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Design and Implementation of a Multilingual AI-Driven Student Support Portal with Chatbot and Peer-to-Peer Forum

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***Abstract*— Handling the vast amount of student inquiries related to enrollment and tuition payments is a major challenge for most universities due to reliance on outdated online portals and manual labor to respond to inquiries creating backlogs and delays in service delivery. To solve this problem, we have developed an AI-Enhanced Student Support System, which includes a multi-language chatbot integrated with a web platform. This AI-based chatbot utilizes Natural Language Processing and Machine Learning technologies to answer students routine questions and issue automated reminders of important deadlines and payment confirmation via Email. The Support System is supplemented with a ticket management function for inquiries that require additional resolution and dedicated dashboards for both students and administrators. In addition, we created a Peer-to-Peer Student Forum for students to ask and answer their peers questions, share stories, and vote for the most beneficial answers provided by their peers to develop a growing reference for future inquiries and enhance the chatbot's automated assistance. Together, with intelligent conversational agents and student-driven collaborative communication, we are developing a more efficient, effective, and dynamic digital support environment for tuition-related administrative processes.**

***Index Terms*— Multilingual Chatbot, Student Support System, Natural Language Processing, Peer-to-Peer Forum, Ticket Management, Rasa NLU.**

I. INTRODUCTION

With an increasing number of students enrolling at universities around India and internationally there is a growing amount of administrative workload as institutions handle queries related to student Admission, Fee Payment, Examination Schedule, Certificate Issuance, and General Campus Information [1], [2]. Universities have a well established traditional support channels (such as email Helpdesk, Walk-In Counter and Static Frequently Asked Questions (FAQ) portal) but these have proven ineffective in meeting the demands for quick response times from today's student population [9]. Students are often faced with slow responses, varying information, and communication barriers due to the widespread use of multiple languages spoken by students, (e.g., English [2], Hindi and Regional languages like Telugu) particularly in multilingual environments (e.g., Indian Institutions). Conversational AI (CAI) Systems are emerging as a viable solution to automate repetitive administrative interactions.

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Rule-Based Chatbots were one of the first conversational systems implemented in Higher Education and were able to provide deterministic responses to strictly structured questions; however, these chatbots were unable to handle the variety of natural language (NL) inputs from students nor could they keep a discussion going from one interaction to the next [3], [12]. Recent advances in Natural Language Processing (NLP) and Machine Learning (ML) based architectures have increased the accuracy of the classification process and improved response fluency; however, these solutions remain limited to working with a single language and continue to lack integrated escalation workflows and do not facilitate peer-driven knowledge collaboration [1], [2], [3].
This paper addresses limitations related to current student support systems by providing sufficient data and details on the design/development of an artificial intelligence (AI) powered student support portal that integrates a multilingual chatbot, automatic ticket creation, and peer-to-peer (P2P) knowledge sharing in a single place.

A. Research Objectives

The research aims to: (a) develop multilingual real-time student support through a chatbot, ticketing system, and P2P communications; and (b) establish a standardized method for processing student inquiries, including complex cases unresolvable by automated means.

II. CONVENTIONAL PROCESS

Early university chatbot implementations relied on keyword matching against response templates stored in relational databases such as MySQL [6], [12]. The conventional pipeline comprised three stages: (1) a frontend interface for query submission; (2) a processing engine for tokenization, keyword extraction, and template matching; and (3) a backend knowledge base storing question-answer pairs and interaction logs [10] .
Parrales-Bravo et al. [1] used TF-IDF and n-gram features with Logistic Regression to classify 58 predefined intents via the Telegram Bot API, achieving an 82% automated resolution rate-but limited to English, without conversational context or peer interaction. Bala et al. [12] designed a comparable AIML/MySQL rule-based system without semantic or multilingual capability. These first-generation chatbots succeed at structured tasks but suffer from language rigidity, lack of stateful interaction, and siloed architecture [3], [5], [7].

III. RELATED WORKS

Parrales-Bravo et al. (2024) research introduced a hybrid chatbot that facilitates both enrollment/fee questions through the combination of standard NLP and machine learning methods (ML) to classify intent [1] . While they noted significant decreases in both time to respond and amount of work needed to administer user queries, the chatbots issued only correspondences in the English language, provided users with static template responses, and did not permanently keep track of conversational context, therefore limiting the ability to scale to all languages.
Halvankar et al. (2024) created an artificial intelligence relational system with a Sequence-To-Sequence (Seq2Seq) architecture that can address many college-oriented questions [2]. This system produced higher fluency and accuracy rates in response to questions compared to traditional keyword-based systems. However, the use of fixed intents and a static dataset limited the ability to adapt the system to any new domains and any potential changes made at an institution.
Additionally, research has explored the use of rule-based chatbots in higher education for automating frequently posed questions about academic and administrative topics [3]. The findings have shown that rule-based university chatbots can be used for providing consistent and institutional - controlled responses. However, rule-based university chatbots do not have statistical learning, multilingual processing capabilities, contextually relevant reasoning, and ticket escalation mechanisms, thereby limiting their use to repetitive and structured interactions.
Multilingual, admission-focused chatbots mainly assist students who are bilingual but lack multi-turn conversational memory and are dependent on an abundant amount of content found on external websites [4]. Hybrid university chatbots using both NLP and ML show an ability to classify intents accurately. However, these chatbots primarily rely on static datasets, do not have multi-language capabilities, do not notify students of ticket escalations, and do not provide opportunities for students to interact with one another [5]. While ticketing systems improve accountability and allow tracking of workflow, they do not have the ability to understand the intent or actions behind the queries that are submitted to them or provide for automating the process of generating responses to those queries [6], [8].
Hybrid conversational agents that have been developed over the years have improved the accuracy of their responses and their availability. However, they still struggle with maintaining the continuity of a conversation

between agents, ambiguity in addressing queries, and providing for secure integration with the institutional systems [7].

Although earlier rule-based chatbots and discussion forums created a way for students to submit structured queries and interact with peers, they did not provide intelligent automated processes for generating responses, contextual reasoning to make informed decisions, or integration with institutional systems [11], [13] .

Alumni portals and chatbot-ticketing systems designed for specific domains show to be effective in engaging people and increasing efficiency but are not suited for use by colleges and universities due the lack of integration with academic workflows, lack of opportunities for peer collaboration, and the absence of student-centric analytics [14], [15]. Recent studies of low-code chatbots and/or low-resource language chatbots further illuminate the increases in accessibility that are possible via chatbots. However, there remain substantial limitations with respect to contextual reasoning and managing multi-turn dialogue [17], [18].

IV. Comparative Analysis

A structured review of existing chatbot literature reveals recurring gaps across four dimensions as shown in Table I: NLP architecture, language accessibility, automation and escalation, and collaboration and knowledge management.

Both AIML and TF and IDF models are able to increase the likelihood of a correct response but do not generalize well. LSTM classifiers, on the other hand, can provide a sequence of information but are not able to provide multi-lingual information in a single classifier. Although Dialogflow can maintain context of the conversation, it does not provide a means for scalability. Model performance is excellent in terms of semantic accuracy and processing time but the cost involved is significant.

A. NLP Architecture and Techniques

TABLE I: NLP Architecture Across Reviewed Systems

Reference	NLP Method	Classifier	Key Limitation
[1] Parrales-Bravo	TF-IDF + n-gram	Logistic Regression	English-only; static intents
[2] Halvankar	TF-IDF; Seq2Seq	Seq2Seq decoder	Fixed intents; no multilingual
[3] Shanmugapriya	Rule-based keyword	None (rule-based)	No NLP; no context memory
[4] Sah et al.	NLP with real-time web scraping	Not specified	Domain-limited; dependent on external web content
[5] Reddy et al.	TF-IDF + LSTM	LSTM classifier	Monolingual; no fallback
[7] Kandari et al.	Rule-based NLP for student enquiries	Not specified	Limited to predefined patterns; no adaptive learning
[11] Ali et al.	Dialogflow NLU	Dialogflow engine	Closed ecosystem
[12] Bala et al.	AIML pattern match	Rule-based AIML	No semantic understanding
[15] Mohan et al.	NLP + NER	SVM/LSTM/BERT	Non-university domain
[16] Channabasamma et al.	Deep neural network for FAQ classification	DNN classifier	Narrow college-information domain only
[17] Aloqayli and Abdelhafez	NLP-based multilingual admission handling	Not specified	No ticketing or peer collaboration reported
[18] Hailu et al.	CNN/LSTM (Amharic)	Neural classifier	Low-resource constraints

B. Language and Accessibility

The majority of the examined systems are English-only, as reflected in Table II [1] - [3], [5], [11], [12], [16]. There have been several multilingual efforts, though most lack stable web scraping methods [4] and ethnicity-agnostic pipeline tools [17]. There are currently very few low-resource language chatbots [18], which are subject to low accuracy rates and the inability to execute multiple turns of reasoning.

C. Collaboration and Knowledge Management.

None of the reviewed systems provide a P2P forum that is linked to a chatbot knowledge base for continual automated enhancement of knowledge. Many forum products [9], [13], [14] allow for the sharing of peer knowledge, but they operate separately from the chatbot component as indicated in Table III.

D. Research Gaps Summary.

Table IV illustrates the repeated constraints found throughout the various dimensions that support this system. The system is based on AI technology and provides support to students by addressing the four (4) identified research gaps in Table IV through the combined efforts of three main functional elements: (1) a multilingual Rasa Natural Language

TABLE II: LANGUAGE SUPPORT AND DEPLOYMENT ACCESSIBILITY

Reference	Language (s)	Real-time Trans	Interface
[1] Parrales-Bravo	English only	No	Telegram Bot
[2] Halvankar	English only	No	Web portal
[4] Sah et al.	Multilingual (scraping)	Partial	Web portal
[15] Mohan et al.	Multilingual (BERT)	No	Web portal
[17] Aloqayli	Multilingual (admission)	Partial	Web portal
[18] Hailu et al.	Amharic only	No	University portal

TABLE III: COLLABORATION AND KNOWLEDGE MANAGEMENT

Reference	P2P Forum	Update Mechanism
[1] Parrales-Bravo	No	Static (SMTP only)
[2] Halvankar	No	Offline dataset feedback
[3] Shanmugapriya	No	Manual staff updates
[9] Kumar et al.	Yes	Manual moderation
[13] Oviya et al.	Yes	Manual moderation
[14] Dhargalkar	Yes	Cosine similarity reco.
[15] Mohan et al.	No	Dashboard analytics

TABLE IV: KEY RESEARCH GAPS

Dimension	Gap in Prior Systems	Proposed Direction
Language Flexibility	Single-language systems; multilingual attempts rely on scraping	Real-time multilingual pipeline across all modules
Integrated Escalation	Ticketing and chatbots operate independently	Confidence-based escalation linking chatbot, ticketing, and SMTP
Peer Collaboration	Forums isolated from chatbot knowledge base	P2P forum with admin-moderated answer promotion into chatbot corpus
LLM Augmentation	No system uses LLM as dynamic fallback	LLM fallback triggered by confidence threshold

V. PROPOSED AI-DRIVEN STUDENT SUPPORT SYSTEM

Understanding chatbot; (2) a ticketing escalation system for tracking ticket confidence; and (3) peer-to-peer sharing of knowledge in a forum.

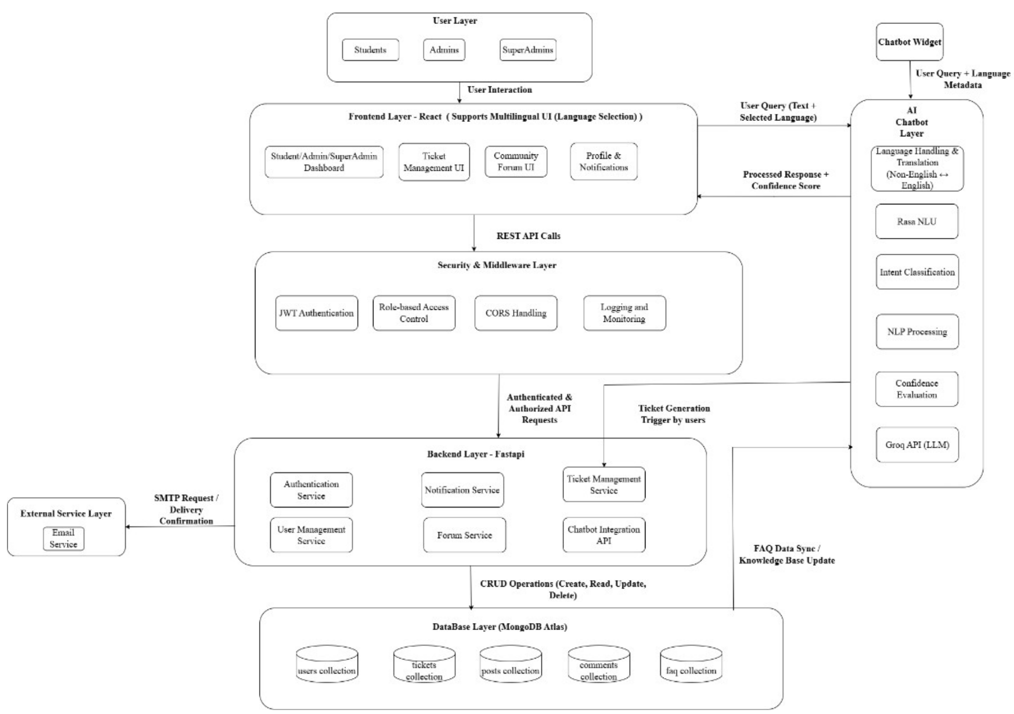

Fig. 1 Proposed System Architecture

A. System Architecture

The system is designed as a modular client - server architecture as shown in Fig. 1 with the following 6 layers: (1) User Layer - all users consist of 3 groups (student user, administrative user(via management role codes), and super admin (via management role codes). Each of these user types has a JWT (JSON Web Token) based role-based access control. (2) Frontend Layer - a React-based application with a multilingual user interface (UI), that allows for management of tickets, posting/participating in forums, and configuring profiles. (3) Security and Middleware Layer - include JWT-based authentication (JWT) & CORS handling (CORS = Cross-Origin Resource Sharing). (4) Backend Layer - consists of FastAPI Micro-services for the following functions: authentication service, user management service, ticket management service, forum management service, notification service, and chatbot integration service. (5) General AI Chatbot Layer - consists of a Rasa NLU (Natural Language Understanding) pipeline for: language handling, intent classification, confidence scoring, and Groq LLM (Longitudinal Language Model) fallback capabilities. (6) Database Layer - consists of a MongoDB Atlas cloud-based database that will store all users, tickets, posts, comments, & FAQs.

B. System Workflow

Students log into the React application and select from seven support categories: Admissions, Fee Payment, Certificates, Examinations, Technical Issues, Grievances, or Contact Information. Each session is routed through one of three workflows based on query type and confidence: chatbot, support ticket, or peer-to-peer forum.

Chatbot Query Processing: Argos Translate is an external software application that rapidly converts text entered in a language other than English into English for Natural Language Understanding (NLU) processing and converts the responses to the original language selected by the student, allowing a real-time NLU experience for the student. Rasa NLU tokenizes the input, recognizes and classifies entities, and classifies intent across nine high-level categories (each having sub-intents) as shown in Fig. 2.

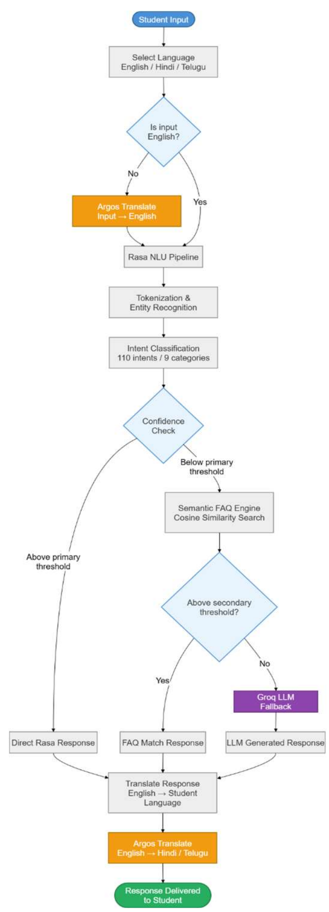

Fig. 2 Multilingual Chatbot Query Processing Pipeline

Confidence-Based Fallback: All queries that receive a confidence score lower than their baseline confidence level are routed to the semantic FAQ engine using cosine similarity on the stored FAQs. When a query receives a confidence score lower than the secondary threshold (zero responses in prior reviewed systems), the request is forwarded to the Groq Large Language Model (LLM).
Ticket Escalation: If a student's query requires the intervention of a direct administrator, the student submits a ticket that is categorized based on the issue (e.g., fee dispute, document request, unresolved technical issue) into the MongoDB Atlas data repository, and an automated SMTP email notification will be sent to the student.
When an administrator resolves a ticket, they do so through the dashboard for the administrator. A notification is then sent to students regarding the resolution. If a ticket has been validated, it can also be promoted directly into the Rasa knowledge base without having to re-train the whole model.
Peer-to-Peer Forum: Students are able to ask questions, reply to those questions with nested comments, and upvote helpful responses. Additionally, all posts can be filtered by their popularity or date of posting, as shown in Fig. 3. The administrators will moderate the content of each post and will remove off-topic threads, as well as pinning those threads which require immediate access; thus, a continuously growing soft reference is created for the community.

C. Implementation and Dataset

They trained the Rasa NLU (Natural Language Understanding) pipeline on an organized data set that included 1,376 examples from 107 different types of requests (intents). The examples covered all nine main categories (domains) of support requests listed below. Each domain contains separate sub-intents; this results in approximately 12.5 training examples per sub-intent. Each set of training data was compiled from existing FAQs and validated by department employees to ensure the training data is consistent with what's available at the institution. All training data - including NLU .yml files, domain configuration, rules, and story line files - has been published [19].

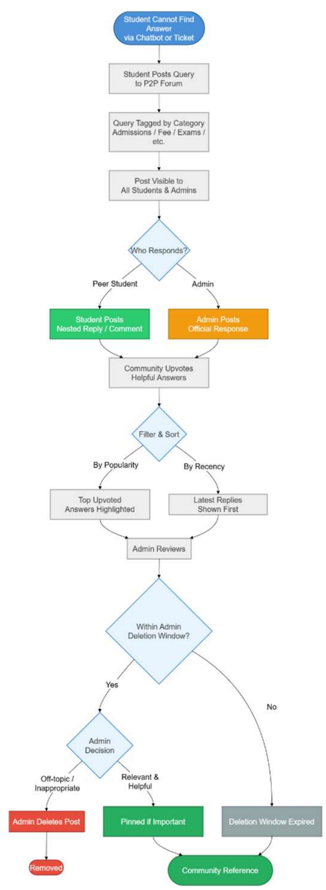

Fig. 3 Peer-to-Peer Forum Workflow

The dialogue management system consists of 30 rule-driven policies that handle predictable conversation flows such as navigating through menus and menus/sub-menus; switching between LLM and returning to menus. The four multi-turn storypaths represent composite user journeys through multiple menu categories.

VI. Results

A. NLU Intent Classfication - Cross Validation.

To evaluate generalization ability, 5-fold cross-validation was done 3 times, as presented in Table V, using the full 1376 instance training set consisting of 107 intents. The number of different independent trials were used for the folds to limit the variance caused by fold randomization.

The average F1 score of 88.89% over the three independent cross validation runs illustrates both the consistency and reliability of the intent classification. The range of F1 scores (0.8816 to 0.9030) represents individual folds and provides a realistic measure of generalization bounds attributed to fold level randomization. Run 3 had the highest F1 score (0.9030) and suggests the highest degree of generalization can occur depending on how packs of overlapping folds are constructed.

B. Verifying the flow of conversations.

Thirty two sample stories (multi-turn) were validated against Rasa's core validation framework and contained examples of four different types of conversation flows (enquiry about fees, documents, resolving a technical issue and exit/goodbye). The results are shown in Table VI.

The expected action sequences for the four predefined conversation flows executed without deviation. The reason for this complete accuracy is due to the dialogue layer being constructed on the basis of 30 deterministic rule policies rather than 30 learned story policies. Therefore, the purpose of the test was to verify the proper configuration of the rule policies and not the generalization of the rule policies, thus, deterministic policies are better suited for those types of flows than would be stochastic story policies

C. System Interface Overview.

We have an admin dashboard that allows access to all elements of ticket management, monitoring of forums, and user administration (through the use of the following items: a system health indicator, quick action panel, and announcement module). The dashboard includes a user-facing ticket dashboard, which allows the user to create, categorize, and track tickets by status open, all of which were identified as escalation gaps across all the systems reviewed. The multilingual pipeline is highlighted with the entire admin user interface being rendered in real-time (i.e., rather than through static data that has been pre-translated) in the Telugu language, including all metadata associated with tickets, including ticket metadata, ticket status labels, and all ticket action controls. The P2P forum provides a threaded discussion capability, providing for nested replies and upvoting, for community-level resolution, which had been absent in all of the other systems reviewed to date. The chatbot widget displays nine levels of chatbot intent, in three different languages that narrows the search space for a proper NLU classification and has improved the disambiguation of intents.

VII. Discussion

This new student query support system has been shown to deliver excellent results providing the correct answer using multi-lingual processing, intent classification, and other mechanisms providing support. The system has demonstrated it can generalise effectively across many intents while maintaining a reliable flow of conversation through rule-based dialogue management. There have been some limitations when trying to actually deploy the system in practice. When translating in real-time, there are semantic inaccuracies due to highly inflectional languages and language mixing to consider. Also, while the system design is modular with respect to scalability, when deploying at scale, careful analysis of the system performance metrics and data privacy will need to take place to integrate with existing institutional ERP systems.Overall, this system provides a reasonable balance of accuracy, scalability and usability thus making it a feasible solution.

TABLE V: NLU CROSS-VALIDATION RESULTS (5-FOLD, 3 RUNS)

Run	Accuracy	Precision	Recall	F1-Score
Run 1	0.9118	0.9167	0.9118	0.9115
Run 2	0.9412	0.9498	0.9412	0.9405
Run 3	0.8824	0.8899	0.8824	0.8820
Average	0.9118	0.9188	0.9118	0.9113

TABLE VI: DIALOGUE FLOW VALIDATION RESULTS

Metric	Value
Action Precision (macro avg)	0.9895
Action Recall (macro avg)	0.9895
Action F1-Score (macro avg)	0.9892
Conversation Accuracy	0.9688 (31/32)

VIII. CONCLUSION

This study presents a comprehensive examination of how AI technologies can help support university-level students by providing assistance in various ways including natural language processing (the technology that enables a computer system to analyze, understand, and generate human language), access to multiple languages, automating tasks, and creating new methods of communication between peers. The findings indicate that while many of the individual parts have advanced significantly, there are no current solutions that integrate all four components into one system and that these components are still very separate from one another.As a solution to the gap identified between the four components, a proposed student portal powered with AI will address the gaps identified in this study via a hierarchical Rasa chatbot with a fallback.

The F1-score for the NLU classifier in our work is 91.13% from an average of 3 cross-validation runs, compared with an F1 score of 82% reported in the As reported by Parrales-Bravo et al. [1]. In addition, The ability to process multiple languages is valuable; providing structure to the escalation process; creating a knowledge base using inputs gathered from the other students facilitates interaction through the portal; and enables all components of the Portal to function efficiently with each language able to be processed simultaneously without needing separate models for each language.

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