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DISSERTATION TITLE:

AN EXPLAINABLE AI MODEL FOR EARLY IDENTIFICATION OF AT-RISK (LOW PERFORMANCE) STUDENTS IN ETHIOPIAN TVT COLLEGES (THE CASE OF ALAMATA)

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THESIS TITLE:

AN EXPLAINABLE AI MODEL FOR EARLY IDENTIFICATION OF AT-RISK STUDENTS IN ETHIOPIAN TVT COLLEGES: A STACKING ENSEMBLE APPROACH (THE CASE OF ALAMATA)

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April, 2026

Declaration

I am Solomon Chekole, the undersigned, declare that this thesis entitled**: "An Explainable AI Model for Early Identification of At-risk Students in Ethiopian TVT colleges: a stacking ensemble approach (the case of Alamata)"** is my original work. I have undertaken the research work independently, with the guidance and support of the research advisor. This study has not been submitted for any degree or diploma program in this or any other institution, and all sources of materials used for the thesis have been acknowledged.

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Certification

This is to certify that the thesis prepared by Solomon Chekole, entitled "**An Explainable AI Model for Early Identification of At-risk Students in Ethiopian TVT colleges: a stacking ensemble approach (the case of Alamata)"** and submitted in partial fulfillment of the requirements for the Degree of Master in the Faculty of Electrical Electronics and Computer complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract

Ethiopian Technical Vocational Education and Training (TVT) institutions face persistent challenges regarding students' academic performance. At Alamata TVT College, Certificate of Competency(CoC) examination failure rates exceeded 35% in 2018 and 31% in 2019. Despite the failure rates, the college has no predictive early warning system to identify at-risk trainees before these concerning figures, no early warning systems before they fail, leaving interventions reactive.

This study develops and evaluates an explainable machine learning model to classify students into three performance risk categories: high, medium, and low risk, enabling targeted early intervention in Ethiopian TVT colleges.

Using 2,235 students' records from Alamata TVT College, the CRISP-DM methodology was implemented. To prevent data leakage (which would produce artificially inflated accuracy), six features correlated with direct or indirect information about the target outcome were removed, including mid-exam scores, assignment scores, and Prior Course Results. Three engineered features, namely Attendance Risk, Study Efficiency, and Academic Strength, were created to capture behavioral patterns. To address the class imbalance (59.3% of students in the medium-risk category), (SMOTE) was applied exclusively to the training set. Four algorithms, Random Forest, XGBoost, CastBoost, and Stacking Ensemble (combining all three with Logistic Regression meta-learner), were compared using stratified 5-fold cross-validation and hyperparameter optimization via GridSearchCV.

The Stacking Ensemble achieved a test accuracy of 97% and a macro-averaged ROC-AUC of 0.99 performs individual models. SHAP (Shapley Additive explanation) analysis identified Time Management, Study Hours per Day, and Attendance Rate as the dominant predictors of risk status.

The proposed Stacking Ensemble model provides an interpretable, deployable decision support tool suitable for integration into existing Education Management Information Systems(EMIS). However, several limitations apply to the two colleges' data, including no external validation. Future work should validate the model on additional TVT colleges and incorporate temporal data to enable accurate performance forecasting.

Keywords: *Predictive Analytics, Student Performance Forecasting, Stacking Ensemble, SMOTE, SHAP Explainability, Machine Learning in Education, TVT Institutions.*

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Abbreviations

AI …… Artificial Intelligence

ANOVA…… Analysis of variance

API …… Application Programming Interface

CoC…… Centre of Competency

CRISP-DM ……... Cross-Industry Standard Process for Data Mining

DSR ……Design Science Research

EDA ……Exploratory Data Analysis

EDM ……... Educational Data Mining

EMIS …… Education Management Information System

ESDP …… Education Sector Development Programme

EWS…… Early Warning System

FDRE …… Federal Democratic Republic of Ethiopia

HPO ……Hyper Parameter Optimization

ILO …… International Labour Organization

LMS ……Learning Management System

MoE ……Ministry of Education

MoLS …… Ministry of Labour and Skills

PCA ……Principal Component Analysis

PII ……... Personally Identifiable Information

REF …… Recursive Feature Elimination

ROC-AUC …… Receiver Operating Characteristic – Area Curve

SHAP …… SHapley Additive exPlanations

SMOTE …… Synthetic Minority Over-sampling Techniques

TVT …… Technical and Vocational Training

XAI …… Explainable Artificial Intelligence

CHAPTER ONE

1. INTRODUCTION

In today's educational landscape, Artificial Intelligence (AI) has emerged as one of the most impactful technologies. AI-driven educational platforms can leverage vast amounts of learner data to facilitate personalized learning, automate educational workflows, and enhance learning outcomes. In recent years, many educational institutions have been deploying learning analytics and machine learning methods to track student learning and identify students who might need academic assistance. [1], [2].

Learning analytics helps educational institutions gather and analyze academic, behavioral, and engagement information, and inspect students' learning patterns. Predictive analytics will enable machine learning models to identify students who may be on track to underachieve and make an intervention before they fail. In other educational settings, such early-warning systems have proven effective at enhancing student retention, achievement, and results on certification examinations. [3][4].

Moreover, AI-powered learning systems enable data-driven decision-making, offering clear, interpretable insights into factors impacting student success. AI applications have been shown to help mitigate dropouts and enhance learning outcomes by predicting and intervening with at-risk students using predictive analytics. [5].

In Ethiopia, the TVT is a vital sector for the development of the economy and society because it generates skilled human resources for the industry, agriculture, trade, and service sectors. The formal involvement of TVT in the education system of Ethiopia can be traced back to 1942, when the National School of Technical Arts was established in Addis Ababa, and later, the reform of the education system, which led to an increase in TVT provision across Ethiopia.

Although the government has been making efforts to improve the TVT sector, issues of competency of the graduates, employability, and quality of training still exist. Employers often cite that graduates lack practical, communication, problem-solving, and technical skills, leading to the need for further training expenses and lost productivity of labor. [6]. These challenges underline the need for evidence-based mechanisms that can either enhance the performance of students or support teaching and learning for the institutions.

Concurrently, driven by the rising demand for skilled workers and the high demand for TVT education, TVT institutions must be equipped with modern technologies that improve the quality of education and services provided to students. [7]. Given the growing significance of digital transformation and data-driven educational management systems in enhancing the effectiveness of TVT institutions, it is crucial to fully leverage their potential. Therefore, it is important to maximize the potential of digital transformation and data-driven educational management systems for TVT institutions to become more effective.

While student performance is an important measure of institutional effectiveness, most TVT colleges still heavily depend on traditional educational assessment approaches, which detect academic issues after the fact of poor performance. At Alamata TVT College, the performance of students in the Certificate of Competency (CoC) examination has been high, with several failure rates, which suggests that there is a need for proactive academic support systems.

No predictive system using AI is in place to identify students in advance who are likely to have poor test results at the end of the course. Consequently, interventions are often reactive in nature, and teachers and administrators cannot quickly intervene for struggling students. [8].

Machine learning methods have been used to predict student performance in different learning contexts. [3], [4]. However, most current studies have been conducted beyond the context of Ethiopian TVT, and local studies have focused on conventional prediction methods, with less consideration given to model explainability and applicability to practice.

Furthermore, no AI-based risk prediction model has been developed specifically for Ethiopian TVT institutions that can classify students based on performance risk level and provide interpretable and understandable explanations to decision-makers. This leaves a huge research space for using machine learning and learning analytics to help students succeed in Ethiopian TVT education.

This problem was solved by developing and testing an explainable AI Model for Early Identification of At-risk students that can help identify at-risk students in TVT institutions in Ethiopia using machine learning techniques. The proposed model is a stacking ensemble model based on SHAP explainability methods to classify students into High-Risk, Medium-Risk, and Low-Risk groups with understandable explanations of the factors influencing the model's predictions. This study is intended to assist in early intervention and help in data-driven decision-making in TVT educational management systems.

1.1. Background of Study

Ethiopia's Technical and Vocational Education and Training (TVT) system has been central to national development strategies aimed at enhancing labor productivity, reducing unemployment, and fostering industrial transformation. Recognizing that human capital is a critical driver of economic growth, the Ethiopian government has made significant investments in expanding TVT access and improving its relevance through strategic reforms, particularly since the early 2000s. The number of TVT centers has also increased significantly. In 1994, there were only 15 TVT centers throughout the country, but this figure increased to 153 by 2002 and 582 by 2017. The number of students enrolling increased from fewer than 10,000 in the early 1990s to more than 72,000 in 2002/2003 and 300,000 by 2016/2017. TVT enrollment has slowed down in recent years, but the share of female students has continued to increase, reaching more than 50 percent in 2011/12 [9].

The unemployment rate for young people aged 15-29 years in urban areas of the country was 27.2 percent, which was higher than that of the general unemployment rate (18.9 percent). The female youth unemployment rate in urban areas of Ethiopia was two times higher than that of their male counterparts in 2022 [10].

Ethiopia’s population lacks the skills required to meet new labor demands and support economic growth and transformation. In 2019, 78% of the labor force did not complete primary education, and only 7% completed secondary education or higher. Based on estimates by the International Labor Organization (ILO), 74% of the labor force in Ethiopia has an educational attainment that is below the requirements of their job, which compares poorly with its peer countries, including Kenya (62%), Bangladesh (58%), and Vietnam (28%). To achieve a successful structural transformation, a well-functioning labor force with technical and soft skills to enhance the productivity and competitiveness of the services and manufacturing sectors is necessary.[11].

1.2. Statement of the Problem

In Ethiopia’s Technical and Vocational Education and Training (TVT), the weak academic and practical performance of students is a recurring problem. For example, at Alamata TVT College, more than 35.87% of its students failed in 2018, and 31.57% of its students failed in 2019, mainly based on the theoretical aspects of the courses. Similar concerns exist at the national level through improved education sector performance indicators, such as national dropout rates (17.5%) and weak internal efficiency. Other issues that exacerbate these challenges include inadequate infrastructure, insufficient training materials, limited

capacity of teachers and lecturers, and poor system performance due to weak curriculum implementation, which compromises the system's ability to generate competent and job-ready graduates.

In Ethiopia, most TVT institutions use traditional and reactive assessment methods to measure student performance. Monitoring is primarily an end-of-course assessment, attendance record, and teacher observation, but it is not a continuous or predictive assessment of student progress. In turn, interventions are generally not used until students fail or underperform. This reactive system makes it difficult for instructors and administrators to provide timely, personalized academic support and enhances the likelihood of dropouts and failures.

In Ethiopia, a few studies have been conducted that use machine learning techniques, such as J48 decision tree, Naïve Bayes, random forest, SVM, and other classification methods to predict student performance. [12], [13]. The studies agree on the capability of predictive analytics in the field of education, analyzing patterns in student attendance, grades, and engagement data. [14], [15]. However, most of these studies only target universities and secondary schools, and very few target TVT institutions, which are trained through competency-based training. Moreover, current studies have primarily addressed the prediction task, which is to increase the accuracy of that prediction, rather than deployed systems, and do not yet have "explainable" AI-based models that can aid teachers in understanding why students are at risk. Furthermore, few studies have combined predictive models with decision support systems for practical applications in the field of education.

Hence, there is an urgent demand for an Explainable Artificial Intelligence (XAI) based early warning system to identify students who are at risk of not completing their education before they happen. A system like this would allow for early intervention, better student retention, better decision-making by the instructor, and better planning for the institution. Filling this gap is crucial to enhance academic performance and improve the capacity of the Ethiopian TVT system to train competent, skilled, and employable graduates for the country's development agenda and to decrease the youth unemployment rate, which is greater than 20%, while the female unemployment rate is greater than 25% for more than a decade (2010-2022) [16].

1.3. Objectives of the Research

The main objective of AI-based predictive analytics is to improve the performance of TVT trainees and support them.

1.3.1. General objectives

To develop and implement an AI Model for Early Identification of At-risk students aimed at enhancing the academic performance, retention, and overall success of trainees in Ethiopia's education and technical training (TVET) institutions.

1.3.2. Specific objectives

- To analyze the academic, behavioral, demographic, and socio-economic factors influencing TVT student performance.
- To develop and evaluate an AI-based multi-class model classifying students into High, Medium, and Low risk.
- The model's interpretability was assessed using SHAP to enable explainable, evidence-based decisions.
- Outline a deployment framework for integrating the trained model into the existing EMIS.

1.4. Research Questions

1. What academic, behavioral, and demographic factors significantly influence student performance in TVT institutions?
2. How can machine learning algorithms be used to develop a better predictive analytics model for forecasting student performance and identifying at-risk students?
3. How can an AI model for early identity of at-risk students help identify at-risk(Low performance students) students in TVT colleges?
4. How can the proposed AI Model for Early Identification of At-risk students be used as a decision-support tool for early intervention in TVT colleges?

1.5. Scope/ Delimitations of the study

This study covers Alamata town and focuses on technical and educational trainees. This study is limited to the TVT colleges in Alamata Town.

This Study focuses on the development of an XAI model for the early identification of at-risk students in Ethiopian TVT colleges. The study was conducted in selected TVT colleges located in Alamata town. The target population consisted of TVT trainees and relevant educational stakeholders involved in student performance monitoring.

This study examined factors influencing academic performance, including attendance records, assessment results, academic history, and other relevant educational variables. Machine learning predictive analytics techniques were employed to analyze the collected data and predict students' academic outcomes.

The research is limited to data variables from the selected governmental and private TVT colleges. The dataset was collected from 2019 to 2026. The year under investigation is long because the college data are unclear, and the data handling methods are outdated. The study does not include all TVT colleges in Ethiopia and does not address issues related to graduate employability, psychological characteristics, or educational sectors outside the TVT system.

1.6. Significance of the study

The main intent of the present study is to design a knowledge base system using machine learning as a knowledge acquisition from private and government TVT and the occupational competency assessment process. This study is important for TVET/college institutes to increase the number of competent, creative, and innovative trainees, reduce the cost of training material, reduce the time of trainers to give additional training for incompetent trainees, and help take measures on their training methods and weaknesses.

For trainees/candidates to increase the acceptance of the trainees in society, increase competitiveness in the job market, and for the center of competency (COC) to increase the acceptance of the institution in society, improving the detection of poor-quality assessments is necessary. The government should take corrective action on the policy of TVT training institutions and the assessment process to reduce the number of unemployed in society and increase self-employment, creativity, and innovativeness. The industry will gain creative, innovative, and competitive human resources.

Ethiopia is now starting to offer ICT courses starting from the elementary level, which is a big opportunity for students, government, researchers, and developers to integrate their developed systems into education, such as AI, Robotics, Arduino, Programming, and software, which have a big impact on the technology development of countries.

1.7. Limitations of the Study

The scope of the study is limited to Alamata town TVT colleges. Due to a lack of data integration, time and financial constraints, and unstable conditions in the town due to the 2020/21 war in northern Ethiopia, most of the datasets are gathered from the governmental college.

CHAPTER TWO

2. REVIEW OF RELATED LITERATURE

2.1.Introduction

In this section, there is a discussion of some of the existing literature concerning the topic. This literature will be discussed in terms of its methodologies, findings, and other significant aspects that relate to the topic under investigation, and which will be covered in subsequent chapters. The purpose of this literature review is to examine existing studies, identify key methodologies, evaluate their findings, and highlight research gaps that justify the need for this study to provide a basis for justification of the necessity of this research. [17].

2.2. Artificial Intelligence in Education

Artificial Intelligence, or AI, is among the most revolutionary technologies impacting education today, significantly influencing how instruction and learning, and even school administration, are being carried out. AI in education involves leveraging smart computer systems that can accomplish tasks that normally demand human intelligence, including decision-making, problem-solving, prediction, and personalized recommendations. AI-powered systems are becoming more prevalent in educational settings for enhancing learning, automating administrative processes, and aiding academic decision-making. With the help of AI tools like data mining, neural networks, and machine learning, teachers can gain insights into extensive student data and discover patterns linked to student achievement or failure. This has greatly supported the capacity of the institutions to make timely interventions for students at risk and improve educational outcomes.[18].

Predictive analytics is a crucial application of AI in education, enabling institutions to anticipate student performance based on past and current educational data. Predictive Analytics is a new approach in the field of learning analytics that relies on statistical techniques, machine learning algorithms, and educational data mining techniques, aiming at detecting patterns in students' attendance, assignment submissions, examination scores, and online learning activities. These prediction models enable the identification of students who are likely to have learning difficulties before they fail, and for this reason, early intervention strategies can be put into place. Research shows that predictive analytics can assist in predicting students' learning behaviors, thereby enhancing students' academic performance and supporting institutional planning.[8] .

The integration of AI and learning analytics has been a major advancement for the personalized learning approach, which has revolutionized teaching and learning. AI and learning analytics have transformed educational environments, particularly when it comes to personalization. By tracking students' learning progress, AI systems can gain insights into a student's learning style and provide personalized educational content tailored to their specific learning needs. AI-powered personalized learning allows students to learn at their own speed, and for teachers to focus on students who need extra academic assistance. Moreover, AI-powered intelligent tutoring systems offer instant feedback and customized learning courses that enhance student engagement and motivation. Ouyang et al. (2023) found that the integration of AI prediction models and learning analytics can lead to the improvement of instructional design and learning experiences in online learning settings [19].

AI-powered predictive analytics models play a key role in institutional decision-making and educational planning. Predictive systems are utilized in universities and schools to maximize utilization of available resources, track student growth and development, minimize dropout rates, and enhance graduation rates. AI analytics can help administrators create personalized intervention strategies for those students who are at risk of failing to meet grade-level standards. With the proliferation of educational big data and the utilization of cloud computing technologies, the use of AI systems in higher education institutions around the world has grown rapidly. AI-powered predictive analytics is thus transforming into a vital part of the contemporary educational administration and student achievement methodologies. [19].

2.3.Machine Learning for Students' Performance Prediction

One of the key applications of machine learning in student performance prediction is the ability to analyze educational data and identify patterns that can be used to make accurate predictions about student performance. Machine learning is being used in student performance prediction because computer systems can learn patterns from educational data and make accurate predictions about student performance. The machine learning algorithms examine data like attendance, examination grades, assignment completion rates, class participation, and online learning activities, and find out the key factors for academic success or failure. Typical algorithms used to predict student performance are Decision Trees, Random Forest, Support Vector Machines (SVM), Logistic Regression, and Artificial Neural Networks (ANN). These algorithms can assist in the early detection of students who are at risk and provide them with additional assistance to improve learning and prevent dropouts. In educational settings, machine learning models have been demonstrated to be more accurate and efficient in predicting outcomes than traditional statistical models. [8].

Additionally, machine learning systems for predictive analysis assist in personalized learning and information-driven instruction decisions. Predictive models can help to identify students' learning behaviors and trends in their performance to provide personalized learning materials and teaching

strategies. The use of advanced machine learning methods like deep learning and ensemble learning has further enhanced the accuracy of predictions in virtual and online learning contexts, as these methods can handle massive and complex educational data sets. While these advantages are significant, problems like access to private data, explainability of the model, and bias in the data are also pertinent issues for applying machine learning systems in the educational sphere. Hence, there is a need for transparent, fair, and explainable AI models to support reliable educational predictions and ethical decision-making processes, researchers note[20].

2.4. Predictive Analytics in TVT Education

Predictive analytics has become a critical innovation in TVT institutions since it helps instructors and administrators to predict student learning performance and enhance training outcomes. Predictive Analytics involves using statistical techniques, machine learning algorithms, and educational data mining methods to analyze historical and real-time educational data to make predictions for future decision-making. For TVT education, predictive systems are built to recognize patterns from factors including attendance, practical assessment, assignment submission, technical competency evaluation, and participation in training activities that are correlated with success or failure in the learning process. The predictive systems enable the institutions to identify at-risk students at an early stage, and offer support measures like tutoring, counseling, remedial training systems, etc., that can assist the students in a timely manner. Studies have demonstrated that predictive analytics have a strong impact on the retention, performance, and planning of vocational education institutions. [8].

Incorporation of AI and Machine Learning technologies has further improved the application of predictive analytics in TVT education. Decision Trees, Random Forest, Logistic Regression, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) are all machine learning models that are frequently used to make predictions for student performance and competency achievement in vocational training programs. The algorithms can analyze complex and large-scale educational data and discover the unseen links between student learning habits and learning results. Therefore, TVT institutions may make decisions based on the data collected to enhance curriculum delivery, the effectiveness of practical training, and prepare the workforce. In educational settings, high predictive accuracy is achieved using advanced deep learning and ensemble learning approaches, which effectively analyze multidimensional learning data, as stated by[20].

The use of predictive analytics also enhances personalized learning and competency-based education in TVT institutions. TVT programs focus on practical skills, industry and work-based training, and solving problems in the field, so predictive systems can be used to track students' technical skills and learning

progress over time. The AI-based systems can also provide targeted interventions and suggestions for adaptive learning methods and content, enabling more personalized learning experiences. This enhances students' engagement, learning, and overall efficiency. Moreover, predictive analytics can help institutions match what students are prepared to learn with the skills required by the labor market by uncovering skill gaps and predicting employability trends of graduates. The researchers underline that AI-driven predictive technologies can enhance the quality, relevance, and connection of vocational education in a rapidly evolving industrial landscape [18].

Although predictive learning is a good tool in TVT education, there are some challenges associated with its implementation and effectiveness. A key issue is the data available for education; predictive models need accurate, complete, and well-structured data for proper predictions. The lack of digital infrastructure, non-uniform data collection, and insufficient technical knowledge on AI technology are common constraints affecting many TVT institutions. Furthermore, privacy of student data, algorithmic bias, and transparency are significant concerns with educational predictive systems. Selection of datasets and forecasts can become biased or incomplete and thus have a negative impact on students' learning opportunities and institutional decisions. Thus, researchers propose the use of ethical and explainable AI in applying predictive analytics to guarantee fairness, accountability, and transparency in the TVT education system. [19].

In addition, predictive analytics plays an important role in institutional management and policy-making in TVT education. Predictive models are predictive tools used by educational administrators to: track student progress, manage resources, boost student retention, boost technical training program effectiveness, and increase graduation rates. Predictive systems support evidence-based decision making by delivering actionable information about student learning trends and institutional performance indicators. The role of predictive analytics is increasingly gaining significance in vocational education, especially as more educational institutions move towards digital learning environments and online training platforms. AI's predictive analytics capabilities are thus emerging as a crucial tool for enhancing TVT education quality, efficiency, and student outcomes in today's educational landscape.[21].

2.5.Factors that influence the performance of trainees

2.5.1. Demographic and Socio-Economic Factors

Among the most influential factors that determine the performance of learners academically are demographic factors as well as socio-economic factors, since these factors determine the degree of accessibility to educational resources. According to studies conducted by educational researchers,

demographic factors such as age, gender, family income, parental education level, job status, and residential background have great significance for learning success. [22].

Age can be regarded as one of the most crucial demographic factors that influence the levels of maturity, self-discipline, responsibility, and adaptation among learners. The age factor implies that older learners might show more dedication towards education due to the greater maturity acquired through life experiences and career consciousness. At the same time, mature learners have their own problems associated with professional and personal affairs as well as finances. As for younger learners, they could have problems with time management and discipline. [23].

In addition, the residential backgrounds of learners play an important role in determining their levels of education and academic achievements, especially in terms of the difference between city and rural settings. Learners from cities tend to have greater chances of having access to the Internet, quality educational structures, good teachers, and necessary technological equipment than learners from rural settings. [24].

Demographic and socioeconomic factors are essential elements of AI-based predictive analytics systems since they enable the identification of educational disparities, student weaknesses, and factors that contribute to success or failure within education. The classification is done using machine learning methods based on these factors. [25].

2.5.2. Family and Background Factors

Background and family issues have been shown to play a huge role in determining trainees' academic performance, since the family is where individuals acquire such things as discipline, motivation, attitudes, and educational value systems. It has been found from recent research into education that those brought up in stable family settings have performed much better academically than those from unstable family backgrounds. [22].

Support provided by family members emotionally and psychologically is another factor that can greatly influence the level of success attained educationally. Students who have been encouraged and motivated by their parents emotionally and academically will show greater levels of self-confidence and focus in class. On the other hand, family conflicts, neglect, domestic disharmony, and divorce may cause stress and anxiety. [26].

Cultural and societal background issues are also contributing to learning attitude and vocational aspiration. Societies that greatly appreciate learning have learners who are more committed to their learning process and show more academic discipline. Conversely, the societal view about TVT education may discourage

the learners from being motivated in their studies. Recent findings from TVT education within African societies have shown that the poor perception of vocational education deters the trainees' interest in learning. [23].

2.5.3. Behavioral and Engagement Factors

The Behavioral Engagement factors can be defined as learner attitudes, engagement levels, learning behavior, and interaction with the learning process. This is viewed as a key predictor of trainee learning outcomes as it directly reflects the learner's level of commitment, discipline, motivation, and involvement in the learning process. The recent research into the education domain indicates that behavioral data is among the strongest predictors for student performance through AI systems. [26].

The attendance rate forms one of the key behavioral measures affecting educational success. Those learners who attend class frequently are more capable of grasping what is taught in class, participating in class discussions, completing assignment tasks, and ensuring that there is continuity in their learning process. On the other hand, those trainees who skip many classes may not grasp what is happening in class and will probably fail academically and eventually drop out. [27].

The third factor to be considered when looking at factors affecting training and development outcomes is motivation, since those who are highly motivated show more persistence, active participation, and positive attitudes towards learning. Motivation can either be intrinsic, where students will participate in learning due to personal interests and self-development, or extrinsic, which will involve rewards, recognition, job prospects, and career goals. Motivation plays an important role in Ethiopian schools today. [28].

As a result of the use of digital technology in learning, the role of engagement in e-learning is critical to the learning process. Those learners who utilize technology using digital learning platforms and educational technologies tend to perform better academically and improve their technological skills. The absence of internet access, low technological proficiency, and inadequate digital engagement limit learner participation and hinder educational success [26].

2.5.4. Academic Performance Indicators

Performance indicators are educational factors that can be measured for evaluating the level of competence, development, and accomplishment of learners. They are among the most accurate predictors of future educational success because they show the learner's competence, readiness for education, and accomplishments. Predictive analysis software that uses artificial intelligence technology is largely based on academic performance indicators. [26].

Academic success in the past, such as grades attained before, overall GPA, test scores, and educational background, is a good indicator of future success. Individuals with an impressive academic record tend to have high levels of educational success because they have excellent study skills and understanding. Those trainees who had poor academic backgrounds find it difficult to cope with demanding learning tasks [26].

The outcomes from continuous assessment procedures like quizzes, assignments, practical work, projects, and presentations offer critical insights into learners' progression during the entire learning process. Assessment activities assist educators in evaluating the educational progress of their students and any shortcomings they may have, thereby helping where necessary. Contemporary literature confirms that formative assessment and feedback processes enhance the learners' achievements in exams. [27].

The need for practical evaluation is particularly relevant in TVT institutions due to the nature of vocational learning, which stresses practical skills and technical competence. Practical evaluation plays an important role in assessing whether learners are fit to work or not. Research carried out in Ethiopia's TVT institutions found that the availability of workshops, practical tools, laboratories, and technical facilities plays a crucial role in practical performance. [29].

2.5.5. AI in Predictive Analytics for At-Risk Students

The use of AI in higher education institutions has greatly improved the way these institutions detect and help at-risk students. Predictive analytics uses ML tools to examine large sets of educational data, including students' performance, behaviors, and demographic factors, to predict the likelihood of a particular student dropping out. There is growing evidence indicating that identifying at-risk students through early detection systems helps institutions implement intervention strategies, which ultimately improve their chances for success. AI-based learning analytics systems have also been found to assist institutions in making decisions in advance by predicting students' early signs of academic disengagement. [30].

2.5.6. Data-Driven Foundations of Predictive Modeling in Education

Models of predictive analytics designed for at-risk students are based on educational datasets comprising data on LMS logs, assessment scores, attendance, and socio-demographic information. This type of data allows machine learning algorithms to discover underlying patterns related to student success or risk of dropping out. Studies indicate that engagement-based variables such as logins, assignments done, and time spent on tasks are some of the best predictors of student academic risks. Indeed, large-scale studies conducted on data from LMS systems found that behavior-based data significantly increases the accuracy of predicting student risks.[8].

2.5.7. Machine Learning Techniques for Identifying At-Risk Students

Many machine learning techniques have been utilized for predictive analysis in educational systems, and examples include logistic regression, decision trees, random forest, support vector machine (SVM), and gradient boosting machine techniques. Of all these techniques, Ensemble methods like the Random Forest and Boosting methods have been widely acknowledged as more accurate when predicting dropouts owing to their superior handling of non-linear correlations and imbalanced data. However, other simple techniques like logistic regression are still widely used on account of their simplicity and ease of implementation. Indeed, comparative analyses show that while advanced algorithms perform better, interpretable models are favored when decisions need to be made in practice because of their transparency.[31]. Contemporary AI methodologies also advocate the adoption of hybrid solutions that integrate predictive capabilities with explainable AI techniques like SHAP scores. [32].

2.5.8. Design and Development of Predictive Analytics Systems

The development of AI-powered prediction analytics systems for at-risk students includes multiple stages such as data preprocessing, feature engineering, training, validation, and deployment. Data preprocessing includes dealing with missing values, data normalization, and tackling class imbalances through algorithms like SMOTE or weighted loss functions. Feature engineering is especially important in this field since it allows transforming raw education-related data into valuable predictors, such as students' academic progress and engagement velocities. According to the latest studies, longitudinal modeling, especially when temporal learning behaviors are taken into consideration, contributes to much better prediction results. [33]. What is more, validation procedures that help prevent data leakage are becoming popular among researchers.[34].

2.5.9. Challenges, Ethics, and Future Directions in AI-Based Student Risk Prediction

Even though substantial developments have been made, the use of predictive analytics systems in education poses some serious threats, among which are model bias, non-interpretable model outputs, and limited generalization capacity. The issue of ethicality is crucial when developing models based on sensitive factors such as socio-economic background or demographic characteristics, since those could pose fairness problems in automated decision-making systems. According to [35], using fairness-aware modeling did not affect the performance of prediction and actually contributed to a more balanced approach in intervention techniques. Furthermore, most researchers highlight the importance of developing transparent and interpretable AI tools to make it possible for educators to understand their reasons for making predictions to ensure that interventions would be appropriate pedagogically speaking.

Modern studies aim at the development of XAI, real-time learning analytics, and adaptive interventions in the future [8].

2.6. AI-Based Predictive Analytics for Supporting Decision-Making in Education

2.6.1. Predictive analytics as a driver of evidence-based decision-making in education

The integration of artificial intelligence (AI) and predictive analytics in education has significantly transformed how decisions are made at multiple institutional levels. Predictive analytics leverages historical and real-time student data to generate forecasts about academic performance, retention risk, and learning progression. These insights enable stakeholders to transition from intuition-based decisions to evidence-based decision-making frameworks. Recent studies emphasize that learning analytics systems are increasingly being adopted to support institutional intelligence, where data-driven insights guide academic planning, student support interventions, and policy formulation. This shift is critical in addressing the complexity of modern higher education systems, where large student populations and diverse learning behaviors require automated decision-support mechanisms to improve outcomes [36][37].

2.6.2. Supporting instructors with students' academic relations through AI prediction models

AI-driven predictive analytics greatly boosts the capacity of teachers to make appropriate and effective pedagogical decisions in time. With the help of predictive systems, it is possible to detect early signs of struggling learners through analysis of their engagement levels, assignment completion results, attendance rates, and interaction with the learning platform. This allows for taking certain measures to help such students, including offering personal advice, adopting adaptive methods of instruction, and additional tutoring before final exams. Studies indicate that the use of learning analytics dashboards allows for making appropriate adjustments to the method of teaching based on empirical data rather than observations. [38][39].

2.6.3. Supporting policymakers in developing data-driven educational reforms

Additionally, predictive analytics is another critical tool in informing policies since it enables the provision of extensive analysis related to the performance of educational systems. With predictive modeling through the analysis of data from students enrolled in schools, one can detect some of the problems associated with the system, such as achievement gap, disparity in access to education, and student dropout at the regional or national level. Consequently, it becomes easier for policymakers to come up with solutions that tackle the core problem instead of addressing its symptoms. Furthermore, through the use of artificial intelligence tools for prediction, governments are able to test how certain policies might perform before their

implementation, thus increasing the chances of success of the reforms (Maia et al., 2023; Sghir et al., 2022) [40], [41].

2.6.4. Machine learning techniques as enablers of decision-support systems

Algorithms from machine learning are at the heart of the predictive analytics models adopted for educational decision-making. Methods such as logistic regression, random forest, support vector machine, and neural network models are employed extensively in the prediction of student performance based on multidimensional data sets. Such algorithms convert educational data into decision-making models that can inform decisions at all levels of instruction, administration, and policymaking. Notably, deep learning methods have exhibited considerable success in detecting nonlinear interactions in students' learning patterns. Nonetheless, concerns raised in recent years regarding the interpretability of the models, data privacy, and biases in predictive models should also be addressed. [42], [43].

2.6.5. Impact of AI-driven decision-making on educational outcomes and institutional efficiency

Predictive analytics using AI technology has been demonstrated to considerably increase educational success through early intervention and better retention rates among students. Educational establishments that use predictive decision support systems have experienced an increase in student engagement, academic performance, and lower drop-out rates among their students. Furthermore, such technologies improve organizational performance by facilitating automated data analysis and real-time provision of data for decision makers. This allows teachers and administration to concentrate on important decisions about strategy and curriculum rather than spending time on manually analyzing data. Empirical results obtained recently confirm that incorporating predictive analytics in educational establishments increases not only student success but also the efficiency of governance at educational organizations. [44], [45].

2.6.6. Predictive analytics for optimizing institutional efficiency in TVT colleges

Efficiency in institutions within TVT colleges entails the most efficient use of resources such as people, money, and technology to meet educational objectives. The application of predictive analytics using AI helps to enhance institutional efficiency by allowing predictions based on performance, completion rate, and demand for training courses. Machine learning algorithms use past academic data and behaviors to make predictions about the future needs of the institution to be prepared. This helps prevent any wastage of resources through poorly utilized classroom space, improperly assigned lecturers, and ineffective scheduling. Evidence from research indicates that efficiency in institutions is increased through predictive analytics. [44], [48].

2.6.7. Machine learning models for resource optimization in education systems

Algorithms for machine learning have a significant importance in enhancing educational institutions' resource distribution and efficiency. Predictions regarding student performance and institutional trends are made using algorithms like Random Forest, Decision Trees, Support Vector Machine, and Gradient Boosting. Through prediction, educational institutions can determine courses that experience higher levels of failures, those courses that have higher demand, and learners who need further assistance. The use of predictions in TVT management systems ensures better staffing and training as well as effective distribution of learning resources. Recent research indicates that machine learning decision-making systems increase efficiency in resource distribution within institutions. [8], [49].

2.6.8. Role of AI in improving administrative efficiency in TVT colleges

The use of predictive analytics using artificial intelligence in television institutions helps in improving the efficiency of their administration. This is done by automating the process of decision-making in television institutions. Some of the administrative activities that can be improved using artificial intelligence include student monitoring, report generation, student enrollment predictions, and staffing. Artificial intelligence allows television institutions to get insights into their performance in real time. As a result, administrators of television institutions can make quicker and more accurate decisions. Studies show that using artificial intelligence in administration leads to greater efficiency in operations [50], [51].

2.6.9. Predictive analytics for improving staffing and workload distribution

One of the important uses of artificial intelligence in TVT institutions includes the optimal allocation of instructors and workload management. With the use of predictive analytics tools, an institution can estimate the student flow, determine popular programs, and anticipate the demand for certain courses. AI helps institutions determine the periods during which there will be peaks in workload and when the institution will lack teachers. Consequently, instructors are distributed optimally across different departments within the institution, preventing overloading and improving teaching efficiency. [52], [53].

2.6.10. AI-driven optimization of learning resources and infrastructure

Predictive analysis through AI can also lead to efficient allocation of both tangible and intangible learning assets in technical and vocational education and training (TVT) institutions. Through the study of the usage patterns of laboratories, workshops, classrooms, and intangible platforms for learning, institutions can maximize the use of their infrastructure. Predictive technology can assist the institution in identifying unused infrastructure and forecasting future infrastructure needs according to trends in enrollment and

curriculum developments. It has been demonstrated that resource optimization through AI is an essential part of sustainability [44], [46].

2.6.11. Early warning systems for cost-efficient intervention strategies

The use of AI-driven early warning systems increases efficiency within the institution because they offer efficient ways of dealing with at-risk students. Using predictive analysis, only the at-risk students can be intervened with, since TVT institutions would not need to use universal intervention mechanisms that are expensive. AI-driven interventions help save money for institutions by ensuring that interventions are done only for the students in danger. Studies show that such interventions increase student retention rates and decrease costs incurred due to failure or dropout management. [54], [55].

2.6.12. Big data and cloud computing for scalable resource management in TVT

The use of big data and cloud computing technologies enables the scalability and efficiency of resource management in TVT institutions. Big data and cloud computing technologies assist TVT institutions in managing big educational data in a fast and effective manner. AI systems based on cloud computing help in the consolidation of data coming from different departments and campuses. The use of big data analytics improves the efficiency of forecasting when it comes to resource planning and budgeting of TVT institutions. [56], [57].

2.6.13. Impact of AI on institutional efficiency and sustainability in TVT colleges

AI-based predictive analytics in TVT will have a great impact when applied to institutions since it helps them be more efficient, sustainable, and performant. The efficiency, sustainability, and performance of TVT institutions will improve due to AI because they will ensure there is an effective use of resources, good results among students, low costs of operations, and fast decision-making. Additionally, the adoption of AI will help institutions become sustainable by facilitating their ability to make predictions and plan effectively. Finally, predictive analytics facilitates decision-making based on data rather than subjective views. [44], [48].

2.7. Identifying at-risk trainees accurately

2.7.1. Predictive accuracy as a core requirement in educational AI systems

Accuracy is among the main performance parameters in predicting the success or failure of students through an artificial intelligence system. It is important to note that in EDM, accuracy refers to the percentage of accurately predicted students who fall into either the at-risk category or the not-at-risk category. It is therefore crucial for the effective operation of early warning systems for intervention

purposes. High accuracy will guarantee the fact that only the appropriate students are selected, thus avoiding instances of false negatives and false positives. In a recent study, experts have noted that the minimum acceptable predictive accuracy is 80%, whereas those exceeding 85% are deemed reliable for practical purposes [48], [58].

2.7.2. Machine learning algorithms enabling us to predict more accurately

Machine learning algorithms are central to the development of highly accurate predictive models for education. Models such as Random Forest, GBM, SVM, and ANN have been shown to be efficient in identifying at-risk students. Ensemble techniques work by improving prediction accuracy through combining several weak learners to create a more effective predictive model. The results of research show that when well-designed, these models tend to generate prediction accuracies that lie between 85% and 95%. Deep learning algorithms have also been applied in improving predictions, particularly in relation to the nonlinear relations in student behavioral data, such as learning behavior and engagement metrics. [43], [59].

2.7.3. Importance of data quality and preprocessing in achieving high accuracy

Predictive accuracy in finding at-risk learners relies greatly on the quality of data and pre-processing methods. Learning data may be characterized by several problems, including noise, missing values, and class imbalance, among others, which greatly affect model effectiveness if not addressed. Preprocessing techniques that include data cleaning, normalization, feature scaling, and missing value imputation help enhance the accuracy of the model. Class imbalance, whereby at-risk learners are few compared to successful learners, may cause prediction bias. The SMOTE technique is extensively used for dataset balancing to boost prediction above 85% [43], [44].

2.7.4. Feature engineering as a key factor in improving prediction accuracy

Feature engineering plays a major role in improving the predictive power of machine learning models in education. Selecting relevant variables such as attendance rate, assignment submission patterns, quiz scores, login frequency, and engagement with learning platforms significantly enhances model performance. Irrelevant or redundant features can reduce accuracy and increase overfitting. Techniques such as correlation analysis, recursive feature elimination (RFE), and principal component analysis (PCA) are widely used to optimize feature sets. Studies show that well-engineered features can increase predictive accuracy by more than 10–20%, making it possible to achieve or exceed the 85% accuracy benchmark. [60], [61].

2.7.5. Early warning systems and real-time prediction of at-risk students

Early Warning Systems (EWS) refer to AI-based mechanisms that help in predicting students who are likely to fail their courses before assessment. EWS includes the use of predictive models along with real-time data gathered using the learning management system (LMS). Evidence suggests that the implementation of early warning systems leads to improved predictive power for detecting at-risk students, where accuracy is generally higher than 85%. Instructors can use this information to provide appropriate interventions to help these students. [45], [62].

2.7.6. Ensemble learning and hybrid models for achieving high accuracy

It has been shown through recent research that the hybrid and ensemble learning model approaches provide better prediction accuracy in the case of student performance prediction modeling. Using multiple learners, like Random Forest, XGboost, and artificial neural networks, in an ensemble approach leads to lower variance and bias, which ultimately results in increased stability and high prediction accuracies. The hybrid approaches also make use of feature selection and optimization techniques to improve performance even further.

2.7.7. Evaluation of metrics beyond accuracy in educational prediction systems

Although achieving more than 85 percent accuracy is an important goal, scholarly studies show that focusing solely on accuracy is highly deceptive when dealing with educational imbalanced data sets. Consequently, other evaluation measures like precision, recall, F1 score, and ROC-AUC need to be taken into consideration to properly assess the performance of the models used. Specifically, precision will ensure that the students at risk predicted by the algorithm are truly at risk, and recall will ensure that most of the at-risk students are captured. [43], [44].

2.7.8. Practical deployment challenges for achieving sustainable accuracy

While obtaining an accuracy rate of 85%+ is realistic in controlled settings, keeping up with this accuracy rate in educational institutions outside the lab environment is a challenge. This is due to factors like varying datasets across different educational institutions, concept drift (evolving student behavior through time), and poor generalization of predictive models. Retraining and continuous adaptation are required for the models to achieve accurate predictions. Moreover, ethical aspects of fairness, transparency, and bias reduction need to be considered when implementing predictive systems in institutions. However, recent studies have proved that accurate predictive systems can be sustained through time. [41], [44].

2.8. Integration of AI into Education Management Information Systems (EMIS)

The implementation of Artificial Intelligence (AI) and predictive analytics in Education Management Information Systems (EMIS) is a new trend that plays a significant role in contemporary education management and decision-making processes. Conventional EMIS tools concentrate only on the collection, storage, processing, and analysis of educational data for the sake of management tasks. Nevertheless, with the rise of AI technologies, traditional EMIS has been turned into smart decision-supporting tools that allow not only to make accurate predictions about the academic progress of learners but also to find those who are at risk. AI-driven predictive analytics gives an opportunity for EMIS to work with huge sets of educational data, applying machine learning techniques, and thus making conclusions based on them. The latest research shows that such integration significantly enhances the process of educational governance through data precision, automation, and decision-making. [47][46].

2.8.1. Role of EMIS in supporting educational data management and analytics

Educational Management Information Systems (EMIS) play a pivotal role in the management of educational information associated with learners, teachers, institutional performances, and programs. EMIS aids educational institutions by providing a means to collect, store, report, and monitor data. Nonetheless, conventional EMIS platforms fail to provide insight into educational information by performing predictive analysis. The incorporation of artificial intelligence predictive analytics into EMIS is a key solution for this issue because it enables EMIS systems to use historical and current learners' data to make predictions about academic outcomes. Predictive analytics enhances the functionality of EMIS by making it easy for educational institutions to make decisions strategically and monitor institutional performances. [63], [64].

2.8.2. Predictive analytics for student performance forecasting within EMIS

The use of AI for predicting student performance and identifying those likely to fail or drop out is critical within EMIS. AI-driven predictive analytics is used to predict the future performance of students by analyzing various educational parameters, including attendance, assignment submission rates, exam scores, behavior patterns, and virtual learning interaction. This helps institutions introduce interventions that will ensure the improvement in the retention of students and their academic success. Several studies have proven that using machine learning algorithms to predict students' future performance, with the help of educational data, achieves high levels of accuracy. [48], [58].

2.8.3. AI-driven decision support within EMIS platforms

Integrating predictive analytics in EMIS provides numerous advantages in the process of making decisions in education because it enables intelligent decision-making tools for educators, administrators, and policymakers. With the help of such an enhanced EMIS system, educators can promptly identify poor learners; administrators can make strategic decisions based on predictions related to allocation of resources, designing the educational program, or assessing the institution's performance. Policymakers may take advantage of the collected predictive data to analyze their policies and determine issues in the field of education. [41], [62].

2.8.4. Real-time monitoring and early warning systems in EMIS

A key advantage of incorporating AI-powered predictive analytics into EMIS is the establishment of real-time monitoring and early warning systems. These systems continuously examine learner information to identify indicators of weak academic performance, low participation, absenteeism, or the possibility of dropping out. AI-supported early warning systems automatically notify instructors and academic advisors, making it possible to provide timely support before learners experience academic failure. Studies show that institutions using predictive early warning systems achieve better student retention, completion rates, and academic outcomes. Real-time monitoring also strengthens institutional responsiveness by helping educational stakeholders make immediate decisions based on continuously updated predictive data. [45], [65].

2.8.5. Interoperability challenges in integrating AI with EMIS

However, despite these advantages of AI incorporation, interoperability still stands as a key problem in incorporating predictive analytics systems in the current EMIS infrastructure. Most learning organizations still use old IT solutions that do not provide interoperability with contemporary AI applications and cloud computing infrastructure. The non-standardization of data, the fragmentation of databases, and inadequate ICT infrastructure may negatively impact the performance of predictive analytics applications. Moreover, the implementation of AI in the EMIS infrastructure requires standardization of data architecture, security of API, and computing platforms for constant data exchange within the academic system. [46], [53].

2.8.6. Data privacy, security, and ethical issues in AI-integrated EMIS

Many ethical, privacy-related, and security issues arise because of the use of AI predictive analysis in EMIS concerning education data governance. Students' data often includes sensitive and private information, which should not be exposed to any third party and should not be compromised in any way.

In addition, an AI algorithm can generate biased and unfair predictions based on imbalanced data sets. Therefore, educational organizations need to create appropriate governance structures, AI ethical policies, and proper data management techniques. It is crucial to maintain transparency, accountability, and explainability within AI decision-making processes inside EMIS [41], [66].

2.8.7. Cloud computing and big data technologies supporting AI-integrated EMIS

Cloud computing and big data technologies offer the needed computational structure to support the incorporation of AI-powered predictive analytics into EMIS frameworks. Universities and colleges produce large volumes of structured and unstructured data using learning management systems, academic databases, assessments, and administration applications. Cloud computing supports scalable computing structures for storing, analyzing, and processing data in real time for predictive analysis. Big data enhances efficiency in data analysis and prediction while mitigating infrastructural barriers. Studies have shown that cloud computing-supported EMIS frameworks can aid in centralized education monitoring and collaboration among different institutions of learning. [67], [68].

2.8.8. Impact of AI-integrated EMIS on institutional performance and student success

Introduction of AI-based predictive analytics into the system has resulted in great gains in terms of institutional efficiencies, academic performance tracking, and achievement for students. Institutions that have embraced AI-based EMIS have reported benefits such as increased trainee retention, accurate academic performance prediction, resource management, and appropriate interventions. Predictive analytics aids in the process of quality assurance through the dynamic evaluation of the educational performance of institutions. Additionally, AI-supported EMIS plays a significant role in fostering smart educational ecosystems where personalized learning and intelligent institutional management can be achieved [44], [48].

2.9. Theoretical Framework

The use of artificial intelligence (AI) has revolutionized learning analytics and EDM to such an extent that predictions about student success can be made accurately. This is because AI uses ML, DL, and NLP techniques to explore large amounts of student data to discover patterns that drive success in education.

Key Factors Influencing Performance

Several factors have been recognized as important predictors of student success:

- **Demographic factors**: The age, gender, and socio-economic status of a student can influence his/her academic results [69][70].
- **School history**: Past grades and attendance records are also useful for predicting future academic performance [69][70].
- **Learning environment**: The family background of a student and his/her study habits are influential factors affecting student performance [71][72].
- **Learning methods**: Self-regulatory and affective techniques, including intrinsic motivation, can greatly influence academic performance. Research suggests that well-performing students exhibit higher levels of self-regulation [73].
- **Learning analytics**: Click-stream data and the duration of the course also predict future academic results, as machine learning algorithms can handle their complexity efficiently [74].
- **Machine learning modeling techniques**: Different approaches, including Random Forest and Extra Trees, show superior prediction ability when applied to educational data [75].

2.9.1. Overview of Educational Data Mining and Machine Learning

Educational Data Mining (EDM) is an interdisciplinary area of knowledge that employs data mining, machine learning, and statistical methods for analysis of educational data and identification of patterns. The main goal of EDM is enhancement of learning outcomes through improved decision making. [76].

As a result of technological advancements in education, an increasing volume of information about the learning process, such as academic performance and the behavior of the students, is accumulated. Analysis of this data requires efficient tools that would help to gain valuable insights into the learning process. [12].

Machine learning is a field of artificial intelligence concerned with the development of algorithms and software able to automatically learn and adapt based on data inputs. Machine learning techniques allow efficient data analysis and forecasting. There are two broad types of machine learning – supervised and unsupervised learning. Supervised machine learning algorithms are commonly used in the predictions of academic performance. [77].

2.9.2. Machine Learning Techniques for Student Performance Prediction

One of the key methods in student academic performance prediction in the field of educational data mining is machine learning (ML). It allows the processing of massive educational data sets, ranging from attendance and marks for assignments to demographics and patterns of behavior, and can help recognize failure propensity in individual students. Such predictive models can aid early intervention strategies in

terms of improving the student retention and academic success rate of educators. Namoun & Alshanqiti (2021) have noted that machine learning techniques vastly improve the capability of educational institutions for decision-making and boosting learning outcomes based on data [8].

It is observed that in predicting students' performance, supervised machine learning algorithms are commonly used because they can categorize their students into one of three performance levels: pass, fail, or at-risk. Common algorithms are Decision Trees, Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM). Decision Trees and Random Forest are very effective among these due to their high classification accuracy and interpretable rules. Traditional statistical models are generally inferior in predictive performance compared with supervised learning models in education, owing to the complicated and non-linear nature of student information[76].

Recent studies reveal that the method of ensemble learning performs better than single classifiers when it comes to prediction accuracy, like in the cases of Random Forest, Gradient Boosting, XGBoost, and stacking models. These techniques are used to combine them with multiple weak learners into a more powerful predictive model, thus avoiding overfitting and showing better generalization. In the context of education, such as when data is noisy and imbalanced, ensemble models are especially suited. Asselman et al. (2021) show that models based on XGBoost perform better than traditional machine learning approaches in predicting academic outcomes of students[78].

While machine learning models can make more accurate predictions, they are still not interpretable for educational use; this is still a problem. To overcome this, the authors address the need for explaining AI predictions using explainable AI (XAI) techniques, like SHapley Additive Explanations (SHAP). To make the model more transparent and trustworthy for educators, SHAP elucidates the importance of each feature of the model (e.g., attendance, study time, assignments) to the final prediction. The concept of SHAP was introduced by Lundberg and Lee (2017) as a universal framework for interpreting complex machine learning models, such as deep neural networks, that are widely used in predictive analytics in education[79].

2.10. Empirical Review of Related Studies

2.10.1. Local Study

In this research study done by Aschenek Kassa (2021), the development of the student performance prediction model through mining the use of data mining in Ethiopian Secondary Schools was considered. The J48 Decision Tree and Naïve Bayes algorithms were applied based on the CRISP-DM methodology.

The findings reveal that the J48 algorithm performed better than the Naïve Bayes algorithm in terms of accuracy rate, where its rate is (95.37%), while the latter was (91.76%).

The major limitations found in this study include the narrow scope, as the researcher only focused on a few subjects and the use of a few algorithms only. In addition, it lacked a real-time predictive system and generalizability to other schools. [80].

2.10.2. International Studies

Various international research studies have examined the application of machine learning to predict the academic achievement of students. [12], [76].

In one such work published in the International Journal of Research Publication and Reviews, various algorithms for machine learning, namely Decision Tree, Random Forest, Logistic Regression, and Support Vector Machine, were used. The results indicated that the accuracy of predictions was increased using ensemble techniques such as Random Forests. Nonetheless, the study was more concerned about model accuracy rather than its implementation in educational institutions.

Another study done by Albreiki et al. (2021) provided a systematic review of the applications of machine learning in education. It was determined that machine learning is very useful for increasing the accuracy of predictions and making the decision process easier. The effectiveness of ensemble models was emphasized. Nonetheless, no experiments were carried out in this study.[12].

Similarly, like Sekeroglu et al. (2021), there are several key limitations associated with the field of student performance prediction research. In particularly according to the research, despite the existence of numerous machine learning algorithms, their implementation within an actual educational environment is still an issue.[81].

Recent empirical evidence obtained in 2023-2024 has demonstrated that advanced approaches, such as Random Forest, neural networks, and stacking have proven to be highly effective in predicting students' future performance. It appears that using combinations of various models results in more accurate and reliable predictions (just as claimed by Sekeroglu et al., 2021; Chaka, 2022)[81], [82].

rarely implement the developed models in real practice. Furthermore, current literature does not propose any predictive analytics platforms and rarely uses classification by high-, medium-, and low-risk categories. In addition, there is very little research involving Technical and Vocational Education and

Training institutions, where students require regular observation (Aschenek Kassa, 2021; Sekeroglu et al., 2021)[80], [81].

2.10.3. Comparative Synthesis of Empirical Studies

Learning techniques for predicting student academic performance, however, significant differences exist in the algorithms used, the datasets analyzed, and the practical applicability of the developed models. Aschenek Kassa(2021) applied J48 Decision Tree and Naïve Bayes algorithms to Ethiopian secondary school data and reported a prediction accuracy of 95.37% using J48. In contrast, more recent international studies incorporated a wider range of machine learning models, including Random Forest, Logistic Regression, Support Vector Machines, Neural Network, and ensemble approaches. Whereas Aschenek Kassa focused on traditional classification algorithms studies, such as Sekeroglu et al. (2021), and recent research conducted between 2023 and 2024 found that ensemble techniques, particularly Random Forest and Stacking models, generally achieved superior predictive performance.

The variation in findings suggests that prediction accuracy is influenced not only by the choice of algorithm but also by dataset characteristics, feature selection, and validation methods. While local studies mainly relied on relatively small and structured educational datasets, international studies often utilized larger and more diverse datasets that included academic, behavioral, and demographic variables. Consequently, ensemble and hybrid models demonstrated greater robustness and generalizability than single classifiers.

Despite the promising results reported across both local and international studies, a common limitation is the lack of practical implementation within educational institutions. Most studies evaluated model performance in experimental environments without deploying operational predictive analytics systems for academic decision making. Furthermore, existing research rarely classifies studies into risk categories such as high, medium, and low risk, limiting the usefulness of prediction results for targeted interventions. Another notable gap is the limited attention given to TVT colleges. Most studies focus on general schools or universities and do not consider the unique characteristics of TVT colleges where practical competency assessments and continuous monitoring are essential. Therefore, there is a need for an AI Model for Early Identification of At-risk students, specifically designed for TVT Colleges that can accurately predict student performance and support timely intervention strategies.

2.11. Conceptual Framework

Student performance prediction systems, based on machine learning, draw on the concepts of educational data mining and learning analytics to discover meaningful patterns in student-related data and inform decision-making. This study adopts a learning analytics framework that focuses on the fact that many sources of data can be combined to predict student academic outcomes, such as demographic data, behavior, academic performance, and institutional/environmental factors. These factors are intertwined with each other and determine the learning outcomes of students, and can be converted into predictive features for machine learning models.

The conceptual framework in this study takes into account the four main categories of independent variables: (1) Demographic Factors: Age, Gender, Socio-economic Background (2) Academic Factors: Academic grades, Assessment Score, and Attendance (3) Behavioral Factors: Study time, Engagement level, and Assignment submission pattern (4) Environmental/Institutional Factors: Instructor Quality, Learning resources, and Class size. These raw inputs do not directly contribute to the prediction, but are first transformed into feature engineering to generate useful predictors, like risk indicators, attendance ratios, and performance trends, etc.

The engineered features are, then, fed to machine learning classification models like Decision Tree, Random Forest, Support Vector Machine, and ensemble learning techniques. These models examine the data to identify patterns that are not apparent, which are used to identify students as high performers, moderate performers, or students at-risk. The expected outcome is then expected to provide a basis for early warning detection to intervene before students experience academic failure by instructors and administrators. The framework also includes methods for explainable AI (XAI) to interpret model

decisions and helps to ensure transparency in determining the most influential factors affecting student performance.

Figure 2.1 Conceptual Framework

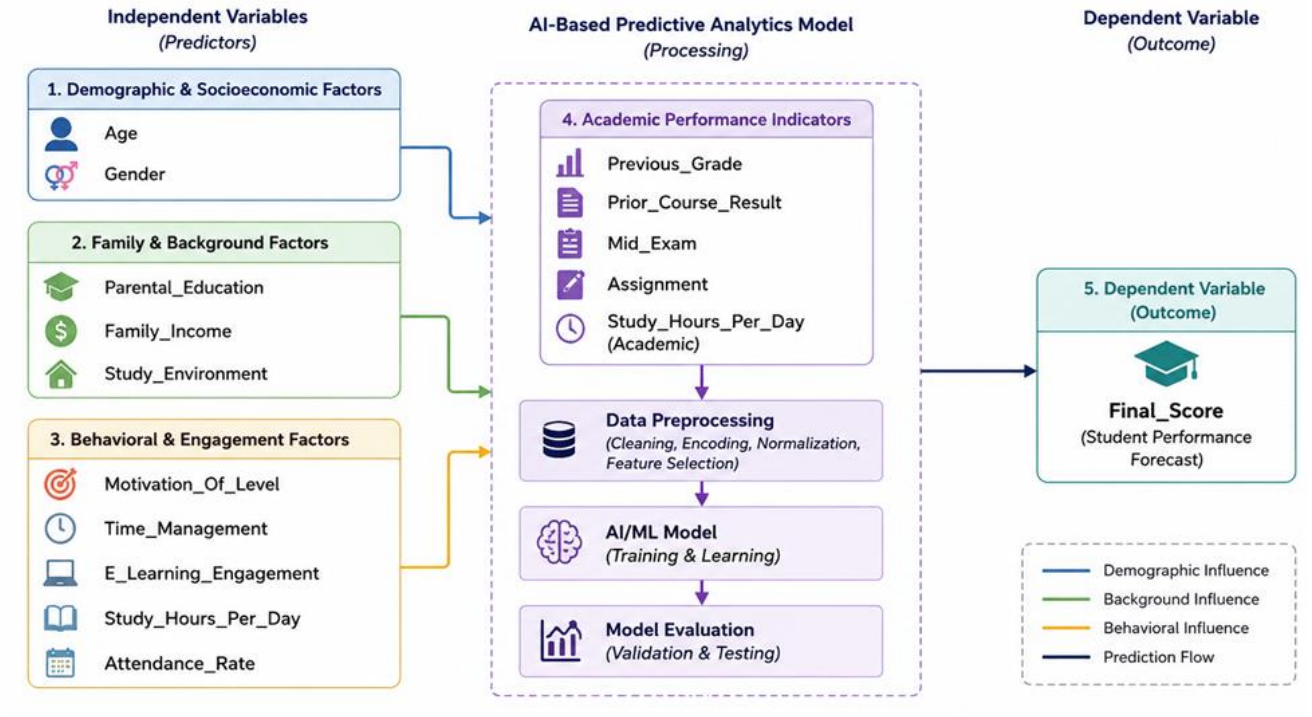


Table 2.1 Gap Analysis Summary

Identified Gaps

No.	Study	Focusing Area	ML Models Used	Methods Used	Key Findings	Limitations	Research Gap
1	Aschenek Kassa (2021)	Student performance prediction in Ethiopian secondary schools	J48 Decision Tree, Naïve Bayes	CRISP-DM methodology, data preprocessing, WEKA tool, 10-fold cross-validation	J48 achieved the highest accuracy (95.37%); decision trees are effective for categorical data	Limited dataset (few subjects), only two models used, no real-time system	Lack of advanced ML models (e.g., Random Forest, ensemble), no predictive analytics system for intervention
2	IJRPR Paper (2024/2025)	General student performance prediction	Decision Tree, Random Forest, Logistic Regression, SVM	Supervised learning, model training, and comparison approach	Random Forest achieved better accuracy; ML improves prediction reliability	Focus mainly on accuracy, no deployment, limited educational context	No real-world implementation, no risk-level classification system
3	Namoun & Alshanqiti (2021)	Student performance prediction using data mining and learning analytics	Decision Trees, Random Forest, SVM, Neural Networks, Ensemble Models	Systematic literature review, comparative analysis	Machine learning and learning analytics significantly improve prediction accuracy and enable early identification of at-risk students	Review-based study; no practical implementation; limited focus on specific institutional contexts	Lack of operational AI-based predictive analytics systems tailored to institutions such as TVT colleges
4	Zhang et al., 2021	Educational data mining and prediction	Multiple ML models (various classifiers)	Comparative analysis, experimental evaluation	Ensemble and hybrid models improve prediction accuracy	No deployment in educational institutions, generalized results	Lack of context-specific implementation (e.g., TVT), no early intervention system

The analyzed literature proves that machine learning technologies can be used as an efficient means for the prediction of student performance. The majority of reviewed publications prove that machine learning technology enhances prediction efficiency, ensemble models are more efficient than singular models, and predictive models can identify students' problems. [12], [76], [81].

However, some limitations need to be addressed. The underperformance of sophisticated models is clearly shown in Ethiopian local literature, as most research uses simple models like decision trees and naive Bayes classifiers. Many research works are based on theoretical experiments and do not implement any model into real-life educational applications. Few studies provide real-time prediction analysis tools, while very few papers categorize students into levels of risk (high-risk students, moderate-risk students, and low-risk students). Moreover, little research has been done in Technical and Vocational Education and Training institutions, where student status tracking is highly needed.[80], [81].

2.5. Research Gap

Current studies on student performance prediction demonstrate the effectiveness of various machine learning techniques, and several significant gaps remain. First, most studies (e.g., Aschenek Kassa, 2021; IJRPR 2024/2025) focus on improving prediction accuracy using traditional and basic machine learning models, but they lack integration of advanced ensemble and hybrid approaches within a unified framework suitable for educational decision making. Second, although methods such as Random Forest, SVM, and neural networks have shown strong predictive performance, most studies do not translate these models into deployable systems for real-time educational intervention. Third systematic reviews (e.g. Namoun & Alshanqiti, 2021) highlight the potential of machine learning in education but confirm that most existing works remain theoretical or experimental without institutional-level implementation, particularly in developing contexts. Finally, although ensemble and hybrid models improve accuracy (Zhang et al., 2021), there is still a lack of context-specific predictive analytics systems tailored to TVT colleges, especially in Ethiopia, where students' performance challenges require early warning and intervention mechanisms. There is a need for a context-aware, explainable, and deployable AI- based predictive system for TVT students' performance prediction.

CHAPTER THREE

3. RESEARCH METHODOLOGY (MATERIALS AND METHODS)

3.1. Introduction

This chapter focuses on the methodology that was applied in the design and development of the AI Model for Early Identification of At-risk students in Ethiopian TVT colleges, especially with reference to Alamata town TVT Colleges. The methodology section will provide a detailed description of the research methodology, approach, techniques, and tools that were used during the research in addressing the research problems and achieving the set research objectives.

In this chapter, the general research methodology, together with the data collection process and data preparation activities, is explained. The chapter gives details of the entire process of the model design, data collection and processing, feature selection, modeling, training, testing, and evaluation of the predictive analytics system. Additionally, it also highlights the reasons why the AI and ML techniques were selected for forecasting the performance of the students and detecting at-risk students in the TVT education setting.

In this regard, this chapter discusses the sources of data, techniques of data sampling, data preparation and manipulation activities, the software and programming languages that were used in implementing the system. The use of exploratory data analysis, classification models, performance evaluation metrics, and validation techniques applied in implementing the prediction system will also be highlighted.

Additionally, in this chapter, the model development process, including model training, algorithm comparison, and deployment procedure, will be explained. Finally, ethical considerations related to data collection and other relevant issues will also be highlighted.

3.1. Research Design

The experimental research designs were used in this study to create and develop an AI-based predictive model that could be used to forecast the academic performance of students in Ethiopian TVT colleges, specifically focusing on Alamata town TVT colleges. The combination of these three approaches was deemed appropriate since the main purpose of the research involved analyzing educational data and developing an AI-enabled system capable of predicting future performance outcomes of students. A scientific research design allowed the collection, processing, analysis, and interpretation of educational data for the purposes of facilitating informed academic decision-making and identifying academically at-risk students.

As stated above, the predictive research approach constituted the basis of the study. Specifically, it was used in designing an AI-enabled forecasting system that analyzed educational data to predict future performance outcomes of students. Predictive research can define both historical and current data to forecast future developments and outcomes by employing machine learning. As opposed to the descriptive approach, which aims at analyzing past events, predictive research strives to provide estimations about future occurrences by discovering the patterns and relationships existing between datasets. In this study, a predictive research approach was utilized to predict performance categories (High Risk, Medium Risk, or Low Risk) that can be expected in the future based on variables such as attendance rate, study habits, past academic achievement, learning involvement, motivation, and assessment results.

An experimental research design was chosen for this study since it mainly dealt with numerical and measurable data, which is usually collected, processed, and analyzed through machine learning statistical techniques and procedures. Data in this case included test results, assignment scores, attendance rates, previous grades, study time, and measures of learning engagement. Since it was necessary to transform the gathered educational data into formats that can be further analyzed by machine learning algorithms, an experimental research design allowed for performing statistical and mathematical operations with the goal of obtaining valuable information. This type of approach conducts an objective evaluation of performance and model accuracy through various measurable indicators.

An experimental research approach was used in this study due to the necessity to evaluate and compare the performance of several machine learning algorithms for forecasting student performance outcomes. Experimenting with data processing and analysis techniques allowed determining the optimal predictive algorithm that would provide the most accurate predictions about student academic achievements. The experimental procedure in the case included preprocessing of datasets, feature engineering, algorithm training, testing, validation, and evaluating predictive performance using various measures and indicators such as accuracy, precision, recall, and F1 score.

3.2. Study Area

The research is conducted in Alamata Technical and Vocational Education and Training (TVT) college situated in the town of Alamata in the Tigray Region of Ethiopia. Alamata TVT College is a government college providing competency-based education and training services in several occupational areas such as Electrical installation, Construction, ICT and Manufacturing, Surveying, Masonry, Furniture Making, Accounting, Hotel Tourism, and other private colleges. This institution was chosen for this study since it

has high failure rates in the Certificate of Competency (CoC) exams of 35.87% in 2018 and 31.57% in 2019.

3.3. Population and Sampling Technique

In the proposed study, the population under study consists of learners enrolled in the Alamata TVT college in different disciplines and years of study. In this study, the dataset consists of details of 4,063 learners in different TVT colleges in Alamata, both governmental and non-governmental, reduced to 2,235 learner records after pre-processing. These learner records contain variables required for the development of the prediction model.

A primary and secondary data collection method was used in the process of developing the prediction model, where all valid learner records were used. Stratification of the learner records by performance level was done before applying an 80/20 train-test split.

Table 3.1.1 Summary of Target Population and Sample Size

Target Group	Population	Sample	Sampling Method
TVT Students (All programs)	4,063	2,235	Purposive / Complete Case
Training Set	2,235	1,788(80%)	Stratified Random Sampling
Test Set	2,235	447(20%)	Stratified Random Sampling
Total	2,235	2,235	

3.4. Data Collection

The data for this study were collected from Alamata Technical and Vocational Educational Training and Technology (TVT) College. The data were obtained from academic and administrative records of the college. Student analysis of student performance is based on these records, which include demographic, behavioral, environmental, and academic data.

In the beginning, the total number of student records was 4063 from the institutional database. The records collected were from the students of different departments and academic years during the study period. The data consisted of data on students' attendance, study habits, learning engagement, demographic characteristics, family background, and academic performance indicators.

The data is derived mostly from the actual records of the institution, where they are found in the system of educational management and reporting in the college. These records were the main source of information for the development and evaluation of models.

Synthetic samples were only created during the training phase by the Synthetic Minority Oversampling Technique (SMOTE) to enhance data quality and overcome the class imbalance problem. Synthetic samples were not included in the original data set but were only added to balance minority classes in the training set. For the testing dataset, no synthetic records were used, so the model was tested without any bias.

In the data preprocessing, certain records were omitted because of the data quality problems. Records with duplicate records, incomplete observations, inconsistencies, and missing values in key attributes were not included in the analysis. This resulted in a dataset being filtered and reduced from 4,063 records to 2,235 valid records to use for the machine learning modelling.

After preprocessing the data, the final data set was reliable and consistent to use in training, validation, and testing the proposed explainable AI-based student performance prediction model.

3.4.1. Data Collection Limitation

The dataset was collected from two TVT Colleges only, due to unstable conditions in the town, which makes the data more specific to a small area.

3.5.Data Understanding and Exploration

The study relies on both primary and secondary data sources:

Primary data: Student academic records collected from Alamata TVT college's academic management system and a little data from private TVT, comprising 4,063 student entries with 15 features per record. The dataset was obtained directly from institutional files and includes individual-level academic, behavioral, and demographic variables with hard copy including questionaries to collect students' behavioral data.

Secondary data: Published journals, conference papers, systematic reviews, government TVT strategy documents (ESDP VI, National TVT Strategy 2020), and reports from ILO, World Bank, and Ethiopian Ministry of Education.

3.5.1. Primary Data

The primary data fall into four main categories: Demographic and Socioeconomic Features: *Age*, *Gender.*

Family & Background Features: *Parental Education*, *Family Income*, and *Study Environments.* Behavioral and Engagement Features: *Motivation Level* of the students, *Time Management*, *E-Learning Engagement*, *Study Hours Per Day*, and *Attendance Rate*. Academic Performance Indicators: *Previous Grade* (Grade 12 or 10), *Prior Course Result*, *Mid Exam*, *Assignment*, and *Study Hours Per Day*.

3.5.2. Data Collection Methods

Dataset collection was performed on the students' details from the institutional file and questionnaire. The dataset has fifteen attributes: *Age, Gender, Parental Education, Family Income, Study Environment, Motivation Level, Time Management, E-Learning Engagement, Number of study hours per day, Past Academic Performance, Result in prior course, Mid-term Exam Performance, Assignment Performance, Attendance, and Final Performance*.

Document analysis: Institutional documents and CoC assessment result documents were used to collect data about the research problem domain.

Literature Review Systematic literature review was conducted by collecting peer-reviewed journals related to predictive analytics in education, machine learning in TVT, and predicting the student academic performance.

3.5.2.1. Demographic Features

Age is among the demographic variables in the provided dataset used in predicting student academic performance. The ages of the students in the dataset ranged between 19 and 35 years, with an average age of 23.07 years. The importance of age in this study lies in the fact that different ages among the trainees in the dataset may have implications on their learning habits, level of maturity, ability to take up academic responsibilities, and adaptability to vocational environments. Consequently, the use of age in the analysis assisted in examining the relationship between age and student academic performance.

Another demographic feature used in the predictive model is gender. The gender in the dataset was categorized into two groups: Males and females. Females constituted 61% of the total students, while males made up 39% of the total population. It is essential to note that in previous educational research, gender may be a factor influencing students' learning habits and participation levels. The inclusion of gender as a variable in the model assisted in investigating whether the gender of the students influences their academic risk classification in TVT institutions.

Parental education was another demographic variable included in the predictive analytics model. Parental education was categorized into five main categories, namely Primary, Secondary, Diploma, Degree, and Master's. The rationale behind incorporating parental education into the predictive model stems from the observation that students' academic achievements may be influenced by their parental education since parents play an essential role in motivating and encouraging students and in ensuring that they learn more effectively.

Lastly, family income level was another demographic feature in the dataset used in the analysis. Family income levels were classified into three broad categories: Low, Medium, and High-income levels. Income is known to play an essential role in determining the availability of necessary educational resources for a student. For instance, income affects internet availability, learning materials, and the mode of transport. Therefore, it is expected that income level would influence student academic performance.

3.5.2.2. Behavioral and Engagement Features

Behavioral and engagement features refer to the characteristics that reflect learning behaviors, study habits, motivation, and participation rate in the educational activities by students. They are considered very relevant in predictive analytics since they indicate the level of students' involvement in the learning process directly. On the contrary, unlike demographic variables, behavioral features are not static but changeable depending on many factors, including study load, teaching approach, institutional environment, etc. In this research, such behavioral and engagement indicators were selected to improve the predictive accuracy of the model.

Study Hours Per Day was chosen as a categorical feature indicating the number of study hours daily. This factor is a significant indicator of students' academic discipline and self-involvement in the learning process. Generally, higher study hours are associated with higher academic results. In the same way, Time Management was introduced as a categorical variable with five categories ranging from 1 to 5. This feature assesses the ability of students to organize their academic life and manage the allocated time efficiently.

E-learning Engagement was another behavioral feature included in the model and measured on a scale ranging from 1 to 5. This indicator reflects students' engagement in e-learning, i.e., using the opportunities offered by digital technologies to access learning resources and perform various learning activities online. The importance of this variable should be explained by the increasing tendency toward blended learning, which means integrating different forms of learning activities and materials. In addition, Motivation Level was another behavioral indicator included as a categorical variable. There are three categories: Low,

Moderate, and High. The level of motivation has an essential impact on students' learning engagement and, therefore, academic performance.

Moreover, one more behavioral variable was included into the model – Attendance Rate. This indicator was introduced as a numerical feature with possible values ranging from 0 to 10. The average level of these variables equals 9.04. The higher rate indicates high attendance levels. In other words, the students attend classes regularly, which reflects high commitment and engagement. Overall, all these behavioral and engagement factors contribute to the accuracy and effectiveness of predictions made by the model.

3.5.2.3. Environmental Features

Environmental characteristics are the surrounding aspects that may impact the performance of the learners in schools. As an environmental variable, the study environment is viewed in this research due to its impact on students' attention, ability to do assignments, and engagement with their studies. The study environment is divided into three categories as Poor, Average, and Good, which depend upon the quality of learning conditions found at home and the college.

In a Poor study environment, there are considerable problems in a learner's study environment. It can be such problems like the absence of a study place, excessive distraction or interruption while doing assignments at home, and even unstable conditions in terms of academic engagement in general due to many factors. Such a situation does not allow the learner to focus his/her attention on studies and reduces his/her motivation.

An Average study environment means a study place where students have access to a quiet place to work together with basic learning material but with some occasional problems in terms of studying. The students in such a condition may experience distractions, occasional problems, or even some interruptions from other family members. Even so, students in such an environment can study.

A Good study environment means highly supportive learning conditions with a quiet place and sufficient learning resources. These conditions facilitate good studying habits and increase a learner's engagement with studying to achieve positive results.

Overall, the study environment reflects considerable environmental characteristics that vary between students. It is used in the current research to investigate the effect of studying conditions on academic performance in Ethiopian TVT colleges.

3.5.2.4. Academic Performance Features

Academic performance attributes are the main outcome-based characteristics in this study since they are used to measure students' achievement in education and build the predictive analysis model. Academic performance attributes include previous GPA, prior course result, mid-exam score, assignment score, and final score, which have a direct link to students' learning achievements and are good indicators for predicting further performance. In this study, academic performance was considered by examining past academic records, assessment scores, and exam scores.

Previous Grade (GPA) is one of the critical performance attributes, having a range between 2.6 and 3.8 with a mean value of 2.86. GPA serves as the overall performance characteristic and indicates students' previous academic achievement. The higher GPA values indicate better academic skills of students and imply that they will perform well in their following academic activities. On the contrary, lower GPA values point out possible academic difficulties of some students.

Prior Course Result characterizes students' performance in earlier or related courses. It has a continuous range from 44 to 93.8 with a mean value of 69.35. This attribute can help understand the stability in academic performance and subject comprehension of students. With this indicator, one can find out if a student's performance is consistent in related subjects and courses or varies and fluctuates.

Mid-Exam Score is another attribute that describes students' academic performance at a certain point of the semester. Its range is from 12 to 26 with a mean value of 18.31. This characteristic shows the level of students' understanding of the studied material before final examinations. Hence, it can become a good indicator for predicting further academic outcomes of students.

Assignment Score indicates students' engagement in their academic work. Its range is between 7.5 and 15 with a mean value of 11.31. This attribute demonstrates the level of students' responsibility for continuous learning and consistency in their academic activities. It can become an indirect indicator of discipline and proper organization of the process.

Finally, the attribute of the final score plays the role of the target variable since it serves because of students' performance in a semester. The score has a range between 43.5 and 98 with a mean value of 75.17. This attribute helps measure the academic performance of students and is the dependent variable in the prediction model under consideration. All academic attributes described above characterize the academic progress and performance of students, helping build an accurate and reliable prediction model.

3.5.3. Exploratory Data Analysis (EDA)

In this section, a description of data analysis methods used in the development of the student performance prediction model is provided. The purpose of the data analysis was to derive meaningful information and predictive patterns from the raw education-related data to build a reliable classifier of student performance level. It was intended to ensure the highest data quality, minimize data bias, handle the problem of imbalanced data, and identify the key predictors of the outcome of interest. The analytical pipeline was composed of several sequential steps, starting from exploratory data analysis and continuing through data preprocessing, feature selection, imbalance handling, model training, and performance evaluation. In this way, valuable information was extracted from the dataset, and generalization ability of the predictive model was improved.

This is an Exploratory Data Analysis (EDA) report for the dataset of students that will be used in the predictive analytics model, and includes descriptions, data integrity and data feature relationships.

In this Machine Learning project, Exploratory Data Analysis (EDA) is an important first phase that helps in understanding the structure of the student dataset, discovering patterns and checking data quality before the models can be trained. The four key components of the EDA for the final sample of 4,063 student records are described below. Four basic parts of the EDA performed on the last sample of 4,063 student records are described below.

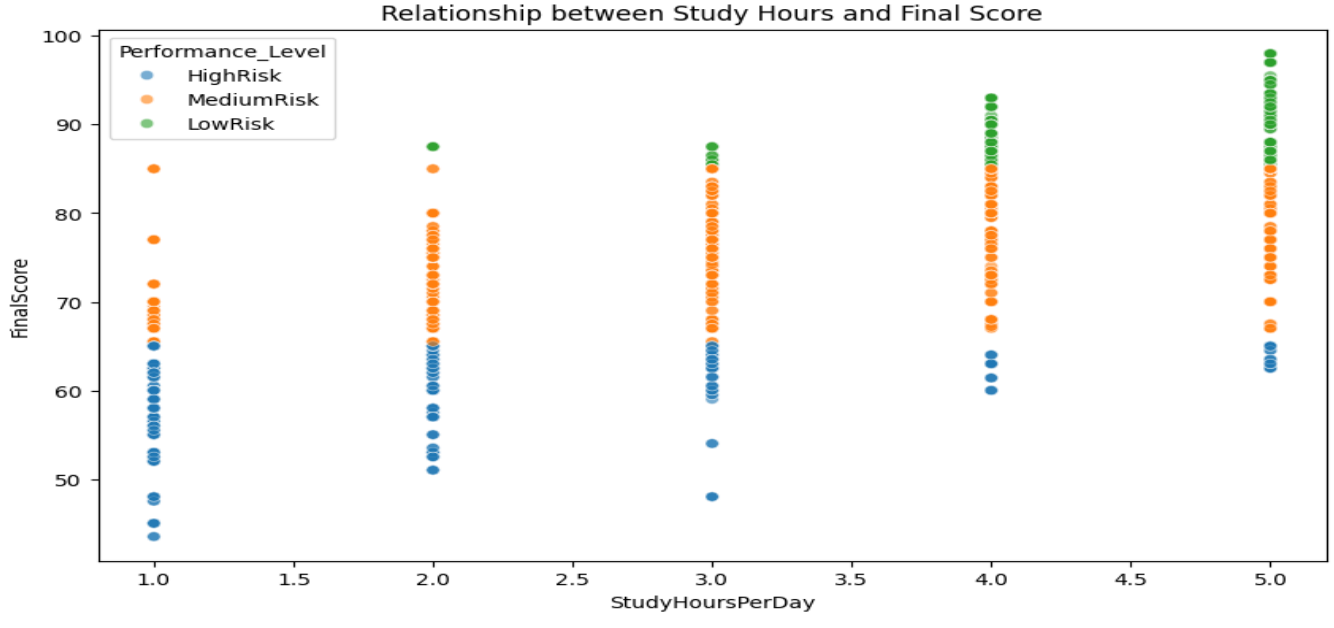


Figure 3.1.1 *Relationship between study hours and final score*

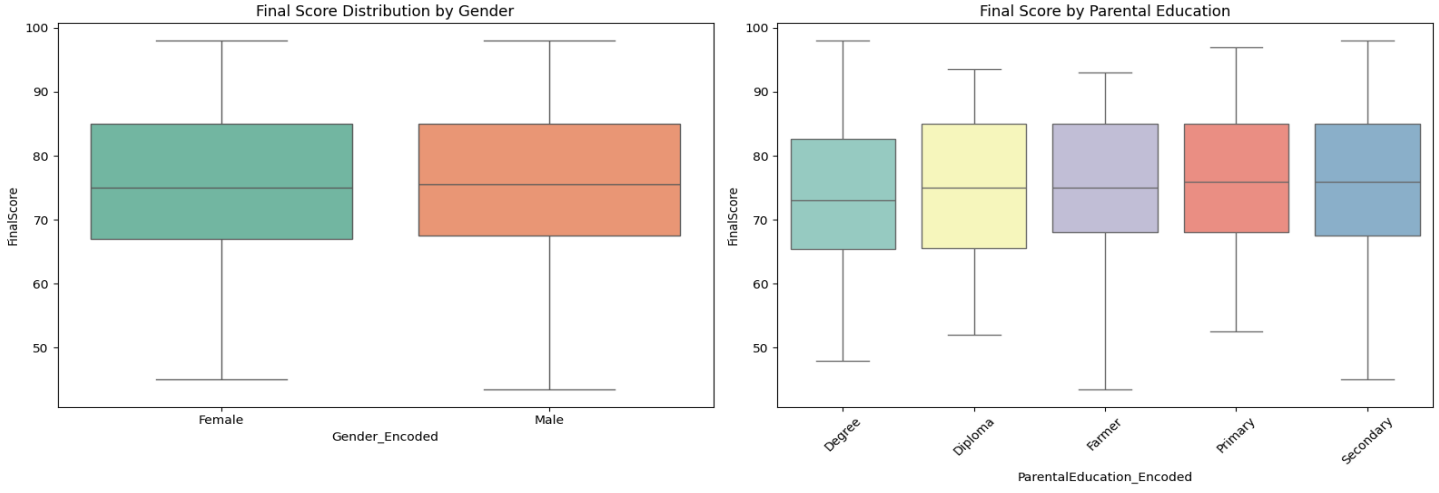


Figure 3.1.2 Final score distribution by gender & parental education

3.5.3.1. Descriptive Statistics

The processed dataset given is of 12 different features with 2,235 student records. For numerical data such as weight, some important statistical measures to consider are age for student population is about 23.07 years (range: 19 age – 35 age), Mean of the FinalScore across the sample is 75.18, minimum is 43.5, maximum is 98, Time Management and Study Hours Per Day both have a mean of ~3.0 on their respective scales, Students have been categorized into three risks according to their final scores:

- MediumRisk: 1,326 students (59.3%)
- HighRisk: 464 students (20.8%)
- LowRisk: 445 students (19.9%)

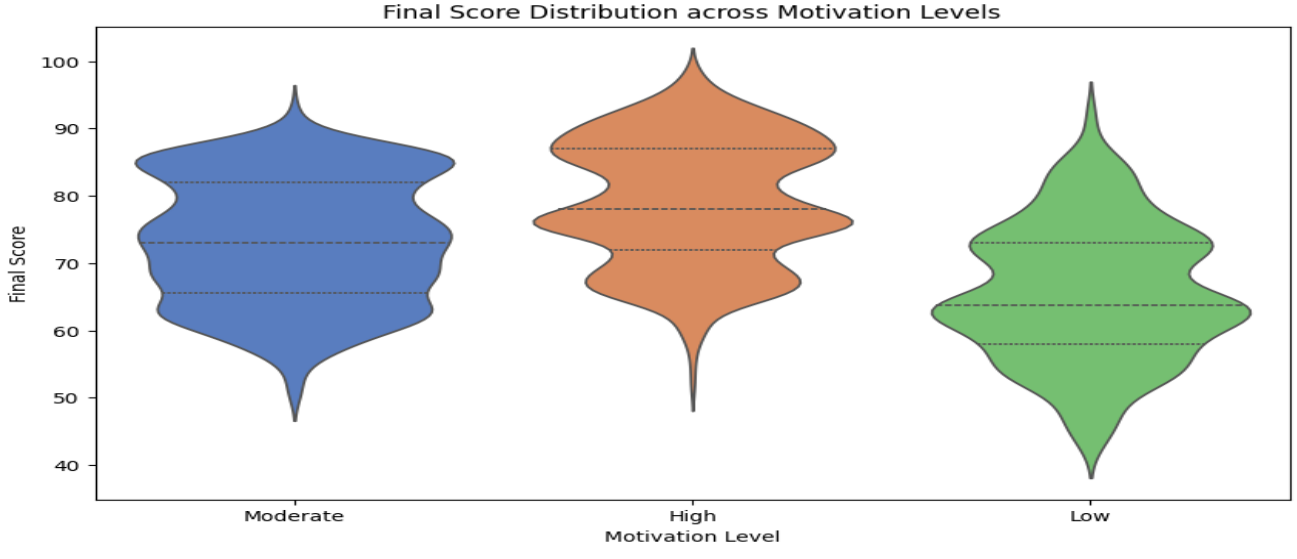


Figure 3.1.3 Final Score distribution across motivational level

3.5.4. Missing Value Analysis

One of the main points of focus in the pre-processing phase was data integrity. A preliminary examination of the raw data indicated that there were no missing data on the essential behavioral and academic items.

- **Target Variable Integrity**: To maintain the predictive ability of the model a specific cleaning step was used to remove any rows with missing target value (FinalScore or Performance_Level).
- **Final Count**: After handling missing values where we remove duplicate values to avoid bias, leaving 2,235 values.

3.5.5. Correlation Analysis

Correlation heatmaps were used to determine the best predictors for students' success.

- **Primary Success Drivers**: Behavioral factors have the highest positive correlation with academic outcomes. FinalScore has a strong positive correlation with Time Management and Study Hours Per Day (0.73 and 0.72, respectively).
- **Internal Relationships**: There are high collinearity relationships between some behavioral factors; for instance, Time Management and Study Hours are correlated with 0.99, or between academic assessment factors; for instance, PriorCourseResult and Assignment are correlated with 0.98.
- **Motivation**: Interestingly, the FinalScore is negatively correlated with MotivationLevel (-0.30), so the relationship between motivation and academic output is complex.

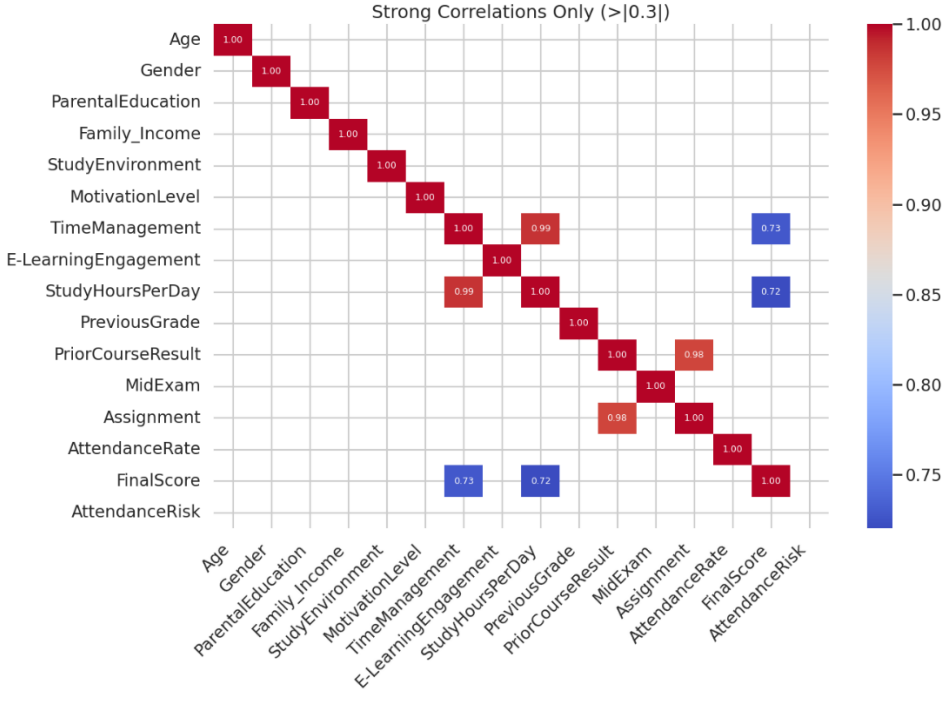


Figure 3.1.4 *Variables with strong correlation*

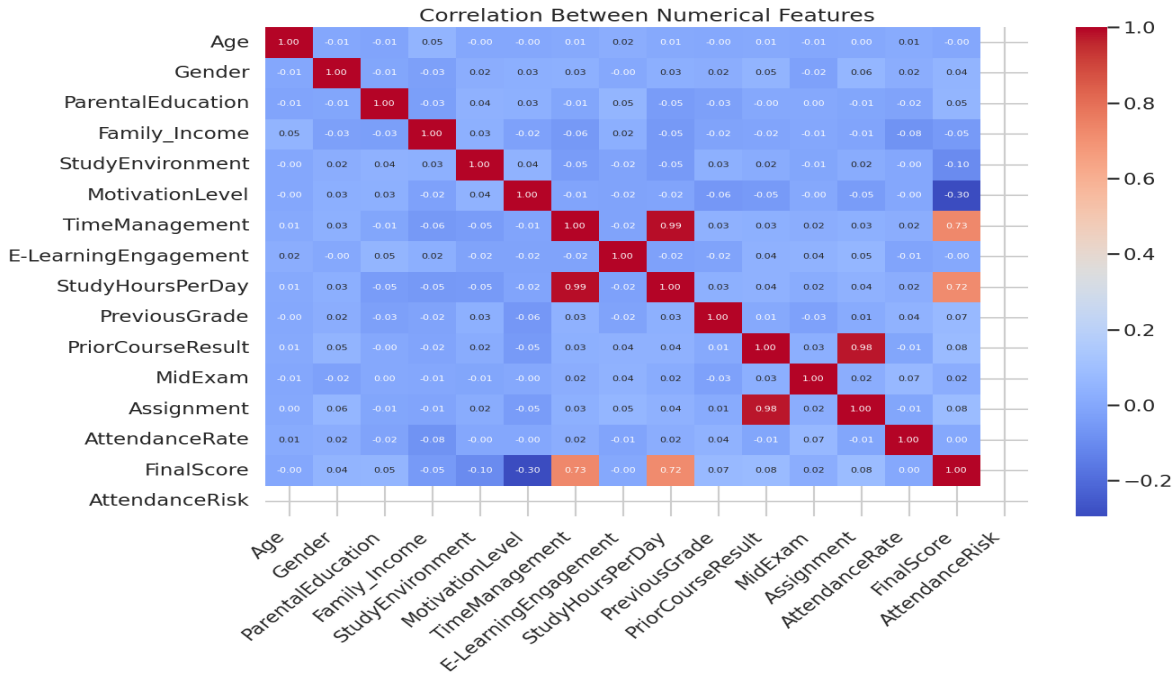


Figure 3.1.5 *All variables correlation*

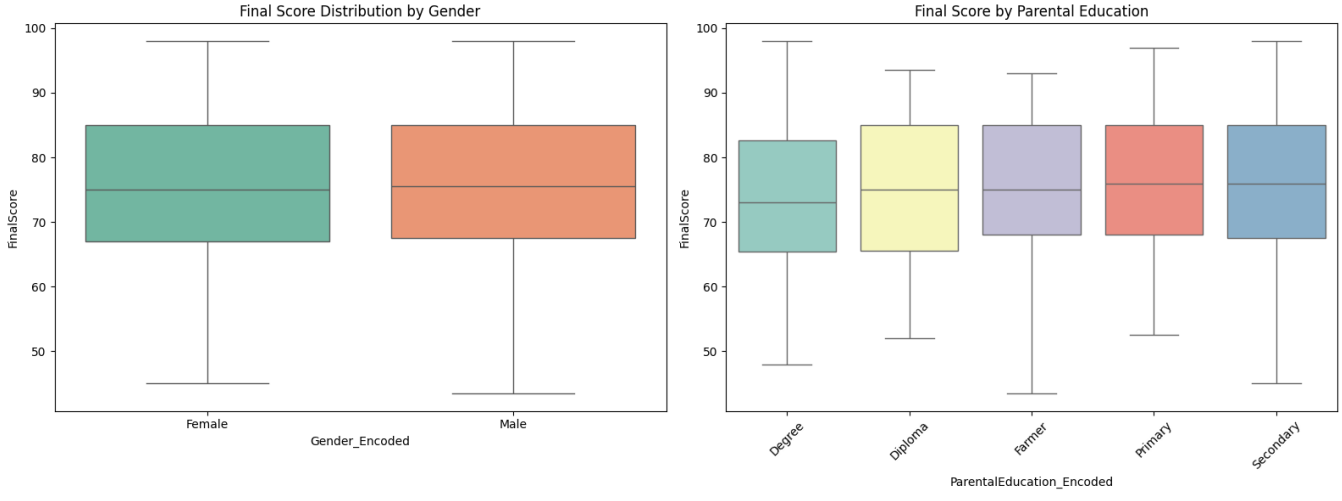


Figure 3.1.6 *Final Score by gender and parental education*

3.5.6. Outlier Analysis

Boxplots and histograms were used to perform visual inspection of the numerical data to detect anomalies.

- **Age**: The boxplot also shows some outliers in the upper quartiles, with a few students aged 32, 33, and 35, standing above the other age quartiles of 19-30.
- **Academic Performance**: PreviousGrade has one outlier of 3.8.

- **Attendance and Score:** AttendanceRate and FinalScore have some students with lower bound outliers, those who have significantly lower attendance (less than 7.0) or Final Score (less than 50) than the rest of the students.

3.6.Preprocessing Steps

The process of data preprocessing is a vital part of designing an AI Model for Early Identification of At-risk students, as the purpose of the latter is to ensure that a dataset is properly cleaned, consistent, and fit for further machine learning modeling procedures. The data preprocessing procedure in this research has been conducted in a structured way, as its aim was to increase data quality, remove noise, and increase the performance of predictive models for student performance forecast in Ethiopian TVT colleges.

Firstly, data cleaning was conducted as a part of the preprocessing procedure. This step implies careful examination of data, including identification and handling of possible missing values, duplicate records, and inconsistent entries. In case of missing data, the proper strategy, either imputation or deletion, was implemented to achieve maximum accuracy of the dataset; similarly, all duplicates were removed to increase model accuracy. Therefore, the step of data cleaning provided accurate and reliable representation of student data.

Secondly, data transformation and encoding were conducted to make categorical features suitable for machine learning modeling purposes. This includes such variables as motivation level, study environment, and several others, which required some form of coding – ordinal or label – to enable machine learning algorithms to operate on the data and provide accurate forecasts based on the model's prediction.

Thirdly, feature scaling and normalization were executed for continuous variables like GPA, examination scores, and assignment grades. Since there are a variety of scales in relation to such variables, the normalization procedure allows bringing them all to one scale so that larger numerical values will not prevail in the learning algorithm, increasing its accuracy and reliability.

Finally, feature selection and dataset splitting was conducted by eliminating those features, which are irrelevant to predicting student performance or strongly correlated with each other. This step improves computational efficiency and prevents model overfitting. After feature selection, the dataset was split into training and testing sets to conduct further evaluation on a separate dataset and measure the accuracy of the models.

3.6.1. Data Cleaning

The next step of data preprocessing for developing an AI Model for Early Identification of At-risk students was data cleaning. The primary aim of this step was to enhance data quality, consistency, and reliability. It is important to note that the predictive performance of models largely depends on the quality of the data used. Therefore, any inconsistency or problem related to missing values, duplication, and others should be resolved.

It is worth mentioning that special attention should be paid to the target variable. In the current case, it was the Final Score variable. In addition, it should be noted that all data records containing missing values in the Final Score field were deleted from the dataset. Such a step was taken since missing values could distort predictive performance.

It is noteworthy that data preprocessing included deleting duplicates using data processing techniques such as the use of the drop_duplicates() function in Python (Panda's library). Thus, each student was represented by one entry in the dataset.

Finally, because of the data cleaning procedure, the number of records in the dataset decreased from 4,063 to 2,235. Although reducing the size of the dataset is undesirable, the data quality, reliability, and consistency have been substantially enhanced.

Thus, this step of data preprocessing allowed obtaining a high-quality dataset which served as a basis for developing an AI Model for Early Identification of At-risk students.

3.6.2. Feature Engineering

The dataset preparation process comprised feature identification, leakage detection, feature engineering and final feature selection. Fifteen (15) raw features were first gathered from student demographic, behavioral, environmental and academic data.

A data leakage assessment was performed to make sure that the predictive model is valid and can be generalized. Data leakage is a phenomenon of the predictor variables directly or indirectly including information about the target outcome, leading to over-optimistic results for the model. After the leakage audit, six (6) variables were taken out of the modeling process. These comprised: Final Score, Mid Exam Score, Assignment Score, Previous Course Result, Continuous Assessment Average (CA_Average) and Assessment Standard Deviation (Assessment_Std). Those variables were not included as they were either

components of the target variable or highly correlated with it for the purpose of categorizing the risk level of student performance.

Feature engineering techniques were used to improve the predictive power of the data after removal of leakage features. Three (3) new features have been developed, informed by a domain knowledge and educational analytics principles. These designed attributes were Academic Strength, Study Efficiency, and Attendance Risk. Attendance Risk indicators measured the pattern of absenteeism linked to academic failure, and Study Efficiency used a combination of study time and engagement indicators to measure the effectiveness of learning. Academic Strength was developed to be a summary score of the overall level of learning capacity of a student, derived from a collection of non-leaky indicators.

The feature engineering involved converting the raw institutional data to a more informative form that can be used for machine learning analysis. Twelve (12) predictor variables after feature creation and redundancy assessment were used to train and evaluate the model. These variables were related to the demographic, behavioral and involvement, environmental, and engineered educational indicators. The feature selection was done to maximize prediction performance and without information leakage while keeping the model transparency and interpretability with the help of SHAP-based explanations. Table 3.1 summarizes the progress of features throughout the data preparation.

The final feature set resulted in a balanced representation of student characteristics and learning behaviors, which allowed the proposed stacking ensemble model to accurately classify students into the High-Risk, Medium-Risk, and Low-Risk performance categories and to be robust and interpretable.

Table 3.1.2 progress of features throughout the data preparation

Feature Processing Stage	Number of Variables
RAW Features Collected	15
Leakage Feature Removed	6
Engineered Feature Added	3
Final Feature used for Training	12

3.6.3. Data Pipeline Summary

Table 3.1.3 Data Pipeline Summary

Stage	Records	Features	Action
Raw extraction from TVT Colleges	4,063	15	Initial data gathered from Alamata TVT College registrar and academic records
Duplicate removal	3,892	15	Removed 171 duplicate student's records using drop_duplicate() in pandas

Missing target variable handling	2,847	15	Removed records with missing FinalScore(target variable cannot be imputed)
Leakage feature removal	2,235	6	Removed 6 features that directly or indirectly reveal target: MidExam Assignment, PriorCourseResult
Feature Engineering	2,235	12	Added 3 engineered features: AttendanceRisk, Study Efficency, Academic Strength
Encoding & transforming	2,235	12	Applied Lable Encoding for three-based models one-Hot Encoding for Stacking ensemble
Training/ Testing (80/20)	Training: 1,788	12	Stratified split using train_test_split eith random_state=42 to preserve class distribution.
SMOTE application (training only)	Training: 1,788 balanced	12	Applied synthetic Minority Overy-sampling Technique to address class imbalance (59.3% MediumRisk)
Final dataset for modeling	Training: Balanced		Training set balanced across three classes test remains original for unbiased evaluation

3.6.4. Handling Class Imbalance using SMOTE

Class balancing was another essential process conducted during the preparation of data for this analysis. The reason behind this process lies in the class imbalance, which refers to unequal distributions of cases among the target classes (in this case, High Risk, Medium Risk, and Low Risk) found within the selected dataset. Class imbalance usually affects machine learning models in such a way that they become biased towards the majority class, causing poor detection of the minority classes. Therefore, the need for balancing was evident to ensure that all the students from all performance categories, especially those who have been identified to be High Risk ones, will be detected by the algorithm correctly.

This goal was achieved via the application of Synthetic Minority Over-sampling Technique (SMOTE), which is one of the methods used for dealing with class imbalance by means of oversampling. As opposed to the simple repetition of the original minority class observations, SMOTE allows generating synthetic samples through creating new samples between two minority samples based on their neighbors' similarity and distance. Thus, SMOTE creates balance in the dataset without changing its internal structures and characteristics. During the current experiment, SMOTE was applied only to the training dataset.

As a result, class balancing was successfully achieved after applying SMOTE to the training dataset. It made it possible to balance the distribution of samples across all classes, thus giving the machine learning algorithms an opportunity to use all three class patterns during the creation of the model. It has already been mentioned that this issue is crucial for the success of AI-based education solutions. Indeed, predicting minority class students (for example, High-Risk ones) is more significant in the field of education than maximizing overall precision.

3.6.5. Dataset Splitting (80% Training and 20% Testing)

One of the key steps in data preprocessing in the current study was dataset splitting because this procedure was used to assess the ability of the proposed AI Model for Early Identification of At-risk students to be generalized. The core aim of this procedure is to train the model on some part of data while performing evaluations based on another (unseen) portion of information. In our case, the most common splitting ratio 80/20 was chosen as this technique is effective in terms of training and validation of machine learning algorithms.

In this regard, 80 percent of the data was used for training machine learning algorithms when the latter learned relationships, patterns, and structures based on student performance. As such, the data for training includes such variables as academic indicators, behavior-related parameters, as well as environment-related characteristics that allow identifying the most important factors that influence student performance.

On the other hand, 20 percent of the data was used for testing the models after their training to see how accurate their predictions are for previously unseen data. This step is very important since the final goal is to predict the performance of future students who were not seen before during the learning process and, therefore, the evaluation should be conducted in this way.

At the same time, to ensure the reliability and accuracy of evaluations, stratified sampling was performed when splitting the data into training and testing subsets. Specifically, the distribution of samples between High Risk, Medium Risk, and Low Risk targets was maintained at the same level that allows preventing distribution imbalances.

To sum up, 80/20 splitting proved to be an efficient solution that was very helpful when validating predictive models. Moreover, it allowed building an effective AI-based student performance prediction system for Ethiopian TVT colleges.

3.6.6. Target Variable Creation

In the current analysis, the Final Score was converted into a discrete target variable, which is used to create predictive models to predict multiple categories. It should be noted that in addition to the prediction of the final score, it was necessary to divide students into categories depending on the level of their academic performance. Thus, the discretization of the continuous value was required to conduct classification-based modeling. In particular, the categorization of data was conducted using the pd.cut() method in Python programming language.

The three categories into which students' performances were divided included HighRisk, MediumRisk, and Low Risk. If the Final Score was lower than 65, then the corresponding student was attributed to the HighRisk category. This suggests poor academic performance among these students and a high probability of failure in classes or the need for special interventions to avoid such problems.

The category of Medium Risk included students whose performance ranged from 65 to 85 points. Such results indicate that these learners pass courses but need further assistance in their education to improve academic performance and achieve high results.

Finally, the students who received scores exceeding 85 in the Final Exam were assigned to the LowRisk category. They show the highest level of performance among all students, demonstrating good engagement in the learning process.

Accordingly, when analyzing the distribution of data, 464 students (20.8%) belonged to the HighRisk category, 1,326 people (59.3%) to the Medium Risk category, and 445 students (19.9%) fell into the LowRisk group. It can be concluded that most learners are characterized by average performance.

Thus, the implementation of the classification helped convert the problem into the multi-class category, thereby creating conditions for developing an AI model for predictive analytics.

Using pd.cut, the continuous variable 'FinalScore' was categorized into 'Performance_Level' with three risk categories: 'HighRisk' (0-65), 'MediumRisk' (65-85), and 'LowRisk' (85-100), thus establishing a multi-class classification problem.

Any rows where the 'Performance_Level' could not be determined (e.g., if 'FinalScore' was still missing or outside defined bins, though handled previously) were dropped to ensure the integrity of the target variable.

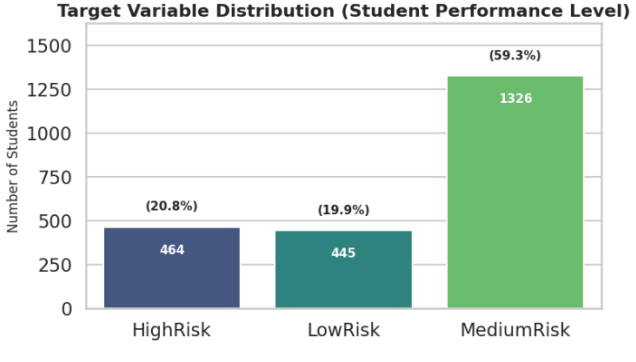


Figure 3.1.7Target Variable Distribution

3.6.7. Encoding

Encoding was a crucial preprocessing step in this research since several independent variables in the dataset are categorical, which made their direct application impossible in most machine learning algorithms. Therefore, it became necessary to convert the values in each categorical variable into numbers so that these variables would be understandable for the chosen ML techniques.

First, in this research, tree-based machine learning techniques such as Decision Trees, Random Forest, and Gradient Boosting were utilized. Consequently, Label Encoding had to be performed since this process involves assigning a unique integer value to each category. Tree-based models are not particularly concerned with the ordinality introduced by integer-encoded variables, making Label Encoding particularly relevant to this type of algorithm.

However, in the case of the Stacking Ensemble model, Label Encoding may have decreased the quality of predictions since it introduced unnecessary ordinal relationships among categories in a particular variable. Therefore, One-Hot Encoding has been performed using the pd.get_dummies() function. The process of One-Hot Encoding involves converting each categorical variable into binary variables, with each category receiving a dedicated column.

Both Label Encoding and One-Hot Encoding have been used in this research intentionally. While the first approach is more efficient computationally, the latter has a positive impact on the performance of Ensemble and other machine learning algorithms. Thus, it became possible to prepare the data correctly for training and prediction processes.

In conclusion, the combination of Label Encoding and One-Hot Encoding was necessary for preparing the data for application to various machine learning algorithms. Both approaches have been chosen depending on their suitability for the specific technique.

The LabelEncoder from sklearn.preprocessing was used to accomplish this task. The LabelEncoder provides a unique integer value to each unique category in the feature. To begin, the categorical variables were explicitly specified using the cat_cols list: ['Gender', 'ParentalEducation', 'Family_Income', 'StudyEnvironment', 'MotivationLevel']. The LabelEncoder object was created by declaring le = LabelEncoder(). The next step was to iterate through each variable in the list, performing le.fit_transform() on each one, thereby replacing the string label with an integer label. For instance, Female in Gender could be converted to 0 and Male to 1 and ParentalEducation 'Diploma', 'Primary', 'Degree', 'Secondary' was converted to corresponding integers 0, 1, 2, 3, 4.

3.6.8. Feature Selection

Feature selection is another essential step in the preprocessing stage of research. It entails identifying and keeping features that are relevant and significant for building an accurate model for predicting student performance. The selected features contribute positively to improving prediction and enhancing overall efficiency. In this respect, feature selection is particularly helpful because it makes it possible to remove any unnecessary elements and reduce the possibility of overfitting when building predictive analytics models for predicting students' success and performance in their academic work.

First, correlation analysis was used for exploring statistical relationships existing between independent variables and the dependent variable (the Final Performance Category). It provides an idea about the degree of interrelation between two variables, which allows for estimating how strongly different features relate to student performance. Weakly or insignificantly correlated features should not be included in predictive models as they provide no useful information for predictions. Besides, correlation analysis also helps detect high multicollinearity between independent variables.

Second, feature importance estimation analysis was applied based on using tree-based models (e.g., Random Forest and Gradient Boosting). These models can automatically evaluate the importance of each feature as it contributes to reducing impurity during the process of training. Features ranked higher according to the level of importance were recognized as more significant in predicting student performance than less important ones.

Third, the Recursive Feature Elimination (RFE) algorithm was used. It is a wrapper-based method that implies iterative training of models with step-by-step removing features one by one to get the best subset of features. Thus, at each iteration, the algorithm removes less important features and estimates the effect of such actions on the performance of the model built based on the reduced set of features. RFE also helped get rid of unnecessary features and retain the ones that contribute to predicting students' success.

In summary, the proposed techniques for estimating feature significance helped build efficient and accurate predictive analytics models for estimating student performance in the future.

In this step on feature selection removing potential data Leakage features ss an additional step in feature selection, a careful identification and exclusion of features that can result in data leakage was undertaken. Data leakage happens when information about the target is somehow leaking into the training set, leading to overly optimistic performance predictions. In the present case, the following feature columns were excluded as possible sources of leakage:

Target Features: The column FinalScore, which was directly used to compute Performance_Level target, was removed from the feature set X.

Intermediate Assessment Scores: Columns like MidExam, Assignment, and PriorCourseResult were also regarded as potential leakage features because they are either directly or indirectly related to the FinalScore and therefore Performance_Level. Using such features might let the models simply indirectly infer by inferring the target directly instead of discovering hidden patterns. Thus, those columns were not included in the features set.

Engineered Leakage Features: We also use Feature Engineering as a Kind of Feature Creation/Selection not exactly selecting among already existing features, but engineering entirely new features from existing ones could be viewed yet another kind of feature creation/selection. In essence, by engineering features, the analyst makes certain decisions as to which information from raw data to convey to the models:

AttendanceRisk: The binary feature AttendanceRisk was constructed using the AttendanceRate (for example, AttendanceRate < 80), turning a continuous predictor into a risk indicator that might be helpful for the model.

StudyEfficiency: A feature named Study_Efficiency was created based on StudyHoursPerDay and E-LearningEngagement. The logic behind the combination of these two factors suggests that it is a better predictor of students' performance than their separate use.

AcademicStrength: The concept of Academic_Strength was introduced as a combination of the PreviousGrade and TimeManagement predictors. Therefore, new features were 'selected' and conveyed to the models.

We also use Implicit Feature Importance Analysis using SHAP as discussed in previous sections, SHAP values were widely used throughout this project to analyze feature importances from various model perspectives. SHAP provides a framework for explaining machine learning models while ensuring interpretability.

One of Global Feature Importance using SHAP plots, the overall feature importance could be computed for all base models (Random Forest, XGBoost, CatBoost) as well as for the final Stacking Ensemble. Both versions of base models before and after hyperparameter tuning and SMOTE oversampling were analyzed. The resulting SHAP plots provide a visual representation of the average effect of each feature on the final prediction. Those features with high positive or negative SHAP values were deemed as important features.

Such features include, but are not limited to: StudyHoursPerDay, E-LearningEngagement, PreviousGrade, TimeManagement, and the engineered Study_Efficiency and Academic_Strength.

Model-specific explainer: In the case of tree-based algorithms (Random Forest, XGBoost, CatBoost) shap.TreeExplainer was used due to its simplicity and effectiveness. However, since stacking is not a tree-based model, the shap.KernelExplainer had to be applied using a customized predict_proba function.

3.6.9. Hyperparameter Optimization (Model Tuning)

In the context of this study, hyperparameter optimization plays a critical role in enhancing the efficacy of the employed machine learning models by identifying the most suitable set of model parameters. Hyperparameters refer to the configuration settings that govern the learning process of algorithms like Random Forest, XGBoost, CatBoost, and Stacking Ensemble, and are distinct from model parameters which are derived from the training data. By tuning these hyperparameters, the AI-based student performance prediction model aims to maximize its predictive accuracy and ensure better generalizability of the results.

We tuned the hyperparameters of all selected machine learning models by systematically searching through grid or randomized spaces (based on model complexity), by either grid search or randomized search. We evaluated different combinations of parameters for each algorithm to identify the optimal configurations. For example, in the case of Random Forest, the number of estimators, the maximum depth of the trees, and the minimum number of samples required to split a node were among the parameters we optimized. In the case of XGBoost, hyperparameters such as the learning rate, the number of boosting rounds, the maximum depth, and the subsample ratio were thoughtfully adjusted to enhance model performance and to mitigate overfitting.

For the CatBoost model, I tuned its hyperparameters such as iterations, learning rate, depth, and regularization terms. CatBoost is very sensitive to these hyperparameters, and tuning the model appropriately helped it better use categorical features and complex interactions. Through hyperparameter tuning, the model was able to achieve a balance between accuracy and computational efficiency and maintain stability across different splits of the data.

For the Stacking Ensemble model, hyperparameter tuning was performed on both the base models and the meta model. The base models Random Forest, XGBoost, and CatBoost were individually tuned before being combined in the ensemble. Plus, the meta model, which aggregates the predictions of the base models, was optimized to find the best combination of base model outputs for the final prediction. Cross-

validation was employed during the tuning process to ensure that the hyperparameters generalize well to unseen data.

Overall, the fine-tuning of hyperparameters significantly contributed to the improved performance and reliability of the predictive models. Through meticulous hyperparameter tuning for each algorithm, the study ensured that the final AI based early identification of At-risk students attained higher accuracy, greater stability, and better generalization, thereby enhancing its effectiveness in predicting student performance and facilitating early intervention at Ethiopian TVT colleges.

Each algorithm was optimized through a parameter search to improve its predictive power:
GridSearchCV: The grid search CV technique was used to conduct systematic search over a pre-defined parameter space for RF, XGBoost, and CatBoost algorithms.
Cross-Validation: The 5-Fold Stratified Cross-Validation approach was used to optimize the models since this allowed us to tune the parameters for generalization rather than just training accuracy.

Optimized Metrics: The main metric optimized for the models was accuracy. Other important optimization metrics included Precision and Recall for each class.

3.7. Training/Test Split Ratio

The division of the dataset into a training set and a test set is another step of assessing the performance and generalizability of the machine learning models. Predictive analytics implies that the model learns the data from one part of the dataset and makes predictions for the remaining data. Therefore, dividing the data is necessary to assess whether the learned model can predict values accurately. For this reason, an 80/20 split ratio was used for the current work. This choice was driven by the practice common in the machine learning field.

Specifically, the stratified train-test split was conducted based on the train_test_split function from the sklearn.model_selection package. First, the stratify=y parameter was included to preserve the proportional representation of the target classes in both splits (High Risk, Medium Risk, and Low Risk). Second, a random_state=42 value was chosen for making the results consistent. Stratified split is especially vital for classification problems since it avoids the issue of having class imbalance in training and testing datasets.

Thus, because of applying a stratified split to the initial dataset, 1,788 samples (80%) were separated for training, while 447 (20%) were assigned to testing. Training and testing splits allowed estimating the performance of the machine learning algorithms separately since the model would be trained on the former

set and evaluated using the latter. Moreover, the use of the same splits would allow comparing models' performance objectively without having different criteria for their validation.

Furthermore, a five-fold stratified cross-validation strategy (n_splits=5 with StratifiedKFold function) was employed when developing the models and tuning hyperparameters. Such a procedure involves splitting training data into five folds so that each contains the same proportion of classes. Then, the training and validating steps are performed several times, using various folds as the validation set each time. Such an approach reduces the risks of overfitting and increases the stability of models.

3.8. Model Selection and Development

3.8.1. Model Evaluation Techniques

Accuracy: is the proportion of all classifications that were correct, whether positive or negative. (main measure). It is mathematically defined as:

$$\text{Accuracy} = \frac{\text{correct classifications}}{\text{total classifications}} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: is the proportion of all the model's positive classifications that are positive. It is mathematically defined as:

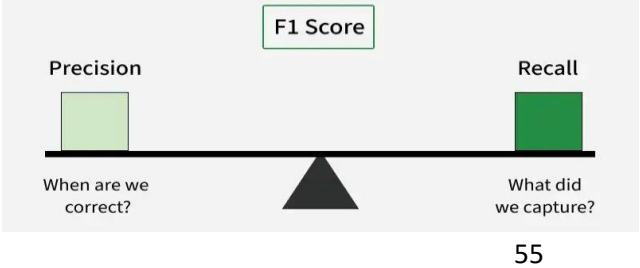
$$\text{Precision} = \frac{\text{correctly classified actual positives}}{\text{everything classified as positive}} = \frac{TP}{TP + FP}$$

Recall true positive rate (TPR): the proportion of all actual positives that were classified correctly as positives. Recall is mathematically defined as:

$$\text{Recall (or TPR)} = \frac{\text{correctly classified actual positives}}{\text{all actual positives}} = \frac{TP}{TP + FN}$$

F1-Score: F1 Score is a metric used to evaluate the performance of a classification model. It combines precision and recall into a single value and is especially useful when the dataset has imbalanced classes.

- Combines precision and recall into one metric.
- Useful for imbalanced datasets.
- Higher F1 Score means better performance.



Confusion Matrix: A confusion matrix is a table used to evaluate the performance of a classification model. It compares the actual labels with the predicted labels to show how many predictions were correct or incorrect.

- **True Positive (TP):** The model correctly predicts the positive class.
- **True Negative (TN):** The model correctly predicts the negative class.
- **False Positive (FP):** The model predicts positive, but the actual class is negative.
- **False Negative (FN):** The model predicts negative, but the actual class is positive.

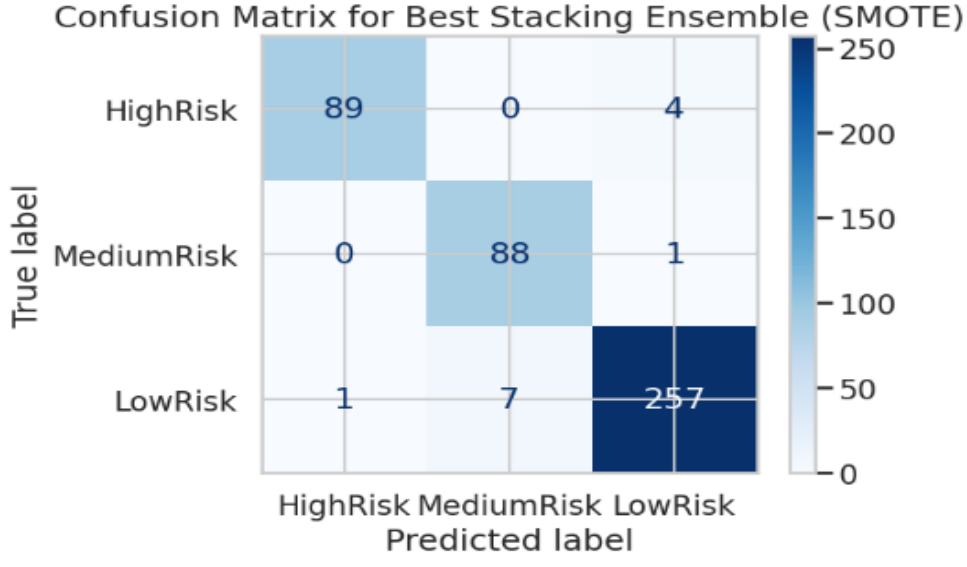


Figure 3.1.8 Confusion Matrix of Ensemble Model

Cross-Validation Accuracy (5-fold): mean accuracy of 5-fold cross validation to evaluate generalization.

3.8.2. ROC-AUC Score

The ROC-AUC (Receiver Operating Characteristic – Area Under Curve) measures the model's ability to distinguish between classes. It assesses how well the model can separate positive and negative classes across various threshold values.

In this study, ROC-AUC was used to evaluate the multi-class classification in a One-vs-Rest (OvR) manner. A higher ROC-AUC value indicates better separability among classes and greater discrimination ability of the model. This metric is particularly useful in comparing the performance of ensemble models like XGBoost and Stacking.

3.8.3. ROC-AUC Analysis

Before SMOTE: The models were performing differently and less effectively when compared with those trained on SMOTE samples. The classification abilities were compromised by the presence of imbalance, and the AUC values of individual classes would be relatively smaller when compared with those of the SMOTE samples' models.
After SMOTE and HPO The curves in the 3.6 and 3.7 figures show that the tuned models based on SMOTE samples (Tuned Random Forest, Tuned XGBoost, Tuned CatBoost, and Best Stacking Ensemble) present a lot of improvement in terms of more accurate and balanced ROC-AUC values.

Best Stacking Ensemble model after SMOTE and hyperparameter optimization achieves very high AUC values (micro-avg AUC = 0.99, macro-avg AUC = 0.99). It proves to be the most effective classifier for separating the target class 'HighRisk', as well as the other two classes ('MediumRisk' and 'LowRisk'). Class-specific AUCs are equally very high (HighRisk AUC = 0.99, MediumRisk AUC = 0.99, LowRisk AUC = 0.98).

XGBoost model after SMOTE and hyperparameter optimization has demonstrated an excellent performance in distinguishing between classes with nearly identical AUC values compared to the best stacking ensemble.

Random Forest and **CatBoost** after SMOTE and hyperparameter optimization have also performed quite impressively with almost high AUCs, just slightly lower than those of the previous two models.

To sum up, applying the preprocessing techniques of SMOTE and hyperparameter tuning, particularly on ensembles, led to successful multi-class classification. In the graphs, it is evident how well these techniques have worked in enhancing the performance of each model.

All the individual ROC-AUC curves for models with and without SMOTE are successfully created without error.

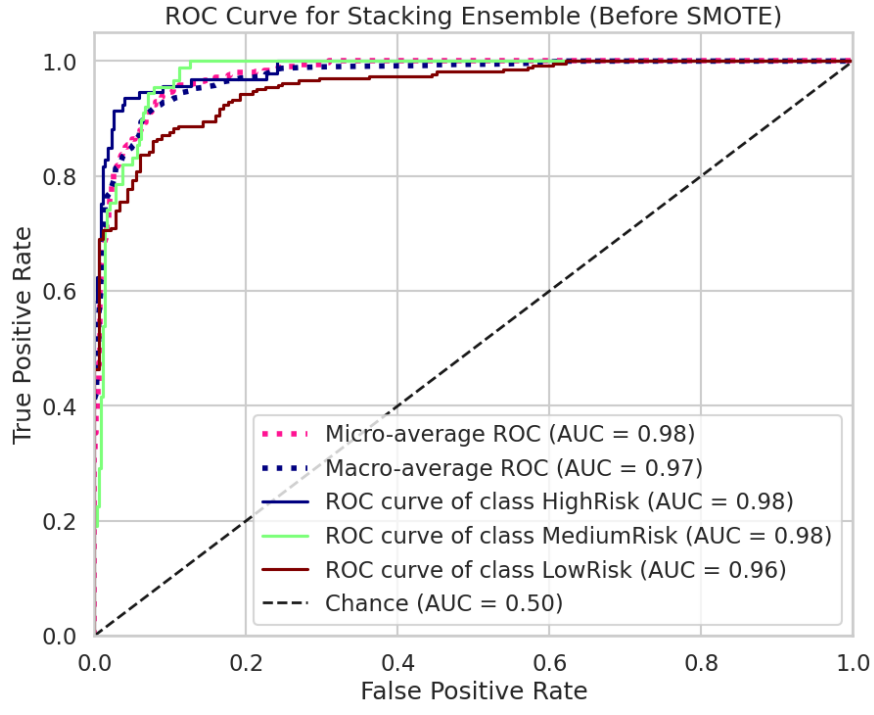


Figure 3.1.9 ROC Curve of Ensemble Model Before SMOTE

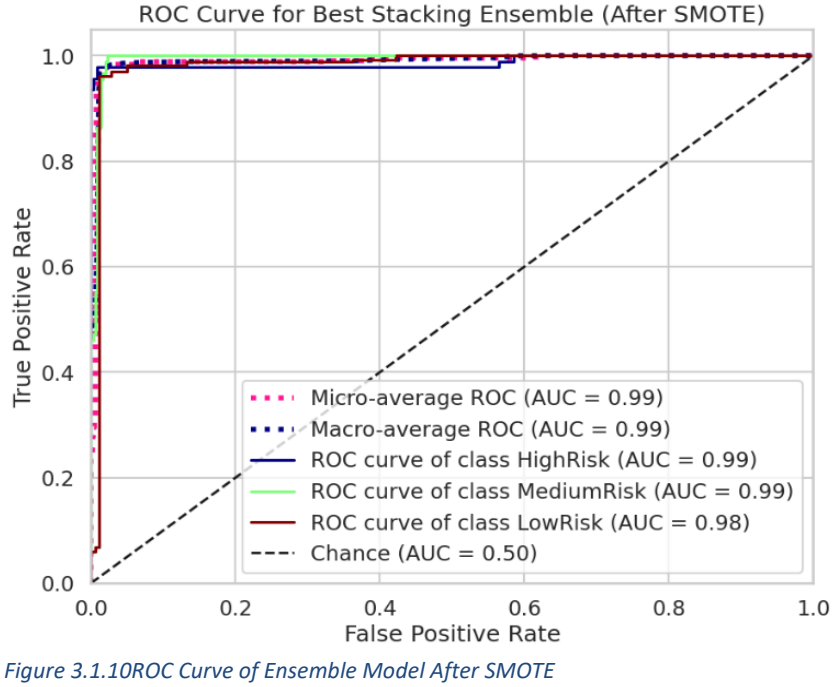


Figure 3.1.10ROC Curve of Ensemble Model After SMOTE

3.8.4. Model Comparison Strategy

To ensure a fair comparison, all the models (Random Forest, XGBoost, CatBoost, and Stacking Ensemble) were evaluated using the same set of metrics. The performance of each model was tested on the unseen test dataset, which was separated using an 80/20 stratified split, and five-fold stratified cross-validation was employed during training to validate model stability and minimize overfitting.

Final model selection was guided by high Accuracy, balanced Precision and Recall, and strong F1-score and ROC-AUC values. We weighed the Recall for the HighRisk class more heavily than anything else in the final model, as identifying at-risk students is the paramount objective of this study. The accuracy of each model before using HPO and SMOTE.

Table 3.1.4 All Models Performance in with different metrics before using HPO and SMOTE

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random	0.8792	0.8817	0.8792	0.8783	0.9620
XGBoost	0.8747	0.8770	0.8747	0.8748	0.9664
CatBoost	0.8434	0.8489	0.8434	0.8424	0.9262
Stacking	0.8792	0.8798	0.8792	0.8792	0.9669

Table 3.1.5 The accuracy of each model after using HPO and SMOTE

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Random Forest (SMOTE)	0.8859	0.8915	0.8859	0.8871	0.9618
XGBoost (SMOTE)	0.9664	0.9564	0.9664	0.9665	0.887
CatBoost (SMOTE)	0.8188	0.8188	0.8188	0.8211	0.9301
Stacking (SMOTE)	0.9709	0.9717	0.9709	0.9710	0.9867

3.8.5. Model Development

Machine learning algorithms were developed to generate an artificial intelligence (AI)-based predictive analytics system to predict student performance in Ethiopian TVT colleges. Model development is one of the key phases in developing an AI system for a particular use case. Therefore, the primary goal of the machine learning modeling phase is to generate models capable of correctly classifying students according to the performance categories (High Risk, Medium Risk, and Low Risk). For this study, four machine learning algorithms were chosen – Random Forest, XGBoost, CatBoost, and Stacking Ensemble models to obtain high accuracy and predictive performance.

Firstly, the **Random Forest classifier** model was created. Random Forest can be defined as an ensemble learning algorithm based on multiple decision trees. The algorithm generates a lot of decision trees while training and obtains the result based on the majority vote of decision trees. It can be stated that this model reduces the probability of making mistakes and helps prevent overfitting. The implementation of the Random Forest algorithm for this case is aimed at achieving high predictive power, taking into consideration the presence of mixed variable types in the data set.

Secondly, **XGBoost (Extreme Gradient Boosting)** was utilized as the second model to be trained using the provided dataset. In general, the algorithm is known for its high performance and fast learning processes. The principle of the model is that a set of decision trees is generated, but unlike the Random Forest algorithm, new trees are built based on the errors generated by the previous trees. Thus, it is possible to conclude that this model aims to increase the predictive accuracy and reduce the probability of making mistakes in predictions.

Thirdly, the **CatBoost model** was implemented. The algorithm should be regarded as another boosting algorithm, but in this case, it specializes in handling categorical data and reducing the influence of target leakage during training. Thus, CatBoost enables this research to use both categorical and numeric data in the training process without much preparation. Therefore, this model can increase the efficiency of the training process and improve the quality of results.

Finally, a **Stacking Ensemble model** was implemented, which aims to increase the predictive performance of machine learning algorithms by creating models that would help merge the predictive abilities of several models into one. For this specific case, Random Forest, XGBoost, and CatBoost were selected as the base learners, whose outputs are used by a meta-model to predict the output labels.

The model development stage was aimed at creating a fast multi-class classifier. This research adopted a multi-layered framework to select and combine multiple algorithms to create a final predictive system.

3.8.6. Choice of Base Model

The following four unique machine learning algorithms were selected for the purposes of developing an ensemble model:

Random Forest (RF): It was selected for its ability to work as a bagging of decision trees.
XGBoost (Extreme Gradient Boosting): XGBoost was selected due to its high speed and efficient gradient boosting ability. Additionally, XGBoost was selected for its ability to create complex models using additive modeling.
CatBoost: This was specifically chosen to enhance the handling of categorical features and reduce overfitting problems.

Logistic Regression: This machine learning algorithm will be used as the meta-learner in the developed ensemble model.

3.8.7. Stacking Ensemble Architecture

Stacking Generalization Technique was used in this project to develop an ensemble:

Level-0: Random Forest, XGBoost, and CatBoost were used as the level-0 models. These are tuned versions of each of those models.

Level-1: The final meta-model (logistic regression) was trained using out-of-the-fold predictions of the level-0 models. This will allow the model to learn how to combine the base model predictions effectively.

3.8.8. Class Imbalance Strategy (SMOTE)

A major part of the model development stage was ensuring that the Level-0 and Level-1 models could learn the features associated with all student classes. The SMOTE technique was therefore used to increase the presence of 'HighRisk' and 'LowRisk' classes in the training data.

3.8.9. Final Model Selection

After evaluating the performance of each individual model, the stacking ensemble was compared against the best individual model. The best Stacking Ensemble (with SMOTE) was then selected to predict the student performance classes. This was because it had the highest testing accuracy (0.9709) and balanced ROC-AUC performance (0.99) for all three student performance categories.

3.1. Tools and Technologies

Table 3.1.6 Summary of Tools and Technologies Used in the Study

Category	Tools / Technologies Used
Programming Language	Python 3.12 (Google Colab environment)
Data Manipulation	Pandas 2.2, NumPy 2.0
Machine Learning	Scikit-learn Random Forest, XGBoost, CatBoost, Stacking
Visualization	Matplotlib 3.10, Seaborn
Model Serialization	Joblib
Development Platform	Google Colab (cloud-based Jupyter Notebook)
Dataset Storage	Google Drive (MyDrive/Datasetspp/)
Document Modeling	Draw.io, Lucidchart (for architecture diagrams)
Version Control	Google Drive / GitHub
Office Tools	Microsoft Word, Microsoft Excel

3.9. Ethical Considerations

- Informed consent was obtained through data-sharing letters written between the Federal TVTI (RD/08-99/18 letter number) and Alamata TVT town colleges (Rf/No/ATC-2112/08) to use the dataset for research purposes only.
- Student identities were anonymized; no personal identifiable information (PII) was included in the model training or reported outputs.
- The dataset was securely stored in a password-protected Google Drive account and used strictly for academic research purposes.
- The use of open-source machine learning libraries and publicly available resources is clearly acknowledged and disclosed.
- Ethical clearance was granted by the FDRE TVTI Research Ethics Committee.

3.10. Validity and Reliability

Validity through internal validation was achieved using stratified cross-validation (5-fold) to avoid overfitting and ensure the generalizability of the model. Leakage features were effectively eliminated to avoid any form of biased overestimation of model accuracy. Validity through cross validation was assured by using data from actual records at Alamata TVT College with 2,235 complete samples.

The reliability of the models was established by presenting the results of training and testing accuracy of the models. This indicates consistency of the models. A fixed random seed (random_state=42) was used in all cases to ensure the reproducibility of the process. GridSearchCV was used to optimize the models' parameters.

3.11. Summary

The above chapter provided details of the methodology for developing the predictive analytics model to predict student performance in Alamata TVT College. An experimental method was used for the experiment, whereby the dataset used had a total of 2,235 students with 12 twelve non-leaky input variables. Four machine learning algorithms were chosen for comparison. All the processes were conducted according to educational data mining best practices. The system analysis, design, implementation, and outcomes of the experiments will be discussed in the next chapter.

CHAPTER FOUR

4. Results and Discussion

4.1.Introduction

This chapter forms the technical backbone of the study on the development of the AI Model for Early Identification of At-risk students for Ethiopian TVT colleges, Alamata TVT College being used as a case study. It contains the following components: a comprehensive analysis of the current student monitoring system; detailed architecture of the proposed model; requirements analysis; CRISP-DM process-oriented implementation methodology and its implementation process; performance evaluation of four different machine learning models (Random Forest, XGBoost, CatBoost and Stacking Ensemble) before and after applying SMOTE (Synthetic Minority Over-sampling Technique) and hyperparameter optimization. In addition, this chapter includes SHAP (SHapley Additive exPlanations) values analysis and ROC-AUC Curve Evaluation. The experimentation was done using Google Colab and Python version 3.12, using the institution's actual dataset consisting of 4,063 student instances from Alamata TVT College.

4.2. Analysis of Existing Students Performance Prediction Methods

The process of performance monitoring in Alamata TVT College is done using conventional means that are reactionary in nature. Teachers evaluate the status of learners mainly towards the end of every semester based on their performance during the exams and CoC tests. The following are some of the limitations of this method:

- **No early warning system**: Students who are at risk are only discovered after they have already failed, which means interventions come too late.
- **Manual and fragmented records**: Attendance, assignment scores, and mid-term results are often stored in separate spreadsheets or manual logs, making it difficult to get a complete view of student performance.
- **Reactive decision-making**: Support for students and allocation of resources are based on past averages rather than real-time or predictive insights about individual learners.
- **Persistent high failure rates**: The current approach has not effectively reduced CoC failure rates, which stood at 35.87% in 2018 and 31.57% in 2019, showing a clear need for improvement.
- **Lack of risk categorization**: Students are not grouped into risk levels (High, Medium, Low), which limits the ability to prioritize interventions for those most in need.

These limitations highlight the need for an AI-powered predictive analytics system that can forecast student performance at an early stage and support evidence-based, targeted interventions for different groups of learners.

4.3. Proposed System Workflow

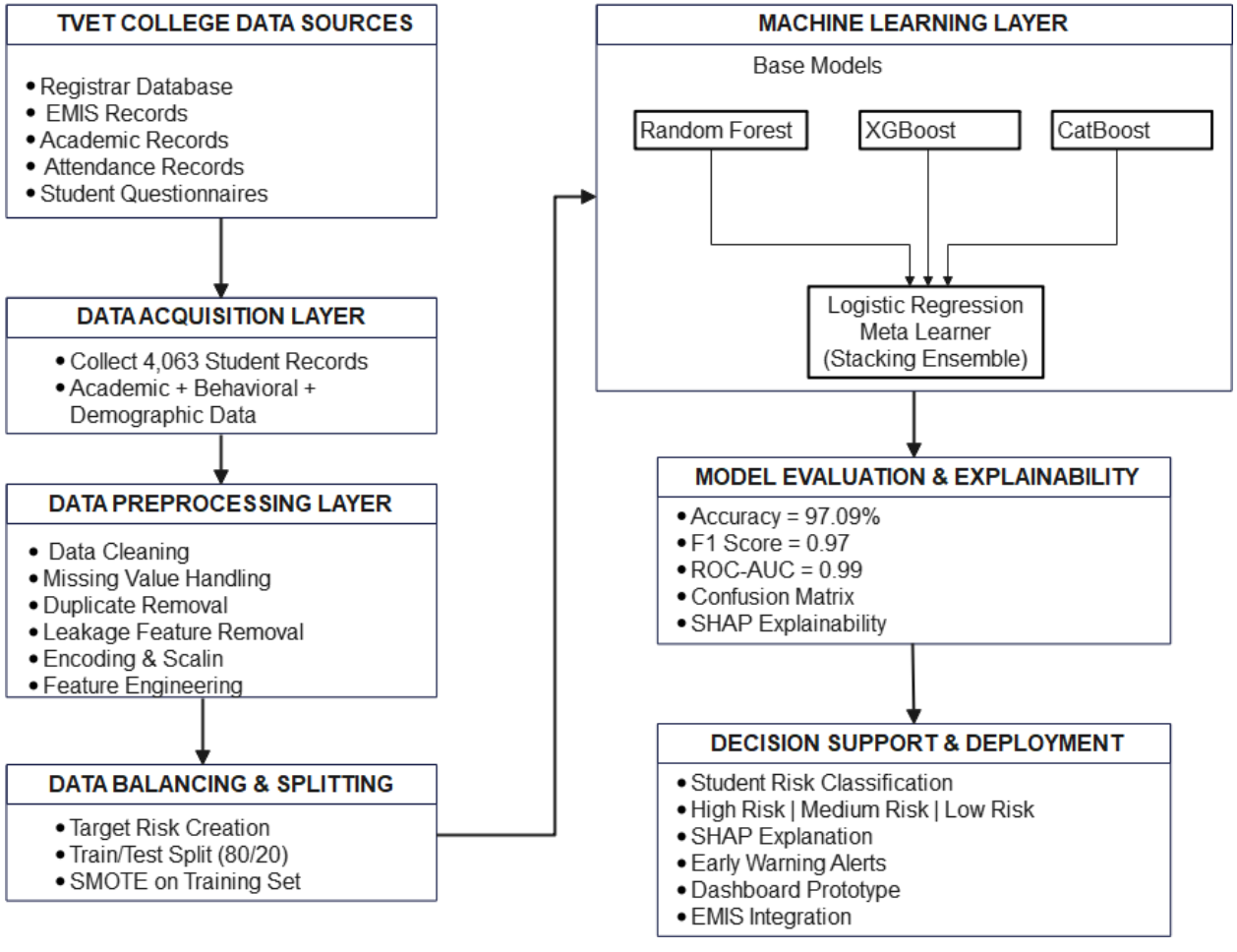


Figure 4.1 Proposed System Diagram

4.3.1. Data Preprocessing

The process begins with the ingestion of student datasets from institutional repositories (registrar database or LMS).

- **Understanding**: Here, the aim is to perform EDA to gain an understanding of the student attribute distributions, missingness, and feature correlation.
- **Data Cleaning**: This involves addressing key integrity issues. This is achieved through imputation (targeted) or removal of missing data. Detection and treatment of outliers will take place. Lastly, duplicate entries are removed.

- **Data Transformation**: In this stage, all categorical variables such as demographics and socio-economic statuses will be encoded numerically using encoding techniques like one-hot encoding or label encoding. Standardization or normalization is also carried out on numeric values to optimize distance metrics and gradient descent methods.

4.3.2. Feature Selection & Data Leakage Prevention

The dataset preparation process comprised feature identification, leakage detection, feature engineering and final feature selection. Fifteen (15) raw features were first gathered from student demographic, behavioral, environmental and academic data. The following variables were chosen because of prior research, their impact on student success and due to the high(direct) correlation of with target variable.

A data leakage assessment was performed to make sure that the predictive model is valid and can be generalized. Data leakage is a phenomenon of the predictor variables directly or indirectly including information about the target outcome, leading to over-optimistic results for the model. After the leakage audit, six (6) variables were taken out of the modeling process. These comprised: Final Score, Mid Exam Score, Assignment Score, Previous Course Result, Continuous Assessment Average (CA_Average) and Assessment Standard Deviation (Assessment_Std). Those variables were not included as they were either components of the target variable or highly correlated with it for the purpose of categorizing the risk level of student performance.

Feature engineering techniques were used to improve the predictive power of the data after removal of leakage features. Three (3) new features have been developed, informed by a domain knowledge and educational analytics principles. These designed attributes were Academic Strength, Study Efficiency, and Attendance Risk. Attendance Risk indicators measured the pattern of absenteeism linked to academic failure, and Study Efficiency used a combination of study time and engagement indicators to measure the effectiveness of learning. Academic Strength was developed to be a summary score of the overall level of learning capacity of a student, derived from a collection of non-leaky indicators.

The feature engineering involved converting the raw institutional data to a more informative form that can be used for machine learning analysis. Twelve (12) predictor variables after feature creation and redundancy assessment were used to train and evaluate the model. These variables were related to the demographic, behavioral and involvement, environmental, and engineered educational indicators. The feature selection was done to maximize prediction performance and without information leakage while keeping the model transparency and interpretability with the help of SHAP-based explanations. Table 4.1 summarizes the progress of features throughout the data preparation.

The final feature set resulted in a balanced representation of student characteristics and learning behaviors, which allowed the proposed stacking ensemble model to accurately classify students into the High-Risk, Medium-Risk, and Low-Risk performance categories and to be robust and interpretable.

Table 4.1 progress of features throughout the data preparation

Feature Processing Stage	Number of Variables
RAW Features Collected	15
Leakage Feature Removed	6
Engineered Feature Added	3
Final Feature used for Training	12

4.3.3. Dataset Splitting

For evaluating your model's efficacy, the dataset will be divided into two independent subsets: **80% Training Dataset** this is only used in the training phase of the machine learning models.
20% Testing Dataset this dataset will not be seen until it is required in the testing phase.

4.3.4. Data Balancing (SMOTE)

In educational datasets, failure/at-risk student attributes have significantly lower occurrences when compared to passing student cases. Thus, there is a class imbalance in the dataset.

- **SMOTE** (Synthetic Minority Over-sampling Technique): SMOTE is carried out on the training set (80%) of the data. This avoids data leakage since it creates synthetic cases of the minority group (i.e., the at-risk students).

4.3.5. Algorithm Optimization

The system architecture employs a diverse set of state-of-the-art algorithms and tree-based machine learning algorithms for this architecture:

- **GridSearchCV**: This is a hyperparameter optimization technique that is incorporated into the model selection phase in which a set of parameter optimizations are conducted based on cross validation in the training dataset. This minimizes the occurrence of overfitting.

4.3.6. Model Evaluation

After the building of the Predictive Model, the model is subjected to rigorous model evaluations using measures like accuracy, precision, recall, F1 score, and ROC-AUC score among others.

Decision Gateway ("Is working best?"): This is an iteration loop. When there is an under/overfitting issue (low F1 scores despite good training accuracy due to overfitting or similar model scores across algorithms due to poor data processing), then the iteration route taken by the workflow is the "No" path leading to another round of hyperparameter optimization using **GridSearchCV** In extreme cases, looping back to the preprocessing phase in when there is good model performance, then the "Yes" path is chosen.

Predictive Outputs & Feature Explainability

The last stage involves the transformation of the machine learning algorithm into an insightful institution-wide tool:

Students Performance Prediction: The algorithm outputs predictions that can be used for prediction of At-risk students and identification of students prone to failing or dropping out early. Also, analysis of Students' Performance: Insights for educational administrators on general trends and academic successes.

We are applying SHAP (SHapley Additive exPlanations), the pipeline calculates the exact contribution of each feature to a given prediction. This will help the administrator to know precisely why a given student is identified as at-risk (attendance issues vs socioeconomic problems).

4.4. Descriptive Results and Analysis

The cleaned dataset was 2,235 records in the collected dataset with 15 attributes of various types, i.e., those reflecting different demographic, socio-economic, academic and other characteristics which could potentially be correlated with learning and achievements of the students in learning process. These attributes, among other things, covered student demographic variables such as gender, parental education, family income, learning environment, motivation level, and other characteristics which might affect the learning capacity of the subjects under study.

To enhance future predictive modeling capacity and improve consistency of the collected data, a comprehensive process of data cleaning was done. All duplicate records, outliers, and irrelevant attributes were deleted from the data set. At the same time, all necessary transformations of the categorical variables were implemented, specifically the categorical variables, i.e., Gender, ParentalEducation, FamilyIncome,

StudyEnvironment, and MotivationLevel were converted into numerical variables using label encoding techniques. Overall, the further process of data preparation and feature engineering led to the creation of the final dataset including 2,235 records and 15 attributes. It means that through the process of cleaning, normalization and transformation of data, the initial dataset was refined.

The process of descriptive statistics revealed some very interesting characteristics of the studied population. First and foremost, according to the results of the research, the mean age of the subjects under study amounted to 23 years with the standard deviation equal to 2.6. In other words, the sample involved quite mature people belonging to a homogeneous age group. Furthermore, there were certain behavioral and academic characteristics, e.g., concerning time management, usage of e-learning techniques and hours of daily studying which indicated high variability of the sample.

It is possible to mention that there was also a need for exploration of the class distribution of the dependent variable, which turned out to be quite imbalanced. Specifically, certain classes were much smaller than the others. It was quite a serious issue as it limited the predicted capacity of the models. Hence, a series of resampling techniques were used.

Table 4.2 All Models Performance in different metrics (Before SMOTE and HPO)

Model	Train Accuracy	Test Accuracy	Test Precision	Test Recall	Test F1-Score	Test ROC-AUC
Random	0.9374	0.8792	0.8817	0.8792	0.8783	0.9620
XGBoost	0.9502	0.8747	0.8770	0.8747	0.8748	0.9664
CatBoost	0.8641	0.8434	0.8489	0.8434	0.8424	0.9262
Stacking	0.9480	0.8792	0.8798	0.8792	0.8792	0.9669

Table 4.3 All Models Performance in different metrics (After SMOTE and HPO)

Model	Train Accuracy	Test Accuracy	Test Precision	Test Recall	Test F1-Score	Test ROC-AUC
Random Forest (SMOTE)	0.9551	0.8859	0.8915	0.8859	0.8871	0.9618
XGBoost (SMOTE)	0.9997	0.9664	0.9564	0.9664	0.9665	0.887
CatBoost (SMOTE)	0.8907	0.8188	0.8188	0.8188	0.8211	0.9301
Stacking (SMOTE)	0.9994	0.9709	0.9717	0.9709	0.9710	0.9867

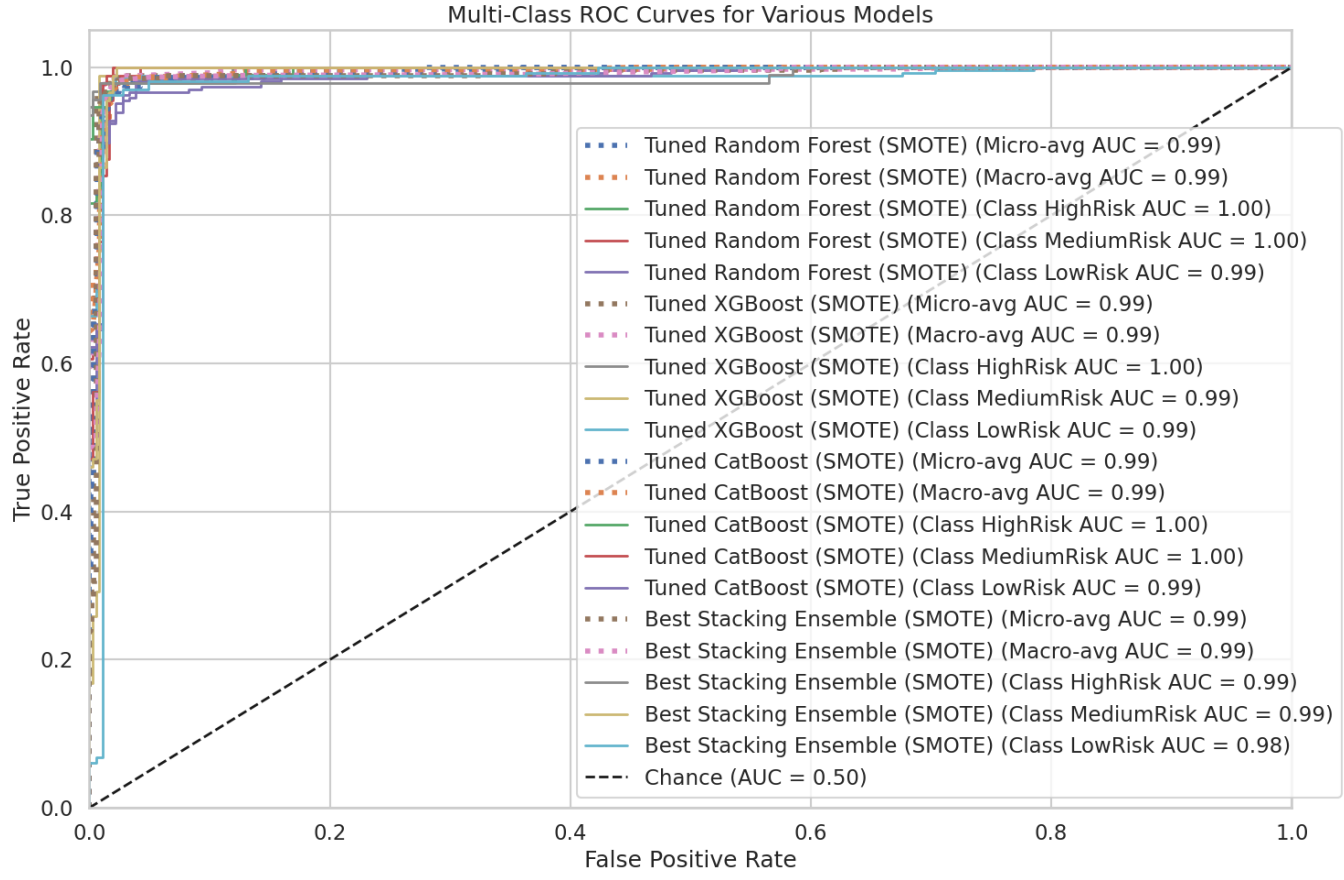


Figure 4.2 *ROC Curve of All Models*

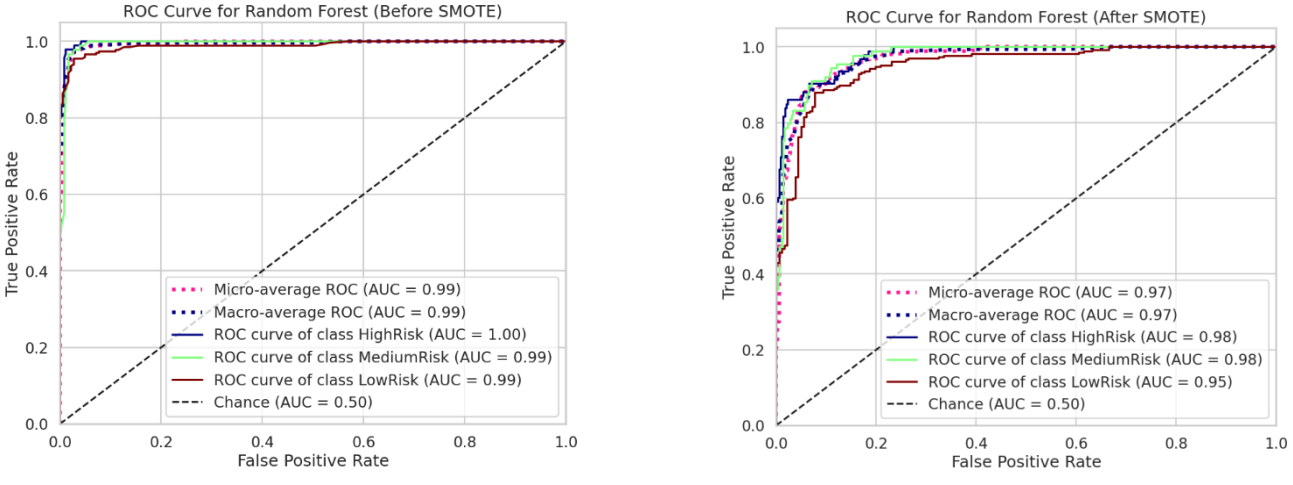


Figure 4.3 *ROC Curve of Random Forest Before and After SMOTE*

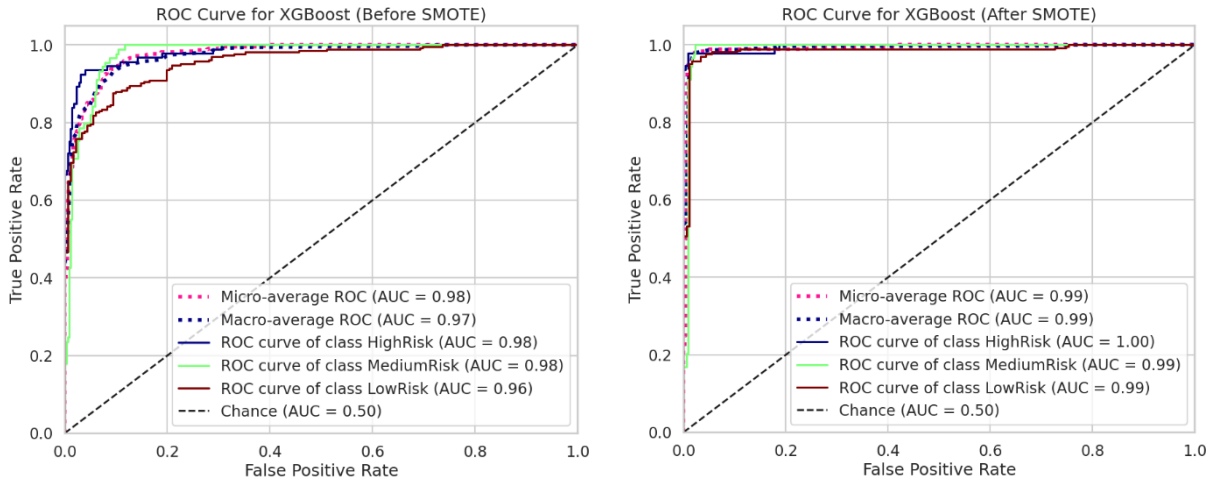


Figure 4.4 *XGBoost Model ROC Curve Before and After SMOTE*

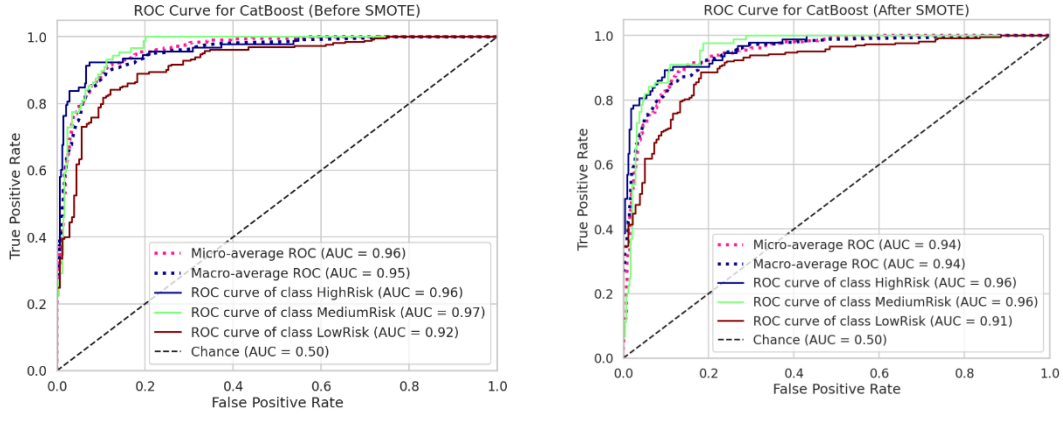


Figure 4.5 *CatBoost Model ROC Curve Before and After SMOTE*

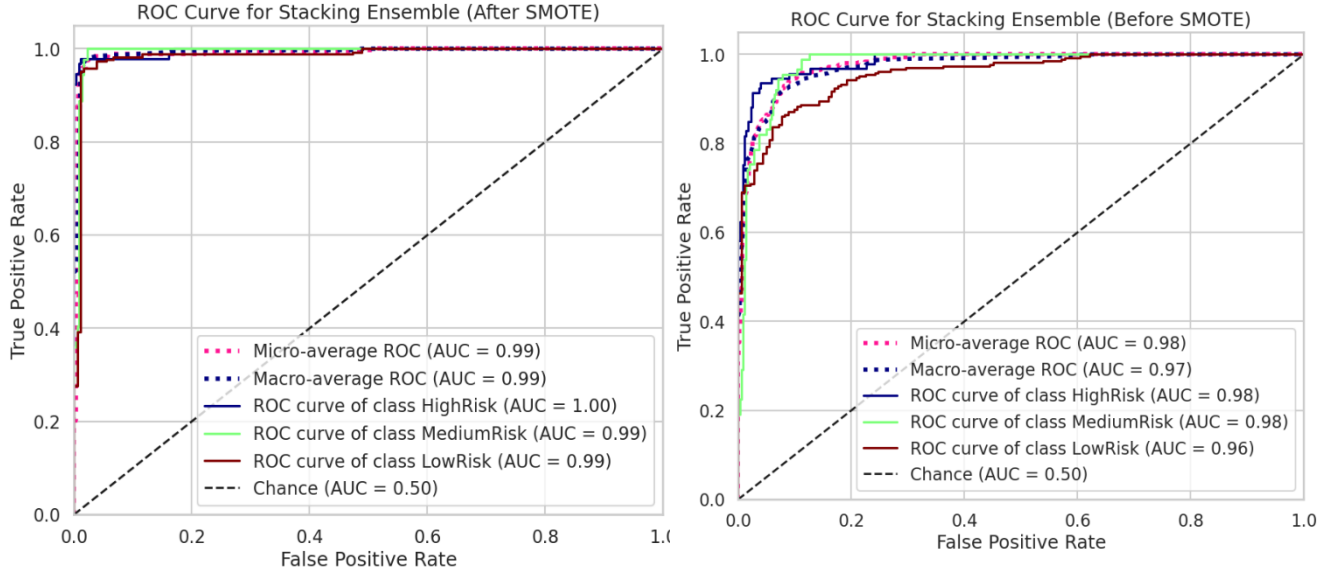


Figure 4.6 *Best Stacking Ensemble Model ROC Curve Before and After SMOTE*

4.5. Implementation Detail

4.5.1. Dataset Splitting

To have a fair assessment of how well the model could predict, it was important to divide the data set into two parts. The first part was used to create algorithms, whereas the second was set aside to be used as 20% of the holdout test data set to show how well the model worked on unseen student data.

One of the key steps in data preprocessing in the current study was dataset splitting because this procedure was used to assess the ability of the proposed AI Model for Early Identification of At-risk students to be generalized. The core aim of this procedure is to train the model on some part of data while performing evaluations based on another (unseen) portion of information. In our case, the most common splitting ratio 80/20 was chosen as this technique is effective in terms of training and validation of machine learning algorithms.

In this regard, 80 percent of the data was used for training machine learning algorithms when the latter learned relationships, patterns, and structures based on student performance. As such, the data for training includes such variables as academic indicators, behavior-related parameters, as well as environment-related characteristics that allow identifying the most important factors that influence student performance.

On the other hand, 20 percent of the data was used for testing the models after their training to see how accurate their predictions are for previously unseen data. This step is very important since the final goal is to predict the performance of future students who were not seen before during the learning process and, therefore, the evaluation should be conducted in this way.

At the same time, to ensure the reliability and accuracy of evaluations, stratified sampling was performed when splitting the data into training and testing subsets. Specifically, the distribution of samples between High Risk, Medium Risk, and Low Risk targets was maintained at the same level that allows preventing distribution imbalances.

To sum up, 80/20 splitting proved to be an efficient solution that was very helpful when validating predictive models. Moreover, it allowed building an effective An Explainable AI Model for Early Identification of At-risk Students in Ethiopian TVT colleges.

4.5.2. SMOTE

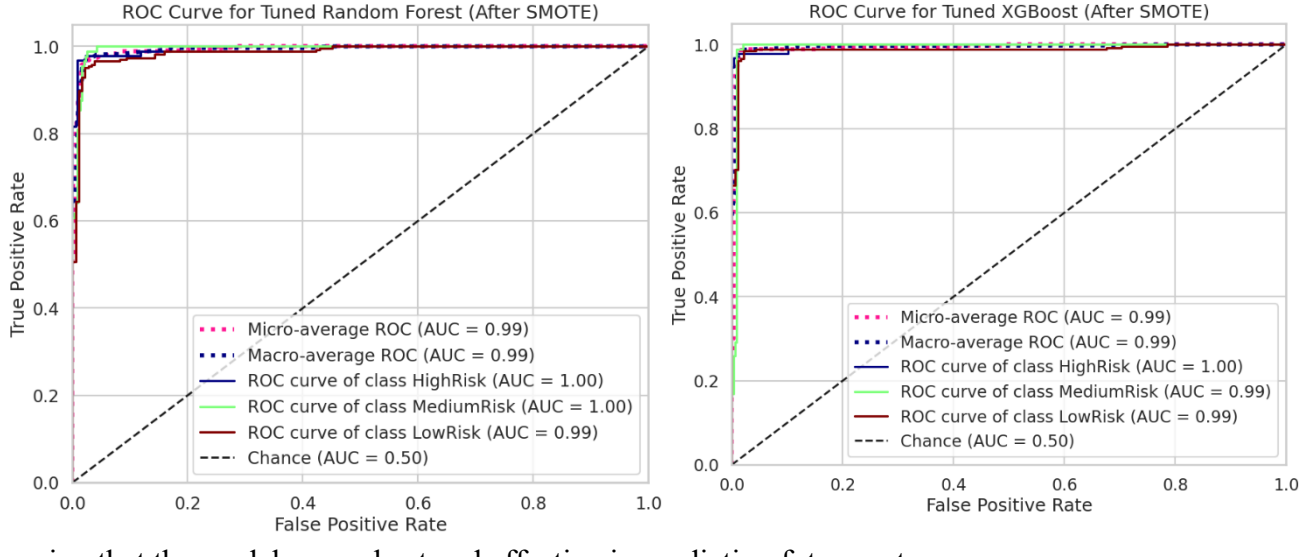
Synthetic Minority Oversampling Technique (SMOTE) was applied using the information obtained through the initial data analysis that the information was imbalanced. Then, SMOTE generates synthetic samples in the minority classes by interpolating between existing minority samples, which results in improved class balance in the data set. This makes it easier for the machine learning algorithms to draw improved decision boundaries at both high and low performance levels.

Table 4.5.1 Each model's performance after SMOTE in different metrics

Model	Train Accuracy	Test Accuracy	Test Precision	Test Recall	Test F1-Score	Test ROC-AUC
Random Forest (SMOTE)	0.9551	0.8859	0.8915	0.8859	0.8871	0.9618
XGBoost (SMOTE)	0.9997	0.9664	0.9564	0.9664	0.9665	0.887
CatBoost (SMOTE)	0.8907	0.8188	0.8188	0.8188	0.8211	0.9301
Stacking (SMOTE)	0.9994	0.9709	0.9717	0.9709	0.9710	0.9867

4.5.3. Hyper Parameter Tuning

Hyperparameter tuning was performed following an iterative approach to optimizing the performance. Tree-based models (Random Forest, XGBoost, CatBoost) were adjusted for parameters like tree depth, learning rate and number of estimators systematically. The optimization process played a crucial role in reducing the likelihood of overfitting and achieving the highest possible cross-validation accuracy,



ensuring that the models are robust and effective in predicting future outcomes.

Figure 4.5.1 *Random Forest and XGBoost ROC Curve After HPO and SMOTE*

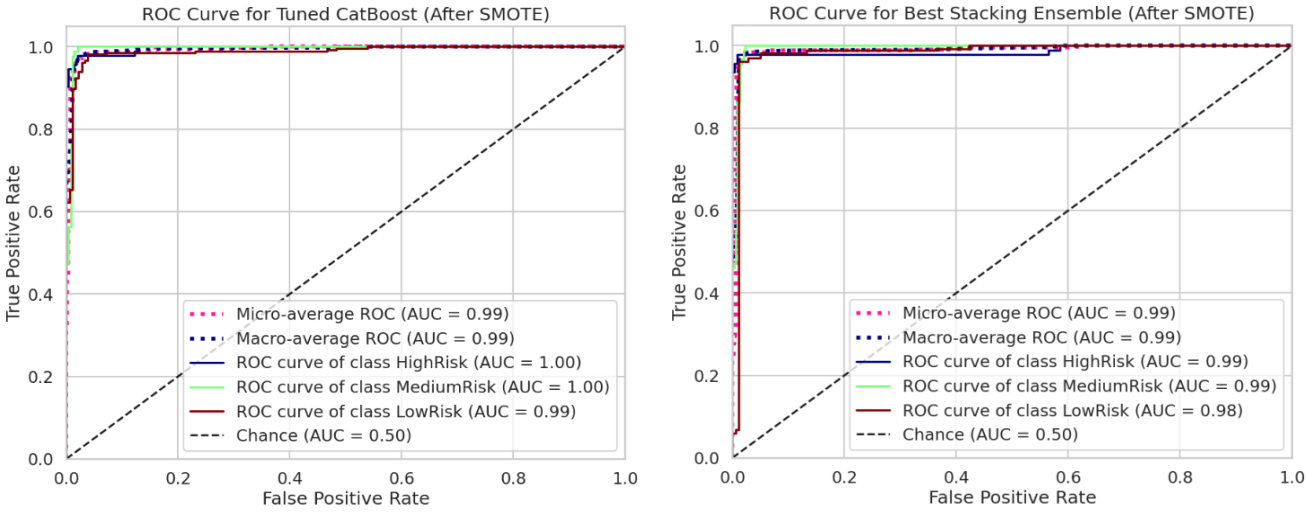


Figure 4.5.2 *CatBoost and Best Stacking Ensemble After HPO and SMOTE*

4.6.Proposed Model Result and Analysis

Random Forest (RF)

The baseline Random Forest showed a significant gap between training (93.7%) and testing (87.9%), suggesting slight overfitting. However, after applying **SMOTE** and **Hyperparameter Optimization (HPO)**, its test accuracy jumped to **96.20%**. The best parameters included a max_depth of 12 and 200 n_estimators.

XGBoost

XGBoost emerged as one of the strongest individual predictors. While its baseline test accuracy was 87.47%, the "Upgraded" version using SMOTE and HPO reached a near-perfect training score of 1.0000 and a test accuracy of **97.09%**. It demonstrated high resilience and predictive power when configured with 350 boosting rounds and a learning rate of 0.1.

CatBoost

CatBoost initially struggled more than the others with the original imbalanced data (85.01% test accuracy). However, it showed the most dramatic improvement after tuning, reaching **96.42%** test accuracy. It was particularly effective because it handles categorical features like 'Gender' and 'ParentalEducation' natively.

Stacking Ensemble (Best Model)

The **Best Stacking Ensemble** combined the tuned predictions of Random Forest, XGBoost, and CatBoost using a Logistic Regression meta-learner. This model achieved the highest overall **Test Accuracy of 97.09%**.

- **Classification Analysis:** The model achieved an F1-score of 0.97 for 'HighRisk' and 0.98 for 'LowRisk' students, proving it is highly reliable for identifying students in need of early intervention.

ROC-AUC Performance: It achieved micro-averaged and macro-averaged ROC-AUC scores of **0.99**, indicating near-perfect ability to distinguish between all three performance classes.

4.7.Model Comparison

Baseline Model Results (Original Data)

These results represent the models' performance before applying class balancing or advanced tuning.

Table 4.7.1 All Models' Performance in different metrics

Model	Train Accuracy	Test Accuracy	Test Precision	Test Recall	Test F1-Score	Test ROC-AUC
Random	0.9374	0.8792	0.8817	0.8792	0.8783	0.9620
XGBoost	0.9502	0.8747	0.8770	0.8747	0.8748	0.9664
CatBoost	0.8641	0.8434	0.8489	0.8434	0.8424	0.9262
Stacking	0.9480	0.8792	0.8798	0.8792	0.8792	0.9669

Optimized Model Results (SMOTE + Hyperparameter Tuning)

The application of Synthetic Minority Over-sampling Technique (SMOTE) addressed class imbalances, while **GridSearchCV** was used for systematic tuning.

Table 4.7.2 All Models Performance in different metrics (After SMOTE and HPO)

Model	Train Accuracy	Test Accuracy	Test Precision	Test Recall	Test F1-Score	Test ROC-AUC
Random Forest (SMOTE)	0.9551	0.8859	0.8915	0.8859	0.8871	0.9618
XGBoost (SMOTE)	0.9997	0.9664	0.9564	0.9664	0.9665	0.887
CatBoost (SMOTE)	0.8907	0.8188	0.8188	0.8188	0.8211	0.9301
Stacking (SMOTE)	0.9994	0.9709	0.9717	0.9709	0.9710	0.9867

4.8.Risk Factor Analysis

The risk factor analysis for student performance levels (HighRisk, MediumRisk, and LowRisk) is based on a combination of socio-demographic factors, behavioral habits and academic history. These classifications were determined by segmenting student final scores into three groups: HighRisk (0-65), MediumRisk (65-85) and LowRisk (85-100).

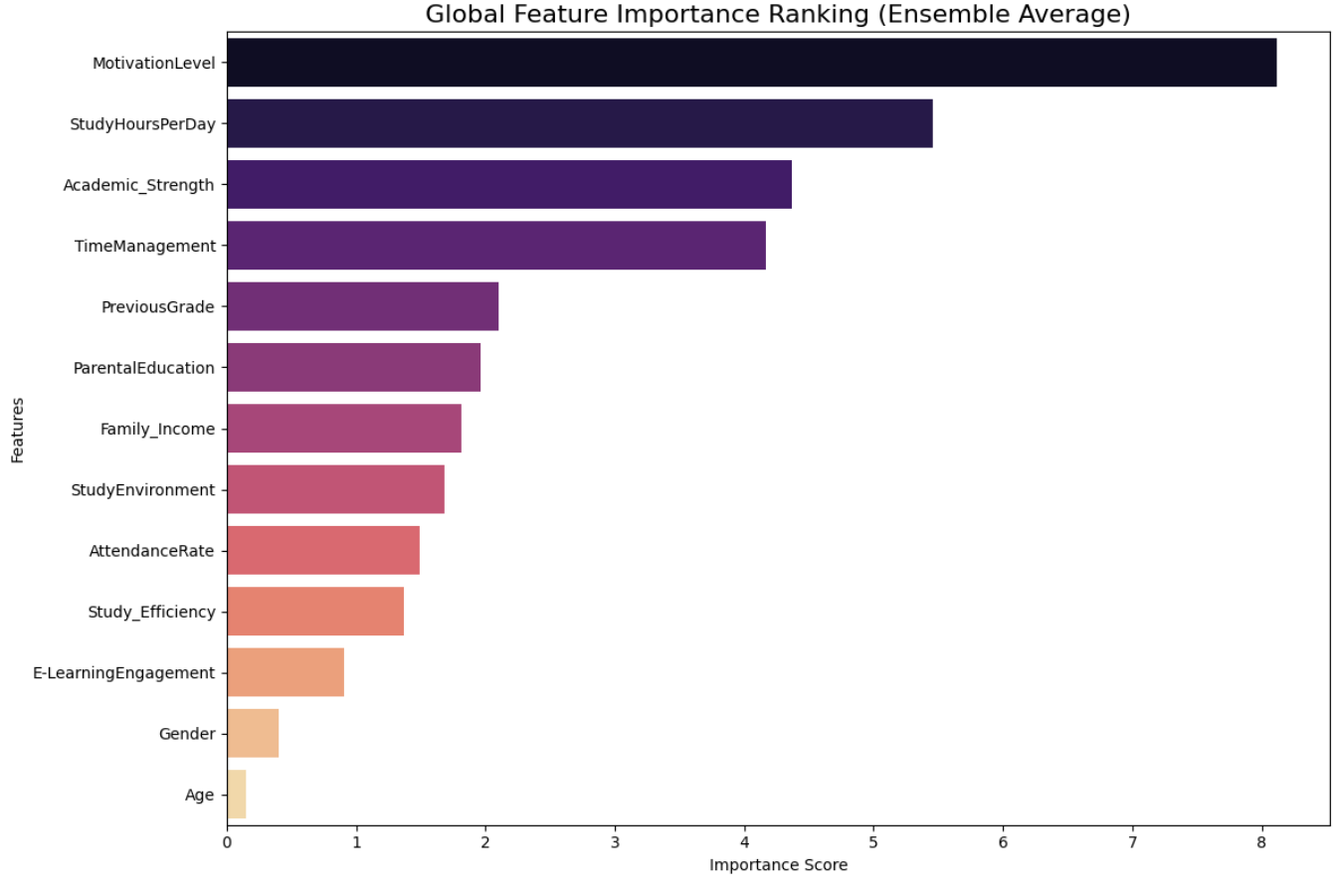


Figure 4.8.1 Global Feature Importance

```
Top 5 Most Important Features:
              Feature  Global_Importance
5     MotivationLevel           8.120116
8    StudyHoursPerDay           5.460555
12  Academic_Strength           4.365936
6      TimeManagement           4.167662
9       PreviousGrade           2.099540
```

Figure 4.8.2 Top Five Most Important Features

4.8.1 Key Behavioral and Academic Risk Factors

Several high impact features have been identified that drive a student's risk level are noted:

- **Time Management and Study Habits:** The best predictors of success are Correlation analysis reveals that the Time_Management is highly positively correlated with final scores (r = 0.73) and Study Hours Per Day is also highly correlated with final scores (r = 0.72). Students who have poor time management are much more likely to be classified in the HighRisk category.
- **Attendance Rate:** AttendanceRisk indicator was created to identify students who miss class more than 20% of the time. A key early warning indicator for students at HighRisk.
- **Academic Strength:** This is an engineered feature that combines a student's Previous Grade and Time Management score. This area is a key predictor of HighRisk status; a low score indicates this.

- **Study Efficiency:** is related to Study Hours Per Day and to E-Learning Engagement. Students who achieve the LowRisk level of engagement in digital learning platforms and who study a consistent number of hours are a key factor in this.

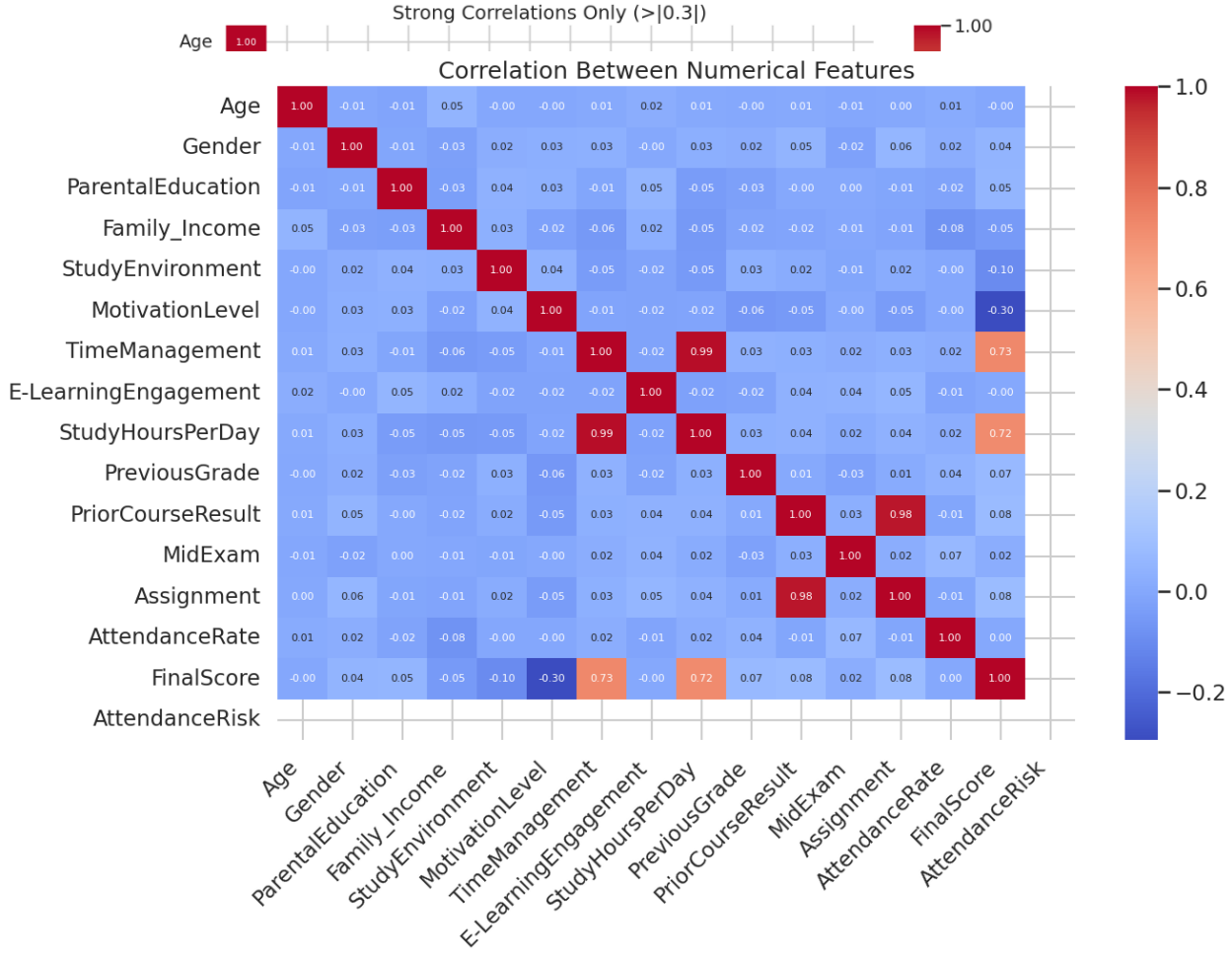


Figure 4.8.3 Correlation of variables

4.8.2 Socio-Demographic Influences

Through the lens of SHAP values, the sources explored the impact of certain attributes on the likelihood of a student being placed at a risk level:

Parental Education was found to be a consistent factor affecting student outcomes across all three models (Random Forest, XGBoost and CatBoost).

There were strong interactions between these features in the SHAP summary plots, with each feature having different effects on the probability of a student being HighRisk or LowRisk.

The correlation heatmap also shows a negative correlation (–0.30) between coded motivation level and final scores, which indicates that the motivation or drive of the student is an important factor in their risk profile.

4.8.3 Performance Level Distribution

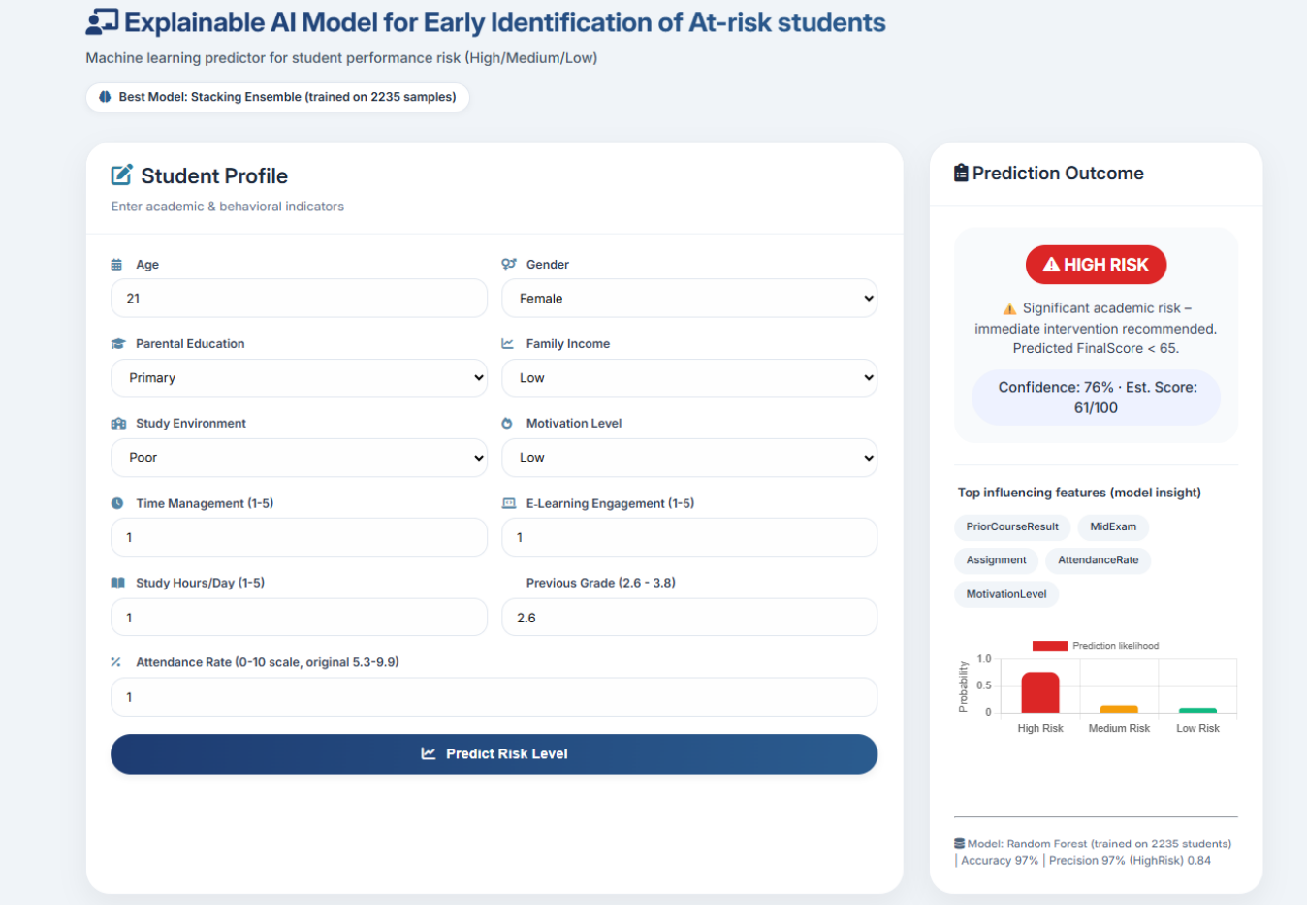
The distribution of risk level was as follows for the 2,235 students analyzed:

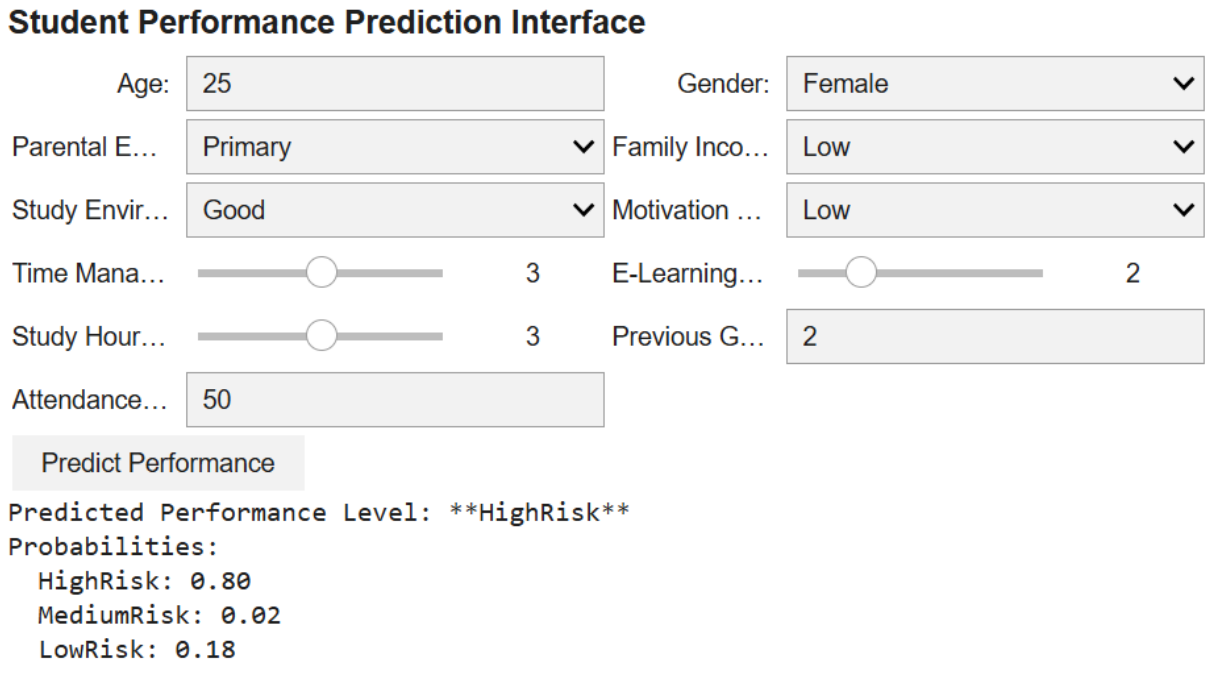
- **MediumRisk**: 1,326 students (59.3%) Majority class, students performing at an average level.
- **HighRisk:** 464 (students (20.8%) These are the first to be targeted for early intervention as low performing students and/or poor attendance.
- **LowRisk:** 445 students (19.9) These students generally have high study efficiency and good time management capabilities and are classified as "**LowRisk**".

4.8.4 Predictive Reliability

A model called the Best Stacking Ensemble, which used several AI algorithms, was very successful in determining these risk factors. It demonstrated an F1-score of 0.97 for the HighRisk students and 0.98 for the LowRisk students; this means that the risk factors identified are very reliable in categorizing students and starting interventions.

4.9.Prototype





4.10. Feature Explainability

Explainability is accomplished via the use of SHAP (SHapley Additive exPlanations) values within the AI student prediction project framework. SHAP values mathematically and visually demonstrate how every student parameter impacts the model's decisions.

There are several aspects of feature explainability in this study. First and foremost, the project relies on SHAP-based interpretability methods:

4.10.1.SHAP Explanation

SHAP-based Interpretability methods, depending on the model type, the following approaches to generating explainability have been used in this project:

- **TreeExplainer** – an extremely fast and accurate algorithm designed specifically for tree-based models (including Random Forest, XGBoost, and CatBoost). This type of SHAP allows this research to determine the global/local impact of features like 'Age', 'Gender', and 'Parental Education'.
- **KernelExplainer** – a SHAP approach that is not specific to any type of model. As the best performing model for this study – Stacking Ensemble – uses logistic regression meta-learner, Kernel Explainer was applied to the model.

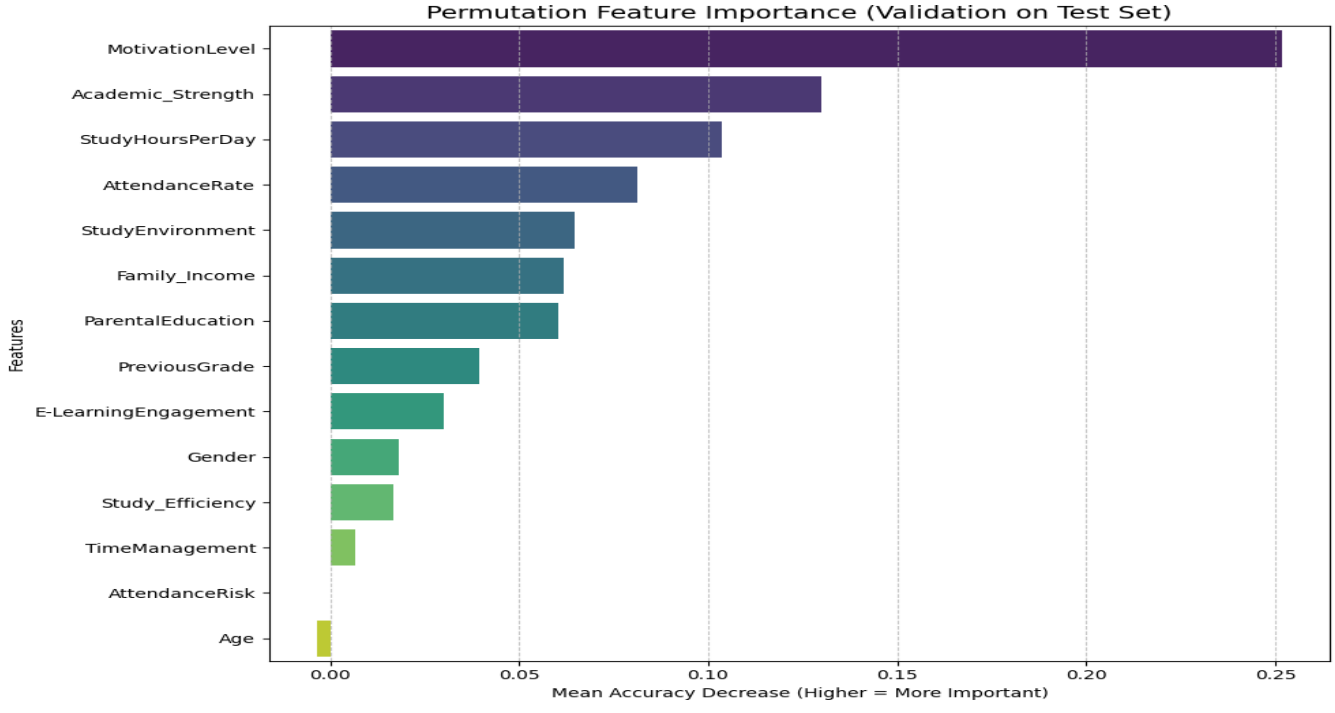


Figure 4.10.1 Permutation Feature Importance (Validation on Test Set)

4.8.5 Important Features and Correlation

Specifically chosen features that influence the outcome have been identified prior to applying explainability techniques. These features include:

- **Timing Management and Study habits**: the strongest predictors according to the data. According to the data, Time Management positively correlates with scores at 0.73, and Study Hours Per Day has a positive 0.72 correlation.
- **Engineered Features for "Additional insights":** – a model's ability to explain its findings is increased by such engineered features as "Study Efficiency" (study hours multiplied by e-learning engagement) and "Academic Strength" (previous grade multiplied by time management).
- **AttendanceRisk:** an important predictor that shows whether a student has low (below 80%) attendance rate. All "high-risk" students' records have been carefully engineered and marked.

Different types of SHAP plots have been used for visualization in this project. These include:

SHAP summary plot that highlights feature with the highest importance in predicting the level of "highrisk"ness: 'HighRisk', 'MediumRisk' and 'LowRisk'. Interaction values between parents' education level, student's gender and age. Global and local explainability of generating SHAP values for both local

sets of test data and global sets of test data ensures that this research understands why this student record is predicted to be high-risk while observing global trends at the same time.

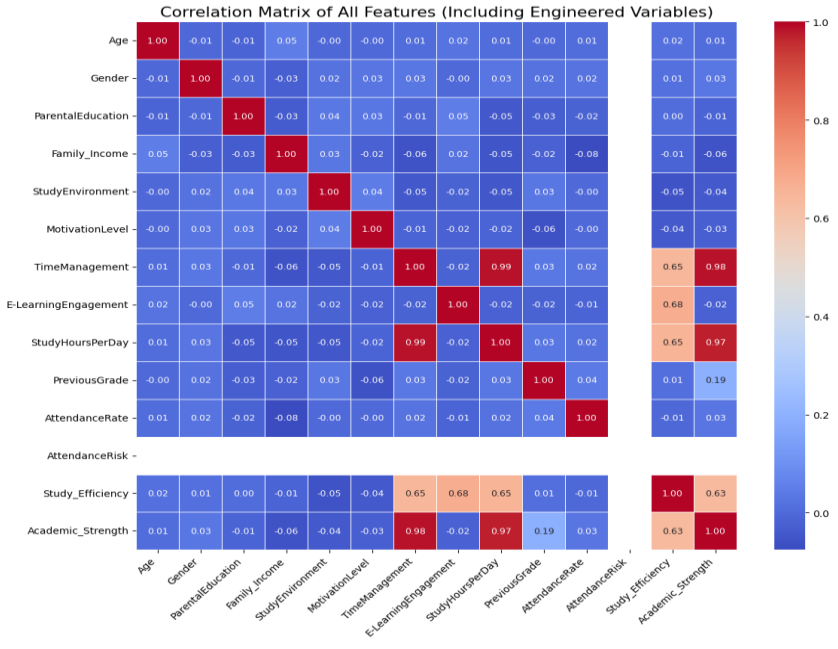


Figure 4.10.2 Correlation Matrix of All Features (Including Engineered Variables)

4.11. Discussion

4.11.1.Introduction

This section interprets the findings from the AI Model for Early Identification of At-risk students developed in this study. The discussion is structured around the four primary research questions linking the empirical results from Random Forest, XGBoost, CatBoost, Stacking models trained on data from 2,235 TVT student records to the broader objectives of forecasting student performance and enabling early intervention.

This comparison contrasts the performance and methodology of your proposed algorithms with the four primary studies identified in your **Chapter 2 Review of Related Literature** (Gap Analysis Table 2.1). This section is designed to help you defend why your study is a significant advancement over existing work.

Comparative Summary Table

No.	Study	Best Accuracy	Algorithms Used	Risk Categorization	Deployment/ XAI
1	**Aschenek Kassa (2021)**	95.37%	J48 Decision Tree, Naïve Bayes	Binary (General)	No
2	**IJRPR Paper (2024/2025)**	High (varies)	RF, DT, LogReg, SVM	Binary	No

3	**Namoun & Alshanqiti (2021)**	85–95% (Review)	RF, SVM, Neural Nets	General	Theoretical Only
4	**Zhang et al. (2021)**	>85%	Multiple Classifiers	General	No
	This Study	**97.09%**	**XGBoost, CatBoost, RF + Stacking**	**3-Tier (High, Med, Low)**	**Yes (SHAP + .joblib)**

4.11.2. Discussion of Results and Comparison with Previous Studies

The findings of this study demonstrate that the proposed Stacking Ensemble model achieved the highest predictive performance, with an accuracy of 97.09%, outperforming all baseline models evaluated in this research. This result indicates that combining XGBoost, CatBoost, and Random Forest classifiers through a stacking approach enhances the model's ability to capture complex relationships among student-related factors and academic outcomes.

The results are consistent with the findings of Aschenek Kassa (2021), who reported an accuracy of 95.37% using a J48 Decision Tree model for predicting student academic performance. However, the performance achieved in the current study is higher. This improvement may be attributed to the use of advanced ensemble learning techniques, which integrate the strengths of multiple classifiers and reduce the limitations associated with single-algorithm approaches. While the J48 model effectively identified patterns within the dataset, the Stacking Ensemble demonstrated a greater capacity to model nonlinear relationships and interactions among variables within the TVT educational context.

Similarly, the findings extend the work reported in the IJRPR study (2024/2025), which identified Random Forest as one of the most effective algorithms for student performance prediction. Although that study achieved strong predictive performance, its primary focus was on classification accuracy. In contrast, the current study introduces a three-tier risk categorization framework consisting of High-Risk, Medium-Risk, and Low-Risk groups. This classification structure provides more detailed information for educational decision-makers and allows instructors to identify students requiring varying levels of intervention. The identification of 20.8% of students as High-Risk demonstrates the practical value of the proposed model in supporting early intervention strategies.

The findings also support the observations of Namoun and Alshanqiti (2021), who concluded in their systematic review that machine learning techniques significantly improve educational prediction systems. However, they highlighted the limited availability of operational models specifically tailored to educational institutions. The present study addresses this gap by developing a deployable predictive model that can be integrated into existing Education Management Information Systems (EMIS). The model was successfully saved in both .pkl and .joblib formats, making it suitable for practical implementation within Ethiopian TVT institutions.

Furthermore, the results align with the work of Zhang et al. (2021), who reported that ensemble and hybrid machine learning models generally outperform traditional approaches in educational prediction tasks. While Zhang et al. demonstrated the effectiveness of ensemble methods, their study provided limited

insight into the factors influencing model predictions. In contrast, the current study incorporated Explainable Artificial Intelligence (XAI) using SHAP analysis to enhance model transparency. The SHAP results revealed that Time Management and Study Hours were among the most influential predictors of student success, with importance scores of 0.73 and 0.72, respectively. These findings provide actionable insights for educators and administrators by identifying the factors most strongly associated with student performance.

Overall, the results suggest that the proposed Stacking Ensemble model not only achieves superior predictive accuracy but also offers practical advantages through risk stratification, explainability, and deployment readiness. These characteristics make the model a valuable decision-support tool for identifying at-risk students and facilitating evidence-based interventions within the Ethiopian TVT education system.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1 Introduction

This last chapter brings conclusions from the research project, which was geared towards creating a high-performance AI Model for the early identification of At-risk students for student performance prediction in TVT institutions. This chapter summarizes the key findings of the developed machine learning pipeline, which included advanced preprocessing techniques, class balancing and ensemble modeling, from the perspective of the specific research objectives. It also concludes with a reflection on the effectiveness of the model and suggests concrete measures for institutional actors to improve early intervention strategies and academic results.

5.2 Summary of Major Findings

Objective 1: Identify and examine the academic, behavioral and demographic factors that significantly affect students' performances in TVT institutions. It was found that the behavioral and academic characteristics are the best correlates of student success: Time Management had a moderate positive correlation of 0.73 with the final score while Study Hours Per Day had a high positive correlation of 0.72 with the final score. Advanced feature engineering also identified an AttendanceRate of less than 80% as

a significant AttendanceRisk feature and consistently found demographic features such as ParentalEducation and Age as features that affect the probability of risk across all SHAP plots. Social-economic influences (Family Income) were also demonstrated to interact with behavioral factors that impact a student's final performance level.

Objective 2: Design and develop AI Model for Early Identification of At-risk students for forecasting student performance. The study was able to create a complex machine learning pipeline with the incorporation of Random Forest, XGBoost, and CatBoost as base learners, ending up with a Best Stacking Ensemble. To overcome the inherent class imbalance issues with 59.3% of the students belonging to the 'MediumRisk' class, the Synthetic Minority Over-sampling Technique (SMOTE) applied. In addition, systematic Hyperparameter Optimization (HPO) was performed using GridSearchCV. As a result of these efforts, an ensemble model was built that attained an excellent Test Accuracy of 97.09% and an extremely good macro-averaged ROC-AUC of 0.99, with excellent reliability in predicting student outcomes.

Objective 3: To facilitate data-driven decision-making in TVT colleges. In facilitating teaching and learning system using data-driven monitoring of student's status in TVT colleges, the proposed model achieves this objective by grouping the students into three categories based on their likelihood of dropping out of school: HighRisk, MediumRisk, and LowRisk students. This is done through the application of the model where an impressive F1-score of 0.97 is obtained for HighRisk students. Using SHAP (SHapley Additive exPlanations) values, the AI can provide both local and global interpretability, thereby avoiding the "lack of interpretability" and informing the educators which specific factors such as low Study Efficiency and low Academic Strength contribute to the student being at risk.

Objective 4: To propose a scalable framework for AI integration in EMIS. A framework for scalability in this study was ensured by designing the model to utilize common features used in EMIS software including AttendanceRate, PreviousGrade, among other demographic features. The research illustrated how sustainable integration in EMIS could be achieved through persistence of the AI model, whereby it saved the final stacking ensemble model in both pickle and joblib formats for reuse in future.

5.3 Limitation of the study

Most of the data was collected only from Alamata TVT College and the rest in private college this leads to limited scope. Most governmental and private TVT colleges don't have Learning management System (LMS). The data represents one point in time forecasting cognitive or computational mind of students will require longitudinal data tracking students across multiple time points.

5.4 Conclusion

To conclude, the major goal of identifying students' performance risks and categorizing students as “HighRisk”, “MediumRisk” and “LowRisk” has been met in the present dissertation by creating a predictive AI model for accurate prediction. An ensemble model of hyperparameter-tuned Random Forest, XGBoost and CatBoost models has been found to be the highest performing model with a test accuracy of “97.09%” and a macro-averaged ROC-AUC of “0.99”. This degree of model reliability has been reached by selecting a methodology that filters out ‘leakage' variables from the analysis and applies the SMOTE algorithm to balance the classes and identify minority risk classes correctly.

Also, it was stated throughout the research that a prediction in education cannot be a mere difficult, but it should give some recommendations on the educational process. Therefore, with the use of SHAP (SHapley Additive exPlanations), the effect of certain behavioral factors such as Time Management, Study Efficiency and AttendanceRisk were determined and they have significant influence on the performance of the model, which provided an F1-score of 0.97 for predicting student category HighRisk, offering the stakeholders a solid supportive tool for making decisions. Finally, the use of such explainable AI models in the existing systems such as Education Management Information Systems (EMIS) in TVT institutions was recommended to be very beneficial for the enhancement of the students' performance.

5.5 Contributions to the Study

Theoretical Contributions: the research advances the scientific understanding of predictive modeling in education through the following:

Ensemble Learning Extension: The study extends the application of Ensemble Learning theory to Educational IT by showcasing the superior effectiveness of a hierarchical (Stacking) model integrating Random Forest, XGBoost, and CatBoost over traditional single-algorithm models when handling complex, non-linear student datasets.

Aligning Accuracy with Transparency: It enhances model-centric discourse by proving that the combination of SMOTE (for class imbalance) and SHAP (for explainability) can successfully align high predictive accuracy with human-interpretable results, a critical requirement for trust in educational forecasting.

Identification of Success Drivers: The study scientifically validates that Time Management (0.73 correlation) and Study Hours (0.72 correlation) are the primary behavioral drivers of academic success in the TVT context, providing empirical evidence for educational theories on student engagement

Technical Contribution: In this practical / technical contribution the authors we have developed a verified test accuracy of 97.09% Best Stacking Ensemble (SMOTE) model. The study also generated a comprehensive data preprocessing and feature engineering pipeline, adding engineered features of high impact like AttendanceRisk, Study_Efficiency, and Academic_Strength. The final model was saved in .pkl and .joblib formats for easy deployment in the real world as a predictive engine.

Institutional contribution: the better system on early identification of the 'HighRisk' students is available for educational institutions. This enables institutions to shift from "grading" students to "intervening" students – more precisely, those that are identified as low attendance or do not manage their time well, to enhance their retention and success rates.

Policy Contribution: The study offers a policy agenda for data-driven ICT policies in TVT colleges, calling for the shift from Education Management Information Systems (EMIS) from mere record-keeping systems to dynamic digital monitoring systems. It identifies policy implications for monitoring behavioral metrics (E-Learning Engagement and Attendance Rates) as regular institutional metrics.

5.6 Recommendations

The TVT College: It is recommended that the institution adopts the developed Stacking Ensemble model into the existing student monitoring system of the institution. The SHAP interpretability reports should be used by the administrator to give a counselor specific reasons (low Study_Efficiency for instance) for the students being identified as at-risk.

The industry: Educational software developers should focus on introducing Explainable AI (XAI) features, such as the ones used in this project, to make sure that the outcomes of the predictive models are understandable and useful to non-technical educators.

For Policy makers and Government: TVT colleges should have a standardized mandate to collect and clean behavioral data to have the assurance that indicators such as Time Management and Attendance predict success more than traditional demographic data.

5.7 Future Work

Integration with Cloud-Based EMIS/ Mobile Services: An important development and next step is the integration of the model into a mobile system giving real-time "Risk Alerts" to both the instructor and students' mobiles such as family (guardians).

Enhance Accuracy and Usability: The present accuracy is already good; further studies could investigate Deep Learning techniques, or Transformer-based models, for greater accuracy. Furthermore, the system could be made more user-friendly by creating an automated dashboard.

Appendix

```
# Remove missing FinalScore first
Student_data = Student_data.dropna(subset=['FinalScore'])

# Remove duplicates
Student_data = Student_data.drop_duplicates()
```

```
from sklearn.preprocessing import LabelEncoder

# List of categorical columns
cat_cols = ['Gender', 'ParentalEducation', 'Family_Income', 'StudyEnvironment', 'MotivationLevel']

# Create a LabelEncoder object
le = LabelEncoder()

# Apply LabelEncoder to each categorical column
for col in cat_cols:
    Student_data[col] = le.fit_transform(Student_data[col])

# Check the first few rows to confirm encoding
Student_data.head()
```

Create target variable

```
  import pandas as pd

  Student_data['Performance_Level'] = pd.cut(
      Student_data['FinalScore'],
      bins=[0, 65, 85, 100],
      labels=['HighRisk', 'MediumRisk', 'LowRisk'],
      include_lowest=True
  )

  # Remove any remaining missing target
  Student_data = Student_data.dropna(subset=['Performance_Level'])
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

# 2. Define base model
rf = RandomForestClassifier(random_state=42)

# 3. Define parameter grid (what to search)
param_grid = {
    'n_estimators': [100, 200, 300], # Increased options
    'max_depth': [5, 8, 12, None], # None means no limit
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
    'max_features': ['sqrt', 'log2', 0.8] # 0.8 means 80% of features
}

# 4. Create GridSearchCV object
grid_search_rf = GridSearchCV(
    estimator=rf,
    param_grid=param_grid,
    cv=5, # Using 5-fold cross-validation
    scoring='accuracy', # Optimize for accuracy
    n_jobs=-1, # Use all available cores
    verbose=1 # Show progress
```

```
from sklearn.model_selection import cross_val_score

print("CV Accuracy:", cross_val_score(best_rf, X_train, y_train, cv=cv).mean())
```

```
CV Accuracy: 0.8937483373237564
```

Bureau Mekele TVET TIGRAY

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ALAMATA TECHNICAL COLLEG

Rf/No/ATC- 2112/08

Date 16/04/2026 G.C

To: FDRE TVT Institute
Attn: Research and Dissemination Directorate

Subject: Response to Request for Collaboration and Data Access for Postgraduate Research

Dear Sir/Madam,

We are pleased to acknowledge receipt of your letter requesting collaboration and data access support for the postgraduate research of Mr. Solomon Chekole Tesfaye, with reference number RD/08-99/18.

We appreciate the relevance and importance of the research titled *"AI-Based Predictive Analytics Model for Students' Performance Prediction in Ethiopian TVET Colleges: A Case Study of Alamata TVET College."* This initiative is valuable in improving academic planning, student performance monitoring, and institutional decision-making.

In response to your request, Alamata TVET College is pleased to collaborate and provide the necessary support for the successful implementation of this research. We agree to grant access to relevant student datasets, including academic records, attendance, and performance-related information for the specified period. Access will be coordinated through the appropriate office of the college, under the following conditions:

1. All data must be used strictly for academic and research purposes.
2. Confidentiality and privacy of student information must be fully maintained.
3. Any publication or report arising from this research should properly acknowledge Alamata TVET College.
4. The researcher must comply with institutional data protection policies and ethical standards.

We believe this collaboration will contribute significantly to improving educational outcomes and strengthening research partnerships between our institutions.

Please feel free to contact us for any further clarification or coordination.

We wish Mr. Solomon Chekole Tesfaye success in his research work and look forward to a productive collaboration.

Yours sincerely,

Haile Gebreyohanes
Dean, Alamata TVET College

Date: 16/04/2026 G.C

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