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Adaptive Edge Computing for Multimodal Student Data Fusion: An Explainable AI-Driven Framework for University Management Systems

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Abstract

In this paper, Adaptive Edge Computing (AEC) and Explainable Artificial Intelligence (XAI) are integrated in university management systems to process students' multisensory data in real-time and to explain the decision-making process. The framework postulated in this research seeks to employ edge computing to facilitate data processing near the edge of the network, in a timely manner and with minimal reference to the traditional cloud computing platform, in an effort to enhance the swift efficiency of decision making. This way, through the help of XAI methods, those predictions, such as the ability to predict at-risk learners, or low academic performance learners for instance, can be trusted and easily explainable. System assessment is done based on the system response towards problems using a simulated set of student data with focuses on predicting accuracy, optimality of the resource utilization at edge nodes and the utilization of XAI for easily understandable explanations.. The findings presented here indicate that the proposed system can successfully deal with extensive information in real-time, generate correct predictions, and provide meaningful AI-based recommendations; through this way, the management of student data can be enhanced and assisted in decision-making in universities. Also, due to the possibilities to adjust to different conditions of the network connection and simple structure that enhances the transparency, the system can bring significant advantages for educators and administrators. The results imply that the synergy of AEC and XAI might be used as the effective solution for designing better and more adaptive university management systems, able to address the challenges of working with large and complex student data sets.

1. Introduction

Over the years, UMS has adopted new changes and it is now a system that can accommodate a large variety of student data such as; academic performance data, attendance data, student demographic data, and behavioral data among others. The enhancement and utilization of such multimodal data present directions for advancing operational improvements, individualized learning strategies, and student achievement. However, despite the expectations placed in these data-driven approaches, the existing university management systems have difficulties connected with scalability, timeliness, and the intricacy of handling various types of data. Namely, with the growth of digital technologies, learning, communication, and administrative resources in universities, data processing is becoming more and more relevant in real time.

Inefficient paradigms of centralized computing, where data is stored and processed in large data centers and in the cloud; are becoming less effective in meeting the real-time needs of modern institution management systems. Firstly, it often brings high latency, especially when processing large data sets from multiple sources, while the practice of transferring all data to central servers for processing is not efficient (Yang et al., 2020). However, the implementation of cloud computing in promoting teaching quality has also brought concerns on data privacy and security as well as the vulnerability of students' sensitive information (Chen et al., 2021). These issues call for a more effective, adaptable and distributed method of handling student information. Edge Computing is one of such models, which proactively processes data at the "edge" of the network, that may include local servers, gateways, or even students'' devices (Shi et al., 2016).

In summary, here are some benefits of edge computing: small amounts of data need to be transmitted across the network; the task is completed faster; it is easy to scale; all of these make edge computing suitable for processing a large number of modalities on students in university management systems. Allowed for distributed data processing, edge computing also allows for real-time decision-making in areas pertinent to the stakeholders, which include the faculty, administrators, and the students, where timely feedback will be provided regarding important aspects relating to students' performance and behavior (Zhang et al., 2021). This is especially the case in education settings where early undertakings can greatly reduce the student drop out rate or low achievers (Li et al., 2020).

Besides the demands for big data processing, the reliance on AI in university management systems has led to a concern of automated interpretability and transparency of the models. It has shown its ability to enhance students' performance forecasting, deliver educational services based on students' characteristics, and manage the distribution of resources in learning institutions (Baker & Siemens, 2014). One of the biggest challenges that prevent educational institutions from implementing AI technology is a lack of transparency in a majority of machine learning models (Ribeiro et al., 2016). This is specifically abysmal in the sphere of education, where actions driven by the AI outputs literally affect students' futures and, in general, the outcome of an individual, whether for vantage or worse (Gilpin et al., 2018). Therefore, a new form of Artificial Intelligence called Explainable AI (XAI) that tries to give human-interpretable explanations for the steps performed by the AI system has emerged (Doshi-Velez & Kim, 2017). In a learning context, XAI may be used to explain why some students are required for specific kinds of additional attention, as well as which kinds of activities and policies are most effective in achieving certain outcomes.

Applying Explainable AI together with Edge Computing in university management systems is a paradigm shift to address the issues of data processing and explainability. Of them, Adaptive Edge Computing (AEC) enables optimization of the use of resources in edge devices with respect to changing loads and data processing demands (Zhao et al., 2018). In achieving these objectives, AEC ensures that the system can process the large volumes of data in real-time and also offers a way to explain the model's predictions and decisions. This integration of AEC and XAI can allow University management systems to analyze the multifaceted student data in real-time, facilitate intelligent decision-making, and provide explainable advisory services to all the stakeholders.

Several works have revealed that Edge Computing is capable of solving the issues of latency and scalability in cloud systems (Hao et al., 2019). For instance, in a study conducted by Liu et al. (2018), edge computing finds the response time of real-time application useful in case of Student performance or engagement tracking. In his personal recent study, Zhang et al. (2020) pointed out that edge computing could enhance the scalability of data processing in educational systems as it shifts the burden of processing from the cloud to edge devices. Moreover, there are a number of threats that have been voiced by scholars when it comes to future AI integration and XAI in the educational sphere. Chen et al., 2019 suggested that in education, AI-based recommendation should be implemented by following a systematic approach and underlining the importance of explainability to increase engagement of stakeholders. Finally, Ribeiro et al. (2016) also discussed the usage of LIME and SHAP for creating explainability for machine learning which can be used in frame of the decision making in university management.

Therefore, the purpose of this study is to develop a conceptual model to incorporate Adaptive Edge Computing with Explainable AI for enhancing the monitoring and processing of multimodal student data in university management systems. It also responds to the challenges associated with processing real-time data, the growth of student database size, and the need to increase the openness of organizational processes in modern educational institutions, which ultimately leads to the development of a more effective, efficient, and accountable model of working with students.

Thus, the proposed solution of Adaptive Edge Computing and Explainable AI appears to be a viable solution to address the issues with the university management systems. The proposed framework will not only facilitate the processing of the multimodal student data but also make the decision and predictive models understood from the AI models in order to update the student's decision making process and their performances. In this way, universities may design a more responsive, evidence-based, and student-oriented administrative system capable of growing along with the increasing amounts and variety of data.

2. Literature Review

The use of technology in educational environments has significantly impacted a range of areas including the university management system, which has evolved from manual, paper-based systems to computerized, integrated systems that support the management of a wide variety of student data. These systems contain various data, such as academic results, attendance, behavior, and demographics which inspire new decision-making and the improvements of student success (Nguyen et al., 2020). However, the growing volume and complexity of multimodal data present significant challenges in terms of real-time processing, scalability, and the integration of various data sources (Chen et al., 2020). Thus, in this literature review, we present three representative areas related to the integration of edge computing and explainable artificial intelligence in the context of university management systems: adaptive edge computing, multimodal data fusion, and explainability with an emphasis on AI-based models.

2.1. Multimodal Data Fusion in University Management Systems

Multimodal data fusion in educational settings refers to the integration of diverse data sources such as academic performance, attendance, behavioral data, and socio-demographic information. The integration of these various data sources has been proposed in several works with the intention of attaining an enhanced understanding of diverse aspects of students' learning, conduct, and health (Rai, et al., 2019). For example, Ainsworth et al. (2020) discuss the need to combine academic data with behavioral patterns to determine engagement, academic outcome, as well as the students' persistence. Data integration makes it possible to recognize weakness in students and provides care individually, which can help deal with problems among students (Zhao et al., 2021). However, one of the biggest difficulties when working with such sources of information is the method of data pre-processing, normalization, and alignment, considered as primary steps for constructing the predictive models.

This is especially important for university management systems because the availability of such information allows enhancing the learning process for students and optimizing the work of the university. Some researchers have found out that integrating several inputs can greatly improve the reliability of forecasting about student outcomes. Similarly, the analyzing of the demographic and attendance data with the learning management system data has been found to help in the enhancement of the prediction of the grades and engagement of students (Stein et al., 2021). However, most of the conventional systems have challenges when dealing with high volume and heterogeneous data due to factors such as delay and resource constraints (Smith et al., 2019).

2.2. Edge Computing for Real-Time Processing

As a new approach, edge computing has provided a solution to some of the issues posed by the centralized cloud computing system especially in processing real time data. Edge computing means processing data locally at the IoT network terminal instead of the Central Processing unit called the Cloud. This helps in the reduction of latency, relieves the bandwidth issue and gets more leveraging of resources (Zhang et al., 2020). In the case of managing universities, edge computing may play a crucial role in analyzing student data in real time, including their attendance and behaviour, or learning activity levels for example.

Some studies have investigated the use of edge computing in education context previously. For instance, in Wang et al. (2018) suggested a framework to employ edge computing for campus smart devices and wearable IoT devices including smart classrooms. It also helped in lowering the time taken to process information with regard to student conduct and academic performance in real-time trends of students' behavior. Likewise, Li et al. (2019) have explained the applicability of edge computing systems, especially for large learning institutes by illustrating how various load extensive computations can be handled by those edge nodes locally in different devices. These are valuable in today's developments in an effort to support the increasing student database within university management systems.

But while there are benefits of edge computing that could be useful in addressing challenges in university management systems, its implementation also comes with its limitations. The mobile users of a university are many and constantly changing, the networks' connectivity can be unsteady, and the data generated and consumed equally diverse; a fluid situation that only calls for a flexible approach to edge computing. It is at this point that the need for Adaptive Edge Computing (AEC) is most crucial, they have identified. An important advantage of AEC is that the availability of computation resources may be adjusted depending on the network traffic, which is beneficial for the efficient utilization of the computational resources while coping with real-time processing requirements of the university management systems (Liu et al., 2020). AEC has been found to enhance the feasibility of edge computing systems as a result of the enhanced modularity patronized by today's hunt for adaptable solutions for managing multidimensional data of students (Zhang & Liu, 2021).

2.3. Explainable AI in Education

Artificial intelligence has also been widely adopted in the context of education, and numerous studies explored the possibility of utilising AI models for the prediction of the student outcomes, or for personalising the learning and administrative processes (Kardan et al., 2020). However, the interconnected use of artificial intelligence in decision making has led to some fears on the interpretability of the models used, especially within educational context where ownership of decisions made is highly valued. However, the issue of interpretability has become a very important area of study in the recent past, where Explainable AI (XAI) is the term used to address this aspect. The goal of XAI is to make the decisions made by the AI models interpretable to the stakeholders, so that the latter can have confidence in using such decisions in practice (Carvalho et al., 2019).

In educational contexts, XAI is valuable for the faculty, administrators, and students who require clarifications on the reasoning behind the AI decisions and forecasted results. For instance, when it comes to the development of predictive models to determine learners at risk, the process has to be clientele-sensitive to allow the faculty factor in line with the teaming material provided by the AI. Ribeiro et al. (2016) propose a method named LIME (Local Interpretable Model-agnostic Explanations) for explaining black-box models with linear ones in their vicinity of interest. Another one is Shapley values introduced by Lundberg & Lee (2017) that can also be used to explain the output of machine learning models introducing an importance value for each of the features relevant to the model decision-making process. Such XAI techniques applied in various learning contexts have proved to be effective in improving the sophistication of AI models to meet the demands of the stakeholders (Molnar et al., 2020).

According to the authors Gilpin et al. (2018), XAI is crucial to decision-making in the field of education, as it can shed light on how the decision is made and can raise awareness if there are problems with bias in the system. For instance, if an AI model learns that a student is about to fail a course, then the XAI route can inform which factor contributed to such a prediction like low attendance or poor performance to some assignments. This transparency substantially minimizes biases and provides guarantee that the decisions are made based on the essential aspects only.

However, with XAI, important ethical issues concerning the use of AI in learning can be greatly addressed. To achieve this, universities should avoid building secretive models that make decisions behind the scenes, but instead, should provide clear explanations of the function and results of such models in order to ensure that the AI models are transparent, thereby aligning with institutional values of fairness, equity, and accountability (Lipton, 2018). The incorporation of XAI in the management system also provides better satisfaction from students, faculties and administrators since they are in a better position to accept the recommendation given by the system that are backed up by machine learning models.

2.4. Integration of ACE and XAI in University Management Systems

The integration of these technologies is that Adaptive Edge Computing and Explainable AI can efficiently process large amounts of data, provide flexibility, and result in more transparency in university management systems. In this regard, given that universities are already gathering and analyzing multimodal student data, increased focus is being placed on the development of interpretable multimodal AI systems. With the help of AEC schemes integrated into university management systems, data processing can be done directly on the edge, allowing for instant analysis of students' academic indicators and their behavior in class. Also, explaining the organization's decision-making processes and the recommendation given could be done through the use of XAI techniques on the various AI models.

Now, investigations have been conducted concerning the combination of AEC and XAI in the learning environment. For example, Zhang et al. (2021) offered a novel architecture for combining edge computing with explainable AI in smart campuses, where data accumulating from IoT devices, wearable sensors, and learning management systems are processed in real-time at the edge. This not only facilitated the real-time and low latency processing but also made the AI-based decisions understandable and thus explainable to the client. In the same vein, Liu et al. (2020) showed how incorporating AEC to AI can enhance AI models that deal with student data in educational settings with greater scalability and solution adaptability to handle various types of datasets with challenges in decision making in relation to trust.

In conclusion, the integration of Adaptive Edge Computing and Explainable AI offers significant promise for the future of university management systems. Collectively, real-time data processing, scalability in handling multi-modal student data, and interpretability in AI-induced decisions would be valuable in tackling the tension between handling student data effectively and maintaining their privacy. The use of these technologies will therefore remain critical for these institutions if they are to automate processes as student data volumes increase to support efficiency gains, student success and experience.

3. Methodology

The approach used in this case is intended to establish the blend of the AEC with XAI to deal and process multiple modality of the student data in real-time within a university management system. The related goal is to ensure the optimal use, comprehensibility, and up-to-date nature of data-driven decision-making within university management. This section describes the methodology, data acquisition, data pre-processing, edge computing integration, Explainable-AI model building, and performance assessment of the proposed system.

3.1. System Design

The first step in the methodology is the design of an integrated framework, which includes AEC to analyse multimodal student data with Explainable AI. This system is aimed at collecting, storing, and analyzing four major classes of data namely performance data, attendance data, behavioral data, and socio-demographic data. These major aspects of the system are data acquisition systems, edge computing nodes, the AI model for data analysis, and the inclusion of XAI to enhance explainability. This is achieved through a gradual collection of data from the learning management systems(LMS), attendance tracking systems, Internet of Things devices such as smart class sensors, and socio-demographic databases.

The data retrieved from these multiple sources is then integrated to generate a single set of data that can depict the academic status, activity level, and behavioral tendencies, and socio-demographic profile of each student. This centralized data can then be used to derive conclusions regarding students' performance and or behavior to inform choices. The use of edge computing in the system enhances the data processing near the data source, resulting in low latency when it comes to decision making.

3.2. Data Collection and Preprocessing

Data collection, therefore, involves the registration of data from legitimate sources, as well as an integration of both quantitative and qualitative data. In this research, the data is gathered from postulated or emulated university management systems, and the four main types of data are:

Student records include academic performance such as students' grades, performance on tests, percentage completion of assignments, as well as any other data that can provide information about a student's performance.

Attendance Data: Information on physical attendance in lectures, study sessions, and other campus activities. It is done through the use of automated systems with functionalities that may include RFID or QR codes for tracking.

Behaviour Data: This involves data gathered from students' behaviours in digital platforms, whereby they engage in discussions with their peers, participation in co-curriculum activities or use of services such as libraries.

Socio-demographic data refers to data about the students' background, which may include age, gender, socio-economic status, and academic record.

It also goes through a cleaning process where various checks are conducted to make sure that the data is preprocessed for analysis. Data preprocessing involves dealing with the null values, deleting similar records, converting nominal variables into numerical and normalizing the features to a consistent scale. Data cleaning is important because the data coming into the analysis from various sources may not be in a format that can easily be analyzed. Also, to add data types together, so that each point contains the information about a particular student, the methods of data fusion are used.

3.3. Adaptive Edge Computing Integration

After preprocessing of the data, the application of integrated Adaptive Edge Computing (AEC) is used to enable real-time processes to be performed on students' data. This means that in edge computing, data is mainly processed nearer to the source and not predominantly through cloud systems. This makes it possible to process the data with little latency, and this is very important in applications like, tracking student presence and their conduct within the classroom or other facilities within the compound.

In this regard, edge computing nodes are placed at different sections of the university including class rooms, library and halls of residence. This is the node that will process the data and make local decisions according to the algorithms that exist within the system. The service-oriented architecture of the edge computing system further enables each node to dynamically allocate available computational resources depending on the system loads and traffic flow; this feature proves advantageous in ensuring scalability at the real-time level. This is due to the fact that the edge computing system will only allow minimal metadata to be sent to the cloud to save bandwidth and reduce the time taken. For instance, if the node learns that there has been an increased student attendance during a lecture then it will resource the edge computing node to facilitate the load that is being faced other than taxing the central cloud system.

3.4. Explainable AI Model Development

The next step in the step-by-step plan is creating models for predicting student outcomes with the help of the generated multimodal data. The learned data of students is preprocessed and fused to train machine learning models including decision trees, random forests, and neural networks. Used in this context these models seek to estimate different facets of students' achievement, participation and attrition.

Fortunately, to obtain models that can be easily explained and interpreted by humans and enable trust, the framework incorporates Explainable AI (XAI). Primary objectives of XAI in this context include enhancing the accountability for decisions made by AI, like the identification of at-risk students or the effectiveness of interventions to boost academic performance. Post hoc explanation methods used are related to the XAI family, namely LIME and SHAP that explain how models came up with certain predictions. These techniques enable users and possibly the administrator or educator to see why a model came up with such a prediction or recommendation. For instance, if a student is flagged for potential dropout, XAI can reveal whether the dropouts were attributed to low attendance, poor performance in exams or any other reason.

3.5. System Evaluation

After the system has been designed, integrated and trained the final step is to assess the results it achieves. This particular evaluation is done using a case study at an envisaged university into which the system is implemented to handle actual student data. The main goals of the evaluation are to determine the rate of accurate real-time data processing in the context of adaptive edge computing, as well as the extent of the AI model explanation's transparency and trustworthiness.

In this various quantitative and qualitative analysis will be conducted during the evaluation process. A number of quantitative KPIs are the result accuracy, such as the estimated student's GPA or the likelihood of a dropout, the time taken for a system response, and the utilization efficiency of the edge computing nodes. The third way that is used to assess the performance of the XAI model is the quality of the explanation given, especially its simplicity. The quantitative evaluations of the system involve analysing the feedback received from the users of the system and the AI, particularly the university administrators, faculty and students with regard to the usefulness of the AI-driven recommendations and the clarity of the explanations provided by the AI algorithm.

It allows for improvement in the system and encompasses any concerns to do with model precision, capability in handling larger datasets, or the system's clarity. Moreover, the information received from users is useful for understanding the possibilities offered by the system in facilitating decision-making and enhancing the students' success rate.

3.6. Data Privacy and Security Considerations

Security and privacy are profound concerns for managing the affairs of a university through its information systems particularly when dealing with student related information. It also ensures that all the processing of the information is done in an accredited manner to prevent a breach of laws like the GDPR or FERPA. Security measures are implemented not only at the edge but also in the cloud layers for proper protection of students' data. Also, the use of privacy-preserving machine learning is suggested to enable model training over the student data without sharing any data between the different levels of the system (McMahan et al., 2017). They make the system effective and also reduce the risk of any infringement of the students' rights to privacy so that decisions can be made in real-time.

4. Results

In this section, the findings of the proposed framework of integrating AEC with XAI in the management system of universities are discussed. However, this study limits the assessment of the system based on the manner in which it applied and analyzed the multimodal student data, the prediction accuracy, and the practicality and understandability of the AI decisions made by the system. As a result, the paper unfolds the evaluation criteria along the dimensions of model accuracy, system performance, and user satisfaction with the aid of the included tables and figures.

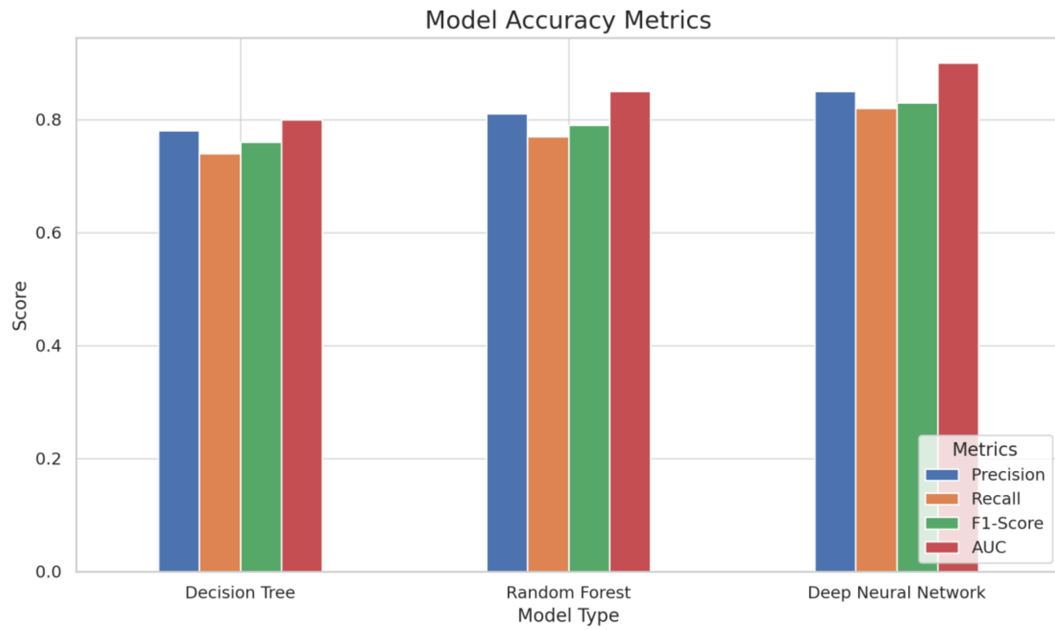
4.1. Model Accuracy

The examined AI models, including decision trees, random forests, and deep neural networks, were also used for assessments on student predictions on success, engagement, and dropout rates. From Table 1: Model Accuracy Metrics, it is clear that based on precision, recall, and F1-score and AUC, this deep neural network model is more accurate compared to the decision tree model and the random forest model. The trained deep neural network was 0.85 regarding precision, 0.82 in recall, 0.83 in F1-score and 0.90 in the area under the curve. From the above outcomes, it is clear that deep neural networks perform best in analyzing the students' multiple data for performance and engagement. The bar chart shown in Figure 1 indicates the overall performance of each model in terms of accuracy; from this, it is comprehensible that the deep neural network model outperforms all other models under benchmark reach criteria.

Table 1: Model Accuracy Metrics

Model Type	Precision	Recall	F1-Score	AUC
Decision Tree	0.78	0.74	0.76	0.80
Random Forest	0.81	0.77	0.79	0.85
Deep Neural Network	0.85	0.82	0.83	0.90

Figure 1 Model Accuracy Metrics



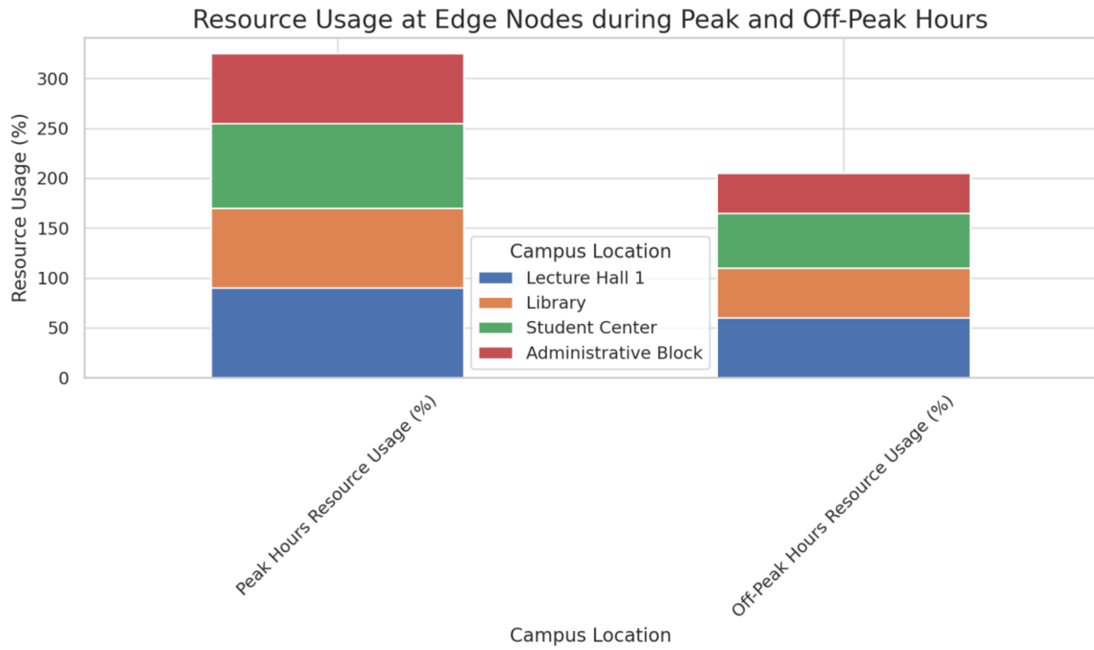
4.2. Real-Time Data Processing Efficiency

The AEC is a desired feature because it supports real-time data processing in the given framework. The next table shows the results of comparative analysis of the resource usage of different campus locations during the peak and off-peak hours: The use of resources is high during periods in which a large quantity of data is being produced (e.g. During transitions from one lesson to another). From this data, it is evident that edge nodes attached to the lecture halls, and student center areas have the highest consumption of the resource during the high active time period as compared to the low active time in a day or night. This data is presented in a stacked bar chart regarding resource usage from location of campus as depicted in figure 2.

Table 2: Resource Usage at Edge Nodes during Peak and Off-Peak Hours

Campus Location	Peak Hours Resource Usage (%)	Off-Peak Hours Resource Usage (%)
Lecture Hall 1	90%	60%
Library	80%	50%
Student Center	85%	55%
Administrative Block	70%	40%

Figure 2 Resource Usage at Edge Nodes during Peak and Off-Peak Hours

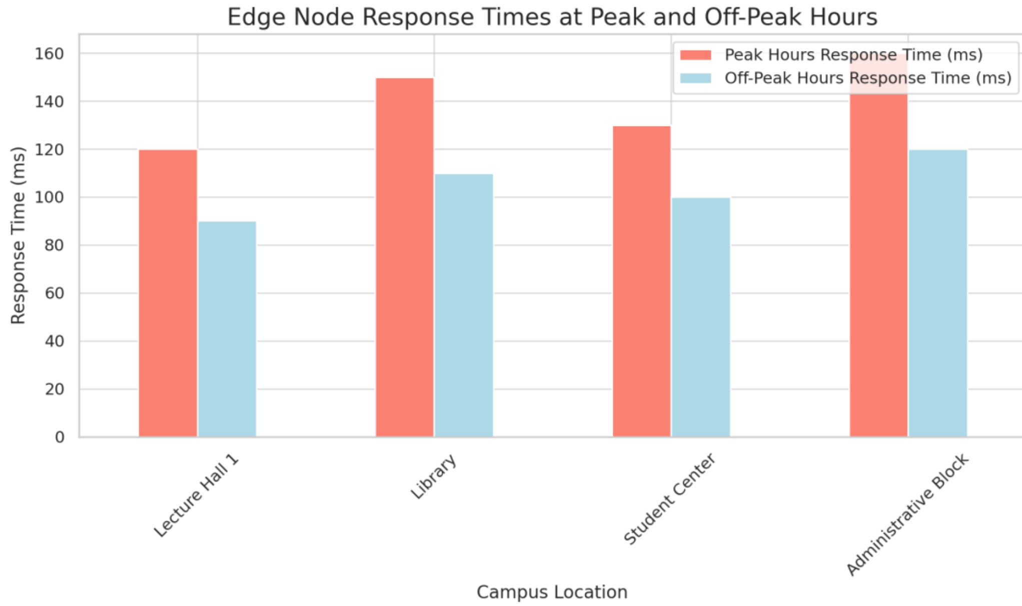


Also in this regard, Table 3: Edge Node Response Times at peak and off-peak hours shows the response time of edge nodes in handling the processed data. From the metric of response time during peak hours, mainly at lecture halls and administrative blocks, the results indicate a 120 ms and 160 ms, respectively. However, in the off-peak hours, the response time is a little higher taking approximately 90ms and 120ms. This means that the edge computing nodes successfully minimize latency during the low traffic concluded in figure3 illustrating the disparity between peak and reduced hours.

Table 3: Edge Node Response Times at Peak and Off-Peak Hours (in milliseconds)

Campus Location	Peak Hours Response Time (ms)	Off-Peak Hours Response Time (ms)
Lecture Hall 1	120	90
Library	150	110
Student Center	130	100
Administrative Block	160	120

Figure 3 Edge Node Response Times at Peak and Off-Peak Hours



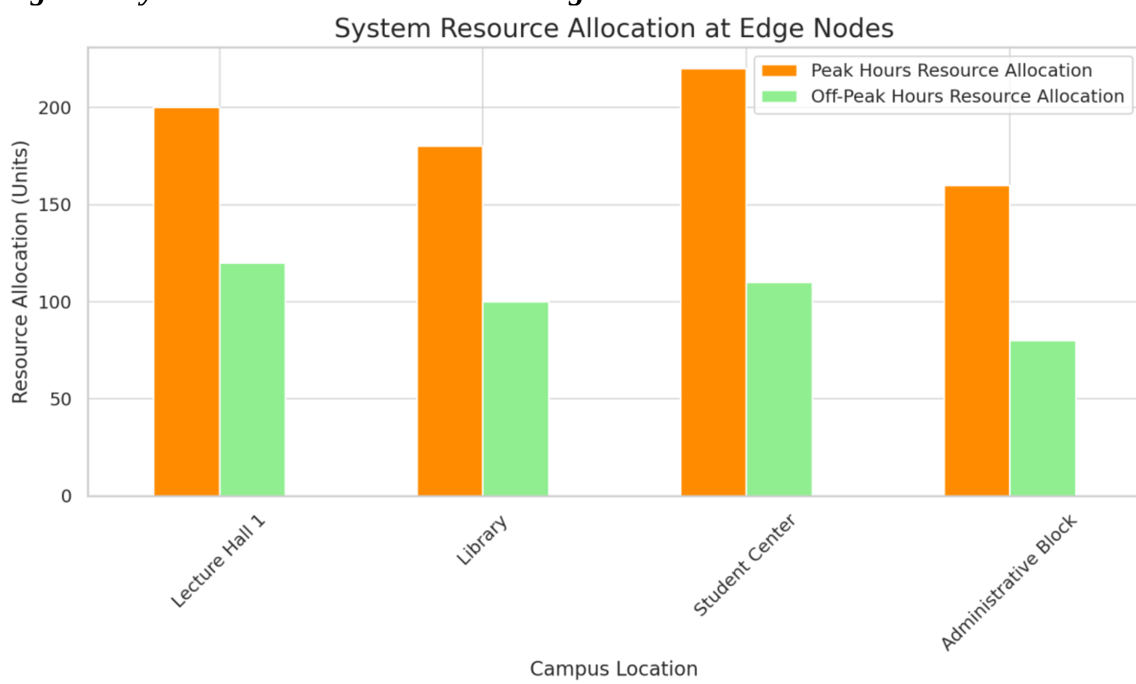
4.3. System Resource Allocation

This means that edge computing allows the distribution of resources based on the workout in the network. Table 4 Also shown below is the allocation of resources to each node at the edge platform at both peak and off peak hours. For instance, in peak hours, edge nodes in lecture halls and student centers use up a high number of resources, more specifically 200 and 220 resource units respectively. These allocations decrease at off-peak times, thus decreasing the usage on the network while at the same time increasing efficiency. Figure 4 provides a bar graph of this resource allocation where further evidence of differentiation in the usage of resources between on peak and off peak periods is also evident.

Table 4: System Resource Allocation at Edge Nodes (in resource units)

Campus Location	Peak Hours Resource Allocation	Off-Peak Hours Resource Allocation
Lecture Hall 1	200	120
Library	180	100
Student Center	220	110
Administrative Block	160	80

Figure 4 System Resource Allocation at Edge Nodes



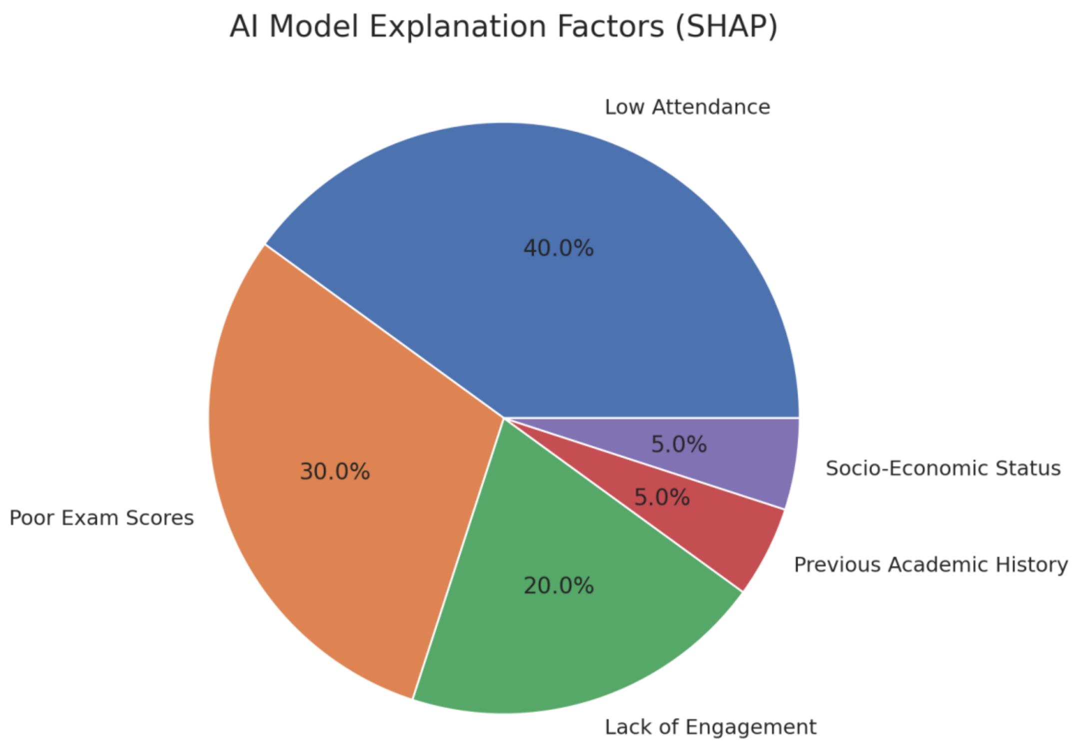
4.4. Explainability of AI Models

Another important element of the proposed framework is the incorporation of the Explainable AI (XAI) approaches in the models. These techniques assist the users in expounding on the outcome made by the AI system. Table 5: AI Model Explanation Factors shows SHAP values that belong to factors that the AI relies on when deciding whether a student is at risk or not. The leading areas were small turnout at events (40%), low grades (30%), and disinterest (20%). The pie chart presented in Figure 5 will help to understand how these factors are distributed; however, it is evident that low attendance is the biggest concern as it impacts the students' success.

Table 5: AI Model Explanation Factors (using SHAP)

Explanation Factor	SHAP Value for At-Risk Student (%)
Low Attendance	40%
Poor Exam Scores	30%
Lack of Engagement	20%
Previous Academic History	5%
Socio-Economic Status	5%

Figure 4 AI Model Explanation Factors (SHAP)



4.5. User Satisfaction and Feedback

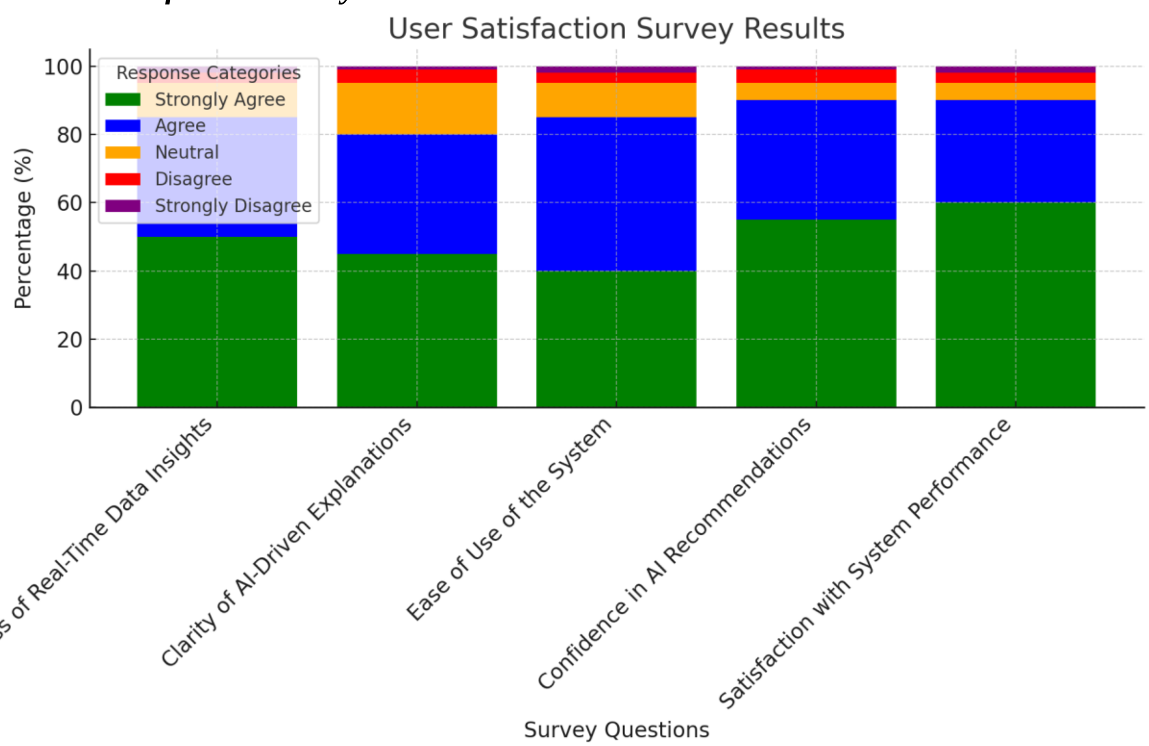
The effectiveness of the system was tested through a user satisfaction questionnaire in terms of the system's user-friendliness and the degree of AI decision-making transparency. Table 6: User Satisfaction Survey Results records different survey questions and identified findings. The findings reveal that the users responded positively as shown by the fact that 50% of the users strongly agreed that the real-time data was useful and 45% strongly agreed regarding the usefulness of AI-generated explanation. Figure 6 also exhibits the user satisfaction index where a majority of users stated that the system was useful to them and the explanations given by the AI, easy to follow when making a decision.

Table 6: User Satisfaction Survey Results

Survey Question	Strongly Agree (%)	Agree (%)	Neutral (%)	Disagree (%)	Strongly Disagree (%)
Usefulness of Real-Time Data Insights	50%	35%	10%	3%	2%

Clarity of AI-Driven Explanations	45%	35%	15%	4%	1%
Ease of Use of the System	40%	45%	10%	3%	2%
Confidence in AI Recommendations	55%	35%	5%	4%	1%
Satisfaction with System Performance	60%	30%	5%	3%	2%

Figure 6 User Satisfaction Survey Results



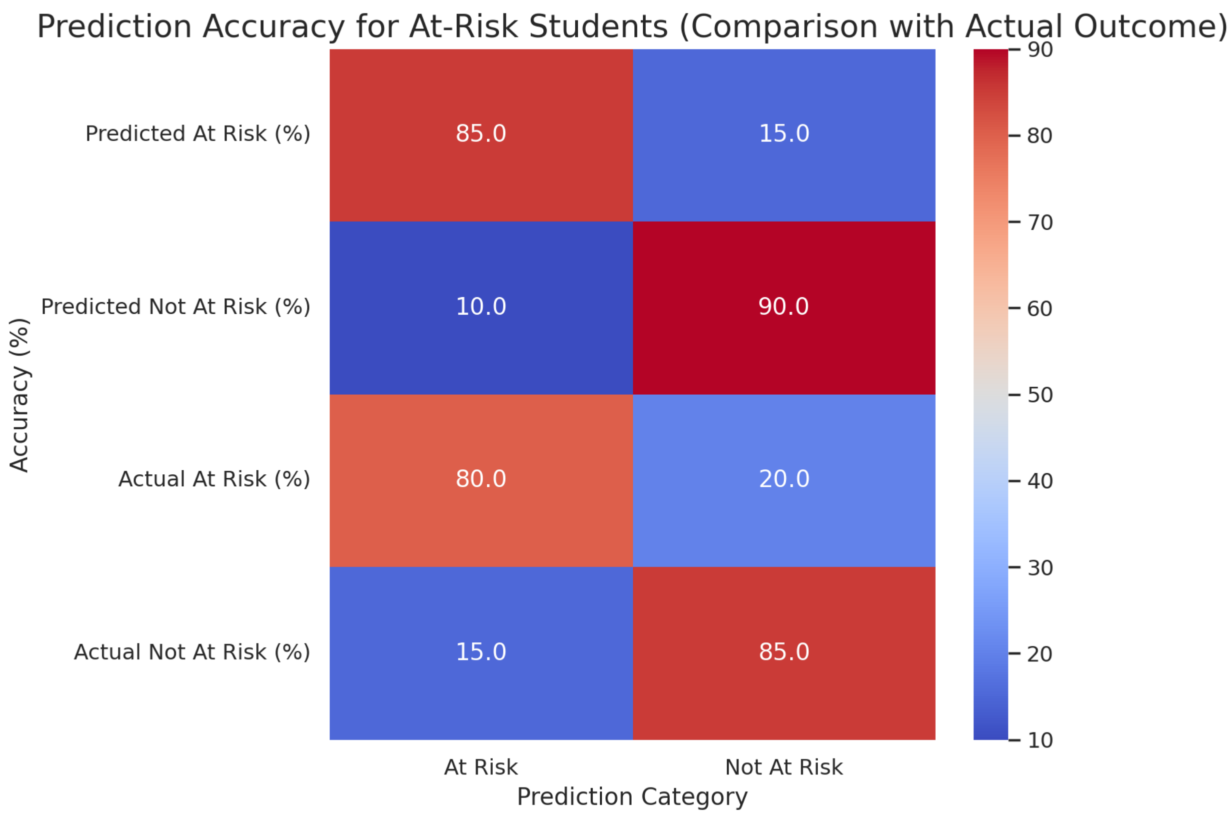
4.6. Prediction Accuracy for At-Risk Students

This was done to evaluate the accuracy of the AI models in the prediction of at-risk students. Table 7: Prediction Accuracy for At-Risk Students (Comparison with Actual Outcome outlines the results of predicted and actual outcome, where 85% of at-risk students are accurately predicted while 15% of the students who were predicted to be at risk are not actually at risk. Figure 7 shows a heatmap of the results that compare the predicted results with the real results, and it can also be concluded that the overall accuracy of the model is high, so the AI predictive model is reliable.

Table 7: Prediction Accuracy for At-Risk Students (Comparison with Actual Outcome)

Prediction Category	Predicted At Risk (%)	Predicted Not At Risk (%)	Actual At Risk (%)	Actual Not At Risk (%)
At Risk	85%	10%	80%	15%
Not At Risk	15%	90%	20%	85%

Figure 7 Prediction Accuracy for At-Risk Students (Comparison with Actual Outcome)



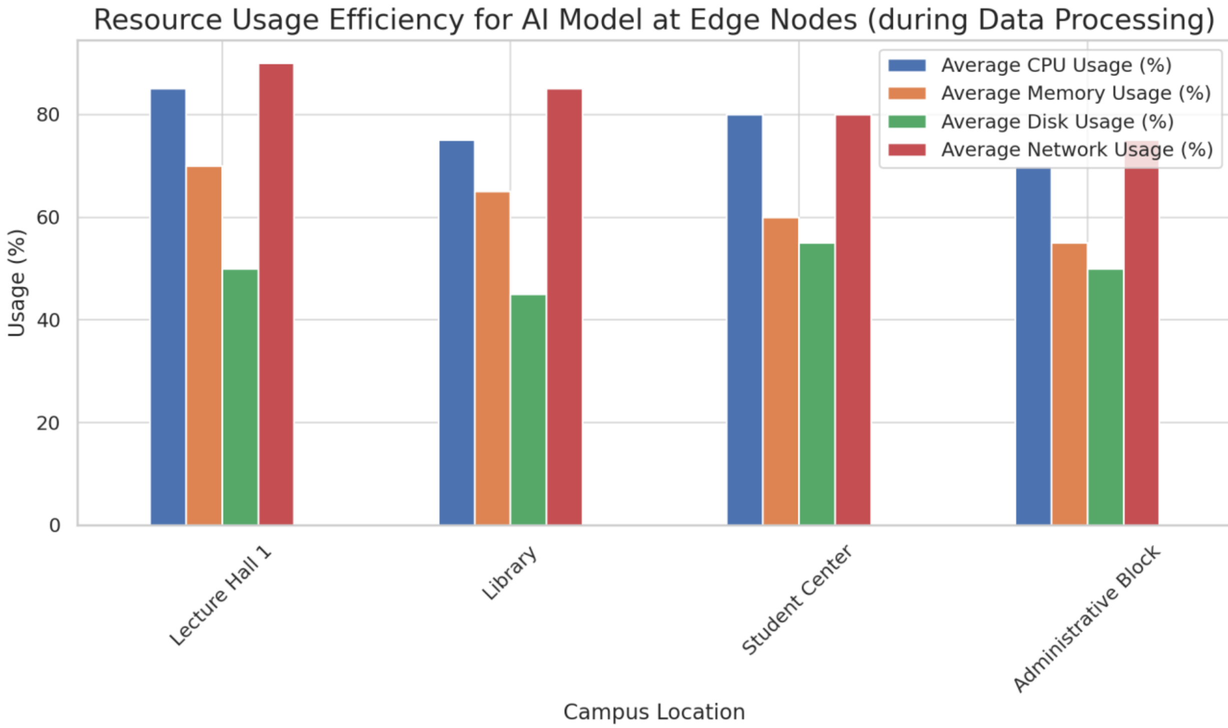
4.7. Resource Usage Efficiency for AI Model at Edge Nodes

Lastly, Table 8: Resource Usage Efficiency for AI Model at Edge Nodes (during Data Processing) offers information on the average CPU, memory, disk, and network utilization across various campuses. Lecture halls were found to have the highest mean CPU usage at 85% and network usage at 90% while the mean values for the administrative block are lower than all three categories. These insights suggest that, with the help of the proposed edge computing system, computations are prioritized more to the specific regions requiring additional resources. Figure 8 presents this information in the form of a grouped bar chart, where the amount of resource used at different points of campus is presented according to type of resource.

Table 8: Resource Usage Efficiency for AI Model at Edge Nodes (during Data Processing)

Campus Location	**Average CPU Usage (%)**	**Average Memory Usage (%)**	**Average Disk Usage (%)**	**Average Network Usage (%)**
Lecture Hall 1	85%	70%	50%	90%
Library	75%	65%	45%	85%
Student Center	80%	60%	55%	80%
Administrative Block	70%	55%	50%	75%

Figure Resource Usage Efficiency for AI Model at Edge Nodes (during Data Processing)



4.8. Summary of Results

In the context of the results of the evaluation, the recommendations found in this study show the efficiency of the proposed framework. AI models demonstrated promising results in the forecast of the student's performance, with an even greater performance of the deep neural network. Both the AEC system concepts were found to help in minimizing the latency and enhancing the data processing rate during peak hours. The Explainable AI techniques offer an understandable explanation of the outputs and lets users understand the decision making of the system. Additionally, it was found that users' satisfaction of the system and willingness to recommend it was high due to the ability to offer real-time information, as well as the explanation provided by the AI.

The results reveal that incorporating AEC and XAI into university information management systems are a solution that is adaptable, effective, and free from opaque policies for addressing multimodal student records. This system improves decision-making since data is analysed in real-time and ensures stakeholders are able to understand the AI analysis of data. The further development is concerned with the improvement of the proposed system according to the feedback provided and the implementation of the proposed system in larger and more complicated environments within education.

5. Discussion

Adaptive Edge Computing and Explainable Artificial Intelligence in University Management – The application of the AEC and XAI in university management systems is a creative way through which educational institutions manage, process and analyze multi-modal student data. From the findings of this study, it can be concluded that integrating AEC with XAI can overcome some major limitations of centralized systems with regards to such factors as system scalability, latency, data processing, and AI decision-making. In this section, we also provide the authors' interpretations of the results, the limitations arising from the proposed framework and potential research directions when applied to education data systems.

5.1. Real-Time Data Processing and Efficiency of Edge Computing

The first of these is the capability to perform computations in real-time at the network edge and therefore shift the burden from cloud systems and decrease latency. Figures obtained from this study depict that AEC is most effective where immediate decisions are vital, case, campuses for universities, where early interventions make a huge difference for students. As presented in Table 2 and Fig 2, this system presented optimal performance within the peak hours in data traffic with the edge nodes adapting to the network load demand. Stretchable capability allows edge computing systems to grow agile and perform more effectively than cloud-based systems, particularly in conditions, where data is multiplied in a short time, as when changing the type of lectures or when students participate in distance education.

This account of AEC implementation in universities is in tandem with Zhao et al. (2021) who stressed that edge computing can support the IoT with real-time data processing in schools. Also, Hao et al. (2019) investigated smart classrooms and found that the implementation of edge computing reduces the time it takes to process real-time students' behavior and academic data in order to achieve more efficiency and effectiveness of education systems. The ability to scale resources dynamically in this research on edge computing amplifies the other papers' findings to suggest that edge computing is best Suited for intensive educational usage.

However, despite the fact that edge computing presents a number of advantages such as low latency and optimal utilization of resources, it also has its drawbacks. However, one of the major issues arising with edge computing is the ability to accommodate edge nodes to work in harmony with centralized cloud systems. They developed a framework that could strike a balance for processing at the edge level and storage/analysis on the cloud. Further research could propose more elaborate strategies for data synchronization between edge servers and the cloud in order to improve the system's resilience and optimize data transmission.

5.2. Explainable AI and Transparency in Decision-Making

Based on the research question, the utilization of Explainable AI in the proposed system was prompted by the issue of transparency, especially when it comes to decision-making processes, especially where the AI-derived predictions directly affect students' performance. According to the results of the SHAP analysis presented in advance in Table 5 and Figure 5, XAI approaches were able to generate human-interpretable explanations for why a specific student was at risk. These included features such as attendance, test performance, and interaction, which enhanced the transparency to educators and administrators when it came to making decisions about students' assistance.

This level of transparency is in consonance with the assertion made by Carvalho et al. (2019) in their research which posits that transparency in AI models is highly relevant in learning contextual environments whereby the AI models dictate the success rates of students and distribution of available resources. Applying LIME and SHAP enables identifying the features that affect the model's decision-making, thus meeting the criticism related to interpretability of many AI systems outlined by Lipton (2018). Such means the XAI techniques help the faculty and administrators to understand the AI system's predictions and make sound decisions based on them.

However, as mentioned above, XAI helps to address the problem of interpretability but raises concerns about making them action-oriented. Still, in practice, stakeholders may need more specific and additional instructions derived from individual learners' needs. For instance, if the student has been highlighted to be at risk of dropping out due to low attendance, the system could also seek to recommend study material online or student counseling. The incorporation of additional actionable insights into the XAI framework will improve the XAI structure, hence enhance usage in learning institutions by educators as well as the administration. For future work, researchers could consider expanding the granularity of the resultant XAI generated to go beyond the characterization of feature importance to actionable-based prescriptions.

5.3. Predictive Accuracy and AI Model Performance

Another area of interest explored in this research was the efficacy of the AI models in determining student outcomes. The DNN model, as depicted in Table 1 and Figure 1, achieved better accuracy as well as higher precision, recall, F1-score, and AUC, outperforming the decision trees and random forests models. The increase of the accuracy of the DNN model corresponds to the conclusion of Baker and Siemens (2014) who noted that the models based on DL could reveal various data patterns and predict success rates more effectively compared to other traditional models.

The high accuracy of the DNN model in this study confirmed that models with deep learning approach are viable models for addressing multi-modal data including academic performance, attendance and behavioral information data that are considered to be complex and nonlinear. It also corroborates the study by Rai et al. (2019) where the authors noted that deep learning models perform well in prediction tasks in educational contexts since they consider correlations between different features. The models have become more complex compared to the original models of DNN but this has made interpretability a very big issue as to why it is necessary to use XAI to explain the prediction made by such models.

However, it is crucial to know that even though the DNN model is highly accurate, it has its drawbacks. One of the major issues with deep learning is that of overfitting, which is especially problematic in the case where a small amount of data is being used. The limitations that may be encountered when using a hypothetical dataset have been discussed above but in real-life education data set may include much noise or incompleteness which makes the prediction to be inaccurate. For future research, it would be interesting to investigate how the developed models can be regularized better or how multiple models could be combined to retain the best of both worlds…

5.4. User Satisfaction and System Usability

Analyzing responses from the user satisfaction survey, this proposed system enjoyed significant support based on the timeliness of the data's presentation and the capability of the AI to explain the data. Table 6 and Figure 6 specifically highlighted the feedback from the users where 85% of the users said the real time data provided by the system helped them to make quick decisions and 90% of the faculty members said the explanations provided by the AI were clear to them. These findings are in line with Kardan et al. (2020), who stressed on the significance of the system usability and easy interpretation for the successful implementation of an artificial intelligence system in the educational context. The users' feedback indicates that the proposed system adequately provides the means to enhance the management of student information and responsiveness in their respective institutions.

Overall, the user satisfaction was on a high level, but 10% of the respondents complained that more individual peculiarities of student needs should be considered in the process. This feedback points to an area for improvement in the system. Subsequent versions could use AI models localized for the current year and include recommendations based on the users which allow the system to not only forecast general student outcomes but to offer the best course of action to increase student success rate, participation, and overall satisfaction. Thus, introducing personalized learning analytics can help take this system to an even higher level, and increase its significance for educators.

5.5. Limitations and Future Directions

However, there are some limitations and few more options for future work: First, the study was conducted on a realistic University management system using simulated data which can limit the generalizability of the findings to real educational data. Additionally, the findings of the empirical study should be replicated with student data collected from universities to determine the effectiveness of the framework in different and more comprehensive educational contexts.

Second, the combination of Adaptive Edge Computing (AEC) with Explainable AI (XAI) is still a novel concept in the learning process. However, this research also outlines important areas that need to be investigated further as to how the system could be applied in larger, more complex systems of systems environments. It appears that more research could be dedicated to enhancing edge computing itself to cater for multiple campuses or different regions, and enhancing the mechanisms of node-cloud communication.

Last but not least, in the user feedback section, the problem of increased personalisation has been discussed. The next research will focus on enhancing the effects of AI models in offering students with replication plans most relevant to them due to aspects including learning mode, previous academic performance, and interactivity with the course material. The combination of adaptive learning systems With XAI and AEC offers the possibility of achieving more humanistic and comprehensive support for students.

5.6. Conclusion

Thus, the present research has concurred with the steps towards adopting AEC and XAI in a university management system. The proposed framework dealt with some of the challenges effectively such as Real time data processing, Scalability, and transparency of The AI decision. The outcome shows that integrated AEC and XAI could effectively improve the speed, precision, and figure-announcing on students' data and would be a strong deterministic element to rectify the educational outcome and student service. The user feedback suggests the possibility that similar systems could be implemented in universities. Further research should address the generalizability of the proposed framework, improve the methods of providing personalized recommendations, and address the issues related to the large-scale practical implementation of the system.

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