Effective Analysis of Chatbot Frameworks: RASA and Dialogflow

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Abstract: In recent times, use of AI based chatbots have increased tremendously. Chatbots have turned to be very helpful in the field of education, marketing, environmental etc. In this study the focus is maintained towards creating a chatbot for the educational organisation namely, Central University of Punjab, Bathinda. The chatbot is created with Rasa and Dialogflow. The queries and response were self-created for dataset. DIET classifier was used for Rasa for intent classification and entity extraction. BERT and RoBERTa for Rasa configuration and LSTM for predicting actions are used .Similarly, same dataset is used for creation of Dialogflow chatbot .Lastly, an analysis is performed on both to check the efficiency. This research depicts the path to create chatbots with Rasa and Dialogflow and also the effectiveness amongst them.

Keywords: Chatbot, Rasa, Conversational Agent, Dialogflow, BERT, DIET

1 Introduction

While exploring more natural ways to integrate automation into daily life, conversational systems are becoming more common as a basis for human-computer interaction. The rapid development of artificial intelligence [Pantic, et al., 2003] and natural language processing are two technologies strongly related to chatbots on the rise currently. It increases the demand for technological advances in AI and NLP. Chatbots are also called conversational agents. It is designed with the help of AI software. A chatbot carries many of the mobile application's features and websites within a messaging service. Increasing popularity of the chatbots in different fields .Conversational agents use Natural Language Processing (NLP) and other AI techniques to engage in contextual discussion. To begin, an agent must comprehend the context of the end user [Singh and Beniwal, 2021]. Any user goal can be gracefully handled by a chatbot and it can assist in completing tasks as efficiently as possible. This does not always imply that the bot gives the answer every query but it will be capable of handling the discussion.

The popularity of chatbots has prompted the creation of a variety of chatbot development platforms and frameworks. There are several chatbot development platforms (e.g. Pandorabots, Manychat, and Chatfue) and frameworks (e.g. Rasa, chatterbot, Dialogflow) out there. It can also be defined as a software with a specific amount of artificial intelligence that can communicate with a person or another chatbot to give the idea that the conversation is taking place with a real person rather than a computer programme *(ZEMČÍK 2019*) A chatbot objective is to facilitate the exchange of meaningful information without the use of a human agent, yet the bot itself mimics a living entity. The MIT Technology Review named chatbot technology as one of 2016's breakthrough technologies. (*Zhi and Metoyer 2020*) . Chatbots, on the other hand, were invented far earlier. Alan Turing was the inspiration for creating a chatbot. "Turing Test" developed in 1950 (*Belfin et al. 2019*). As per Krol (1999), the test works as follows: an interrogator asks two subjects the same questions, and both respond in the same way. A computer will be one of the participants, while a person will be the other. The machine behaves intelligently just like a human.

1.1 Types of Chatbots

Based on work, the chatbots are divided into Rule-based chatbots and AI-based chatbots. Rule-based chatbot work on specific instructions given by the user. The commands could be given through typing. The Rule-based system is a straightforward but it is difficult to manage. Developers use AIML (Artificial intelligence Mark-up Language) to write rules for that chatbot system. AIML is XML based language. Machine learning and natural language processing are used by AI-based chatbots to give more interactive experience. Chatbots powered by AI learn interactions through a mechanism based on human thinking. Machine learning is used by chatbots. Machines can forecast and act in previous situations and interact with the humans (*Hasan, 2019).*

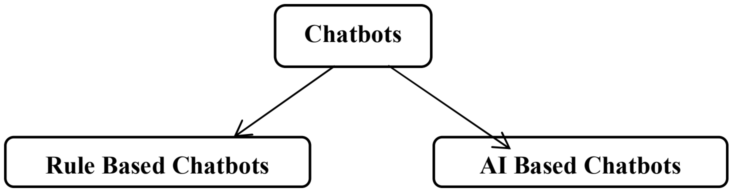

Fig.1. Types of Chatbots

1.2 Natural Language Understanding (NLU)

Natural language understanding NLU [Kang, et al., 2020] is a branch of natural language processing (NLP) that requires converting human language into a machine-readable format. Computers can automatically examine data using natural language understanding (NLU) and machine learning. Rasa NLU and Dialogflow NLU can be used in the Chatbot.

1.3 Rasa

Rasa stack *(Rasa 2020)*[1] aims to bridge the gap among the research and implementation by making recent developments in machine learning accessible to non-experts interested in implementing conversational AI systems. Introduce the Rasa stack, Rasa NLU, and Core as simple building blocks for conversational systems. Rasa stack is a open-source machine learning technologies for building contextual AI assistants and chatbots. Rasa NLU is a natural language understanding library that includes entity extraction and purpose categorization. Rasa Core is a chatbot framework that uses machine learning to manage interaction and anticipates the optimal next steps based on NLU input, conversation history, and training data. (Tom Bocklish et.al.2017)

1.4 Dialogflow

Dialogflow *(Dialogflow 2020)*[2] is a Google service that allows anyone to create interesting speech and text-based conversational agents. Using the Google cloud platform a natural language processing (NLP) platform for creating conversational applications. API.AI was the previous name of the company, which was acquired by Google in 2016. It was renamed Dialogflow after that. Virtual assistant services for chatbots and contact centres are provided by CX and ES.

2 Related Work

Pavel, (2021) provided the research community with the comparative analysis of two chatbot frameworks i.e. Botkit and Rasa. For the comparison, each framework and a set of criteria were used to create two identical chatbots were can be taken. The comparison was made utilising those types of characteristics, as well as the implemented chatbots and available documentation for various frameworks. When those criteria are considered, the Rasa Framework is more versatile and provides assistance than the Botkit Framework, according to the findings of this study.

Flores, et al., (2020) focussed on Performance Comparison of Natural Language Understanding Engines in the Educational Domain. Compare the most popular natural language understanding (NLU) engines to see which one will perform better in the educational setting. In the educational area, a Rasa service to identify which chatbot solution performs the best. With the right settings, Rasa's performance can be significantly enhanced. It's important to remember that it's an open-source chatbot platform with a powerful natural language understanding engine.

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[1] https://rasa.com/

[2] https://cloud.google.com/dialogflow/

Tseng, et al., (2020) anticipated the topic An Intelligent Disease Query System Based on Rasa NLU The method uses data from Taiwan's disease control centre. The research was succeeded in making the health service's question and response intelligent. In the actual world, this system was providing a win-win situation for both individuals and health call centres.

Ngugen, et al., (2021) focused on the research NEU-chatbot: Chatbot for admission of national Economics University. Most of the communication of students and university performed manually it consumed more time. Researchers was developed an AI-based chatbot that allows students to receive daily curriculum updates and admission information for new students. Proposed the Vietnamese chatbot .NEU – Chatbot achieved the best 97.1% accuracy on test set. Using whitespace tokenizer customizes a tokenizer for only Vietnamese words. In this research. After three months the chatbot was adding to the Facebook fan page 50,000 questions in total.

Shin, et al., (2020) proposed the topic Designing Everyday Conventional Agents for Managing Health and Wellness provided the conventional conversational agents have been developed for supported the wide array of areas, including, decision making, autonomous vehicles and health behavior change design heuristics and recommendations for conversational agents that support health and wellness and beyond. The design heuristic of conversational agents formalises 11 heuristics for conversational agents. Researchers was improved the conversational agents.

Shah and Shah, (2019) provided the comparison of various chatbot frameworks. The research gives an overview of each and also states its features. Compared these frameworks on a certain features and identify the Google best work. The steps on how to select a framework for the business were also discussed and which would be suitable based on what the user needs the features in the chatbot.

Roman, et al., (2020) provided the research on "Hey assistant, how I can become a donor?" In the case of the blood donation virtual agent it can be used the Dialogflow framework to develop the chatbot. 50 participants who was interacted with the virtual agent. It is capable to respond to the utterances exactly related to the 30 common questions and concerns about the blood donation. A cognitive agent is a creative way for spreading knowledge and engaging the people regarding the blood donation.

Yan, (2018) provided the research chitty-chitty Chatbot: Deep Learning for Conversational AI. This research focused on the surveyed of non-task-oriented chabots assistant. It is open domain research work.

Meshram, et al., (2021) provide a review on conversational AI: chatbots. None of the chatbots were bi- or multi-lingual, according to reports. The chatbot's capacity to talk in a variety of languages gives better results and reaches different communities in the world. The chatbot has a lot of advantages that can be used everywhere, 24 x 7 accessibility.

Stoica, et al., (2021) provided the research is to offer an empirical investigation of the influence of Romanian diacritics using the performance of two well-known frameworks for intent recognition and slot filling: Rasa and wit.ai API. The slot filling task appears to be the most affected by this factor, with performance drops of up to 30% for Rasa and more than 40% for wit.ai.

Gamage, et al., (2021) providing the traditional interfaces to it services make it easier for more individuals to use them. Such interfaces must be available in the community's native language. The paper improves the employing Sinhala word embeddings in an implementation based on the frequently used Rasa Stack, accuracy can be improved.

Christopherjames, et al., (2021) focuses on the researcher are of the people are not medically qualified for studying or understanding the extremity of disease or symptoms.AI powered healthcare chatbots are beneficial for assisting patients. The health based assistant system we developed the chatbot using Dialogflow Application Program Interface (API). This Chatbot system related to the health system.

Vartimiadis, et al., 2021 focus on the research of for museums, a graph-based conversational approach to a distributed collaborative multi-chatbot technique is being developed. Museums are creating chatbots to assist tourists and give a more enjoyable visit. They define the predefined proper dialog routes. The paper proposed a representative set of developed museum chatbot and the systematic evaluation approach for evaluating both chatbot and platform. Utilizes KGs has strongly conversational with NLU and ML techniques. It is critical to emphasise that the proposed approach's success is contingent on the quality of the KGs used as the underlying knowledge representation technology.

Rahman, et al., 2019 focused on the study of some healthcare chatbot available in English and their languages but not in Bangla. Machine Learning based closed domain chatbot on Bangla Language is known as 'Disha'. The user can converse the chatbot in Bangla Language and learn from interaction with the user. Decision tree, Random Forest, Multinomial NB, SVM, Adaboost, and KNN are six supervised machine learning methods used. The best accuracy is shown by SVM.

Bharti, et al, (2020) anticipated the topic Medbot: Conversational Artificial Intelligence Powered Chatbot for Delivering Tele-Health after COVID-19 it focused on telemedicine can be used by the practitioner to cure the patients during the coronavirus outbreak. Without having the physical visit for their treatment in a hospital employing a conversational artificial intelligence-based application. Developing the bot can use a multilingual conversational bot based on Natural Language Processing (NLP) will provide free primary therapy. On the Google Cloud Platform, researchers suggest a conversational Bot called "apka chikitsak" for conveying information. Even after the lockdown, our programme will make it easier for doctors to relieve their workload without having to visit hospitals. Patients can consult and get information in the comfort of their homes.

Khadija, et al., (2021) proposed AI-powered health chatbots: toward a general architecture A chatbot is a conversational or cognitive agent that invigorates human conversation, through text or voice messages. This research provided us with the general architecture four AI-powered health chatbots available. Natural language understanding (NLU) and natural language production were used by the four chatbots (NLG) for communicating with the user. The main part used deep learning for providing solutions to the requests raised by the user. The main four components mentioned in the study are the client platform, the APIs, the NLP Engine, and the core engine.

Mnasri, (2019) focused on Recent advances in conversational NLP: Towards Chatbot Standardization compares the regarding the present state of the art of conversation systems, their categories, and alternative ways to constructing them. Sequence-to-sequence, reinforcement learning, and hybrid approaches. Developing the problem of the natural conversational agent is too complex to be handled in a single model. As was the situation with a lot of issues. When many systems are combined, the results are frequently better than when they are used alone.

Liu, (2021) anticipated the benchmarking of natural language understanding services for building conversational agents. The analysis mentioned about wide coverage evaluation and precision of on a huge, a multi-domain dataset of around 25k user utterances was gathered and evaluated with intent and entity type. NLU services were used. the performance of Watson outperformed. Dialogflow, LUIS, and Rasa were also used and all of the frameworks performed well. This study focused on the evaluation of Watson NLU, Dialogflow, LUIS, and Rasa. The result showed that out of all the given frameworks Rasa gave the best output.

Adellatif, et al. (2021) proposed the comparison of Natural Language Understanding Platforms for Chatbots in Software Engineering. The performance of NLUs in identifying intents, calculating confidence ratings, maintaining stability, and extracting entities was investigated. IBM Watson, Google Dialogflow, Rasa, and Microsoft LUIS were used to evaluate the performance of four major NLUs. The NLUs' performance in intents classification, confidence score, and entity extraction was examined in the study utilising two independent tasks generated from a Repository and Stack Overflow contexts.

3. Methodology

We used Rasa platforms to create a chatbot for Central University of Punjab in this project. The Rasa platform is made up of two primary components: Rasa Core and Rasa NLU. The conversation flow is managed by Rasa Core. The purpose of Rasa NLU is to interpret and categorise intents, as well as extract entities from text inputs. The Rasa Core is a solid performer. This demonstrates how to build a Rasa and Dialogflow chatbot for Central University of Punjab,

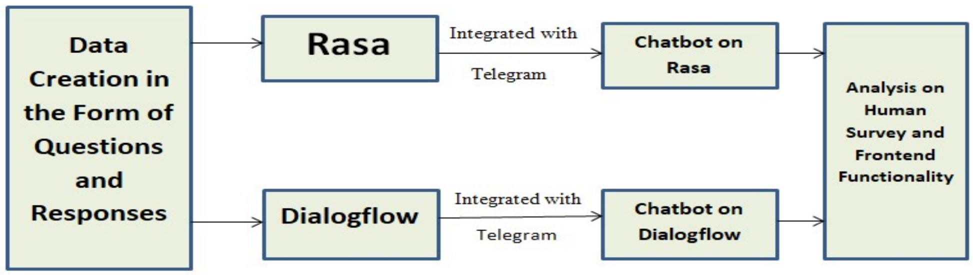

Fig.2. Proposed Work

3.1. Dataset

In Rasa and Dialogflow can make a Knowledge Base chatbot so have to define the data in the rasa template and Dialogflow template. In the Rasa chatbot, manually constructed a dataset with 84 distinct intents, 1324 intent examples 1580 sentence patterns of intents, 371 entities, and 650 stories. Also, constructed the corpus of the conversations for the Dialogflow and RASA. In the Dialogflow constructed he knowledge base chatbot. Development of Artificial Intelligence (AI) based chatbot was developed for university inquiry for handling the FAQs in Central University of Punjab, Bathinda. the implementation of the chatbot using Dialogflow and Rasa, a Natural Language Processing NLP [Kaur and Singh, 2021] module is used to translate students' queries during conversations to structure the data.

In Rasa framework having the dataset in three files nlu.yml, rule.yml, and stories.yml. We have customized the dataset in a suitable format in the Rasa Framework. The main component of the Rasa dataset is nlu.yml. Giving the intents and stories in the yml file. Giving the dataset in the Rasa Framework in the Rasa template and CSV form. In the Dialogflow the dataset is given in the CSV form with a CSV file. Given the dataset in the Dialogflow template like intents and entities.

3.2 Workflow of Rasa

The action server can handle the call to the action, which may acquire the use of various external services. The chat tracker is saved in the tracker storage. External database is used to save tracker objects. Conversation locks are saved in a lock store. To keep the dialogue synchronised, Rasa employs a ticket lock system. Unless otherwise provided, conversation locks, like tracker stores, are saved in memory. Trained models can be accessible via a file system, such as a local hard drive or an HTTP server, or from the cloud (such as AWS).

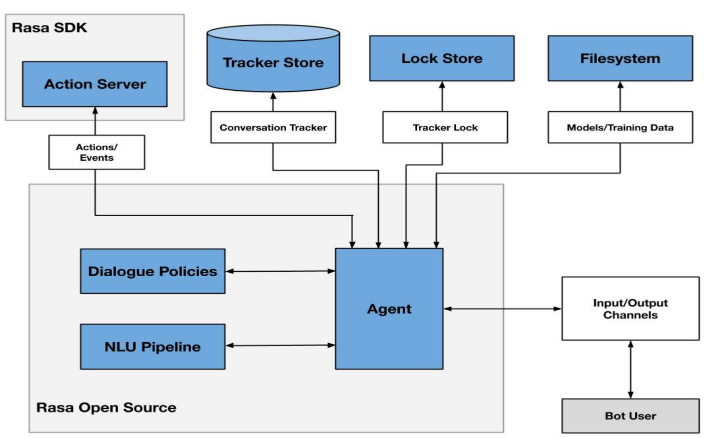

Fig.3. Workflow of Rasa [From Rasa Documentation https://rasa.com/docs/rasa/arch-overview/]

3.3 Workflow of Dialogflow

Agent: Dialogflow converts end-user text or audio into structured data that your apps and services. A Dialogflow agent resembles a human call centre representative.

Intent: Dialogflow matches end-user expressions to the best intent in your agent when they are written or spoken by an end-user. Intent classification is the process of matching intent.

Training phrases: Dialogflow matches the intent when an end-user expression resembles one of these phrases. Because Dialogflow built-in machine learning expands on your list with other, comparable phrases, you don't have to define every possible example.

Action: For each intent, you can provide an action. When an intent is matched, Dialogflow sends an action to your system, which you may use to trigger specific activities in your system.

Parameters: Dialogflow offers the extracted values from the end- user expression as parameters when intent is matched at runtime.

Responses: To return to the end-user, you define text, speech, or graphic answers. These can deliver replies to the end-user, ask for more information, or stop the interaction.

Entities: Entities can be extracted the data from the end user expression.

Contexts: Contexts is similar to natural language contexts. Dialogflow handle an end user expression. It requires providing with context in order to correctly match intent.

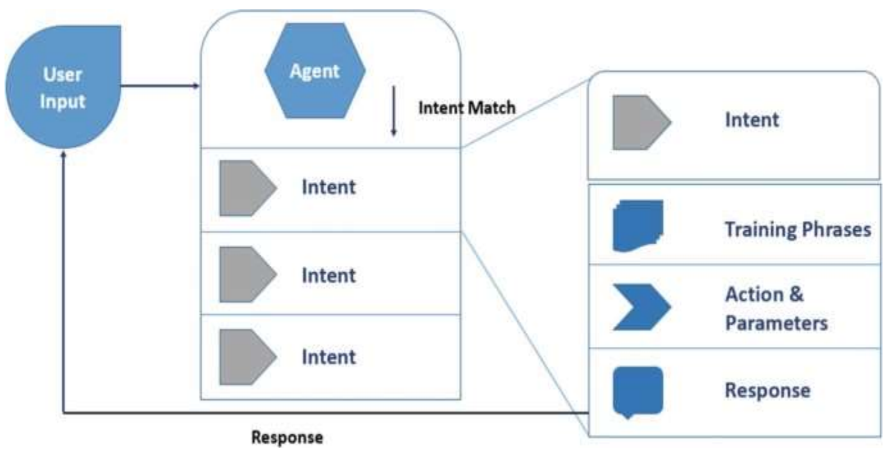

Fig. 4. Workflow of Dialogflow [Sabharwal and Agrawal (2020)]

3.4 DIET Classifier

The Dual Intent and Entity Transformer (DIET) [Astuti, et al., 2021] is a transformer that can handle both intent categorization and entity recognition at the same time, as its name suggests. With Rasa 1.8. DIET's greatest advantage is its adaptability. It allows to such pre-trained embeddings such as BERT, Glove, Convert, and others. As a result, depending on your information and the quantity of training samples, the overall loss is calculated by adding entity, mask, and intent losses together. This is called DIET may be trained to perform all three NLP functions at the same time. By default, mask loss is disabled.

Pipeline

Messages are processed by a series of components in Rasa Open Source. These components are executed in a processing pipeline described in config.yml, one after the other. Customise the model and fine-tune it on your dataset by using an NLU pipeline. There was the word embeddings that have been pre-trained. Pre-trained word embeddings are advantageous since they already contain some linguistic information.

3.5 LSTM

Long short-term memory (LSTM) networks [Egan, et al., 2017] are a type of recurrent neural network that can learn the order in which dependencies in prediction tasks should be learnt. This is a need in a broad range of tasks, including machine translation and speech recognition, to name a few. The LSTMs of deep learning are a difficult issue. LSTM may be used for intent classification.

3.6 BERT

BERT is called as the machine learning framework for the most natural language processing that is open source (NLP). BERT is a program that given the environment to give the meaning words in a text. The BERT framework was trained using Wikipedia text and may be fine-tuned using question and answering datasets. BERT (Bidirectional Encoder Representations from Transformers [Devlin, et al., 2016] s a deep learning model in which every output element may be linked to every input element, and the weightings between them are dynamically interrogated and decided depending on their relationship. The basic model of BERT (uncased). A masked language model (MLM) objective was used to train a model on the English language. I am using BERT in the Rasa configuration.

3.7 RoBERTa

RoBERTa introduced on Facebook, Robustly optimized BERT approach. RoBERTa computation power is more. To improve the training procedure, RoBERTa [Liu, et al., 2019] removes the next sentence prediction Roberta uses 160 GB of text for pretraining. RoBERTa base Using a masked language modelling (MLM) aim, a pre-trained model was applied to the English language. RoBERTa can be used in the Rasa configuration.

4. Results and Discussions:-

4.1 Experimental setup of RASA

In this work, experimented with the dataset. In Rasa dataset includes 84 intents, 1324 intent examples, and 650 stories. As see in the table 1 want to ask about the courses at the Central University of Punjab, Bathinda, send the message what about the courses in the central university of Punjab. The Rasa NLU extracts the necessary data and determines the user's intent "courses." Because dataset had a large number of observations, constructed nlu.yml global train/test split is 80% train, 20% test. To perform k fold cross-validation, the training data was divided into five groups of equal size. Although this cross-validation method is computationally intensive, it produces a model when the dataset is substantial.

Table 1. Intent Example

Intent	Example
Courses	What different courses are offered?
Ask_apply_online	Can I apply online?
Fee Schedule	What are the admission fees?
CUPB	Why is CUPB best?

Once finished requiring the model: how much good the model to assess the effectiveness of each response. Need to categorize comments based on whether they are rational or intelligible, as determined by an independent person. Precision, F1-Score, and accuracy measures will be used to assess the chatbot. When anticipate that an observation belongs to a class when it doesn't, get a false positive (FP). A false negative (FN) is a result in which the model forecasts the negative class inaccurately.

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

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

$$F1 = 2 * (\text{Precision}*\text{Recall}/\text{Precision}+\text{Recall})$$

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

Firstly, using LSTM in the Rasa model the metrics can be defined and predicted the actions. The intent classification is evaluated by F1-Score, accuracy, and precision.

Table.2. Intent Classification

Metric	Score
F1-Score	85.2
Accuracy	85.2
Precision	86.3

Use the DIET classifier for the Intent Classification and the Entity recognition. The Intent Classification is evaluated by F1-Score, accuracy, and precision using cross-validation using DIET Classifier.

Table.3. Intent Classification

Metric	Score
F1-Score	97.1
Accuracy	97.4
Precision	97.2

Compared three different pipeline 4 configurations: an original configuration, a light configuration, and a heavy configuration using the Bert model and RoBERTa model.

Table.4. Configuration

Configuration	**Accuracy**	**Precision**	**F1-Score**
Original Configuration	94.9	94.3	94.4
Diet-Light Configuration	95.3	94.7	94.7
Diet-Heavy Configuration using Bert	97.4	97.1	97.2
Diet-Heavy Configuration Using RoBERTa	95.6	95.2	95.6

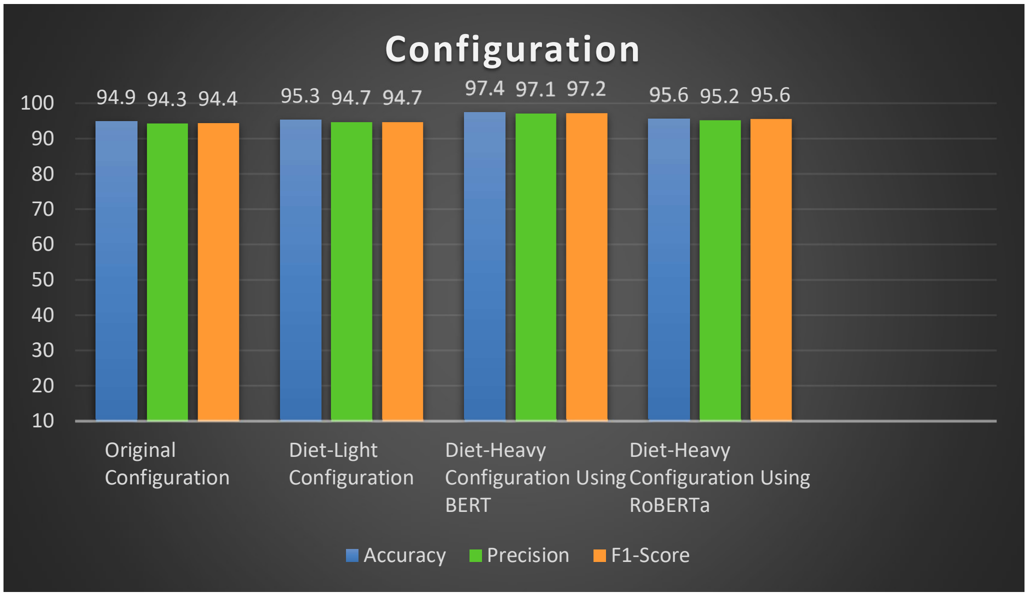

Fig.5. Configuration

4.2 Some screenshots of the Rasa Framework Chatbot

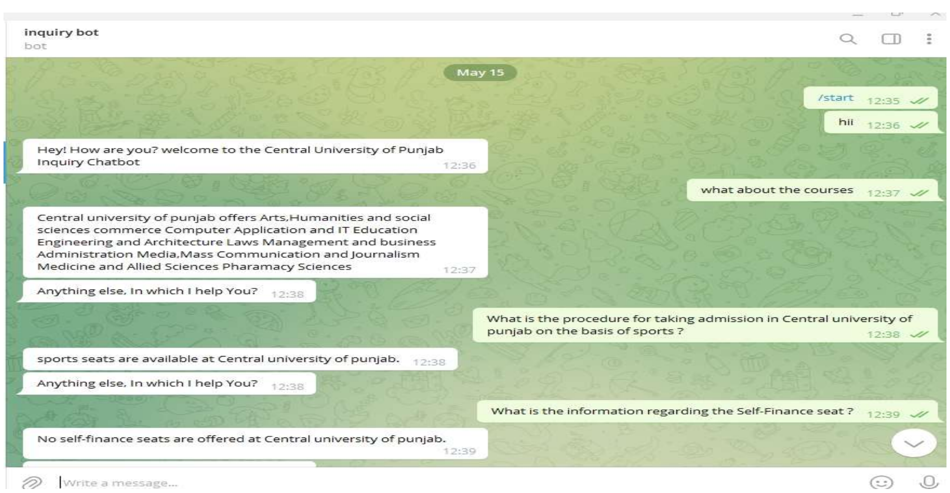

Fig.6. Chatbot of Rasa

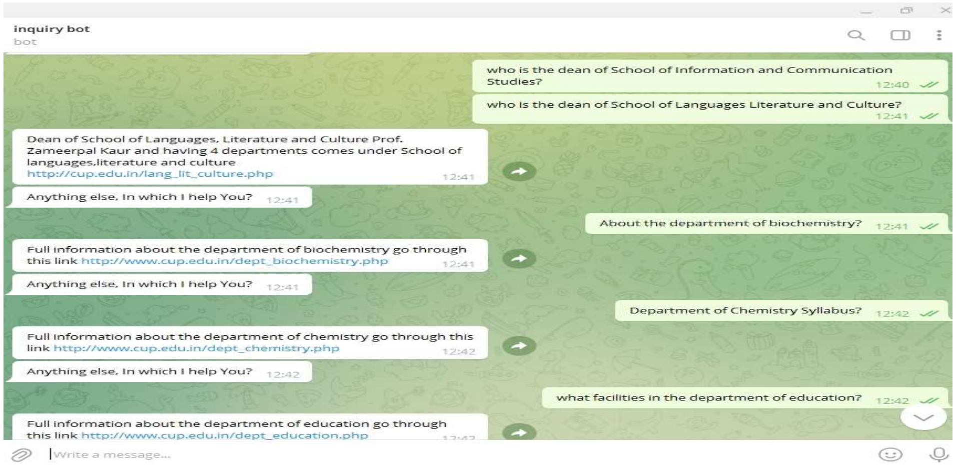

Fig .7. Chatbot of Rasa

4.4 Experimental Setup of Dialogflow

In this work experimented the same dataset on Dialogflow with 84 intents 1324 intent examples. This procedure was repeated for the second time. In the Dialogflow we have to put the intent and entities. In the Dialogflow constructed the knowledge base chatbot. AI based chatbot was developed under dialogflow framework. The chatbot was designed for handling CUPB university inquiries and fAQs. For the implementation of the chatbot using agent trained in the DialogFlow NLU. The Agent Training has completed then the agent was ready to talk. When working with Dialogflow, after providing it with data, it gives us the results in the form of Intent Detection Confidence and Match Confidence. In experimental phase we provide Central University of Punjab dataset. Here are some queries results in table.5

Table.5 Dialogflow Results

Query	Intent Detection Confidence	Match Confidence
Hii	97.4	97.3
What different courses are offered in Central University of Punjab?	92.8	91.1
What does the academic year ends?	96.4	96.4
Location of Central University of Punjab?	96.3	96.3
What is the merit required for M.A?	80.3	80.3
Is cafeteria available in Central University of Punjab?	96.1	96.1

4.5 Some Screenshots of Dialogflow Chatbot.

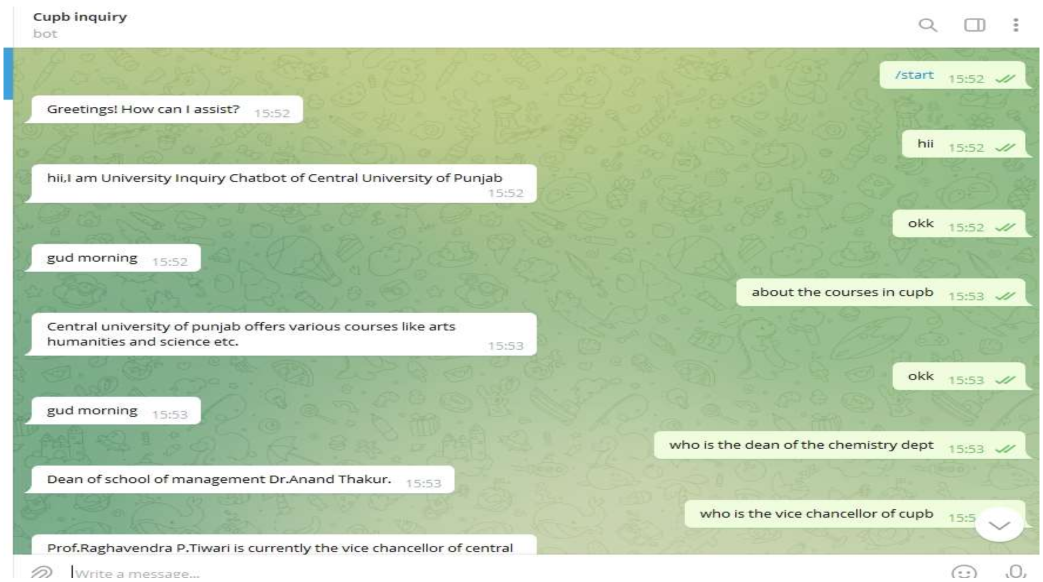

Fig. 8. Chatbot of Dialogflow

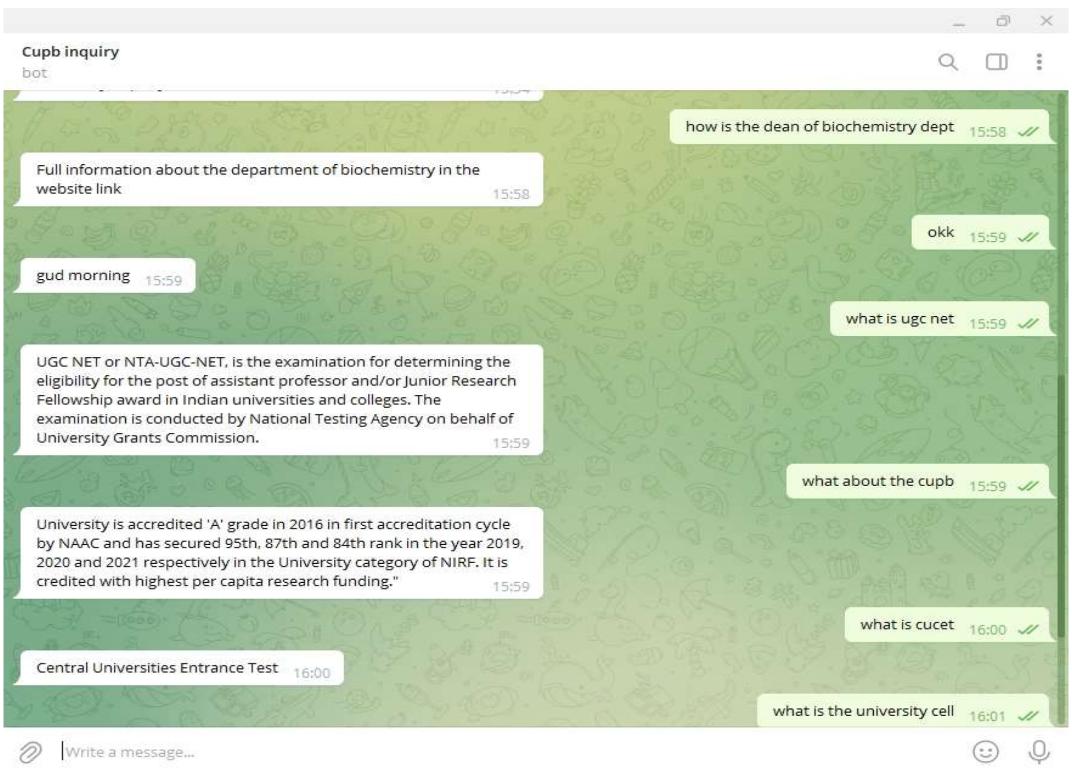

Fig.9. Chatbot of Dialogflow

4.6 Analysis of Rasa and Dialogflow

Analysis through human survey

The integration of the chatbot was done on social network application called telegram. Both the chatbots built under rasa and dialogflow framework were integrated on telegram for the efficiency analysis. Compared the

Rasa and Dialogflow. One of the objectives of this research was to analyse the effectiveness of both the chatbots. Integrate the chatbot in the telegram and surveyed it, around 100 students of the university used the chatbots, 63% of people found the RASA to be an effective chatbot and 37% of people found Dialogflow effective. The Chatbot has brought about several benefits without any human intervention. Inquiry chatbot to the university, especially the Central University of Punjab, Bathinda.

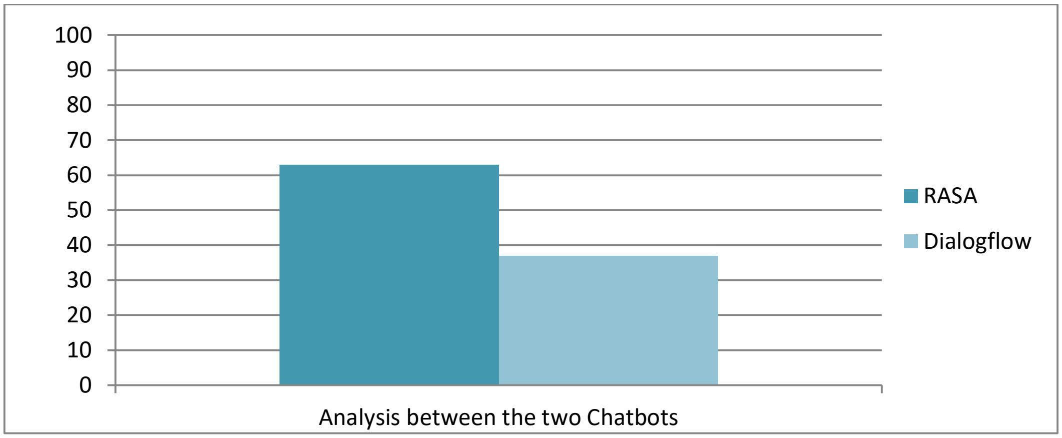

Fig.10. Effectiveness of two chatbots

Analysis through frontend work

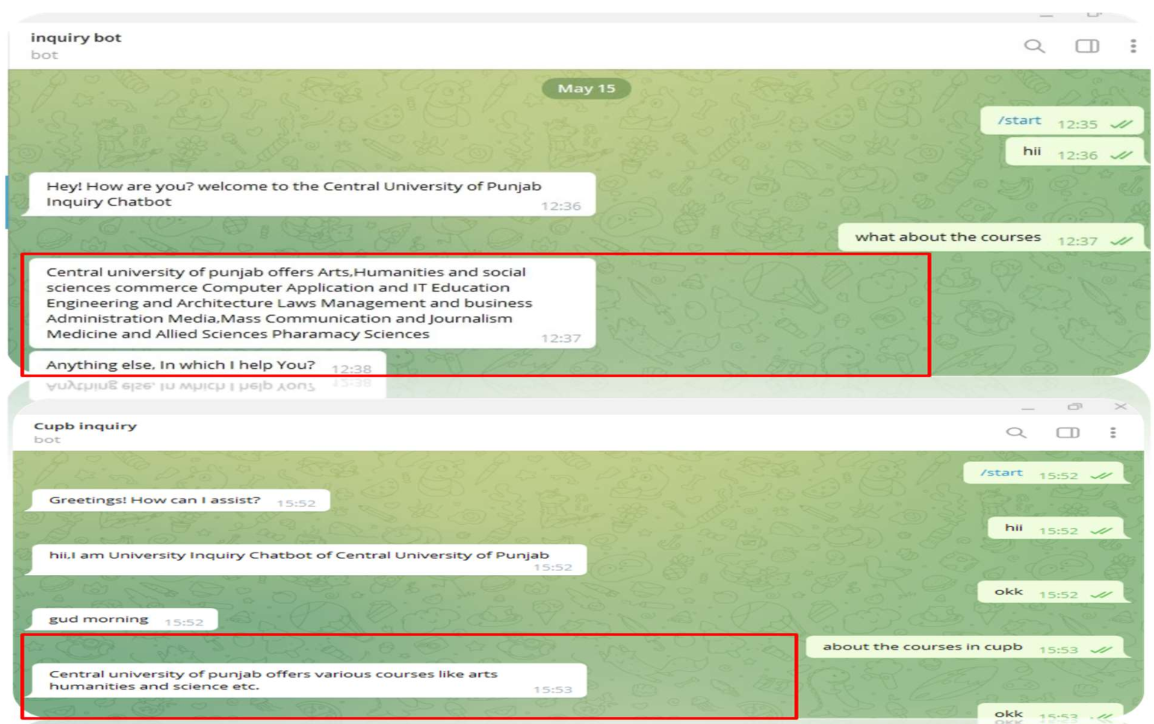

Fig. 11. Comparison of Chatbot

In this Fig.11the two chatbots screenshots are there one is Dialogflow and another one is Dialogflow. See the Screenshot and analyse the query. In RASA the query is “what about the courses “the bot will reply correctly with greet. In Dialogflow try the same query and see the response. The Dialogflow bot will never gave the response properly.

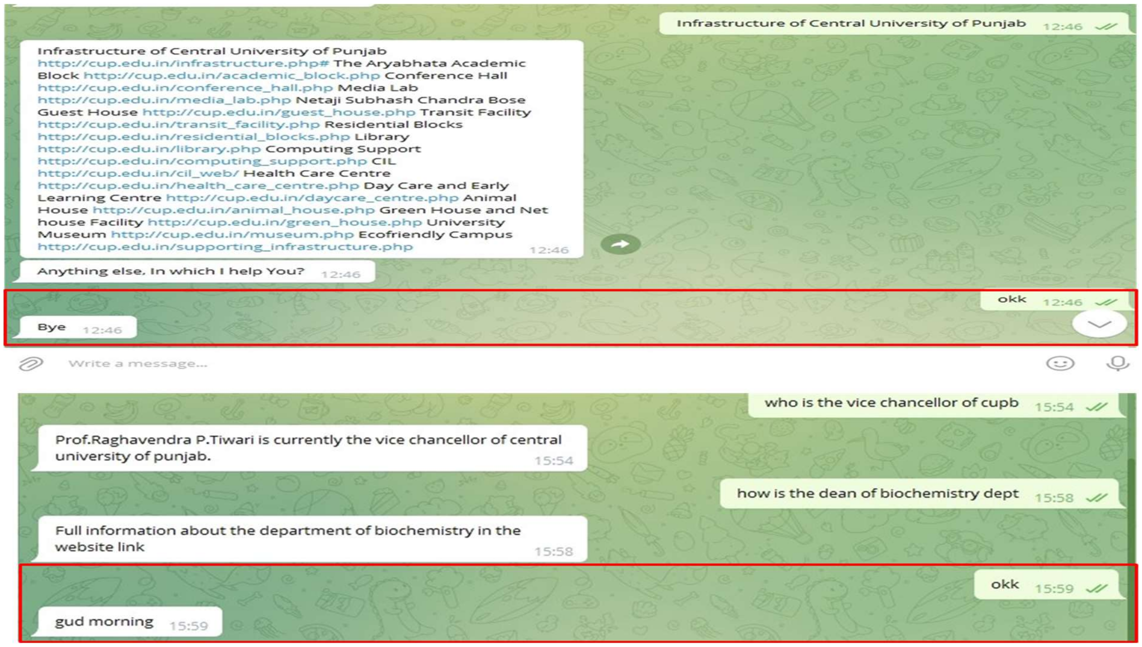

Fig.12. Comparison of Chatbot

In this fig.12 the two chatbots screenshots are there one is Dialogflow and another one is Dialogflow. See the Screenshot and analyse the query. In RASA the query is "okk "the bot will reply correctly with response bye. In Dialogflow try the same query and see the response. The Dialogflow bot will never gave the response properly and correctly.

5. Conclusion

Effective Analysis of Chatbot Framework: Rasa and Dialogflow. This Framework can develop the chatbot. The Knowledge domain of our chatbot is about the Central University of Punjab, Bathinda. Analysis of both the chatbot frameworks which one is more customizable. Using the right setup the dialogue management may very effectively accomplish the work of intent extraction and user interaction in the discussion. Using this chatbot will not only benefit the student to get the knowledge about the Central University of Punjab, Bathinda. Use another huge dataset in the Rasa and Dialogflow give the better accuracy.

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