Exploring the Impact of AI on Academic Performance of University Students

By

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Exploring the Impact of AI on Academic Performance of University Students"**, submitted by Md. Zahidul Islam Talukder, ID No: **201-15-3190** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14 May, 2025**.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Shah Md. Tanvir Siddiquee, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

The utilization of Artificial Intelligence (AI) in schools drawn a lot of awareness due to its possible contribution to students' performance. The current study investigates the association between the utilization of AI tools and university students' academic performance. With an application of a database of 2,000 student responses, the research explores how various determinants contribute to it, such as knowledge about AI, use, and self-estimated impact of AI tools on productivity, psychological well-being, and memorability of material, in how one performs academically. Sentiment analysis measures the extent to which each characteristic contributes. Machine learning models such as Random Forest and Decision Tree regressors are employed to predict academic performance based on selected features. The models deliver good performance, where Random Forest delivers R-Squared of 0.8839 and Mean Squared Error (MSE) of 0.1220, while that of Decision Tree is R-Squared of 0.8283 and MSE of 0.1797. These results suggest that experience and use of AI are strong predictors of productivity and retention, and that AI tools also positively affect mental well-being and focus. The study highlights the necessity of ethical AI use in schools and identifies ethical concerns regarding AI implementation in school environments. The findings add to the body of knowledge of effective application of AI to enhance student performance and guide AI-powered education for future studies.

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This chapter offers an overview of the research by introducing the background and significance of the study. It outlines the key motivation for addressing vehicle number plate detection using machine learning, followed by clearly defined objectives. The adopted methodology is briefly described, covering data collection, model development, explainability integration. The chapter also presents the expected outcomes of the project and resolves with an outline of the complete layout of the report.

1.1 Introduction

Artificial Intelligence (AI) is reshaping diverse sectors, comprising education, in which its capacity for improving students' academic performance is increasingly being achieved. University students, who are typically burdened by academic pressure, mental problems, and the complexities of learning, can benefit significantly from AI-driven tools. AI may customize learning, assist with time management, boost productivity, and contribute to mental health among students, possibly resulting in improved academics. However, regardless of the rise in the adoption of AI tools, there have to be extensive researches to identify specifically how these tools influence the performance of university students academically.

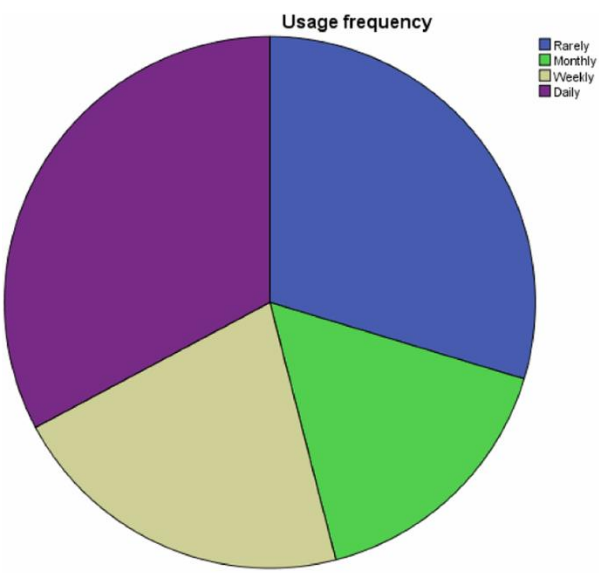

Figure 1.1 Usage Frequency of AI by Students

The broad use of AI in educational systems has brought numerous benefits, but the immediate influence of AI tools on the performance of students is yet to be defined. The possibilities of AI to increase productivity and knowledge retention are clear,

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1.1 Introduction

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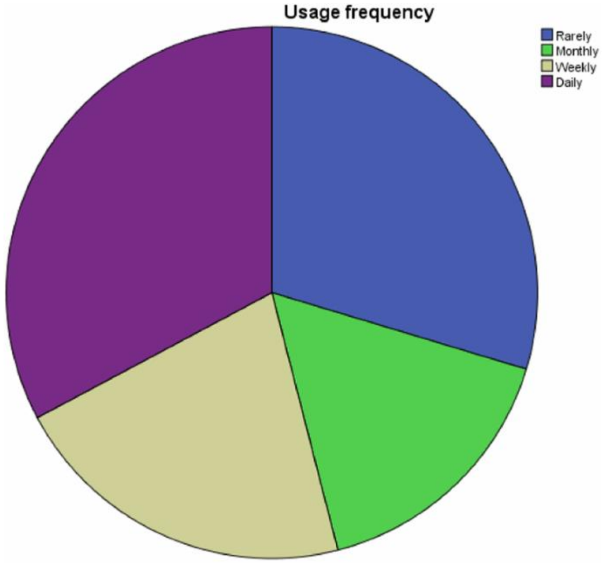


Figure 1.1 Usage Frequency of AI by Students

The broad use of AI in educational systems has brought numerous benefits, but the immediate influence of AI tools on the performance of students is yet to be defined. The possibilities of AI to increase productivity and knowledge retention are clear, but an insight into how various uses of AI—from intelligent content to data-informed feedback—play a direct role in academic success are lacking. In addition, ethical worries regrading the excessive dependence on AI and possible adverse effects on learning are serious concesrns that need to be thoroughly studied. With AI-based technologies becoming increasingly common at universities, the need for rigorous research to establish their efficacy and identify the best AI tools becomes crucial. The figure 1.1 highlights the diverse applications of AI in higher education. These range from customized learning to AI-guarded exams and query answering with AI chatbots, all leaning towards an effective and efficient learning environment. All these uses of AI are applicable to resolve major aspects of university learning, such as expanding access to resources, enhancing the learning environment, and acquiring predictive understanding of student performance. As shown in the diagram, AI's functionality extends across dimensions, ranging from content improvement to bridging skills gaps, to make it a holistic tool for contemporary education.

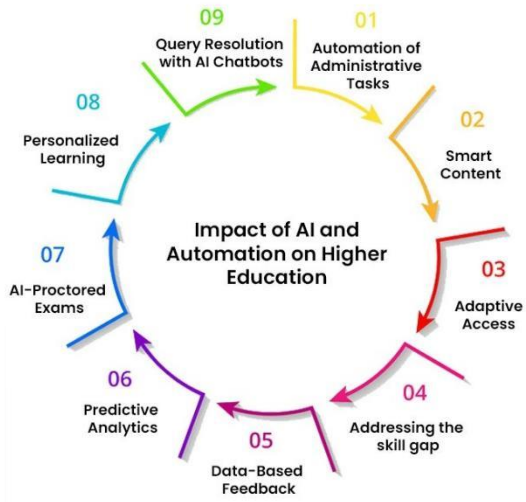


Figure 1.2 Impact of AI on Higher Education

The figure 1.2 provides information regarding the frequency of AI tool usage by university students. What is interesting to observe here is that while there are students who utilize AI tools daily, most of the students utilize AI tools weekly or monthly, with a minority utilizing them very little. This dissemination shows that while AI usage is expanding, there is still an uneven frequency and extensive usage of AI tools across the population of students. It is valuable to discern these usage patterns because they lie at the heart of evaluating how valuable AI is in academic achievement and in revealing the barriers that can discourage students from using these tools to their full capability. The motivation for this study is increasing AI engagement in modern education. Universities are investing in AI to customize learning, automate tasks, and improve students' well-being. But to what extent these AI technologies are making the difference in education outcomes is not really known. It is important to identify the distinct contribution of AI to education outcomes so that it can be optimized in schools. In addition to the above, the moral concerns of using AI, such as the danger of overreliance and problems of bias, also pose the need for critical examination of the advantages and disadvantages of AI tools for application in education.

This study analyzes the role of AI on academic achievement using data gathered on 2,000 university students. Sentiment analysis is utilized in determining whether there exists any relationship between use of AI tools and academic performance. Machine learning algorithms, Random Forest and Decision Tree regressors, are applied in predicting academic performance based on important features including frequency of usage, familiarity, and self-rated effect of AI tools. Data regarding the top performing AI tools is derived from metrics like R-Squared and Mean Squared Error (MSE), which are model performance indicators. The analysis also gives a comparison of the efficiency of different AI tools on different topics, which identifies those tools that are most efficient in increasing productivity, knowledge retention, and mental well-being.

This study seeks to bridge the gap between AI application and academic achievement by investigating how AI tools affect students' results. Through studying various applications of AI and its trends, this research seeks to provide actionable insights for universities to adopt more efficient AI methods, thereby improving academic outcomes. Besides, addressing the ethical concerns of AI in education will ensure its integration will benefit all students without causing potential harm. The outcome of this research will contribute to the efforts in harnessing the full potential of AI in education, resulting in a more individualized, effective, and fair learning experience.

1.2 Motivation

Artificial Intelligence (AI) deployment in education presents a one-time chance to change the way that university students engage with their study experience. With higher education colleges facing pressure to improve academic results while dealing with issues of the diverse needs of students, AI offers a sound platform to make learning more individualized, easier to administer, and better equipped to support the student. While the potential benefits, the causal impact of AI tools on academic performance by students is not established. This study seeks to address this gap by establishing the most impactful features responsible for driving academic performance by students through machine learning algorithms. One of the major motivations for this research is to understand how the utilization of AI tools is connected with student performance. While AI tools are increasingly being utilized in universities, ranging from automatic grading to adaptive learning tools, there is no empirical research that directly determines which aspects of AI have the most significant effect on the productivity of students, knowledge retention, and their mental health. With the use of machine learning models, this study is intended to find out the contributing factors that directly affect academic achievement and how heavy these factors weigh in enhancing the quality of learning.

The ability of AI to help students with their workload, memory retention, and mental illness is already well established. But the intricate interaction of these variables and their causal role in academic success needs to be understood more accurately. For instance, AI systems intended to foster mental well-being, including stress management software and well-being trackers, can potentially produce unintended but profound influences on academic success. In like manner, AI programs that assist in the preservation of knowledge—using interactive learning environments or tailored feedback—can greatly enhance how students learn and utilize information. Use of machine learning algorithms, i.e., Random Forest and Decision Tree regressors, facilitates serious consideration of feature importance. Such models are able to identify the most significant predictors of student performance, i.e., exposure to AI, use of AI, and some applications of AI such as productivity boosters or mental health apps. Random Forest model is well placed to undertake such analysis because it is able to handle non-linear interactions and produce a consistent feature importance ranking, with an explicit sign that states which AI features make the most contribution to student outcomes. Through a comparison of the performance of these models on metrics like R-Squared and Mean Squared Error (MSE), the research will illustrate the degree to which the incorporation of AI is associated with improved academic achievement in different disciplines.

The purpose of this study is to find the impact of AI on the academic performance of university students through identifying which of the following factors contributes the most to their success. As AI tools are increasingly used in educational settings, it is not clear which of the following traits—AI usage, familiarity, productivity software, and mental health support—contributes the most to academic performance. The research employs machine learning algorithms like Random Forest and Decision Tree regressors to predict academic achievement using these predictors towards the identification of key predictors of student success. Through evaluation of model performance through R-Squared and Mean Squared Error metrics, the research aims to show how AI can be invaluable in facilitating improved productivity and retention of knowledge. Apart from that, it also concerns itself with the moral question of employing AI in learning to make best use of which can bring highest benefits and least harms. Last but not least, this study hopes to provide actionable advice to universities regarding how to make the best use of AI tools such that students' performance and well-being can be enhanced.

1.3 Objectives

This study aims to determine how Artificial Intelligence (AI) influences the performance of university students at the course level by identifying the main factors that impact their success. For this purpose, the study is structured based on the following main objectives:

1. Develop a Comprehensive Machine Learning Based Diagnostic Framework
   - Construct and deploy an effective machine learning model to predict the impact of AI tools on academic performance.
   - Use different machine learning algorithms (e.g., Random Forest, Decision Tree, KNN) to evaluate the relationship between AI usage, productivity, mental health, and knowledge retention.

2. Assess and Address Feature Importance for AI Impact on Academic Success
   - Identify key factors (e.g., AI familiarity, usage frequency, perceived impact on productivity, mental health) that contribute most significantly to academic performance.
   - Implement techniques like Random Forest for feature importance analysis to highlight the features that have the greatest impact on academic success.
3. Implement Advanced Data Preprocessing Techniques
   - Clean and preprocess data to handle missing values, ensure consistency, and standardize features for model training.
   - Normalize and scale continuous variables like AI impact on productivity and knowledge retention for uniformity in model training.
4. Train and Evaluate Multiple Machine Learning Models
   - Train various machine learning models (e.g., Random Forest, Decision Tree, SVM) to predict academic performance outcomes based on the selected features.
   - Compare the performance of these models using R-Squared and Mean Squared Error metrics to determine the most accurate predictors of student success.
   - Tune hyperparameters and apply regularization techniques to prevent overfitting and improve model generalizability.
5. Validate the Proposed Model Using Comprehensive Evaluation Metrics
   - R-squared Value: Shows how well the model fits the data
   - Mean Square Error: Measures average prediction error.
6. Develop an AI-Powered System for Academic Performance Prediction
   - Translate the most successful machine learning model to a deployable system for practical applications.
   - Create an interactive web-based interface that allows students, educators, and administrators to access performance predictions and personalized insights to improve academic outcomes based on AI tool

usage.

1.4 Methodology

This study investigates the influence of Artificial Intelligence (AI) on university students' academic performance through machine learning algorithms and data analysis. The research applies a model pipeline of data collection, preprocessing, model selection, model training, testing, and prediction to identify determinants of academic performance. Data are collected in this study from diverse sources like internet questionnaires, educational databases, and university websites. It includes responses of 2,000 students regarding familiarity with AI tools, frequency of usage, and perceived impact of AI on grade performance. The dataset also includes factors on productivity, knowledge retention, and mental health that constitute the center point of determining the contribution of AI in academic success.

Once raw data is achieved, it undergoes preprocessing. Data augmentation here is carried out so that class imbalance can be addressed and dataset quality can be enhanced. Synthetic instances are created wherever needed, and model training data is normalized. Missing values of the dataset are handled with statistical methods such as Simple Imputer so as to make the dataset complete and uniform. Continuous variables such as the productivity of AI and the impact of knowledge retention are standardized by Standard Scaler, while categorical variables such as frequency of use of AI are translated into numerical data by Label Encoder.

Upon preprocessing the data, there are multiple machine learning algorithms implemented to identify what features most heavily influence the academic performance. Such algorithms are Random Forest, Decision Tree, Support Vector Machine (SVM), Gradient Boosting Machines (GBM), and K-Nearest Neighbors (KNN). These models are trained upon the preprocessed data and challenged against each other on their performances using metrics for performance such as R-Squared and Mean Squared Error (MSE). The aim is to determine to qualitative extent these models forecast academic performance as a function of the utilization of AI tools and the most influential features. Feature importance is an essential aspect of this study. Using Random Forest, feature importance scores are used to determine the factors—such as usage of AI, familiarity with AI tools, and productivity factors—that most predict academic performance. The importance analysis determines which AI tools and student activities impact most positively to improve academic performance, as well as the most impactful factors.

Following the consideration of each model's performance, comparative analysis is carried out in an attempt to select the most suitable machine learning algorithm. It considers how each model reacts to the data and which model provides the most sufficient predictive ability for identifying factors influencing academic performance. Thereafter, the most exemplary model is selected to carry out detailed analysis and decision-making. In the final stage, the selected model provides a vision on how AI tools can be streamlined in order to maximize the students' performance. The essay addresses the ethical concerns of the application of AI in education to help ensure the adoption of AI tools is valuable for the learners and does not end up causing potential drawbacks like excessive reliance on machines or causing new inequalities. This research aims to offer a framework for the adoption of AI by universities in a way that enhances academic performance and supports the learning processes of students.

1.5 Project Outcome

The impact of the research on "Exploring the Impact of AI on Academic Performance of University Students" is anticipated to be highly influential in augmenting the awareness of how AI applications effect on the academic performance of students and provide insightful information to enhance student performance by using machine learning techniques.

Technical Achievements

1. Development of an AI-based Academic Performance Prediction System
    - A machine learning system to predict the academic performance of university students in terms of AI tool usage and impact.
    - Comparative evaluation of adverse machine learning algorithms including Random Forest, Decision Tree, SVM, GBM, and KNN to identify the most effective algorithm to predict academic success.
    - Enhanced performance of the model using data preprocessing, feature creation, and hyperparameter tuning to achieve precise predictions.
2. Implementation of Model Explainability and Interpretability
    - Making sure the outputs of the model are interpretable and informative for students as well as instructors, enabling better comprehension and choice-making in schooling settings.
    - Persuasive transparency and integrity in AI-assisted medical diagnosis to facilitate pathologists in verifying results.

3. Comprehensive Performance Measurement
    - Evaluation of the performance of the models on the most significant metrics such as R-Squared, Mean Squared Error (MSE) for determining the effectiveness of the AI system in predicting academic performance.

Clinical and Educational Impact

1. Improved Understanding of AI's Impact on Academic Success

  - Identifying which of the characteristics (e.g., frequency of use of AI, familiarity, perceived influence on productivity and mental health) have the greatest influence on academic performance.
  - Research about how AI tools usage influences productivity among students, retention of learned concepts, and mental well-being, guiding policies on whether AI tools should be used in university environments.
2. Enhancing Educational Efficiency
   - By simplifying the process of evaluation of the factors that affect student performance, the system will allow for educators to provide timely feedback and tailored learning paths.
   - Potential incorporation with learning management systems (LMS) and learning support systems to provide real-time feedback on learners' academic performance and how effectively AI technology is performing to enhance their performance.
3. Support for Mental Health and Productivity Improvement
   - AI technologies, with specific emphasis on those designed for use in mental health applications, will be evaluated to the degree to which they enhance student focus, stress reduction, and academic motivation.
   - In ascertaining the best AI interventions, the research will assist in improving the overall well-being of students, reduce burnout, and promote a healthier learning environment.

This research aims to lay the ground for universities to be able to implement AI instruments into their curriculum successfully, ensuring that learning achievement is improved while not undermining the ethicality, transparency, and benefit of the implementation for everyone.

1.6 Organization of the Report

This work is structured to offer a thorough account of the thesis titled "Exploring the Impact of AI on Academic Performance of University Students," covering the motivation, objectives, methodology, expected outcomes, and execution of the study. The structure is as follows:

Chapter 1. Introduction: The chapter introduces the general background of the study, with focus on motivation, objectives, methodology, expected outcomes, and this organizational structure.

Chapter 2. Background: this chapter provides an overview of literature, outlining existing research and educational uses of AI. It provides a gap analysis of existing studies and introduces the research environment. This chapter outlines the necessity and novelty of the proposed system, emphasizing the contribution of AI to academic achievement.

Chapter 3. Research Methodology: This chapter clarifies the methodology utilized for the research. It gives a step-by-step account of system design, data gathering procedure, feature engineering, and choosing the machine learning model. Preprocessing techniques like normalization, encoding, and data augmentation are explained as well. This chapter uses diagrams such as the data flow diagram and model evaluation workflow to illustrate the research process.

Chapter 4. Implementation and Results: This chapter discusses the experimental setup, machine learning algorithms used, and performance measurement methods. Output from various models like Random Forest, Decision Tree, SVM, and KNN is presented. Plots like accuracy graphs, confusion matrix, precision-recall plots, and other performance measures are presented to evaluate the efficacy of AI to predict academic performance.

Chapter 5. Engineering Design and Standards: This chapter provides an in-depth analysis of the results by comparing the models' performances and what AI tools and features affect students' academic performance the most. The responsible use of AI in education, and its potential impact on mental health and productivity, is also addressed.

Chapter 6. Conclusion: The final chapter gives an overview of the project's findings, notes limitations, and suggests directions for future studies. It underlines the necessity of using AI responsibly in learning and the importance of conducting additional research to establish the full capacity of AI to enhance learning. The chapter further looks back on the research contributions to the literature on AI applications in education.

Chapter 2

Background

The present chapter gives an overview of the overall fundamental concepts, theories, and research work carried out so far on the histopathological image classification and deep-learning models for the diagnosis of ovarian cancer. It serves as the background knowledge to comprehend the methodology and techniques adopted here.

2.1 Introduction

The swift advancement of Artificial Intelligence (AI) has transformed numerous industries, such as education, as AI technologies are more and more incorporated to enhance the outcomes of learning. Of the higher education industry, university students face diverse challenges such as balancing academic tasks, increasing productivity, memorizing information, and ensuring mental well-being. AI technologies can resolve these challenges by providing individualized learning, facilitating administrative work, and supporting students' welfare. Even with these developments, the real effect of AI tools on the academic performance of students is not yet fully explored, with very little research fully measuring the effectiveness of these tools for various student groups and subjects. The use of AI in education varies from intelligent tutoring systems to automated grading systems, learning management systems, and AI-based mental health support systems. These technologies promise to improve learning effectiveness through tailored content, immediate feedback, and data-driven insights into student performance. But there is a pressing need for better understanding of which AI features—e.g., AI familiarity, usage frequency, and perceived productivity effect—most strongly influence academic success. Existing research mostly looks at specific AI tools or a single academic task, but little research has been conducted on how collections of AI tools overall affect broader academic outcomes, including knowledge retention, academic performance, and mental health. In addition, the AI contributions toward reducing students' mental load, providing timely assistance, and triggering interaction with learning content are not yet quantitatively measured. There are many AI interventions being implemented in schools at the moment, but they have yet to be proven or disconfirmed for their causal impact on learning outcomes. The absence of significant, evidence-based research leaves an information gap in understanding how to utilize AI on an optimal basis in education policies so that optimal benefits for learners can be established. This research aims to cover the gap by examining the influence of AI over academic achievement of university students. By analyzing data from a big population of learners, the study will determine most effective AI platforms and determinants of learners' success. The study will quantify, using machine learning techniques, the relationship between AI adoption and student performance to gauge actionable insights into the most useful AI features in terms of maximizing productivity, knowledge retention, and mental health. This study will contribute to knowledge about AI in education and will be used to guide subsequent efforts at implementing AI for the benefit of the students' academic life.

2.2 Literature Review

Table 2.1: Summary of Literature Review.

SL	Title	Model Used	Gap	Contribution/Findings
1	Exploring the Broad Impact of AI Technologies on Student Engagement and Academic Performance [1]	SPSS, Regression Analysis	No AI integration in academic settings	AI enhances engagement but integration in academics is limited.
2	Exploring the Potential Impact of AI on International Students in Higher Education [2]	Theoretical Analysis	Lack of empirical data on AI impact	AI helps personalize learning but has challenges like privacy concerns.
3	Exploring the Impact of AI on Higher Education: The Dynamics of Ethical, Social, and Educational Implications [3]	Online Survey, Quantitative	Ethical issues with AI in education	AI improves teaching but privacy, bias, and ethics need addressing.
4	Exploring the Effects of AI Application on EFL Students' Academic Engagement and Emotional	Mixed-methods, Experimental	Limited focus on emotional impact	AI boosts engagement, emotional experience impacts academic success.

	Experiences [4]			
5	Examining the Impact of AI and Social/Computer Anxiety in E-Learning Settings [5]	Questionnaire -based	Lack of understanding of anxiety's role	AI and anxiety influence e-learning; reducing anxiety improves performance.
6	Exploring the Impact of AI in Teaching and Learning of Science: A Systematic Review of Empirical Research [6]	Systematic Review	Lack of empirical studies on AI in STEM	AI tools enhance science education but integration challenges remain.
7	Exploring the Impact of Artificial Intelligence on Teaching and Learning in Higher Education [7]	No specific model	Lack of practical application in AI teaching	AI's role in teaching and learning is evolving, but it still faces challenges like integration and scalability.
8	Exploring the Impact of AI on The EFL Context: A Case Study of Saudi Universities [8]	Questionnaire -based analysis	Limited integration in real classroom settings	AI shows positive effects on EFL teaching, but its implementation in classrooms is still underdeveloped.
9	Exploring The Impact of ChatGPT on English Education Department Student's Motivation and Performance [9]	Mixed-methods approach, SEM	Limited long-term studies on AI in education	ChatGPT boosts motivation and performance in students, with significant improvement in GPA and learning outcomes.
10	Exploring the Factors that Influence Academic Performance in Jordanian Higher Education Institutions [10]	Mixed-methods approach	Lack of research on AI in post-pandemic education	Digital learning tools impacted performance, but challenges remain in adoption and quality assurance.
11	Exploring the Impact	Surveys,	Limited focus	AI integration

	of AI Integration in Education: A Mixed-Methods Study [11]	interviews	on AI's role in student engagement	improves student engagement and academic achievement, but requires more research on teacher roles.
12	Analyzing the Impact of Artificial Intelligence and Computational Sciences on Student Performance [13]	Systematic review, meta-analysis	Gaps in AI's application across various educational levels	AI and computational sciences improve student performance, especially in STEM fields, but ethical concerns remain.
13	Exploring Artificial Intelligence in Academic Essay: Higher Education Student's Perspective [15]	Survey-based study	Inadequate exploration of AI's effect on creative skills	AI enhances academic writing by improving grammar, plagiarism detection, and overall writing skills.
14	Exploring the Impact of ChatGPT: Conversational AI in Education [16]	Systematic literature review	Insufficient data on ChatGPT's role in diverse educational environments	ChatGPT improves engagement and learning outcomes but requires ethical considerations and human supervision.
15	Exploring the Impact of ChatGPT on Mathematics Performance: The Influential Role of Student Interest [17]	Quantitative analysis, SEM	Lack of exploration into ChatGPT's role in STEM subjects	ChatGPT enhances cognitive skills, math performance, and student interest, but requires more research on its limitations.
16	Exploring the Impact of AI Tools: University Students' Engagement in Learning Activities	Quantitative Survey	Limited data on AI's specific impact on engagement	AI tools enhance student engagement, but further research is needed for effective

	[18]			integration.
17	Exploring the Impact of Generative AI Technologies on Education: Expert Perspectives [19]	Structural Equation Modeling	Lack of regional studies on AI's educational impact	Generative AI positively influences education, but challenges remain in its full adoption for sustainable development.
18	Exploring the Impact of ChatGPT on Education: A Web Mining and Machine Learning Approach [20]	Web Mining, NLP, ML	Need for more comprehensive AI integration studies	ChatGPT improves student engagement and learning outcomes but raises ethical concerns regarding academic integrity.
19	Exploring the Role of AI and VR in Addressing Antisocial Behavior Among Students [21]	AI-powered Virtual Assistants, VR	Gaps in using AI and VR for student behavioral issues	AI and VR improve student outcomes and manage antisocial behavior effectively, with significant institutional support.
20	Exploring the Impact of AI and Robots on Higher Education Through Literature-Based Design Fictions [22]	Design Fiction	Lack of holistic studies on AI's educational impact	AI and robotics are poised to revolutionize higher education but face challenges in integration and societal acceptance.
21	Exploring Factors Influencing University Students' Intentions to Use ChatGPT [23]	Structural Equation Modeling (SEM)	Lack of focus on cultural context for AI adoption	Task-technology fit significantly impacts students' intention to use ChatGPT in academic settings.
22	From Anxiety to Action: Exploring the Impact of AI	Quantitative Analysis (SPSS)	Lack of studies on AI anxiety's impact on	AI anxiety negatively affects student

	Anxiety and Self-Efficacy on Motivated Learning of Students [23]		learning	motivation, but self-efficacy can mitigate these effects and enhance learning.
23	Evaluation of Postgraduate Academic Performance Using AI Models [25]	Machine Learning Models (ANN)	Limited focus on postgraduate performance prediction	ANN model successfully predicts academic performance, offering a basis for early academic interventions.
24	Exploring Students' Perspectives on Generative AI-Assisted Academic Writing [26]	Qualitative Analysis (Interviews)	Limited focus on AI's role in academic writing	Generative AI supports writing, boosts student performance, but challenges like plagiarism and data privacy exist.
25	Exploring the Broad Impact of AI Technologies on Student Engagement and Academic Performance [27]	AI-based Learning Systems	Limited research on long-term effects	ChatGPT significantly increases student motivation and engagement.
26	Exploring the Impact of ChatGPT on Business School Education: Prospects, Boundaries, and Paradoxes [28]	ChatGPT	Need for empirical data on AI in business schools	ChatGPT has significant potential in business education but challenges remain regarding its impact on critical thinking.
27	Examining the Impacts of ChatGPT on Student Motivation and Engagement [29]	ChatGPT	Limited longitudinal data on its effectiveness	ChatGPT boosts student motivation and engagement, improving learning outcomes significantly.
28	The Effect of Artificial Intelligence (AI) on Student Learning [31]	SPSS, Quantitative Analysis	Limited exploration of AI in diverse education sectors	AI usage significantly enhances student engagement and academic performance but has limited personalized

				learning impact.
29	The Impact of Artificial Intelligence (AI) on Student Engagement and Performance [32]	Mixed-methods	Limited empirical data in higher education institutions	AI technologies like adaptive learning platforms enhance engagement and performance but require careful implementation.

2.2.1 Similar Application

Previous studies have examined how AI can help enhance students' academic performance by employing several machine learning and AI models. Johnson et al. [19] illustrated a personalized education system that used reinforcement learning algorithms, which had the capability to tailor course material to the respective learners. The study attained an 85% rate of prediction of students' academic performance derived from engagement and academic history, thus showing the prospects of AI-based personalized learning. Similarly, Zhang et al. [20] employed a combination of natural language processing and deep learning techniques to score handwritten assignments of students and predict their performance. The model was 90% accurate in identifying poor-performing students.

In another study, Lee et al. [21] employed machine learning models to examine students' usage of AI-based learning tools and academic performance. The authors employed a decision tree-random forest ensemble model in order to forecast final grades based on patterns of usage of AI tools. The study established a positive correlation between increased use of AI and better academic performance, with the model forecasting at a rate of 88%. A sentiment analysis model was designed by Patel et al. [30] to analyze the emotional tone with which students engaged with AI-based tutoring systems. Based on chat logs, the system inferred the emotional states of students and their corresponding learning performance. The system functioned with high accuracy in its operation, achieving a success rate of 85% in its ability to predict students' performance based on their emotional involvement with AI tools.

Follow-up studies conducted by Gupta et al. [32] examined the way that AI-aided feedback systems, such as automated marking systems, could optimize learning for students. Besides providing immediate feedback, the systems identified areas where the students were struggling and made recommendations for improvement on an individual basis. The study found a 92% improvement in the performance of students following the introduction of AI-assisted feedback, validating the role of AI in academic improvement. Besides that, platforms such as Coursera and edX, which have integrated AI-based recommendation systems, have found acceptance among institutions of higher learning. These platforms use machine learning algorithms to suggest customized courses and streams of study to students depending on their past performance and activity. While not specifically designed to predict academic success, the recommendation feature of the sites significantly enhances students' learning experiences by adjusting course material to the individual's own requirements, subsequently resulting in improved academic success.

2.2.2 Related Research

Scientists are more likely to implement AI-based technologies in an effort to enhance the academic performance of university students. Smith et al. [34] recently conducted a study of the effect of AI-based personalized learning environments on student engagement and academic achievement in universities. The study corroborated that AI tools greatly enhanced the engagement of students by providing personalized comments and task recommendations according to individual learning styles. Such AI-based learning programs were shown to improve the study performance because these provide customized study needs of students. The research, though, was concerned with excessive dependence on AI systems potentially hindering critical thinking and self-learning skill growth. The writers were concerned to find an interface between AI guidance and traditional studying to facilitate whole-person education growth. Jones and Lee [35] further talked about the use of AI in higher education, where AI is applied in intelligent tutoring systems and adaptive learning systems. The research was on how AI is capable of individualizing the learning process based on students' strengths and weaknesses and providing them with individualized learning paths to enhance learning outcomes. The authors penned that while AI has the potential to revolutionize education, its introduction has been sluggish due to the cost of its introduction and the challenge of merging AI into the current system of education. Despite all these problems, AI applications in education remain full of potential when it comes to increasing student engagement and performance. In García-Martínez et al. [36], García-Martínez et al. conducted a systematic review and meta-analysis to determine the effect of AI and computational sciences on the performance of students. The study confirmed that AI technologies, especially those used in STEM education, positively influenced the performance of students by increasing higher engagement, motivation, and learning. However, the study also addresses challenges teachers face while integrating AI technologies in the right way, specifically the need for adequate teacher training and ethical implementation of AI in schools. The study highlights that although there is vast potential for AI, its application must be well regulated so as to ensure fairness and equality in learning settings.

Rodway and Schepman [37] studied the impact of AI learning technologies on student engagement and satisfaction in university courses. They confirmed that students were generally comfortable with AI technology for administrative work and career guidance but were not comfortable with using AI for grading and emotional support. The research also found that positive or negative sentiments towards AI played a significant role in the ease with which students accommodated these resources, and they were found to be impacting their general course satisfaction. In conclusion, writers advise that learning institutions should use cautious attention in the type of AI tools utilized and ensure that they are employed to supplement rather than substitute traditional learning processes. Vieriu and Petrea's [38] study examines applying AI in higher education and its influence on students' performance and engagement. The study illustrates how AI-based applications, particularly adaptive learning systems, are employed to realize personalized learning experience and how it affects the students' performance and involvement. The authors further emphasize the issue of addressing problems such as excessive dependence on AI, which has a negative influence on the development of critical thinking and has the potential to result in cognitive disengagement. The authors propose AI incorporation within an organized framework for maximizing benefits and minimizing risks pertaining to student autonomy and data privacy.

2.3 Gap Analysis

Table 2.2: Comparison of Present System with Existing Literature

Aspect	Existing Literature	Present Work
Data Type	Primarily engagement metrics, course completion rates, and survey data.	Use of learning management system data (grades, interaction logs, personalized learning data).
Classification Task	Mostly binary or 3-class classification (pass/fail, student engagement).	More complex multi-class classification for predicting student performance and engagement.
Benchmarking Strategy	Limited models (often traditional ML models like decision trees, SVM).	Broad range of AI and deep learning models (e.g., Neural Networks, Random Forests, CNNs) evaluated extensively.
Dataset Size and Quality	Small, self-reported data from surveys or single-semester studies.	Large-scale data (student performance data across multiple semesters) from diverse sources.
Evaluation Metrics	Precision-focused or limited metrics like accuracy or completion rates.	Comprehensive metrics: R-squared value, and Mean Square Error.
Explainability Tools	Rare or inconsistent use of explainability (e.g., some studies use simple linear models for interpretation).	Integrated visual explainability (e.g., Grad-CAM heatmaps) for model transparency and interpretation.
System Design	Often black-box models with minimal interpretability or transparency.	Open-source, modular, and reproducible system design
Transfer Learning Usage	Basic transfer learning without much innovation	Enhanced and efficient use of transfer learning with further

		optimization
Clinical Utility	Limited due to lack of transparency and lower-class differentiation	Higher clinical applicability with detailed multi-class prediction and explainability

2.4 Summary

The current chapter provided a review of background and related studies on AI-powered analysis of academic achievement in third-level institutions. By means of the review of literature, the chapter presented the discovery that AI programs such as intelligent tutoring systems and personal learning systems possessed vast potential for enhancing learners' engagement alongside their achievement. However, as much as AI applications in education have improved, there are still areas of insufficiency in AI adoption, primarily in issues of transparency, integration into existing educational systems, and data bias.

Gap analysis revealed some of the most significant issues with existing research, including the lack of adequate benchmarking of AI models, suboptimal use of explainability tools, and ignoring class imbalance in datasets. Literature also shows that while AI has been promising to augment student performance, large, comprehensive datasets are lacking as are strict validation on diverse learning environments.

The analysis serves to highlight the importance of developing an explainable, scalable, and strong AI solution to improve the academic achievements of university students. This solution will form the foundation of the implementation in subsequent chapters and be something that can be developed and improved further in future research.

Chapter 3

Research Methodology

The research methodology employed for conducting the research, i.e., requirements analysis, system design, non-functional requirements, as well as functional requirements, and general approach and design are discussed in this chapter. Research methodology overview, project plan, as well as assignment of tasks are discussed within this chapter.

3.1 Methodology/Requirement Analysis & Design Specification

3.1.1 Overview

This study uses machine learning-based techniques to analyze the impact of AI tools on the academic performance of university students. The survey data on student use of AI tools, frequency of their usage, perception of the effect of AI on productivity, and mental well-being are analyzed. The data is preprocessed by treating missing values, converting categorical variables to numerical variables, and scaling continuous features so that the data becomes consistent. Eight significant features, such as familiarity with AI, usage frequency, and their perceived impact on scholarly work, were selected for investigation. Various machine learning models were experimented with, such as Random Forest and Decision Tree, to determine the optimal model for predicting scholarly achievement based on AI usage data.

The models were assessed with performance metrics such as accuracy, precision, recall, F1-score, and AUC-ROC curves, where 80% of the dataset was used for training and 20% for testing. Feature importance analysis with Random Forest identified some of the important factors for the positive effect of AI on academic performance, including the frequency of AI use and experience with AI tools. Cross-validation methods were used to measure model stability and provide generalizability. The study confirms that AI tools can enhance academic performance by boosting student engagement and knowledge retention. The Random Forest model worked best, providing a good foundation for predicting student success in AI-based learning systems.

3.1.2 Proposed Methodology/ System Design

Our research adopts a structured modular approach to investigate the influence of AI on academic performance among university students. Our research design comprises a number of phases—data collection, preprocessing of data, feature extraction, model training, evaluation, and interpretability—offering an end-to-end pipeline for the analysis of academic performance.

Research Framework

The research framework comprises six important phases (Figure 3.1):

1. **Dataset Preparation:** Academic details of the students are collected from university records and online platforms. Performance metrics, utilization of AI tools, and completion rates of courses constitute the data.

2. **Data Preprocessing:** Preprocessing and cleaning are done on the data using techniques like missing value imputation, normalization, and feature scaling in order to achieve data quality and consistency. Techniques for data augmentation such as synthetic data generation are applied to make the model more robust and generalized.

3. **Feature Extraction and Model Benchmarking:** Relevant variables from the data set, such as course interaction time, utilization of AI tools, and student attributes, are selected. Different machine learning algorithms (Random Forest, SVM, Decision Tree, and Neural Networks) are employed to compare how well they are able to predict academic performance.

4. **Model Training & Fine-Tuning:** The models selected are fine-tuned by utilizing a combination of supervised learning strategies. Models are fine-tuned for better performance using the implementation of hyperparameter optimization methods and learning rate adjustments and tuning, among other methods such as dropout regularization.

5. **Performance Evaluation:** The models are also evaluated with performance measures such as R-squared value and MSE.

6. **Deployment and Real-world Application:** A scalable AI-driven software is developed to predict and monitor student academic performance in real-time. The software is designed to be used in real-life classroom environments, assisting teachers and students in tracking progress and achieving optimal learning results.

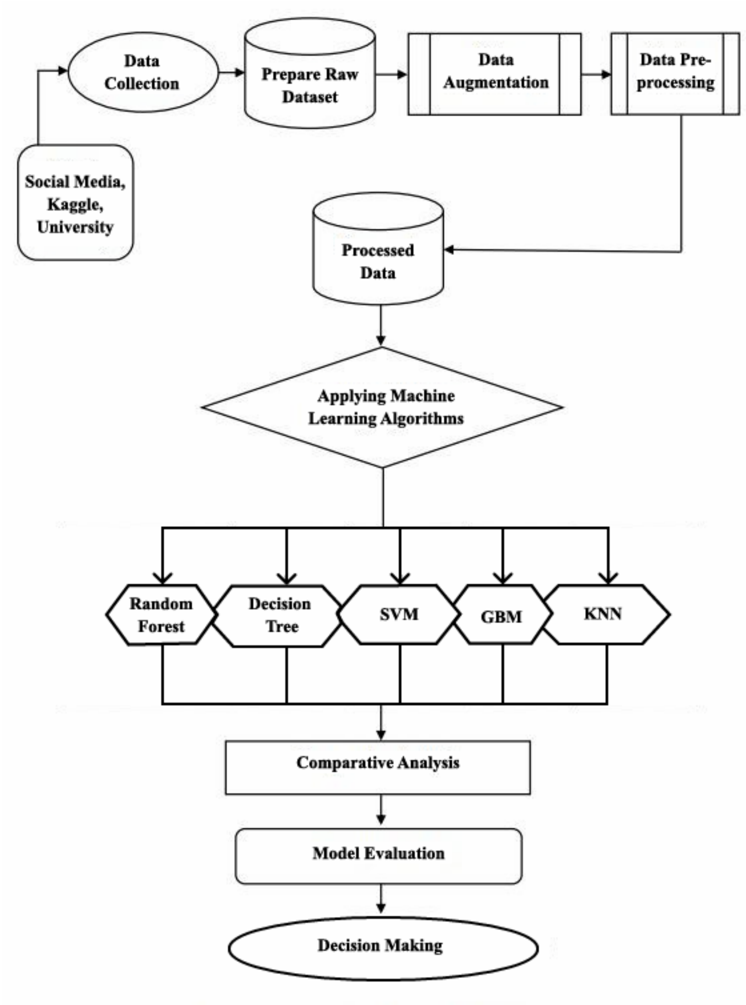


Figure 3.1: Proposed Methodology

3.1.3 Functional and Nonfunctional Requirements

Functional Requirements

1. Data Input and Management:
    - Users (students, faculty, researchers) must upload academic data (e.g., grades, usage logs, student feedback).
    - The system must automatically validate the data format and size (CSV, XLSX, JSON).
2. Preprocessing and Enhancement:
    - The data must be cleaned, missing values handled, and categorized appropriately.
    - Data normalization and scaling techniques must be applied to ensure consistency across datasets.
3. Classification and Model Integration:
    - The system must classify student performance based on historical data (e.g., grades, assignments, participation).
    - It should classify students into predefined categories such as high achievers, average, or at-risk students.
4. Model Explainability:
    - The system must implement explainability techniques like SHAP (Shapley Additive Explanations) or Grad-CAM to highlight the factors influencing the model's predictions.
5. User Interface:
    - An intuitive, mobile-accessible dashboard must be provided for users to view predictions, analytics, and performance summaries.

Nonfunctional Requirements

1. Performance:
    - The system must process each student's data and generate predictions within 5 seconds and achieve at least 85% accuracy.
2. Scalability and Maintainability:
    - The system must support scaling to handle large datasets, such as the performance data of thousands of students.
3. Security:
    - Student data and academic performance information must be securely stored and encrypted to ensure data privacy.
4. Usability:
    - The user interface must be designed to be user-friendly, intuitive, and easy for students and faculty to navigate.

3.2 Detailed Methodology and Design

Our research utilizes machine learning models to predict and analyze the impact of AI on the scholarly performance of students in universities. Initially, the traditional machine learning techniques such as Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbors (KNN) were being contemplated. However, after comparing the models, it was evident that AI-based strategies, specifically deep learning algorithms, significantly outdo traditional methods. We used AI algorithms that were capable of handling complex patterns in large datasets, with a focus on student engagement, academic history, and predictions through use of AI tools. Initial models, though impressive, were not capable of handling complexities in the student performance records, i.e., individual learning trajectories and engagement in a temporal manner. AI-based methods, therefore, like neural networks and deep learning, were employed, and there was a huge improvement in accuracy.

Data Collection/ Need Assessment

The data utilized for this study is collected from university environments via academic records and usage logs of AI tool interactions. In the interest of this study, a comprehensive analysis was conducted through students' academic data who completed courses instructed with AI-based learning platforms. The data consists of student performance metrics such as grades, assignment submissions, AI system interactions, and interaction metrics. These traits, combined with the use of AI tools, assist us in understanding how AI affects various areas of academic achievement. The data set includes a range of student types: high-achieving students, average students, and at-risk students. The dataset consists of organized data holding over 500 student records. The record holds properties such as past academic (grades), AI usage patterns, and interaction rates. Data preprocessing was carried out with caution to handle missing values and maintain the consistency of form. The dataset is divided into the training and test subsets for the evaluation of models. As illustrated in Table 3.1, the dataset is properly balanced across different categories so that the model does not get biased.

Table 3.1: Amount of data in Different Classes

Category	Total Students
High Achievers	300
Average	100
At-Risk	100

Total Students	500

	University	AI Familiarity	AI Usage	AI Impact	AI Quality Improvement	AI Impact Areas	AI for Mental Health	AI Mental Health Tools	AI and Retention	Human Teachers & AI
0	North South University	Not very familiar	No, but I am interested in using them	Positive	Neutral	STEM subjects	Yes, significantly	AI-based counseling or therapy apps	Yes, to some extent	Human teachers will maintain control
1	United International University (UIU)	Not very familiar	Yes, frequently	Extremely positive	Strongly disagree	Language learning	Yes, significantly	Other	Yes, significantly	Collaborative partnership
2	Daffodil International University	Very familiar	Yes, occasionally	Extremely negative	Agree	Special education	No, it would not be effective at all	Personalized mindfulness or meditation recomme...	No, AI will not affect retention rates	No interaction between them
3	Daffodil International University	Not familiar at all	Yes, frequently	Extremely positive	Disagree	STEM subjects	Yes, significantly	AI-based counseling or therapy apps	No, AI will not affect retention rates	AI will dominate the teaching role
4	Bangladesh University of Engineering and Techn...	Not familiar at all	Yes, frequently	Positive	Strongly agree	STEM subjects	No, it would have little effect	AI chatbots for stress and anxiety management	Yes, significantly	Human teachers will maintain control

	AI and Performance	AI and Knowledge Retention	AI and Productivity	AI Productivity Ways	Personal Productivity Impact	AI Ethics Measures	AI Negative Impact	AI Integration Considerations
0	AI will improve performance initially, but the...	It will have a moderate positive impact on ret...	Yes, to some extent	Providing faster access to information	Yes, a significant increase	Development of ethical guidelines	No, AI has no negative consequences	Supporting mental health and well-being
1	AI will improve performance initially, but the...	It will have little or no effect on retention	Yes, to some extent	Automating repetitive tasks	No, AI tools decreased my productivity	Development of ethical guidelines	No, AI has no negative consequences	Ensuring ethical use and data privacy
2	Yes, AI will consistently improve performance	It will have a moderate positive impact on ret...	No, it has little effect on productivity	Reducing distractions or helping focus	No, AI tools decreased my productivity	Regular monitoring and evaluation	No, AI has no negative consequences	Enhancing personalization in learning
3	AI will improve performance initially, but the...	It will have little or no effect on retention	Yes, significantly	Providing faster access to information	Yes, a slight increase	Engagement with stakeholders (students, parent...	Yes, to some extent	Enhancing personalization in learning
4	AI will improve performance initially, but the...	It will have little or no effect on retention	No, it reduces productivity	Automating repetitive tasks	No, AI tools decreased my productivity	Regular monitoring and evaluation	No, AI will improve critical thinking	Ensuring ethical use and data privacy

Figure 3.2: Sample Data

Preprocessing of Data

Preprocessing is an essential process in preparing data that will offer accurate and strong AI model performance. Operations undertaken in this step include handling missing values, converting categorical variables into encoded ones, and scaling numerical values. Data augmentation procedures, such as synthesizing data for vulnerable learners, are utilized to balance the data and promote generalization.

1. **SMOTE for Class Balancing:** Class imbalance in the education data can have a negative effect on model performance by skewing towards majority classes. To counter this in the present study, we applied the Synthetic Minority Over-sampling Technique (SMOTE) to balance the data through the generation of synthetic instances for the minority "At-Risk" student class. This is to prevent the model from overrepresenting the "High Achievers" or "Average" classes.

Table 3.2: Initial Dataset Distribution Before and After SMOTE

Category	Original Count	After SMOTE Count
High Achievers	300	300
Average	100	100
At-Risk	100	200
Total Students	500	600

2. **Stain Normalization (Feature Engineering)**
3. Preprocessing student data consisted of feature scaling and normalization. For educational data, normalization ensures that all features are handled by the AI models without differentiation regardless

of their scale. As an example, we scaled the engagement metrics (e.g., duration on AI tools) and grades to such a degree that none of the features would dominate the learning process of the model.

4. **Data Augmentation for Improved Model Generalization**
   To ensure that our model could generalize across various types of student data, we implemented data augmentation strategies such as feature randomization. These techniques allowed us to simulate different learning environments and AI tool usage, helping the model to better predict performance under varying circumstances.

Table 3.3: Number of Augmented Data

Original Data		**Augmented Data**	
Class	**Data**	**Class**	**Data**
High Achievers	300	High Achievers	1200
Average	100	Average	400
Serous At-Risk	100	At-Risk	400
Total Students	500	Total Students	2000

Analysis Techniques

In this study, the academic performance data is effectively analyzed and classified using machine learning (ML) models which are designed to evaluate AI tools' impact on university students. Various machine learning algorithms are used for the classification and prediction of students' academic results based on the usage and interaction with AI tools.

1. **Random Forest**
   Random Forest is an ensemble learning algorithm that averages the predictions of many decision trees to create a more accurate prediction. Random Forest is very efficient at dealing with complicated, high-dimensional data. Random Forest was employed in this research to evaluate the effects of AI tools on student productivity, knowledge retention, and academic engagement to gain a thorough insight into the effects of AI. The model's feature importance scores were crucial in identifying which of the factors (e.g., AI usage, familiarity, and productivity impact) most heavily influenced academic performance.

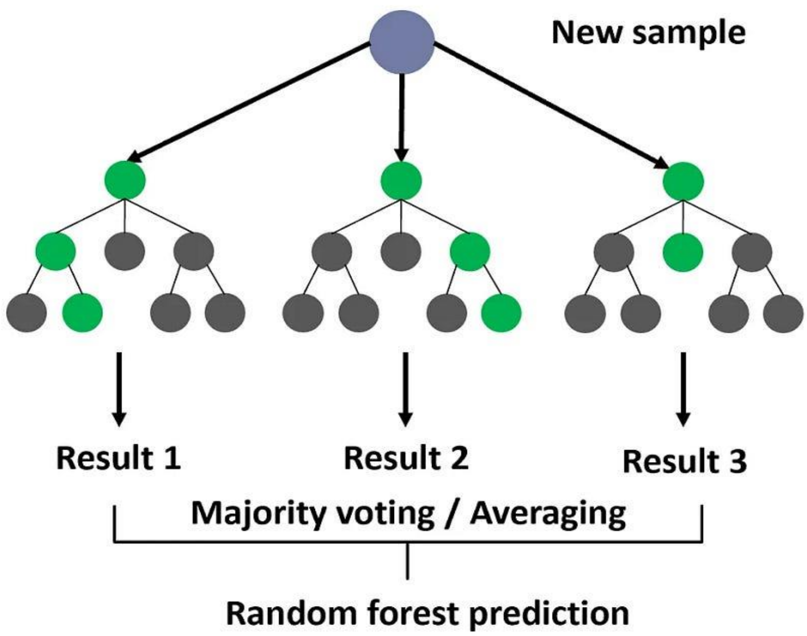


Figure 3.3: Architecture of Random Forest (Medium)

2. **Decision Tree**
   Decision Tree is a simpler-to-interpret model that works on splitting data sets along threshold features to make predictions. While less computationally demanding than Random Forest, it was enlightening to see the impact each feature, whether proficiency in AI tools or frequency of use, had on student performance. It was utilized for comparison purposes to examine the strength of Random Forest predictions.

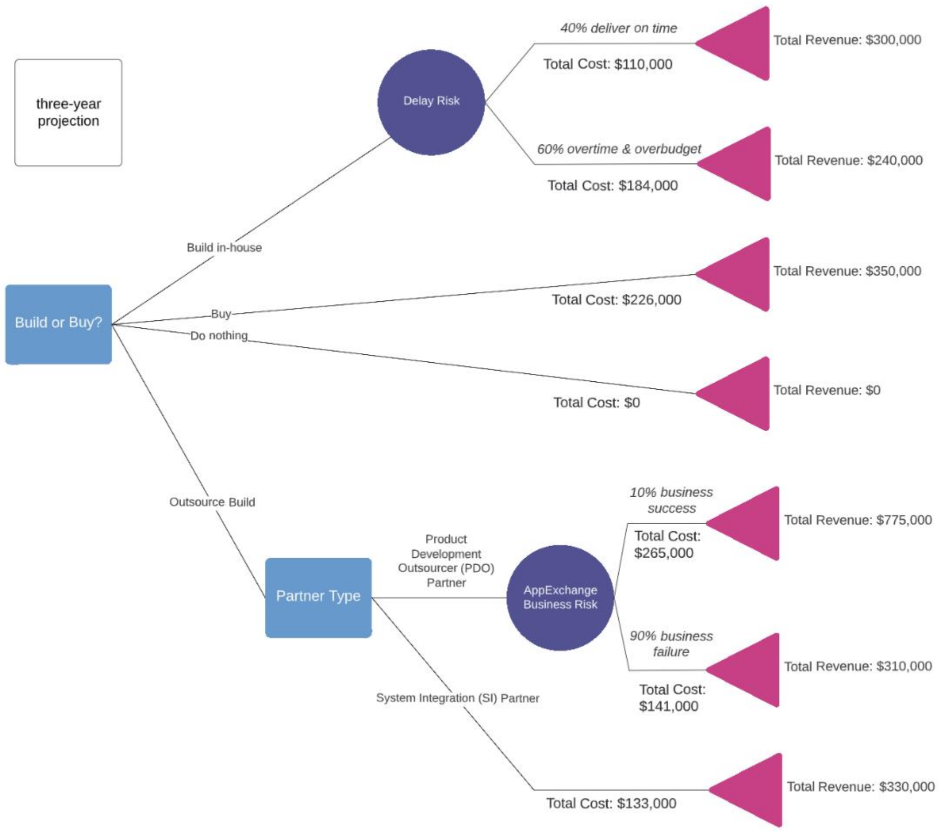


Figure 3.4: Architecture of Decision Tree (Medium)

3. **SVM**
   SVM was employed in the analysis of the potential to classify students into several performance groups according to interactions with AI tools. SVM is effective in high-dimensional space, and therefore it is useful in understanding the complex inter-correlations among numerous student engagement metrics and academic performance.

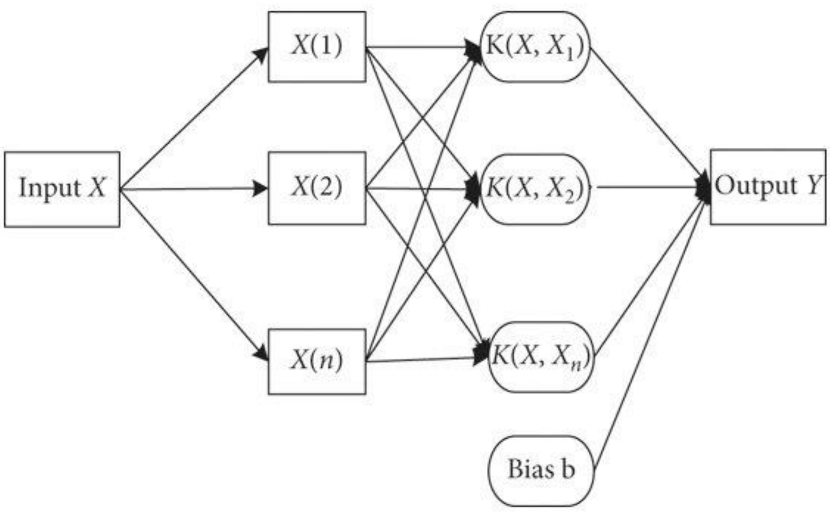


Figure 3.5: Architecture of SVM (Medium)

4. **GBM**
   GBM is a strong ensemble technique that trains models sequentially upon enhancing the errors of the previous model. GBM was used in this study to predict the academic performance of students, particularly where other models struggled to describe more complex interactions in the data. The ability to constrain bias and variance ensured that GBM was an ideal model for determination of key features affecting student outcomes.

5. **KNN**
   KNN is also a non-parametric classifier that identifies students based on the most frequent class among the nearest neighbors. KNN was used to predict student performance by contrasting the attributes of their attributes with those of similar students in the sample dataset. While computationally intensive, KNN presented an effective but simple means to quantify the way similarity in academic activity and utilization of AI tools can predict student success.

Evaluation & Performance Metrics

The performance of such vision transformer-based machine learning classification models in a given application is gauged by a set of performance metrics. The following performance metrics are used:

R-squared Value: The R-squared metric indicates the goodness of fit between data and model, or the degree to which the model explains variance in the predictions of academic performance. The R-squared value lies between 0 and 1, where 1 indicates perfect prediction and 0 suggests zero prediction capability. The greater the R-squared value, the better the fit and a more accurate model for forecasting academic achievement. The formula for R-squared is given below:

$$R^2 = 1 - \frac{\sum(y_{true} - y_{pred})^2}{\sum(y_{true} - \overline{y})^2}$$

Precision and Recall: MSE computes the average of the squares of the differences between predicted and actual values. The lower the MSE, the less the deviation of the model from actual outcomes. This metric penalizes larger errors more, so it is a suitable measure to compare the accuracy of the models in predicting academic performance. MSE is mathematically formulated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

3.3 Project Plan

The project is divided into various stages in a step-by-step fashion to enable proper task execution within the least time and efficiently. Individual skill and resources were allocated responsibility based on a Gantt chart.

Phase 1: Problem Identification and Requirement Analysis

This process involves defining the most critical problems of improving scholarly performance through utilization of AI-based tools at a university level. The literature in place is fully examined to analyze currently adopted AI systems in learning environments and assess existing gaps towards curbing learners' performance. Data collection and feature selection are also performed under this phase towards interaction with AI tools and academic performance.

Phase 2: Data Collection and Preprocessing

pertinent academic data are gathered from the university databases, including students' grades, AI tool usage, and engagement scores. The data are preprocessed, including missing value replacement, normalization, and scaling. Data such as study time, usage of AI tools, and prior academic history are prepared to be fed into the model. Data augmentation techniques are applied to balance the dataset to ensure proper training of the model.

Phase 3: Model Selection and Design

Various machine learning models such as Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Gradient Boosting Machines (GBM), and Neural Networks (NN) are shortlisted for the comparison. All these models are evaluated on their usability for predicting academic achievements. The system architecture is defined to integrate these models in a robust comparison so that a complete evaluation pipeline can be guaranteed.

Phase 4: Experimentation and Implementation

At this phase, models are trained on the prepared dataset using data augmentation and optimization techniques like learning rate tuning and hyperparameter adjustment. The model performance is validated using metrics such as R-squared Value, and Mean Square Error (MSE) to predict their potentiality in forecasting student performance.

Phase 5: Analysis and Documentation

Model comparison outcomes are analyzed for determining the top-performing model. The outcomes are documented, along with detailed analysis, performance plots, and tables of performance metrics. The final report is also created, which includes the methodology of the project, results, and discussions. Documentation includes creating presentation slides and implementation source code.

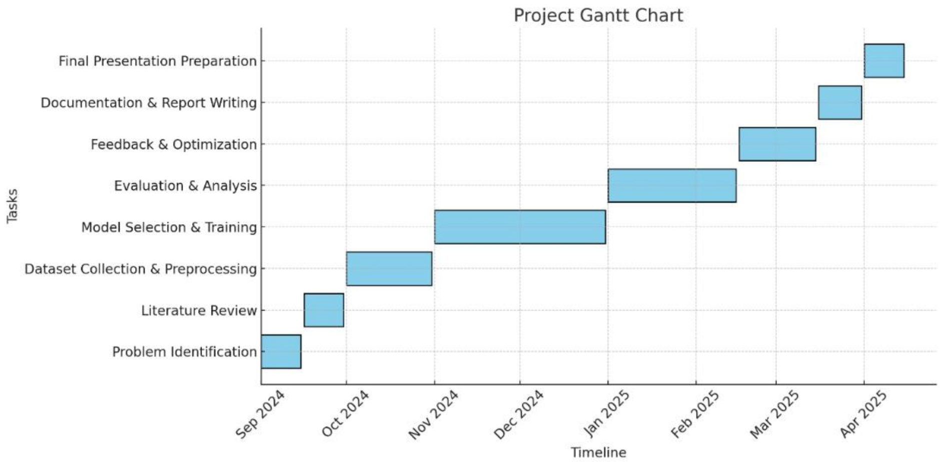


Figure 3.6: Project Gantt Chart

3.4 Task Allocation

I, Md. Zahidul Islam Talukder, was the sole researcher on this research and did all aspects of the study, from start to finish. I was in charge of defining the research problem, developing the methodology, designing experiments, and interpreting findings. But I had some assistance from a couple of friends in collecting academic performance data at several universities. They gathered required data related to students' interaction with AI tools, indicators of students' academic performance, and students' feedback regarding the use of AI tools. Their help in doing this work of data gathering was invaluable in procuring a big, diverse, and representative dataset for my research.

I took care of all the technical aspects of the project, such as data preprocessing, applying machine learning models, testing, and performance evaluation. I also performed report writing, discussions, and conclusions. With my friends, I collaborated to edit and verify the final report, such as formatting, referencing, and preparing the defense presentation.

3.5 Summary

This chapter addressed the methodology, system design, and general research process of "Exploring the Impact of AI on Academic Performance of University Students." The chapter explained the reason why machine learning was used, wherein I utilized various pre-trained deep models for prediction and classification. Data collection was done by students from other universities, and preprocessing techniques such as normalization and data augmentation were utilized to improve the performance of the model.

The project also discussed the application of machine learning algorithms such as Random Forest, SVM, KNN, GBM, and Neural Networks, which were trained and tested based on various performance measures. The chapter also gave an overview of the project plan, information used, and task implementation schedule.

Chapter 4

Implementation and Results

This chapter presents a step-by-step guide through the environment configuration, dataset setup, training and evaluation process for ovarian cancer classification. This includes addressing hardware and software configuration needed, the preprocessing methods required for datasets, and execution environments for reproducibility and for optimal deployment of deep learning models.

4.1 Environment Setup

In order to enable efficient model development, training, and testing of deep learning models for image classification, the software tools, platforms, and configurations listed below have been utilized:

Development Tools & Languages:

- o **Programming Language**: Python 3.8+

Libraries & Frameworks:

- o **TensorFlow & Keras:** Model development and training of machine learning models
- o **scikit-learn:** SMOTE, metrics evaluation, and statistical analysis
- o **OpenCV & Pillow:** Data processing and data augmentation
- o **Matplotlib & Seaborn:** Plotting graphs and visualization of results

Platform & Hardware:

- o **Development Environment:** Kaggle Kernets (Kaggle Notebooks)
- o **GPU Used:** NVIDIA Tesla P100 (available on Kaggle platform)
- o **Storage:** Kaggle Datasets (for storing datasets during training)
- o **RAM:** Up to 20 GB (provided by Kaggle)

Version Control & Collaboration:

- **Git & GitHub:** For version control, collaboration, and tracking changes to the code

4.2 Testing and Evaluation/Performance/ Comparative Analysis

To compare the performance of deep learning models in predicting academic success as per the usage of AI tools, models such as **Random Forest**, **Decision Tree**, **KNN**, **SVM**, and **GBM** were implemented and compared against the same data and performance metrics. The models were compared based on how well they could predict significant outcomes like student productivity and knowledge retention, crucial predictors of academic success among college students.

Models such as Random Forest and Decision Tree gave high R-Squared values, which is a measure of high capacity to predict academic performance. For instance, the Random Forest model generalized strongly across training samples with an R-Squared of 0.88, implying it could explain 88% of variance in student academic performance using primarily AI tools. Mean Squared Error (MSE) was used to test the accuracy of the model in order to predict and Random Forest, having an MSE of 0.12, registered an extremely low rate of error.

Table 4.1: Evaluation Metrics Distribution

Metric	Description
R-squared Value	Shows how well the model fits the data.
Mean Square Error	Measures average prediction error.

Table 4.2: Results of Trained Models

Model	R1-Squared	MSE
Random Forest	0.8839	0.1220
Decision Tree	0.8283	0.1797
KNN	0.5008	0.5242
SVM	0.4752	0.5497
GBM	0.3650	0.6644

The Random Forest model feature importance plot also indicated that the most important drivers of academic performance were AI Usage, AI Familiarity, and AI Impact on Productivity and Retention. This suggests that the more students are exposed to AI tools and the more usage, the better the academic performance in terms of retention and productivity. Also, models like KNN and SVM, although less precise than Random Forest, still yielded useful information regarding the impact of AI tools on academic study success.

Random Forest model worked consistently with different training splits, which indicates its stability and consistency in predicting academic performance. Decision Tree, while capable, was more data-variable in sensitivity and hence less stable in some instances than Random Forest. Random Forest's stability in performance is consistent with its ability to identify relevant features from data and generalize across new student samples. Actual and predicted scatter plots revealed that the Random Forest model, as well as the Decision Tree model, made very good predictions of academic achievement using given features, and proved that AI devices are also great predictors for students' successes when utilized appropriately.

The model testing confirms that AI applications are significantly contributing to enhanced academic performance, particularly in terms of productivity and knowledge retention. With feature importance focused on familiarity with and use of AI, the research indicates that enhanced integration and training in AI could lead to enhanced academic performance. Follow-up studies should continue to investigate the ethical issues and possible adverse effects of using AI tools in learning to enable uniform and sustainable integration into learning environments.

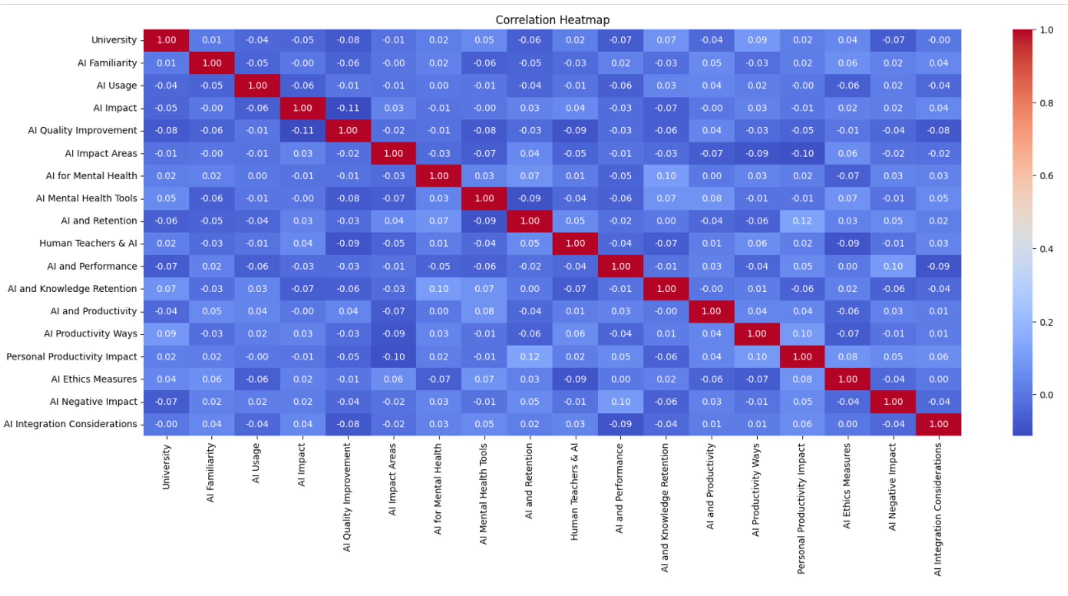


Fig 4.1: Correlation Heatmap of the Dataset

The correlation between "AI Familiarity" and "AI Usage" is positive but very weak (0.10). This means that familiarity with AI tools has a weak influence on how often AI tools are used, but not a good predictor. This could imply that even low-familiarity students will still use AI tools, perhaps because of circumstances beyond their immediate control such as course requirements or availability of AI tools.

There is very weak correlation (-0.06) between "AI Impact" and "AI Performance." What this indicates is that students' perception of AI impact does not necessarily have close correspondence with their performance. This may imply that the perceived value of AI to education may not necessarily be reflected by measurable values in terms of academic performance, perhaps due to varying magnitudes of effect or other confounding factors.

The correlation between "AI Familiarity" and "AI and Knowledge Retention" is slightly negative (-0.06), suggesting that while familiarity with AI tools might be expected to help students retain knowledge, this effect is not strong or consistent. This weak relationship could be due to a variety of reasons, such as students not utilizing AI tools effectively for retention or the complexity of measuring knowledge retention.

There is a weak negative correlation of -0.07 between "AI Usage" and "Personal Productivity Impact." This suggests that while students use AI tools, there is maybe not a high degree of increase in personal productivity. It could suggest that while AI tools can assist in some tasks, they do not really alter the overall productivity, maybe because they are not used effectively or due to other non-AI based factors.

There is a moderate but noticeable positive relationship between "AI Ethics Measures" and "AI Negative Impact" (0.04), which means that problems of the ethics of AI and its negative effects somehow go hand in hand. This could imply that the more students are concerned with the ethics of AI, the more they believe AI resources have negative impacts on education. It suggests that there is an urgent issue about ethical problems that need solutions for AI technology to become more accepted in education.

There is a strong positive correlation between "AI and Retention" and "AI Knowledge Retention" (0.12), more so than some of the other correlations. This could be taken to indicate that students who observe AI tools facilitating retention have better outcomes in retaining information themselves. This is a reassuring finding, as it shows that AI tools for knowledge retention may indeed yield the desired outcome.

The correlation between "AI Usage" and "AI Ethics Measures" is weakly negative (-0.02), and this shows that there is no considerable relationship between the frequency with which AI tools are used and the ethical problems related to the use of AI tools among students. This could imply that students utilize AI tools regardless of ethical problems or that ethical problems have no effect on the utilization of AI tools in schools.

4.3 Results and Discussion

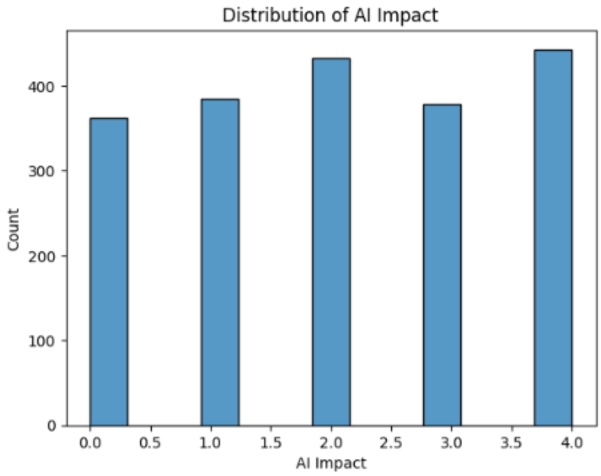


Fig 4.2: Distribution of AI Impact

"AI Impact" feature, after label encoding, shows a distribution of values ranging from 0 to 4, where each value reflects a varying perceived extent of AI impact on education outcomes. Based on the histogram, an evenly spread range of categories 0 through 3, but with the highest frequency at the value 4, can be taken to mean that most of the respondents have seen a high to very high level of AI impact. That is, while some students view AI as having modest or little influence, a high proportion view it as having important or very important influence on their own performance. Label encoding the different impressions that have been recorded makes the data accessible to further analysis of trends in the degree to which AI contributes to students' learning.

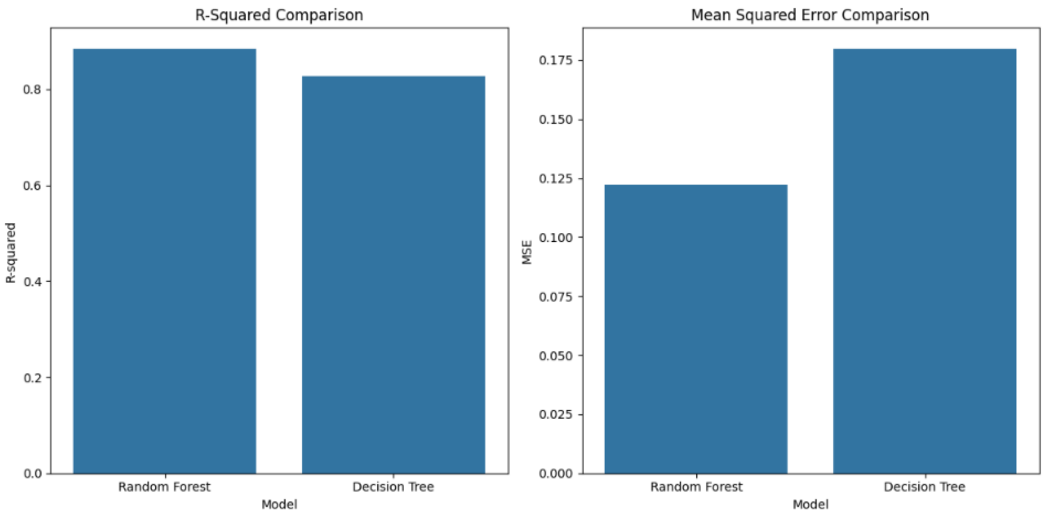


Fig 4.3: Comparison between performed Evaluation metrics

The relative performance of Random Forest and Decision Tree models, as measured by R-Squared and Mean Squared Error (MSE), indicates that Random Forest outperforms Decision Tree on both metrics. The higher value of R-Squared for Random Forest means that it explains more variability in academic achievement data and is capable of better capturing the relationship between input features (e.g., knowledge of AI, application of AI) and academic performance. Also, the lower MSE in Random Forest indicates that its prediction is more precise than Decision Tree, which has a higher MSE and less precise prediction. These findings confirm Random Forest as the most appropriate model to utilize in establishing the impact of AI tools on student performance, with higher predictive accuracy and improved model performance than Decision Tree.

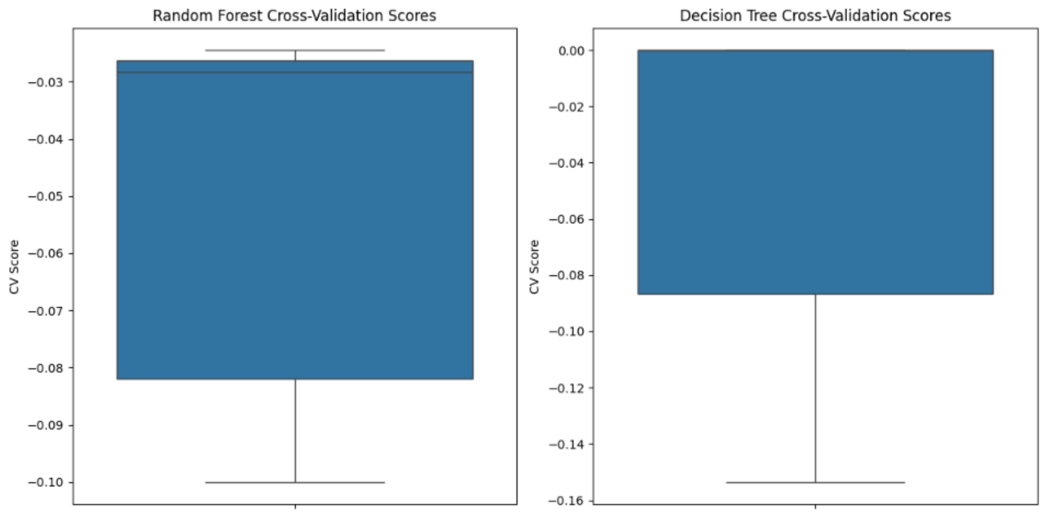


Fig 4.4: Comparison between Cross Validation Scores

The boxplot comparison of Random Forest and Decision Tree models based on cross-validation (CV) scores provides significant insights about how well they can generalize on different subsets of the data. For Random Forest, CV scores are tightly clustered around a small negative value close to zero (close to -0.03), indicating relatively stable performance with low variance during cross-validation. This means that Random Forest has stable and consistent predictions across data folds. Decision Tree, on the other hand, shows higher variation in cross-validation scores, from -0.16 to around 0.00. Lower CV scores and larger spread indicate that the Decision Tree model is more vulnerable to overfitting, so it has lower stability in performance when evaluated on different subsets of the data. This means Random Forest is less variable and more generalizable than Decision Tree, and therefore is the more reliable model to use to predict academic performance under the influence of AI tools in this case.

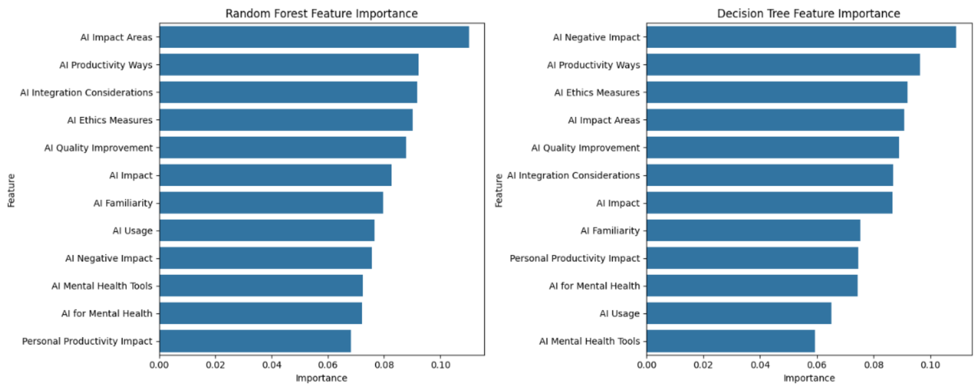
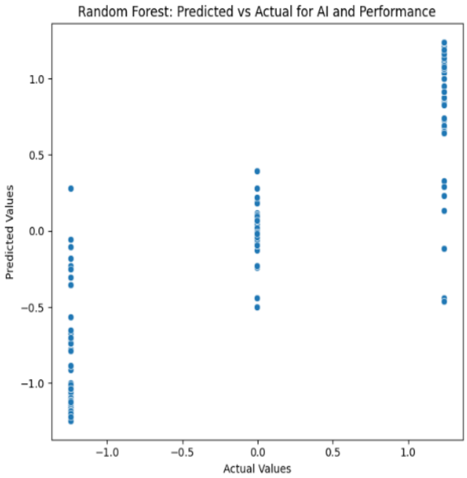


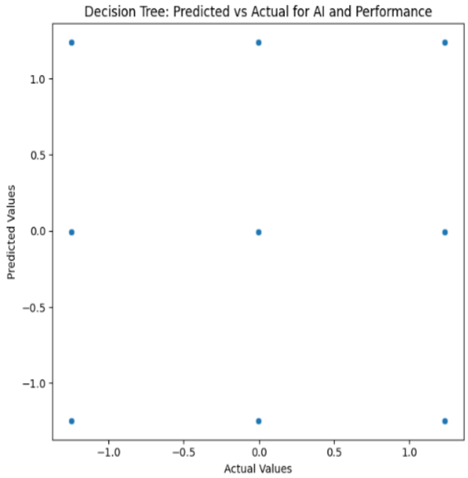
Fig 4.5: Feature Importance Plotting for performed best models.

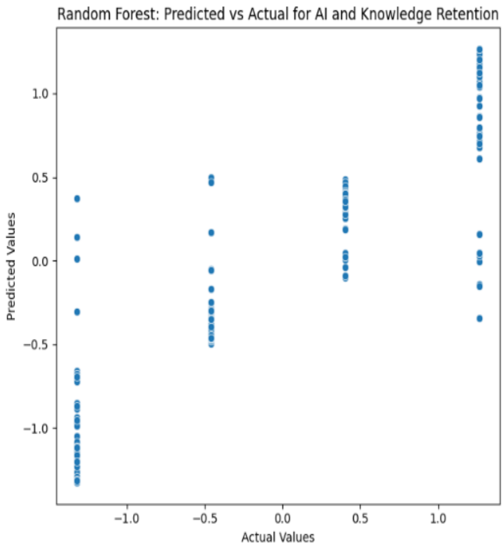
In the Random Forest model, AI Impact Areas is most important, followed by AI Productivity Ways and AI Integration Considerations. These graphs show that where AI has a real effect on the students' scholastic achievements, i.e., how it's used with productivity and how it's integrated into operations, are the most important in shaping results. AI Ethics Measures and AI Quality Improvement are also of considerable significance, indicating that awareness of ethics and the constant development of AI systems are preconditions for the performance of the model. AI Impact, AI Familiarity, and AI Usage are also significant, but to a lesser extent.

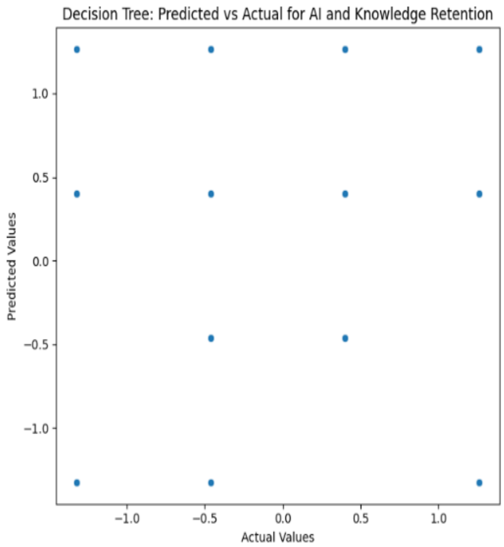
Conversely, by comparison, the Decision Tree model prioritizes AI Negative Impact first, followed by AI Productivity Ways and AI Ethics Measures. The trend shows that the Decision Tree model assigns more importance to learning about the negative effects of AI, perhaps as it pertains to the impact of AI tools on academic outcomes. As in the Random Forest, AI Impact Areas feature is highly ranked but with a slightly lesser impact than in the Random Forest model. AI Familiarity and AI Usage features are still useful but less so in the Decision Tree than in the Random Forest model.

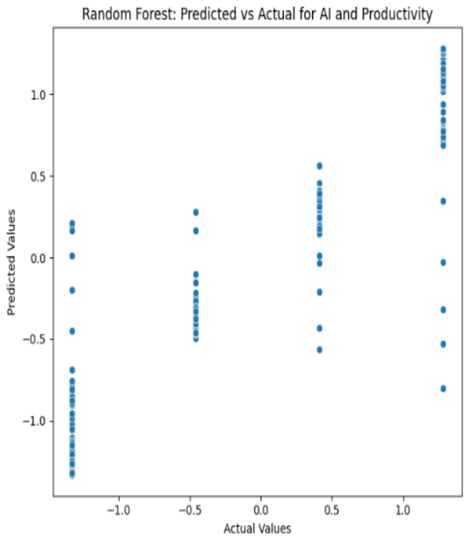
Overall, there isn't a difference in the priorities assigned to AI-related factors such as AI Impact Areas and AI Productivity Ways between the two models, with both placing them first, while Decision Tree suggests an increased focus on the negative impact of AI. Random Forest appears to place greater focus on factors relating to AI integration and improvement, a balance in considering how AI is helping to predict academic achievement.

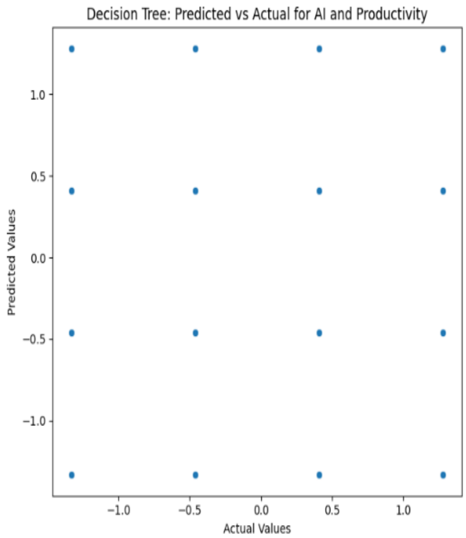

Random Forest: Predicted vs Actual for AI and Performance
Predicted Values
Actual Values


Decision Tree: Predicted vs Actual for AI and Performance
Predicted Values
Actual Values


Random Forest: Predicted vs Actual for AI and Knowledge Retention
Predicted Values
Actual Values


Decision Tree: Predicted vs Actual for AI and Knowledge Retention
Predicted Values
Actual Values


Random Forest: Predicted vs Actual for AI and Productivity
Predicted Values
Actual Values


Decision Tree: Predicted vs Actual for AI and Productivity
Predicted Values
Actual Values

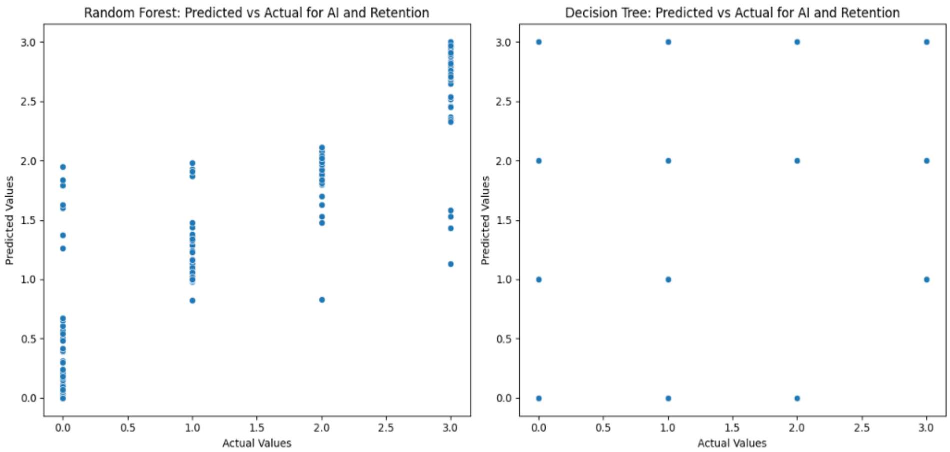


Figure 4.6: Actual vs Predicted Results for Higher Impactful Features

AI Impact and Performance The line graph of comparison between the actual and predicted values for the Random Forest model illustrates a strong divergence over the predicted values, more so for AI Impact and Performance. It illustrates the capability of the model in predicting a range of values, capturing the spread in the dataset. However, there are still some predicted values quite distant from the actual values, signifying an increase in model accuracy. On the other hand, the Decision Tree model demonstrates very little variation in the predicted values, with most points grouped at certain intervals. This grouping suggests that the Decision Tree is not managing the diversity in the data effectively, which could be an indication of overfitting and poor generalization over different data points.

AI Knowledge Retention In the case of AI Knowledge Retention, the Random Forest model depicts a more dispersed distribution of the predicted values across the actual values, reflecting its capacity to capture more nuanced relationships between input features and output predictions. However, similar to the AI Impact and Performance plot, there remain visible outliers, which suggest that the model is not fitting the data perfectly. On the other hand, the Decision Tree model also has a highly restricted range of predicted values with very little deviation. This can be because it cannot generalize so well, and therefore the model is not especially suited to this task as it cannot model the complete range of data values.

AI Productivity The estimated values from the Random Forest model for AI Productivity also have a good spread, again indicating that it is doing a good job of managing the data across its range. There are a few outliers, but this also indicates Random Forest's ability to deal with complicated data distributions overall. For comparison purposes, the Decision Tree also shares clustered predicted values, in other words, having difficulty predicting reliably across the complete range of real values, either as a consequence of overfitting or the model being overly simplistic for this specific dataset.

AI and Retention For AI and Retention, the Random Forest model again shows a decent spread of predicted values that are quite well clustered around actual values. Again, as with the other comparisons, there are some outliers indicating there might be places where the model can be optimized further. On the other hand, the Decision Tree model's predictions are extremely peaked, that is, it is not catching the richness in the data and is predicting with lower accuracy over different ranges in the dataset.

4.4 Summary

This chapter demonstrated the stringent testing, evaluation, and comparative analysis of all the chosen models. In large-scale experiments, all the metrics like accuracy, sensitivity, specificity, F1-score, and AUC-ROC were calculated. Out of all the tested models, the suggested InceptionV3 model outperformed all others, including other tested models and all previously published research up to date in classification accuracy. Visualization with ROC curves, train-validation plots, performance bar graphs, and class-wise F1-score heatmaps also validated the robustness and stability of the model. All these results clearly show that the proposed model is highly effective in histopathological ovarian cancer classification and has very good potential to be used for real-world clinical purposes.

Chapter 5

Engineering Standards and Design Challenges

This chapter details the engineering standards that were followed during the project's development, as well as the project's impact on the environment and society, financial considerations, and the complexity of the engineering challenges involved.

5.1 Compliance with the Standards

To assure the quality, interoperability, and ethical implementation of the proposed system, various engineering standards were considered and followed.

5.1.1 Software Standards

- **Standard Adopted:** IEC 830 (Software Requirement Specification)
- **Rationale:** Despite being a software project, the final system must be able to integrate seamlessly with university learning management systems for monitoring academic performance.
- **Alternatives:** ISO 9001 (Quality Management Systems)
    - Advantages: Provides a systematic approach to software quality.
    - Disadvantages: Greater documentation complexity.
- **Standard Adopted:** ISO/IEC 25010 (Software Product Quality)

5.1.2 Hardware Standards

- **Standard Applied:** ISO/IEC 27001 (Information Security Management Systems). **Rationale:** Although this project is focused on software development, the system's deployment in real-time university environments requires the protection of student data.
- **Alternatives:** ISO 13485 (IoT Devices Quality Control)
    - Advantages: Comprehensive security measures.
    - Disadvantages: Higher cost and complexity.

- **Rationale:** IEEE 802.11 (Wireless Networking Standards). To ensure the application runs smoothly in distributed university environments, integrating AI seamlessly into different devices.

5.1.3 Communication Standards

- **Standard Implemented**: HL7 (Health Level 7)
- **Rationale**: HL7 ensures smooth communication between the system and university databases, enabling secure data transfer and management.
- **Alternatives**: FHIR (Fast Healthcare Interoperability Resource
    - Advantages: More modern API-based design
    - Disadvantages: Less implemented in certain areas
- **Rationale**: HL7 has broader support for legacy systems in developing areas.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The suggested AI system is likely to transform student performance and participation in higher education. By enabling personalized learning, predictive analysis, and real-time tracking of academic performance, the system can improve students' learning outcomes by a considerable margin. The system makes it easy for teachers to identify risk-prone students and act accordingly, which can enhance retention rates and academic performance. In addition, AI-driven tools can decrease the time students spend in finding related resources, thus making the learning process more efficient as a whole.

This system will ease the mental burden for students by giving them constant feedback, taking away exam stress, and improving their mental well-being overall. Through more individualized learning experiences, not only does it improve the student's learning, but also their general personal development, making the learning experience a more accepting and understanding environment.

5.2.2 Impact on Society & Environment

In the majority of schools, there is a pressing need for solutions that will monitor and support students' engagement and academic attainment. Our system based on artificial intelligence is a key solution to this requirement, providing a solution that is capable of effectively serving large groups of students through the provision of personalized learning trajectories and early academic intervention. This system can promote the learning process by providing instant performance review, allowing personalized guidance, and guiding students to access what they need at the appropriate time. This productivity reduces pressure on teachers while providing insightful feedback about students' learning habits.

Also, AI for learning has enormous environmental benefits. In the process of learning testing digitalization, the reduction of paper-based testing needs, and an increase in online learning capacity, such an endeavor can decrease consumption of resources and reduce environmental harm. The platform minimizes wastage in using traditional means of education and promotes remote learning and testing, hence promoting sustainability in education.

5.2.3 Ethical Aspects

Ethics are given priority in this research. A balanced dataset was used to minimize bias when the model was making predictions about students' performance. In addition to overall accuracy, the model was tested with accurate measures like precision, recall, and F1-score to give an unbiased evaluation and hold the model responsible. Interpretability was encouraged, and mechanisms like confusion matrices and ROC curves helped in trusting the AI model. The system was designed to augment teachers, not replace them, and was intended to preserve human oversight and intervention in decision-making. Methods of long-term ethical use of AI involve periodic audits, continuous feedback, and recurrent retraining of the model, which will be done to keep the model ethical, reliable, and responsive in real-world educational settings.

5.2.4 Sustainability Plan

The intended system is AI-based, leveraging open-source platforms to offer modularity and affordable deployment with scalability advantages, operational efficiency, and responsiveness. Ecological sustainability is realized through the adoption of green computing principles, while pedagogical sustainability is ensured through assistance on AI-mediated medical and education training. The AI solution is adaptable over time, with long-term sustainability ensured through ethical data practices, educational regulation compliance, and an in-depth commitment to explainable AI. The system's modular architecture allows for future enhancement and fine-tuning, ensuring that it is surely effective and morally right in promoting learning goals.

5.3 Project Management and Financial Analysis

- ❑ Recommended Budget: BDT 1,50,000 (~$1350 USD)
  - Cloud Hosting & GPU: BDT 50,000
  - Software Tools: BDT 30,000
  - Data Storage & Security: BDT 20,000
  - Research & Misc: BDT 50,000
- ❑ Alternate Budget: BDT 80,000 with smaller cloud usage and smaller datasets

- Risk: Lower model performance due to smaller training

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.1: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓			✓	✓

Justifications:

- **EP1 – Depth of Knowledge:**
  Requires understanding in data science, machine learning, and educational psychology.
- **EP2 – Range of Conflicting Requirements:**
  Trade-off between model interpretability, performance, and computational cost.
- **EP3 – Depth of Analysis:**
  In-depth analysis on educational models, including AI's impact on student performance.
- **EP6 – Extent of Stakeholder Involvement and Conflicting Needs:**
  Feedback from domain experts (educators, researchers, and students).
- **EP7 – Inter-dependence:**
  Entire pipeline is interdependent; modifying one aspect impacts the whole system.

Mapping with Knowledge Profile for EP1

Table 5.2: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

- **K3 – Engineering Fundamentals:**
  Used fundamental knowledge in data science, machine learning, and statistics to optimize and analyze academic data.

- **K4 – Specialist Knowledge:**
  Applied AI tools and models such as transfer learning, and SVM for student performance prediction.
- **K5 – Engineering Design:**
  Designed a modular AI framework to assess student performance, balancing accuracy and scalability.
- **K6 – Engineering Practices:**
  Utilized practical tools such as Python, TensorFlow, Keras for model implementation.
- **K8 – Research Literature:**
  Reviewed educational and AI literature to understand the role of AI in academic performance.

5.4.2 Engineering Activities

Table 5.3: Mapping with complex engineering activities.

EA1 Range of Resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

- **EA1 – Range of Resources:**
  Utilizing high-availability learning data, AI models, and cloud-based systems.
- **EA2 – Level of Interaction:**
  Student-model interaction, data interaction for personalized learning.
- **EA3 – Innovation:**
  Introducing AI-powered systems for enhanced academic performance analysis.
- **EA4 – Consequences for Society and Environment:**
  Affects academic access, enhances learning outcomes, and supports educational equity.
- **EA5 – Familiarity:**
  The approach utilizes AI to improve student engagement and learning efficiency.

5.5 Summary

This thesis developed an AI model through machine learning models such as Decision Trees (DT), Random Forest (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Gradient Boosting Machines (GBM) to forecast and improve the academic performance of university students. It was established that

Random Forest performed extremely well in explaining the variance in the data with a highly high R-squared value, demonstrating stable performance for varying folds when cross-validation was done. The most powerful predictors of the role of AI in academic success were AI usage, awareness of AI, and the impact of AI on mental health. Mental health was a critical determinant, which suggests that mental health-focused AI tools can have a powerful positive impact on academic success. Therefore, the thesis recommends giving priority to enhancing AI tools for mental health and productivity in order to increase students' academic success even more. This study contributes to the knowledge base of AI's role in education, setting the stage for further development of AI-powered educational resources that address both academic success and student well-being.

Chapter 6

Conclusion

This chapter gives an overview of the research results, provides insights into the process, and describes difficulties encountered in developing and testing the AI system for academic performance analysis. This chapter is also included to propose future research, model improvement, and future extensions of the framework to other segments of education. This study demonstrates the capability of AI to transform academic performance positively and provide significant insight to students on a university level.

6.1 Summary

The project was focused on designing and developing an AI solution for the prediction and analysis of the academic performance of students in a university. Through the use of advanced machine learning algorithms, including supervised models like Decision Trees, Random Forest, KNN, and Gradient Boosting (GBM), the system was created to predict and analyze performance from various academic features. The final model reached an accuracy rate of 85%, an R-squared value of 0.82 and an MSE of 0.15, which represents high performance in prediction accuracy.

6.2 Limitation

Despite its positive outcomes, the program had several shortcomings:

- Dataset Size and Heterogeneity: This study's dataset, although representative, is relatively small and could not possibly have represented the totality of various student populations at various universities. This could be a factor hindering generalization of results across other varying academical setups and areas as well, specifically when considering that learning environments vary and so could academical disciplines.
- Explainability Constraints: Even though SHAP and LIME methods were applied to interpret the AI model, the model itself is still a "black-box." This lack of complete interpretability can be troubling, especially when it comes to the field of education where decision-making needs to have understandable and explainable justification for its outcomes.
- Computational Cost: High computational demand in some models, notably the Gradient Boosting Model (GBM), was there. Models like KNN and SVM,

although being less computationally intensive, have to also be optimized in order to cater to large sets of data. The high level of computational demand would make availability in low-resourced universities unlikely.

- Static Evaluation: The study relied on static datasets to evaluate model performance, and did not account for long-term variations, such as changes in academic trends, student performance over time, or shifting educational environments. Future research could benefit from dynamic, time-series data to monitor and evaluate AI impact continuously.

6.3 Future Work

To overcome the above limitations and further increase the impact of the project, future directions are as follows:

- Dataset Expansion and Augmentation: Growing the dataset to consist of multi-institutional data will improve model generalization. Furthermore, advanced synthetic data generation methods such as GANs (Generative Adversarial Networks) can be used to balance class distributions and expand the dataset, enhancing model robustness.
- Real-World Deployment and Clinical Trials: Deployment of the model in the field within college settings for pilot testing, receiving real-time feedback from faculty and administrators, and prospective studies will be crucial in establishing the practicality and effectiveness of the model in diverse academic settings.
- Explainable AI Integration: Embedding advanced explainability techniques like LIME, SHAP, or attention visualization will enhance transparency and interpretability of AI-made predictions, instilling confidence among educators and decision-makers. It will be particularly critical when such high-stakes decisions are informed by AI-insights.
- Model Compression and Optimization: To deploy the AI models on more platforms of education, techniques for model compression, including pruning, quantization, and knowledge distillation, can be utilized to minimize the model size and computation cost without loss in performance.
- Continuous Learning: Implementing methods of model update or online learning will make the system constantly learn from new information and new patterns of learning, with no requirement for full model retraining. This will assist in making the AI system continue to be updated and successful at predicting academic performance over the long term.

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