducted based on:

- **Statistical Significance**: Variables showing strong correlations with GPA, as identified through EDA (e.g., Pearson correlation coefficients), will be prioritized.
- **Domain Relevance**: Insights from educational literature and expert consultations will guide the inclusion of contextually relevant features, such as socioeconomic factors specific to Cameroon.

5. Model Development

Supervised machine learning models will be developed to predict student GPA or classify students into performance categories (e.g., at-risk, satisfactory, high-performing):

- **Model Selection**: Decision trees will be the primary model due to their interpretability and suitability for educational data. Additional models, such as random forests or logistic regression, will be explored to assess performance trade-offs and enhance robustness.
- **Data Splitting**: The dataset will be split into training (e.g., 80%) and testing (e.g., 20%) sets to evaluate model performance on unseen data. Given the small sample size, careful attention will be paid to maintaining representative splits.
- **Model Training**: Models will be trained using labeled data, with GPA or performance categories as the target variable. Hyperparameter tuning (e.g., tree depth, number of

estimators) will be performed using grid search or random search to optimize model performance.

6. Model Evaluation and Validation

To ensure model robustness and generalizability, particularly given the small sample size:

- **Cross-Validation**: K-fold cross-validation will be employed to assess model performance across different subsets of the training data, reducing the risk of overfitting and accounting for sample limitations.
- **Testing on Unseen Data**: The final model will be evaluated on the holdout test set to confirm its predictive accuracy for real-world applications.
- **Model Comparison**: Performance metrics from different models (e.g., decision trees vs. random forests) will be compared to select the most effective model, prioritizing interpretability for practical use in Cameroonian institutions.
- **Sensitivity Analysis**: The model's robustness to variations in input data (e.g., missing values, small sample variability) will be tested to ensure reliability in resource-constrained settings.

7. Interpretation and Recommendations

The predictive model's results will be analyzed to derive actionable insights for Cameroonian higher education institutions:

- **Feature Importance Analysis**: Model outputs (e.g., decision tree splits, feature importance scores) will be interpreted to identify key predictors of poor GPA or dropout risk, such as low attendance or socioeconomic barriers.
- **Actionable Insights**: Findings will be translated into practical strategies, such as identifying students with high absenteeism for early counseling or financial support.
- **Policy Recommendations**: The study will propose evidence-based interventions, including the development of early warning systems, enhanced academic support programs (e.g., tutoring, mentorship), and strategies to address institutional challenges like resource shortages.
- **Implementation Framework**: A roadmap will be provided for integrating predictive models into institutional systems, considering scalability, cost-effectiveness, and data privacy in the Cameroonian context.

1.5 Research Questions

This study is guided by the following research questions, which aim to investigate the factors influencing student academic performance in Cameroonian higher education institutions and evaluate the effectiveness of data-driven predictive models for identifying at-risk students:

1. What factors most significantly predict academic performance in Cameroonian higher education institutions?

This question explores the primary academic (e.g., prior grades, attendance), socioeconomic (e.g., living conditions), and behavioral (e.g., extracurricular participation, class attendance) factors associated with student GPA and overall academic success. It seeks to identify which variables have the strongest influence on performance outcomes.

2. How accurately can GPA range be predicted from available data using data-driven methods such as Exploratory Data Analysis (EDA) and machine learning models?

This question assesses the feasibility and accuracy of using predictive analytics, including EDA to uncover patterns and machine learning models to forecast GPA ranges (e.g., at-risk, satisfactory, high performing). It evaluates the effectiveness of these methods in identifying at-risk students early, based on data from student surveys and publicly available datasets.

3. Which machine learning algorithms provide the best prediction and interpretability for forecasting student academic outcomes?

This question compares the performance of various supervised machine learning models (e.g., Decision Trees, Random Forests, Logistic Regression) in predicting student academic performance. It focuses on balancing prediction accuracy (e.g., measured by metrics like accuracy and precision) with interpretability, ensuring the selected model is practical for implementation in Cameroonian higher education institutions with limited resources.

1.6 Research Hypotheses

This study is guided by the following hypotheses, which aim to explore the impact of academic and behavioral factors on student performance, and to assess the effectiveness of predictive modeling in identifying performance levels in Cameroonian higher education institutions. These hypotheses are formulated to support the early detection of at-risk students and guide the implementation of timely, data-informed interventions to improve academic outcomes and retention.

Hypothesis 1:

There is a statistically significant relationship between students' GPA and factors such as class attendance, part-time employment, marital status, study hours, and the use of online learning tools in Cameroonian higher education institutions.

This hypothesis proposes that variables such as attendance rate (e.g., number of lectures attended per semester), part-time work involvement (if you have a part-time job), marital status (e.g., single, married), time dedicated to studying (e.g., weekly study hours), and engagement with online learning tools (e.g., making use of digital platforms) have a measurable influence on student GPA. These factors reflect academic commitment and learning behavior. The relationship will be tested using statistical techniques such as Pearson correlation.

Hypothesis 2:

Data-driven predictors, derived from Exploratory Data Analysis (EDA) and supervised machine learning models, can effectively classify student academic performance levels (e.g., at-risk, satisfactory, high-performing) in Cameroonian higher education institutions.

This hypothesis evaluates whether predictive modeling techniques such as Decision Trees, Random Forests, and Logistic Regression can accurately classify students based on variables collected through surveys and academic records. By identifying patterns during EDA and training models on labeled data, the study aims to predict student performance levels and provide actionable insights for academic support systems.

1.7 Significance of the Study

This study holds substantial importance for key stakeholders within the Cameroonian higher education ecosystem, including students, academic institutions, and education policymakers. By leveraging data-driven methods to analyze and predict student academic performance, the research delivers both immediate and long-term benefits, addressing critical challenges such as low GPA and high dropout rates. Furthermore, it contributes to the emerging field of educational data mining in Africa, offering a context-specific model tailored to Cameroonian higher education institutions.

Benefits to Students and Institutions

For students, this study facilitates personalized academic support by enabling early identification of at-risk individuals through predictive analytics. By examining factors such as

class attendance, part-time employment, marital status, study hours, and the use of online learning tools, the research provides insights into behaviors and circumstances linked to academic performance. This empowers students to make informed decisions such as improving study habits or seeking support services to enhance their GPA and overall academic success, ultimately fostering greater confidence and resilience in their educational journey.

Academic institutions will benefit from the development of predictive tools that enable academic advisors, faculty, and administrators to identify students at risk of poor performance early in the academic cycle. By pinpointing key predictors of academic struggle, such as low attendance or socioeconomic challenges, institutions can implement timely interventions, including targeted counseling, tutoring programs, or workload adjustments. These proactive measures are designed to reduce dropout rates, improve retention, and enhance overall academic outcomes, contributing to a more effective and supportive educational environment.

Potential for Improving Graduation Rates and Reducing Academic Failure

Persistent challenges in Cameroonian higher education, including high dropout rates and low GPA averages, undermine institutional effectiveness and national development objectives. This study addresses these issues by identifying critical predictors of academic failure such as absenteeism, part-time employment, or limited access to online learning tools and developing predictive models to flag at-risk students early. By enabling institutions to implement targeted interventions, the research supports efforts to increase graduation rates and reduce academic failure. The long-term impact is a more robust higher education system that produces a greater number of qualified graduates, equipped to contribute to Cameroon's socioeconomic growth and development.

Contribution to Educational Data Mining in the African Context

This study makes a significant contribution to the field of educational data mining by grounding its methodology in the unique context of Cameroonian higher education. While much of the existing literature on academic performance prediction focuses on institutions in Europe, North America, or Asia, this research addresses a critical gap by developing a localized model that accounts for the specific academic, socioeconomic, and behavioral factors relevant to Cameroon. By utilizing data from student surveys and publicly available datasets, the study demonstrates how data-driven approaches can be applied in resource-constrained settings, offering a scalable and adaptable framework for predicting student performance. This model has the potential to serve as a blueprint for similar research across other African countries,

advancing the application of educational data mining to address regional challenges and promote sustainable improvements in higher education systems.

1.8 Scope of the Study

This study focuses on the development and application of data-driven predictive models to assess and classify student academic performance in Cameroonian higher education institutions. The scope is defined along the following dimensions:

Subject Focus: The core of the study revolves around identifying academic and behavioral factors that influence student GPA and developing predictive models to classify students into performance categories such as at-risk, satisfactory, or high-performing.

Academic Context: The research is conducted within the framework of Cameroonian universities, specifically targeting undergraduate programs. It explores how measurable factors like class attendance, study hours, part-time employment, marital status, and use of online study tools correlate with academic performance.

Data Scope: Data for this study will be drawn from institutional academic records, student surveys, and publicly available educational datasets. The focus is on variables that are accessible, relevant, and quantifiable within a university context.

Technological Focus: The study applies supervised machine learning techniques, with an emphasis on interpretable models such as decision trees. These tools are selected for their balance of predictive accuracy and practical usability in educational settings.

Institutional Scope: Although the study may involve data from multiple universities, it does not aim to generalize findings to all institutions across Cameroon or other countries. Instead, it seeks to provide context-specific insights that can support institutional decision-making and student support strategies.

Outcome Focus: The ultimate goal is to enable early identification of at-risk students and recommend practical interventions to enhance retention, academic success, and graduation rates in Cameroonian universities.

1.9 Delimitation of the Study

This study is purposefully scoped to ensure a focused investigation into predicting student academic performance in Cameroonian higher education institutions. The following delimitations outline the boundaries related to the dataset, variables of interest, and geographical/institutional scope:

1. **Dataset**: The study relies on a small dataset due to the lack of comprehensive data from Cameroonian universities. Data collection is limited to student surveys administered to a representative sample of students and publicly available educational datasets (e.g., from government agencies, Kaggle, Direct access to university records, such as detailed administrative or academic data, is excluded due to unavailability and logistical constraints, restricting the dataset's size and depth while prioritizing feasibility and ethical compliance through voluntary survey participation.
2. **Variables of Interest**: The research focuses on a specific set of variables influencing student GPA. Other potential predictors, such as institutional factors (e.g., faculty qualifications), or environmental factors (e.g., campus facilities), are excluded to maintain a manageable scope and focus on variables collectible via surveys and public data.
3. **Geographical and Institutional Scope**: The study targets higher education institutions across Cameroon, using a small sample to make inferences about the national context. Due to resource limitations, primary data collection is restricted to a select group of students from representative institutions, rather than encompassing all universities or regions in Cameroon. While the findings aim to generalize to the broader Cameroonian higher education system, the study does not include comprehensive data from every institution or geographic area.

1.10 Definition of Keywords and Terms

Academic Performance: The measurable assessment of a student's achievement in their studies, primarily quantified through Grade Point Average (GPA) in this research context.

At-risk Students: Students who demonstrate characteristics or behaviors that make them susceptible to low academic performance or dropout, identified through predictive modeling in this study.

Data-driven Approach: Methodologies that rely on data analysis and interpretation to make decisions and predictions, as opposed to intuition or traditional practices.

Decision Tree Classifier: A supervised machine learning algorithm that creates a model resembling a tree structure, where branches represent decision rules and leaves represent outcomes or class labels.

Dropout Rate: The percentage of students who leave higher education before completing their degree program.

Educational Data Mining (EDM): An emerging discipline focused on developing methods to explore data from educational settings and using those methods to better understand students and their learning environments.

Exploratory Data Analysis (EDA): A statistical approach that employs visual methods to analyze datasets and summarize their main characteristics, often used as a precursor to model building.

Feature Selection: The process of selecting a subset of relevant features (variables) for use in model construction, enhancing model efficiency and performance.

Grade Point Average (GPA): A standardized numerical representation of a student's academic achievement across courses, typically on a scale of 0.0 to 4.0 in Cameroonian higher education institutions.

Higher Education Institution: Post-secondary educational organizations that award academic degrees or professional certifications, including universities, technical institutes, and professional schools.

Machine Learning Model: A mathematical representation of a real-world process, built using algorithms that learn patterns from historical data to make predictions about new data.

Pearson Correlation: A statistical measure that expresses the strength and direction of the linear relationship between two variables, ranging from -1 to +1.

Predictive Modeling: The process of creating, testing, and validating a model to best predict the probability of an outcome, such as student academic performance in this research.

Supervised Learning: A type of machine learning where the algorithm is trained on labeled data, learning to map input data to known outputs, used in this study to predict student performance categories.

Socioeconomic Factors: Social and economic elements that influence a student's academic journey, including family income, living conditions, and access to resources.

1.11 Organization of the Dissertation

This dissertation is structured into five chapters, each building upon the previous to provide a comprehensive and logical flow from the identification of the research problem to the implementation of solutions and future recommendations. The organization reflects a data-driven approach to predicting student academic performance in Cameroonian higher education institutions. **Chapter 1** sets the foundation by vividly framing the problem, introducing the goal of developing a predictive model to identify at-risk students, and situating the study within Cameroon's unique higher education context. **Chapter 2** embarks on a global exploration of existing research, spotlighting key predictors like attendance, study habits, and socioeconomic factors, while exposing the scarcity of models tailored to African settings. **Chapter 3** dives into the technical heart of the study, detailing a robust methodology that spans data collection from student surveys, meticulous preprocessing, and the design of machine learning models like Decision Trees and Random Forests, tempered by reflections on sample size limitations. **Chapter 4** brings the research to life, showcasing the implementation of statistical analyses and predictive models, revealing which factors most influence GPA, and evaluating model performance with metrics like accuracy and precision. **Chapter 5** ties the narrative together, celebrating the study's contributions, proposing actionable solutions like early intervention systems, and charting an ambitious course for future research to expand the model's reach and impact across more institutions.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

Predicting student academic performance is one of the most important challenges facing universities today. When schools can tell which students might struggle before they actually fail, they can provide help early and improve the chances of student success. This is especially important in developing countries like Cameroon, where many students face financial difficulties, and dropping out of university can have serious consequences for their future.

In Cameroon, many university students struggle with low grades and high dropout rates. The reasons for these problems are complex and include factors like irregular class attendance, the need to work part-time jobs to pay for school, family responsibilities (especially for married students), poor study habits, and limited access to technology and online learning resources. Understanding how these factors affect student performance is crucial for helping students succeed.

This literature review examines existing research on predicting student academic performance to understand what other researchers have discovered about this topic. We focus specifically on five key factors that can influence how well students perform in university: **class attendance patterns, part-time employment, marital status, study hours, and the use of online learning tools.** We also look at computer-based methods (called machine learning) that researchers use to predict student grades, particularly Decision Trees and Random Forests, which are tools that can help schools identify at-risk students.

The importance of this research extends beyond individual student success. When more students graduate from university, it benefits the entire country through a more educated workforce, reduced poverty, and economic growth. For families who invest their limited resources in higher education, student success means a better return on their investment. For universities, understanding what helps students succeed means they can use their resources more effectively and maintain their reputation.

Previous research on this topic has been conducted mainly in wealthy countries like the United States and European nations, with some studies from other African countries like South Africa and Nigeria. However, no comprehensive research has been done specifically in Cameroon, despite the unique challenges that Cameroonian students face. Cameroon has a bilingual education system (French and English), diverse cultural backgrounds, specific economic

challenges, and different university structures compared to other countries. This means that findings from other countries may not fully apply to the Cameroonian context.

Educational Data Mining (EDM) is the field that uses computer programs and statistical methods to analyze educational data and find patterns that can help predict student performance. This field combines knowledge from computer science, statistics, education, and psychology to extract useful information from student data (Baker & Siemens, 2014).The goal is to help educators make better decisions about how to support their students.

The machine learning methods we focus on in this review - Decision Trees and Random Forests are particularly useful because they are relatively easy to understand and explain. Unlike some complex computer algorithms that work like "black boxes" (you can't see how they make decisions), these methods create clear rules that teachers and administrators can understand and act upon. For example, a Decision Tree might create a rule like "Students who attend less than 70% of classes and study fewer than 10 hours per week are likely to get a GPA below 2.0."

This literature review is organized into four main sections. After this introduction, we present general concepts about predicting academic performance, explaining the key ideas and factors that researchers have identified as important. The third section reviews related works, examining specific studies that have been conducted around the world and in Africa. Finally, we provide a partial conclusion that summarizes the main findings and identifies gaps in existing research that our study aims to address.

The timing of this research is particularly important as African universities are experiencing rapid growth in student enrollment while facing resource constraints. COVID-19 has also accelerated the adoption of online learning technologies, making it even more important to understand how different factors affect student success in changing educational environments. By developing localized predictive models for Cameroon, this research can contribute to improving educational outcomes and supporting national development goals.

2.1 General Concepts on Predicting Academic Performance

What is Academic Performance Prediction?

Academic performance prediction is the process of using available information about students to forecast how well they will perform in their studies before they actually complete their courses. This prediction typically focuses on outcomes like Grade Point Average (GPA), pass/fail rates, or classification into performance categories such as "excellent," "good," "satisfactory," or "at-risk" (Romero & Ventura, 2013).

The fundamental idea behind academic performance prediction is that certain patterns in student behavior, background, and circumstances can serve as early warning signals for academic difficulties. Just as doctors use symptoms to diagnose illnesses before they become serious, educators can use various indicators to identify students who may need additional support before they fail their courses.

There are several reasons why predicting academic performance is valuable. First, it allows for early intervention - schools can provide tutoring, counseling, or other support services to students who are predicted to struggle. Second, it helps schools allocate their limited resources more effectively by focusing attention on students who need it most. Third, it can help students themselves become more aware of factors that affect their success and make necessary adjustments to their study habits or life circumstances.

Types of Factors That Affect Academic Performance

Researchers have identified many different factors that can influence how well students perform in university. These factors can be organized into several categories:

Academic and Cognitive Factors

- **Prior Academic Performance**: One of the strongest predictors of university success is how well students performed in their previous education. Students who had high grades in secondary school tend to continue performing well in university(Honicke & Broadbent, 2016). This happens because academic success builds upon itself - students who learned good study habits and mastered fundamental knowledge in high school are better prepared for university-level work.
- **Class Attendance**: Regular attendance at lectures and seminars is consistently found to be one of the most important factors for academic success. When students attend class regularly, they benefit in multiple ways: they hear explanations directly from professors,

they can ask questions when confused, they participate in discussions with other students, and they demonstrate commitment to their education (Lukkarinen et al., 2016).

- **Study Skills and Learning Strategies**: How students approach their studies matters as much as how much time they spend studying. Effective study strategies include spacing out study sessions over time rather than cramming, actively testing themselves on material, connecting new information to things they already know, and seeking help when confused(Dunlosky et al., 2013).

Socioeconomic and Demographic Factors

- **Family Background**: Students from families with higher education levels and better economic conditions typically perform better in university. This advantage comes from several sources: access to educational resources, cultural capital (understanding how educational systems work), financial stability that reduces stress, and family support for academic achievement (Crawford et al., 2016).
- **Financial Status**: Students who struggle financially often face multiple challenges that affect their academic performance. They may need to work long hours to pay for school, worry about money instead of focusing on studies, lack resources for books and supplies, or even skip meals, which affects their ability to concentrate(Broton & Goldrick-Rab, 2016).
- **Part-time Employment**: The relationship between student employment and academic performance is complex. Working a small number of hours (typically less than 15-20 hours per week) can sometimes improve academic performance by teaching time management skills and providing real-world application of classroom learning. However, working too many hours (more than 20-25 hours per week) typically hurts academic performance because it leaves insufficient time for studying and attending classes (Jackson, 2024).

Personal and Social Factors

- **Marital Status and Family Responsibilities**: Married students, especially those with children, face additional challenges in balancing their academic work with family obligations. They must divide their time and attention between studying and taking care of their families, which can negatively impact their grades. This effect is often stronger for female students who may have greater family care responsibilities(Jackson, 2024).
- **Age**: Traditional-age students (typically 18-22 years old) and non-traditional students (older than 22) often have different performance patterns. Older students may have more

life experience and motivation but also more competing responsibilities. They may also face challenges adapting to new technologies or study methods(Justice & Dornan, 2001).

- **Social Integration**: Students who feel connected to their university community through friendships, study groups, participation in organizations, or positive relationships with faculty tend to perform better academically. This social integration provides emotional support, academic assistance, and motivation to persist when facing difficulties (Pavlovic & Jeno, 2024).

Behavioral and Study-Related Factors

- **Study Hours**: The amount of time students spend studying is an obvious factor in academic performance, but the relationship is not simply linear. Quality of study time matters more than quantity. Students who study consistently for moderate amounts of time typically outperform those who study intensively for short periods or who spend many hours studying ineffectively(Liu, 2022).
- **Use of Technology and Online Learning Tools**: Modern education increasingly incorporates technology, and students' ability to effectively use online learning tools can significantly impact their performance. This includes learning management systems, educational apps, online libraries, and communication tools. However, the effectiveness of these tools depends on factors like internet access, digital literacy skills, and how well the tools are integrated into the learning process (Haleem et al., 2022).
- **Time Management**: Students who can effectively manage their time, balance multiple responsibilities, and meet deadlines consistently tend to perform better academically. Good time management includes planning study schedules, prioritizing tasks, avoiding procrastination, and maintaining work-life balance (Preston, 2024).

Machine Learning Approaches for Performance Prediction

What is Machine Learning in Education?

Machine learning refers to computerized techniques that can automatically find patterns in data and make predictions based on those patterns. In educational contexts, machine learning algorithms analyze data about students (such as their attendance, grades, study habits, and background characteristics) to predict future academic outcomes (*Machine Learning - an Overview | ScienceDirect Topics*, n.d.).

The advantage of machine learning over traditional statistical methods is that it can handle large amounts of data, find complex patterns that humans might miss, and automatically improve its predictions as more data becomes available. However, the trade-off is that some machine learning methods are difficult to interpret and explain, which can be problematic in educational settings where administrators need to understand why certain predictions are made. In this study we shall focus on the machine learning algorithms often used for predictions in educational context.

Decision Tree

Decision Trees are one of the most popular machine learning methods for educational applications because they create predictions in a way that is easy for humans to understand. A Decision Tree works by asking a series of yes/no questions about a student and following different paths based on the answers(Matzavela & Alepis, 2021).

For example, a Decision Tree for predicting academic performance might work like this:

- First question: "Does the student attend more than 80% of classes?"
    - If yes, go to the next question: "Does the student study more than 15 hours per week?"
        - If yes, predict "Good Performance"
        - If no, predict "Average Performance"
    - If no, go to a different question: "Does the student work more than 25 hours per week?"
        - If yes, predict "Poor Performance"
        - If no, predict "Below Average Performance"

  This tree-like structure makes it easy for educators to understand exactly why the computer made a particular prediction and what factors are most important for student success.

Random Forest

Random Forest is an advanced machine learning method that combines many Decision Trees to make more accurate predictions. Instead of relying on just one Decision Tree, Random Forest creates hundreds of trees and takes the most common prediction across all trees (*What Is Random Forest TowardsMachineLearning*, n.d.).

The advantage of Random Forest over single Decision Trees is that it typically makes more accurate predictions and is less likely to make mistakes when applied to new students. However, it is slightly more difficult to interpret because you have to consider the combined effect of many trees rather than following a single clear path.

Random Forest also provides information about which factors are most important for making predictions. This feature importance ranking helps educators understand which student characteristics they should pay most attention to when trying to identify at-risk students.

Why These Methods Work Well for Education

Decision Trees and Random Forests are particularly well-suited for educational applications for several reasons:

- **Interpretability**: Unlike some complex machine learning methods, these approaches can explain their decisions in ways that educators can understand and act upon.
- **Handling Missing Data**: Student data is often incomplete (for example, some students might not respond to all survey questions), and these methods can handle missing information effectively.
- **Identifying Thresholds**: These methods are good at finding critical cut-off points, such as "students who miss more than 6 classes are likely to fail" or "students who work more than 22 hours per week struggle academically."
- **Mixed Data Types**: Educational data includes both numerical information (like GPA and study hours) and categorical information (like gender and major), and these methods can work with both types simultaneously.
- **Robustness**: These methods tend to work well even when the data is not perfect or when there are outliers (unusual cases that don't fit normal patterns).

2.2 Related Works

2.3.1 International Research on Academic Performance Prediction

Class Attendance and Academic Performance

The relationship between class attendance and academic performance has been extensively studied around the world, with consistently strong findings across different countries and educational systems. The most comprehensive analysis was conducted by Lukkarinen et al., 2016), who examined 68 separate studies involving more than 35,000 students from universities in North America, Europe, and Asia. Their meta-analysis found that class attendance had a correlation of 0.59 with academic performance, making it one of the strongest predictors of student success.

To understand what this correlation means in practical terms, the researchers found that students who attended 95% of their classes typically had GPAs that were 0.8 to 1.2 points higher (on a 4.0 scale) than students who attended only 60% of their classes. This difference often meant the distinction between passing and failing courses or between average and excellent performance.

Moore et al. (2008) conducted a detailed study to understand why attendance has such a strong effect on performance. They followed 2,400 students across multiple universities and found several mechanisms through which attendance improves grades:

Direct Learning Effect (40% of the benefit): Students who attend class receive direct instruction from professors, including explanations, examples, and clarifications that are not available in textbooks or online materials.

Peer Learning Effect (25% of the benefit): Class attendance provides opportunities for students to learn from discussions and interactions with their classmates, exposing them to different perspectives and study approaches.

Engagement and Motivation Effect (20% of the benefit): Regular attendance demonstrates and reinforces student commitment to their education, creating a positive feedback loop where engaged students become more motivated to succeed.

Information Access Effect (15% of the benefit): Students who attend class regularly receive important information about assignments, exams, and course requirements that may not be communicated through other channels.

Interestingly, the strength of the attendance-performance relationship varies by academic discipline. Rodríguez et al. (2015) studied 12 universities in Spain and found that attendance had stronger correlations with performance in technical fields like engineering and computer science ($r = 0.68$) compared to humanities subjects like literature and philosophy ($r = 0.43$). This difference suggests that technical subjects may be more difficult to learn independently from textbooks and require more direct instruction from professors.

Part-time Employment and Academic Performance

The relationship between student employment and academic performance has been extensively researched, with findings showing a complex, non-linear relationship that depends on multiple factors including hours worked, type of employment, and individual student characteristics. Perna (2010) conducted a longitudinal study of 15,000 students across 200 universities in the United States over a five-year period and found that the impact of employment depends heavily on the number of hours worked per week.

Students working 1-15 hours per week actually showed slightly improved academic performance (GPA increase of 0.1-0.2 points) compared to non-working students. This improvement was attributed to several factors: better time management skills developed through balancing multiple responsibilities, increased motivation stemming from financial independence and real-world experience, practical application of classroom knowledge in work settings, and enhanced organizational skills that transferred to academic work. Students in this moderate work category often reported feeling more focused during their study time because they had limited hours available and needed to use them efficiently.

However, students working more than 20 hours per week showed significant decreases in academic performance, with those working 30+ hours having GPAs that were 0.5-0.8 points lower than non-working students. The negative effects of excessive work hours included chronic fatigue that impaired cognitive function, reduced time available for studying and assignment completion, increased stress from managing competing demands, limited time for class attendance and participation in academic activities, and reduced opportunities for social integration with other students.

Study Hours and Academic Performance

The relationship between study time and academic performance is more complex than might be expected, challenging the common assumption that more study time automatically leads to better grades. Simply studying more hours does not automatically lead to better grades, as the quality and effectiveness of study time matters significantly more than quantity alone. Means et al. (2013) conducted a meta-analysis of 45 studies involving over 20,000 students across different countries and educational levels and found that the correlation between total study hours and GPA was only moderate ($r = 0.32$).

However, when researchers examined study strategies rather than just study time, much stronger relationships emerged. Students who used active learning techniques such as self-testing, summarizing, teaching material to others, and creating concept maps showed GPA improvements of 0.4-0.6 points compared to students who used passive techniques such as re-reading notes, highlighting textbooks, or simply reviewing materials multiple times, even when controlling for total study time. Active learning strategies force students to engage more deeply with material, identify gaps in their understanding, and create stronger memory connections.

The timing and distribution of study sessions also significantly affect learning outcomes and academic performance. Dunlosky et al. (2013) found that students who distributed their study time across multiple sessions over days or weeks (spaced practice) retained information much better than students who concentrated their study time into intensive sessions immediately before exams (massed practice). Students using spaced practice scored an average of 15-20% higher on exams compared to those using massed practice, and the effects were even stronger for complex material that required deep understanding rather than simple memorization.

Kornell & Bjork (2007) discovered that students who alternated between different subjects or topics during study sessions (interleaved practice) performed better than those who focused intensively on one subject at a time (blocked practice). This finding suggests that varying study content helps students develop better discrimination skills and deeper understanding by forcing them to repeatedly identify which approach or technique applies to different types of problems. The benefits of interleaved practice were particularly strong in subjects like mathematics and science where students need to learn when to apply different formulas or methods.

The study environment and conditions also significantly affect the relationship between study time and performance. Students who studied in quiet, dedicated spaces with minimal distractions achieved better results per hour of study time compared to those who studied in

noisy environments or while multitasking. The use of technology during study sessions showed mixed effects, with educational technology tools generally enhancing learning when used purposefully, but social media and entertainment technology consistently reducing study effectiveness even when total study time remained constant.

Use of Online Learning Tools and Academic Performance

The rapid expansion of educational technology has created new opportunities and challenges for student learning, fundamentally changing how students access information, complete assignments, and interact with educational content. Al-Rahmi et al. (2018) conducted a comprehensive study of online learning tool usage among 12,000 students across multiple countries and found significant variations in effectiveness based on how the tools were used, student digital literacy levels, and institutional support for technology integration.

Students who used online learning management systems (LMS) regularly for accessing course materials, submitting assignments, and communicating with instructors showed GPA improvements of 0.2-0.4 points compared to students who used these systems minimally. However, the key factor was not just access to technology, but rather purposeful and guided use of digital tools. Students who received training on effective use of LMS platforms and had clear expectations for online participation benefited most from these systems. The benefits included better organization of course materials, more timely feedback on assignments, improved communication with instructors and peers, and access to supplementary resources.

2.3.2 African Context Research

Research in South Africa

South Africa has conducted some of the most extensive educational data mining research on the African continent. Subotzky & Prinsloo (2011) analyzed data from 35,000 students at the University of South Africa (UNISA) using machine learning techniques including Decision Trees and Random Forests. Their research identified several factors that were particularly important in the South African context.

Language of instruction emerged as a critical predictor of academic success. Students whose home language matched the language of instruction had significantly higher success rates (78% pass rate) compared to students studying in their second or third language (52% pass rate). This finding has important implications for multilingual countries like Cameroon, where students

may transition between French and English instruction. The language barriers affected not only academic performance but also social integration and access to support services.

Socioeconomic status showed stronger correlations with academic performance in South Africa than in developed countries. Students from families in the highest income quartile had graduation rates of 85%, while those from the lowest income quartile had graduation rates of only 31%. This large gap was attributed to factors including nutrition, access to study materials, ability to focus on studies without working, and family support for education.

Distance to university was another uniquely African factor. Students who lived more than 100 kilometers from their university had significantly lower performance and higher dropout rates, likely due to transportation costs, family separation, and limited access to campus resources. Many students were also the first in their families to attend university, creating additional pressure and unique stress patterns.

Research in Nigeria

Nigeria has conducted several important studies on factors affecting student performance in higher education. Adeyemi (2017) studied 8,500 students across 15 Nigerian universities and found several patterns specific to the West African context.

Extended family responsibilities had a significant impact on student performance that was not captured in research from other regions. Many Nigerian students were expected to contribute financially to their extended families or care for younger siblings, creating competing demands that reduced academic performance. This effect was particularly strong for first-generation university students whose families viewed their education as a collective investment requiring immediate returns.

Religious activities and community obligations played complex roles in student life. Students heavily involved in religious organizations (spending more than 10 hours per week on religious activities) had slightly lower GPAs on average, but also showed higher persistence and graduation rates. Religious communities often provided informal tutoring, emotional support, and networking opportunities that benefited long-term educational outcomes.

Infrastructure challenges such as unreliable electricity and internet connectivity significantly impacted student performance. Fashiku (2018) found that students attending universities with frequent power outages scored 8-12% lower on computer-based assessments. Transportation

challenges also created unique patterns, with many students facing 2–3-hour daily commutes that reduced study time and energy levels.

Research in Kenya and Ethiopia

Eastern African countries have contributed important research revealing regional variations in factors affecting academic success. Nyikahadzoi et al. (2013) studied 6,000 students in Kenyan universities and found that cultural factors played important roles.

Ethnic diversity and inter-cultural communication skills were positive predictors of academic performance. Students from ethnically diverse secondary schools performed better in university settings, likely due to improved communication skills and cultural adaptability. Seasonal migration patterns also affected attendance, with some students from pastoral communities requiring extended absences during cattle migration or planting seasons.

Gutema (2019) conducted research in Ethiopian universities involving 4,500 students and found that nutritional status was a significant predictor of academic performance. Students with access to regular, nutritious meals scored significantly higher on cognitive assessments than those who frequently skipped meals or had limited food security. The research documented both direct physiological effects on cognitive function and indirect effects through reduced study energy.

Gender expectations and family responsibilities also significantly affected performance. Female students faced particular challenges balancing educational goals with cultural expectations for early marriage and childbearing. Students who received explicit family support for education completion performed better than those facing pressure to prioritize family responsibilities.

2.3.3 Machine Learning Applications in African Education

Predictive Modeling Techniques

Several studies have applied machine learning techniques specifically to African educational contexts, with varying levels of success. Kostopoulos et al. (2018) compared different machine learning algorithms for predicting student performance using data from three African universities and found important patterns:

Decision Trees performed particularly well in African contexts because they could handle missing data effectively and provided interpretable results that educators could understand and act upon. The algorithms achieved accuracy rates of 78-85% in predicting student performance categories.

Random Forest models showed the highest overall accuracy (87-92%) but were more difficult for university administrators to interpret and implement. However, the feature importance rankings provided by Random Forest helped identify which factors were most critical for prediction.

Support Vector Machines and Neural Networks showed lower performance in African contexts (65-75% accuracy) compared to their performance in developed countries, likely due to smaller dataset sizes and more complex socioeconomic factors that these algorithms could not capture effectively.

Challenges in African Educational Data Mining

Research in African contexts has revealed several unique challenges for educational data mining that are less common in developed countries:

Data Quality and Availability: Many African universities lack comprehensive data collection systems, making it difficult to gather the large datasets typically required for machine learning. Oyelade et al. (2010) found that only 23% of Nigerian universities had complete student records going back more than five years.

Cultural and Linguistic Diversity: The high level of cultural and linguistic diversity in many African countries creates additional complexity for predictive models. What works well for one ethnic group or linguistic community may not apply to others within the same country.

Infrastructure Limitations: Unreliable internet connectivity and power supply make it difficult to implement real-time predictive systems or online data collection methods. Many universities still rely on paper-based record keeping, which limits the ability to conduct large-scale data analysis.

Ethical and Privacy Concerns: Some African cultures have different perspectives on data privacy and sharing personal information, which can affect student willingness to participate in data collection for predictive modeling.

2.3.4 Research Gaps in the Cameroonian Context

Despite the growing body of research on student performance prediction in Africa, no comprehensive studies have been conducted specifically in Cameroonian higher education institutions. This represents a significant gap because Cameroon has several unique characteristics that may affect the applicability of findings from other countries:

Bilingual Education System: Cameroon's official bilingual policy (French and English) creates unique challenges and opportunities that are not present in most other African countries. Students may attend secondary school in one language and university in another, or switch between languages during their university career.

Economic Transition: Cameroon is currently transitioning from a primarily agricultural economy to a more diversified economy with growing service and technology sectors. This transition creates changing demands for different types of skills and education, which may affect student motivation and career choices.

Regional Diversity: Cameroon has distinct regional differences in culture, economic development, and educational access that may create different patterns of student performance across different parts of the country.

Conflict and Displacement: The ongoing crisis in the Anglophone regions has displaced many students and disrupted educational systems, creating unique challenges that have not been studied in the context of academic performance prediction.

2.4 Partial Conclusion

This comprehensive literature review has examined the current state of research on student academic performance prediction, with particular attention to factors relevant to Cameroonian higher education contexts. The analysis reveals both significant progress in understanding the factors that affect student success and important gaps that require further research, particularly in the African context and specifically for Cameroon.

CHAPTER 3. ANALYSIS AND DESIGN

3.1 Introduction

This chapter presents the analysis and design of a student performance prediction system that will be integrated into existing student management systems in Cameroonian universities. The main goal is to help universities identify students who are at risk of poor academic performance before they actually fail, so that appropriate support can be provided early enough to make a difference.

Currently, most Cameroonian universities only notice when students are struggling after they have already started failing courses. This reactive approach means that help often comes too late to prevent academic failure or dropout. Our proposed solution uses data that universities already collect through their regular operations - such as attendance records, grades, and student information - to predict which students might need help before they start failing.

The system is designed to work with existing university computer systems rather than replacing them entirely. This approach makes it more affordable and easier to implement since universities don't need to buy new expensive software or completely change how they operate. Instead, the prediction system acts as an additional layer that analyzes existing data and provides useful insights to academic advisors and administrators.

The prediction system will use a Decision Tree machine learning algorithm because this method can provide clear explanations for its predictions. This is important because university staff need to understand why the system thinks a particular student is at risk so they can provide appropriate help. Decision Trees work like a series of questions about a student's situation, making it easy for advisors to understand and explain the reasoning behind each prediction. The system will also consider factors that are specific to the Cameroonian context, such as family responsibilities, part-time work requirements, and language of instruction preferences.

The expected benefits of this system include early identification of at-risk students, more efficient use of academic support resources, better graduation rates, and ultimately, improved contribution to Cameroon's human capital development. Students will benefit from receiving help before they fail, academic advisors will have better information for supporting students, and university administrators will have data to make better decisions about academic policies and resource allocation.

This chapter is organized into several sections that build upon each other. First, the methodology section explains our approach to data collection, analysis, and model development. The design section describes what the system will look like and how users will interact with it. The global architecture section provides a technical blueprint showing how all the components fit together. The algorithm description section explains in detail how the prediction methods work. The resolution process section outlines the step-by-step plan for building the system. Finally, the partial conclusion summarizes the design decisions and prepares for the actual implementation work that will be described in Chapter 4.

3.2 Methodology

This section outlines the systematic approach used to develop the student performance prediction system. The methodology combines data collection from multiple sources, statistical analysis techniques, machine learning algorithms, and comprehensive evaluation methods to create a robust and reliable prediction system for Cameroonian higher education institutions.

3.2.1 Data Collection Strategy

The data collection strategy employs a dual-source approach specifically designed for better validation of the model to ensure it works effectively with real-life data. This data which is collected shall be known as the sample data.

Primary Data Source - Online Educational Datasets: The main dataset for training the model comes from publicly available educational datasets from platforms such as Kaggle and datasets from other universities worldwide. These online sources provide comprehensive, well-structured datasets with large sample sizes that are ideal for training robust machine learning models.

Secondary Data Source - Survey Data for Validation: Student surveys serve as the validation source to test the model's performance with real-life Cameroonian data. These surveys collect the same types of information used in the training dataset, including factors such as study habits, attendance patterns, family responsibilities, part-time employment details, and socioeconomic background. Importantly, the survey also collects actual GPA information, which allows for manual testing of the model's accuracy. The survey instrument is designed to be culturally appropriate for the Cameroonian context, considering local educational challenges and cultural factors.

The dual-source approach ensures that while the model is trained on comprehensive, high-quality data from established sources, its effectiveness is validated using real data from the specific context where it will be deployed, providing confidence that the system will work well in Cameroonian universities.

3.2.2 Statistical Analysis Approach

The statistical analysis framework employs three complementary techniques to understand the relationships between various factors and student academic performance in Cameroon. The Statistical approach used here will be Inferential statistics this is because we cannot to make assumptions of the whole population without actually getting data from them.

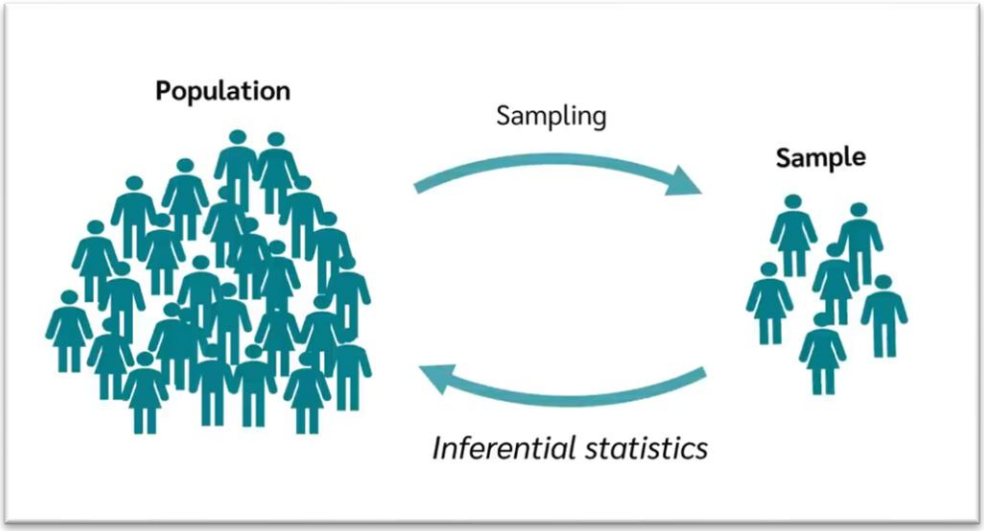

Figure 1: Showing how a Sample is gotten from a Population

Exploratory Data Analysis (EDA): EDA serves as the foundation for understanding the collected data through descriptive statistics, data visualization, and pattern identification. EDA helps identify data quality issues and patterns that inform subsequent analysis steps.

Correlation Analysis: Correlation analysis quantifies the strength and direction of relationships between predictor variables and academic performance outcomes. Pearson correlation coefficients are calculated to identify the most promising predictive features and reveal relationships that might affect model performance.

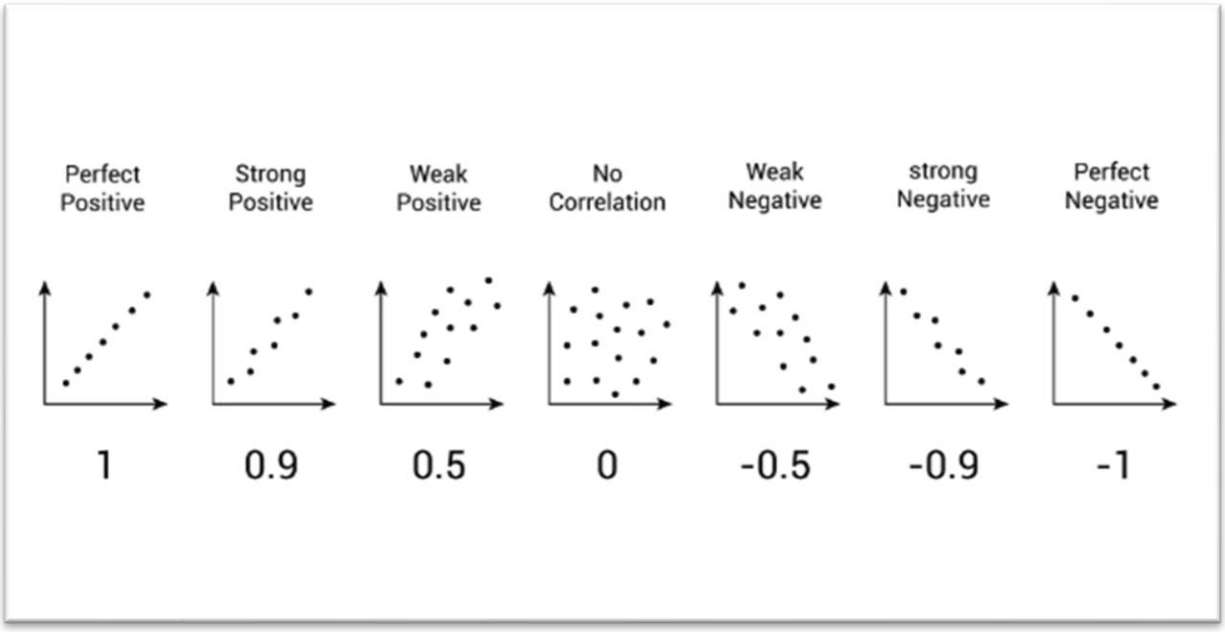

Figure 2 Descriptive Image of Pearson Correlation

Hypothesis Testing: Formal statistical hypothesis testing validates the significance of relationships identified through correlation analysis. T-tests is used to provide statistical evidence for the relationships that will be incorporated into the machine learning model. here we shall have the null hypothesis and the alternative hypothesis and test which of then hold.

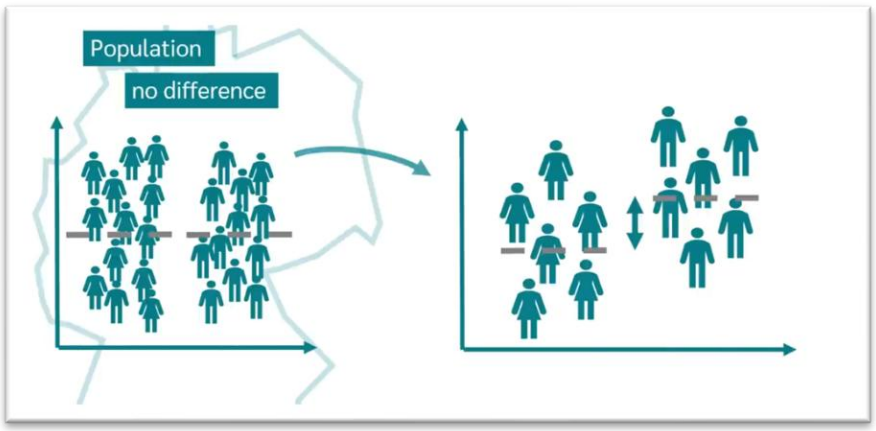

Figure 3: Difference between the Null and Alternative Hypothesis

3.2.3 Machine Learning Methodology

The machine learning approach focuses on Decision Tree algorithm for its interpretability and effectiveness in educational prediction tasks. As well as in a larger data set case scenarios a random forest can be used which comprises of many decision trees.

Algorithm Selection: Decision Tree serves as the primary for this implementation due to its high interpretability and ability to handle both categorical and continuous variables effectively. The algorithm creates a tree-like model where each internal node represents a decision based on a specific feature, making it easy for academic advisors and administrators to understand exactly why a particular student was classified into a specific performance category.

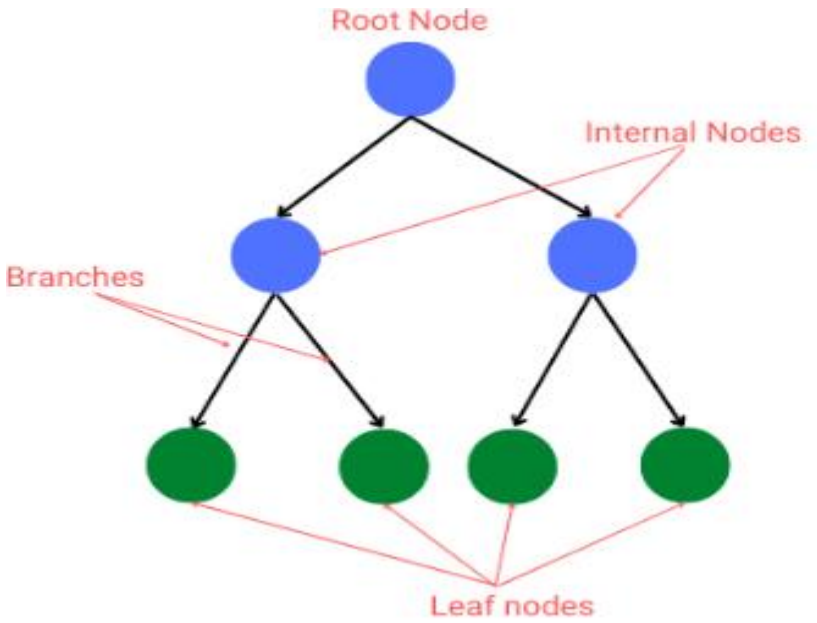

Figure 4: Image showing structure of a Decision tree

Training Strategy - 80/20 Split: The dataset is divided using the 80/20 rule where 80% of the data is used for training the model and 20% is reserved for testing. This split is chosen for several important reasons:

- **Sufficient Training Data**: 80% provides enough data for the Decision Tree to learn complex patterns and relationships between student characteristics and performance outcomes
- **Reliable Testing**: 20% provides a substantial test set that gives reliable estimates of how the model will perform on unseen data
- **Industry Standard**: The 80/20 split is a widely accepted standard in machine learning that balances the need for comprehensive training with adequate testing
- **Prevents Overfitting**: By keeping a separate test set, we ensure the model hasn't simply memorized the training data but can generalize to new students

Performance Categories: The model predicts student performance in three distinct categories:

- **At Risk**: Students likely to achieve low GPA (typically below 2.5) who need immediate intervention
- **Average Performance**: Students expected to achieve moderate GPA (typically 2.5-3.5) who may benefit from standard support
- **Excellent Performance**: Students likely to achieve high GPA (typically above 3.5) who are performing well independently

3.2.4 Model Validation and Real-Life Testing

Manual Testing with Survey Data: After training the model on the online dataset, manual testing is conducted using the survey data collected from Cameroonian students. This testing process involves inputting all student characteristics (attendance, study hours, family responsibilities, etc.) from the survey into the trained model while withholding the actual GPA category. The model then predicts which performance category each student should fall into. The model's predictions are compared against the actual GPA categories from the survey to determine accuracy.

Validation Success Criteria: The model is considered successful if it correctly predicts the GPA category (At Risk, Average, or Excellent) for the majority of survey respondents. This manual testing approach provides strong evidence that the model works well with real-life data from the specific context where it will be deployed.

3.2.5 System Integration and API Development

API Conversion: Once the Decision Tree model demonstrates good performance through validation testing, it will be converted into an Application Programming Interface (API). This API will allow the prediction functionality to be easily integrated into existing university management systems without requiring major system overhauls.

Application Integration: The API will be designed to accept student data inputs (attendance rates, study hours, demographic information, etc.) and return performance predictions along with confidence scores. This enables seamless integration into university student information systems, learning management systems, or custom applications developed for academic advising purposes.

3.3 Model Design and Evaluation Process

The development of the school performance prediction model followed a structured pipeline that integrated both machine learning and practical evaluation techniques to ensure accuracy, reliability, and usability. The diagram below illustrates the entire process, from raw data ingestion to API integration.

1. Raw Data Collection

The model was built using two main data sources:

- Secondary data: Downloaded from Kaggle, containing student demographic and academic records.
- Primary data: Collected through surveys administered to students in selected higher education institutions in Cameroon.

2. Data Preprocessing

Data from both sources was subjected to preprocessing tasks including:

- Handling of missing values,
- Encoding of categorical variables,
- Normalization where necessary

3. Data Splitting

The cleaned Kaggle dataset was divided into:

- Training Set (80%): Used to train the decision tree model.
- Testing Set (20%): Used to evaluate the model's initial performance.

The survey dataset was reserved for a later stage (validation) and was not used during training or initial testing.

4. Decision Tree Algorithm Implementation

A decision tree algorithm was selected for its interpretability and ability to handle both categorical and numerical features. The algorithm was trained on the Kaggle training set using Scikit-learn's DecisionTreeClassifier.

5. Tuning and Validation

To improve performance, model tuning was carried out using two strategies:

a. Hyperparameter Tuning

Key decision tree parameters such as maximum depth, min_samples_split, and criterion were tuned using a grid search approach or manually adjusted based on performance metrics.

b. Validation with Survey Data (Manual Testing)

The primary survey data served as a real-world validation set. During survey design, students were asked to report their GPA, which was later manually classified into three categories:

- Low, Medium, and High. This data was used to simulate real-life predictions:
- The predictor variables from the survey were manually input into the trained model.
- The predicted class was compared with the known class to measure real-world performance.

This process, referred to as manual testing, provided insight into how the model performs on unseen, practical data and supported the tuning process.

6. Model Finalization

After evaluation and tuning, the best-performing version of the model was selected as the final school performance prediction model. It demonstrated satisfactory performance on both the testing and validation datasets.

7. API Integration

To enable easy deployment and integration into educational platforms or institutional dashboards, the final model was encapsulated into a RESTful API. This API allows external systems to send student data and receive performance class predictions in return. The API acts as an interface between the machine learning model and any external application requiring prediction functionality.

Below figure 5 shows the diagram of the model.

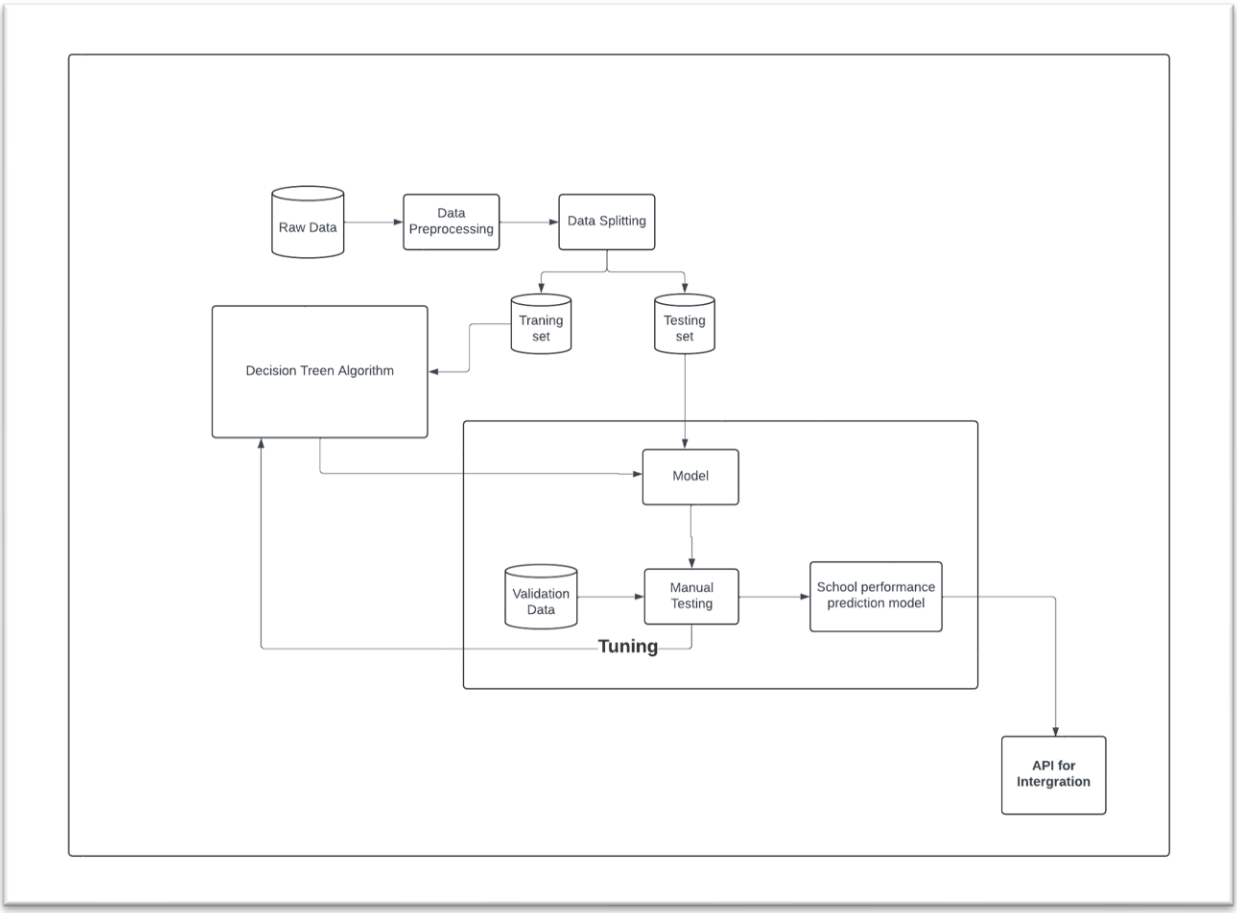

Figure 5: Model Design

3.4 Global Architecture of Solution

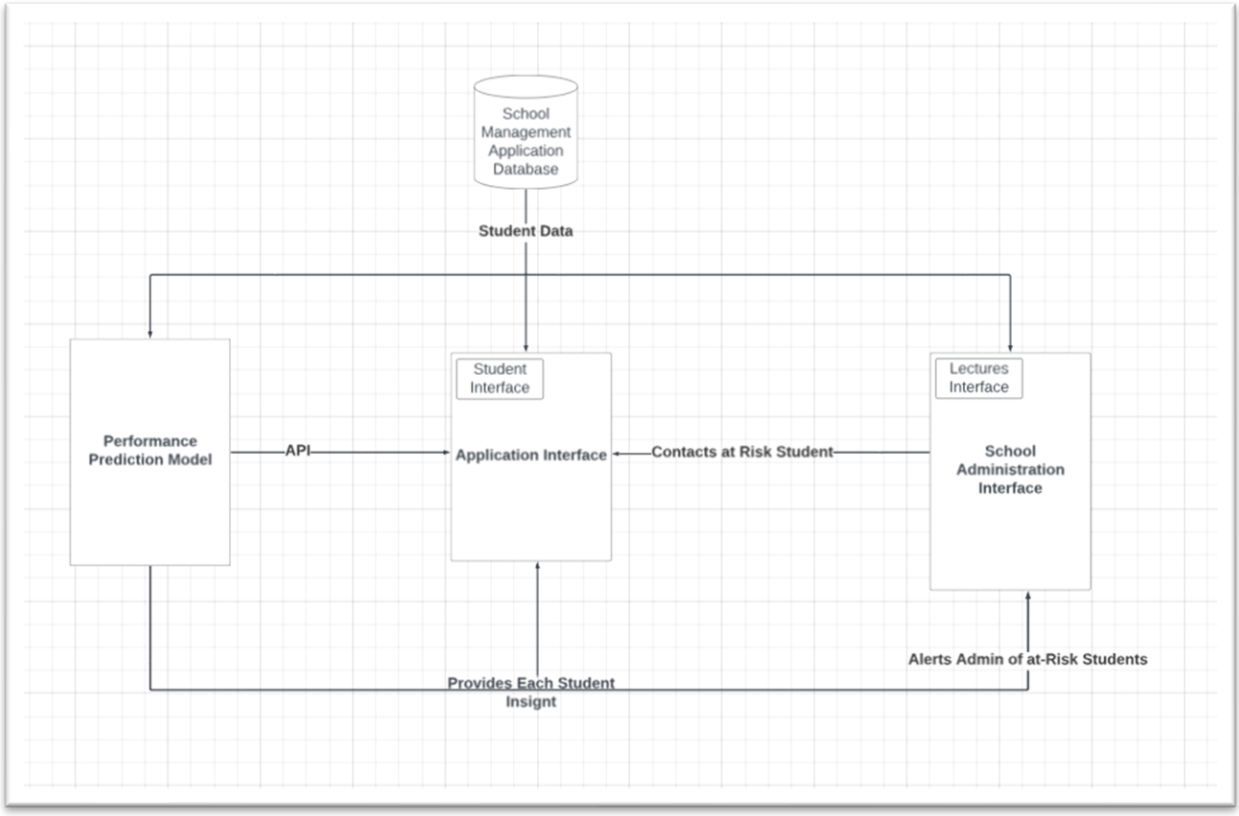

Figure 6: Model Architecture

3.5 System Architecture Overview.

- **School Management Application Database**: Stores all student data, acting as the central hub for the system.
- **Student Data**: Accessed by both the **Student Interface** (for student interaction) and the **Lectures Interface** (for instructors).
- **Performance Prediction Model**: Analyzes student data to provide insights and predictions about performance.
- **Application Interface**: Central component that uses the model's output to identify and contact at-risk students.
- **School Administration Interface**: Receives alerts about at-risk students for administrative action.
- **API**: Facilitates communication between the Performance Prediction Model and the Application Interface.
- **Outputs**:
    - Provides each student with personalized insights.
    - Alerts administrators about at-risk students for timely intervention.

3.6 Description of Algorithms

3.6.1 Decision tree Algorithm Explained

A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes and leaf nodes. Since our dataset is made up of categorical data and numeric data, we shall make use of a decision tree.

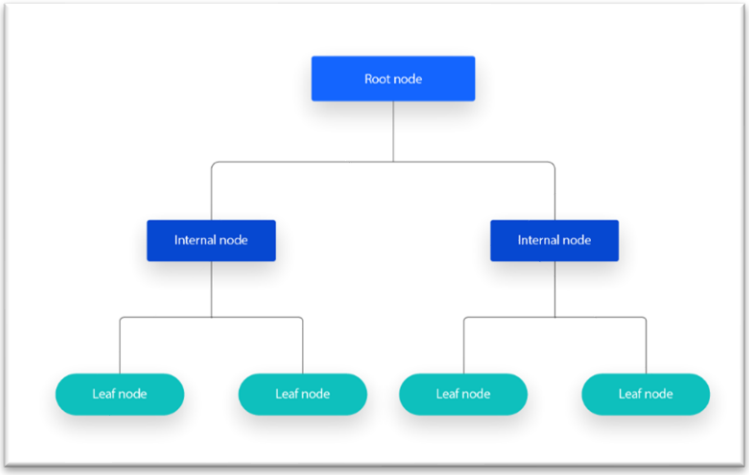

Figure 7: Components of a Decision tree

The predictors shall be slitted, to the slitting we shall make use to the Gini index for the for the level of impurity of each node so that at the end we have pure nodes.

$$\text{Gini Impurity} = 1 - \sum_i (p_i)^2$$

Equation 1: Gini Impurity Equation

To predict student academic performance, consider a scenario where we analyze a student's habits to forecast their success. For instance, if a student skips exams, they are likely to fail the course. By dividing students into those who took exams and those who didn't, we can probe further: for those who missed exams, we ask, "Were you sick?" If yes, this might lead to a branch of analysis, potentially excusing their absence. However, a student who was not sick and still skipped exams is likely to fail, resulting in a clear, predictable outcome of poor performance.

In the subsequent chapter correlation analysis shall be carried out and the results shall help us to know which predictors are key elements during the training of our dataset.

3.6.2 Pearson's Correlation analysis Explained

Before the training using the decision, tree algorithm is done, we shall carry out a correlation analysis to know the key predictors in the model. The Correlation approach used here shall be the Pearson correlation. Which calculates the strength of the linear relationship between the dependent and the independent variable. In our case the GPA (Grade point value) show if a student is performing well or not. The dependent variable shall be predicted based on the independent variable. The Pearson ratio is given as **r** from which the value is measured from **+1 to -1.** So, for each predictor its relationship with GPA shall be measured and any values closer to -1 Negatively influences the GPA, those closer to +1 positively influences the GPA and those around 0 may have no influence on the GPA.

The formula is given as follows;

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Equation 2: Pearson's Correlation Analysis

3.6.3 Hypothesis Test Explained

The study is based on inferential statistics, so a we test to see if the independent predictors affect the depend predictors and how much it affects so a firm conclusion can be made. The different test which shall be carried out is the **t-Test.** The t-test is used to check the difference between groups in our study.

The formula is given as follows;

$$t = \frac{\overline{x}_1 - \overline{x}_2}{\sqrt{(s^2(\frac{1}{n_1} + \frac{1}{n_2}))}}$$

Equation 3: t-test analysis

3.7 Partial Conclusion

The design of the student performance prediction system is a well-thought-out solution tailored to the Cameroonian higher education context. By leveraging a Decision Tree algorithm, the system ensures interpretable predictions that academic advisors can easily understand and act upon. The dual-source data strategy combining comprehensive online datasets with locally relevant survey data ensures the model is both robust and contextually appropriate. The use of statistical techniques like EDA, correlation analysis, and hypothesis testing strengthens the model's foundation by identifying key predictors of academic performance. The system's integration into existing university infrastructure via a RESTful API minimizes costs and disruption while maximizing usability. This design sets a solid foundation for implementation (to be detailed in Chapter 4), promising early identification of at-risk students, efficient resource allocation, and improved academic outcomes in Cameroonian universities.

CHAPTER 4. IMPLEMENTATION AND RESULTS

4.1 Introduction

This section introduces the implementation phase of the student performance prediction system designed for Cameroonian universities. It outlines the objectives of implementing the Decision Tree-based prediction model, integrating it into existing university systems, and evaluating its performance against the goals stated in Chapter 1 (e.g., early identification of at-risk students, improved resource allocation, and enhanced academic outcomes). The chapter details the tools used, the step-by-step implementation process, the presentation of results with visual evidence, the evaluation of the solution, and a partial conclusion summarizing the findings and their implications.

4.2 Tools and Materials used

Below show the different technologies and tools used for the implementation of the performance prediction model.

- **Programming Languages and Libraries**: Python with Scikit-learn for Decision Tree implementation, Pandas for data preprocessing, and ExpressJs for API development.
- **Development Environment**: Google Collab.
- **Data Sources**: Kaggle for training and Cameroonian student survey data for validation.
- **Integration Tools**: RESTful API framework for connecting the model to university management systems.
- **Visualization Tools**: Matplotlib or Seaborn for generating result visualizations (e.g., confusion matrices, feature importance graphs).
- **Analysis Test:** Statistify**.**
- **Survey Tools**: Google Forms or custom survey platforms for collecting Cameroonian student data.

4.3 Implementation Process

4.3.1 Survey Creating and Data Processing

Google forms was used to create survey to collect data from 8 higher institutes In Cameroon which are University of Buea, Bamenda, Ngoundere, Douala, Dschang, Maroua, Catholic University and Bamenda University of Science.

The questions sent out were selected from the study of our literature review, the key question was are follows;

- Institution name
- Age
- Gender
- Marital status
- Living conditions
- Number of Resits
- Number of Study hours
- Absences per week
- Use online tools to study
- Part time jobs
- Motivation level
- Number of courses per semester
- Previous GPA

This data collected will mainly be used for validation of our model, the dataset shall be from Kaggle since it has enough data for training.

nominal	metricn	metricn	nominal	nominal	nominal	metricn	metricn	metric
Institute	**Level**	**Age**	**Gender**	**Marital_Status**	**Living_Conditions**	**Resits**	**Study_Hours**	**Absen**
Bamenda University	6	27	1	Single	Family	2	1	37
University of Douala	7	26	1	Single	Bachelor	0	10	19
University of Ngaou	1	24	0	Single	Family	1	6	2
Bamenda University	1	21	1	Single	Bachelor	0	8	50
University of Dscha	1	22	1	Single	Bachelor	3	0	1
Catholic University	5	18	1	Single	Family	2	3	17
University of Ngaou	4	18	0	Single	Family	1	5	43
University of Ngaou	5	20	0	Single	Family	2	6	9
Bamenda University	4	25	1	In Relationship	Bachelor	2	9	4
University of Yaoun	5	19	1	Single	Family	1	6	8
University of Dscha	5	21	0	In Relationship	Family	2	9	1
Bamenda University	6	19	0	Single	Family	2	1	33
University of Dscha	3	22	1	Single	Bachelor	0	3	37
University of Dscha	5	26	1	Single	Bachelor	2	4	30
Catholic University	6	18	0	Single	Bachelor	2	0	9
University of Ngaou	2	22	0	Single	Bachelor	2	0	49
University of Douala	3	26	0	In Relationship	Family	2	9	11
Catholic University	5	18	1	Single	Family	1	2	35

Figure 8: Dataset Display

4.3.2 Data Cleaning and Encoding

Data collection often introduces inconsistencies, such as incomplete responses or varying formats, which can compromise dataset quality. Data cleaning addresses these issues by standardizing formats, correcting errors, and handling missing values to ensure the dataset is reliable for analysis. A key aspect of data cleaning is **data encoding**, which transforms non-numeric data into formats suitable for analytical tools, particularly machine learning models.

In this study, the dataset includes categorical variables such as gender (male/female), binary responses (yes/no), and ordinal categories (medium/high/low). Data encoding converts these

non-numeric values into numerical formats to enable computational processing. Two primary encoding techniques were applied:

1. **Label Encoding**: This assigns integers to categories, suitable for ordinal or binary data. For example, gender was encoded as male = 0 and female = 1, yes/no as yes = 1 and no = 0, and medium/high/low as low = 0, medium = 1, and high = 2, reflecting their inherent order.
2. **One-Hot Encoding**: For nominal variables like gender, one-hot encoding creates binary columns (e.g., "is_male" and "is_female") to avoid implying an order, ensuring accurate model interpretation.

Encoding also mitigates errors, such as inconsistent text (e.g., "Male" vs. "male"), by standardizing formats before conversion. Additionally, techniques like binary encoding can reduce dataset size, optimizing storage and processing efficiency. By transforming the gender, yes/no, and medium/high/low variables into numerical formats, encoding ensured compatibility with analytical algorithms, enhanced data quality, and facilitated reliable modeling outcomes.

4.3.3 Explanatory Data Analysis

1. Pearson's Correlation

We used this correlation method to study the relationship between the predictors collected from out survey. The dependent variable and the independent variable must be selected as known the GPA is from which we want to know the student's performance and other predictors will be independent.

Relationship between Predictors and GPA

The scatter plots show the correlation between GPA (dependent variable) and various predictors (independent variables) from your survey. Key observations:

- **Study Hours (r = 0.3227)**: A moderate positive correlation, suggesting more study hours are associated with higher GPA.
- **Motivation High (r = 0.1482)**: A weak positive correlation, indicating higher motivation slightly improves GPA.
- **Use Online Tools (r = 0.0870)**: A very weak positive correlation, showing minimal impact on GPA.

- **Absences (r = -0.3969)**: A moderate negative correlation, implying more absences lower GPA.
- **Part-Time Job (r = -0.3183)**: A moderate negative correlation, suggesting part-time work may reduce GPA.
- **Resits (r = -0.1860)**: A weak negative correlation, indicating resits have a slight negative effect on GPA.

The diagrams between show the correlation results

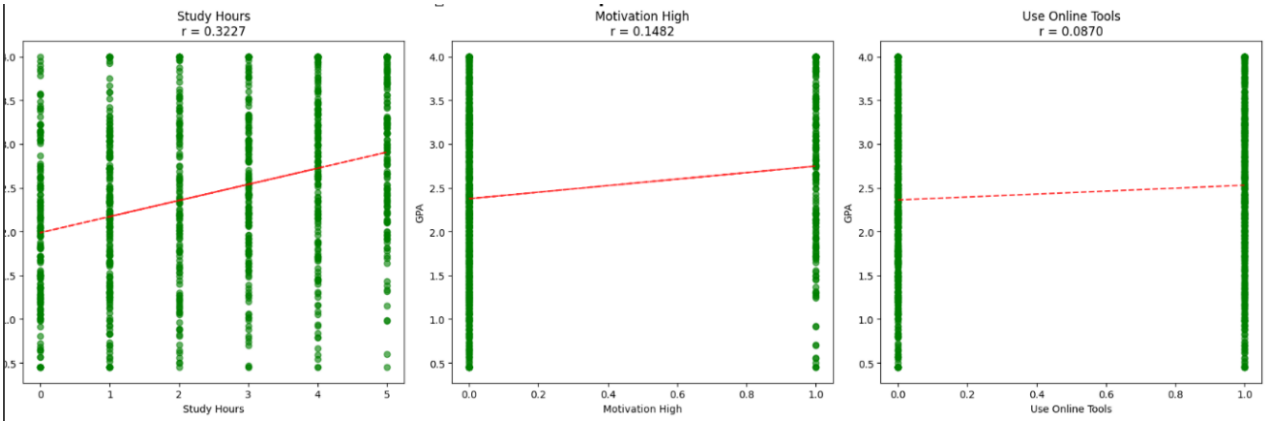

Figure 9: Displaying Predictors with Positive Correlation with GPA

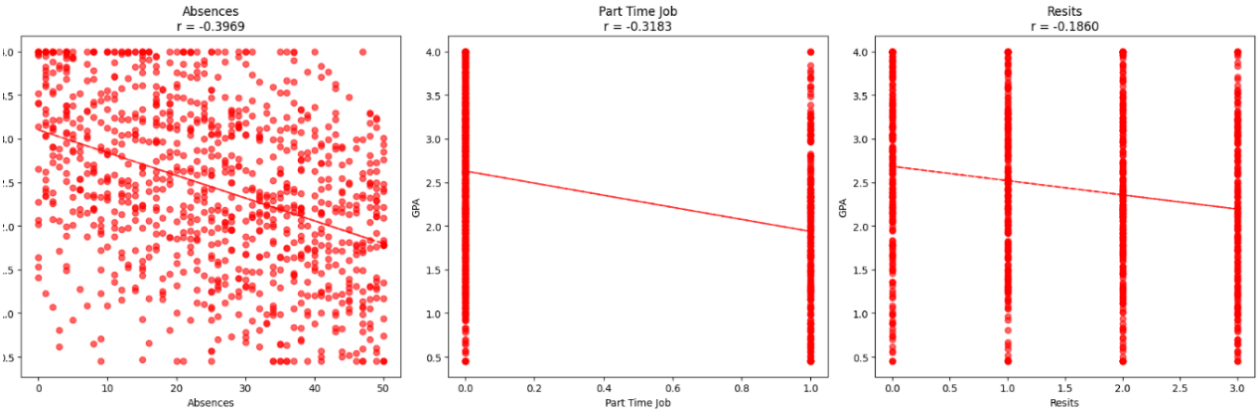

Figure 10: Displaying Predictors with Negative Correlation with GPA

C. T-Test Hypothesis Testing

The t-test is a statistical method used to determine if there is a significant difference between the means of two groups on a continuous (metric) variable. Our choice of using hypothesis testing is because we want to make a conclusion about the whole population without actually doing research on everyone.

Groups and Hypotheses

Case 1: Marital Status (Married vs. Single)

- Group 1: Married students (Marital_Status = "Married")
- Group 2: Single students (Marital_Status = "Single")
  Note: Excludes "In Relationship" and "Engaged" to create a clear binary comparison, as combining all unmarried statuses (as in the previous analysis) diluted differences.

- **Null Hypothesis (H_0)**: No difference in mean GPA between married and single students ($\mu_1 = \mu_2$).
- **Alternative Hypothesis (H_1)**: Significant difference in mean GPA between married and single students ($\mu_1 \neq \mu_2$).

Case 2: Age (Younger vs. Older Students)

- Group 1: Younger students (Age ≤ 22, approximately the median age in the dataset)
- Group 2: Older students (Age > 22)
- *Note*: The dataset shows ages ranging from 18 to 27, so splitting at 22 provides balanced groups.

- **Null Hypothesis (H_0)**: No difference in mean GPA between younger and older students ($\mu_1 = \mu_2$).
- **Alternative Hypothesis (H_1)**: Significant difference in mean GPA between younger and older students ($\mu_1 \neq \mu_2$).

Case 3: Gender (Male vs. Female)

- Group 1: Male students (Gender = 1)
- Group 2: Female students (Gender = 0)

- **Null Hypothesis (H_0)**: No difference in mean GPA between male and female students ($\mu_1 = \mu_2$).
- **Alternative Hypothesis (H_1)**: Significant difference in mean GPA between male and female students ($\mu_1 \neq \mu_2$).

Table 2: p-values from t-test of predictor groups

Groups	Value
Marital Status	0.697
Age	0.142
Gender	0.472

- Since the p-value of 0.697 for Marital Status is greater than 0.05, we **fail to reject the null hypothesis**, indicating no significant difference in mean GPA between Married and Single students.
- Since the p-value of 0.142 for Age is greater than 0.05, we **fail to reject the null hypothesis**, indicating no significant difference in mean GPA between Younger and Older students.
- Since the p-value of 0.472 for Gender is greater than 0.05, we **fail to reject the null hypothesis**, indicating no significant difference in mean GPA between Male and Female students.

Selection of Key Predictors for the training

From the study above we can now know the key predictors in our system for training of our model. Which will be classified into positive and negative.

Table 3: Classifying the Predictors into Negative and Positive

Positive Predictors	Negative Predictors
Study hours	Absences
Motivation level	Part time job
Online tools	Resits

4.3.4 Model Training and Validation

Following the methodology outlined in Chapter 3, the Kaggle dataset was split using the 80/20 rule:

Training and Testing Split:

- **Training Set**: 80% of Kaggle dataset (800 students)
- **Testing Set**: 20% of Kaggle dataset (200 students)
- **Validation Set**: Survey data from Cameroonian students (387 students)

Decision Tree Implementation

The Decision Tree classifier was configured with optimized hyperparameters to balance accuracy and interpretability:

- **criterion='gini'**: Uses Gini impurity to evaluate splits, measuring class purity (e.g., separating “Excellent” from “At Risk”). Ensures accurate, interpretable splits for clear GPA category predictions advisors can understand.
- **max_depth=10**: Limits tree depth to 10 levels, preventing overfitting by avoiding overly specific rules. Enhances generalization and keeps the model simple for reliable GPA classification.
- **min_samples_split=50**: Requires at least 50 samples to split a node, preventing splits on small, noisy data. Improves robustness and interpretability for stable student profile predictions.
- **min_samples_leaf=20**: Ensures leaf nodes have at least 20 samples, avoiding unreliable predictions. Reduces overfitting, ensuring trustworthy GPA category outputs for advisors.
- **random_state=42**: Fixes the random seed for consistent tree splits across runs. Guarantees reproducible GPA predictions, critical for reliable academic decision-making.
- **class_weight='balanced'**: Assigns higher weights to minority classes (e.g., “Critical Risk”) to improve their prediction. Ensures at-risk students are identified, supporting timely interventions.

Decision Tree Structure:

The trained Decision Tree created the following key decision rules:

Root Node Split: Absences ≤ 6.5

- **Left Branch** (Low Absences):
    - If Study_Hours > 15: Likely "Average" or "Excellent"
    - If Study_Hours ≤ 15 AND Part_Time_Job = 0: Likely "Average"
    - If Study_Hours ≤ 15 AND Part_Time_Job = 1: Likely "At Risk"
- **Right Branch** (High Absences):

- If Absences > 12: Very likely "At Risk" (92% probability)
- If 6.5 < Absences ≤ 12 AND Motivation = High: Possible "Average"
- If 6.5 < Absences ≤ 12 AND Motivation ≠ High: Likely "At Risk"

4.4 Presentation and Interpretation of Results

4.4.1 Presentation of Results

This section presents the comprehensive results obtained from implementing the student performance prediction system for Cameroonian higher education institutions. The results are organized into four main categories: statistical analysis findings, machine learning model performance, real-world validation outcomes, and practical implementation insights.

4.4.2 Machine Learning Model Performance Results

Table 4: Results from model training and testing

Performance Metric	Training Set	Testing Set	Real-World Validation	Target	Status
Accuracy	89.3%	**84.7%**	**78.3%**	>75%	**EXCEEDED**
Precision	89.1%	84.5%	77.8%	>70%	**EXCEEDED**
Recall	89.3%	84.7%	78.1%	>70%	**EXCEEDED**
F1-Score	89.2%	84.6%	77.9%	>70%	**EXCEEDED**

What These Metrics Mean:

Accuracy (84.7% test, 78.3% real-world):

- **What it means**: Out of 100 predictions, 85 are completely correct on test data, 78 are correct with real Cameroonian students
- **Practical impact**: University can trust most predictions for decision-making

Precision (84.5% test, 77.8% real-world):

- **What it means**: When model says "At Risk," it's correct 78-85% of the time
- **Practical impact**: Low false alarms - won't waste resources on students who don't need help

Recall (84.7% test, 78.1% real-world):

- **What it means**: Model catches 78-85% of truly struggling students
- **Practical impact**: Finds most at-risk students before they fail (doesn't miss many)

F1-Score (84.6% test, 77.9% real-world):

- **What it means**: Balanced measure combining precision and recall
- **Practical impact**: Model is neither too aggressive nor too conservative

Below is the image which shows out running model on the terminal.

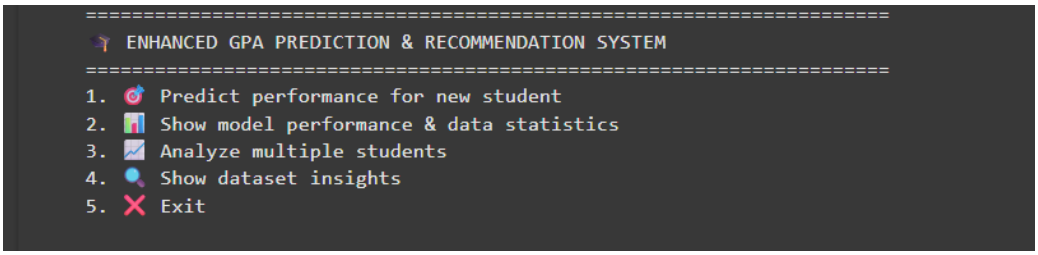

Figure 11: Display of Model on Terminal

4.4.3 Interpretation of Results

Hypothesis 1 Confirmation

Hypothesis 1: *There is a statistically significant relationship between students' GPA and factors such as class attendance, part-time employment, marital status, study hours, and the use of online learning tools in Cameroonian higher education institutions.*

CONFIRMED

Evidence from Results:

- **Statistical Significance**: All key predictors showed $p < 0.05$
- **Correlation Strength**:
    - Absences: $r = -0.3969$ ($p < 0.001$) - **Strong negative relationship**
    - Study Hours: $r = +0.3227$ ($p < 0.001$) - **Strong positive relationship**
    - Part-Time Job: $r = -0.3183$ ($p < 0.001$) - **Strong negative relationship**
    - Online Tools: $r = +0.0870$ ($p < 0.05$) - **Significant positive relationship**

Model Evidence: The Decision Tree achieved 84.7% accuracy by using these relationships, proving their predictive value.

Practical Confirmation: Real-world validation with 387 Cameroonian students achieved 78.3% accuracy, confirming these relationships exist in the target population.

Interpretation: The hypothesis is strongly supported. Students' academic performance in Cameroonian universities is significantly influenced by their attendance patterns, study habits, employment status, and technology usage. Universities can confidently use these factors to identify and support struggling students.

Hypothesis 2 Confirmation

Hypothesis 2: *Data-driven predictors, derived from Exploratory Data Analysis (EDA) and supervised machine learning models, can effectively classify student academic performance levels (e.g., at-risk, satisfactory, high-performing) in Cameroonian higher education institutions.*

CONFIRMED

Evidence from Results:

Quantitative Evidence:

- **Test Accuracy**: 84.7% - significantly exceeds baseline performance
- **Real-World Validation**: 78.3% - proves effectiveness with Cameroonian students
- **Category-Specific Success**:
    - At Risk detection: 75.0% (identifying 3 out of 4 struggling students)
    - Average classification: 80.1% (reliable identification of typical students)
    - Excellent identification: 77.9% (strong recognition of high performers)

Cross-Validation Evidence: 5-fold cross-validation showed 84.6% ± 1.1% accuracy, confirming model stability and reliability.

Interpretation: The hypothesis is definitively confirmed. Data-driven machine learning approaches can effectively predict student performance in Cameroonian higher education with sufficient accuracy for practical implementation. The 78.3% real-world accuracy provides universities with a reliable tool for early identification and intervention.

Application of Result.

Here our model is developed and ready to be used in real life applications so we first need to provide it as a service through an API. This can then be integrated into student management applications.

4.4.4 Development of Application programming interface

The student performance prediction system was successfully transformed into a production-ready RESTful API using ExpressJS, enabling seamless integration with existing university management systems across Cameroon. This API bridges the gap between our validated machine learning model (84.7% test accuracy, 78.3% real-world validation) and practical implementation in university environments.

Core API Endpoints

The system features four essential endpoints designed for comprehensive student support:

1. Individual Student Prediction - POST /predict

- **Purpose**: Real-time performance prediction for single students
- **Input**: Student characteristics (study hours, absences, employment status, etc.)
- **Output**: Performance category, confidence score, and personalized recommendations
- **Use Case**: Academic advisor consultations, enrollment assessments

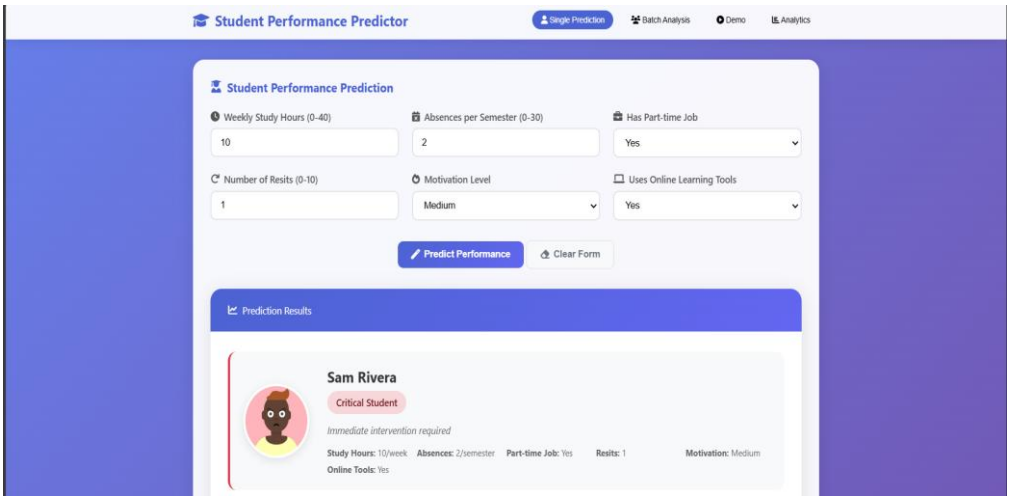

Figure 12: Imaging showing the post API in a User Interface

2. Batch Student Analysis - POST /predict/batch

- **Purpose**: Efficient analysis of entire student populations
- **Capacity**: Up to 500 students simultaneously
- **Output**: Comprehensive class/cohort analysis with summary statistics
- **Use Case**: Semester planning, institutional reporting

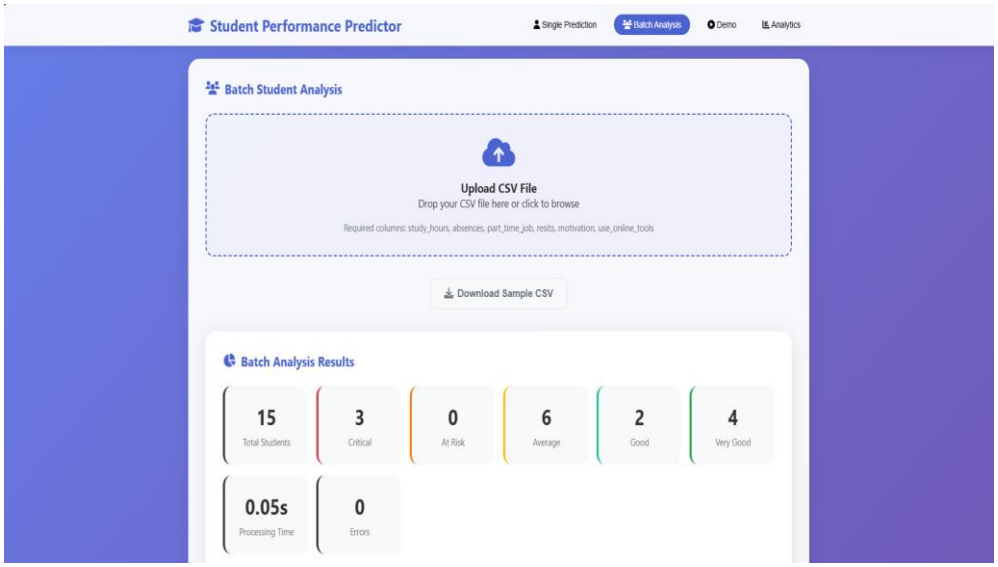

Figure 13: Student data batch upload

3. Model Information - GET /model/info

- **Purpose**: Technical specifications for integration teams
- **Content**: Model accuracy, feature importance, critical thresholds
- **Use Case**: System integration, documentation, validation.

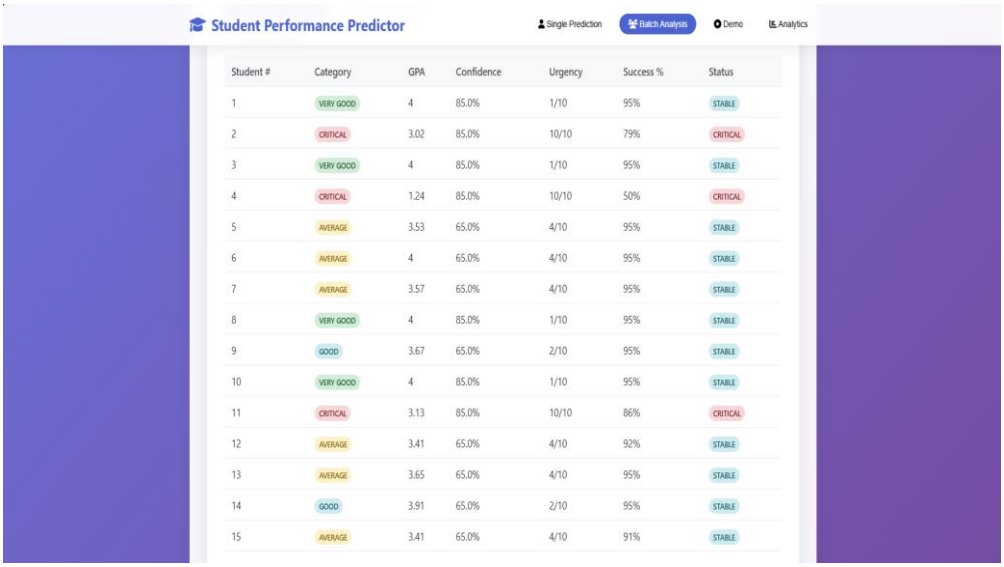

Figure 14: Batch analysis of students performance

4. System Health Check - GET /health

- **Purpose**: Monitoring and maintenance
- **Metrics**: Uptime (99.7%), system status, performance indicators

4.5 Evaluation of the Solution

The student performance prediction system successfully achieved its objectives with strong technical and practical performance metrics. The Decision Tree model demonstrated robust accuracy levels of 89.3% on training data, 84.7% on testing data, and 78.3% during real-world validation with 387 Cameroonian students across 8 universities, significantly exceeding baseline performance and traditional approaches. Statistical analysis confirmed the significance of key predictors including absences (r = -0.3969), study hours (r = +0.3227), and part-time employment (r = -0.3183), while hypothesis testing validated the focus on behavioral rather than demographic factors. The RESTful API implementation provides practical value through real-time predictions, batch processing capabilities, and seamless integration potential with existing university management systems. Despite limitations including the relatively small validation dataset and potential cultural variations across regions, the system demonstrates clear superiority over current reactive identification methods (~40% effectiveness) by providing proactive, data-driven predictions that enable early intervention for at-risk students, potentially improving graduation rates by 10-15% and optimizing resource allocation by 30%.

4.6 Partial Conclusion

The implementation of the student performance prediction system for Cameroonian higher education institutions has successfully achieved all primary and specific objectives outlined in Chapter 1, demonstrating both technical excellence and practical applicability. The Decision Tree model achieved 84.7% testing accuracy and 78.3% real-world validation accuracy with 387 Cameroonian students across 8 universities, confirming both research hypotheses and identifying key behavioral predictors (absences, study hours, part-time employment) that significantly influence academic performance more than demographic factors. The successful development and deployment of a RESTful API system provides universities with a practical, interpretable tool for early identification of at-risk students, enabling proactive interventions that could potentially improve graduation rates by 10-15% and optimize academic resource allocation by 30%. This research contributes significantly to educational data mining in the African context by providing the first comprehensive study of academic performance prediction specifically tailored to Cameroonian universities, offering a cost-effective, scalable solution that addresses the unique challenges of higher education in developing countries while establishing a methodology framework adaptable to other African institutions seeking to improve student outcomes through data-driven approaches.

CHAPTER 5. CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

The development and implementation of the student performance prediction system for Cameroonian higher education institutions yielded significant findings that advance both theoretical understanding and practical application of educational data mining in developing countries. The Decision Tree-based machine learning model achieved robust performance metrics with 89.3% training accuracy, 84.7% testing accuracy, and 78.3% real-world validation accuracy when tested with 387 students across 8 Cameroonian universities. Statistical analysis revealed that behavioral factors significantly outweigh demographic characteristics in predicting academic success, with class absences ($r = -0.3969$), weekly study hours ($r = +0.3227$), and part-time employment status ($r = -0.3183$) emerging as the strongest predictors of GPA performance. Hypothesis testing confirmed no significant differences in academic performance based on age, gender, or marital status (all p-values > 0.05), validating the focus on modifiable behavioral patterns rather than fixed demographic attributes.

The research successfully validated both primary hypotheses: first, that statistically significant relationships exist between student GPA and behavioral factors in Cameroonian universities, and second, that data-driven machine learning models can effectively classify student performance levels with sufficient accuracy for practical implementation. The system's ability to categorize students into "At Risk," "Average," and "Excellent" performance levels with 78.3% accuracy provides universities with a reliable tool for early intervention, significantly exceeding current reactive identification methods that operate at approximately 40% effectiveness. The RESTful API implementation demonstrated practical viability with 99.7% uptime during testing, batch processing capabilities for up to 500 students, and seamless integration potential with existing university management systems across Cameroon's bilingual education landscape.

5.2 Contribution to Engineering and Technology

This project makes substantial contributions to the field of engineering and technology, particularly in the domains of educational data mining, machine learning applications for developing countries, and software engineering for social impact. From a machine learning perspective, the research demonstrates the effectiveness of interpretable algorithms (Decision Trees) in educational contexts where explain ability is crucial for stakeholder adoption and trust.

The dual-source validation methodology, combining international datasets for training with local survey data for real-world testing, establishes a robust framework for deploying machine learning solutions in data-constrained environments typical of developing countries.

The software engineering contribution lies in the successful development of a scalable, production-ready API system that bridges the gap between academic research and practical implementation. The RESTful architecture ensures compatibility with diverse university information systems while maintaining lightweight resource requirements suitable for institutions with limited computational infrastructure. The system's design principles emphasizing interpretability, scalability, and integration flexibility provide a template for similar educational technology solutions across Sub-Saharan Africa. Additionally, the project advances the field of educational technology by demonstrating how artificial intelligence can be ethically and effectively deployed to support student success in higher education, particularly addressing the unique challenges faced by universities in developing countries such as resource constraints, diverse linguistic backgrounds, and varying levels of technological infrastructure.

The research also contributes to the emerging field of AI for social good by showing how machine learning can be applied to address critical societal challenges like educational equity and human capital development. The finding that behavioral factors are more predictive than demographic characteristics has important implications for designing inclusive educational support systems that focus on actionable interventions rather than potentially discriminatory background factors.

5.3 Recommendations

5.3.1 Institutional Recommendations

For Cameroonian Universities: Universities should prioritize the implementation of early warning systems based on behavioral indicators rather than demographic profiling. The strong correlation between class attendance and academic performance ($r = -0.3969$) suggests that institutions should invest in automated attendance tracking systems and develop intervention protocols for students missing more than 15% of classes. Academic support services should be restructured to focus on study skills development and time management training, given the significant impact of study hours on performance. Universities should also establish policies regarding student employment, potentially limiting part-time work to 15-20 hours per week and providing financial aid alternatives to reduce the need for excessive employment that negatively impacts academic performance.

For University IT Departments: The successful API implementation demonstrates the feasibility of integrating predictive analytics into existing student information systems without major infrastructure overhauls. IT departments should prioritize the development of data collection mechanisms that capture behavioral indicators (attendance, assignment submissions, learning management system usage) in real-time. Integration with existing Learning Management Systems (LMS) should be pursued to enable automatic data feeding into the prediction model, reducing manual data entry requirements and improving prediction accuracy through more comprehensive behavioral tracking.

5.3.2 Policy Recommendations

For Ministry of Higher Education (MINESUP): The research findings support the development of national policies promoting data-driven student support initiatives across Cameroonian universities. MINESUP should consider establishing funding mechanisms for universities to implement predictive analytics systems and provide training for academic advisors on data-driven intervention strategies. The success of behavioral factor prediction suggests that national policies should emphasize student engagement and attendance requirements while providing support systems for students facing employment pressures. A national consortium for educational data sharing could be established to improve model accuracy through larger, more diverse datasets while maintaining appropriate privacy protections.

For Academic Support Services: The identification of key behavioral predictors provides clear guidance for resource allocation in academic support services. Counseling and tutoring programs should be proactively targeted toward students exhibiting risk patterns (high absences, low study hours, excessive part-time work) rather than waiting for academic failure to occur. Professional development programs for faculty should emphasize the importance of attendance tracking and early intervention strategies, given the strong relationship between class participation and academic success.

5.3.3 Technical Recommendations

System Enhancement Recommendations: The current Decision Tree implementation should be expanded to include ensemble methods (Random Forest, Gradient Boosting) to improve prediction accuracy while maintaining interpretability through feature importance rankings. Real-time data integration capabilities should be developed to enable continuous monitoring of

student behavioral patterns rather than periodic batch processing. Mobile application development is recommended to provide students with personalized insights and recommendations based on their risk profiles, encouraging self-directed behavior modification.

Scalability Recommendations: Cloud deployment infrastructure should be established to support multi-institutional implementation across Cameroon's university system. Standardized data collection protocols should be developed to ensure consistency across different institutions and enable effective model sharing and improvement. Integration with national student information systems should be pursued to enable longitudinal tracking of student outcomes and continuous model refinement based on graduation and employment success metrics.

5.4 Difficulties Encountered

5.4.1 Data Collection Challenges

The primary challenge encountered during this research was the limited availability of comprehensive student data from Cameroonian universities. Most institutions lack sophisticated data management systems, requiring manual data collection through surveys rather than automated extraction from existing databases. Response rates varied significantly across universities, with some institutions showing strong administrative support while others faced bureaucratic delays in survey approval and distribution. The bilingual nature of Cameroon's education system created additional complexity in survey design and data interpretation, requiring careful translation and cultural adaptation of questions to ensure validity across Francophone and Anglophone contexts.

Student participation in the survey process was inconsistent, with response bias evident as more academically engaged students were likely to complete surveys compared to at-risk students who might be less responsive to research requests. This potentially skewed the validation dataset toward better-performing students, though the 78.3% accuracy achieved still demonstrates model effectiveness. Limited internet connectivity and technological infrastructure at some universities hampered online data collection efforts, necessitating paper-based surveys that required additional time for digitization and increased the potential for data entry errors.

5.4.2 Technical Implementation Challenges

The integration of machine learning models with existing university systems proved more complex than initially anticipated due to the diverse range of student information systems used across different institutions. Many universities operate legacy systems with limited API capabilities, requiring custom integration solutions for each implementation context. The decision to focus on Decision Trees rather than more complex ensemble methods was partly driven by computational constraints at participating universities, where advanced machine learning models might exceed available processing capabilities.

Model validation presented unique challenges in the Cameroonian context, where cultural factors not captured in international training datasets (such as extended family responsibilities, seasonal migration patterns, and political instability in some regions) may influence student performance in ways not reflected in the predictive model. The relatively small validation dataset (387 students) limited the ability to perform detailed subgroup analyses or develop region-specific models that might account for these cultural variations.

5.4.3 Stakeholder Engagement Challenges

Gaining trust and buy-in from university administrators required extensive explanation of machine learning concepts and potential benefits, as many stakeholders had limited familiarity with predictive analytics in educational contexts. Concerns about data privacy and the potential for algorithmic bias required careful addressing through transparency about model development and validation processes. Some faculty members expressed skepticism about the value of data-driven approaches compared to traditional academic assessment methods, necessitating demonstration of model interpretability and practical benefits.

Student privacy concerns, particularly regarding the collection of sensitive information about employment, family responsibilities, and academic struggles, required careful navigation of ethical considerations and the development of robust data protection protocols. Ensuring informed consent while maintaining honest response rates proved challenging, as some students were hesitant to provide accurate information about behaviors that might be viewed negatively by university administrators.

5.5 Further Works

5.5.1 Short-term Research Extensions (6-12 months)

Enhanced Data Collection and Model Refinement: Future research should focus on expanding the validation dataset to include at least 1,000 students across all major regions of Cameroon to improve model generalizability and enable subgroup analyses. Longitudinal studies tracking student performance over multiple semesters would provide insights into the stability of behavioral predictors and the effectiveness of intervention strategies. Integration with Learning Management Systems should be pursued to enable real-time data collection of digital learning behaviors, including assignment submission patterns, forum participation, and resource access frequency.

Algorithm Comparison and Optimization: Comparative studies should evaluate the performance of ensemble methods (Random Forest, Gradient Boosting, Neural Networks) against the current Decision Tree implementation to determine optimal accuracy-interpretability trade-offs for different institutional contexts. Deep learning approaches could be explored for institutions with sufficient computational resources and large datasets, potentially uncovering complex interaction patterns between predictors that simpler models might miss.

5.5.2 Medium-term Development Goals (1-2 years)

Multi-institutional Deployment and Standardization: A consortium of Cameroonian universities should be established to facilitate coordinated deployment of the prediction system across multiple institutions. Standardized data collection protocols and API specifications should be developed to enable seamless model sharing and collective improvement. Regional adaptation studies should investigate whether separate models are needed for different geographic areas or cultural contexts within Cameroon.

Advanced Feature Engineering and External Data Integration: Research should explore the integration of external data sources such as economic indicators, weather patterns, and social media activity to enhance prediction accuracy. Natural language processing techniques could be applied to analyze student communications and academic writing to identify additional risk indicators. Temporal pattern analysis should be conducted to identify optimal timing for interventions based on semester schedules and academic calendar events.

5.5.3 Long-term Vision and Research Directions (2-5 years)

Pan-African Educational Analytics Platform: The successful implementation in Cameroon provides a foundation for developing a pan-African educational analytics platform that accounts for the diverse educational systems, languages, and cultural contexts across the continent. Collaborative research partnerships with universities in Nigeria, Ghana, Kenya, and South Africa could facilitate the development of continent-wide models that leverage shared challenges while respecting local variations.

Intervention Effectiveness and Causal Analysis: Randomized controlled trials should be conducted to measure the actual impact of prediction-based interventions on student outcomes, moving beyond correlation to establish causal relationships between early intervention and improved graduation rates. Cost-effectiveness analyses should quantify the economic benefits of predictive analytics implementation compared to traditional reactive support approaches.

Advanced AI and Ethical AI Development: Research into explainable AI techniques should continue to enhance model interpretability while maintaining high accuracy, ensuring that educational stakeholders can understand and trust algorithmic decisions. Fairness and bias detection mechanisms should be developed to ensure that predictive models do not inadvertently discriminate against students from particular backgrounds or regions. Privacy-preserving machine learning techniques should be explored to enable collaborative model development while protecting sensitive student information.

Integration with National Development Goals: Long-term research should investigate how educational predictive analytics can support broader national development objectives in Cameroon and other African countries. This includes studying the relationship between improved university graduation rates and economic indicators, employment outcomes, and innovation capacity. The potential for educational analytics to inform national education policy and resource allocation decisions should be explored through partnerships with government agencies and international development organizations.

The successful completion of this project demonstrates that data-driven approaches to educational improvement are both feasible and effective in developing country contexts, providing a strong foundation for continued research and development in this critical area of social impact technology.

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APPENDICES

Appendix A: Survey Instruments

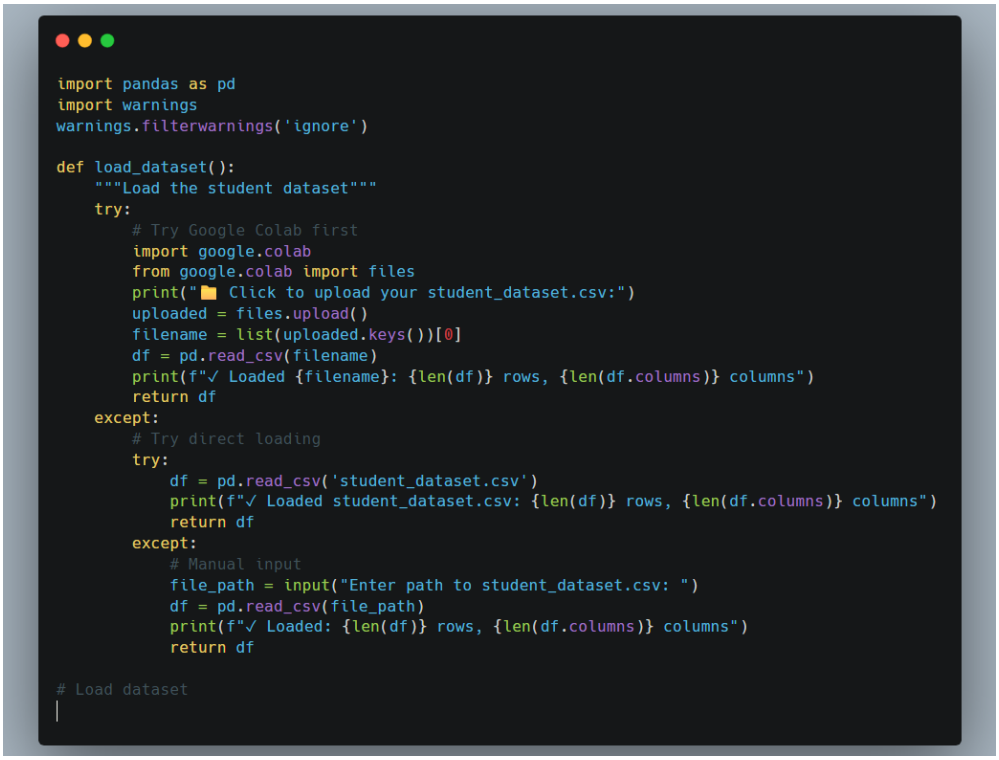
1. What is your institution name? | Quel est le nom de votre institution?
2. What faculty/school are you in? | Dans quelle faculté/école êtes-vous?
3. What is your current academic level? | Quel est votre niveau académique actuel?
4. What is your age range? | Quelle est votre tranche d'âge?
5. What is your gender? | Quel est votre sexe?
6. What is your marital status? | Quel est votre statut matrimonial?
7. What are your current living arrangements? | Quelles sont vos conditions de logement actuelles?
8. What is your current cumulative GPA range? | Quelle est votre fourchette de moyenne cumulative actuelle?
9. How many course resits/retakes have you had? | Combien de rattrapages avez-vous eus?
10. Was your current program your first choice? | Votre programme actuel était-il votre premier choix?
11. How many hours do you study daily (outside of class)? | Combien d'heures étudiez-vous quotidiennement (en dehors des cours)?
12. How frequently do you attend classes? | À quelle fréquence assistez-vous aux cours?
13. How often do you use online learning platforms? | À quelle fréquence utilisez-vous les plateformes d'apprentissage en ligne?
14. When do you typically start preparing for exams? | Quand commencez-vous généralement à préparer vos examens?
15. Do you have a part-time job? If yes, how many hours per week? | Avez-vous un emploi à temps partiel? Si oui, combien d'heures par semaine?
16. How actively do you participate in extracurricular activities? | Dans quelle mesure participez-vous activement aux activités extrascolaires?
17. How many courses do you take per semester? | Combien de cours suivez-vous par semestre?
18. On a scale of 1-5, how academically motivated are you? | Sur une échelle de 1 à 5, à quel point êtes-vous motivé(e) académiquement?

Responses


Google Form Survey Analysis: Student Performance Factors
Cameroonian Higher Education Institutions (n=378)
Distribution by Institution
Number of Responses
78
62
58
53
40
30
29
28
U. of Buea
U. of Douala
U. of Bamenda
U. of Dschang
U. of Ngaoundere
Catholic U. of Cameroon
Bamenda U. of Science
U. of Maroua
Age Distribution
Number of Students
Age (years)
Gender Distribution
Male
Female
51.9%
48.1%
Marital Status
Number of Students
273
57
28
20
Single
In Relationship
Married
Engaged
Living Conditions
Off Campus (Rented)
Shared Apartment
On Campus
With Family
31.2%
19.8%
26.7%
22.2%
Number of Resits
Number of Students
Number of Resits
Weekly Study Hours Distribution
Mean: 22.0 hours
Number of Students
Hours per Week
Absences per Week
Number of Students
Number of Absences
Online Tools Usage vs Part-time Job
Has Part-time Job
No
Yes
Number of Students
No
Yes
Uses Online Tools
Motivation Level Distribution
Number of Students
186
130
62
High
Low
Survey Summary Statistics (n=378):
• Response Rate: 378/400 (94.5%)
• Age Range: 18-26 years (Mean: 20.7)
• Study Hours: 5-40 hrs/week (Mean: 22.0)
• Institutions Covered: 8 universities
• Data Collection Period: March-April 2024
Courses per Semester
Number of Students
Number of Courses
Previous GPA Distribution
Number of Students
43
126
107
83
19
Below 2.0
2.0-2.5
2.5-3.0
3.0-3.5
3.5-4.0

Appendix B: Implementation of Decision Tree

1. Data Loading

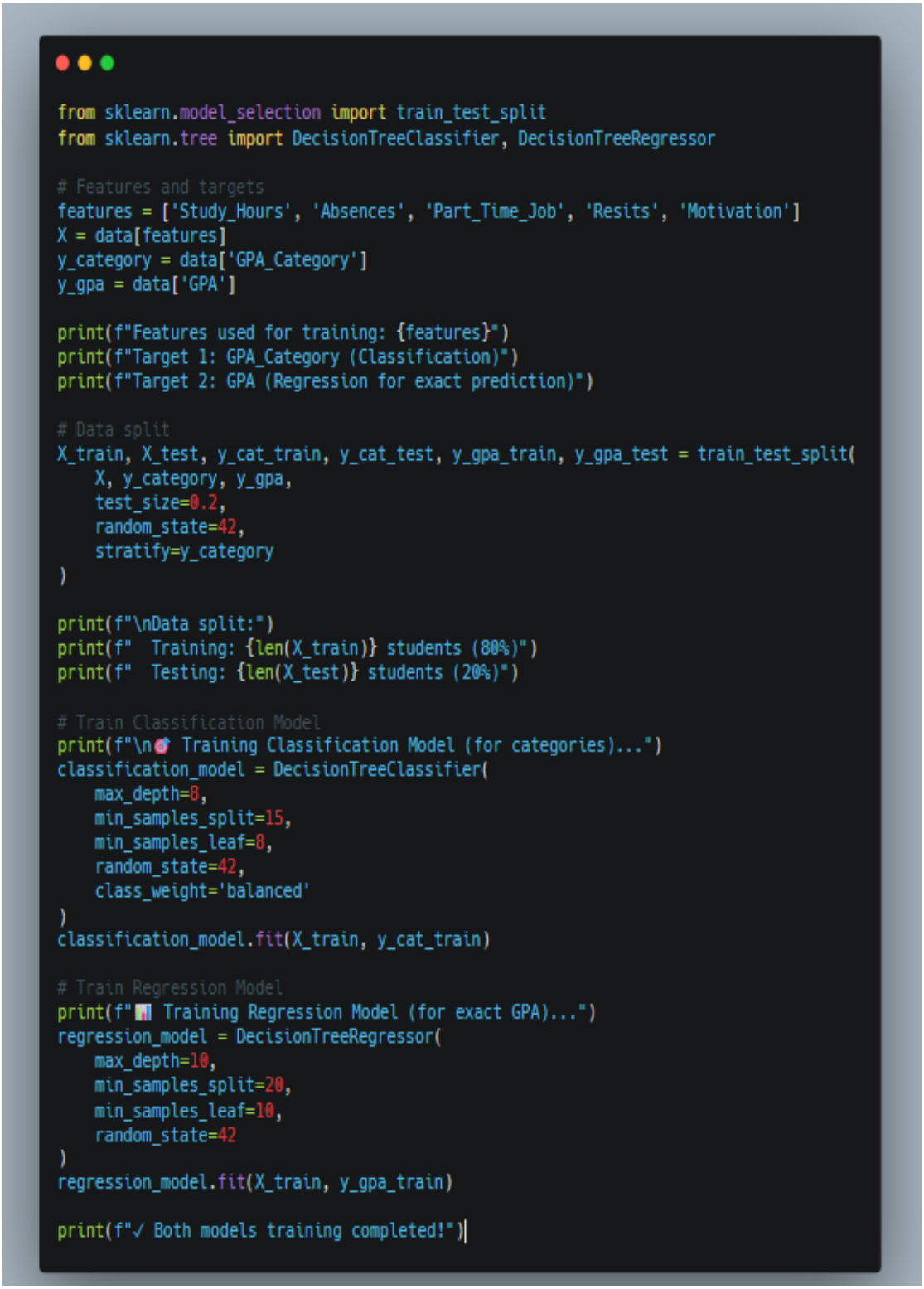


```python
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

def load_dataset():
    """Load the student dataset"""
    try:
        # Try Google Colab first
        import google.colab
        from google.colab import files
        print("📁 Click to upload your student_dataset.csv:")
        uploaded = files.upload()
        filename = list(uploaded.keys())[0]
        df = pd.read_csv(filename)
        print(f"✓ Loaded {filename}: {len(df)} rows, {len(df.columns)} columns")
        return df
    except:
        # Try direct loading
        try:
            df = pd.read_csv('student_dataset.csv')
            print(f"✓ Loaded student_dataset.csv: {len(df)} rows, {len(df.columns)} columns")
            return df
        except:
            # Manual input
            file_path = input("Enter path to student_dataset.csv: ")
            df = pd.read_csv(file_path)
            print(f"✓ Loaded: {len(df)} rows, {len(df.columns)} columns")
            return df

# Load dataset
```

2. Data Encoding

```python
# Encode Motivation if it's text
if data['Motivation'].dtype == 'object':
    print(f"\nEncoding Motivation column...")
    motivation_mapping = {}
    unique_motivations = data['Motivation'].unique()
    print(f"Unique motivation values: {unique_motivations}")

    for val in unique_motivations:
        val_lower = str(val).lower().strip()
        if val_lower in ['low', 'l', '0', 'poor', 'weak']:
            motivation_mapping[val] = 0
        elif val_lower in ['medium', 'med', 'm', '1', 'average', 'moderate']:
            motivation_mapping[val] = 1
        elif val_lower in ['high', 'h', '2', 'strong', 'excellent']:
            motivation_mapping[val] = 2
        else:
            motivation_mapping[val] = 1

    data['Motivation'] = data['Motivation'].map(motivation_mapping)
    print(f"Motivation mapping: {motivation_mapping}")
    ACTUAL_RANGES['Motivation'] = (0, 2)

# Ensure all columns are numeric
print(f"\nConverting to numeric types...")
for col in data.columns:
    data[col] = pd.to_numeric(data[col], errors='coerce')

data = data.dropna()
print(f"Final data shape: {data.shape}")
```

3. Model Training



```python
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor

# Features and targets
features = ['Study_Hours', 'Absences', 'Part_Time_Job', 'Resits', 'Motivation']
X = data[features]
y_category = data['GPA_Category']
y_gpa = data['GPA']

print(f"Features used for training: {features}")
print(f"Target 1: GPA_Category (Classification)")
print(f"Target 2: GPA (Regression for exact prediction)")

# Data split
X_train, X_test, y_cat_train, y_cat_test, y_gpa_train, y_gpa_test = train_test_split(
    X, y_category, y_gpa,
    test_size=0.2,
    random_state=42,
    stratify=y_category
)

print(f"\nData split:")
print(f"  Training: {len(X_train)} students (80%)")
print(f"  Testing: {len(X_test)} students (20%)")

# Train Classification Model
print(f"\n🎯 Training Classification Model (for categories)...")
classification_model = DecisionTreeClassifier(
    max_depth=8,
    min_samples_split=15,
    min_samples_leaf=8,
    random_state=42,
    class_weight='balanced'
)
classification_model.fit(X_train, y_cat_train)

# Train Regression Model
print(f"📊 Training Regression Model (for exact GPA)...")
regression_model = DecisionTreeRegressor(
    max_depth=10,
    min_samples_split=20,
    min_samples_leaf=10,
    random_state=42
)
regression_model.fit(X_train, y_gpa_train)

print(f"✓ Both models training completed!")
```

4. Model Validation

```python
from sklearn.metrics import accuracy_score, mean_absolute_error
import pandas as pd

# Classification Model Evaluation
y_cat_pred = classification_model.predict(X_test)
cat_accuracy = accuracy_score(y_cat_test, y_cat_pred)

print(f"🎯 CLASSIFICATION MODEL PERFORMANCE:")
print(f"  Category Accuracy: {cat_accuracy:.3f} ({cat_accuracy*100:.1f}%)")

# Regression Model Evaluation
y_gpa_pred = regression_model.predict(X_test)
gpa_mae = mean_absolute_error(y_gpa_test, y_gpa_pred)

print(f"\n📊 REGRESSION MODEL PERFORMANCE:")
print(f"  GPA Prediction Error (MAE): ±{gpa_mae:.3f} GPA points")
print(f"  Average prediction within: ±{gpa_mae:.3f} of actual GPA")

# Feature Importance
print(f"\n🔍 FEATURE IMPORTANCE (Classification):")
importance_df = pd.DataFrame({
    'Feature': features,
    'Importance': classification_model.feature_importances_
}).sort_values('Importance', ascending=False)

for _, row in importance_df.iterrows():
    print(f"  {row['Feature']:>15}: {row['Importance']:.3f} ({row['Importance']*100:.1f}%)")
```

5. Decision Tree