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Implementation of an Educational Chatbot using Rasa Framework

Supreetha H V, Sandhya S

Abstract: *The growth in Artificial Intelligence (AI), Big-data, and Internet-of-Things (IOT) technologies has increased chabot's application in many areas. Some of the applications of chatbot can be seen in areas such as social media, e-commerce, healthcare, stock market, education, banking sector etc. Most of the high-end chatbots are deployed inside e-commerce, banking and health websites. There is a need to deploy the chatbots in educational website to improve interactivity of the educational platforms. The main target users of this website is rural students. In rural areas, probability of students dropping school after some age is common because, there won't be proper monitoring of students and also sometimes facilities will be less. With e-learning, anyone can learn everything with limited cost. The key insight of developing this e-learning website is to provide a chatbot which can motivate rural students towards education. Thus a single platform where users can learn different courses, take quizzes, and chat with the bot is developed. It also provides an additional facility of tracking the scores of the quizzes and giving personalized recommendation systems to improve the scores. The chatbot will also help users to find details about faculties and help users to set an appointment with distant faculties in online mode for doubts clarification. Flask micro-framework is used for developing the website. Firebase is used to store the data. RASA framework is used in developing the chatbot. Finally a content based filtering is used to give personalized recommendation systems.*

Keywords: *Chatbots, Content based learning, Firebase, Natural Language Processing, Recommendation Systems, RASA.*

I. INTRODUCTION

A chatbot is a software which is designed to understand what human wants and guides them to their desired output. These chatbots work using Artificial Intelligence (AI) and Natural Language Processing (NLP). The aim of the chatbot is to reduce the work load of humans. Chatbots are used to automate customer service and reduce tedious tasks performed by employees so they can spend their time more productively on higher priority tasks. The chatbots are used in many areas such as health, e-commerce, customer services, education etc. With the increase in the chatbots, many tasks have become easy. Say previously it was difficult to handle large number of customer calls. Back then people need to wait for more time for their turns when they call for toll-free numbers.

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* Correspondence Author

Supreetha H V, Department of Computer Network Engineering at RV College of Engineering (RVCE) Bengaluru (Karnataka), India. E-mail: supreethahv.scn20@rvce.edu.in

Dr. Sandhya S, Assistant Professor, Department of Computer Science and Engineering, RV College of Engineering (RVCE) Bengaluru (Karnataka), India.

Answering the calls would become tedious for service providers also. Thus if a chatbot is pre-fed with set of questions and answers there won't be any delay in attending customers and the business would acquire a positive growth. The evolution of chatbots can be seen in Figure 1. Based on the complexity of the functionalities, the levels of chatbot can be described. Generally chatbots can be grouped into five levels based on the applications and its functionalities. The Figure 1 shows the level of chatbot with its working.

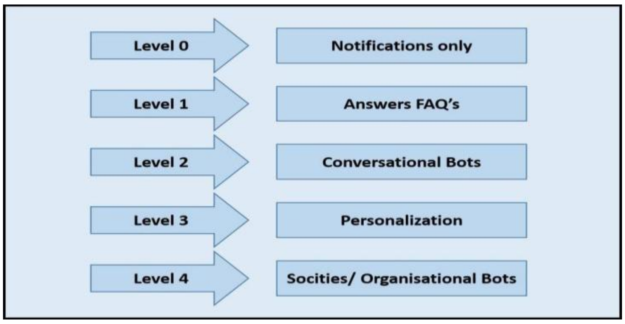

Figure1. Levels of chatbots

The Level 0 chatbots are those which sends some notifications or messages to the customers. They are bots or programs but not persons. For sending similar data to huge customers these bots are used. The Level 1 chatbots are used for answering FAQ's. Generally in many customer care centers it will become difficult for persons to answer similar questions again and again. Level 1 bots will be pre-fed with set of questions and answers. These bots will answer on behalf of persons to reduce time and cost. The Level 2 bots are conversational bots which are used in e-commerce and social media platforms. These bots will pop-up when user visits a website. They act as virtual assistants and have information about the context and answer accordingly. The Level 3 bots are advanced and they are highly personalized. They will track even daily activities and from users previous likes and dislikes to give final output. The Level 4 chatbots can be thought as future bots where many bots interact with each other and learn from each other to give better results. With the inclusion of chatbot in education, many universities, students and faculties are obtaining advantages. Some of the ML and AI enabled chatbots will also help users interact with students to understand the mindset of users and give personalized learning systems. A number of chatbots are already present in the market. Some examples include Google's voice assistant, amazon's Alexa, Siri etc. These assistants or bots will interact with the users and try to understand what user is in need of and gives output accordingly. Much growth of chatbots can be seen in the health, customer services, e-commerce websites. But not much work is done in using chatbot efficiently in the educational field.

The aim of this paper is to develop a chatbot which can help in the educational fields. The rest of the paper is organized as follows. The section II will give Literature Survey, section III will give System Architecture, section IV discusses about Results and Analysis. Finally section V will give Conclusion of the work carried.

II. LITERATURE REVIEW

The below section discusses about various previous works carried out in building chatbots in different domains. The Paper [1] discusses the advantages of using chatbot in education. This paper discusses insights about how students and teachers can both use chatbot. Teachers will pre-feed the chatbot with set of questions and answers and thus when students ask questions the chatbot can answer all the questions. Hence time will be saved. Natural Language Understanding and DL are used. The drawback of this model is it can answer only set of questions and is not interactive.

The Paper [2] discusses how chatbots are designed inside messaging apps like Facebook, Messenger. In this about 47 chatbots were found to be of good quality. The concepts include discussions about humanity, information retrieval and how best bot can send personalized outputs. Discoverability of bot in social media platform is one of the major challenges as it requires text processing and more training is needed to obtain accurate results. Paper [3] discusses how chatbot is used in e-commerce. It will suggest the products and will keep track of user's social media to send updates about his recommended products. Giving personalized recommendation is difficult and the suggestions given by bot may not be liked by users. Paper [4] discusses steps involved in English learning. The bot will teach the pronunciation of words, meaning and how one can use phrases of English in communication. The stages include Automatic Speech Recognition (ASR), Dialog Management (DM), Natural Language Generation (NLG) and Speech Synthesis (SS)[4]. The ASR stage will take input from users, The DM stage will process the input taken from the user, the NLG stage will produce the output for the questions asked by the user the output can be either a text or a voice based and finally the SS will generate voice for given output text for users. Understanding what user will give as input is difficult as it requires processing of text and more training is needed to give accurate results. In Paper [5] a chatbot which can answer all frequently asked questions (faq's) is designed. The model uses neural network Sequence to Sequence model based on RNN encoder decoder. Seq2Seq model with attention mechanism provides some insights for the question answering system in the education chatbot and accuracy of the model is less. Paper [6] is defined to help elderly people to engage them. It will provide news both in voice and text. It will work like an intelligent radio system to entertain the people. Many Ml models are used in finding suitable radio or news systems for the users. The system is mainly helpful for elderly people to motivate and keep them away from loneliness. But, Only 80% of the people were found to be satisfactory by the performance of this system. In Paper [7] an android application is developed for the key insight of providing education for specially visualized people. It will try to answer queries asked by the users. Give voice based output so specially visualized person can also be benefited. Many people will not come forward to use this application and proper training must be given to users. Problems like understanding user input, user sentiment, processing input, giving suitable output were some of the challenges suggested in paper [8]. The observations obtained from this paper is it is easy to find the challenges but difficult to improve upon these challenges. Paper [9] discusses how e-learning is helpful in personalized learning and how time can be saved in e-learning platforms. The advantages include interesting conversations and instant responses at any time of day or night. The limitations of this is chatbot still falls short of real human teachers in solving learning problems due to the fact that its current datasets and knowledge base are still in infancy, a huge constraint for any kind of chatbot. Paper [10] discusses about a platform where all students can learn different concepts in a single platform. Through this learning platform, students can search for similar sentences in the two knowledge bases respectively. They are video knowledge base and article knowledge base. After this students can understand solutions very quickly. But in this model training is less so the accuracy of this model is not good. An analysis from paper [16] will show us about different frameworks which can be used in developing chatbots considering various parameters. The Table 1 will show the analysis between different frameworks. The Table 2 will give a detailed difference between AI chatbots and Non AI chatbots. It could be observed that Non AI chatbots are not advanced as compared with AI chatbots. Non AI bots are keyword driven which means based on the answer given in the top questions, next set of questions will be decided. But where as in AI bots, it is context driven which means they try to understand the meaning of queries asked by the user and then answer all the questions. Training is easy and less time consuming in Non AI chatbots and it is more time consuming in AI chatbots.

Table 1 Comparison of common chatbot Frameworks [16]

	Company	Paid/Free	Ease of Use	Out of Box Integration	Open Source	Popularity	Web Based	Language
QnA Maker	Microsoft	Free	High	Yes	No	Medium	Yes	C#
Dialogflow	Google	Free	High	Yes	No	High	Yes	JS
RASA	RASA	Free	Low	No	Yes	High	No	Python

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Wit.ai	Facebook	Free	High	Yes (Facebook)	No	High	Yes	JS
Luis.ai	Microsoft	Free	High	Yes	No	Medium	Yes	JS
Botkit.ai	Botkit	Free	Low	Yes	No	Medium	No	JS

Table 2. Difference between Non-AI and AI chatbots

	ConversationCapabilities	**People Insights**	**SuitableTasks**
Non-AI Chatbots	* Linear, rigidchat flow primarily driven by radiobutton selections. * Ignore user freetext input * Context insensitive	only from user explicitchoices	* task-orientedapp * structured,simple tasks that require little user input
AI Chatbots	* non-linear, flexible chat flow that supports digressions andinterruptions * handle user free-text input * context sensitive	Read between the lines to infer people insights	*task oriented +socital chitchat *semi- structured tasks with varied paths * diverse user actions orqueries

III. SYSTEM ARCHITECTURE

The Figure 2 gives the details about system architecture of the RASA chatbot design. Mainly there are two components in RASA Open Source architecture. They are: RASA NLU and RASA Dialogue Policies. The RASA NLU(shown as NLU Pipeline) is like eyes and ears of the chatbot. This will receive input from the users and will identify the intents and entities from the user given input. It is also responsible for handling response selection. The dialogue management(shown as Dialogue Policies) will decide the next action in a conversation based on the context. RASA SDK is an action server. This is responsible for creating custom actions needed as per chatbot design and it is optional. More the number of customized actions, the interactivity of chatbot will increase.

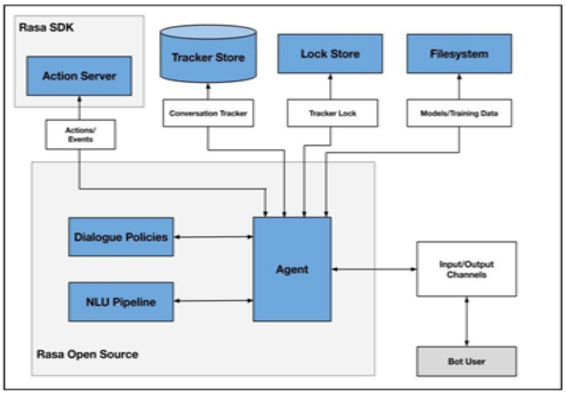

Figure 2. Architecture of RASA chatbot [11]

The Tracker store is responsible for storing the conversation of the chatbot. The bot will save the context which can help to give personalized interactions. Rasa uses a ticket lock mechanism to ensure that incoming messages for a given conversation ID are processed in the right order, and locks conversations while messages are actively processed[17]. File system consist of Models and Training data. List of ml models and data will be present in different files. According to the application one can use different ML models and data-set for training the chatbot.

IV. METHODOLOGY

This section discusses about the different stages and methods used while deploying a RASA chatbot inside a flask web application. The system is mainly divided to facilitate three functionalities, namely:

1. Learn Courses
2. Take Quizzes
3. Converse with chatbot

Detailed description and working about each sections are discussed below.

A. Learn Courses

Once a user logs into the website list of courses available in different subjects will appear. The user can choose any subject of his interest and start to watch the course. The Figure 3 shows the page where user can choose to watch any subject of his interest. Here a data set is created with four subjects namely Maths, Science, Computer Science and Aptitude. For each subject number of topics along with demo videos are attached in the data set. The contents of course will be dynamically loaded from the data set. Any user can have access to these videos once user logs into the website.

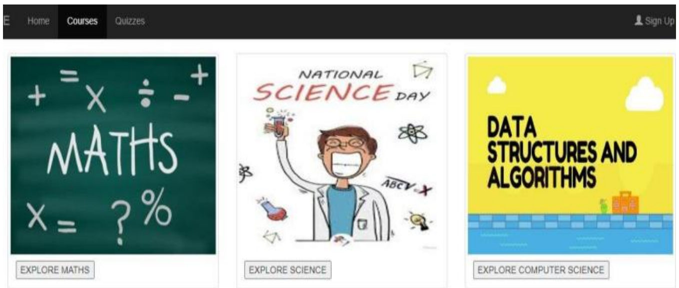

Figure 3. Courses page from website

B. Take Quizzes

Taking quiz is necessary after watching the courses to track learning progress. The developed website will provide quiz for each section and users can take up those quizzes. According to the marks obtained in the quiz, a content based recommendation system is incorporated which will recommend users to re-watch the courses where they get below average scores. This will enable personalized learning systems.

Figure 4 shows a sample quiz page. Figure 5 will display us with the marks obtained in the quiz and here we can see there will be sujjest and quit quiz options. If a user selects sujjest option, content based filtering will give topics user can re-watch to improve the performance.

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The Figure 6 will show the pages recommended for user to watch to improve the performance.

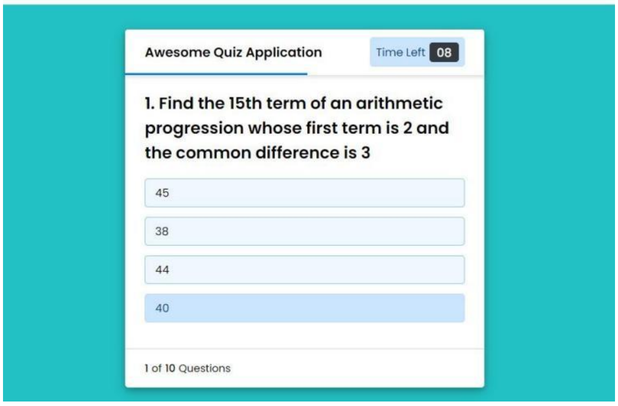

Figure 4. A sample quiz page from website.

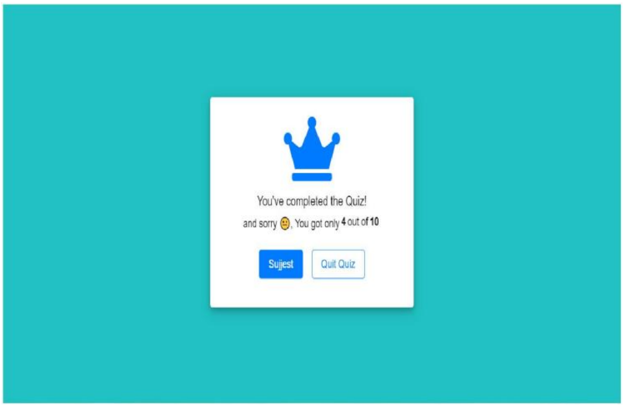

Figure 5. A sample page showing marks scored.

❖ **Content Based Filtering:**

Its one of the kinds in recommendation system, which gives suggestion based on user's previous activities. It gives recommendation based on the keywords and attributes taken from the database. The model is trained for "Topic" attribute of courses.csv file. It is trained on Topic attribute because, other users who watched particular topic course and got more scores must be given as a recommendation to users who scored less marks. The algorithm uses cosine similarity distance vectors to give next suggestions.

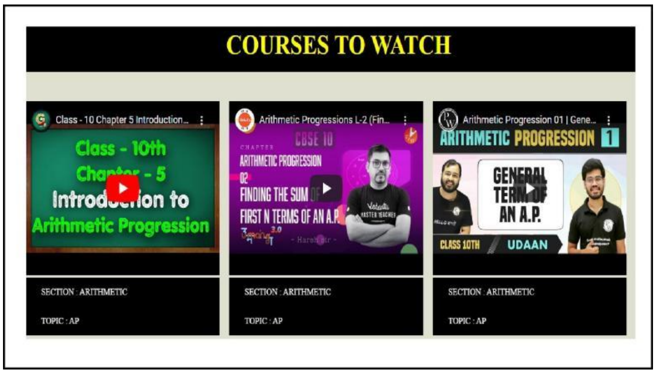

Figure 6. Recommendation courses to watch page.

C. Converse with chatbot

RASA framework is used in developing a chatbot which is deployed inside flask web application. RASA is an AI enabled platform which can be used to create conversational chatbots. It mainly includes three stages. They are:

1) Natural Language Understanding Stage
2) Response Selection Stage
3) Output Stage

1) Natural Language Understanding Stage:

The input given by the user is processed in this stage. Mainly the chatbot will try to understand what a user is trying to ask in this stage. The given input is matched with an intent from set of trained intents. Mapping of input with corresponding intent is very much necessary to get accurate response from the chatbot. Variety of examples must be trained for intent classification as different users can ask different kind of queries. Training must be enough to map user input with correct intent. After the intent is mapped, entities must be extracted from the input. Let us consider some example:

2) Response Selection Stage:

RASA Core is responsible for giving responses for the queries asked by the users. A set of action sequences will be pre- defined for each intent. For each query asked by user, the Core will decide the action to be performed. The actions may be of two kinds - static and dynamic. The static actions begin with an utter key word which will perform only uttering of some static messages. The example for a static action maybe

Query1: find CS courses.
Query2: find some CS courses.
Query3: Get me list of CS courses.
Query4: could you please get me CS courses list?

In all these cases the chatbot must understand that the intent is search_courses and entity is "CS". The intent describes what a user wants. An entity is a piece of information identified from query. If a bot can extract this intent entity set accurately, then only it can provide correct outputs. The RASA NLU will take care of the training the model which in-turn takes care of mapping intent entities. Table 3 will describe the list of intents along with the description.

Table 3. List of Intents with its description

Intent	Description
greet	Bot greets user with a message
goodbye	Say bye to user
affirm	Ask user if he agrees wit the bot's response
deny	Ask user if he deny wit the bot's response
mood_unhappy	Queries related to ask user whether he is unhappy
book_appointment	Queries related to book an appointment
search_courses	Queries related to find some subject courses
search_faculty	Queries related to find faculty list
search_faculty_details	Queries related to get details about searched faculties
bot_challenge	Ask bot if it is human or bot?

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Utter greet, in this case only greeting message is given to users. Here, no processing is required. The dynamic actions are created in action.py a python file which will retrieve all the contents from database to perform customized actions for an intent. One example for this is action_find_faculty, this action will search all the faculties in the database and give a list of faculties along with their contact details for users. Table 4 will give list of action with its descriptions.

Table 4 List of Actions with its description

Action	Description
utter_greet	Greets user
utter_happy	Express happiness
utter_did_that_help	Ask user whether response given by bot is useful or not
utter_cheer_up	Tries to cheer user when mood is unhappy
utter_goodbye	Say goodbye
utter_iambot	Say I am bot
action_search_course	Searches courses available
action_find_faculty	Finds list of faculties
action_faculty_description	Detailed description about faculty
action_book_appointment	Books an appointment of user with bot

Figure 7. Chatbot deployed inside website.

Writing Stories: Stories defines path of the intent action sequence which a user may follow while interacting with a chatbot. More the number of stories created, better will be flow of the interaction between user and the bot. It will reduce sudden abrupt stop of the conversation between the user and a chatbot. Stories are not rules but they are simply guides which chatbot can follow for smooth working.

DIET Classifier: Dual Intent and Entity Transformer, also shortly known as DIET classifier, is a state-of-the-art classifier which is lightweight and is designed with a multitask transformer architecture for NLU. It handles both intent finding and entity extraction together. This is used in the model building because using this fast training and parallel performance is possible.

3) Output Stage

The response selected by the model must be given to the user. The output stage or Natural Language Generation stage is responsible for giving the final output. The output can be of many forms. It could be either in form of text or a speech. If the output is of speech another text-to-speech conversion methodology must be followed. Finally the outputs can be obtained through many channels. The chatbots can be deployed inside conversational platforms like whatsapp, facebook, telegram etc. Or it can also be deployed inside websites. The Figure 7 shows how the chatbot is deployed inside a website.

V. RESULTS AND ANALYSIS

The core of the RASA chatbot is build using deep learning models, so the chatbot is expected to perform with accurate results. The accuracy of the chatbot is decided on the basis of how best the bot can understand the intents and entities of the input given and how best it can give response back to the user.

Accuracy of the stories can be calculated by running the test stories. Multiple test stories can be created to check the accuracy. Test stories are similar to stories where intent action pairs are written to define a flow of working of chatbot. But in the test stories user defined stories can also be added to get more accurate results. Along with test stories, one element is added to the test stories. The element is user response for given intent and action to be taken for that intent. This will be used as reference to check whether predicted responses are correct or not. RASA provides multiple testing commands to check the accuracy of the model built. Testing can be done both for RASA core and RASA NLU. The command for testing RASA NLU and RASA core are respectively:

- rasa test nlu
- Rasa test core

The RASA NLU test will perform analysis of the intents and entities. It will check whether for given input correct intent entity mapping is done or not.

The RASA Core will test whether the response and actions given to the user is valid or not. The actions will search the database to retrieve data asked by the user. The test will provide output in the form of confusion matrix and histogram. The confusion matrix will give the true positive, true negative, false positive, false negative predictions for intent, entity and actions defined. Diagonal elements are true positive elements. Thus the diagonal elements of the confusion matrix are correct predictions. If any non diagonal entries are seen those are wrong predictions. The Figure 8 will show the confusion matrix of intents. From the matrix it could be seen almost all intents are predicted correctly for test input instances. For intents, there is no non diagonal elements so, almost all intents are predicted correctly. Figure 9 will give the confusion matrix of entities prediction. From the figure it could be seen that some of the entities are not correctly predicted as non diagonal entries could be seen. Figure 10 will give the details about confusion matrix for action. From the matrix it could be seen some of the actions are not predicted correctly. More number of training intent action pair can make more correct predictions. The RASA cross Validation test will perform testing for different user instances by taking random train test split.

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Finally average of all these tests will be calculated to give final accuracy of the model. The command used for performing RASA cross validation test is mentioned below:

- Rasa test nlu --cross-validation

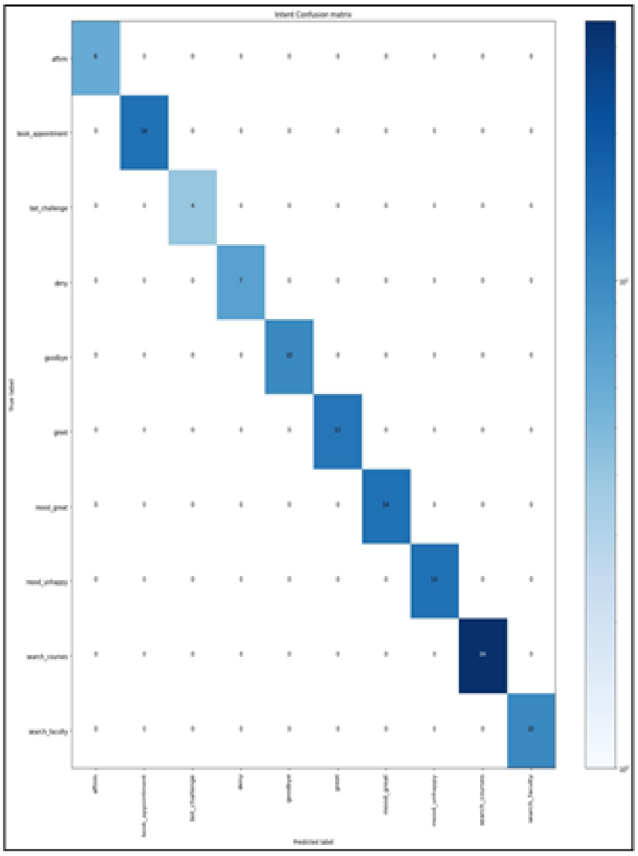

Figure 8. Confusion matrix for Intents

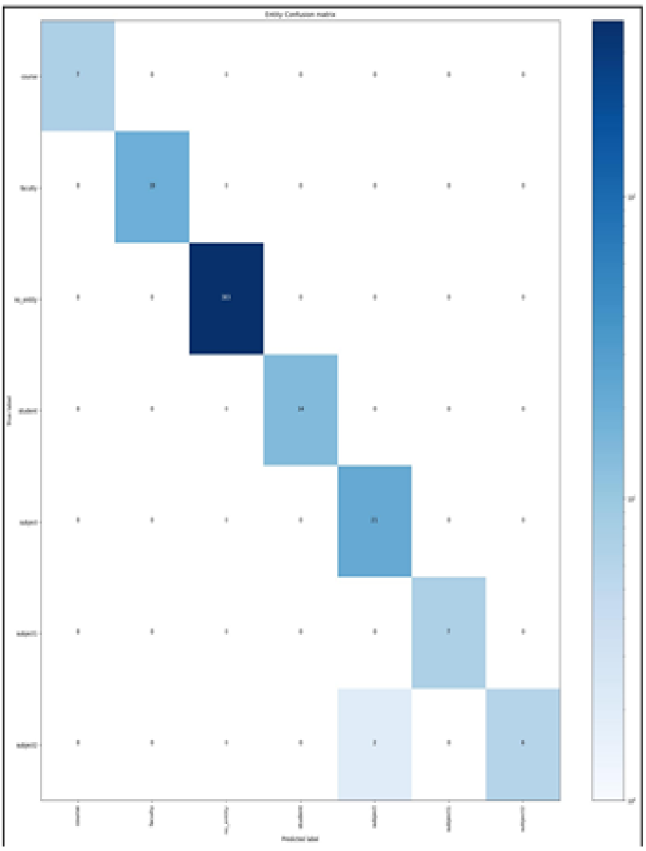

Figure 9. Confusion matrix for Entities

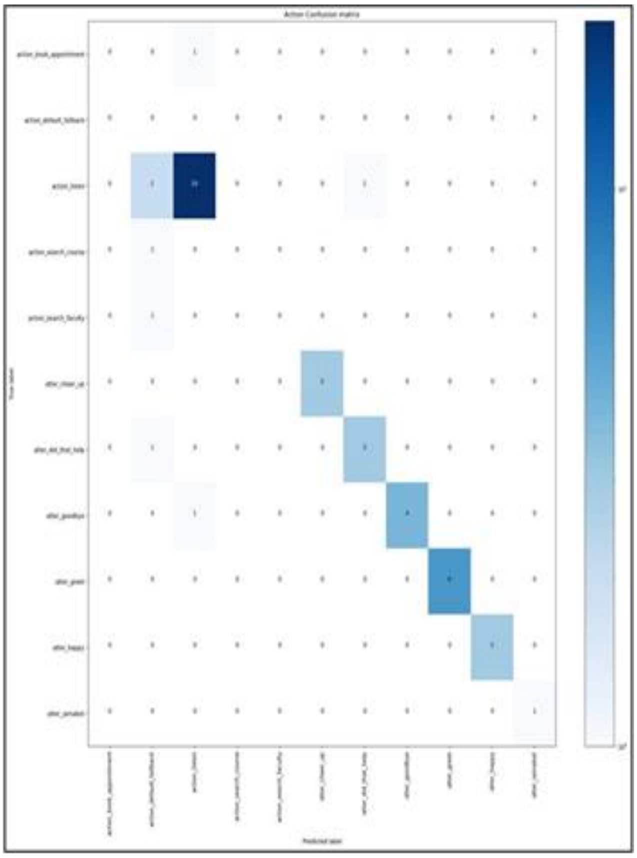

Figure 10. Confusion matrix for Actions

The cross validation test will give Precision, Accuracy and F1 score for both train and test splits. Precision is how related the developed chatbot can give output related to training data. Developed model gave precision of 0.881 for intent classification and 0.993 for entity evaluation. The F1 score is needed to seek balance between precision and recall. The model have F1 score of 0.884 for intent classification and 0.988 for entity evaluation. All these details are discussed in Table 5 and Table 6.

Table 5. Cross Validation test results for Intent classification

Precision	**0.881**
Accuracy	**0.898**
F1 score	**0.884**

Table 6. Cross Validation test results for Entity Evaluation

Precision	**0.993**
Accuracy	**0.967**
F1 score	**0.988**

VI. CONCLUSION AND FUTURE SCOPE

The chatbot developed is deployed inside a web application. This chatbot will interact with the user to help them to search courses, find faculties, get details about faculties and fix an appointment with the distant faculties.

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The developed bot is interactive enough to help users and motivate them towards education. The main functionality of the bot is to give accurate responses for the queries asked by the user. The bot is performing well in this aspect.
Tracking the progress of the quiz and giving recommendation system using content based filtering will give personalized learning experience to users. The accuracy of the model is found to be 89% and 96% for Intent classification and entity extraction respectively. Further there is a chance to improve accuracy by providing more training to the RASA NLU component by increasing number of instances for each intent. Many tools such as chatito can be used to generate training dataset to increase number of training instances. The bot can also be deployed inside whatsapp, telegram to reach out large audience. Finally as a future enhancement bot can be developed using native language to reach large rural population.

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AUTHOR'S PROFILE

Supreetha H V, is a B. Tech graduate in Computer Science and Engineering from VTU Belagavi. Currently is pursuing M.Tech in Computer Network Engineering at RV College of Engineering(RVCE) Bengaluru, Karnataka. Supreetha has done her internship in Android development from Bobble.Ai. Supreetha is good at communication, is a quick learner and love implementing new things to gain knowledge. Supreetha has previously published paper based on ML for IEEE-CSITSS conference in 2021 which was held in RVCE Bengaluru. The name of paper is “Detection of Anomalies in Time Series Data”. Mail id-(supreethahv.scn20@rvce.edu.in)

Dr. Sandhya S, is an Assistant Professor, in Dept. Of CSE from RV College of Engineering(RVCE) Bengaluru. Dr. Sandhya S is having 17 years of teaching experience and 10 years of research experience. Area of Interest of Dr. Sandhya S include, Networking, Distributed Systems and Virtualization. Dr. Sandhya S is working in the project of Karnataka Udyog Mitra Under the group headed by Dr. N K Srinath. Dr. Sandhya S is highly motivated, supportive professor who always encourages students in achieving their goals. Many UG and PG students are undertaking multiple projects under Dr. Sandhya S.