ARTIFICIAL INTELLIGENCE (AI) IN EDUCATION: OPPORTUNITIES AND CHALLENGES

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This Report Presented in Partial Fulfillment of the Requirements for
The Degree of MS in Management Information System

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APPROVAL

This Project titled "**ARTIFICIAL INTELLIGENCE (AI) IN EDUCATION: OPPORTUNITIES AND CHALLENGES**" submitted by Name: **Israt Jahan**, ID No: **241-17-008** 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 MS. in Management Information System and approved as to its style and contents. The presentation has been held on **27 September 2025.**

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DECLARATION

I hereby declare that, this project has been done by me under the supervision of **Dr. Arif Mahmud, Associate Professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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Abstract

The integration of Artificial Intelligence (AI) in education has transformed teaching and learning, offering new opportunities to enhance student experiences. However, understanding how students perceive this integration remains a critical concern. This study examines the prediction of students' satisfaction with AI in education using machine learning classifiers applied to an imbalanced survey dataset, where responses were unevenly distributed across satisfaction levels. Initial evaluations revealed that while classifiers such as Random Forest, Logistic Regression, SVM, AdaBoost, Decision Tree, KNN, and KNN achieved high accuracy scores, their performance in capturing minority satisfaction responses was limited, as reflected in low F1-scores. Several classifiers on an imbalanced survey dataset using different balancing methods, including SMOTEENN, SMOTE oversampling, and class weight adjustment. Although accuracy appeared high across models (0.93–0.99), it was not reliable because it primarily reflected majority class performance and overlooked minority class predictions. F1-score, which accounts for both precision and recall, provided a more meaningful measure for imbalanced data. Based on F1-scores, SMOTEENN proved most effective, with Random Forest achieving the highest score of 0.99, followed by SVM, Decision Tree, and KNN (0.96–0.97). These findings suggest that advanced class balancing techniques are essential for reliable prediction of student satisfaction in AI-enabled education. Moreover, the study emphasizes that F1-score provides a more meaningful measure of model effectiveness than accuracy in imbalanced educational survey data. The study offers actionable insights for institutions seeking to optimize AI integration and enhance student satisfaction.

Keywords: Artificial Intelligence (AI), Education, Student Satisfaction, Machine Learning, Imbalanced Dataset, F1-Score, SMOTEENN, Random Forest, SVM, Decision Tree, KNN, AdaBoost.

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CHAPTER 1

Introduction

1.1 Introduction

AI, or artificial intelligence, is becoming more and more important in our daily lives and in school. AI is when machines, especially computers, do things that people do when they use language, learn, think, and make decisions. Because of this, they can learn, think, and talk. By making smart systems that can tailor lessons to each student, take care of administrative tasks, and get students more involved.

AI is starting to make its way into every part of the learning environment, including grading tools, language tutoring apps, mind-training software, and teaching platforms that give you feedback right away. Schools all over the world are using artificial intelligence (AI) more and more to help their students. AI now promises a more personalized learning experience for each student, as well as help with college and career planning. But using AI in schools on such a large scale is also bringing up new problems and moral questions. Some of these are our overreliance on machines, keeping information private, being fair, and the fact that people will probably meet less in places where they can learn. This chapter explains the studies' background, goals, and structure, which lays the groundwork for them. It also makes it easier to figure out what role AI should play in schools today. The current research objectives for this study are:

- To evaluate how effectively different machine learning classifiers can predict students' satisfaction with AI integration in educational settings, particularly when the survey data is imbalanced.
- To investigate which data balancing strategy—SMOTE oversampling, class weight adjustment, or a hybrid approach using SMOTEENN provides the most accurate and reliable predictions for minority satisfaction categories.

1.2 Background

People have been interested in artificial intelligence for a long time, but its use in education has grown quickly in the last few years, especially since the COVID-19 pandemic. The sudden switch to online learning made it necessary for teachers and schools to use virtual tools to make sure that training continued. During this time, AI tools became popular because they could adapt learning, automate tests, and give feedback. AI can personalize learning by changing the content to fit the student's pace and style. It can also help teachers find gaps in their students' learning more quickly.

Even with these improvements, many academic systems, especially in developing countries like Bangladesh, have a hard time using AI because of limited infrastructure, a lack of knowledge, high implementation costs, and a lack of trained staff. Moreover, students and teachers share differing perspectives regarding the evolving role of AI in education. This study seeks to examine both the beneficial impacts and the difficulties related to the integration of AI in educational contexts, utilizing primary data collected from students at the school, college, and university levels.

1.3 Motivation

The main reason for this research is the increasing use of AI tools in schools and the fact that students don't know enough about how they affect them. Students are using tools like ChatGPT, Grammarly, and adaptive learning systems more and more, but there may not be much real-world data on how students of different levels of education feel about them. Are students ready for this change? Do they think AI helps or hurts their learning? Are they aware of the ethical risks associated with data sharing and automation?

The studies are also driven by the desire to assist educators and policymakers in making informed decisions. Understanding how students feel about AI tools will help make sure that they are used responsibly and that technology development works with, not against, human-led education. This topic is also timely and relevant because it fits in with the global conversation about AI ethics, virtual literacy, and the future of work.

1.4 Problem Statement

Even though AI has a lot of potential to improve education, there are still a lot of problems that need to be solved. These include:

● Not knowing how AI affects students' ability to learn about outcomes.
● Students don't know enough about the AI device they use and what it means for them.
● Problems with keeping data private, safe, and using AI in schools in a moral way.
● Educators are worried about task safety because automation is becoming more common.
● Not sure what AI will do to teaching methods and student growth in the long run.

This study seeks to address these concerns by gathering perspectives directly from students, who are the principal stakeholders in the educational system. The challenge is to determine if AI is being utilized effectively and ethically in education, and whether students perceive it as beneficial or complex.

1.5 Objectives

The goal of this thesis is to:

- **Primary Goal:** To utilize machine learning techniques for predicting students' satisfaction with the integration of AI in education.
- **Key Focus:** To handle class imbalance present in the survey dataset by applying suitable resampling and balancing strategies.
- **Final Objective:** To build robust and unbiased predictive models that ensure reliable performance across all levels of student satisfaction.

By achieving those objectives, the study enhances the understanding of how AI is influencing the future of education and the measures implemented to ensure its proper utilization.

1.6 Research Methodology

The study uses a survey method that involves numbers. We have a list of basic questions to ask students about their thoughts on AI in education, what they use it for, what they like and dislike about it, and what bothers them. The survey was given to students in high school, college, undergraduate, and graduate school. These questions could be answered by people of all levels of technical knowledge since they were clear and simple.

We got the information from online survey and applied simple statistics to detect patterns or common points of view in the results. This strategy helped them get objective, measurable data that would help them talk about AI policy and instruction.

1.7 Proposed Solution

Here are the suggested fixes based on the survey and the literature:

- Workshops, training, and curriculum integration to teach both instructors and students about AI.
- Setting rules for the fair use of AI, ethical applications, and algorithms that protect data.
- Encouraging a balanced use of AI tools that focuses more on critical thinking and interacting with people than on learning.

- We shouldn't be afraid that AI will take over teachers' jobs instead, we should see it as a friend.

This method aims to merge ethical pedagogy with technological innovation to enable AI to serve as a tool for enhancement rather than disruption.

1.8 Conclusion

This chapter outlined the overall background of the research, highlighting its aims, rationale, and scope. To strengthen the study's depth, the next chapter will analyze the outcomes of related work conducted in this field.
It described what the study was trying to do, which was to look into AI in education, and how the data was collected and analyzed. The next chapters will talk about the most recent research, survey results, and possible future uses of AI in education.

CHAPTER 2

Literature Review

2.1 Introduction

Education is also following the trend of a global revolution, which was made possible by lightning-fast AI-tech development. With schools eager to digitize their teaching and learning methods, AI is seen as a tool to finally address long-standing educational problems. We venture out of the research studies to cover articles in magazines for theories about AI and education. This paper is a review paper that its goal is to create solid foundation for understanding on how AI has been used in education, what are the advantages and drawbacks of this technology and where most studies have not cover. The progress of artificial intelligence in education, AI technologies for teaching and learning, advantages and prospects, risky sides and tough tasks to do as well as ethical issues are the major four area in which literatures are categorized.

2.2 Literature Review:

The literature review is an extensive evaluation on the previous studies about potential and challenges of AI in education.

Paper	Method	Dataset / Context	Performance (Accuracy / Findings)	Key Finding	Limitation
Deng et al. (2025)[1]	Meta-analysis of Generative AI in Education	Multiple peer-reviewed studies (2019–2024)	Average effect size: positive but heterogeneous	Generative AI can enhance learning outcomes, especially writing & feedback	Limited long-term studies, effect varies by context
Wang et al. (2024)[2]	Systematic Literature Review (SLR)	120+ studies on AI in Education	N/A (review study)	AI supports adaptive learning, intelligent tutoring and teacher productivity	Many studies lack rigorous experimental design

Lee (2025)[3]	Systematic Review (Language Learning)	Studies using LLMs in language classrooms	Reported improvements in writing fluency, feedback and engagement	Generative AI beneficial in second language acquisition	Risks of over-reliance, plagiarism, limited cultural context
Liu et al. (2025)[4]	Meta-analysis of GenAI in education	49 studies across K-12 and higher education	Effect sizes: achievement = 0.857, motivation = 0.803	Generative AI has a generally strong positive impact on learning outcomes and motivation	Effects vary by education level, interface type, subject, duration
Möller et al. (2024)[5]	Comparative study using AI-driven tutoring	Distance learning university students across 40+ courses	Study time reduced ~27% by month three	Generative AI accelerates learning pace via personalization	Early months only; long-term and learning quality not assessed
Altukhi & Pradhan (2025)[6]	Systematic review on Explainable AI	19 studies using PRISMA method	Identified 15 XAI definitions, 62 challenges	Clear need for consensus on explainability in educational AI	Inconsistent definitions and overlapping concepts across literature
Yusuf (2025)[8]	SLR (PRISMA) on AI in primary education	45 studies (2016–2024)	N/A	AR, VR, LMS, adaptive systems offer promising results	Infrastructure, cost, teacher training and data privacy remain barriers
Kohnke & Zaugg (2025)[7]	Review on AI in STEM equity & access	STEM education context	N/A	AI holds potential to increase equity and access for students with disabilities	Need for more empirical studies and inclusive design strategies

Vargas-Murillo et al. (2023) [9]	Systematic review on ChatGPT & AI-assisted learning	Higher education ChatGPT use	N/A	Emphasizes opportunities (efficiency, drafting) and challenges (misuse, ethics)	Focused on ChatGPT only and lacks quantitative impact data

2.2.1 AI in Education

The literature review starts with a brief history of AI in education. It looks at research that shows how AI is affecting topics like personalized learning, teaching methods, and helping students think critically. This step's purpose is to find out exactly what high-quality hardware and capacity challenges come up when training AI. This helps make sense of things. This is a moment of victories, battles, and new ways that AI can change higher education for the better.

2.2.2 Evolution of AI in Education

The idea of using machines to help people learn came about in the 1960s when people first tried computer-assisted education. The creation of Intelligent Tutoring Systems (ITS) in the 1980s and 1990s, on the other hand, was the start of real AI integration in training. Those systems aimed to mimic human instructors with the aid of adapting learning materials based on student performance. According to recent research, current AI programs now move past ITS, such as adaptive learning systems, predictive analytics, AI teaching assistants and natural language processing tools utilized in gaining knowledge of management systems.

2.2.3 AI Tools and Applications in Education

Today, schools and other places of learning use a lot of different AI-powered solutions. Machine learning is used by Duolingo and other services to make learning a language more personal. Knewton and DreamBox, on the other hand, offer math training that changes based on how well you do. IBM Watson Tutor and other chatbots can answer students' queries in real time, while automated grading systems can quickly grade tests and assignments. This makes teachers' jobs easier.

Schools can use AI and predictive analytics to find pupils who are likely to fail before they really do. Computers that can think creatively, see into the future, and interpret speech are helping students with disabilities in special education. AI-based proctoring systems are employed to keep an eye on students during online tests, however there are moral problems with using them.

2.2.4 Benefits and Opportunities of AI in Education

Many experts stress how AI has had a huge impact on both teachers and students. One of the best things about it is that it lets you learn at your own pace. AI algorithms can look at how a student studies, how fast they learn, and what their strengths are to make lessons more personalized. This guarantees that students obtain the necessary content in a format that suits them well.

Another benefit is that you can keep track of your performance and get feedback right away. Using AI to give students real-time feedback can help them learn faster and be more aware of their mistakes. AI tools help teachers automate tasks like scheduling, taking attendance, and grading, which gives them more time to teach and help students.

Researchers say that AI can help with inclusive education. For example, students with learning disabilities can get a lot out of AI-based tools that let them turn text into speech or speech into text. AI can also help make education more accessible by making it easier for people to learn at their own pace and from a distance, especially in rural areas.

2.2.5 Challenges and Negative Impacts

Some studies had raised questions regarding the pros and cons of utilizing AI in schools. "And it's even worse that people only talk to people in their own network." Learning is a social activity, and if students just use AI to learn, it might be harder for them to engage with each other in ways that are vital for academic progress between teacher and student and between peers.

It's very important to keep your information confidential. AI systems usually need to know a lot about pupils in order to do their jobs. He said, "I don't really know of a clear line between what this data can and can't be used for that is in an ethical or legal space." She said that AI proctoring systems, such those that keep an eye on a student's behavior throughout an exam, "can feel pretty intrusive."

Another concern is that A.I. algorithms might not be fair. If the AI model's training database was built on biased data, it could unfairly grade students, give them bad advice, or treat a competent student agent badly. Key word: FICTION Some teachers and schools might not even try to understand how to use some AI tools effectively, which could lead to frustration and inappropriate use.

This is how A.I. could benefit teachers. A.I. could aid teachers with many different problems. The A.I. can help teachers, but nothing can replace the expertise, experience, and common sense that a genuine teacher has. Experts suggest that AI should be used, not set up as a bunch of machines that act like people and make decisions on their own.

2.2.6 Ethical and Policy Considerations

Putting the ethical and teaching framework of AI in place There are several resources you can use while you learn how to be a good steward. But if smart policies aren't in place, A.I. should make those gaps in schooling bigger, not fewer. For AI to train securely and fairly on such data, these kinds of ethical challenges must raise strange moral issues about transparency, consent, and accountability. UNESCO and other international organizations have also started to talk about A.I. literacy, which means that kids and, eventually, their teachers should at least know what A.I. is, how it works, and what it could do. But what we need now is a school system that plans for the future and makes technology that is ethical.

2.2.7 Integrating AI Responsibly in Education:

This chapter contributes to the discourse on responsible AI by offering frameworks and guiding principles for the ethical application of AI skills in educational settings. It makes the call for more openness, responsibility, and access to AI work in schools even stronger.

2.3 Conclusion

Some current research reviews have illuminated the impact of AI in the training domain, as depicted in this chapter. It will show how AI technology has changed from CAI, which used simple computer programs, to intelligent systems that let people learn by doing things like personal remediation, automated grading of drill and practice exercises, managing computer (paperless) activities, and being creative. But it's hard to say that AI couldn't make jewel learning more interesting, useful, and easy to use. For example, teaching AI systems could help them make content that is tailored to each student's specific learning style and level of understanding. Administrative AI systems could also help teachers by letting them spend less time on paperwork and more time with students.

Second, the evidence also supports the notion that AI could transform the dynamics of inclusive education. It comes in the form of assistive technology, like speech-to-text, real-time translation, and predictive learning analytics. AI can also let us picture a different version of our actual world through simulations (which are foolish) or digital twins. AI could help older learners overcome some of the challenges they confront because of disability, language issues, and geographical distances. AI is making learning something that is most likely to be demo tied, and it is leveling the playing field for students from varied social, cultural, or even economic origins.

But the literature also talks about some important issues that this revolution in technology brings up. But in the where’s, you can't talk to other people anymore, which has always been a crucial aspect of good teaching and learning. If we misuse that AI, our students will be a tool for learning instead of being a part of it. They also talk about moral problems including privacy of data, bias in algorithms, and being open. Many AI systems are "black boxes," which means that teachers and students don't know how judgments were reached. People may not trust the system or its decisions if they don't know what's going on.

The research proposes solutions to these difficulties and questions whether better-resourced or wealthier schools may initially utilize and/or access technology, so exacerbating the divide between digital haves and have-nots. Countries like China, and especially those in the poor world, don't have the infrastructure, money, or training for teachers to use AI tools properly. And that brings us to the key question: Will AI make the education gap greater or smaller?

Perhaps most importantly, the literature reveals a clear gap in student-centered research. While technical developments and policy recommendations are well-documented, fewer studies focus specifically on how students perceive AI and how it impacts their learning experiences. Most available research emphasizes the capabilities of AI systems or examines their use from an institutional or administrative perspective. The voices of students the very individuals most affected by these technological shifts are often underrepresented in the academic conversation.

This hole justifies the point of interest of the modern study, which places student perspectives at the middle of its research. By gathering direct comments from students at school, college, undergraduate and postgraduate degrees through a dependent survey, this research seeks to provide practical insights into how AI is experienced and evaluated by beginners themselves. This student-focused approach aims to complement the present body of literature and offer valuable suggestions for educators, policymakers and technology builders.

The literature appears optimistic regarding AI in education, advocating for its implementation in a manner that is equitable, ethical, and accessible to all. It's evident when there are clear procedures and strong rules, like what makes for a good education, fair entry points, and the need for everything to be perfect. In the following chapter, I'll speak about how I did an empirical investigation of these things and how I came up with a technique to group and combine them as part of figuring out how AI is currently affecting education.

CHAPTER 3

Research Methodology

3.1 Introduction

Every type of inquiry you are likely to hear talk about within a context of education paradigm is in some sense "just" one way that somebody at one time or another happened to think about how they would go about doing something like the kind of research we undertake, and what they thought was appropriate to do and how they went about doing it can be viewed as something like what we might call a process that could describe either some sort of logical sequence related (although typically not identical) with whatever you're going to want to follow when investigating something. Similarly to other chapters in this book, here we propose a research design and methodology that investigates “education and challenges” by asking students what they know about possibilities of AI. The objective of these studies has been to provide us reliable factual data on students in some area and at Ditter cut level (school, college, bachelor or more) by asking them very simple and clear questions using survey.

The research methodology of this study is designed to systematically examine students’ satisfaction with the integration of Artificial Intelligence (AI) in education using machine learning techniques. A quantitative approach was adopted, where survey data was collected, preprocessed, and analyzed through various supervised learning classifiers. Since the dataset suffered from class imbalance, different balancing strategies such as SMOTE oversampling, class weight adjustment, and a hybrid approach combining SMOTEENN were applied to improve fairness in prediction. Multiple algorithms, including Random Forest, SVM, Decision Tree, KNN, Logistic Regression, AdaBoost, and Naive Bayes, were evaluated on key performance metrics such as accuracy, precision, recall and F1-score,. This structured methodology ensured that the research not only identified the most effective predictive model but also addressed the challenges posed by imbalanced survey data, leading to more reliable and meaningful insights.

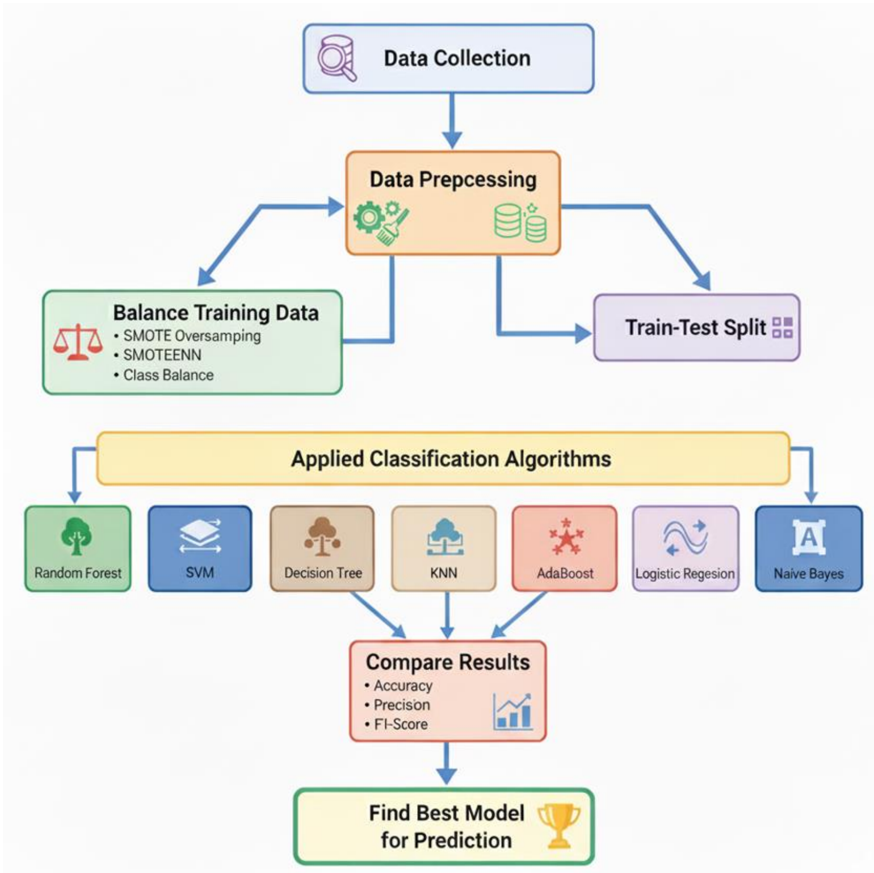

Figure 3.1: Experimental work flow of this research

3.2 Research Subject and Instrumentation

❖ **Research Subjects**

The studies had been designed to include and recruit as much and broad a sample on educators. The study focused on the four major levels of the students:

- School Students
- College Students
- Undergraduate Students
- Postgraduate Students

We included these groups in order to create a comprehensive portrait of how AI is perceived at different education levels, and given different levels of virtual exposure. Contributors were a mix of city and semi-urban schools, with the motivation to diversity background, tech access and experience with AI tools.

❖ **Instrumentation**

In the present study, it is one of main tools to collect primary data from the respondents and its consist 20 questions related to AI in education which use for student attitude & knowledge toward AI in education are student recognition, experiences, perceive benefit and afraid, future expectation with AI in educations.

The individual questions were categorized into five groups:

1. Consciousness and Exposure to AI
2. Opportunities and Advantages of AI
3. Challenges and Concerns
4. Moral and Social Perspectives
5. Future Intentions and Readiness

Indeed, we have to work in this way since the survey, besides that should being fillable on an enough rapid and faster algorithmic order by answers of nontechnical user as nontechnical languages, it is a very little information just to shop about.

3.3 Data Collection Procedure

This online survey through Google Forms of the present analysis is the sole source or data for this research. This method was selected based on its universal applicability, popular availability and the ability of responding at any level such as high school student, undergraduate student or postgraduate. Online administration allowed participants to take the survey at their convenience, from anywhere, and greatly reduced constraints on the availability of venues for collecting physical data.

The link to the survey was shared through a number of online channels, including e-mail as well as social media– twitter, Facebook, WhatsApp and students' group chat. These are the channels that have been chosen as a result of college students typically talk on them (school and undergraduate college students specifically being extra digitally lively). This may have been due to the extensive reach of such platforms (the majority of respondents were from tweeters), which could be influencing this somewhat fairly large and representative sample.

A 20-item scale, intentionally written in basic and understandable language and include students from wide areas of study as the participants is developed. Those questions included the subjects of awareness to AI, its perils, ethical considerations and what people want from the future.

Participants were given a very brief presentation of the study and its purpose before beginning. Participation was anonymous and voluntary: no personally identifiable information (i.e., names, e-mail addresses, phone numbers or background of education) were required. This was to ensure the anonymity of respondents and getting honest, unaided feedback from them.

Overall, the online approach was an efficacious, economic and ethical way to gather the essential data. The raw data was output to a Google Sheet with automated aggregation -At the next level of the research design.

Table 3.3.1: Questionnaire to Collect Data

Serial	Attributes	Attribute Values
1	Gender	● Male ● Female ● Other
2	Age	● 12-20 ● 21-28 ● 29-38 ● 38-50 ● 50 and above
3	Educational Background	● School ● College ● Bachelor’s Degree ● Master’s Degree ● PhD / Higher Degree

4	Have you heard about Artificial Intelligence (AI)?	• Yes • No
5	Do you know that AI is used in education?	• Yes • No
6	Have you experienced AI tools in your educational environment?	• Yes • No
7	Are you recently using any AI-based educational tools or platforms?	• Yes • No
8	Did your teacher ever use an AI tool in class?	• Yes • No
9	Do you think AI can help students learn better?	• Yes • No
10	Can AI make learning easier for slow learners?	• Strongly Agree • Agree • Neutral • Disagree • Strongly Disagree
11	Can AI help students learn from home?	• Yes • No
12	Do you think students can become lazy if they use AI too much?	• Yes • No
13	Are you worried that AI might take teachers jobs?	• Yes • No
14	Do you think AI tools can make mistakes?	• Yes • No
15	Are you concerned that AI may use your personal data?	• Yes • No
16	Do you want to learn more about AI?	• Yes • No
17	Do you want AI to be part of your school or college?	• Yes • No
18	Do you think AI will be very important in the future?	• Yes • No
19	Do you feel informed about how AI applications use your personal information?	• Yes • No
20	How satisfied are you with the recent integration of AI in your educational experience?	• Satisfied • Dissatisfied

Google form had been created based on those 20 questionnaires. Data was collected through this form from the students.

3.4 Data Analysis Procedure

When data were collected from survey results, these were statistically treated in classical and in machine learning classifications algorithms. The possibility of identifying the patterns in place, sorting similar responses and comparing student perceptions towards AI in education more objectively and with a data-driven approach was anticipated.

1. Data Preparation

The first was to clean, categorize and organize the raw Google Form data I had downloaded. Questions have been mostly transformed into binary format 'Yes' 1, and 'No' 0. The information was arranged into a table where each row corresponded to one survey participant, and each column matched with a survey question.

2. Handling Class Imbalance

The dataset used in this study presented a noticeable imbalance in the target column, where one class contained significantly fewer instances compared to the others. Such imbalance often leads to biased predictions, as machine learning models tend to favor the majority class while overlooking patterns in the minority group. To mitigate this issue and enhance the reliability of the predictive models, the Synthetic Minority Over-sampling Technique (SMOTE) was employed. Unlike simple replication, SMOTE generates new synthetic samples for the minority class by interpolating between existing instances. This approach helps create a more balanced dataset, allowing classifiers to learn the distinguishing characteristics of both majority and minority classes more effectively. Consequently, the application of SMOTE not only reduces bias but also improves key evaluation metrics, particularly recall and F1-score, ensuring a fairer and more accurate model performance.

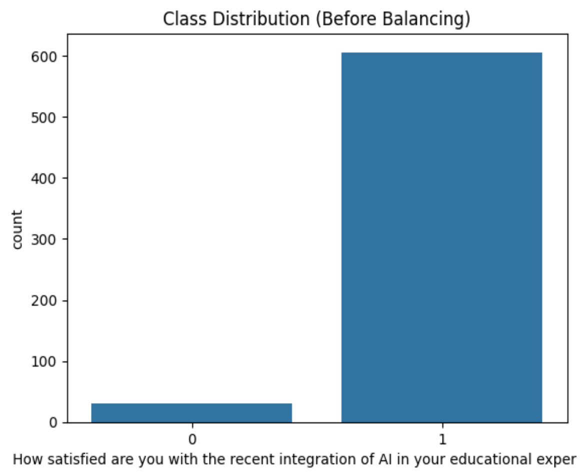

Figure 3.4.1.1: Before Balancing

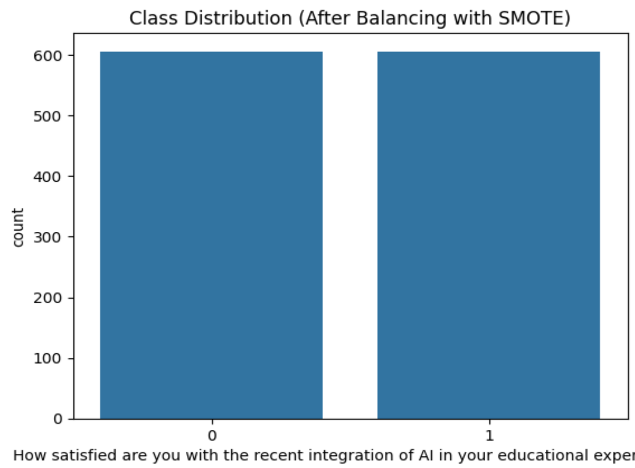

Figure 3.4.1.2: After Balancing

3. SMOTEENN (SMOTE + ENN)

SMOTEENN is a hybrid resampling strategy that combines oversampling with data cleaning–based undersampling. In the first step, the Synthetic Minority Oversampling Technique (SMOTE) generates artificial samples of the minority class to increase its representation. Following this, the Edited Nearest Neighbors (ENN) algorithm is applied to remove ambiguous and noisy samples, mainly from the majority class, that lie close to the decision boundary. This dual process not only balances the dataset but also improves data quality by eliminating misleading instances. As a result, SMOTEENN often produces a cleaner and more informative training set, which can lead to improved model generalization and classification performance compared to using oversampling or undersampling alone.

4. Classification Analysis

A classification model becomes used to predict student categories (including academic level or overall attitude toward AI) based on their responses. Some of the steps covered:

- **Labeling**: Responses had been grouped into outcome labels, inclusive of positive perception, negative perception or impartial based on total affirmative responses.
- **Training and Testing**: The dataset will become split into training and testing units for model validation.

- **Algorithms Used**: Simple and easy classification algorithms such as Decision Trees, KNN, Random Forest, SVM, AdaBoost, Naive Bayes or Logistic Regression have been implemented the usage of tools like Colab or Pythons scikit-learn.

- **Performance Metrics**: Accuracy, precision, recall and F1-rating had been calculated to assess the versions capability to properly classify student's attitudes based on their responses.

The classification helped to understand which features (questions) were the most influential in shaping student's overall perceptions of AI.

5. Descriptive Analysis

Before applying algorithms, a primary descriptive statistical analysis became conducted to:

- For survey questions, the responses have been analyzed to determine the frequency of key classes: 'Yes' and 'No', reflecting binary choices; 'Satisfied' and 'Dissatisfied', indicating user satisfaction; and 'Agree' and 'Disagree', representing stages of agreement.

- Calculate percent distributions throughout specific educational levels (school, college, bachelors and masters).
- Visualize responses to the using of bar charts and pie charts for a quick understanding of dominant reviews.

This step helped discover initial trends and guided the selection of suitable algorithmic strategies.

6. Correlation between features

In this figure 3.54.1.3 we can see relationship of each columns pair from the dataset. Correlation values colored with 2 colors are displayed below the right part of this figure. The lighter is week association and darker is strong correlation among them.

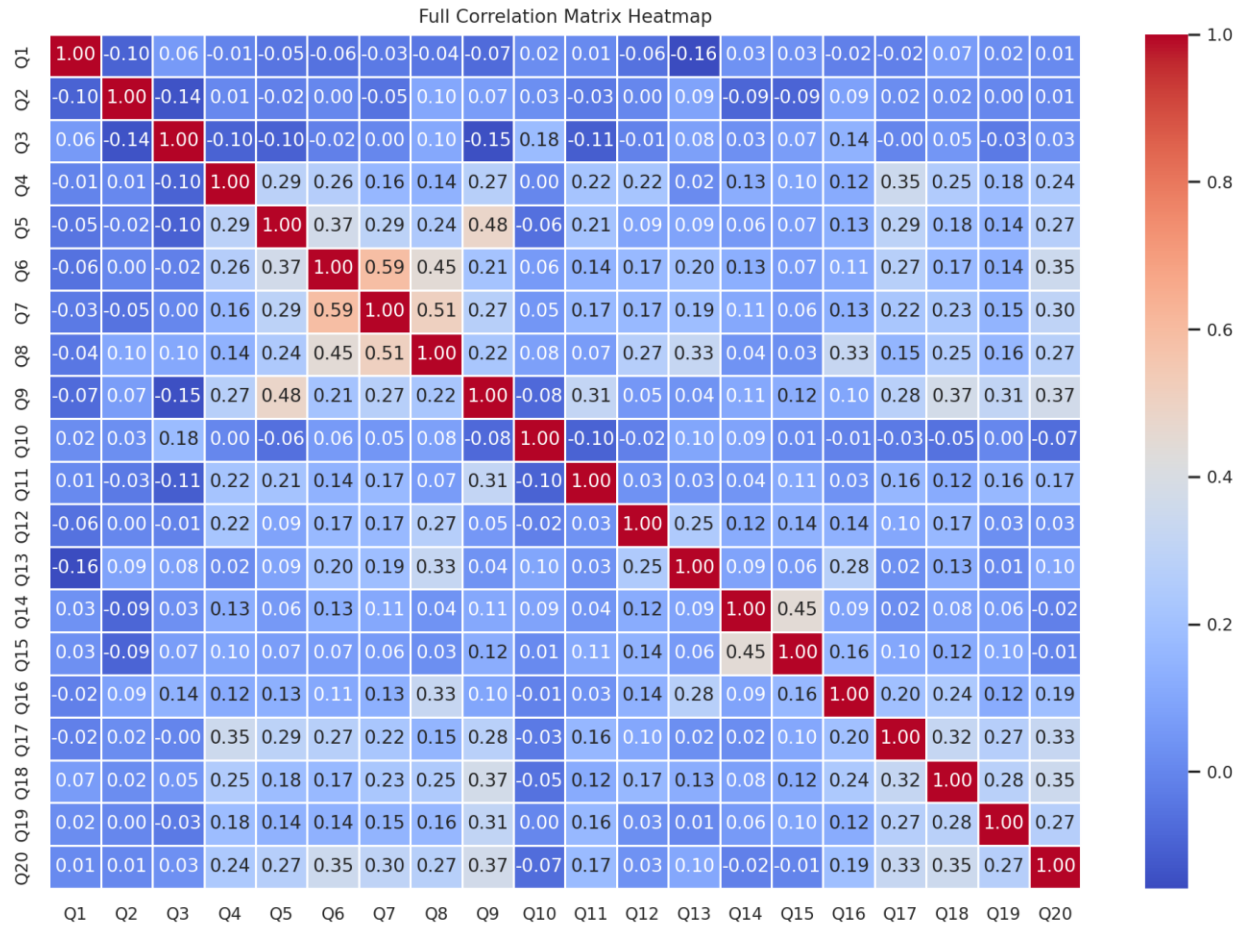

Figure 3.4.1.3 Heatmap of Correlation

7. Tools and Software

The analysis was executed using the following tools:

- Use Colab tools for smooth and easy implementation of classification algorithms.
- Google Sheets / Microsoft Excel for initial data cleaning and descriptive data.

8. Outcome of Analysis

The mixture of classification provided:

- A deeper knowledge of which elements impact effective or bad views of AI.
- Evidence-based segmentation of student attitudes.
- A data-driven foundation for the discussion of results in the next chapter.

This multi-method analysis not only enhanced the reliability of the findings but also contributed to the academic depth of the research by applying machine learning in the educational domain.

3.5 Conclusion:

This chapter has provided a complete overview of the research methodology hired in this research to analyze student perceptions of Artificial Intelligence (AI) in education. A quantitative survey-based method became selected as the primary method because of its effectiveness in taking measurable data from a wide and various group of participants. The usage of a based questionnaire with simple questions allowed for the inclusion of respondents from various educational stages, including school, college, undergraduate and postgraduate students. This simplicity ensured that even respondents with limited exposure to AI or studies practices may want to participate confidently and meaningfully.

Google Forms It was easy to collect data online, and it was also straightforward to send it in. It made it easier for students from diverse places to take part in the survey, saved money, and made it easy for a lot of people to take part. The survey was open to students of all ages and levels of technology because it used popular internet tools like email and social media sites like WhatsApp and Facebook. Because the data gathering was digital, the method for collecting data also allowed for on-the-spot testing of accurate responses by inputting and writing down while nesting.

The improvement of the questionnaire was guided by a thematic framework that considered both the potential benefits and challenges of AI in education. The study effectively captured a comprehensive understanding of students' perceptions of AI and the alignment or divergence of their reviews from educational literature by structuring the questions around major topics such as AI awareness, opportunities, problems, ethics, and future outlook.

The method for assessing the data was also made to be simple and reliable from a statistical point of view. We used simple counts like frequency counts, percentage distributions, and themes to seek for patterns in the answers. When designing rules, courses, or using AI technologies in school, this strategy makes the data easy to view and understand in a way that can be applied in the real world.

The design of the study also brings up some evident moral issues. Everyone who might desire to take part was told that the study was not required and that their names would not be disclosed. The surveys didn't ask for any personal information, and the setting was supposed to make respondents feel secure and honest. This also helped make sure that the rules of ethics in educational research were followed and that the material was correct.

The strategy in this chapter is a good place to start for more research. This, together with a good survey method and a wide range of responses, makes sure that the results are both real and a realistic representation of what students at all levels of the educational hierarchy have gone through. In this approach, our results would be highly useful for figuring out how AI genuinely affects education and might help reduce the gap between what people assume about technology and what it can do.

The following chapter looks at and talks about the answers to the survey. This second part of the analysis will look at the data in a more open-ended approach, based on the study goals and the literature review. This will help us understand better how AI is used in today's schools.

CHAPTER 4

Experimental Results and Discussion

4.1 Introduction

This chapter discusses the results and analysis of a survey of students from different levels of education to find out what they think about using AI in the classroom. The analysis integrates descriptive statistics with machine learning methodologies, namely classification algorithms, to discern patterns, categorize students according to their responses, and forecast views on the integration of AI in education.

We used different classification models, like Decision Trees, Naïve Bayes, Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), Logistic Regression, and AdaBoost, to figure out if students are supportive, neutral, or skeptical about AI being used in their classrooms. We used information from the survey about kids' behavior, academics, and technology use to make these predictions.

The data for this study were gathered by a standardized questionnaire distributed at the school, college, undergraduate, and postgraduate levels. The questionnaire gauged student awareness, previous experiences, perceived advantages, and possible apprehensions related to AI in education. This chapter presents the descriptive findings of the dataset alongside the outcomes from the categorization models. It also shows what AI can and can't do in the classroom, depending on what the students said.

Using more than one, we could directly compare and choose the best machine learning algorithm for what people think and predict what they will do. The purpose of this study is to establish an evidence base for current perceptions about AI in education and the potential implications for future teaching and learning.

4.1.1 Decision Trees

According to Figure 4.1.1, the Decision Tree achieved an accuracy of 97%. It correctly classified both classes with high precision and recall, showing balanced effectiveness across the dataset. Class 0 achieved a precision of 0.95 and recall of 0.99, while Class 1 obtained a precision of 0.99 and recall of 0.94, indicating reliable detection for both classes. The macro and weighted average

F1-scores of 0.97 further confirm the model's consistent and well-balanced classification capability

```
====== Decision Tree ======
Accuracy: 0.9671
Confusion Matrix:
[[121   1]
 [  7 114]]
Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.99      0.97       122
           1       0.99      0.94      0.97       121

    accuracy                           0.97       243
   macro avg       0.97      0.97      0.97       243
weighted avg       0.97      0.97      0.97       243
```

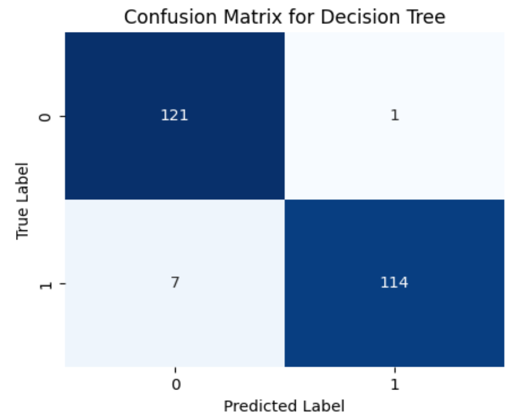

Figure 4.1.1: Decision Tree

4.1.2 Naive Bayes

Figure 4.1.2 shows that the Naive Bayes classifier was correct 88% of the time. It discovered both classes with the same level of accuracy and recall (0.88), which means that the predictions were balanced but not as accurate as those made by the Decision Tree. It was easy to tell that Class 0 and Class 1 were there, and each had an F1 score of 0.88. The model scored well on the complete dataset, as evidenced by the macro and weighted average F1-scores of 0.88. However, the confusion matrix shows that some things were misclassified.

```
====== Naive Bayes ======
Accuracy: 0.8807
Confusion Matrix:
[[107  15]
 [ 14 107]]
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.88      0.88       122
           1       0.88      0.88      0.88       121

    accuracy                           0.88       243
   macro avg       0.88      0.88      0.88       243
weighted avg       0.88      0.88      0.88       243
```

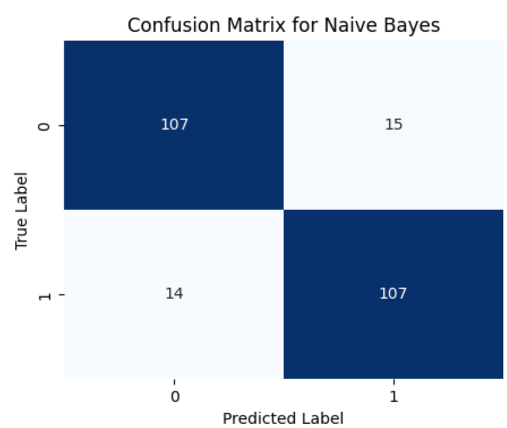

Figure 4.1.2: Naive Bayes

4.1.3 Support Vector Machines (SVM)

Figure 5.1.3 shows that the SVM classifier was 97% right. It got both classes right 98% of the time, which means that its forecasts were pretty accurate and fair. It was possible to correctly identify Class 0 and Class 1, both of which had an F1-score of 0.98. The macro and weighted average F1-scores of 0.98 suggest that the model can sort things correctly and consistently, with very few mistakes, as evidenced by the confusion matrix.

```
====== SVM ======
Accuracy: 0.9794
Confusion Matrix:
[[119   3]
 [  2 119]]
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98       122
           1       0.98      0.98      0.98       121

    accuracy                           0.98       243
   macro avg       0.98      0.98      0.98       243
weighted avg       0.98      0.98      0.98       243
```

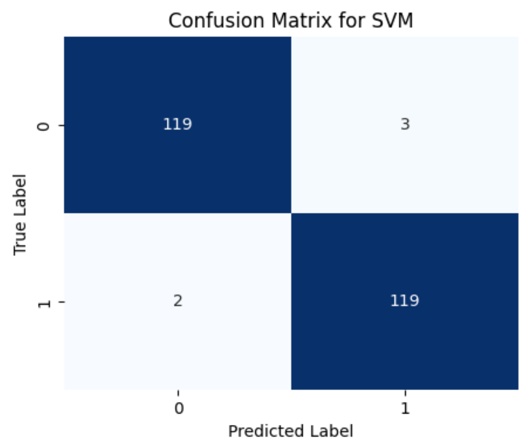

Figure 4.1.3: Support Vector Machines (SVM)

4.1.4 Random Forest

According to Figure 4.1.4, the Random Forest classifier achieved an accuracy of 98%, demonstrating strong overall performance. It classified both classes reliably, with Class 0 achieving a precision of 0.98 and recall of 0.99 and Class 1 achieving a precision of 0.98 and recall of 0.98, resulting in balanced F1-scores of 0.98 for both classes. The macro and weighted average F1-scores of 0.98 confirm the model’s consistent and well-balanced classification capability, with very few misclassifications as reflected in the confusion matrix.

```
====== Random Forest ======
Accuracy: 0.9835
Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       122
           1       0.99      0.98      0.98       121

    accuracy                           0.98       243
   macro avg       0.98      0.98      0.98       243
weighted avg       0.98      0.98      0.98       243

Confusion Matrix:
[[121   1]
 [  3 118]]
```

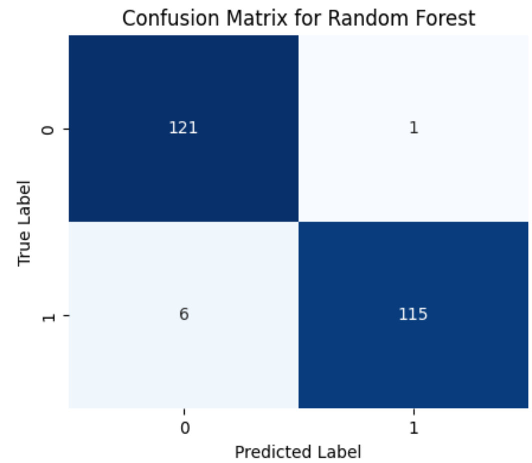

Figure 4.1.4: Random Forest

4.1.5 K-Nearest Neighbors (KNN)

As in Figure 5.1.5, the KNN classifier achieved an accuracy of 95%. It correctly detected both the classes with a precision and recall of 0.93 and 0.99 for Class 0, and precision and recall of 0.99 and 0.93 for class1. This resulted in an F1-score of 0.96 for both classes. An F1-score (both the macro and weighted averages) of 0.96 demonstrates that categorization across the corpus is uniform and balanced. It can be seen from the confusion matrix that very few wrong classifications have been happened.

```
====== KNN ======
Accuracy: 0.9588
Confusion Matrix:
[[121   1]
 [  9 112]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.99      0.96       122
           1       0.99      0.93      0.96       121

    accuracy                           0.96       243
   macro avg       0.96      0.96      0.96       243
weighted avg       0.96      0.96      0.96       243
```

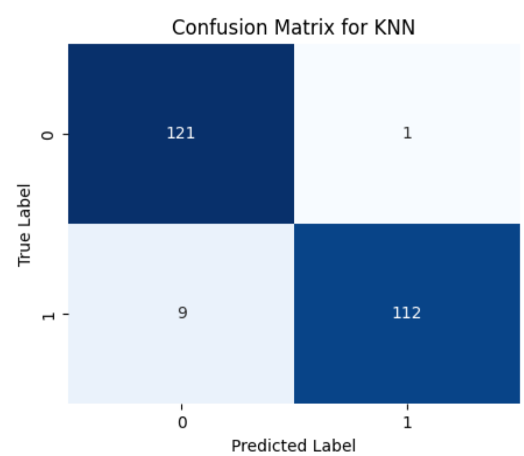

Figure 4.1.5: K-Nearest Neighbors (KNN)

4.1.6 Logistic Regression

According to Figure 5.1.6, the Logistic Regression classifier achieved an accuracy of 92%. It classified both classes reliably, with Class 0 achieving a precision of 0.93 and recall of 0.92 and Class 1 achieving a precision of 0.92 and recall of 0.93, resulting in balanced F1-scores of 0.93 for both classes. The macro and weighted average F1-scores of 0.93 indicate consistent and effective classification across the dataset, with only a few misclassifications as shown in the confusion matrix.

```
====== Logistic Regression ======
Accuracy: 0.9259
Confusion Matrix:
[[112  10]
 [  8 113]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.92      0.93       122
           1       0.92      0.93      0.93       121

    accuracy                           0.93       243
   macro avg       0.93      0.93      0.93       243
weighted avg       0.93      0.93      0.93       243
```

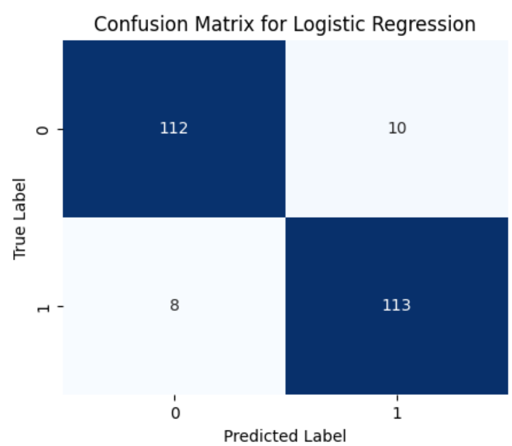

Figure 4.1.6: Logistic Regression

4.1.7 AdaBoost

According to Figure 5.1.7, the AdaBoost classifier achieved an accuracy of 90 %. It classified both classes reliably, with Class 0 achieving a precision of 0.91 and recall of 0.90 and Class 1 achieving a precision of 0.90 and recall of 0.91, resulting in balanced F1-scores of 0.91 for both classes. The macro and weighted average F1-scores of 0.91 indicate consistent and effective classification across the dataset, despite some misclassifications as reflected in the confusion matrix.

```
====== AdaBoost ======
Accuracy: 0.9053
Confusion Matrix:
[[110  12]
 [ 11 110]]
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.90      0.91       122
           1       0.90      0.91      0.91       121

    accuracy                           0.91       243
   macro avg       0.91      0.91      0.91       243
weighted avg       0.91      0.91      0.91       243
```

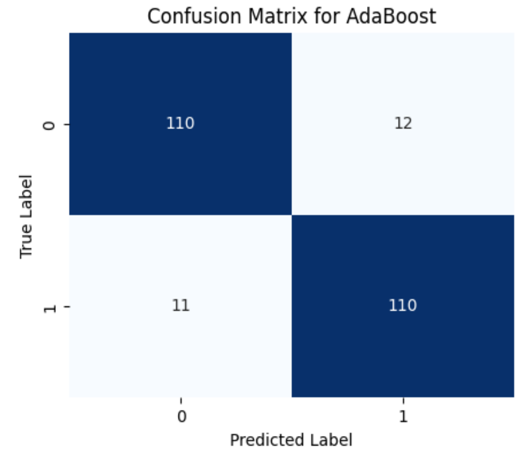

Figure 4.1.7: AdaBoost

4.2 Results without Balancing

Table 4.1 Performance Parameters (Without Balancing)

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.98	0.75	0.99	0.83
SVM	0.98	0.49	0.50	0.50
Decision Tree	0.97	0.67	0.98	0.74
KNN	0.99	1.00	0.75	0.83
Logistic Regression	0.98	0.75	0.99	0.83
AdaBoost	0.98	0.75	0.99	0.83
Naive Bayes	0.84	0.55	0.92	0.54

The 4.1 table reports the performance of the classifiers on the raw imbalanced dataset. At first glance, the accuracy values appear very high, ranging from 0.84 for Naive Bayes to 0.99 for KNN. However, the F1-scores tell a different story. While Random Forest, Logistic Regression, and AdaBoost achieved an F1-score of 0.83, SVM lagged far behind with an F1-score of only 0.50, despite having 0.98 accuracy. This mismatch highlights that the classifiers, especially SVM, were heavily biased toward the majority class. The relatively higher recall values for Random Forest, Decision Tree, and Logistic Regression (all close to 0.99) indicate that these models predicted most positive cases, but their lower precision values (around 0.67–0.75) suggest they also produced many false positives. Thus, the results from this table confirm that accuracy is misleading in imbalanced datasets, and more balanced metrics like the F1-score are needed for fair evaluation.

4.3 Results after SMOTE Oversampling

Table 4.2 Performance Parameters (SMOTE Oversampling)

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.98	0.98	0.98	0.98
SVM	0.98	0.98	0.98	0.98
Decision Tree	0.97	0.97	0.97	0.97
KNN	0.96	0.96	0.96	0.96
Logistic Regression	0.93	0.93	0.93	0.93
AdaBoost	0.91	0.91	0.91	0.91
Naive Bayes	0.88	0.88	0.88	0.88

The 4.2 table demonstrates the effect of applying SMOTE oversampling, which generated synthetic samples for the minority class. The improvements were dramatic across all models. Random Forest, SVM, Decision Tree, and KNN achieved precision, recall, and F1-scores all above 0.96, with Random Forest and SVM reaching almost perfect 0.98 across metrics. This indicates that oversampling successfully reduced class imbalance and enabled the models to detect both classes equally well. Logistic Regression, AdaBoost, and Naive Bayes also improved, though their F1-scores remained slightly lower (0.93, 0.91, and 0.88 respectively), suggesting that oversampling introduces synthetic noise that impacts simpler or more linear models. Nevertheless, compared to the unbalanced results, SMOTE oversampling provided a significant enhancement in minority class detection and overall model stability.

4.4 Results using Class Balancing (Class Weights)

Table 4.3 Performance Parameters (Class Balancing)

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.94	0.88	0.83	0.85
SVM	0.89	0.74	0.87	0.78
Decision Tree	0.92	0.79	0.79	0.79
KNN	0.94	0.90	0.79	0.83
Logistic Regression	0.88	0.72	0.86	0.78
AdaBoost	0.92	0.81	0.79	0.80
Naive Bayes	0.88	0.72	0.87	0.77

The 4.3 table presents the outcomes when class weights were applied to penalize misclassification of the minority class more heavily. This method produced a mixed outcome. Recall values generally increased, showing that models became better at identifying the minority class, but this came at the expense of precision, which dropped in most cases. For example, Random Forest recorded a recall of 0.83 but a precision of 0.88, resulting in an F1-score of 0.85, lower than the oversampling approach. Similarly, SVM had an improved recall of 0.87 but only a precision of 0.74, leading to an F1-score of 0.78. These results indicate that class weight balancing helps capture more positive cases but also increases false positives, which reduces overall balance in performance. Compared to SMOTE oversampling, the improvement was modest, suggesting that class weighting alone may not be sufficient for datasets with severe imbalance.

4.5 Results after SMOTEENN (Hybrid Approach)

Table 4.4 Performance Parameters (SMOTEENN)

Model	Accuracy	Precision	Recall	F1 Score
Random Forest	0.99	0.99	0.99	0.99
SVM	0.96	0.96	0.96	0.96
Decision Tree	0.97	0.97	0.97	0.97
KNN	0.97	0.97	0.97	0.97
Logistic Regression	0.94	0.94	0.94	0.94
AdaBoost	0.95	0.95	0.95	0.95
Naive Bayes	0.87	0.87	0.87	0.87

Table 4.4 presents the impact of the SMOTEENN hybrid balancing method on model performance. This approach consistently achieved the best results across nearly all classifiers. Random Forest demonstrated exceptional performance, attaining precision, recall, and F1-score of 0.99, the highest among all models. SVM, Decision Tree, and KNN also performed strongly, with F1-scores ranging from 0.96 to 0.97. Logistic Regression and AdaBoost achieved slightly lower but still robust scores of 0.94 and 0.95, respectively, while Naive Bayes maintained a balanced F1-score of 0.87 despite being the weakest model overall. These results indicate that applying SMOTEENN not only enhances the representation of minority classes but also mitigates the dominance of majority classes, producing a cleaner and more balanced dataset. Overall, the SMOTEENN

approach provided the most reliable and generalizable outcomes, with Random Forest showing particularly impressive performance.

Questionnaire for the Students

1. Gender.

Among all respondents, 56.2% were ‘Male’, 43% were ‘Female’ and 0.8% identified as 'Others'.

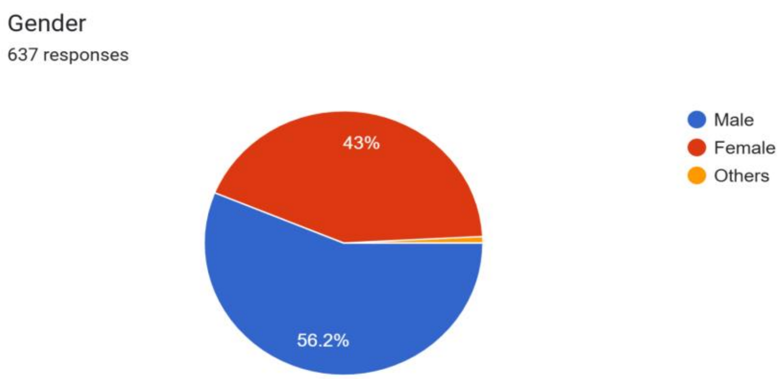

Figure 4.2.1: Gender.

2. Age.

Among all respondents, 13% were aged between 12–20 years, 39.6% were between 21–28 years, 35% were between 29–38 years, 10.7% were between 38–50 years and 1.7% were aged 50 and above.

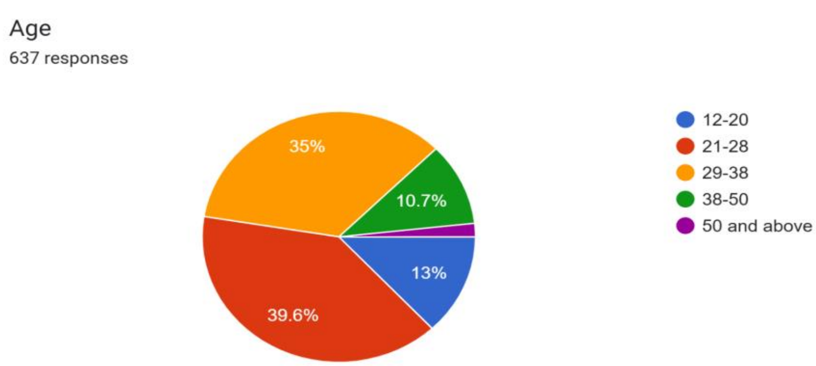

Figure 4.2.2: Age.

3. Educational Background.

Among all respondents, 11.9% Responder School Students, 13% Responder College Students, 39.1% Responder Bachelor's Degree Students, 24% Responder Master's Degree Students and 11.9% Responder PHD/ Higher Degree Students.

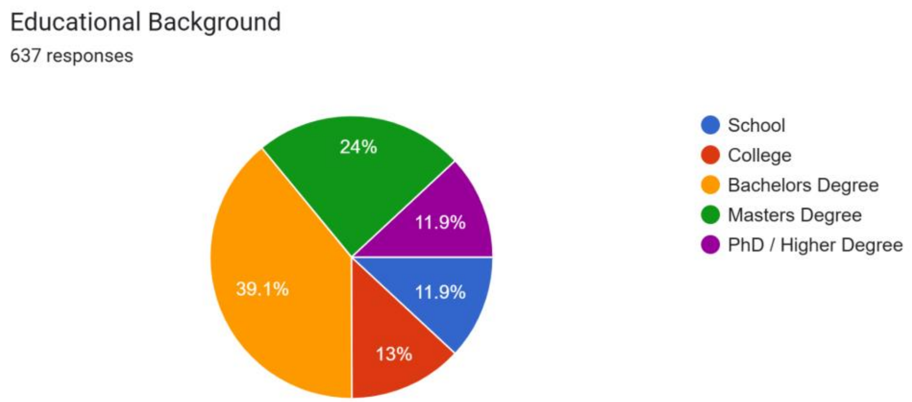

Figure 4.2.3: Educational Background.

4. Have you heard about Artificial Intelligence (AI).

Among all respondents, the majority of respondents, 96.5%, answered 'Yes', with only 3.5% answering 'No'.

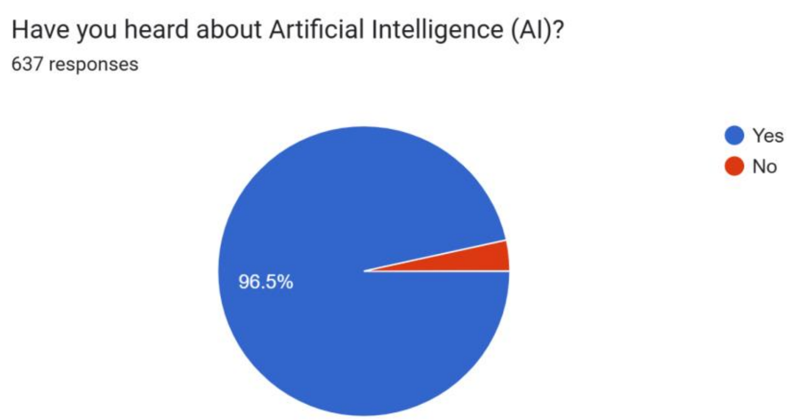

Figure 4.2.4: You heard about Artificial Intelligence (AI).

5. Do you know that AI is used in education.

Among all respondents, the majority of respondents, 96.4%, answered 'Yes', with only 3.6% answering 'No'.

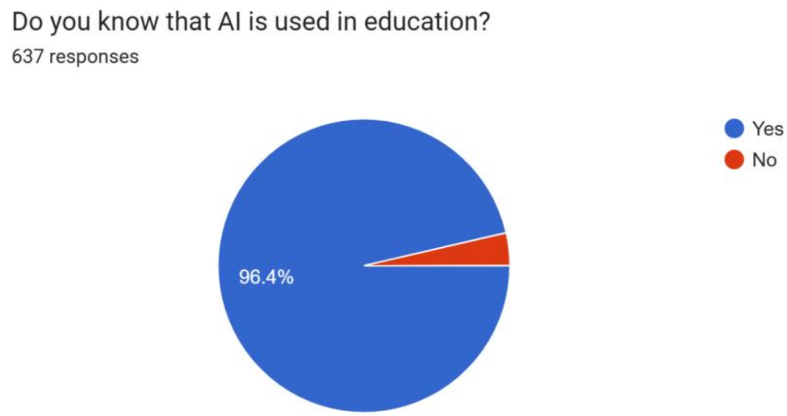

Figure 4.2.5: You know that AI is used in education.

6. Have you experienced AI tools in your educational environment.

Among all respondents, the majority of respondents, 90.6%, answered 'Yes', with only 9.4% answering 'No'.

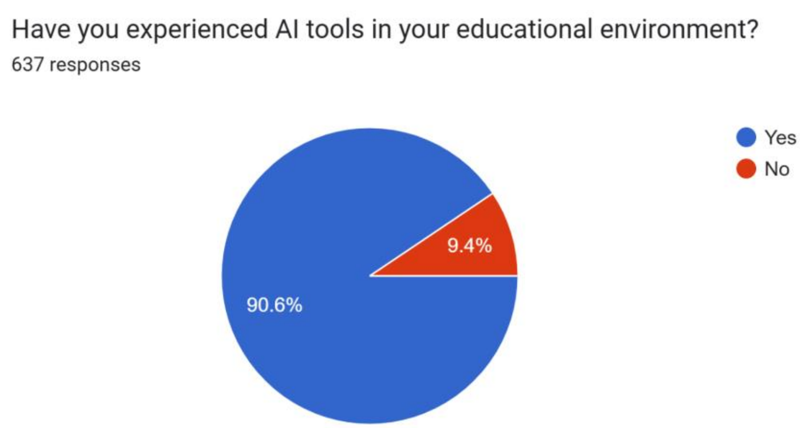

Figure 4.2.6: You experienced AI tools in your educational environment.

7. Are you recently using any AI-based educational tools or platforms.

Among all respondents, the majority of respondents, 89.5%, answered 'Yes', with only 10.5% answering 'No'.

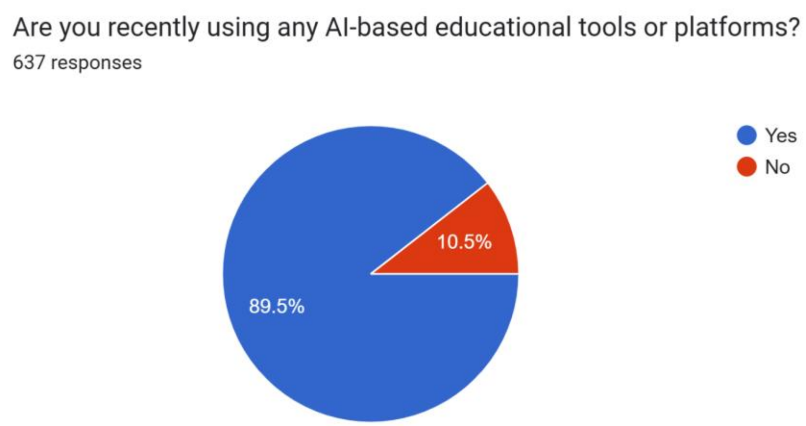

Figure 4.2.7: You recently used any AI-based educational tools or platforms.

8. Did your teacher ever use an AI tool in class.

Among all respondents, the majority of respondents, 80.2%, answered 'Yes', with only 19.8% answering 'No'.

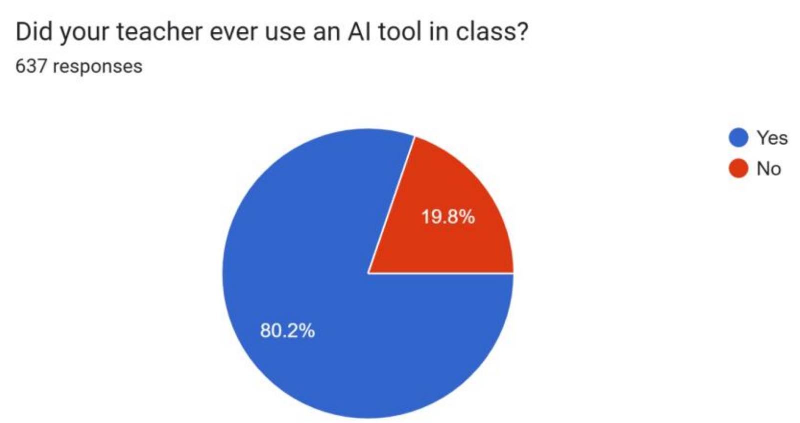

Figure 4.2.8: Your teacher uses an AI tool in class.

9. Do you think AI can help students learn better.

Among all respondents, the majority of respondents, 96.1%, answered 'Yes', with only 3.9% answering 'No'.

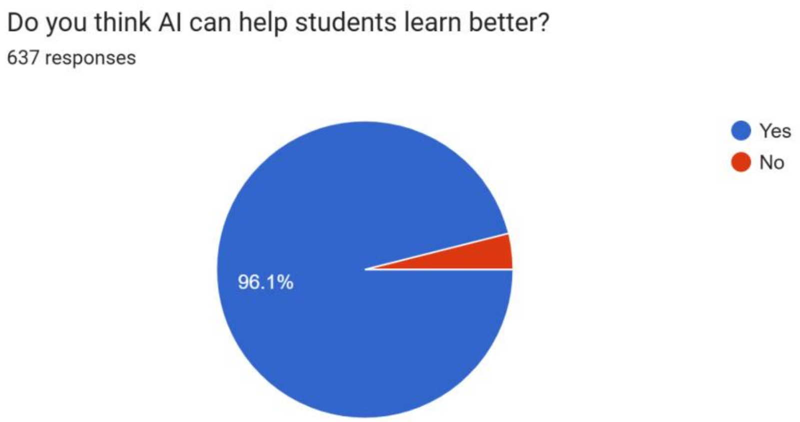

Figure 4.2.9: You think AI can help students learn better.

10. Can AI make learning easier for slow learners.

Among all respondents, 30.3% Strongly Agreed, 41.9% Agreed, 18.8% were Neutral, 4.6% Disagreed and 4.4% Strongly Disagreed.

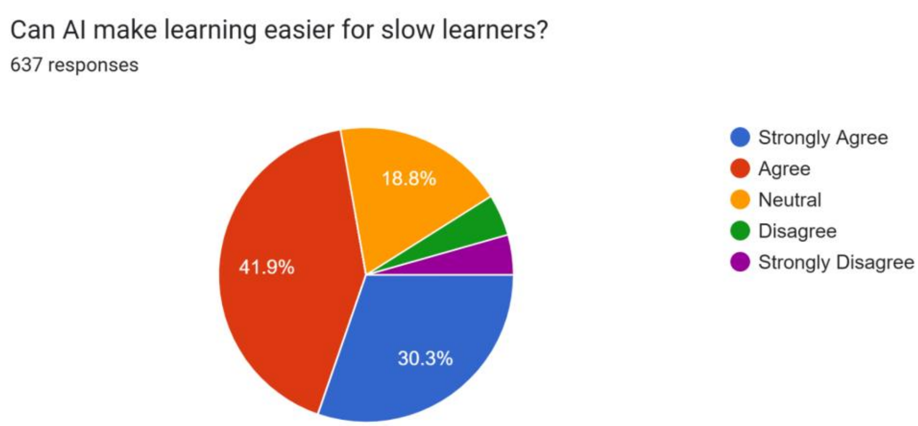

Figure 4.2.10: AI makes learning easier for slow learners.

11. Can AI help students learn from home.

Among all respondents, the majority of respondents, 98%, answered 'Yes', with only 2% answering 'No'.

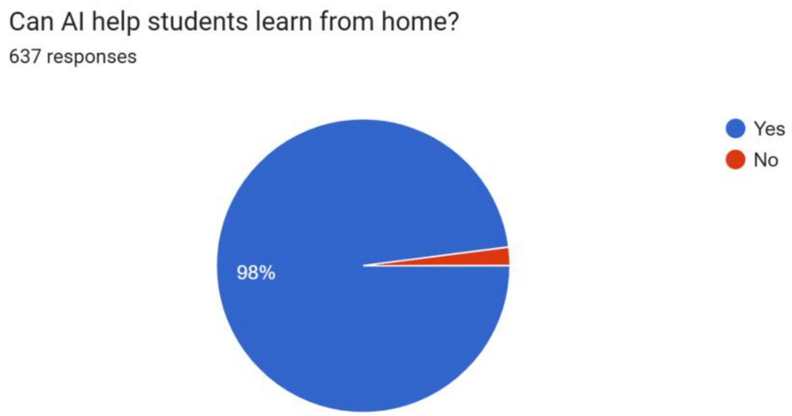

Figure 4.2.11: AI helps students learn from home.

12. Do you think students can become lazy if they use AI too much.

Among all respondents, the majority of respondents, 91.4%, answered 'Yes', with only 8.6% answering 'No'.

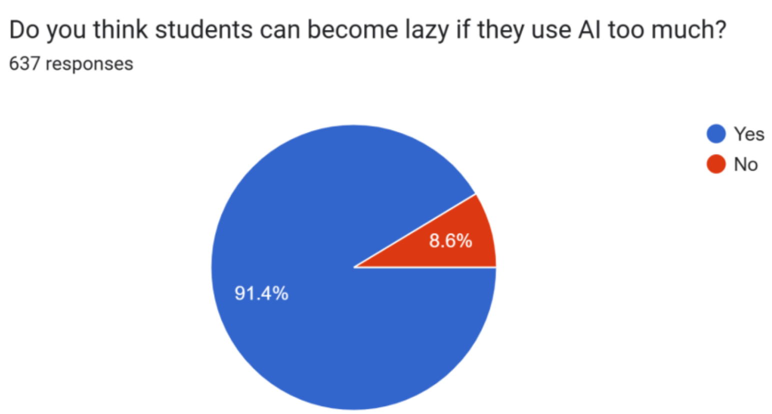

Figure 4.2.12: You think students can become lazy if they use AI too much.

13. Are you worried that AI might take teachers jobs.

Among all respondents, the majority of respondents, 72.2%, answered 'Yes', with only 27.8% answering 'No'.

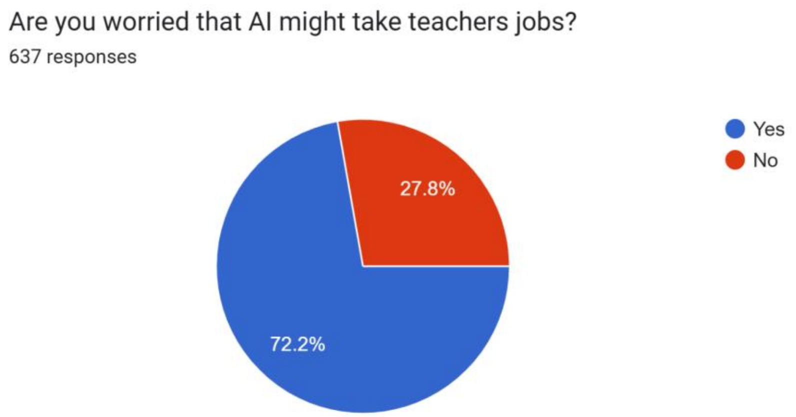

Figure 4.2.13: You worried that AI might take teachers jobs.

14. Do you think AI tools can make mistakes.

Among all respondents, the majority of respondents, 80.8%, answered 'Yes', with only 19.2% answering 'No'.

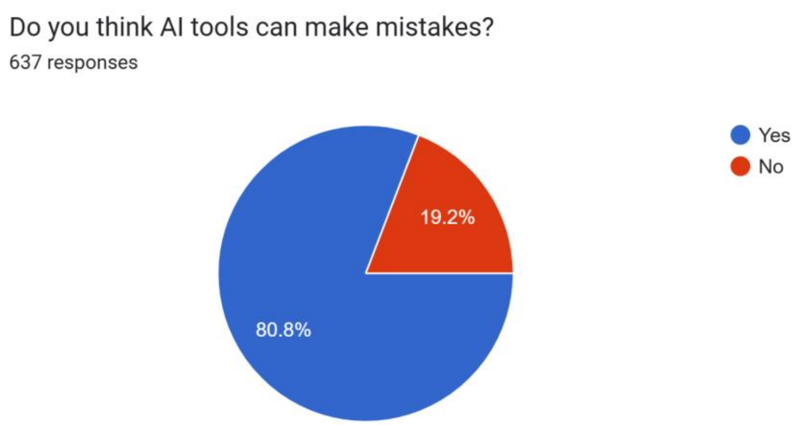

Figure 4.2.14: You think AI tools can make mistakes.

15. Are you concerned that AI may use your personal data?

Among all respondents, the majority of respondents, 82.9%, answered 'Yes', with only 17.1% answering 'No'.

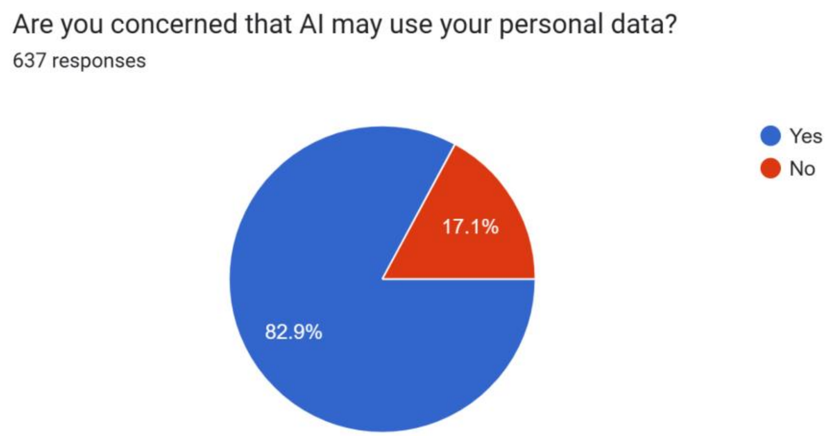

Figure 4.2.15: You are concerned that AI may use your personal data.

16. Do you feel informed about how AI applications use your personal information**.**

Among all respondents, the majority of respondents, 85.2%, answered 'Yes', with only 14.8% answering 'No'.

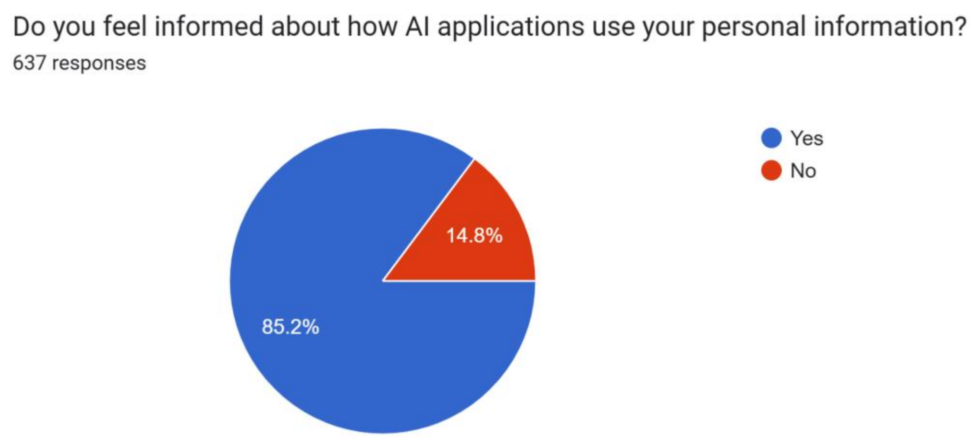

Figure 4.2.16: You feel informed how AI applications use your personal information

17. Do you want to learn more about AI?

Among all respondents, the majority of respondents, 96.7%, answered 'Yes', with only 3.3% answering 'No'.

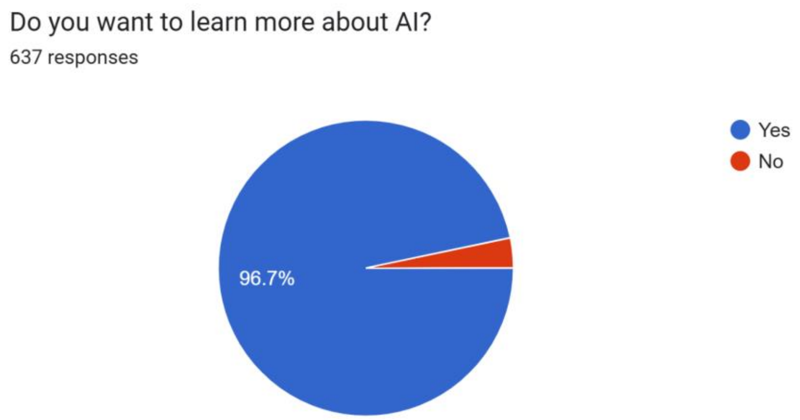

Figure 4.2.17: You want to learn more about AI.

18. Do you want AI to be part of your school or college.

Among all respondents, the majority of respondents, 91.5%, answered 'Yes', with only 8.5% answering 'No'.

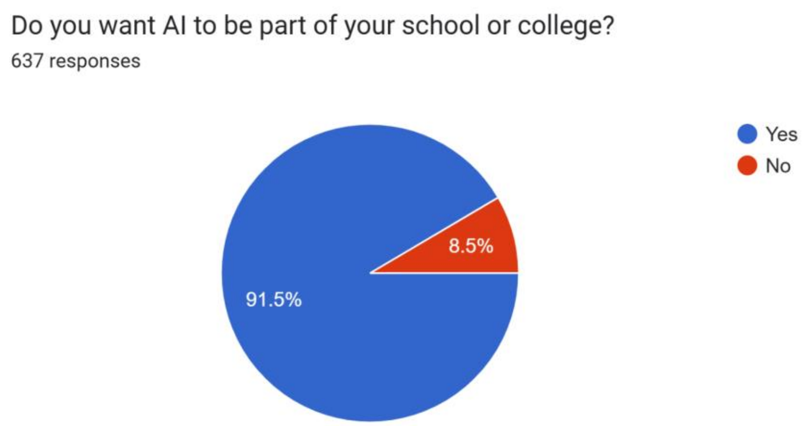

Figure 4.2.18: You want AI to be part of your school or college.

19. Do you think AI will be very important in the future.

Among all respondents, the majority of respondents, 94.7%, answered 'Yes', with only 5.3% answering 'No'.

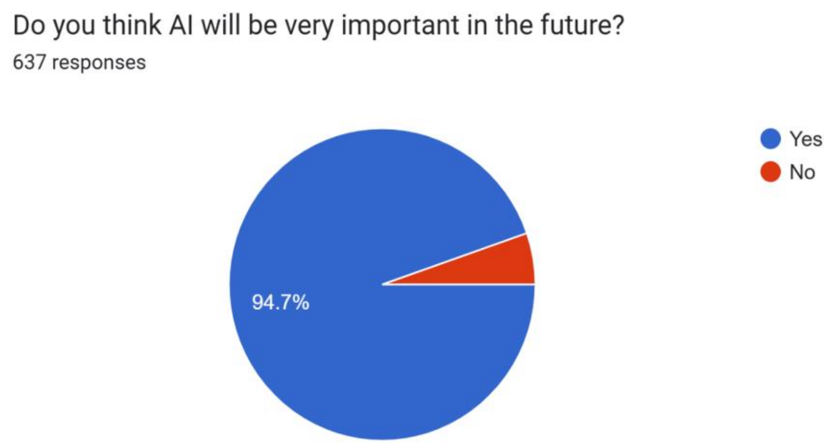

Figure 4.2.19: You think AI will be very important in the future.

20. How satisfied are you with the recent integration of AI in your educational experience**.**

Among all respondents, 91.5% answered 'Satisfied', while only 8.5% answered 'Dissatisfied'.

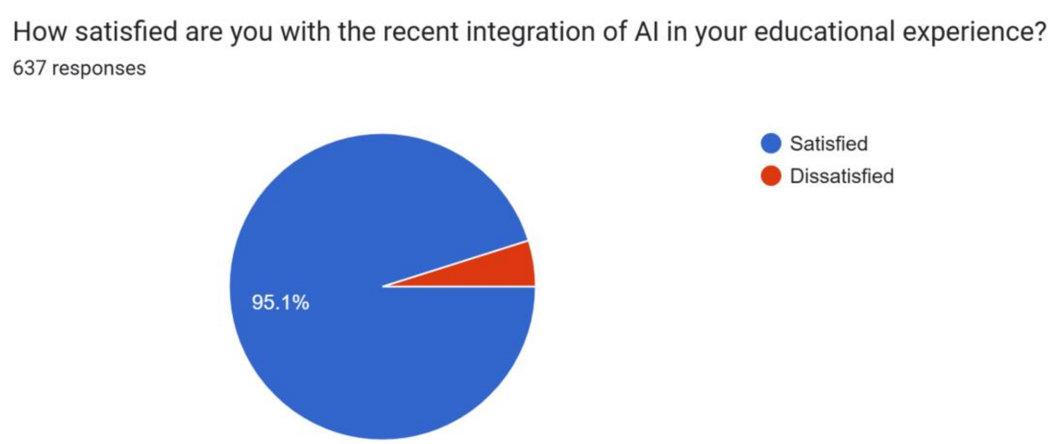

Figure 4.2.20: You are satisfied with recent integration of AI in educational experience.

SL	Question	Most Common Answer	Count
1	Gender	Male	357
2	Age	21-28	252
3	Educational Background	Bachelors Degree	248
4	Have you heard about Artificial Intelligence (AI)?	Yes	615
5	Do you know that AI is used in education?	Yes	614
6	Have you experienced AI tools in your educational environment?	Yes	577
7	Are you recently using any AI-based educational tools or platforms?	Yes	570
8	Did your teacher ever use an AI tool in class?	Yes	511
9	Do you think AI can help students learn better?	Yes	612
10	Can AI make learning easier for slow learners?	Agree	267
11	Can AI help students learn from home?	Yes	624
12	Do you think students can become lazy if they use AI too much?	Yes	582
13	Are you worried that AI might take teachers jobs?	Yes	460
14	Do you think AI tools can make mistakes?	Yes	515
15	Are you concerned that AI may use your personal data?	Yes	528
16	Do you feel informed about how AI applications use your personal information?	Yes	543
17	Do you want to learn more about AI?	Yes	616
18	Do you want AI to be part of your school or college?	Yes	583
19	Do you think AI will be very important in the future?	Yes	603
20	How satisfied are you with the recent integration of AI in your educational experience?	Satisfied	606

Figure 4.3.1: All Questions and Best values of All Questions with Response Count

4.3.1 Results and Discussion

The initial evaluation of the classifiers on the imbalanced dataset produced high accuracy values but revealed limitations when examined with more informative metrics. Random Forest, Logistic Regression, and AdaBoost each recorded an accuracy of around 0.98, yet their F1-scores dropped to approximately 0.83. In the case of SVM, accuracy reached 0.98 while the F1-score was only 0.50, highlighting that the minority class was not being effectively captured. These findings demonstrate that accuracy, while seemingly strong, can be misleading in imbalanced datasets because it reflects the dominance of the majority class rather than a balanced classification performance.

To mitigate these shortcomings, SMOTE oversampling was applied, which generated synthetic minority class samples. This adjustment significantly improved performance across nearly all classifiers. Random Forest, SVM, Decision Tree, and KNN all reached F1-scores between 0.96 and 0.98, indicating that both precision and recall were well balanced. The results show that oversampling successfully addressed the imbalance problem, though some algorithms such as Logistic Regression, AdaBoost, and Naive Bayes remained slightly weaker due to sensitivity to synthetic noise.

Another method, class weight balancing, worked a little better. The recall values went up, which meant that the detection of the minority class got better, but the precision went down, which meant that there were more false positives. So, the F1-scores for most models, like Random Forest (0.85) and SVM (0.78), were lower than those from SMOTE. This result indicates that class weighting may be advantageous in scenarios with moderate imbalance, although is less effective in datasets with significant skewness.

The SMOTEENN hybrid method, which coupled synthetic minority oversampling with ENN based cleaning of majority samples, showed the biggest improvement. This method not only made the minority classes more representative, but it also cut down on repetition in the majority class, making the dataset more balanced. The performance was great: Random Forest got an F1- score of 0.99, and both precision and recall were also 0.99. SVM, Decision Tree, and KNN also did well, with F1-scores between 0.96 and 0.97. Logistic Regression and AdaBoost got scores of 0.94 and 0.95, respectively. Naive Bayes had a slightly lower F1-score of 0.87, but it was still better than the original imbalanced dataset.

From this analysis, it is evident that the best overall results were obtained using the hybrid balancing technique (SMOTE + ENN) in combination with the Random Forest classifier, which achieved an F1-score of 0.99. This model consistently demonstrated the most stable and reliable performance across different balancing strategies, confirming its robustness for handling imbalanced classification problems. The study also reinforces the idea that F1-score, rather than accuracy, provides the most reliable measure of effectiveness in imbalanced datasets, since it captures the balance between precision and recall.

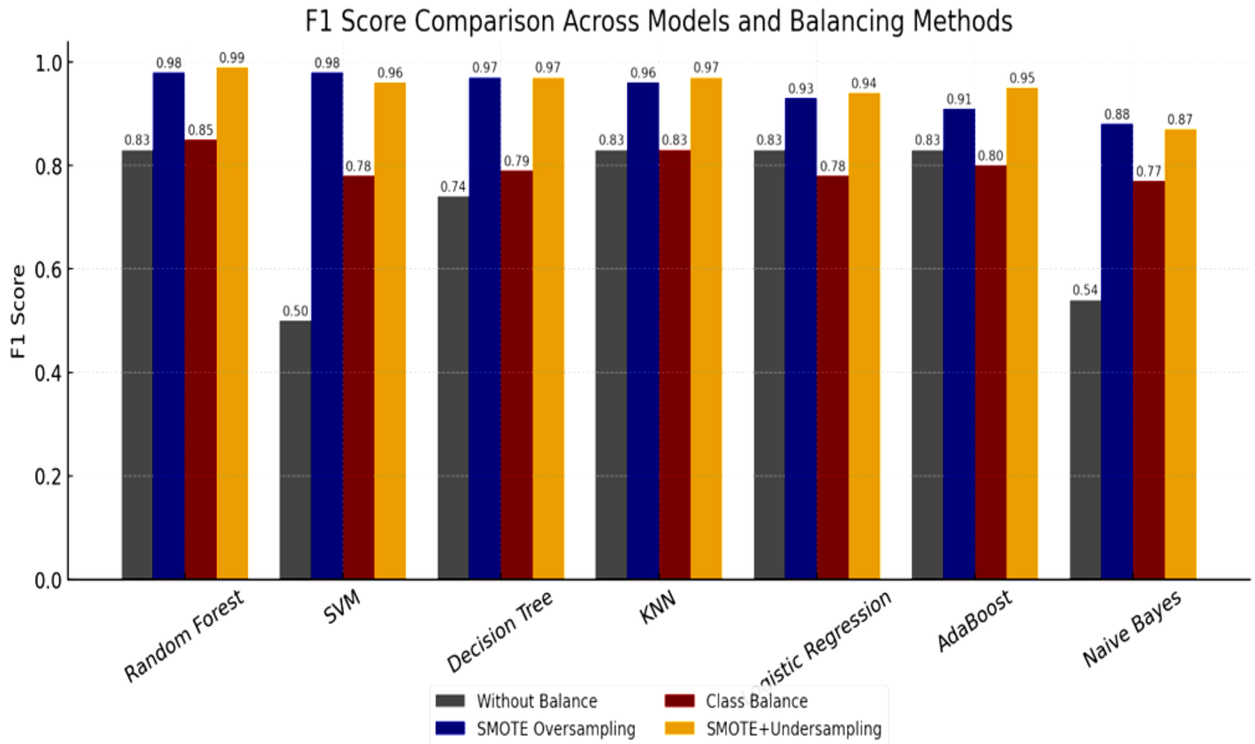

Figure 4.3.2: F1-Score Comparison

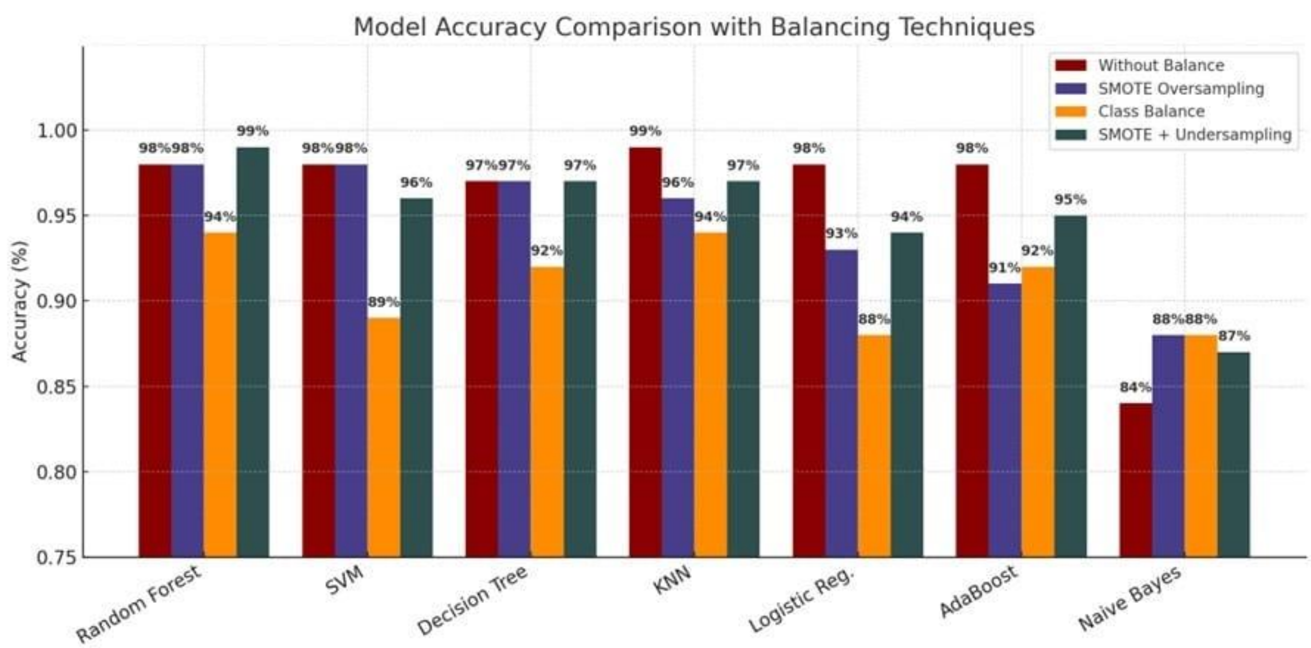

Figure 4.3.3: Accuracy Comparison

4.3.2 Impact on Business Operations:

This part shows and talks about the experimental results that show how utilizing AI in schools in Bangladesh makes a difference. The findings indicate that AI technologies have enhanced education, personalized learning, and increased administrative efficiency. Participants' answers show that they have a positive view of AI's ability to improve educational outcomes, make procedures more efficient, and help people make decisions based on data at all levels.

4.3.3 Technological and Security Challenges

This part talks about the problems that schools and other places of learning experience when they seek to add AI systems to their technology and infrastructure. The results show that people are worried about how ready the technology is now, how many skilled people there are, and how well AI tools work with the technology that is already in schools. Cybersecurity threats and data protection are still very hard problems to solve, especially for smaller organizations that don't have a lot of IT resources.

4.3.4 Data Privacy and User Concerns

This portion talks about the ethical and privacy issues that arise when schools deploy AI. It examines the extent of stakeholders' awareness regarding AI platforms that collect, retain, and utilize sensitive information pertaining to students and educational institutions. The results show that people are anxious about data privacy, following privacy rules, and trusting AI companies to different degrees. This part also talks about how important it is for stakeholders to feel safe by having strong data governance frameworks and explicit guidelines for AI.

4.4 Descriptive Analysis

The high results on all of the evaluation metrics show that the chosen features, such technological readiness, faculty training, policy backing, and perceived benefits of AI, did a good job of finding the factors that affect AI adoption and how stakeholders feel about it. Random Forest also worked well even when there was a small class imbalance, showing strong sensitivity to both classes.

In short, Random Forest turned out to be a useful and dependable model for figuring out how ready schools are for AI. Its result shows how well machine learning can make sense of complicated educational data, giving policymakers, educators, and institutional planners useful information that might help them improve AI use and implementation in Bangladeshi schools.

4.5 Summary of Comparison:

The research assessed various classifiers using an unbalanced survey dataset employing distinct balancing techniques, such as SMOTEENN, SMOTE oversampling, and class weight adjustment. Even while the accuracy across models (0.93–0.99) seemed high, it wasn't dependable because it mostly showed how well the majority class did and didn't show how well the minority class did. F1-score, which takes into consideration both precision and recall, was a better way to measure unbalanced data. SMOTEENN was the best based on F1-scores, with Random Forest getting the best score of 0.99, followed by SVM, Decision Tree, and KNN (0.96–0.97). These results suggest that the F1-score is a better way to choose models that make fair and accurate predictions for all classes.

4.6 Conclusion

The objective of this study was to assess the performance of various machine learning classifiers on an imbalanced dataset and to evaluate the efficacy of multiple balancing procedures. The first findings showed that models trained directly on the unbalanced data seemed to be quite accurate, with some getting close to 99%. But more research showed that this metric was not helpful since it hid the models' failure to correctly identify the minority class. The very low F1- score of SVM in the imbalanced case made this point very clear: even if accuracy stayed high, the model was mostly ignoring the class that was underrepresented. This demonstrated that we need to go beyond accuracy and use more dependable metrics like precision, recall, and especially the F1-score when there is class imbalance.

To fix the class imbalance, three methods were used: SMOTEENN, changing the class weight, and SMOTE oversampling on its own. The results showed that these methods were very different from one other. SMOTE oversampling increased performance by creating synthetic minority samples. This made it possible for models like Random Forest, SVM, Decision Tree, and KNN to get precision and recall that were almost equal. Adjusting the class weight made recall better but precision worse, which led to lower F1-scores than SMOTE. The SMOTEENN hybrid method worked best since it made minority samples and cleaned majority samples, which made the dataset more balanced.

When using SMOTEENN, Random Forest was always the most stable and best-performing classifier, with an F1-score of 0.99. The SVM, Decision Tree, and KNN also worked well, but Random Forest was the most reliable. These findings indicate that tree-based ensemble methods are most effective when combined with sophisticated balancing techniques on datasets that exhibit uneven distribution.

In conclusion, high accuracy alone may be misleading in imbalanced data; metrics such as the F1-score provide a more informative assessment of performance. The study shows that balancing tactics have a big effect on how well a model works, and that hybrid methods like SMOTEENN make the most accurate and generalizable predictions. We can utilize this combo of SMOTEENN and Random Forest to produce accurate and fair predictions with real-world educational data.

CHAPTER 5

AI in Education: Opportunities and Challenges

5.1 Introduction

AI, or artificial intelligence, is one of the most important new things in education today. There are several ways that it affects teaching, such as how materials are presented, how students are graded, how they are involved, and how they are managed. Schools that wish to keep up with the digital world and make studying more fun need AI. It has solutions that are current, can grow, and can be changed.

This chapter discusses about how AI can make the overall system run better, help kids learn better, and help teachers do their jobs better. It also talks about the problems and bad effects, like becoming too dependent, having moral difficulties, losing jobs, and worrying about privacy of data. This chapter presents a detailed picture of how AI is affecting education by putting together ideas from current research and answers from students who took a structured survey.

5.2 AI in Education: Opportunities and Challenges in General

❖ **Opportunities:** AI in education provides a lot of advantages that could improve schools, teaching, and learning. These are:

1. Personalized Learning: AI systems can change the class content based on each student's performance data.

2. Automated Administrative Tasks: AI can do tasks that are boring and repetitive, including grading multiple-choice tests, keeping track of attendance, making reports on how students are doing, and answering students' simple questions with chatbots. This lets teachers spend more time on personalized practice and how pupils get along with each other.

3. 24/7 Learning Support: AI-powered tools and digital assistants are always there to help, unlike human teachers. This lets students learn at their own pace, which is wonderful for folks who live far away or have a lot going on.

4. Data-Driven Decision Making: AI helps schools gather and look at a lot of information on how well students are doing. This helps teachers find kids who are in danger early on, change how they teach, and arrange their sessions better.

5. Language Translation and Accessibility: AI features like real-time translation and text-to-speech make it easier for students with impairments or language issues to join in. These technologies help close the gap between people who have access to technology and those who don't, making learning easier for everyone.

6. Support for Teachers: AI can help instructors, but it won't take their job. For instance, intelligent tutoring systems can assist students remember what they've learned, and AI grading tools can provide students instant feedback and save teacher's time.

❖ **Challenges:** There are a lot of problems that need to be fixed when AI is employed in schools, even though the benefits are great.

1. Too Much Dependence on Technology: Students may rely too much on AI to find answers, which could make it harder for them to think deeply or figure things out on their own. Students who always rely on technology for answers could miss the essential step of figuring things out on their own.

2. Fears of Losing Your Job: Some teachers are scared that AI could make their jobs less important or perhaps take over some parts of education. Some people might not want AI in schools because they don't think it can achieve everything a teacher can do.

3. Not enough time with people: AI can't provide students the same warmth and support that real teachers can. It could be very lonely and far away to learn without that personal touch, especially for younger kids. If students don't have someone to talk to or who knows how they feel, they can stop caring about school or lose interest in it.

4. Unequal Access: In many regions of the world, especially in developing nations, it is challenging to get to digital infrastructure, dependable internet, and AI-based educational platforms. This difference makes the digital gap bigger and makes it extremely tough for kids who are already behind in school to catch up.

5. Barriers to Training and Technology: Some teachers don't know how to use AI tools. If you don't teach and support technologies correctly, they can be misused or not used at all, which can lead to bad results in the classroom.

6. Legal and ethical problems: Schools usually use AI to gather a lot of information about their students, to be honest. Most people don't think about where that data travels or who sees it. That already gives you a clue that something is amiss. But the worst part is that if the system is unfair in any way, it could start treating some kids unfairly, and no one would know until it was too late. Not just technology, but people are the problem.

5.3 Negative Impact

The negative consequences of AI in education must be considered carefully, as their effects can influence both short-term learning outcomes and long-term educational values.

1. Student Dependency and Reduced Thinking Skills: A lot of students don’t just use AI tools like ChatGPT or Grammarly to help them learn they use them as a shortcut to finish homework faster. This reduces deep learning, creativity and the development of problem-solving skills.

2. Academic Cheating Issues: AI can make it easier for students to cheat or plagiarize. With AI-generated essays, solutions and summaries available instantly, maintaining academic honesty becomes a major challenge.

3. Mental Health: Spending too much time on AI platforms or online learning means more screen time and less face-to-face talk. Without human support, students might feel isolated or emotionally checked out.

4. Unfair Judgements: AI isn’t perfect it can misunderstand what students do or use biased info, which might lead to wrong grades or even false cheating claims during AI-monitored tests.

5. Cultural and Language Bias: AI tools often end up showing the same biases as the people who made them or the data they learned from. Because of that, students from different cultures or those who speak other languages might not get the same quality of help, which isn’t fair and can hold some learners back.

6. Threat to Teacher Roles: Even though AI is supposed to be a helping hand for teachers, a lot of them worry it could take over their jobs someday. That fear makes some teachers hesitant to use AI at all, which can slow down how quickly schools adopt new technology.

5.4 Conclusion

AI has the potential to seriously improve educational outcomes, streamline administrative techniques and personalize the learning experience. But these opportunities include notable risks and boundaries that want to be noted and addressed. Even as students usually recognize the usefulness of AI tools for fast learning, comfort and reviews, their problems which includes loss of important thinking, privacy risks and reduced teacher involvement are similarly important.

As determined via this study's survey and supported by modern literature, the dual nature of AI in education, considerate technique. Institutions must make investments not only in technology but also in training, policy development and student attention to ensure AI is used responsibly and inclusively.

This chapter has provided an in-intensity evaluation of both the opportunities and challenges posed by AI in education. The next chapter will delve into the experimental results and discussion, presenting the survey data collected from students and decoding it in mild of the themes explored in this chapter.

CHAPTER 6

Conclusion and Future Work

6.1 Summary of the Study

This research focused on predicting students' satisfaction with AI in education using machine learning models on an imbalanced survey dataset. To handle class imbalance, three strategies were tested: SMOTEENN, SMOTE, and class weight adjustment, with SMOTEENN showing the best performance. Random Forest achieved an F1-score of 0.99, while other classifiers like SVM, Decision Tree, and KNN also performed effectively. The study emphasizes that F1-score provides a more reliable evaluation than accuracy for imbalanced data and highlights the importance of advanced balancing methods for accurate and fair prediction of student satisfaction.

6.2 Conclusion

This study investigated student satisfaction with the integration of Artificial Intelligence (AI) in education using machine learning classifiers on an imbalanced dataset. While initial experiments showed that models such as Random Forest, SVM, Decision Tree, and others achieved high accuracy, further analysis revealed that accuracy alone was not a reliable indicator due to its bias toward the majority class. To overcome this limitation, balancing strategies including SMOTE oversampling, class weight adjustment, and the hybrid SMOTEENN method were applied. Among these, SMOTEENN delivered the most effective results, with Random Forest achieving an F1-score of 0.99 and other classifiers such as SVM, Decision Tree, and KNN also performing strongly.

The findings confirm that F1-score is a more dependable metric than accuracy when working with imbalanced educational survey data. They also highlight the importance of advanced balancing techniques to ensure fair and reliable predictions across all student groups. By adopting such approaches, institutions can gain a clearer understanding of learners' perceptions and take informed steps to strengthen AI-driven education. Ultimately, the research provides both methodological insights and practical guidance, emphasizing that balanced data and robust models are key to building trustworthy and impactful AI applications in education.

6.3 Limitation

- **Limited sample size:** The survey dataset may not represent the entire student population, which can affect the generalizability of the results.
- **Imbalanced data:** Even after applying oversampling or hybrid balancing techniques, some minority classes may still be underrepresented, potentially affecting model reliability.

6.4 Future Work

Although the current study has shown that balancing strategies such as SMOTE and hybrid approaches can significantly improve the performance of machine learning models on imbalanced educational survey data, several directions remain open for future exploration. First, the dataset used here is relatively small, with only 637 responses, and the minority class ("Dissatisfied") is heavily underrepresented. Collecting a larger and more balanced dataset from diverse institutions and regions would provide stronger evidence and allow models to generalize more effectively.

Another promising direction is to move beyond traditional machine learning algorithms and experiment with advanced deep learning methods, such as neural networks or attention-based models, which may capture hidden patterns in students' perceptions of AI integration more effectively. In addition, ensemble learning techniques that combine multiple models could be explored to further improve predictive stability and robustness.

Feature engineering also represents an important area for future work. While the present study primarily used the raw survey features, further analysis could involve deriving new composite features, applying dimensionality reduction, or incorporating external contextual data such as academic performance or digital engagement metrics. These enhancements could help uncover deeper relationships between student demographics, attitudes toward AI, and their overall satisfaction.

Finally, beyond prediction, future studies could focus on interpretability and fairness. Explaining why certain groups of students are more likely to be satisfied or dissatisfied with AI integration could provide valuable insights for educators and policymakers. Incorporating explainable AI (XAI) techniques would allow stakeholders to trust and understand model outputs, while fairness-aware approaches could ensure that predictions do not unintentionally disadvantage particular demographic groups.

In summary, expanding the dataset, experimenting with advanced modeling techniques, enhancing feature engineering, and integrating explainability and fairness considerations represent important future directions that can build on the present findings and contribute to a deeper understanding of students' satisfaction with AI in education.

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Appendix

Google Form Link: https://forms.gle/oHP3RFWByRXLTKWr7

SL	Question
1	Gender
2	Age
3	Educational Background
4	Have you heard about Artificial Intelligence (AI)?
5	Do you know that AI is used in education?
6	Have you experienced AI tools in your educational environment?
7	Are you recently using any AI-based educational tools or platforms?
8	Did your teacher ever use an AI tool in class?
9	Do you think AI can help students learn better?
10	Can AI make learning easier for slow learners?
11	Can AI help students learn from home?
12	Do you think students can become lazy if they use AI too much?
13	Are you worried that AI might take teachers jobs?
14	Do you think AI tools can make mistakes?
15	Are you concerned that AI may use your personal data?
16	Do you feel informed about how AI applications use your personal information?
17	Do you want to learn more about AI?
18	Do you want AI to be part of your school or college?
19	Do you think AI will be very important in the future?
20	How satisfied are you with the recent integration of AI in your educational experience?

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