Integrating Generative and Machine Learning Models for Predicting University Admission in an AI-based Education System

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Abstract

Education industry has been transformed due to the development in technology. Artificially intelligent (AI) involvement within the sub-domains of university admissions and registration processes has, in essence, transformed every dimension of higher education administration. The research will explore the current AI adoption within these fields using four key dimensions: automated application review, predictive analytics, conversational agents, and course recommendation systems. While AI offers increased efficiency, reduced biases, and personalization, it also raises crucial ethical dilemmas that cut across issues of transparency, privacy, and implicit biases in the algorithms. This study reviews recent literature to facilitate the benefits and disadvantages of AI in admissions and registration processes, identify relevant case studies, and describe potential future lines of research. Moreover, it presents the implementation of machine learning models such as support vector machine, decision tree and generative model such as transformer to predict chance of admission in the university based on some features such as GRE score, TOFEL score, etc. Moreover, it recommends universities based on ratings according to the admission chances score of the student.

Keywords:
AI; Education System; Explainable AI; LSTM, Transformer, Support Vector Machine, Machine learning.

1. Introduction

In higher education, the admission and registration process are the most complicated process because each year millions of students seeking to take admission in higher education. Processing millions of requests is a big hazard for higher education. Lately, artificial intelligence (AI) proved to be the game-changing solution for the universities when higher education institutions started using AI techniques for greater access, fairness and operational roots in their processes [1]. AI can process huge data sets, find patterns, and make predictions and has transformed various sectors from health care to finance. AI, in higher education, has increasingly been involved in streamlining admissions and registrations to make a faster, fairer, and more personalized decision-making possible decision-making process possible. All of this, starting from an automated screening of applications up to AI-enabled chatbots that would guide the student through registering these faithfulness applications exist in this very realm. But just like every technological advancement, there comes the adoption of AI into the processes in academics that poses its set of problems and issues to address ethically [2]. This paper provides an overview of AI roles in academic admission and registration along with the implementation of some of the AI models that predict chances of admission in certain universities. Recently, there has been strong motivation to integrate AI into the higher education admission process and yet many areas are still undiscovered related to the AI response in the registration process. The following are the main queries that have been highlighted:

1. How does AI apply nowadays to the process of admission and registration?
2. What are the benefits and challenges involved with the usage of AI in these areas?
3. Can AI models be used to predict chances of admission into the educational institute?
4. Can ethical considerations be identified and the measures that must be adopted to make AI responsible in the education system?

Academic admissions are highly complex. The globalization of education has gone up exponentially and more applicants have been streaming all over the world into universities seeking admissions. The volume has thus brought intense pressure upon the admission offices since the scrutiny process of evaluation requires every applicant without delay. Traditionally, the old methods of admissions decisions revolved around the both quantifiable measures and assessments which include grades and test scores, essays, and letters of recommendation. Although such a process is inherently subjective and time-consuming, it may take hours for admission officers to consider each application, thus causing bottlenecks and possible inconsistencies in the decision-making process. Moreover, subjective

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assessments have room for conscious or unconscious bias in the admissions process. Figure.1 depicts a simple admissions process that is being adopted in the educational system and in this process the adaptation of AI is quite motivating and appealing and can be integrated at various stages [3].

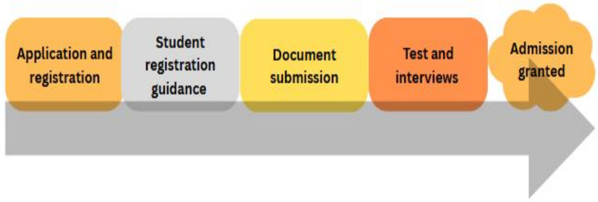

Figure 1: Registration and Admission Process

Student registration in educational institutions is a very sensitive process, posing many challenges for students, administrators, and faculty members. It is an issue of accessibility, data management, security, and efficiency as these institutions transform their institutions to be digital. In case the challenge is not mitigated, these issues will adversely affect student satisfaction, the workflow of the administrators, and the credibility of the institution. Accessibility is the first main challenge in student registration. Many students cannot complete the registration process because they do not have access to the internet or because the areas, they come from are remote. Other technical issues that can prevent the student from being able to complete the registration process involve website downtime or slow response times and poor user interface designs that may also hinder disabled students where platforms might not support accessibility features such as screen readers or alternative navigation methods [4]. Registration systems need to be accessible and comprehensive as this gives every student an equal opportunity. The other challenge is that of data management and accuracy. Students registration process handles voluminous personal and academic information that must be captured and maintained correctly. The wrong entry, duplicate records, or missing information create delays and confusion. There must be robust database management in institutions. Registration information is very technologically complex when put together with other systems of the institutions, such as Student Information System (SIS) and Learning Management System (LMS), since it requires a lot in terms of technology investment and technological expertise. The primary issues in students' registration are security and privacy. Since educational institutions retain the personal details of students, they are vulnerable to cyber-attacks and data breaches [5]. Because of unauthorized access, hacking, or insider misuse of student information, privacy can be compromised, and room for identity theft or fraud may open. Registration processes also present other challenges, including system scalability and reliability. A high number of students might register at one time and cause online systems to crash. This is more likely to occur during peak registration times such as the beginning of a semester. Institutions must therefore have scalable registration platforms that can handle a large volume of traffic efficiently. Load balancing, cloud-based infrastructure, and real-time monitoring will prevent failures in the systems and ensure a smooth registration experience. Institutional failure is another inefficient part of the registration. Students fail to register within the set time frames due to delays brought about by manual approvals and the absence of automation on a departmental level. Academic institutions should accelerate the processes of accepting payments, verifying prerequisites, and course approvals. Instead of using academic officers to answer student queries, AI chatbots can be used to handle student queries in a minimal time, taking a lot of burden off the staff and saving a lot of cost from the higher education budget. A lot of students cannot afford the university fees so publicity of aid such as grants, and scholarships can be publicized to the students using the recommender system, etc. [6]. Issues like accessibility, data management, security, scalability, administrative efficiency, and budget constraints are the few critical issues that are faced by the student and must be carefully and timely planned and executed. User experience and strengthening cybersecurity are a few essentials of any academic instruction, higher education should leverage all these to and create a more equitable and streamlined student registration process. These few steps would lead to more satisfactory results for the students and improve the institution's reputation, ultimately resulting in greater efficiency.

2. The Rise of AI in Higher Education

Academic institutions recently have adopted AI to tackle the issues of students in the admission and registration process. AI covers a variety of techniques such as machine learning (ML), deep learning (DL), natural language processing (NLP), and predictive analytics, all of which can individually or combined significantly change how institutions manage these essential functions [7]. By adopting these technologies, automation and streamlining can be achieved in the admissions process, enhancing efficiency for both administrators and applicants. Characteristics like extracurricular involvement and academic performance are the most important aspects of any student. To identify promising students based on these characteristics can be very difficult. ML algorithms can be utilized to sift through large amounts of application data to identify the most promising candidates. Using Machine learning in the process eliminates the factors of human bias and gives a fairer chance of selection, allowing admissions staff to make better-informed, data-driven decisions [8]. NLP techniques can assess the checking of the essay and personal statement of the students [9]. To fit the institution's goals and culture NLP can be utilized to analyze language, structure, and alignment with the university's values, these technologies help identify applicants who are fit for the institution. Students' academic records can predict student performance. This gives more leverage to higher institutions to allow those students who thrive more success across various programs. Furthermore, identifying those students at early stages who are at risk of failure may benefit the institutions to intervene and early stages and consult that student at early stages. AI can be used to determine the admission chances of the students based on these academic records. This helps universities to forecast expected numbers of students in a particular year. AI is transforming the process of registration significantly. With the help of AI technologies, manually intensive and tiresome tasks, such as scheduling courses, payment processing for fees, and verifications of documents, can be automated. For instance, with AI, the automatic generation of efficient course schedules based on students' likes and needs becomes possible. As a result, students find it easier to attend the classes of their choice without the problem of scheduling issues.

AI also eases the processing of fee payments by providing timely payment facilities in real-time and automatically creating bills, thereby preventing errors and easing the workload. AI-facilitated chatbots are becoming indispensable as part of the student registration process [10]. These provide students with instant and 24/7 assistance in answering queries concerning financial aid, deadlines, registrations, and available courses. In helping students throughout the process, these chatbots not only make the workload less for the admin staff but improve the student experience as well. This improves students' satisfaction, and they feel better equipped for the process of registration. AI is rapidly transforming the registration process and the admission process of higher education. Institutes are becoming increasingly data-driven, student-centric, and efficient as they adopt the use of machine learning, natural language processing, and predictive analysis. All these developments make higher education easier to access, more responsive, and responsive to the requirements of contemporary students and improve the experience of the overall student while efficiently streamlining tasks. Table 01 is a comparison table based on the tools, techniques, methods, and focus areas of the reference papers have been discussed in this paper.

Table 1 AI used in the educational system contributions.

Paper	Focus Area	Tools/Techniques	Key Contributions
Holmes, W., Bialik, M., & Fadel, C. (2019)	AI in Education (Teaching & Learning)	Conceptual framework, ethical considerations	Discusses AI's potential and ethical implications in education.
Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021)	Ethical AI (Language Models)	Critical analysis, ethical frameworks	Highlights the risks of large language models (e.g., bias, environmental impact).
Burstein, J., Chodorow, M., & Leacock, C. (2004)	Automated Essay Scoring (AES)	Natural Language Processing (NLP), rule-based systems	Early work on AES, cross-disciplinary perspective.
Attali, Y., & Burstein, J. (2006)	Automated Essay Scoring (AES)	E-rater V.2, NLP, machine learning	Introduces e-rater V.2 for automated essay scoring.
Dong, F., Zhang, Y., & Yang, J. (2017)	Automated Essay Scoring (AES)	Attention-based Recurrent Neural Networks (RNNs)	Proposes neural network models for AES with improved accuracy.
Shermis, M. D., & Burstein, J. (Eds.) (2013)	Automated Essay Evaluation	NLP, machine learning, rule-based systems	Comprehensive handbook on AES applications and future directions.
Page, E. B. (1966)	Automated Essay Grading	Early computational methods	Pioneering work on the feasibility of grading essays by computer.
Baker, R. S., & Inventado, P. S. (2014)	Educational Data Mining (EDM)	Data mining, predictive modeling	Explores EDM techniques for improving learning outcomes.
Siemens, G., & Long, P. (2011)	Learning Analytics	Data analytics, visualization tools	Discusses the role of analytics in understanding and improving education.
Aguilar, S. J., Lonn, S., & Teasley, S. D. (2014)	Early Warning Systems (EWS)	Predictive analytics, data mining	Examine the use of EWS in higher education transitions.
Romero, C., & Ventura, S. (2020)	Educational Data Mining & Learning Analytics	Survey of EDM and LA techniques	Provides an updated survey of EDM and LA methods and applications.
Jayaprakash, S. M., et al. (2014)	Early Alert Systems	Open-source analytics, predictive modeling	Introduces an open-source initiative for identifying at-risk students.
Arnold, K. E., & Pistilli, M. D. (2012)	Learning Analytics (Course Signals)	Predictive modeling, dashboards	Describes Purdue's Course Signals system for improving student success.
Adamopoulou, E.,	Chatbots (History	Literature review, chatbot frameworks	Reviews the history,

Paper	Focus Area	Tools/Techniques	Key Contributions
&Moussiades, L. (2020)	&Applications)		technology, and applications of chatbots.
Wollny, S., Schneider, J., & Schuetz, S. W. (2021)	Student-Centered Chatbots	Systematic review, chatbot frameworks	Analyzes student-centered chatbots in education.
Khanna, P., & Kelkar, D. (2021)	AI-Powered Chatbots	Literature review, AI frameworks	Reviews benefits, limitations, and future directions of AI chatbots in education.
Pérez-Marín, D. (2021)	Conversational Agents in Education	Literature review, chatbot frameworks	Examines the impact of conversational agents on education.
Okonkwo, C. W., & Ade-Ibijola, A. (2021)	Chatbots in Education	Systematic review, chatbot frameworks	Reviews applications of chatbots in education.
Samek, W., Wiegand, T., & Müller, K. R. (2017)	Explainable AI (XAI)	Model interpretation, visualization techniques	Discusses methods for understanding and interpreting deep learning models.
Doshi-Velez, F., & Kim, B. (2017)	Interpretable Machine Learning	Conceptual framework, interpretability metrics	Proposes a rigorous framework for interpretable machine learning.
Guidotti, R., et al. (2018)	Explainable AI (XAI)	Survey of XAI methods	Reviews methods for explaining black-box models.
Lundberg, S. M., & Lee, S. I. (2017)	Explainable AI (XAI)	SHAP (SHapley Additive exPlanations)	Introduces a unified approach to interpreting model predictions.
Arrieta, A. B., et al. (2020)	Explainable AI (XAI)	Taxonomy of XAI methods	Provides a comprehensive overview of XAI concepts, opportunities, and challenges.
Lemoine, B., & Khorram, S. (2020)	AI in Admissions	Predictive modeling, AI frameworks	Explores AI-driven admissions processes and their implications.
Kizilcec, R. F., et al. (2017)	Machine Learning in Admissions	Predictive modeling, fairness metrics	Examines bias, fairness, and predictive power of machine learning in admissions.
Zhang, X., & Xu, W. (2021)	Predictive Analytics in Higher Education	Predictive modeling, AI frameworks	Investigates AI for student admissions and success prediction.
Barton, S., & Nguyen, T. (2022)	Automated Decision-Making in Admissions	Conceptual analysis, case studies	Discusses challenges and opportunities of automated decision-making in admissions.
Li, H., & Chen, J. (2020)	Deep Learning in Admissions	Deep learning models, case studies	Case study on deep learning for international student admissions.
Chen, Y., et al. (2022)	Blockchain for Academic Credentials	Blockchain technology	Explores blockchain for secure academic credential verification.
Casino, F., Dasaklis, T. K., & Patsakis, C. (2019)	Blockchain and AI Integration	Systematic literature review	Reviews the integration of blockchain and AI technologies.
Zhang, P., et al. (2018)	Blockchain for Data Sharing	Blockchain, FHIRChain framework	Proposes blockchain for secure and scalable clinical data sharing.
Kumar, R., Kalla, A., & Verma, S. (2020)	Blockchain for AI Trust	Blockchain, AI frameworks	Explores blockchain for enhancing trust in AI systems.
Jiang, S., et al. (2021)	Blockchain-Based Federated Learning	Blockchain, federated learning	Proposes blockchain for secure AI collaboration in federated learning.
Salah, K., et al. (2019)	Blockchain for AI	Literature review, blockchain frameworks	Reviews blockchain applications for AI and identifies research challenges.
O'Neil, C. (2016)	Ethical AI and Big Data	Critical analysis, case studies	Critiques the ethical implications of big data and AI in society.

3. AI for Education at various levels

In this section, the integration of AI into academic registration and admissions is described. In this perspective, a lot of methods have been processed so far, each used for a different purpose and use case. Below are highlighted are some of the most used approaches:

3.1 Machine Learning for Application Screening:

Machine learning models are trained using admissions data to predict the trends in the admission and registration process of students in higher academia. The success determinants could be forecast by a machine learning model by examining the coursework, test scores, and extracurricular activities of previous applicants. Universities and higher education institutes can make use of artificial intelligence system that ranks admission applicants by potential for success. Moreover, they can leverage AI that can facilitate the application ranking system based on a machine learning mechanism to forecast applicants' potential for success. Different factors, such as extracurricular activity, standardized tests, and previous academic records, are considered in this process to forecast the results. ML can also facilitate universities to perform predictive analysis to identify the issues during the admission process, a particular type of machine learning that examines previous trends, and potentially problematic students can be spotted by the university and provided with more support. Apply-Board uses ML to pair applicants with the most appropriate school based on student and school fit. To recommend the best-fit universities, the website considers information about a user's academic history, degree of language competence, and occupation [11].

3.2 Natural Language Processing for Essay Evaluation:

NLP techniques, such as GPT-4 and BERT, are now used to evaluate essays and personal statements. These tools scan the structure, content, and style of writing, providing admissions personnel with additional information. The use of NLP in admissions has also been raised as an issue, however, regarding bias, as the models themselves may unconsciously prefer one type of writing style or subject matter [12]. Natural Language Processing (NLP) has transformed automatic essay evaluation (AEE) by enabling computers to assess writing for grammar, coherence, relevance, and originality. NLP techniques, such as machine learning and deep learning, enable lexical, syntactic, and semantic feature analysis, making grading more logical and efficient. Automated essay scoring (AES) tools such as e-rater and Project Essay Grade (PEG) utilize these methods to grade essays. A cross-disciplinary perspective reports early NLP-based AES models. Machine learning, syntactic parsing, and coherence scoring, and how effective they are to enhance grading accuracy are described by them [13]. The author of [14], introduced an automated essay-scoring e-rater V.2. It describes how the e-rater system has been enhanced using machine learning models. An assessment process is yielded by the improvement in AI-based scoring models, grammatical analysis, and semantic interpretation. Deep learning techniques in automated essay scoring (AES) are discussed by Dong in [15], in Attention-based recurrent neural network models for automated essay scoring. The use of Recurrent Neural Networks (RNNs) with attention mechanisms is proposed by them to yield coherence and contextual understanding in essay grading. In [16], the author discussed current applications and new directions giving an in-depth overview of AES technologies. They compare rule-based, AI-based, and statistical scoring approaches and state challenges in the implementation of NLP-based grading systems. in the imminence of grading essays by computer presents Project Essay Grade (PEG), one of the earliest AES models. The study forms the basis of NLP-based essay grading, emphasizing statistical and linguistic approaches in automated scoring. NLP-based essay grading continues to improve, employing AI and deep learning in grading reliability and feedback processes, ultimately enhancing student learning outcomes [17].

3.3 Predictive Analytics for Student Success:

Predictive analytics apply the history of a system to make predictions. When it comes to admissions, it may predict who is likely to succeed using past students' academic records. For example, Georgia State University was among the first to use predictive analytics because it determined which students were most likely to need special attention using focused support mechanisms [18]. Predictive analytics applies data mining, machine learning, and statistical modeling to forecast student performance and academic success. Institutions can improve retention rates, recognize at-risk students, and tailor learning experiences using past data. To provide instructors with useful information, these models analyze variables such as attendance, grades, engagement, and behavioral patterns.

In the context of analytics in learning and education, the author gives insights on the application of predictive analytics in the classroom. They highlight how learning analytics could be applied to identify students who are struggling, enhance student engagement, and employ the most effective teaching methods [19]. Perceptions and use of an early warning system during a higher education transition program examine early warning systems in the context of student success prediction. In their work, they identify the role that predictive models play by utilizing real-time academic data for timely intervention [20]. In educational data mining and learning analytics: An updated survey review data-driven approaches for predicting student performance. They compare machine learning models and discuss their applications in adaptive learning and personalized education [21].

In [22], an open-source analytics initiative has been presented that detects at-risk students. The paper demonstrates how machine learning algorithms help institutions implement targeted academic support. Predictive analytics in education continues to advance, integrating AI and big data to refine student success models, making academic interventions more efficient and impactful [23].

3.4 AI-Powered Chatbots for Student Support:

Chatbots driven by AI help in giving on-the-spot assistance to applicants, help guide applicants through the admission or registration process and give recommendations to individual users. AI-powered chatbots are changing the face of student support with instant help, answering questions, and academic counseling. These smart systems use NLP and machine learning to make students more interactive, reduce the administrative burden, and make them more accessible. Universities use chatbots for tasks such as admissions, course selection, and mental health support to ensure 24/7 availability.

AI-driven conversational models and their role in enhancing student interactions have been presented in [24]. A systematic review of student-centered chatbots in education analyze chatbot applications in higher education along the classification of chatbots into tutoring, administrative support, and psychological counseling have been described in [25]. A review of benefits, limitations, and future directions discuss the pros and cons of chatbots in student support and the ethical concerns such as data protection along with enhanced learning outcomes and participation have been presented in [26].

The paper [27] mentions AI chatbots that adjust their responses depending on students' needs as part of adaptive learning procedures. In chatbots applications in education, a systematic study, concentrated on academic guidance applications of chatbots and the work indicates how AI chatbots enhance institutional effectiveness and student satisfaction by automating administrative processes [28]. As more advanced AI-powered chatbots evolve, they incorporate deep learning and predictive analytics to enhance student support systems and ensure personalized, effective, and readily accessible academic assistance. Table 02 is a comparison table based on the methodologies for implementing AI and ML for application screening, NLP for Essay Evaluation, predictive analytics for student success, and AI-Powered chatbots for student support.

Table 2: Comparison of methodologies for implementing AI

Factor	Paper	Methodology	Tools/Techniques	Key Contributions
Machine Learning for Application Screening	Lemoine, B., & Khorram, S. (2020)	Predictive modeling for admissions decisions	AI frameworks, predictive analytics	Explores AI-driven admissions processes and their implications.
	Kizilcec, R. F., et al. (2017)	Machine learning for fairness and bias reduction in admissions	Fairness metrics, predictive modeling	Examines bias, fairness, and predictive power of machine learning in admissions.
	Zhang, X., & Xu, W. (2021)	Predictive analytics for student admissions and success	Predictive modeling, AI frameworks	Investigates AI for student admissions and success prediction.
	Barton, S., & Nguyen, T. (2022)	Automated decision-making in admissions	Case studies, conceptual analysis	Discusses challenges and opportunities of automated decision-making in admissions.
	Li, H., & Chen, J. (2020)	Deep learning for international student admissions	Deep learning models, case studies	Case study on deep learning for international student admissions.
Natural Language Processing for Essay Evaluation	Burstein, J., Chodorow, M., & Leacock, C. (2004)	Rule-based systems for automated essay scoring	NLP, rule-based systems	Early work on automated essay scoring with a cross-disciplinary perspective.
	Attali, Y., & Burstein, J. (2006)	E-rater V.2 for automated essay scoring	NLP, machine learning	Introduces e-rater V.2 for automated essay scoring.
	Dong, F., Zhang, Y., & Yang, J. (2017)	Attention-based RNNs for automated essay scoring	Attention-based RNNs, NLP	Proposes neural network models for automated essay scoring with improved accuracy.
	Shermis, M. D., & Burstein, J. (Eds.) (2013)	Comprehensive handbook on automated essay evaluation	NLP, machine learning, rule-based systems	Provides a comprehensive overview of AES applications and future directions.
	Page, E. B. (1966)	Early computational methods for essay grading	Early computational methods	Pioneering work on the feasibility of grading essays by computer.
Predictive Analytics for Student Success	Baker, R. S., & Inventado, P. S. (2014)	Educational data mining for student success	Data mining, predictive modeling	Explores EDM techniques for improving learning outcomes.
	Siemens, G., & Long, P. (2011)	Learning analytics for student success	Data analytics, visualization tools	Discusses the role of analytics in understanding and improving education.
	Aguilar, S. J., Lonn, S., & Teasley, S. D. (2014)	Early warning systems for at-risk students	Predictive analytics, data mining	Examine the use of early warning systems in higher education transitions.
	Romero, C., & Ventura, S. (2020)	Survey of EDM and learning analytics for student success	Survey of EDM and LA techniques	Provides an updated survey of EDM and LA methods and applications.
	Jayaprakash, S.	Open-source	Open-source	Introduces an

Factor	Paper	Methodology	Tools/Techniques	Key Contributions
	M., et al. (2014)	analytics for early alert systems	analytics, predictive modeling	open-source initiative for identifying at-risk students.
	Arnold, K. E., & Pistilli, M. D. (2012)	Course Signals for student success	Predictive modeling, dashboards	Describes Purdue's Course Signals system for improving student success.
AI-Powered Chatbots for Student Support	Adamopoulou, E., & Moussiades, L. (2020)	Chatbots for student support	Chatbot frameworks, NLP	Reviews the history, technology, and applications of chatbots.
	Wollny, S., Schneider, J., & Schuetz, S. W. (2021)	Student-centered chatbots in education	Systematic review, chatbot frameworks	Analyzes student-centered chatbots in education.
	Khanna, P., & Kelkar, D. (2021)	AI-powered chatbots for education	Literature review, AI frameworks	Reviews benefits, limitations, and future directions of AI chatbots in education.
	Pérez-Marín, D. (2021)	Conversational agents in education	Literature review, chatbot frameworks	Examines the impact of conversational agents on education.
	Okonkwo, C. W., & Ade-Ibijola, A. (2021)	Chatbots in education	Systematic review, chatbot frameworks	Reviews applications of chatbots in education.

Recent developments in the fast-developing field of artificial intelligence are creating new opportunities for its use in academic registration and admissions. A few of the famous advancements are mentioned below:

3.5 Explainable AI (XAI):

The "black box" character of how some decisions is made is arguably the most common criticism of technology. transparent and interpretable models are used to mitigate problems in Explainable AI (XAI). AI-based admissions systems can be trusted because XAI technologies can produce explanations for accepting or rejecting a given applicant. A lot of improvement has been shown in explainable AI (XAI) which shows the transparency of artificial intelligence by making its decisions more comprehensible to humans. It is important to get explainable results in areas like healthcare, finance, and education. XAI techniques are incorporated to make consumers embrace AI-based decisions, using rule-based explanations, feature importance analysis, and visualization. Visualization techniques are offered to improve transparency and highlight the significance of model interpretability for mission-critical operations [29].

The author indicates that measurements must be formalized such that AI explainability is testable towards a rigorous science of interpretable machine learning [30]. In [31], the author debates and emphasizes the intrinsic XAI guidelines of faithfulness, comprehensibility, and fairness, leading to enhanced model transparency. In their review of black-box model explanation techniques, they delve deep into various approaches to understanding AI judgments. Their research classifies XAI techniques into model-specific and model-agnostic techniques and shares insights into such technique's demerits and merits. The author introduces SHAP (Shapley Additive explanations), a model-agnostic technique of feature attribution for machine learning, as "A unified approach to interpreting model predictions". In their research, SHAP values are shown to enhance interpretability through quantification of feature importance in AI models [32].

A thorough description of the concept behind XAI is given by an author in Explainable Artificial Intelligence (XAI): Concepts, taxonomies, possibilities, and Obstacles toward Responsible AI. The authors emphasize responsible AI development through a discussion of ethical and legal issues on AI transparency. To enhance trust, accountability, and fairness in AI applications, explainable AI keeps developing using interpretable machine learning approaches [33].

3.6 AI for Global Admissions:

Universities are seeking means to automate international student admissions because of the greater globalization of higher education. Language translation, credential authentication, and visa processing are some of the tasks AI systems are being designed to perform. Apply Board, for instance, uses AI to match international students with universities based on their profiles and interests. AI for Global Admissions automates university application procedures by leveraging machine learning and predictive analytics. Automating student success prediction, qualification evaluation, and candidate screening, improve decision-making, removes bias, and increases efficiency. In AI-driven admissions: The future of university selection, author shows how AI automates the application evaluation process. They highlight how machine learning algorithms are used to objectively evaluate candidates by validating test results, academic records, and recommendation letters [34]. To guarantee equitable decision-making, their study addresses methods for removing bias from prediction models [35]. Analytics that predict student performance and admissions talk about the effectiveness of AI in application selection. They show improved prediction accuracy by contrasting AI-based selection with conventional selection procedures [36]. In [37], automated decision making for a university admission is presented and discussed while in [38], deep learning models have been presented for university admission.

3.7 Integration with Blockchain

For improvement in the security and transparency of registration and admissions procedures, blockchain technology is being researched and implemented. For instance, it can be used to authenticate academic credentials, prevention from hacking, and make them authentic. Blockchain can be integrated with machine learning for easy verification of information and fraud prevention [39]. Blockchain improves security, transparency, and efficiency in AI systems through interoperability and data integrity, privacy preservation, and support for decentralized AI applications are offered by blockchain, making it unavoidable for secure and auditable AI transactions, The security advantages of blockchain, such as data traceability, immutability, and fraud prevention, are explained in a systematic literature review of blockchain and AI integration [40]. Blockchain technology capability in protecting AI-based healthcare applications is discussed in the context of secure and scalable sharing clinical data [41]. Analysis of the experiments considers how blockchain protects the authenticity of data with the integration of machine learning models [42]. Enhancing trust in blockchain technology is being studied to understand how it can mitigate AI bias and enhance model trust. A framework integrating blockchain with federated learning is presented in [43] for secure AI integration.

Review and open research challenges are presented in [44]. Table 03 is a comparison table focusing on recent advancements in AI for admissions and registration, organized by the factors such as: Explainable AI (XAI), AI for global admissions, and integration with blockchain. The table.03 includes methodologies, tools, and key contributions.

Table 3: Comparison of the most recent advancements in AI for admissions and registration such as blockchain and explainable AI.

Factor	Paper	Methodology	Tools/Techniques	Key Contributions
Explainable AI (XAI)	Samek, W., Wiegand, T., & Müller, K. R. (2017)	Model interpretation and visualization for deep learning models	SHAP (SHapley Additive exPlanations), visualization tools	Introduces methods for understanding and interpreting deep learning models.
	Doshi-Velez, F., & Kim, B. (2017)	Framework for rigorous interpretable machine learning	Interpretability metrics, conceptual frameworks	Proposes a rigorous framework for interpretable machine learning.
	Guidotti, R., et al. (2018)	Survey of methods for explaining black-box models	Survey of XAI methods (e.g., LIME, SHAP)	Reviews methods for explaining black-box models in AI systems.
	Lundberg, S. M., & Lee, S. I. (2017)	Unified approach to interpreting model predictions	SHAP, model-agnostic interpretation	Introduces SHAP for unified interpretation of model predictions.
	Arrieta, A. B., et al. (2020)	Taxonomy of XAI concepts and challenges	Taxonomy of XAI methods, conceptual analysis	Provides a comprehensive overview of XAI concepts, opportunities, and challenges.
AI for Global Admissions	Lemoine, B., & Khorram, S. (2020)	AI-driven admissions for global student recruitment	Predictive modeling, AI frameworks	Explores AI-driven admissions processes and their implications for global admissions.
	Kizilcec, R. F., et al. (2017)	Machine learning for fairness and bias reduction in global admissions	Fairness metrics, predictive modeling	Examines bias, fairness, and predictive power of machine learning in global admissions.
	Zhang, X., & Xu, W. (2021)	Predictive analytics for international student admissions	Predictive modeling, AI frameworks	Investigates AI for international student admissions and success prediction.
	Li, H., & Chen, J. (2020)	Deep learning for international student admissions	Deep learning models, case studies	Case study on deep learning for international student admissions.
Integration with Blockchain	Chen, Y., et al. (2022)	Blockchain for secure academic credential verification	Blockchain technology	Explores blockchain for secure academic credential verification in admissions.
	Casino, F., Dasaklis, T. K., & Patsakis, C. (2019)	Systematic review of blockchain and AI integration	Systematic literature review	Reviews the integration of blockchain and AI technologies for secure systems.
	Zhang, P., et al. (2018)	Blockchain for secure and scalable data sharing	Blockchain, FHIRChain framework	Proposes blockchain for secure and scalable data sharing in admissions systems.
	Kumar, R., Kalla, A., & Verma, S. (2020)	Blockchain for enhancing trust in AI systems	Blockchain, AI frameworks	Explores blockchain for enhancing trust in AI-driven admissions

Factor	Paper	Methodology	Tools/Techniques	Key Contributions
				systems.
	Jiang, S., et al. (2021)	Blockchain-based federated learning for secure AI collaboration	Blockchain, federated learning	Proposes blockchain for secure AI collaboration in federated learning for admissions.
	Salah, K., et al. (2019)	Blockchain for AI applications	Literature review, blockchain frameworks	Reviews blockchain applications for AI and identifies research challenges in admissions systems.

4. Ethical Considerations and Challenges

Though AI application to the academic admissions and registration processes has many potential advantages, there are certain hurdles to be cleared up. One of them is the likelihood of bias within AI algorithms. The resultant models can reinforce or even increase the existing disparities if the data used to develop such algorithms are skewed. Female students, for instance, could be unfairly penalized by an AI system built upon data from a population of students that is predominantly male [45].

Lack of transparency in AI decision-making is another huge hurdle. The nature of most AI models, particularly those employing deep learning methods, is that they are black boxes. It can be challenging to identify and eliminate bias or errors in the system due to its "black box" nature. The application of AI to the admission process raises issues of privacy because it is most likely to include the collection and processing of personal student data.

The future of AI in academic admissions and registration in the future, artificial intelligence in higher education admissions and registration also has much potential, with the promise of increased efficiency, security, and personalized experience in higher education. The capacity of artificial intelligence (AI) to automate and simplify administrative tasks is likely to become more sophisticated as AI technology continues to evolve. How colleges and universities screen and process applications, forecast student success, and distribute resources is likely to be radically changed by advanced algorithms and machine learning technology. These management tasks could further be optimized, especially by tapping artificial intelligence as a complement to other emerging technologies like blockchain and the Internet of Things (IoT). While IoT could be utilized to facilitate more dynamic, real-time monitoring of students' behavior and needs, optimizing the academic experience on an individual basis, blockchain technology can better secure data and enhance transparency with the provision of permanent student records.

But there are also significant cultural and ethical implications of the rapid integration of AI into academic registration and admissions as well. AI systems will have to operate in fair, transparent, and accountable processes as they increasingly get embedded into decision-making processes. It is necessary to regularly audit algorithms for fairness and bias. Preventive measures must be in place to ensure administrators, educators, and students can view the reasons behind AI decisions. The confidentiality of student information must remain equally significant, and strong defenses against misuse or illegal access are necessary. Ethical and regulatory norms must evolve to keep check and balance with technological advancements, to protect public confidence in AI systems, and to contain risks they may pose.

Collaboration must be made by all the stakeholders like, educators, technologists, legislators, and students to influence the evolution of these systems as artificial intelligence becomes more deeply embedded in the very aspect of higher education. Diverse student populations will be provided with AI-driven solutions attuned to their needs, creating equity and inclusiveness in learning environments. The potential application of AI in academic registration and admissions is less about profound technological innovation; rather, it is about creating a system reflective of accountability, transparency, and fairness. If these hurdles are overcome, AI can be a transformative tool for re-imagining higher education, making it more efficient, accessible, and responsive to the needs of students and institutions.

5. Methodology

In this work, the data set that is available in [46], is used. The data set contains certain features such as Graduate Record Examination (GRE) Score, Test of English as foreign language (TOFEL) Score, University Rating, statement of purpose (SOP), letter of recommendation (LOR), Cumulative Grade Point Average (CGPA), Research, and Chance of Admit. These features are used to learn AI models to chance of admission in the university. The exploratory data analysis (EDA) has been performed to extract more insights about the data set. There are 400 samples in the dataset containing GRE, TOFEL, university rating, SOP, LOR, CGPA and chance of admit as a key feature. Subsequently, figures 2,3,4,5,6,7,8 and 9 show the distribution of individual features in the given data set. Figure.10 depicts the heat map that shows the correlations among all features of the data set. It is evident that features are not overlapping and do not have correlation among them. This leads to building strong AI-models that can predict chances of admission based on input features. After performing necessary features analysis, several predicted models were used to predict chances of admission. The following is the detail.

1. **K-Nearest Neighbors (KNN)**
   The KNN algorithm is used for classification and regression solutions. This performs classification on new data points based on the majority of their nearest K neighbors among previous stored feature points. Large datasets pose computational complexity to KNN because the algorithm requires distance computation, while it is effective in working with low-dimensional datasets [47].

2. **Decision Tree**
   The decision tree is a fundamental and robust machine learning algorithm to handle classification and regression. This algorithm achieves its goal through recursively splitting the dataset into branches based on feature values, forming a tree-like structure. Decision tree is easy to implement due to their clear interpretability though their effectiveness decreases because overfitting that occurs when executed properly [48].

3. **Random Forest**
   Random Forest is an ensemble learning method which utilizes various decision trees to improve predictive accuracy together and reduce overfitting. Each tree trained on a random subset of data, and the final prediction is determined by classification or averaging regression. This method enhances robustness and generalization [49].

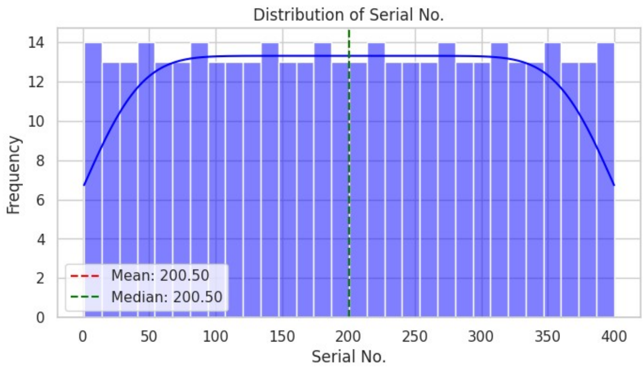

Figure 2: Serial number distribution

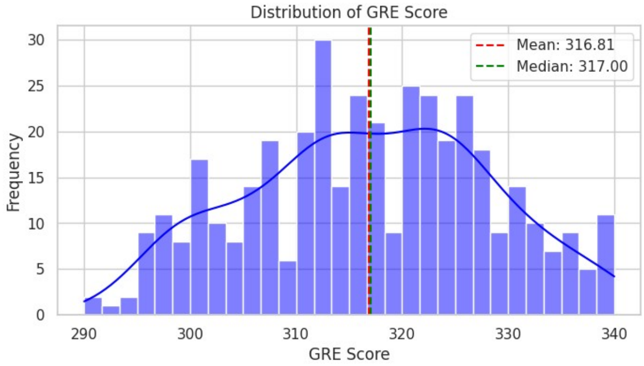

Figure 3: GRE Score distribution

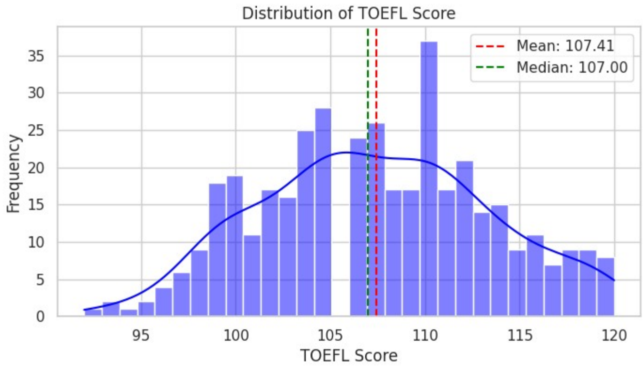

Figure 4: TOFEL Score distribution

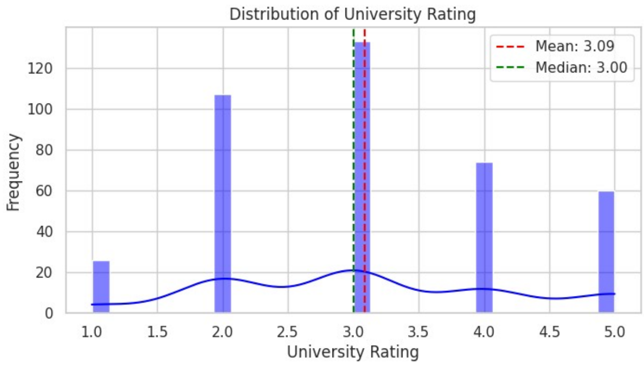

Figure 5: University rating distribution

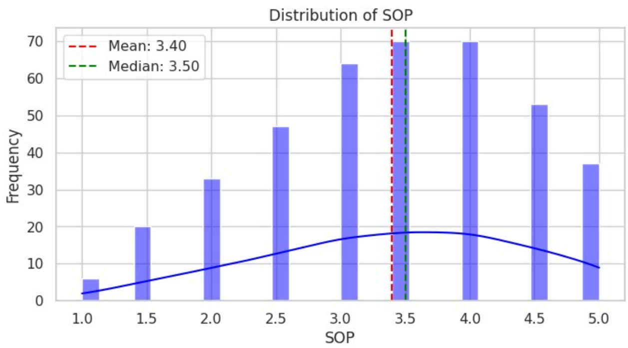

Figure 6: SOP distribution

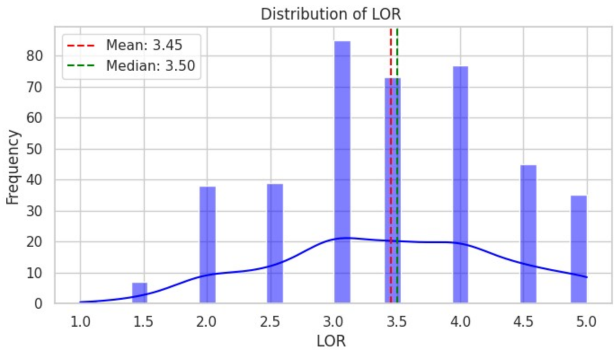

Figure 7: Letter of recommendation distribution

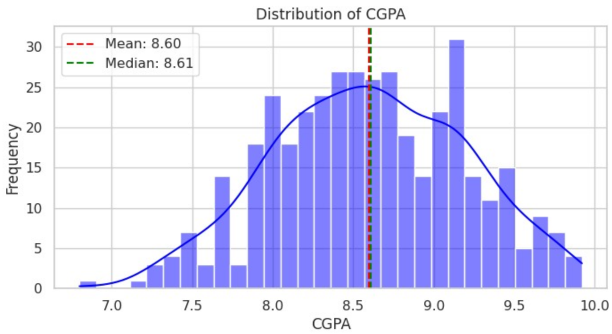

Figure 8: GPA distribution

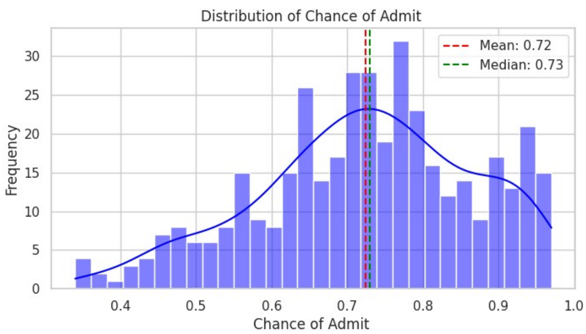

Figure 9: Chances of admission

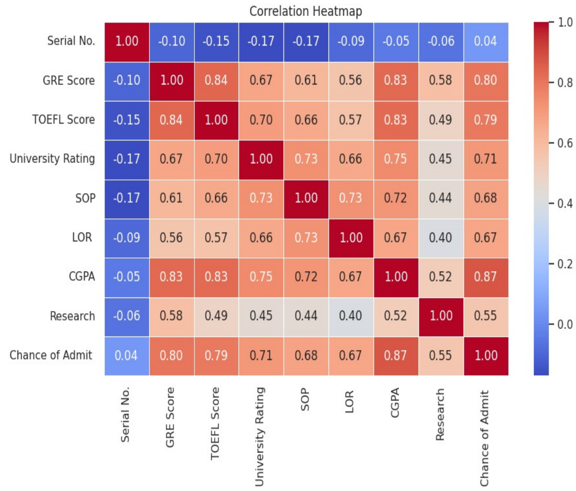

Figure 10: Heatmap showing correlation among various features of the dataset.

4. **Support Vector Machine (SVM)**
SVM is a supervised learning algorithm which is used for both classification and regression tasks. This algorithm identifies an optimal hyper plane to properly segregate different classes contained in a dataset. The SVM is particularly effective for high-dimensional spaces and is robust against overfitting, especially through kernel transformations of data into higher dimensional spaces [50].

5. **Long Short-Term Memory (LSTM)**
The LSTM architecture serves as an enhanced version of RNN, it provides better long-range dependencies detection for sequential data. LSTM operates through memory cells together with three gates: input, forget, and output which control information flow to prevent the gradient vanishing. LSTM operates extensively throughout the applications like speech recognition alongside time series forecasting and NLP [51].

6. **Gated Recurrent Unit (GRU)**
GRU represents an RNN variant which handles sequential data while mitigating the vanishing gradient problem. The update and reset gates together serve as gating mechanisms inside GRU to regulate information flow and advance long-term dependency learning, making it faster and simpler than LSTM [52].

7. **Transformer**
Transformers function as deep learning models that execute sequence modeling tasks like Natural Language Processing (NLP). Unlike traditional recurrent models, transformers use self-attention

mechanisms to simultaneously process entire sequences, making them highly effective for tasks such as machine translation along with text generation and large-scale language models such as GPT and BERT [53]. In this work, transformer model is used as a predictor to forecast chance of admission into the university.

6. Results and Simulation

The implementation phase consisted of training and testing sets, and after processing the data, different models are trained on them including KNN, Decision Tree, Random Forest, SVM, LSTM, GRU, and Transformer models. After training process, learned models were tested on the unseen data. The dataset consists of 400 entities. Consequently, the dataset was divided into two sets with the ratio of *70:30* as a training and testing set. The analysis of all the models on the data for predicted chance of admission to the university, resulted in the evolution of interesting findings, unveiling the outcomes and efficiency of different architecture. Table 04 presents performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 Score, thus providing a comprehensive evaluation of the implemented model's effectiveness. While Table 04 shows the prediction of how many chances there are to be able to get admission in university using different models.

Table 4: Performance Matrix of Different Trained Models

Model	MAE	MSE	R^2 Score
KNN	0.0525	0.0061	0.7627
Decision Tree	0.0467	0.0045	0.8273
Random Forest	0.0437	0.0038	0.8536
SVM	0.0833	0.0164	0.3631
LSTM	0.0472	0.0046	0.8066
GRU	0.0478	0.0045	0.8263
Transformer	0.0531	0.0047	0.818

Table 5: Predicted Chance of Admit Across Trained Models

Model	Predicted Chance of Admit
KNN	0.8101
Decision Tree	0.8275
Random Forest	0.8130
SVM	0.8239
LSTM	0.7736
GRU	**0.9062**
Transformer	0.8793

As per the results obtained from the models, GRU provides a higher number of chances to get admission with a **90.62%** score, outperforming other models. While Transformer follows closely with **87.93%** chance and this is shown in Table 05. The learning curves in Figures 11, 12,13,14,15,16 and 17 illustrate the training and validation performance levels of various models used in the study. The KNN, Decision Tree, and Random Forest models demonstrate decreasing training scores with increasing data while maintaining a gap with validation scores, which indicates progressive degrees of over-fitting. The SVM model causes unstable validation loss, suggesting sensitivity to training size. The LSTM, GRU, and Transformer models display smooth convergence of training and validation loss over epochs, reflecting stable learning. The evaluation curves demonstrate how different models perform in terms of generalization and learning efficiency. Moreover, the work proposes recommendations of the universities based on the chances of admission. Consequently, models are trained based on university ratings that have been obtained according to the following criteria: there are seven universities from A-G under 5 rating, there are four universities from H to L under 4 rating, five universities from M to Q under 3 rating, four universities from R to U under 2 rating, 3 universities from V to X under rating 1. The universities names have not mentioned due to privacy concerns. When students' chance of admission is given as an input, it recommends the university based on the ratings. The following table shows the output of the model. Consider x is the predicted chance of admission in a university by the machine learning model described above and y is the output of the recommendation system based on the universities ratings. This scenario can be represented in the form of following equation:

$$y = \boldsymbol{f}(x) \qquad \text{……………equation (1)}$$

where, $\boldsymbol{f}$ is the recommender system function that maps chances of the admission to the universities based on the ratings.

Predicted Chance of Admit	**Recommended University**
0.645135	M university
0.721586	J university
0.942837	A University
0.820524	B University
0.562084	S University

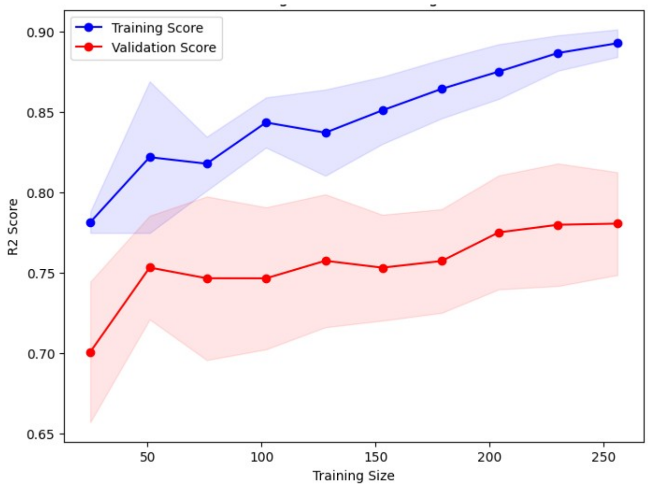

Figure 11: Learning curves of KNN

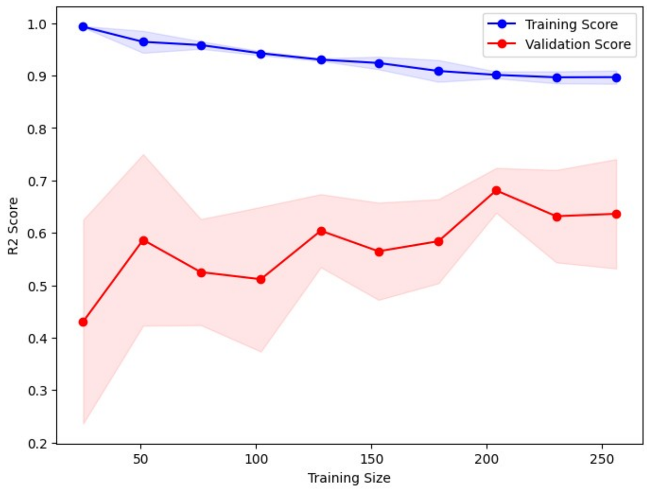

Figure 12: Learning curves of DT

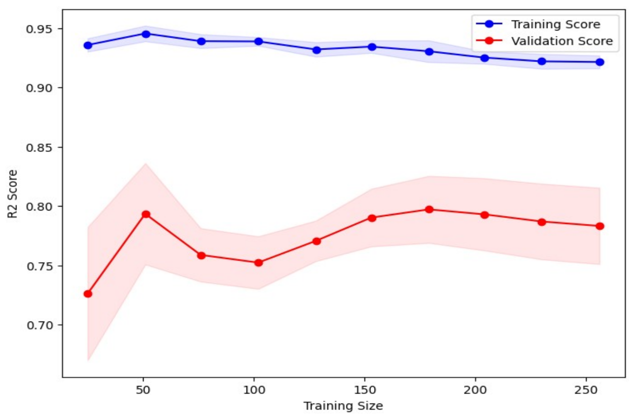

Figure 13: Learning curves of RF

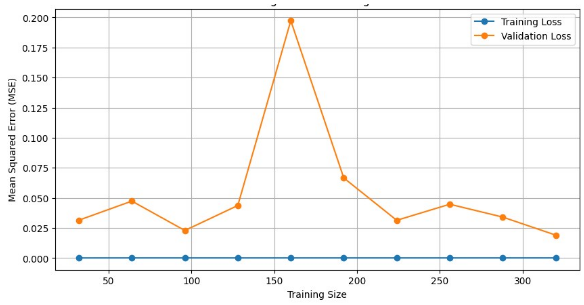

Figure 14: Learning curves of SVM

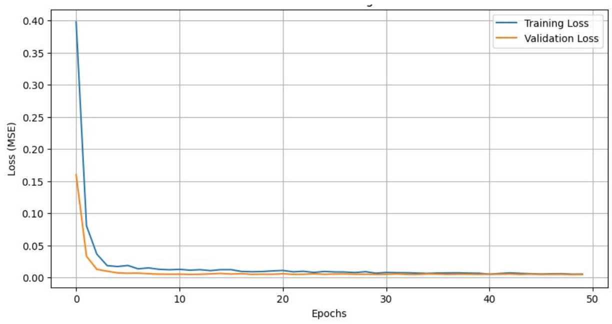

Figure 15: Learning curves of LSTM

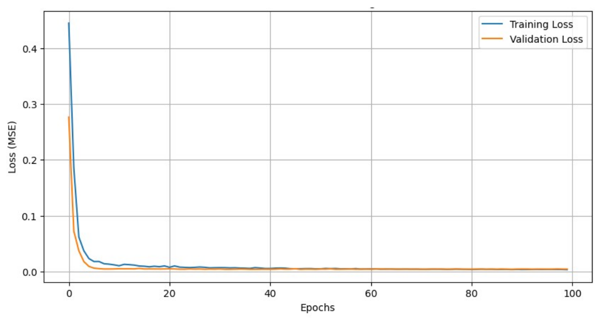

Figure 16: Learning curves of GRU

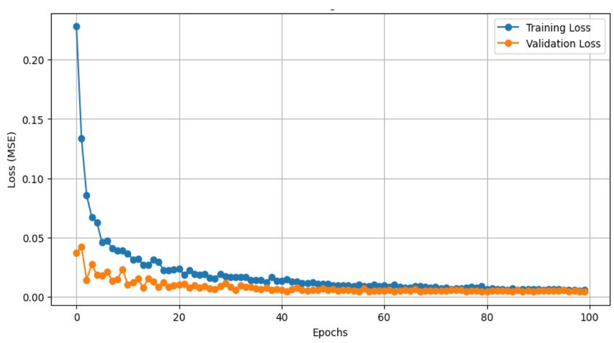

Figure 17: Learning curves of Transformer

7. Conclusion and Future directions

The application of artificial intelligence (AI) in student admissions and enrollment has the potential to transform higher learning radically. Educational institutions not only save time but also reduce administrative burdens by removing mechanical tasks such as data entry, application sorting, and course registration. This allows them to focus on higher-order activities such as enhancing the quality of education and developing student support systems. Databases are rapidly and accurately assessed by AI, taking human prejudices away from decision-making and creating an equal, objective platform for registrations and admissions. The individual needs of each student are analyzed by AI, and the learning experience is customized. Higher education functionalities such as chatbots, predictive analytics, and machine learning algorithms assist students in navigating the complex world of higher education. They can assist with admissions, answer questions, and predict issues students may face. Personalized assistance results in increased student satisfaction and retention, making the registration process seamless and user-friendly. Numerous barriers must be confronted and overcome in a proactive way if artificial intelligence can be implemented at institutions of higher learning. Ensuring that AI systems don't inadvertently perpetuate bias or discrimination, there are ethical considerations involving data privacy, algorithm transparency, and fairness. It is the responsibility of colleges and universities to ensure student information is protected against unauthorized access. Organizations must commit to continuous development and update their AI systems to reflect the most recent advancements and industry's best practices. The integration of technology in higher education will be successful when AI is leveraged for its strengths and overcome its weaknesses. A more efficient, student-oriented, and egalitarian higher education environment can be built by AI. AI can lead to a brighter and more inclusive future for students and schools with proper implementation and ongoing assessment. Nevertheless, the developed framework based on AI models in this work provides an insight to predict the chance of admission into the university based on GRE, TOEFL, and other features. The universities can integrate an AI framework in the university admission portal so that students can get to know the chance of admission and can make better decisions for their future studies. This will also assist parents and guardians in making necessary arrangements for their kid's admission to the university.

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