Library Book Recommendation Chatbot Using Rasa NLU

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***Abstract*— In response to the growing demand for streamlined library management, this project introduces an innovative system centered around a friendly and intuitive chatbot. The motivation behind this endeavor stems from the need for a cost-effective, personalized recommendation system tailored specifically to local library collections. By harnessing the power of Rasa NLU, a conversational agent was developed to seamlessly assist library visitors in discovering their next favorite read. Through a meticulous integration of Rasa NLU's capabilities, including custom actions for book and author inquiries and entity extraction for genres and descriptions, the chatbot effectively navigates user queries within the library's context. With a keen focus on precision and user engagement, the system's DIETClassifier ensures accurate intent recognition, facilitating seamless interaction and meaningful responses. The project outcomes underscore the chatbot's ability to understand nuanced requests, provide tailored book recommendations, and enhance user experience within library environments. This initiative serves as a testament to the transformative potential of open-source AI tools in enhancing public service offerings and fostering greater accessibility to library resources [1][2][6][8][12].**

Keywords: Rasa NLU, Personalized recommendation system, Conversational agent, User engagement, DIETClassifier, Intent recognition.

I. INTRODUCTION

In today's digital era, the creation of effective and user-friendly systems for accessing and navigating library resources has grown significantly important. The conventional methods of searching for books within libraries, often through websites or manual inquiries, can be time-consuming and cumbersome. Additionally, the lack of personalized recommendations tailored to individual preferences presents a significant challenge for users seeking relevant reading materials. [10][16]. The motivation behind this research lies in the necessity to confront these challenges and improve the user experience when accessing library resources. By leveraging the capabilities of natural language understanding (NLU) technology, this project aims to design a book recommendation chatbot specifically tailored for students, researchers, and library patrons. Unlike generic recommendation systems that rely on costly API calls and provide global recommendations, the proposed chatbot focuses on delivering personalized recommendations based on the unique inventory of each library. [6][7][8][13][15].

The significance of this research lies in its potential to revolutionize the way users interact with library systems. By providing tailored book recommendations aligned with individual preferences, the chatbot not only simplifies the process of finding relevant reading materials but also fosters greater engagement with library resources. Moreover, the integration of NLU technology allows for more intuitive and natural interactions, enhancing the overall user experience. [12][17][19]. In addressing the research gap, this study explores the novel application of Rasa, an open-source NLU framework, in the context of library management. While existing literature may discuss generic recommendation systems or chatbot applications, few studies focus specifically on designing a library-centric recommendation system using NLU technology. This research fills this gap by proposing a tailored solution that caters to the unique needs and constraints of library environments [13]. The primary objective of this research is to design and implement a book recommendation chatbot using the Rasa framework, capable of providing personalized recommendations based on user queries and preferences. The methodology involves leveraging NLU capabilities to understand user intents, extracting relevant information from user input, and matching it with the library's inventory to generate tailored recommendations. [15][18]. The organization of the paper is structured as follows: Section II provides an overview of related work in the field of chatbot development and library management systems. Section III outlines the proposed methodology, including the design and implementation of the chatbot using Rasa. Section IV presents the experimental results and evaluation of the chatbot's performance. Finally, Section V concludes the paper with a summary of findings and suggestions for future research directions.

II. LITERATURE REVIEW

Conversational AI Chatbots in Library Research: Aboelmaged et al. (2024) conduct an integrative literature review to explore the evolving role of conversational AI chatbots in library services. Their study identifies key themes such as the technological evolution of chatbots, antecedents for their use, user experience, COVID-19 implications, and challenges faced [2]. Artificial Intelligence Chatbots for Library Reference Services: Nawaz and Saldeen (2020) investigate the integration of AI chatbots into academic library reference services, particularly focusing on meeting the needs of millennial users [3]. Novel Study on AI-Based Chatbot (ChatGPT) Impacts on Traditional Library Management: Verma (2023) presents a novel study on the impacts of AI-based chatbots, specifically ChatGPT, on traditional library management. The study delves into the potential of AI-based data to enhance library operations by mimicking human intelligence patterns and improving data sharing and retrieval activities

Enhancing the Academic Library Experience with Chatbots: An Exploration of Research and Implications for Practice, authored by Indra Ayu Susan Mckie and Bhuva Narayan (2019), delves into the potential of chatbots in

enhancing the academic research experience for university students. The paper discusses a prototype being developed at the University of Technology Sydney (UTS) and proposes the adaptation of emerging technologies like chatbots by information professionals to innovate and support library services. The authors stress the importance of designing a positive user experience to ensure the sustainability of such technological solutions. They argue that librarians should collaborate with technology developers to ensure that library chatbots are useful, friendly, trustworthy, and customizable for university students [3]. These studies collectively underscore the transformative potential of AI and chatbot technologies in reshaping library operations, enhancing user experiences, and addressing evolving user needs in the digital age. From exploring the integration of chatbots into academic library reference services to examining their impacts on traditional library management and improving the academic research experience, these works highlight the growing significance of chatbots in modern library settings.

III. Methodology

The methodology adopted in this research encompasses several key stages, including data collection, pre-processing, model development, and evaluation. The overarching goal is to design and implement a robust book recommendation chatbot using the Rasa framework, leveraging natural language understanding (NLU) techniques to interpret user queries and preferences.

A. Data Collection:

The dataset utilized in this study was meticulously curated to support the development of a book recommendation chatbot. It comprises a comprehensive collection of book data, including essential attributes such as ISBN-13, ISBN-10, title, subtitle, authors, categories, thumbnail URL, description, published year, average rating, number of pages, and ratings count. The data collection process involved sourcing information from reputable sources to ensure accuracy and reliability. To ensure the effectiveness and relevance of the chatbot's recommendations, the dataset was carefully curated to cover a wide range of genres, authors, and publication years. This approach aimed to provide users with diverse and personalized book suggestions tailored to their preferences and interests. By incorporating a diverse array of books into the dataset, the chatbot can offer recommendations that cater to a broad spectrum of user tastes and preferences. Furthermore, the dataset was subjected to thorough preprocessing to ensure consistency and quality. This preprocessing stage involved handling missing values, cleaning data inconsistencies, and standardizing formatting conventions. By ensuring data cleanliness and consistency, the chatbot can deliver reliable and accurate recommendations to users.

B. Rasa Configuration:

1) Domain Configuration: The domain.yml file serves as a central component in defining the behavior and capabilities of a conversational AI chatbot developed using the Rasa framework. It encapsulates various elements crucial for effective communication between the chatbot and the user, facilitating seamless interaction and fulfillment of user requests. These elements include intents, entities, slots, responses, and actions, each playing a specific role in shaping the chatbot's functionality. Intents represent the underlying goals or purposes behind user messages, indicating what users want to achieve through their interactions with the chatbot. In the domain.yml file, a comprehensive set of intents is defined for the chatbot to recognize and respond to appropriately. Entities, on the other hand, represent specific pieces of information extracted from user messages that are relevant to fulfilling the user's request. By defining entities such as "author", "title", "description", and "genre", the chatbot can effectively identify and process key elements in user queries, enhancing its ability to provide accurate and relevant responses. Slots are like memory slots for the chatbot, where details shared by users during the chat, such as book titles, authors, descriptions, and genres, are stored. These details help the chatbot keep track of the conversation flow and provide personalized recommendations or information. Think of them as handy notes the chatbot refers to when needed. Moreover, responses are pre-written messages that the chatbot can use to reply to users based on what they say or ask. They include greetings, offers for help, goodbyes, checking how the user feels, and confirming if the book suggestions were helpful. These responses make the chatbot's interactions feel more human-like and engaging. Actions represent the tasks or functions that the chatbot can perform in response to user inputs, ranging from providing recommendations to querying databases for book details or author information. In the domain.yml file, custom action names corresponding to Python functions defined in the actions.py file are specified. These actions enable the chatbot to execute specific tasks seamlessly, enhancing its utility and effectiveness in assisting users with their requests.

2) Pipeline Configuration: The pipeline configuration in the config.yml file is a critical aspect of designing a conversational AI chatbot using the Rasa framework. It defines the sequence of components or processing steps involved in natural language understanding (NLU) and dialogue management. The pipeline begins with tokenization, where the input text is split into individual tokens or words. This process is essential for breaking down the input into manageable units for further analysis. The WhitespaceTokenizer and RegexFeaturizer components handle tokenization and extract features from the text based on predefined patterns or regular expressions. These features provide valuable info about the structure and content of the input text, facilitating subsequent processing steps. Following tokenization, the LexicalSyntacticFeaturizer component extracts lexical and syntactic features from the text, capturing linguistic patterns and relationships between words. The CountVectorsFeaturizer then converts these features into numerical vectors, which serve as input to the machine learning models for classification. In the pipeline, two CountVectorsFeaturizer components with different settings are used to capture both word-based and character-based n-grams, enhancing the model's ability to understand text at different granularities. The DIETClassifier, powered by the Dual Intent and Entity Transformer, is a state-of-the-art model for intent classification and entity recognition. It leverages contextual information and self-attention

mechanisms to make accurate predictions, with customizable settings such as the number of training epochs and constraints on similarity scores. In addition to NLU components, the pipeline includes modules for dialogue management and response selection. The EntitySynonymMapper resolves synonyms and aliases for entities, ensuring consistent interpretation across different user inputs. The ResponseSelector component employs machine learning models to select the most appropriate response from a predefined set based on the detected intent and context. Finally, the FallbackClassifier acts as a safety net, predicting fallback actions when the confidence of the primary classifiers falls below a certain threshold. It helps the chatbot handle unexpected or ambiguous inputs gracefully, improving the overall user experience. In implementing the book recommendation chatbot project, emphasis centered on the precise selection of the Sentence Transformers library, specifically leveraging the MiniLM-L6-v2 model. This strategic decision was driven by its robust capability to encode textual data into semantic embeddings, thereby enhancing the chatbot's comprehension of both book descriptions and user inputs. Through this meticulous integration, the chatbot delivers highly personalized book recommendations tailored to individual preferences and requirements, thereby ensuring a seamless and gratifying user experience.

3) Custom Actions: Custom actions are defined to perform specific tasks essential for the functionality of the chatbot. These actions are triggered based on user inputs and are responsible for interacting with the dataset to provide recommendations, retrieve book details, and gather information about authors. The dynamic querying approach ensures that the chatbot can recommend newly added books, enhancing its utility and relevance to users over time. The ActionRecommendBook class implements the action for recommending books based on user input. It utilizes a Sentence Transformer model to encode book descriptions and calculate similarities between the user's query and existing book descriptions. By considering user-provided genres, authors, or descriptions, the action filters the dataset dynamically to generate personalized recommendations. The fuzzy matching technique is employed to handle variations in user input, ensuring robustness and accuracy in recommendation generation.

The ActionInquireBookDetails class handles inquiries about book details, such as title, author, and other metadata. It retrieves relevant information from the dataset based on the user's input and formats the response to provide a comprehensive overview of the requested book. The action employs string matching techniques to search for matching titles and authors in the dataset, ensuring accurate retrieval of book details even with partial or misspelled inputs. The ActionInquireAuthorDetails class facilitates inquiries about author information, including the number of books authored, average ratings, and genres. It dynamically filters the dataset to identify books authored by the specified author, providing insights into their body of work. The action calculates metrics such as the average rating of authored books and identifies genres associated with the author's works, offering users a comprehensive understanding of the author's literary contributions. The custom actions leverage a dynamic querying approach to interact with the dataset, ensuring that the chatbot can recommend newly added books and provide up-to-date information to users. By loading the dataset into memory upon action initialization and dynamically filtering it based on user inputs, the chatbot remains agile and responsive to user queries, enhancing the overall user experience. Additionally, the use of advanced natural language Understanding techniques and fuzzy matching algorithms enhances the chatbot's ability to understand and respond to user inputs accurately, contributing to its effectiveness as a conversational AI interface.

C. Chatbot Stories:

The stories.yml file serves as a collection of predefined conversation paths or stories that illustrate various scenarios and user interactions that the chatbot can encounter. These stories are essential for training the chatbot's dialogue management model, enabling it to understand user intents and respond appropriately based on the context of the conversation. Each story consists of a sequence of steps, with each step corresponding to a user intent, entity, or action. These stories provide a structured framework for training the chatbot's dialogue management model by showcasing different conversation flows and outcomes. By defining various paths that users might take during interactions with the chatbot, these stories help ensure that the chatbot can handle a wide range of user inputs and scenarios effectively. Additionally, the stories enable developers to identify and address potential gaps or inconsistencies in the chatbot's behavior. In the stories.yml file, there is a diverse range of conversation paths, including the happy path, sad paths, book recommendation flows, and inquiries about book details and author information. Each story presents a unique interaction scenario, such as greeting the user, recommending a book based on different criteria (author, description, genre), and providing details about specific books or authors. These stories cover a comprehensive spectrum of user intents and actions, allowing the chatbot to handle various user queries and requests proficiently. Overall, the stories.yml file plays a crucial role in shaping the chatbot's conversational abilities and ensuring a seamless user experience.

D. NLU Training Data:

The nlu.yml file serves as a crucial component in training the Natural Language Understanding (NLU) model of the chatbot. It contains examples of user messages annotated with their corresponding intents and entities, providing the necessary training data for the chatbot to understand and extract relevant information from user inputs. The examples cover a diverse range of user intents, including greetings, farewells, expressions of mood, inquiries about books, and requests for book recommendations. Each intent in the nlu.yml file is associated with a set of example utterances that users might input to convey that intent. For instance, the "greet" intent includes examples such as "hey" and "hello", while the "goodbye" intent includes examples like "cu" and "good by". These examples help the NLU model learn patterns and variations in user messages, enabling it to accurately classify user intents during conversations with the chatbot. In addition to intents, the nlu.yml file also includes examples for entity extraction. Entities are specific pieces of information mentioned in user messages that are relevant to

fulfilling the user's request. For example, the "inquire_book" intent includes examples like "Tell me about the book Zondervan Handbook to the Bible" and "Tell me about the book Velvet Elvis", where the entity "title" is annotated to indicate the specific book title mentioned in the user query. Similarly, the "inquire_author" intent includes examples like "Tell me about the author Marilynne Robinson" and "Tell me about the author Charles Osborne;Agatha Christie", where the entity "author" is annotated to identify the author's name mentioned in the user query.

E. User Interface

The index.html file serves as the user interface for the chatbot, providing a straightforward way for users to engage with the system. It features a clean design with minimal distractions, ensuring a smooth user experience. The background image enhances the aesthetic appeal of the interface, depicting a futuristic library setting that aligns with the theme of the chatbot. Embedded within the HTML file is the Rasa Chat widget, which facilitates communication between the user's web browser and the Rasa server. This widget enables users to input messages and receive responses from the chatbot in real-time. The WebSocket URL specified in the data attribute of the chat widget establishes a connection with the Rasa server, allowing seamless communication between the frontend and backend components. The simplicity and elegance of the user interface make it accessible to users across various devices and platforms. Whether accessed on desktop computers, tablets, or smartphones, the interface provides a consistent experience, ensuring users can interact with the chatbot effortlessly. Additionally, the use of asynchronous communication via WebSocket technology ensures efficient message transmission and responsiveness, enhancing the overall usability of the interface. The architecture of the book recommendation chatbot comprises several components that work together to facilitate user interactions and provide personalized recommendations. The architecture follows a client-server model, where the chatbot server handles user requests and responds with relevant information.

F. Running the Servers

Running the Rasa server involves activating the virtual environment containing the necessary dependencies and then executing the command rasa run --enable-api --cors="*" --port 8098. This command starts the Rasa server, enabling its API endpoint for communication with the chatbot. The --enable-api flag activates the API functionality, allowing external applications to interact with the chatbot. Additionally, the --cors="*" flag enables Cross-Origin Resource Sharing (CORS), which permits web browsers to make requests to the server from different origins. The --port 8098 parameter specifies the port number on which the server listens for incoming connections. Simultaneously, the actions server is launched by executing the command rasa run actions. This command initializes the server responsible for executing custom actions defined in the actions.py file. These custom actions perform specific tasks such as recommending books, providing book details, or retrieving author information based on user inputs. The actions server communicates with the Rasa server to execute these actions in response to user queries or requests. By running both servers simultaneously, the chatbot system becomes fully operational, capable of receiving user messages, processing them through the Rasa NLU and Core components, executing custom actions as needed, and delivering appropriate responses. The Rasa server handles the natural language understanding, dialogue management, and response generation aspects, while the actions server executes custom business logic and interacts with external systems or databases as required.

IV. IMPLEMENTATION

The core functionality of the chatbot revolves around its ability to understand user input, extract relevant information, and provide personalized book recommendations. At the heart of this functionality lies a sophisticated processing pipeline that tokenizes user messages, classifies entities, and leverages pre-trained embeddings to derive semantic representations of text. Let's delve into the intricate workings of each component and how they come together to create a seamless user experience.

A. Tokenization and Featurization:

Upon receiving user input, the chatbot begins by tokenizing the text, splitting it into individual tokens or words. This process is crucial for understanding the structure and semantics of the user's message. The tokenized text is then transformed into numerical representations known as features, which capture the semantic meaning of the text. Techniques such as CountVectorsFeaturizer and RegexFeaturizer are employed for this purpose, generating numerical vectors that encapsulate the essence of the user's message.

B. Entity Classification:

Once the user's message has been tokenized and featurized, the chatbot proceeds to identify and classify relevant entities within the text. Entities represent specific pieces of information that the chatbot needs to extract and process, such as book titles, authors, genres, or descriptions. The EntitySynonymMapper is utilized to map different ways of expressing the same entity to a standardized form, ensuring consistency in entity extraction across user messages.

C. Pre-trained Embeddings:

For tasks involving understanding the semantic similarity between texts, such as recommending books based on descriptions, the chatbot leverages pre-trained embeddings. These embeddings are high-dimensional representations of text that capture semantic relationships between words and sentences. In this implementation, the SentenceTransformer model is employed to encode book descriptions into dense numerical vectors. These embeddings encapsulate the semantic meaning of the descriptions, enabling efficient comparison and retrieval of similar books based on user preferences.

D. Dialogue Management:

Once entities have been extracted and classified, the chatbot's dialogue management component orchestrates the conversation flow. This involves tracking the dialogue state using slots, which serve as memory cells to store important information throughout the conversation. Slots are filled

based on extracted entities and user input, allowing the chatbot to maintain context and provide relevant responses. For example, if the user expresses interest in a particular book genre, the corresponding slot is filled, enabling the chatbot to tailor subsequent recommendations accordingly.

E. Custom Actions:

To execute complex tasks such as retrieving book recommendations or providing book details, the chatbot utilizes custom Python actions defined in actions.py. These actions interface with external systems, such as the dataset containing book information, to fetch and process relevant data. For instance, the ActionRecommendBook class employs the pre-trained SentenceTransformer model to calculate similarity scores between user-provided descriptions and descriptions in the dataset. The top matching books are then presented as recommendations to the user.

F. Backend Workflow:

When a user interacts with the chatbot, their message is first processed by the NLU pipeline, which tokenizes the text, classifies entities, and extracts relevant information. Based on the identified intent and entities, the dialogue management component determines the appropriate action to execute. If the user requests book recommendations, the ActionRecommendBook action is triggered, utilizing the pre-trained embeddings to retrieve relevant books based on the user's preferences. Similarly, if the user inquires about book details or author information, corresponding actions are executed to fetch and present the requested data.

G. Integration with Rasa Servers:

The chatbot operates within the Rasa ecosystem, consisting of the Rasa server and actions server. The Rasa server manages the conversation flow, maintaining dialogue state and coordinating the interaction between the user and the chatbot. The actions server executes custom actions in response to user messages, fetching and processing data as necessary. Together, these components form a seamless conversational experience, allowing users to interact naturally with the chatbot and receive personalized book recommendations tailored to their preferences.

H. Frontend chat widget

The web interface of the chatbot serves as the primary point of interaction for users, providing a seamless and intuitive platform to engage with the system. The HTML file defines the structure and appearance of the interface, while JavaScript enables dynamic communication with the Rasa server. When a user accesses the web interface, the HTML file is loaded into their browser, presenting a visually appealing layout with background imagery to enhance the user experience. The embedded JavaScript code establishes a WebSocket connection with the Rasa server, enabling real-time communication between the user's browser and the chatbot backend. As the user interacts with the chatbot interface, their messages are sent to the Rasa server via the WebSocket connection. The Rasa server processes these messages using the trained machine learning models and responds with appropriate actions or recommendations. The responses from the Rasa server are then displayed in the chat interface, providing users with instant feedback and guidance. Behind the scenes, the action endpoint specified in the configuration file facilitates communication between the Rasa server and custom Python actions. When the chatbot needs to perform a specific task, such as retrieving book recommendations or fetching details about a book or author, it triggers the corresponding custom action. These actions execute within the actions server, which handles the necessary logic and communicates with external systems, such as the book dataset, to retrieve relevant information.

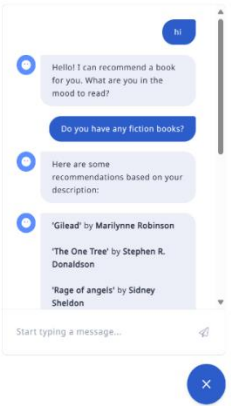

Fig 1. Recommendation based on Genre

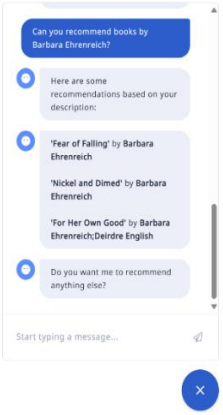

Fig 2. Recommendation based on Author

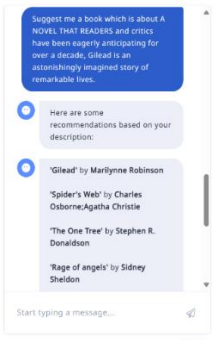

Fig 3. Recommendation based on Description

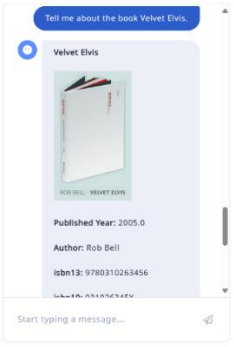

Fig 4. About the Book

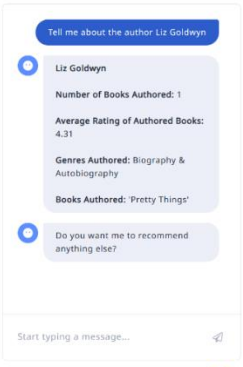

Fig 5. About the Author

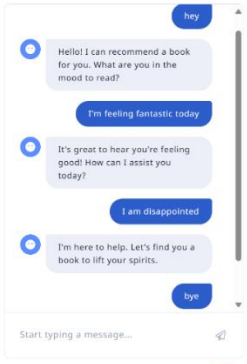

Fig 6. General user intends

V. THEORETICAL EXPLANATION

The flowchart delineates a structured process where a user's interaction initiates a series of logical decision points within the chatbot. Upon receiving a message, the chatbot first discerns if it's a greeting, employing Natural Language Understanding (NLU) techniques to recognize conversational

cues indicative of such. A positive identification triggers a pre-programmed cordial response, setting a conversational tone.

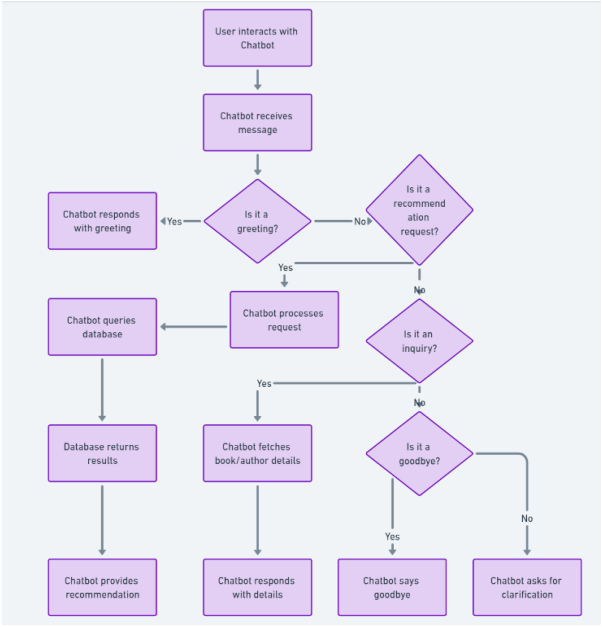

Fig 5. Flow Diagram

Absent a greeting, the chatbot employs NLP to detect if the message pertains to a book recommendation request, scrutinizing the text for keywords or contextual clues linked to genres, authors, or specific book descriptors. This identification prompts the chatbot to engage algorithms that analyze user preferences against a database, leveraging information retrieval systems to fetch book data aligned with the query parameters. The chatbot's recommendation output is then formulated based on this data, personalized to the user's expressed interests. If the message isn't a request for recommendations, the chatbot assesses whether it concerns a specific inquiry about a book or author. This requires the chatbot to query the database for detailed information, demonstrating the system's capability to access and relay intricate data points on demand.

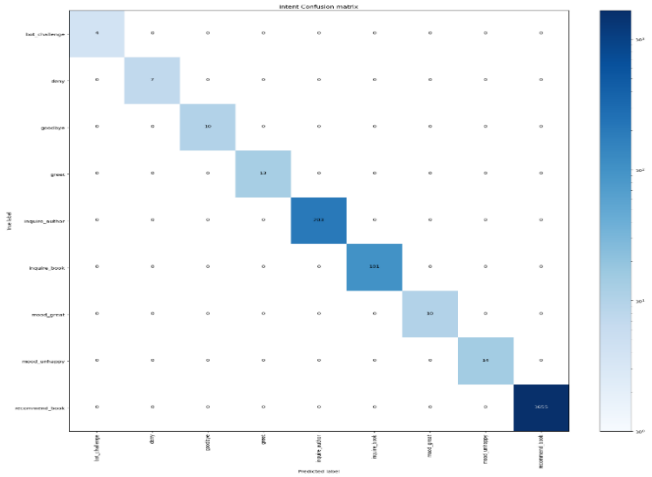

Fig 6. Confusion Matrix for Intent Classification Performance

The Confusion Matrix for Intent Classification Performance, depicted in Figure 6, provides a comprehensive overview of the model's performance in categorizing user intents. With eight distinct intent classes identified, the matrix highlights varying degrees of accuracy across different categories. Notably, the intents "Inquire_author" and "recommend_book" emerge as the most accurately predicted, with 203 and 1655 correct classifications, respectively. Through this visualization, the model's proficiency in distinguishing between different intents becomes apparent, laying the foundation for understanding its overall effectiveness in natural language processing tasks.

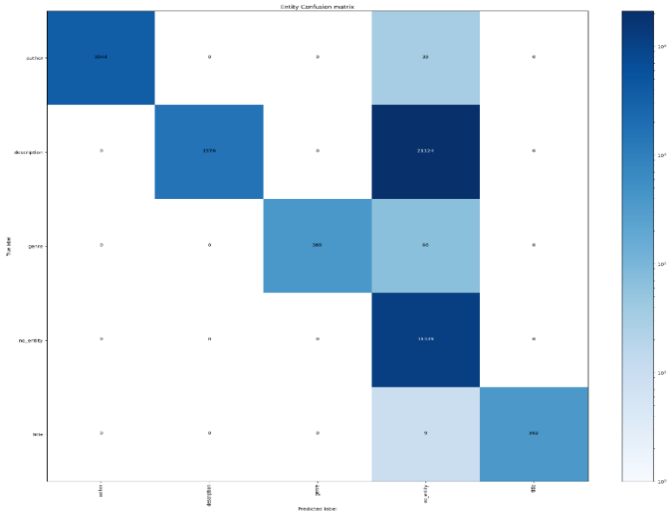

Fig 7. Confusion Matrix for Entity Recognition Performance

The Confusion Matrix for Entity Recognition Performance, as illustrated in Figure 7, offers valuable insights into the model's proficiency in identifying entities within user input. Each row represents the true label, while each column signifies the predicted label, with darker shades indicating higher counts. The analysis reveals notable trends across various entities: the "author" and "description" entities exhibit strong performance, with accurate predictions prevailing, albeit with occasional misclassifications as "genre" or "no_entity." Similarly, the "genre" entity demonstrates robust recognition capabilities, with minimal confusion between entities. Notably, the "no_entity" category showcases high correct predictions, indicating the model's success in identifying instances without detected entities. Overall, this visualization underscores the model's efficacy in entity recognition, particularly for key categories such as "author," "description," and "genre," with minimal confusion between them, thus enhancing its overall performance in natural language understanding tasks.

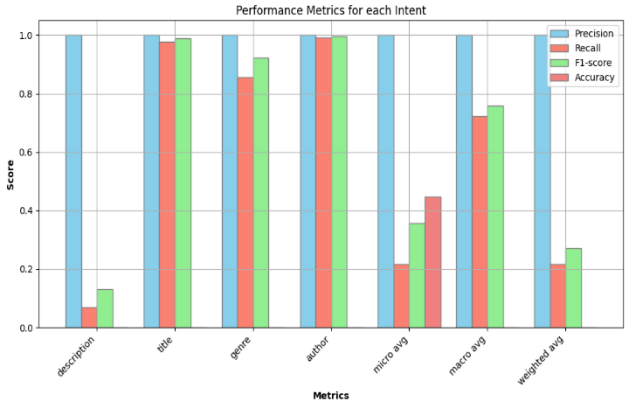

Fig 8. Precision, Recall, F1-score for each intent

The overall performance of the model, as depicted in Figure 8, showcases its exceptional capability in handling various intents with high precision, recall, and F1-score values consistently reaching 1.0 for individual intents such as "inquire_author," "mood_great," "greet," and others. Both macro and micro-average metrics demonstrate strong overall performance, with macro-average precision, recall, and F1-score reaching 1.0, and micro-average precision, recall, and F1-score hovering around 1.0, except for recall, which is at 0.217. Despite this discrepancy, the model's accuracy remains at 1.0 for individual intents, and the weighted average precision, recall, and F1-score also maintain consistent high values. These results collectively highlight the model's excellence in intent classification tasks, emphasizing its reliability and accuracy in understanding user queries and affirming its robustness in handling diverse intents effectively.

VI. Conclusion

In concluding the exploration of the book recommendation chatbot developed using Rasa, it becomes evident that this innovative solution holds significant promise for enhancing the accessibility and relevance of library resources. The implementation of the book recommendation chatbot using Rasa offers a tailored solution for students, researchers, and library users seeking personalized book recommendations. By leveraging natural language understanding (NLU) capabilities, the chatbot efficiently categorizes user intents and recommends books based on genre, author, description, and other criteria. Through the integration of Rasa's open-source framework, the chatbot provides a cost-effective and library-specific solution, avoiding the need for expensive API calls and ensuring relevance to the available library resources. With its ability to understand user queries, retrieve book details, and offer insightful recommendations, the chatbot enhances the user experience, facilitating efficient access to relevant reading materials within the library's collection. Additionally, the model's impressive accuracy in intent classification and entity recognition tasks further underscores its reliability and effectiveness in delivering tailored book suggestions, enhancing user satisfaction and engagement.

A. Future Works:

In future work, several avenues can be explored to enhance the capabilities and user experience of the book recommendation chatbot. Firstly, fine-tuning the NLU pipeline with advanced techniques such as contextual embeddings or transformer-based models could improve recommendation accuracy by better understanding the nuances of user queries. Integration of external data sources, such as book reviews or user ratings, can provide additional insights into book preferences and enhance the relevance of recommendations. Secondly, implementing multi-turn conversation capabilities and context tracking mechanisms would enable the chatbot to engage in deeper interactions, allowing for more personalized and context-aware recommendations. Furthermore, expanding support for voice and multimodal inputs would increase accessibility and cater to a broader user base, ensuring inclusivity in the recommendation process.

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