Machine Learning based Student Complaint and Priority Determination Support System

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Abstract

The rapid expansion of digital learning environments has necessitated the development of intelligent systems that enhance student support services in higher education. This study presents a Machine Learning-Based Student Complaint and Priority Determination Support System with Automatic Responder, designed to improve response efficiency, reduce delays, and enhance accessibility to academic and administrative information. The system leverages Knowledge Discovery in Databases (KDD), Data Mining (DM), and Artificial Intelligence (AI) to analyze student queries, classify complaints, and provide automated responses based on a structured knowledge base. To ensure a structured and efficient development process, the system was designed using the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which provides a systematic approach to data understanding, preparation, modeling, evaluation, and deployment. Additionally, Object-Oriented Programming (OOP) principles were employed to ensure modularity, scalability, and maintainability of the system components. Traditional student support mechanisms in Nigerian universities, particularly in distance learning, are often semi-automated, relying on email-based communication and manual responses, which lead to inefficiencies, delays, and a lack of structured prioritization. To address these limitations, this research designs a smart ticketing system integrated with a machine learning classifier that categorizes and prioritizes student inquiries based on urgency and relevance. The system features automated response and tracking, and self-service functionalities that enable students to receive immediate resolutions to common queries. A Decision Tree Classification Model was implemented to analyze historical complaint data, establish relationships between student inquiries, and improve automated response accuracy. The model dynamically learns from past interactions, allowing the system to continuously enhance its predictive capabilities. By implementing graph-based relationships among tickets, the system identifies recurring queries and delivers intelligent responses without human intervention. The new framework significantly reduces response time, improves the quality of student support, and enhances the student-university interaction experience. This research contributes to the advancement of Educational Data Mining (EDM) by demonstrating how AI-driven student support systems can optimize information retrieval and streamline administrative processes. The findings suggest that machine learning, CRISP-DM,

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and OOP-based system architecture can play a pivotal role in developing scalable, efficient, and student-friendly support systems, fostering better academic engagement and institutional efficiency.

Keywords: Machine Learning, Knowledge Discovery Database(KDD), Data Mining, Support system, Decision Tree, Cross Industrial Standard Process for Data mining(CRISP-DM),Ticket.

1.Introduction

Most higher education institution relies on manual or semi-automated systems for handling student complaints. These systems often suffer from several drawbacks, including slow ticket processing, inconsistent classification of complaints, poor prioritization and limited feedback mechanism. As complaint volumes increase, administrators struggle to response to timely and efficient manner. Existing studies in automated complaint handling lack of effective integration of machine learning, intelligent agents and knowledge-based systems to enhance accuracy and responsiveness.

Therefore, there is a need for an intelligent automated system capable of classifying student complaints, prioritize them based on urgency and context, supporting administrative decision-making and providing instant responses through a knowledge discovery approach

The transformation of educational systems worldwide, especially in higher education, has been significantly accelerated by the increasing reliance on digital platforms and technologies. Over the past decade, the integration of technology in education has reshaped how teaching, learning, and support services are delivered. This transformation has been further intensified by the global COVID-19 pandemic, which necessitated a rapid shift to online learning environments. As universities and educational institutions around the world moved their courses online, the need for robust, digital, and efficient systems to support students became more critical than ever (Cai, 2021).

The increasing complexity and diversity of student needs ranging from academic inquiries to administrative issues pose a major challenge for traditional support mechanisms in educational institutions. Traditionally, universities have relied on manual systems, such as in-person interactions, phone calls, and email exchanges, to handle student inquiries. While these methods were once effective in smaller, more localized educational settings, they have become inefficient as student populations grow, and as educational models shift to distance and blended learning approaches. The reliance on manual responses results in significant delays in addressing student concerns, inconsistency in the quality of support, and an overall inefficient use of resources (Bowers & Kumar, 2020). This is particularly evident in Nigerian universities, where administrative processes are often overwhelmed by the sheer volume of student inquiries and the lack of fully automated systems (Adeyemi, 2022).

In Nigerian universities, these challenges are particularly prevalent due to issues such as limited access to technology, inadequate infrastructure, and heavy administrative workloads. Despite the advancements in digital systems, many educational institutions still rely on outdated methods to handle student queries. This scenario exacerbates the problem, especially as students' expectations for real-time, personalized support continue to rise. The existing systems struggle to keep pace with the growing volume of inquiries, often resulting in delayed responses and confusion. Consequently, the need for an

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efficient and scalable solution has never been more pressing (Adebayo & Nwachukwu, 2021).
This system will ultimately bridge the gap between the increasing demand for timely, efficient student support and the limited resources available in many universities. The integration of **AI-powered automation** can significantly reduce administrative bottlenecks, improve the overall efficiency of student support, and, most importantly, enhance the student experience by providing quick, accurate, and personalized responses to a variety of student queries. By automating this process, universities will also benefit from reduced operational costs, allowing them to redirect resources towards more critical tasks, such as improving course content and providing additional academic support (Cai, 2021).
Thus, this study represents an innovative step toward transforming how educational institutions, particularly those in Nigeria and other developing countries, approach student support. It leverages the latest advancements in machine learning and artificial intelligence to solve long-standing challenges in educational administration, providing an automated, intelligent system that can scale and adapt as the needs of the institution evolve.
Intelligent based student support system aims to provide efficient and personalized support to students through a combination of artificial intelligence (AI) and automation. Intelligent Knowledge Base is a comprehensive database containing information on various student support topics like: Academic resources (course materials, library access), Administrative procedures (registration, financial aid) and University services (counseling, health center). It utilizes machine learning to analyze student questions and match them with relevant information from the knowledge base using knowledge discovery database (KDD). Provides immediate responses to frequently asked questions (FAQs) and basic queries.
The application of data mining methods in the field of education has attracted great attention in recent years. Data Mining (DM) is the discovery of data. It is the field of discovering new and potentially useful information or meaningful results from big data (Witten et al., 2011). It also aims to obtain new trends and new patterns from large data- sets by using different classification algorithms (Baker &Inventado, 2014).
This paper therefore, advances a solution to the persistent delays in addressing critical questions, the constraints associated with limited scalability and the inadequacy existing mechanism to prioritize
students enquire, with the overarching aim of ensuring that high-priority complaints receive appropriate and timely attention.

II.Literature Review

Research was carried out on availability, use and contribution of support services to students academic and Social development in Nigeria University system, to examine the availability ,use and contribution of support services to student services to student's academic activities and social life. Result showed that the students endorsed that most of support services were not available in their institutions.
From the finding, there are no adequate media facilities for counselling so as to ensure that students are guided as expected.
In a research presented by Feras (2021), he proposed a help desk system that acts as a single point of contact between users and IT staff. It utilizes an accurate ticket classification machine learning model to associate a help desk ticket with its correct service from the start and hence minimize ticket resolution time, save human resources, and enhance user satisfaction.

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The model is generated according to an empirically developed methodology that is comprised of the following steps: training tickets generation, ticket data preprocessing, words stemming, feature vectorization, and machine learning algorithm tuning. Nevertheless, the experimental results showed that including the ticket comments and description in the training data was one of the main factors that enhanced the model prediction accuracy from 53.8% to 81.4%. Furthermore, the system supports an administrator view that facilitates defining offered services, administering user roles, managing tickets and generating management reports. Also, it offers a user view that allows employees to report issues, request services, and exchange information with the IT staff via help desk tickets. Moreover, it supports automatic email notifications amongst collaborators for further action. Yet, it helps in defining business processes with well-defined activities and measuring KPIs to assess the performance of IT staff and processes.

Albert, et. al (2020) in their research said that in handling internal complaints, some companies have implemented a helpdesk system while some other processes are still carried out manually. The helpdesk ticket is categorized manually by human operators. This procedure is prone to an error resulting in many tickets bounced to the wrong business unit and delaying the complaint handling. They i an automated problem categorization based on the title of helpdesk ticketing using machine learning. The results show that the random forest classification has the highest accuracy value of 82%.

Ratthida and Limpiyakorn (2019) presented a paper titled "Development of IT Helpdesk with Microservices". an IT helpdesk that allows users to submit service requests for reporting problems or their requirements to IT teams for trouble shooting. The paper presents a design of IT helpdesk with microservice architecture to promote scalability of the system. The implementation includes the classification service that automatically categorizes tickets to the associated IT teams for support. The thesaurus database is utilized for clustering the request subjects. The benefits of the new approach were to enable the scalability and fortify the availability of the system. They recommended an improvement of the classification service, and the enhancement of the Ticket to enable attachment with a ticket as a future research update.

Antonio, et. al (2020) for creating a recommender system to support higher education students in the subject enrollment decision. They were of the opinion that higher education plays a principal role in the changing and complex world of today, and there has been rapid growth in the scientific literature dedicated to predicting students' academic success or risk of dropout thanks to advances in Data Mining techniques. Degrees such as Computer Science in particular are in ever greater demand. Although the number of students has increased, the number graduating is still not enough to provide society with as many as it requires. The study contributed to reversing the situation by introducing an approach that not only predicts the dropout risk or students' performance but takes action to help both students and educational institutions. The focus is on maximizing graduation rates by constructing a Recommender System to assist students with their selection of subjects. In particular, the challenge is addressed of constructing reliable Recommender Systems on the basis of data which are both sparse and few in quantity, imbalanced, and anonymized, and which might have been stored under imperfect conditions. The approach was successfully applied to create a Recommender System using a real-world dataset from a public Spanish university

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containing performance data of a Computer Science degree course, demonstrating its successful application in real environments. The construction of a support system based on that approach is described, its results are evaluated, and its implications for students' academic achievement and for institutions' graduation rates were discussed. Through the construction of the decision support system for students, they intended to increase the graduation rates and lower the dropout rate.

Uka and Ekwonwune (2019) new web based students' record management system for Tertiary Institutions. Their paper was borne out due to the problems associated with student academic record management which include improper course registration, late release of students' result, reconciliation of students' result, malpractices at various students clearing units, inaccuracy due to manual and tedious calculation and record retrieval difficulties in the institution.

Having identified the drawbacks in existing research, we aim to develop a machine learning based student complaints determination and prioritization system. The proposed solution will employ an intelligent agent to automatically classify complaints tickets, assign priority levels and support timely resolution.

Furthermore, we plan to integrate a knowledge-discovery database technique to enable automatic responses and provide a self-help service for student thereby improving efficiency, accuracy and user satisfaction within the complaint handling process.

III Methodology

This study adopted a mixed method approach, combining both quantitative and qualitative approach .The research was conducted in Ebonyi state, Nigeria. The study relies on multiple data sources to ensure comprehensive insights into student inquiries and system performance. These sources include real-time data from the student portal, stakeholder feedback, historical data on student support requests, and simulated scenarios.

Data collection and preprocessing were carried out by gathering historical student complaint data, datasets were cleaned and labeled for training and text preprocessing(tokenization).

Model Development was carried out through Implementation of Natural Language Processing (NPL) based feature extraction implementation using TF-IDF, train classification models using decision tree and random forest and priority-prediction model was done using machine learning NPL features.

CRISP-DM is selected for its iterative nature and strong focus on both the analysis and practical deployment of machine learning models. The feedback-driven process is crucial in the context of the dynamic nature of student support systems, where continuous data influx and evolving student inquiries require constant updates to the system's models.

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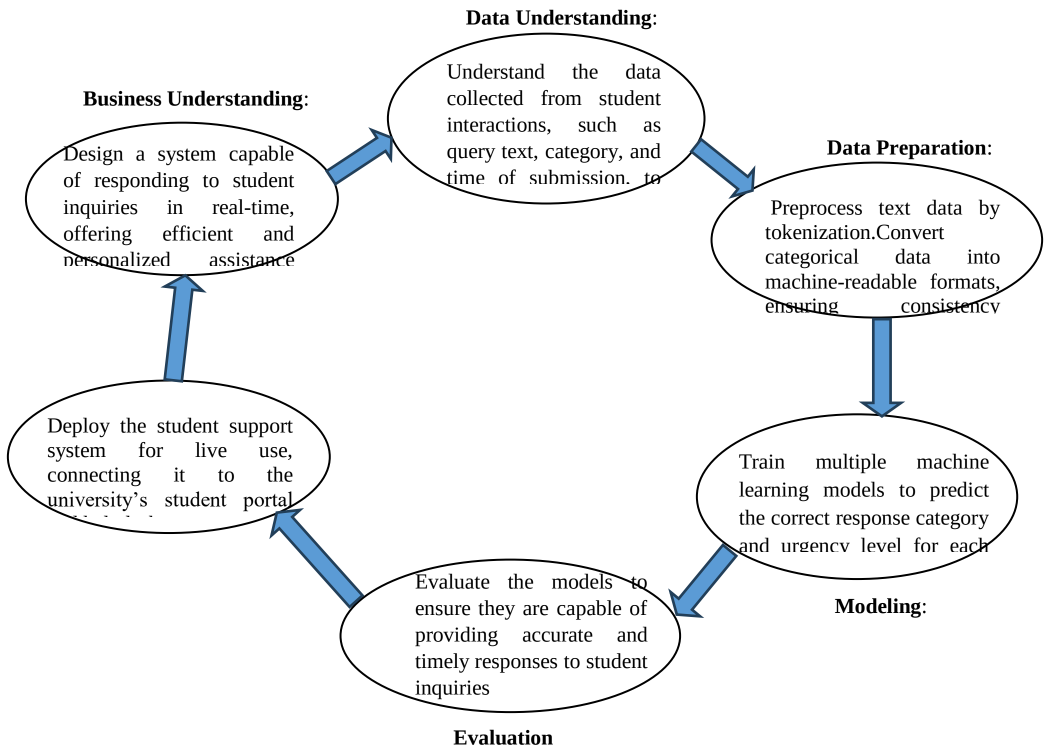

Data Collection

Figure 1: The CRISP-DM Framework for the Machine learning based student complaint and priority determination support system

Data collection

A) Stakeholder Interviews: Interviews with tertiary institution administrators, faculty members, and IT support staff was carried out to gather first-hand insights into operational challenges, current support systems, and the specific needs that the new automated system must address.

B) Literature Review: Reviews were carried out to ensure adequate information.Review of existing institutional workflows paid a role in identifing System gaps and user challenges .

C) Simulations and Prototyping: Prototypes of the automated system was tested in controlled environments to simulate real student interactions. This allows for the refinement of machine learning models and the identification of potential areas of improvement.

4) Expert Surveys: Online surveys was distributed to AI and machine learning experts within the field of education to gather perspectives on best practices, emerging trends, and system integration1strategies.

Dataset Used

The testing requires a minimum of 5,000 ticket data obtained directly from the Open and Distance Education ticketing website application. Data that will be used to carry out this test are shown in *Table 1*.

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Table 1: Dataset and Attribute

Dataset	Attribute	Description	Type
	Category	Category Type of Ticket	Varchar
	Request	Title of the Ticket, User Inputted	Varchar
	Date	Date and time the ticket was submitted	Date
	Email	The email address the ticket will be forwarded to	Varchar

The data is filtered by the date that the ticket is created. The dataset used to conduct the test is based on the title of the tickets, and the ticket category with date submitted, as shown .

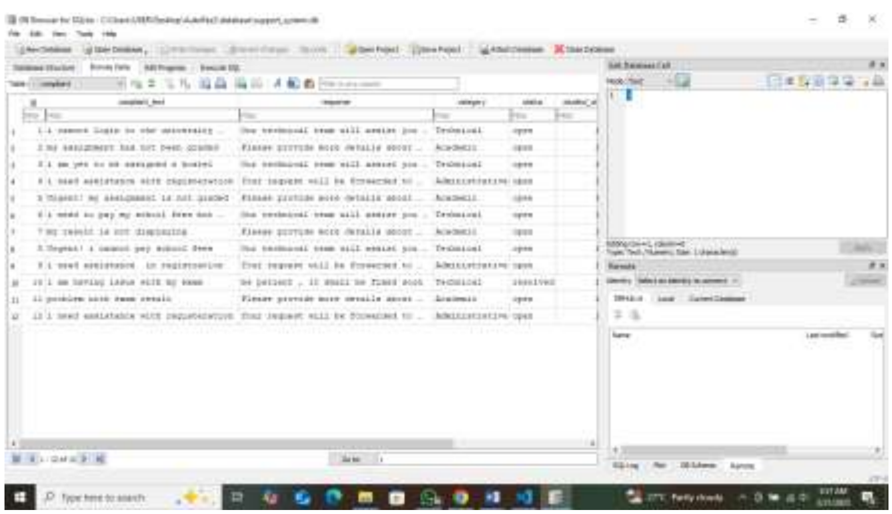

Figure 2: Sample Ticket Dataset used

This system is to predict the category of the ticket and the priority based on the user's inputted request. The system uses machine learning for ticket's title classification. The system will conduct semantic analysis with Decision Tree classifiers. After the tests are conducted, the classifier with the highest accuracy will be used. It's within our capabilities and expectation that this research can be applied to its related application with the goal of automatic category and ticket priority selection. Thus, the system can route the ticket directly to its support team personnel without the need of human assistance. This will shorten the workflow of the system and freed up some human resources on more pressing matters.

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The use case diagram in *figure 3* depicts all the actors in the intelligent based student support services and how they interact with the system.

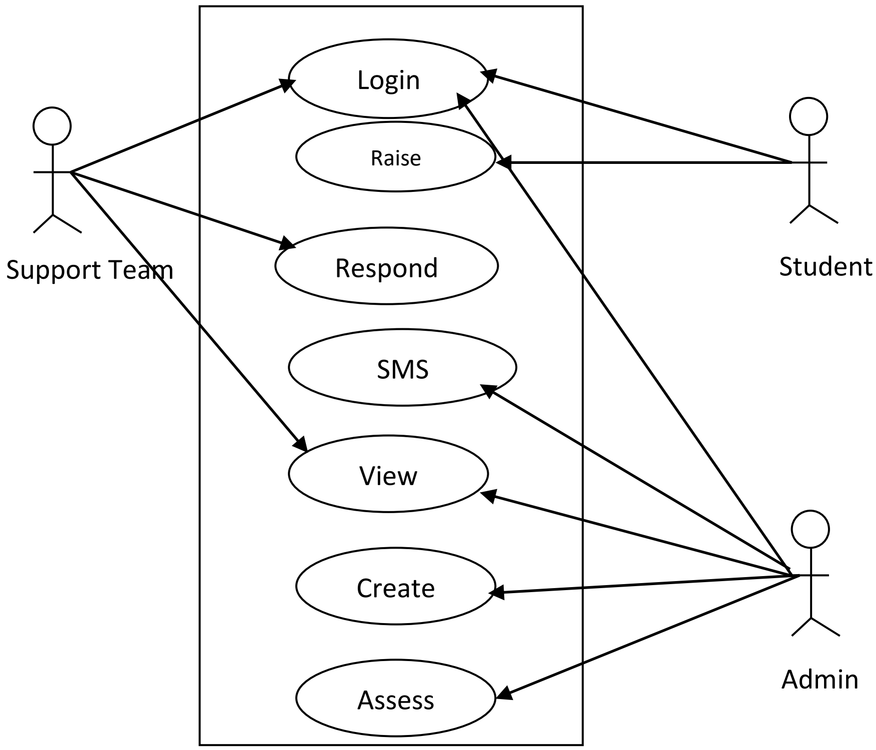

Figure 3: Use Case Diagram of machine learning based student complaint and priority determination support system

The user requirements describe functions that are performed by the users on the system. The users are categorized into three levels namely students, support team and Admin.

The sequence diagrams show how objects interact with one another and in what order. It depicts the objects and classes involved in the scenario.

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Sequence Diagram (Student)

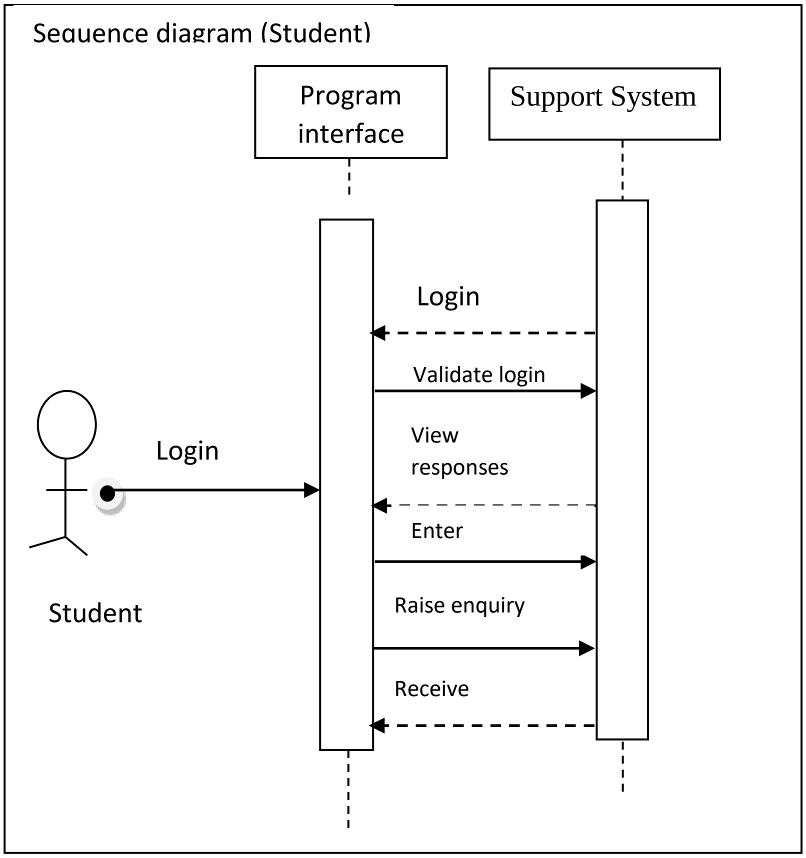

Figure 4: Sequence Diagram(student)

The students can do the following things.

i.The login page is the first page from where the student can login to the intelligent based student support system.

ii.Student can view frequently asked questions and responses

iii.They can also sign up on the system

iv.Students can raise complaint tickets

v.Students can receive response on the ticket raised

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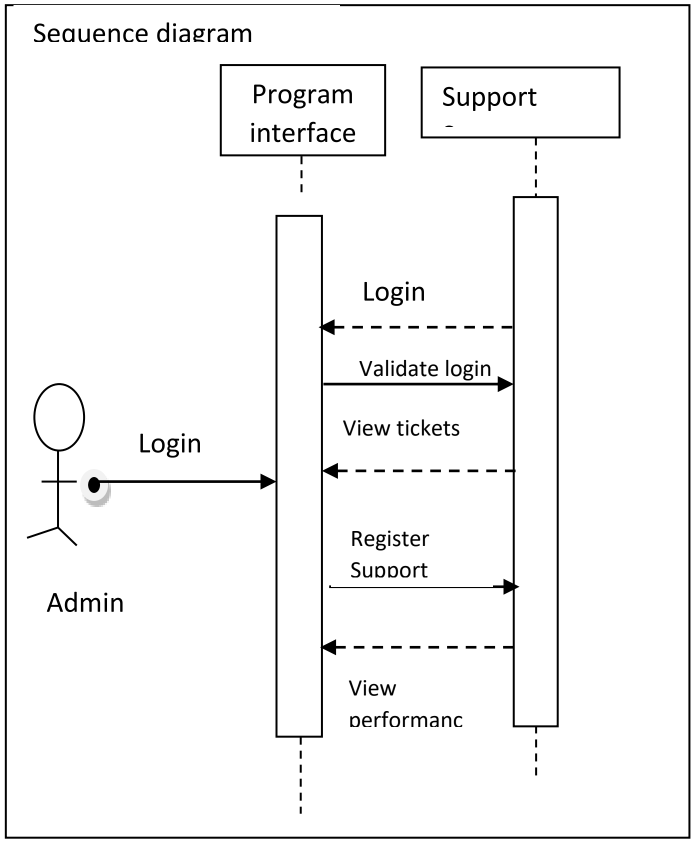

Figure 5: Sequence Diagram (Admin)

The Admin can do the following things.

i. The login page is the first page from where the Admin can login to the system.
ii. Admin can equally register support team members
iii. Admin can view tickets
iv. Admin can also view the performance of the support team in terms of timely response to tickets

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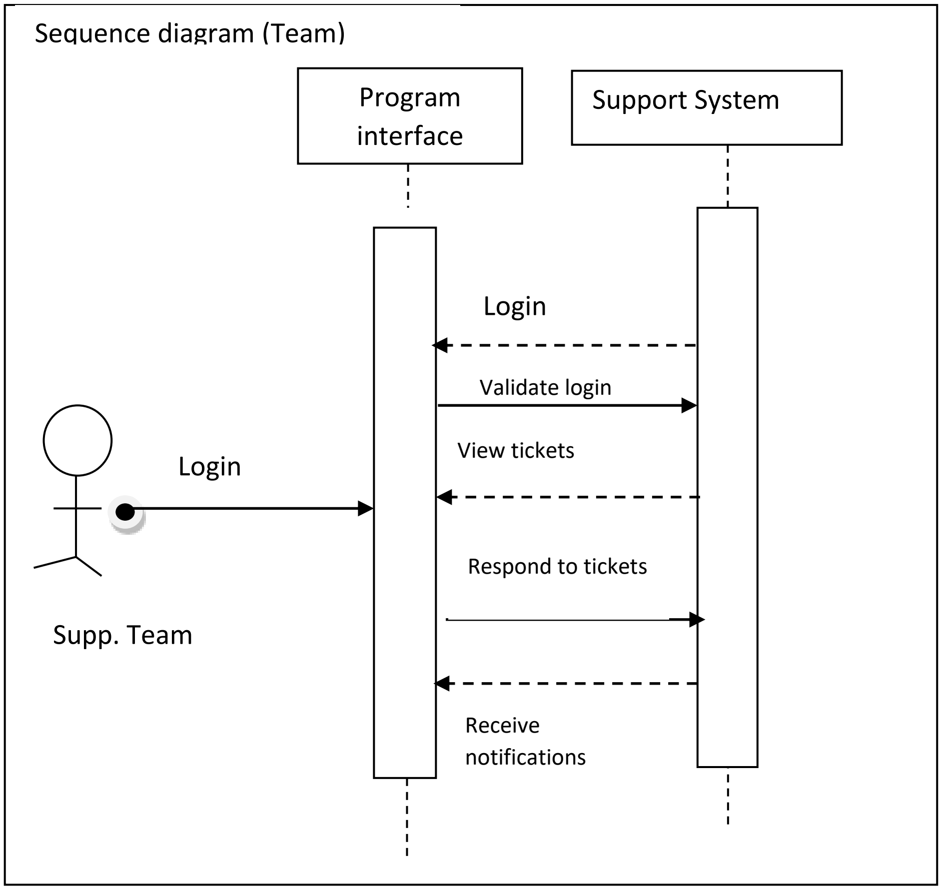

Figure 6: Sequence Diagram (Support Team)

The support team can do the following things.
i.The login page is the first page from where the support team can login to the system.
ii.They can receive SMS notification for any ticket raised
iii.They can respond to tickets
iv.They can view pending tickets

IV Result and Discussion

The study outcome demonstrates an improvement in accuracy, reduction in administrative workload, prioritization and optimization of response time. The result showed significant improvements in complaint handling efficiency through the use of intelligent automation.
Evaluation metrics include; classification accuracy, scalability, response time and user satisfaction.

Test Cases and Scenarios

Summary of the test cases and expected outcomes.

Table 2: Test Cases and Expected Outcomes

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Test Case	Descript	Expected Outcome	Result
User Login	Verify login with valid/invalid credentials	Grant access or show error	Pass
Submit Complaint	Ensure students can submit complaints	Store in database & assign priority	Pass
View Complaint Statu3	Track progress of submitted complaints	Display current complaint status	Pass
Automated Response System	Verify if ML model provides correct FAQ responses	Retrieve best-matched FAQ or escalate to staff	Pass
Complaint Classification	Test ML model's accuracy in categorizing issues	Correctly classify 85%+ cases	Pass
Staff Response Handling	Ensure support staff can manually respond	Update complaint and notify student	Pass
Notification System	Test email/SMS alerts for complaint updates	Send notifications successfully	Pass

All test cases were executed, and no critical issues were found. Minor UI improvements were suggested.

Ticket submission testing

This shows a form for a student to enter and submit a ticket and view and automatic response and status of the ticket.

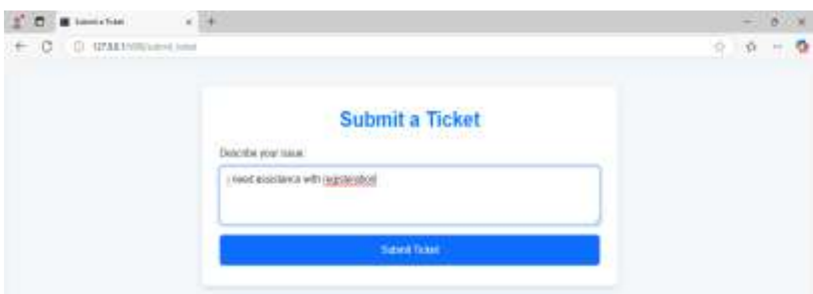

Figure 7: A student submits a ticket

The Figure below shows the response from the system, ticket classification and status.

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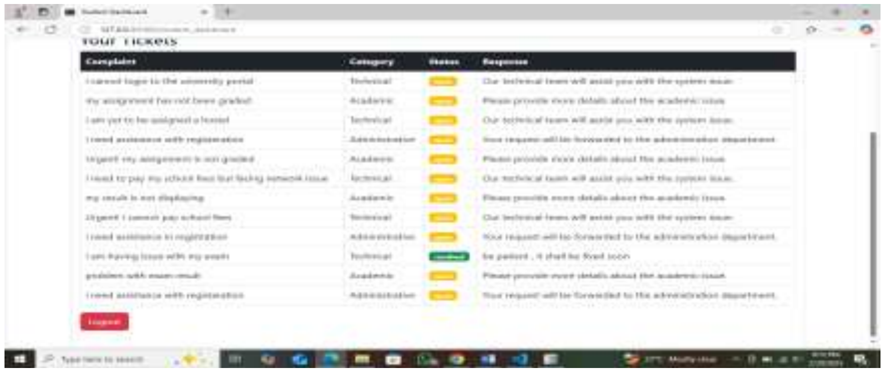

Figure 8: Response from the system

Where a similar solution is already existing in the Knowledge base and how the system suggests the solution to the student. With this, there is no need sending a ticket to the support staff.

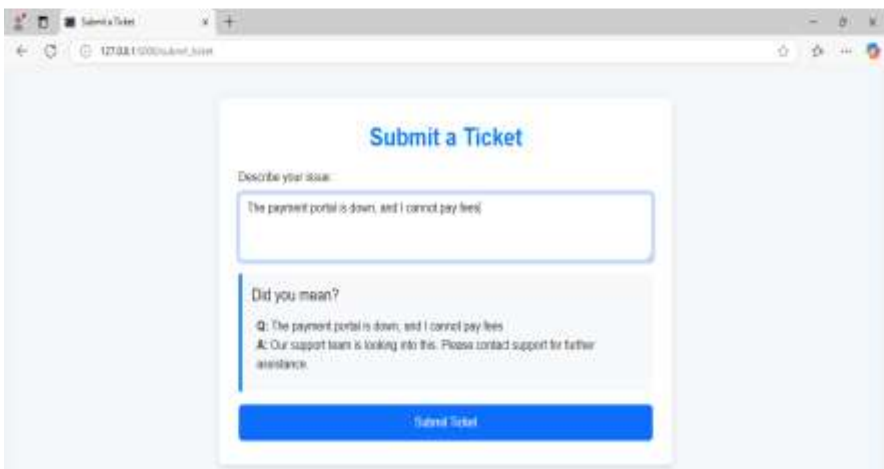

Figure 9: Auto suggestion from the KB.

Performance Evaluation Metrics

The system was evaluated using the metrics as shown in the table.

Table 3: Performance Evaluation Metrics

Metric	**Description**
Accuracy	**Percentage of correctly classified complaints**
Response Time	**Time taken to provide an automated response**
Scalabiity	**Ability to handle increasing complaint volumes**
User Satisfaction	**Measured through surveys (Likert scale)**

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Experimental Results and Analysis

This summarizes the experimental results and analysis. Figure 31 shows complaint (ticket) classification.

Table 4: Experimental Results and Analysis

Metric	**System Result**	**Benchmark (Existing Systems)**
Complaint Classification Accuracy	**91.2%**	**80% (Typical ML-Based Systems)**
Response Time (Automated)	**1.3 sec**	**2.5 sec**
Scalability (Max Complaints Handled)	**10,000+**	**~5,000**
User Satisfaction Score	**4.7/5**	**3.8/5**

The analysis is a discussed below:

i. The classification accuracy of 91.2% surpasses existing models.
ii. The response time (1.3 sec) is faster than manual systems.
iii. Scalability allows handling of twice the number of complaints as existing systems.
iv. User satisfaction is significantly higher (4.7/5) due to quick and relevant responses.

Figure10:Ticket classification (Administrative in this case)

This shows where the support staff views the priority of a ticket and other details. He also responds to the user ticket and hence the status of the ticket is changed to resolved.

The assigned priority levels are; High(Red), Medium(Yellow), and Low(Green)

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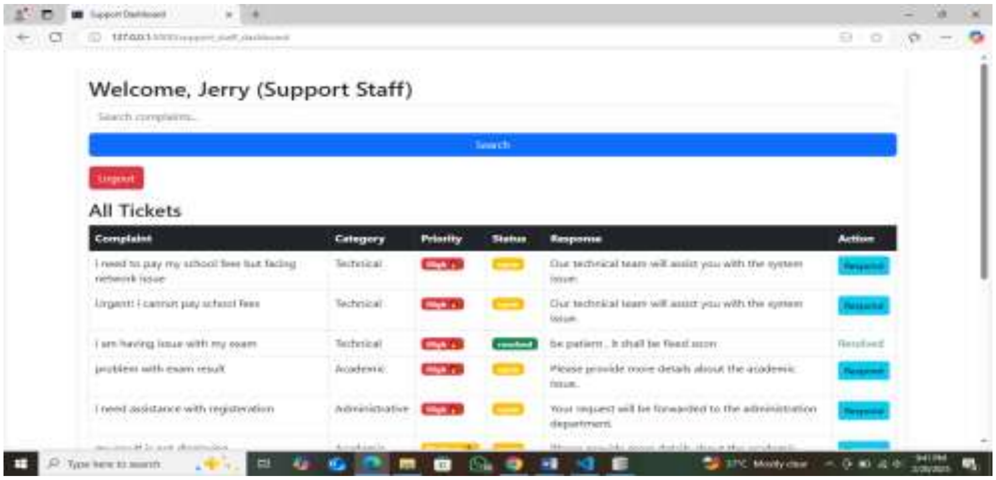

Figure 11: Ticket prioritization

V Conclusion

Machine learning based student complaint and priority determination support system aimed at improving the efficiency and responsiveness of handling student complaints. The system fulfils its core objectives by providing an intelligent interface capable of automatically classifying student queries and delivering context-aware responses using predefined knowledge. Though the integration of knowledge discovery techniques, the system can recognize and address previously answered questions, further streamlining the support process.

A modular and scalable architecture, built using object-oriented programming principles, ensures that the system can be easily extended or adapted to evolving institutional needs.

Additionally, the implementation of smart ticketing module enables automatic categorization and prioritization of complaints based on urgency, ensuring that critical issues are addressed promptly.

Performance evaluation results demonstrate the system's effectiveness, achieving an impressive classification accuracy of 91.2%, a fast average response time of 1.3 seconds, high user satisfaction (4.5/5) and scalability to handle over 10,000 users. These results highlight the system's potential as a robust solution for academic institutions seeking to enhance student support services through intelligent automation.

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