JNEC Q-BOT: A Rule-Based Chatbot for Enhancing Student Services and Institutional Accessibility

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Abstract

In this 21st century, with all the digitalization, universities face challenges in handling the same repeated questions from visitors, freshmen, and current students regarding admission, fee structures, courses, and campus facilities. This project introduces a rule-based college inquiry chatbot, which aims to provide 24/7 automated responses to frequently asked questions, thereby reducing administrative workload. The chatbot is built using the Rasa framework and follows a rule-based architecture, where user questions are processed and matched with predefined intents to give responses stored in files (nlu.yml, domain.yml). The chatbot provides instant, accurate, and context-aware answers using a rule-based NLU approach without relying on machine learning. This chatbot has the capability to curl information based on different college services and activities through simple, human-like conversations. It helps tackle problems and offers scalable solutions for providing quick services to users through a conversational interface.

Keywords— Chatbot; rasa; rule-based NLU

1 Introduction

NEC Q-BOT is an AI virtual assistant made with Rasa, mainly used to provide seamless information based on educational settings that are related to course details, tuition fees, admission procedures, and other administrative inquiries. This chatbot gives quick as well as nearly accurate answers to many users question through user-friendly conversational interface.

With this chatbot giving automatic and instant responses to the users repeated asked questions, the burden on administrative staff is reduced; also ensuring the availability of services for 24/7. In addition, the chatbot promotes a self-service approach to the information access and it also aligns with JNECs commitment to digital transformation, improving efficiency and the overall student experience. Whether for quick updates or detailed guidance, the JNEC Q-BOT is a reliable, always-available digital assistant.

2 Related Papers

A chatbot is a type of program (software) that is created to talk to users in a way that feels like a real human conversation [1]. It can be used for many tasks like answering questions, giving suggestions, or helping with services. In colleges, chatbots are becoming popular because they provide quick and correct information to students. They help reduce the workload of staff by answering common questions automatically. Following the traditional approach, getting the answers for the educational setting-related queries takes a lot of time and effort. However, chatbot can answer these questions instantly and at any time ensuring easy access to information.

Studies [2] mention that in recent years chatbots are usually developed using GPT-3.5, Falcon 7B, and Mistral 7B which are advance model. These models are customizable based on the client data to give response to the specific business queries. On contrary, with that model it requires high computing power which may result in raising concern about privacy when hosting on the cloud [2]. T-BOT and Q-BOT are developed using AIML, where it provides tutoring and evaluation support using rule-based response[3].

Phalle proposed a college enquiry chatbot using the Rasa framework, which is based on machine learning [4]. Nguyen and Shcherbakov stated that the Rasa allows local deployment, so it ensures better control as well as privacy [5]. Using Dialog Flow and FastAPI, Ahmed have developed a chatbot, mainly focusing on user-friendly design and fast performance [6]. Ingale also built a college chatbot using Rasa, integrating features like slots, forms, and supervised learning to handle complex conversations [7].

2.1 Rasa Architecture

Rasa is an open-source tool used to develop virtual assistants chatbot. Fig. 1. shows the overview of the Rasa framework. It explains how gives response to the user queries [7]. The JNEC Q-BOT leverages SQLite to persistently log conversation events through Rasas built-in SQLTrackerStore. This enables analysis of user engagement and chatbot performance.

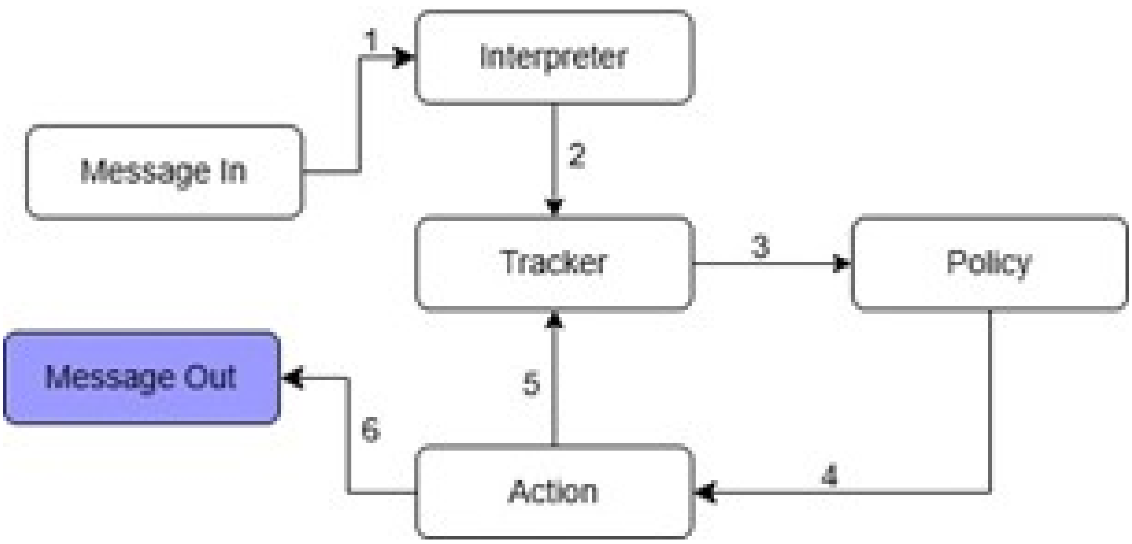

Figure 1: Architecture of Rasa Framework

Rasa NLU understands intent and the detail of the message send by the users. All the conversation history are tracked by the Tracker. The policy module decides the next action of the chatbot; executing these actions provides replies for the users query. For further conversation, the process is continuously repeated [8].

2.2 Rasa NLU Pipelines

Rasa NLU is core part of the Rasa framework. It identifies the intents and extracts entities like locations and weathers. Intent and entity help chatbots to understand users input. Custom data were used to train the chatbot for specific areas, ensuring correct responses. The data was prepared using JNEC student handbook.

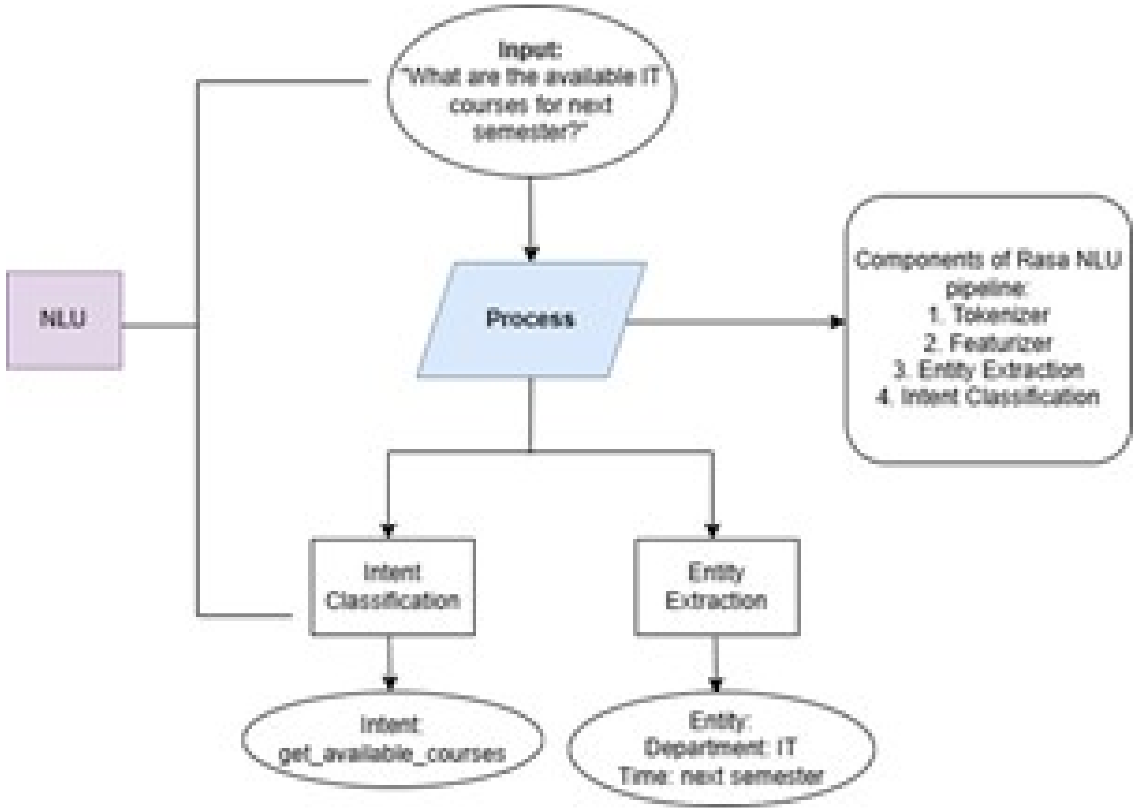

Figure 2: Architecture of Natural Language Understanding

The input message goes through several stages: tokenization, where the text is broken into smaller units; featurization, where these units are converted into numerical features; entity extraction; where relevant details are identified; and intent classification, where the overall purpose of the message is determined. These steps help the system understand what the user wants and extract any important information needed to generate an appropriate response as demonstrated in the enhanced Rasa NLU architecture

3 Methodology

The methodology used to develop JNEC Q-BOT is Iterative Development Model (fig.3.), which allows the systems to improve through repeated cycle. The process begins with initial planning, setting goals like reducing student dependency on staff for information. During requirement gathering, the team collaborates with administrative departments and refers to the JNEC student Handbook.

The analysis and design phase involves creating conversational flows and planning chatbot architecture. In the implementation stage, a basic version is built and connected to the dummy website. It undergoes testing with real users, and after resolving issues, its deployed online. The team then evaluates feedback and enters new iterations to add features and enhance performance continuously.

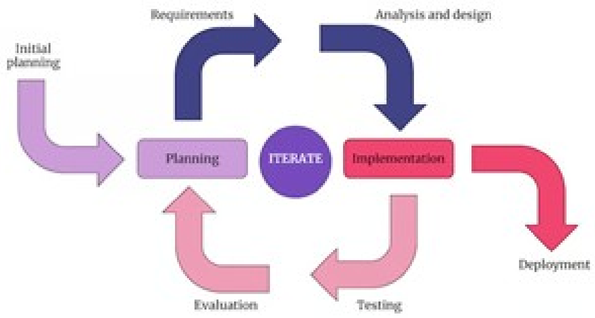

Figure 3: Project methodology

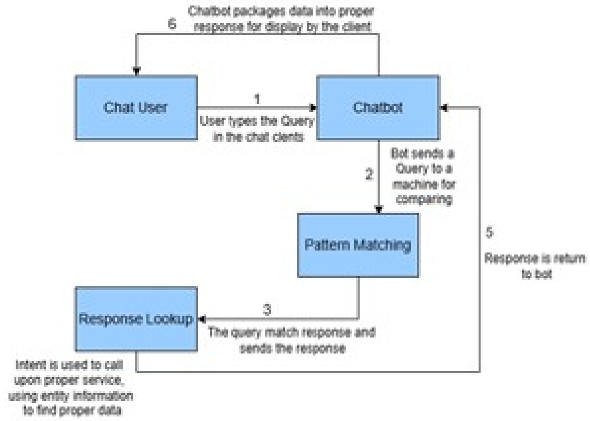

Figure 4: System Architecture

3.1 System Architecture

The figure 4 shows how different parts of the system works together. In the chatbot system, when a user asks a question, the chatbot matches it with patterns (set in files like nlu.yml) to find the users intent. Then, it checks domain.yml to pick the right answer and sends that reply back to the user.

3.2 Flow Chart

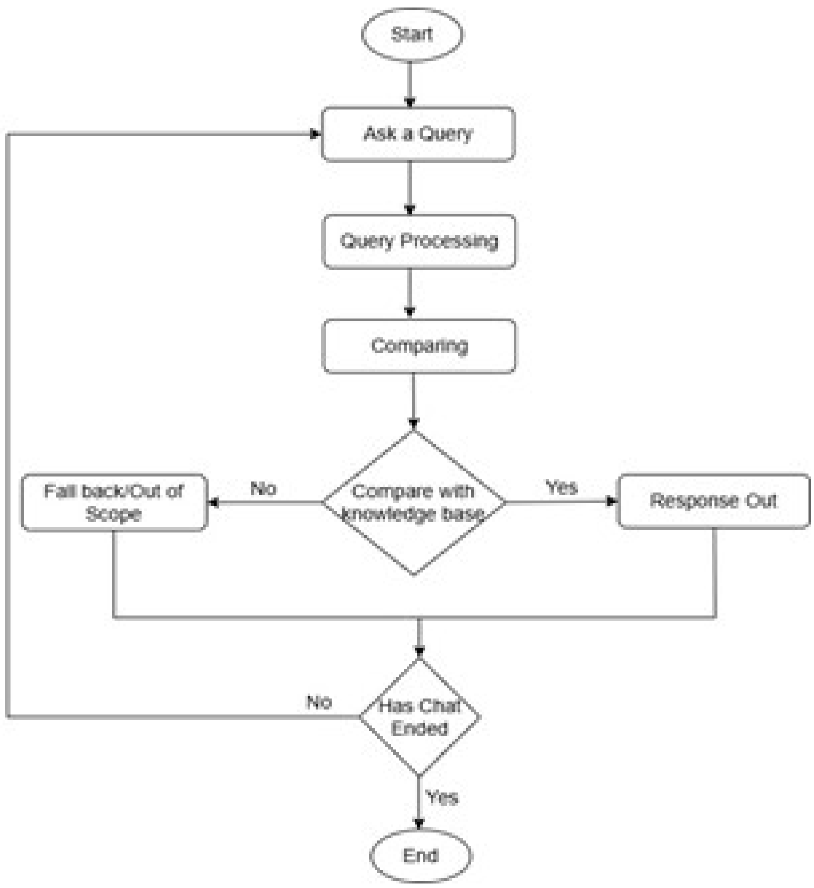

Figure 5: Flow Chart

Figure 5 illustrates the core operational logic of a query-response system, similar to a chatbot or a simple question-and-answer (Q & A) engine. It outlines the step-by-step process that the system follows, providing relevant responses when users ask questions, all within a continuous conversational loop.

4 Results

The JNEC Q-BOT was developed and tested on a simulation dummy website to evaluate its functionality in a controlled environment. The chatbot. The chatbot was trained on data extracted from the JNEC Student Handbook, enabling it to provide almost accurate responses to college-related queries.

4.1 Pre-built Questions and Stop Button

The chatbot provides quicker access to information by suggesting questions that are pre-built on the chatbots interface (fig. 6). The users can simply click suggested questions features for quicker access to information. It is faster ans effective for a new user who does not know what to ask initially.

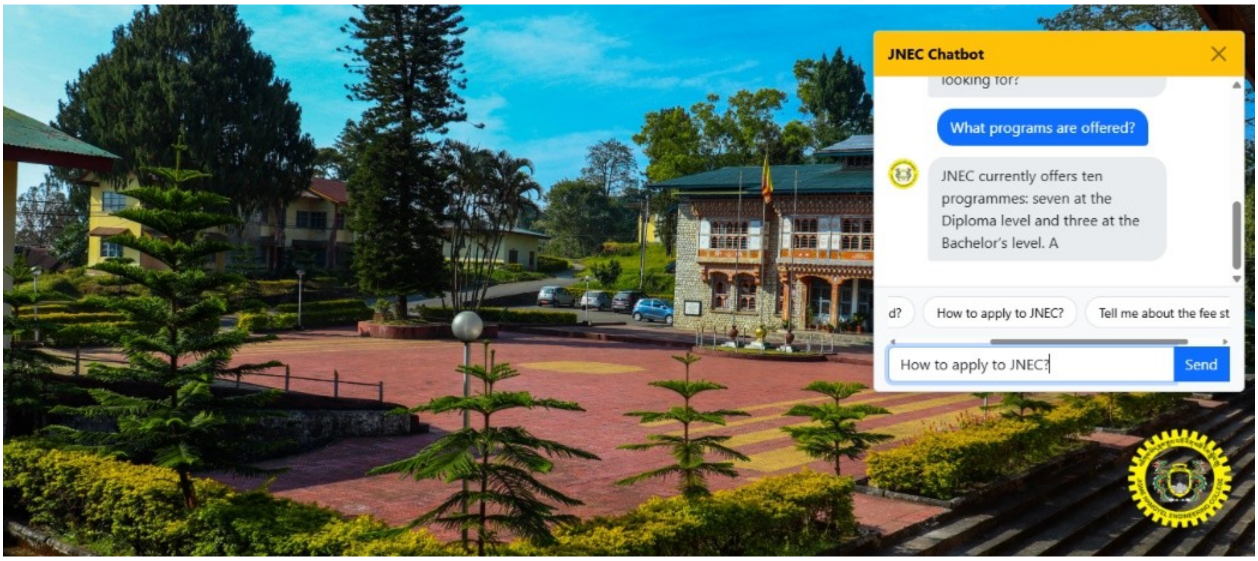

Figure 6: Pre-built questions

There is also a feature such as stop. This function helps the user to control the conversation. If the chatbot is taking too long to response to the asked question, they can interrupt the process by clicking the stop button.

5 User Testing

To evaluate the real-world effectiveness of the JNEC Q-BOT, functional testing was performed with a selected group of 30-40 students and faculty members. Each user was asked to interact with the chatbot by posing typical college-related questions based on scenarios from the student handbook.

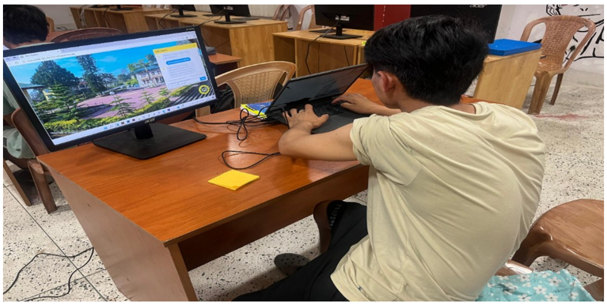

Figure 7: Student interacting with chatbot

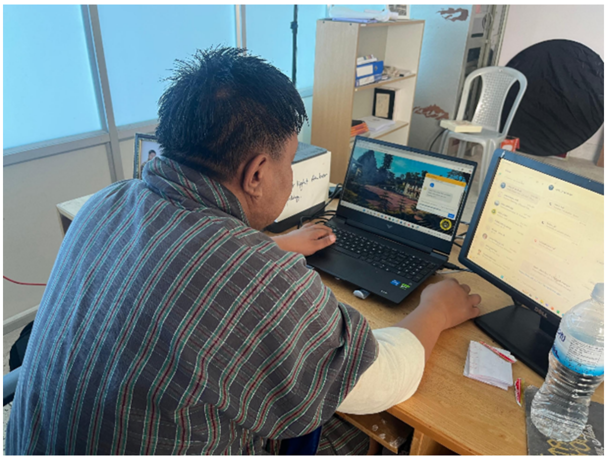

Figure 8: Staff interacting with chatbot

5.1 Findings

The results indicate that a chatbot can significantly reduce the workload of administrative staff by automatically answering frequently asked questions. Both students and staff can receive assistance at any time, even after office hours, which enhances convenience for them. Many users appreciated the design and found it user-friendly, demonstrating that chatbots like this can make obtaining information faster and more enjoyable.

Figure 9: ITSU interacting with chatbot

5.2 Findings

The results indicate that a chatbot can significantly reduce the workload of administrative staff by automatically answering frequently asked questions. Both students and staff can receive assistance at any time, even after office hours, which enhances convenience for them. Many users appreciated the design and found it user-friendly, demonstrating that chatbots like this can make obtaining information faster and more enjoyable.

5.3 Performance Testing

This section presents the results from automated testing conducted using the rasa test nlu command, which evaluates the chatbots Natural Language Understanding model. This test assesses how effectively the model can classify user intents and extract entities from test data.

Fig 11 and 12 depict the confusion matrix for intent and entity recognition, where the model achieved an overall accuracy of 91.11% and 99.15%, respectively, indicating that most user intents and tokens were correctly identified. The weighted-average F1-Score was 90% and 97.11%, suggesting balanced performance while considering the proportion of each intent and entity class. These results demonstrate that the model is effective in accurately recognizing user intents and is accurate and reliable in extracting entities from the text.

F1-Score Formula:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Definitions:

- TP (True Positive): The model correctly predicted a positive instance.
- FP (False Positive): The model predicted positive, but it was actually negative.
- FN (False Negative): The model predicted negative, but it was actually positive.

Accuracy Formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TN (True Negative): The model correctly predicted a negative instance.

5.4 Intent and Entity Recognition Performance

After analyzing the results shown in (fig. 11), the intent recognition component of the model achieved an Overall Intent Accuracy of 91.11%, indicating that most user intents were correctly identified. The Micro-average F1-Score was 91.19%, reflecting strong overall performance across all intent predictions. The Macro-average F1-Score stood at 89.80%, showing consistent performance across various intent classes, regardless of their frequency. Additionally, the Weighted-average F1-Score was 90%, suggesting balanced performance while considering the proportion of each intent class. These results demonstrate that the model is effective in accurately recognizing user intents.

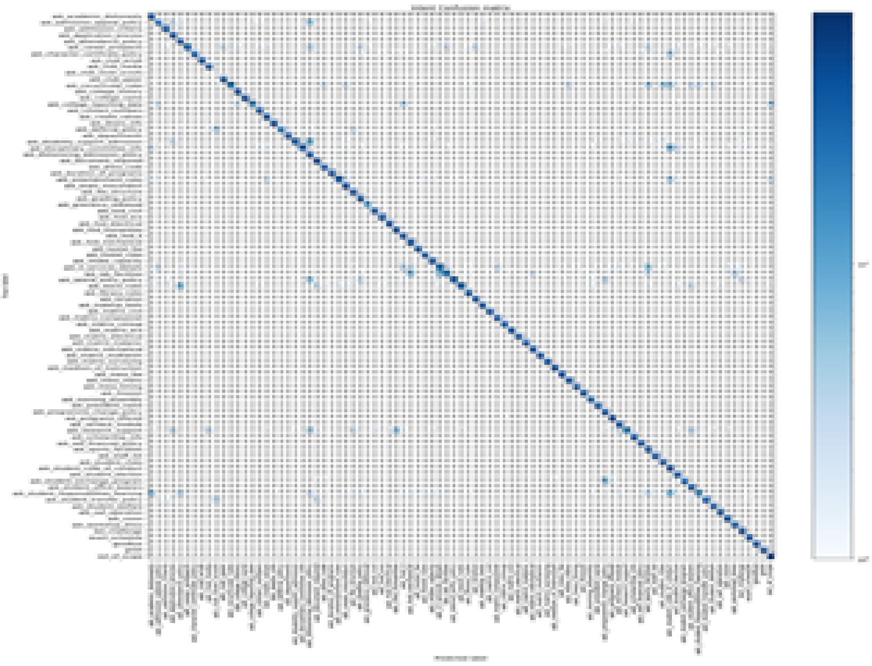

Figure 10: Intent confusion matrix

5.5 Entity Extraction Result

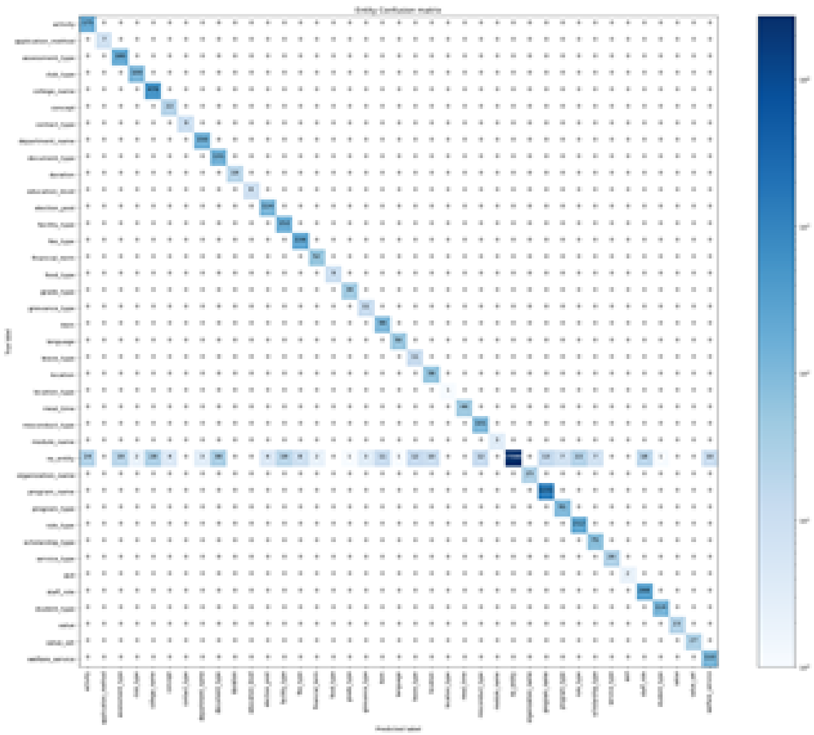

Figure 11: Entity confusion matrix

After analyzing the results presented in (fig.12), the entity extraction model demonstrated strong performance metrics. The Entity Token Accuracy reached 99.15%, indicating that nearly all tokens labeled as entities were correctly identified. The Micro-average F1-Score was 97.01%, reflecting the overall effectiveness across all entity predictions regardless of type. The Macro-average F1-Score stood at 96.42%, showing consistent performance across different entity categories. Additionally, the Weighted-average F1-Score was 97.11%, accounting for the varying frequencies of entity types in the dataset. These results confirm that the model performs accurately and reliably in extracting entities from the text.

6 Conclusion

The JNEC Q-BOT, developed using the Rasa Framework solves the problem of inefficiencies in JNEC information dissemination by replacing manual inquiries with an automated, rule-based chatbot. It provides instant, accurate responses on admissions, academics, fees, and campus facilities, reducing administrative workload. By using the student handbook 2024 structured data, the bot ensures reliability for common queries while operating 24/7. Though it improves communication efficiency. Future enhancements could integrate machine learning for dynamic updates and broader knowledge. The project lays a scalable foundation for digital transformation at Jigme Namgyel Engineering College, enhancing student experience.

7 Acknowledgment

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