https://doi.org/10.26682/sjuod.2023.26.2.52

Journal of University of Duhok., Vol. 26, No.2 (Pure and Engineering Sciences), Pp 578 - 587, 2023
(Special Issue)

CHATBOT-BASED TOURIST GUIDE USING ARTIFICIAL INTELLIGENCE MARKUP LANGUAGE

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(Accepted for Publication: November 27, 2023)

ABSTRACT

The tourism industry heavily relies on effective communication, guidance, and assistance to ensure a positive experience for travelers. With the advent of technology, chatbots have emerged as a popular solution for providing aid and direction to tourists. This research paper presents a comprehensive exploration of the design and implementation of a cutting-edge chatbot tailored for tourist guidance, leveraging the power of Artificial Intelligence Markup Language (AIML). The case study focuses on Sulaimani City, wherein a robust dataset comprising 352 meticulously crafted questions and corresponding answers was curated. The developed chatbot model was then seamlessly integrated and deployed on a dedicated test website, enabling real users to interact and engage with it. To gauge the efficacy of the model, a multifaceted evaluation encompassing user satisfaction, accuracy, and response type was conducted. The results unequivocally demonstrate that the AIML-based chatbot surpassed the performance of traditional web-based tourist guides, achieving higher levels of user satisfaction. However, one notable limitation of this research is the use of a small-scale dataset, potentially affecting the chatbot's real-world performance and generalizability. This pioneering research underscores the immense potential of chatbot technology as an indispensable tool for delivering comprehensive and reliable tourist information, thereby revolutionizing the tourism industry.

KEYWORDS: Chatbot, Rule-Based, AIML, Tourist Guide

1. INTRODUCTION

Tourism is an industry that relies heavily on communication, guidance, and support. With the advancement of technology, chatbots have become a popular solution for providing assistance and guidance to tourists [1]. Chatbots are computer programs that can simulate conversation with humans using natural languagae processing (NLP) and machine learning algorithms [2]. These chatbots can be designed to answer queries, provide recommendations, and offer personalized experiences to users.

One of the most promising developments in this field is the use of Artificial Intelligence Markup Language (AIML) to create chatbots for close-domain such as tourist guides. AIML is an XML-based markup language that is used to create chatbots that can understand and respond to natural language queries [3]. With AIML, sophisticated chatbots can be created that can interpret complex questions and provide accurate answers.

In this context, a chatbot-based tourist guide using AIML can help tourists plan their trips, find information about destinations, and get recommendations on attractions, restaurants, and events. Such chatbots can also provide real-time assistance and support to tourists during their travels. The use of AIML can enable chatbots to understand and respond to natural language queries, making it easier for tourists to communicate and interact with them.

Chatbot-based tourist guide has the potential to enhance the overall tourist experience, making it easier for travelers to navigate new places, discover hidden gems, and make the most out of their trips. The proposed chatbot offers details about Sulaimani City, such as accommodations, dining places, cultural sites like museums,

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recreational spots like parks, shopping centers, and other places worth visiting.

The structure of the remaining parts of this paper is as follows: Section 2 displays a review of some related works, Section 3 presents information about the theoretical backgrounds, and Section 4 discusses the methodology used. The results and findings of the research are outlined in Section 5, while the limitations are summarized in Section 6. Lastly, Section 7 concludes the research.

2. Related Work

This part provides a brief overview of some of the related studies. [4] discusses the use of chatbots in tourism and proposes a mobile application called "Smart Guidance" to provide a natural language interface for users to navigate a city and plan their trips. The chatbot was evaluated in Jeddah, Saudi Arabia, and found to be effective and engaging for users. [5] explores the use of chatbots in cultural heritage, and explains the process of programming a chatbot using machine learning, deep learning, and semantic web technologies while discussing the challenges involved. [6] highlights the importance of tourism and introduces AIRA, an AI tool developed to enhance customer service for AirAsia Berhad. AIRA gathers the latest information to provide efficient and user-friendly service and has a simple GUI with high efficiency. It aims to improve the quality of customer service and entertain travelers. [7] presents a recommender system that uses a chatbot to suggest tourist routes for cultural sites in Campania, Southern Italy, based on the user's profile and context. The system aims to enhance cultural heritage and meet the needs of various users. [8] created a web-based Chatbot app using Random Forest (RF) algorithm and Rapid Automatic Keyword Extraction (RAKE) for virtual tour guiding in Bandung, Indonesia. The model was evaluated with a dataset of 192 questions, achieving an average accuracy of 98% and precision and recall of 96%. [9] propose a chatbot for e-tourism that uses model-based reasoning to enhance the user experience and allow them to book hotels, plan trips, and ask for interesting sights. It provides a use case from the tourism domain to demonstrate its effectiveness. [10] discusses improving tourism in Mauritius by developing a chatbot using off-the-shelf technologies like Rasa and Telegram. The chatbot provides information and recommendations to tourists, with innovative features like Google search and weather acquisition based on location and COVID-19 statistics. [11] presents a Neo4J database for tourism information and a knowledge base created from over 1300 Jeju tourism data. The authors plan to develop a multilingual smart tour chatbot using named entity recognition, intention classification, and transfer learning. [12] presents the creation of Korean and English smart tourism Name Entity datasets and their use in training a NER model for a tourism chatbot system. The model achieved high precision, recall, and f1 scores on both datasets. The model was trained on the developed datasets, and the precision, recall, and f1 scores were found to be 0.94, 0.92, and 0.94 for both Korean and English datasets. [13] Proposed a speech-based virtual tour guide that suggests places provides information, and interacts with users. It is designed for use while driving or in situations where texting is inconvenient. Utilizes speech recognition and natural language techniques and has been found to be efficient in recognizing user queries. [14] discusses using chatbots as virtual tour guides in the travel and tourism industry, particularly in Italy and India. The goal is to boost tourism, generate revenue for hotels and airlines, and provide customized experiences for each tourist using NLP technology. The main limitation of the studies that were analyzed is the absence of information regarding the method used to collect data, the quantity of data that was utilized to train the chatbot, and the criteria used to evaluate the effectiveness of the model. In their work, [15] presents a methodology that offers a significant advancement in the creation of chatbots for museums, enabling them to guide users through carefully prepared itineraries corresponding to exhibit stories and conveying specific messages. This approach addresses the limitations of existing methods that focus solely on exhibits, lack proper user guidance, and provide only a single navigation path. By overcoming these limitations, the proposed methodology enhances the user experience and engagement during museum visits. In their viewpoint paper, the authors of [16] discuss ChatGPT's explosive interest since OpenAI's GPT-3 prototype launch in November 2022. They highlight its disruptive potential for digital transformation and offer preliminary guidelines for adopting ChatGPT in the tourism field. in another effort, [17] introduces a novel framework that integrates intangible and tangible cultural objects into a unified data model, aimed at enhancing tourists' journeys. The framework utilizes a Micro-service architecture, offering various services accessible to tourists through a conversational agent based on the Seq2Seq model. These crucial details could have influenced the reliability and generalizability of the findings. In addition, the methods in the related works primarily relied on machine learning approaches. As [1] indicates, machine learning-based chatbots demand substantial computational power and vast volumes of online data, making them infeasible for many problems, especially in low-resource scenarios like creating a touring guide for a specific area or city. In this context, our rule-based solution using AIML proves to be advantageous, requiring less computational power and a limited dataset. Based on this viewpoint, we confidently assert that our approach surpasses the existing literature, as our findings indicated a high level of user satisfaction with the proposed model.

2. BACKGROUNDS

In this section of the research, the theoretical backgrounds related to Chatbots, including chatbot models, and AIML, are discussed in detail.

3.1Chatbots

Chatbots are computer programs designed to simulate conversation with human users through text or voice interfaces. The history of chatbots can be traced back to the 1960s when ELIZA, a computer program designed to mimic a psychotherapist, was created by Joseph Weizenbaum [18]. ELIZA was able to understand and respond to certain types of natural language inputs by using pattern recognition and substitution techniques. It was considered a breakthrough in computer science and led to further research in the field of conversational agents. In the 1990s, chatbots became more prevalent with the rise of the internet and instant messaging platforms. Some of the earliest chatbots were SmarterChild, created by ActiveBuddy, and ALICE (Artificial Linguistic Internet Computer Entity), created by Dr. Richard Wallace [19]. These chatbots were primarily used for entertainment purposes and could answer basic questions.

With the advent of smartphones and messaging apps, chatbots became even more ubiquitous. Companies began to use chatbots as a means of providing customer service, with many major brands, including Apple, Microsoft, and Amazon, developing their own chatbots. Chatbots have also been used in healthcare, education, and finance, among other fields.

3.2 Chatbot Models

Based on their underlying architecture or approach, chatbot models can be classified as Rule-based, Retrieval-based, and Generative chatbots (Figure-1). Rule-based chatbots follow a pre-defined set of rules and are designed to respond to specific keywords or phrases; Retrieval-based chatbots use a combination of predefined responses and machine learning algorithms to select the best response to a user's input. They work by matching the user's input to a database of pre-existing responses; Generative chatbots use deep learning techniques like neural networks to generate responses from scratch [2]. The utilization of AIML, a rule-based technique, was deemed appropriate for close-domain and task-oriented problems, as evidenced by this work.

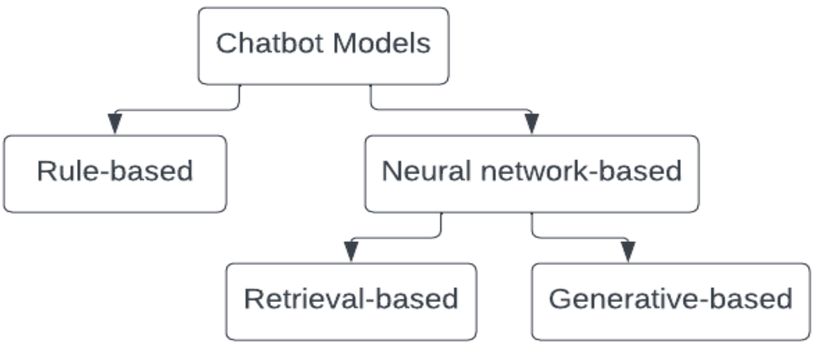

Fig.(1):- Chatbot Models Classification

3.3 AIML

Artificial Intelligence Markup Language (AIML) is a widely used programming language for creating chatbots and virtual assistants. It is an XML-based language that uses pattern matching and natural language processing techniques to simulate conversation with human users.

AIML was first developed in the late 1990s by Dr. Richard Wallace as a way to create a chatbot named ALICE (Artificial Linguistic Internet Computer Entity). The development of ALICE was motivated by the desire to create a program that could simulate natural language conversation and provide assistance to users on the internet [3].

AIML is based on a set of predefined templates that are used to define the rules and patterns for creating chatbots. These templates are called AIML categories, and they contain information on how the chatbot should respond to specific user inputs [20].

One of the key features of AIML is its ability to handle variations in user input. The language uses a pattern-matching algorithm that allows chatbots to recognize variations in user input and respond accordingly. For example, if a user asks a chatbot "What is the weather like today?", the chatbot can respond with information on the current weather conditions in the user's location. The common and basic tags used in AIML are described in Table-1.

Table(1):- AIML Tags

Tags	Description
<aiml>	Refers to the starting and ending of the AIML file.
<category>	A category is the fundamental building block of knowledge. Every category consists of both an input pattern and a response template.
<pattern>	matches or specifies the pattern to what the user says.
<template>	contains a response to the user's message.
<random>	provide a variety of different responses to a single user's query randomly.
<srai>	This tag can be used for more than one purpose; it can tell the bot to look for another corresponding category and output its response; unnecessary words can be removed via <srai> tag from the user's input; it can be used with wildcards to define synonymous.
<that>	It is used to make a context which means being able to remember the things that have been previously said.
<learn>	This tag lets the bot to learn new things from the user.

4.METHODOLOGY

This section outlines the procedures and techniques utilized to collect, analyze, and interpret data for the research study. The methodology comprises eight related steps (Figure 2):

data collection: Data has been gathered on Sulaimani city, which includes information on popular hotels, restaurants, shopping centers, museums, and tourist destinations.

data preparation: The data that has been gathered is structured in sets of questions and answers, and is stored in AIML files.

prototype creation: The initial model is established by making use of the AIML files that have been generated.

deploy prototype: The prototype that was made has been deployed on a website that is hosted locally.

user interaction: The deployed bot was engaged with by the users.

update prototype: The prototype undergoes review and modification based on the feedback and engagement from users.

deploy final model: The final version of the model is once again released for users to employ.

user feedback: after deploying the bot and utilizing it by the users, feedback was gathered to assess teir level of user satisfaction, usability, and user engagement.

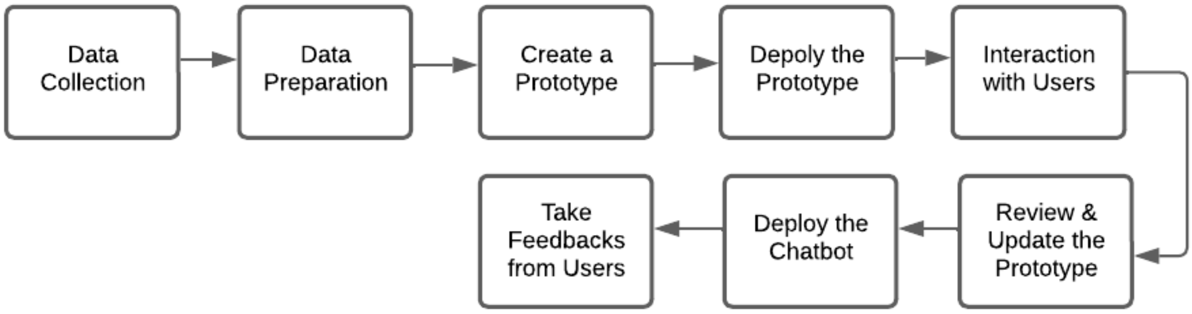

Fig.(2):- Model Flow Diagram

4.1.Data Collection

Since there isn't a comprehensive dataset or tourist guide for Sulaimany City, we had collected information manually from various sources such as hotel, restaurant, and shopping mall websites as well as other tourist attractions. We also utilized documents provided by the General Directorate of Sulaimani Tourism. The information we collected has been saved in a text file in a question-and-answer format, and it consists of 352 question-and-answer pairs. The answers are comprised of text, links, and maps generated through the Google Maps API. From the data that was collected in the dataset, five distinct AIML files were generated, namely hotels.aiml, restaurants.aiml, mall.aimls, museums.aiml, and parks.aiml. each file contains the required related categories. There are a total of 511 categories across all AIML files.

4.2 Implementation

This sub-section presents the detailed implementation of AIML.

4.2.1 Input preprocessing

Normalization is a feature of the AIML bot that involves correcting certain spelling errors made by users, such as changing "wanna" to "want to" and ":-)" to "smile". In addition to correcting spelling errors, the AIML bot's normalization feature divides sentence into segments using specific punctuation marks such as "!", ".", and "?". After splitting the sentences, the bot eliminates these punctuation marks, resulting in text input that is free of punctuation.

4.2.2 Pattern matching

The bot will scan its entire set of categories to find a corresponding match for the user's input. To prepare the input for processing, any punctuation marks are removed by the input pre-processor. So, it's important to avoid using punctuation marks in all patterns.

4.2.3 Ultimate default category (UDC)

If the bot is unable to find an appropriate category to match a query, it will utilize the Ultimate Default Category (UDC) to give a response. In such cases, the asterisk symbol is utilized to match any undefined category, here is an example of UDC:

```
<category>
<pattern>*</pattern>
<template>Sorry, I have no response to your query. </template>
</category>
```

4.2.4 Randomized responses

The <random> tag can be utilized to generate multiple responses for a given input pattern, which is particularly advantageous in the UDC as it can offer some diversity to the default response.

4.2.5 Wildcards

Using a single category, wildcards can capture a multitude of inputs. AIML utilizes four different wildcards, The * symbol has the capability to catch one or more words that are entered by the user; The symbol "^" functions as a wildcard too, but it has the ability to match zero or more words; The underscore (_) wildcard represents "1 or more" like the asterisk wildcard (*), while the hashtag wildcard (#) represents "0 or more" like the caret wildcard (^).

4.2.6 Variables

AIML offers three distinct types of variables for storing data: Properties, which are global constants that can only be modified by the botmaster; Predicates, which are global variables that are usually set by the client during a conversation when a template is activated; and Local Variables, which are essentially the same as predicates except they have a restricted scope limited to a single category.

4.2.7 Recursion

AIML offers the option of creating a template that refers to another category, providing several advantages such as reducing input length, grouping similar inputs, fixing the client's spelling mistakes, replacing informal language with formal language, and eliminating unnecessary words from the input. Here is a simple example of recursion:

```
<category>
<pattern>HELLO</pattern>
<template><srai>HI</srai></template>
</category>
```

Recursion is implemented through <srai> tag. Here, If the input "Hello" corresponds with a certain category, the bot will initiate a recursive function. Prior to outputting any text, it will search for another category that matches "HI".

4.2.8 Context

Context refers to the ability of bots to recall information that has been previously discussed during a conversation. The <that> tag is utilized to establish context, and it is positioned between the pattern and template. This tag enables the bot to recall the previous sentence it said. Here is an example regarding context:

```
<category>
<pattern>^ HOTEL ^</pattern>
<template>Do you need a hotel? </template>
</category>

<category>
```

<pattern>YES</pattern>
<that>DO YOU NEED A HOTEL</that>
<template>Do you prefer an expensive or a cheap one? </template>
</category>

If the user's input contains the "HOTEL" keyword, the bot asks the user "Do you need a hotel?", if the user's answer is "YES", the bot remembers the previous sentence said and again asks the user "Do you prefer an expensive or a cheap one?", and this is called a context.

4.2.9 Rich media tags

AIML offers an extensive variety of multimedia tags that aid in displaying information in a more appealing manner. A few examples of these tags include Buttons, Links, Images, Videos, Cards, and Carousels. Figure 3 illustrate an example of using multimedia tags:

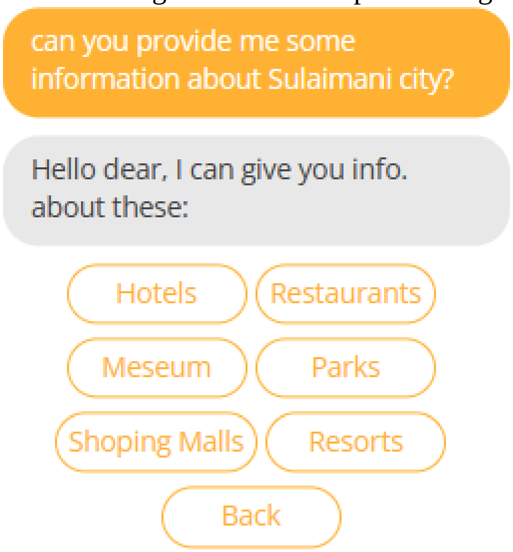

Fig.(3):- Multimedia tags

4.3. Patter Matching Algorithm

However, while AIML primarily relies on a string-matching technique to identify suitable patterns, it does incorporate certain concepts that exhibit elements of artificial intelligence. For instance, the use of context tags allows the chatbot to recall previous user interactions, enhancing its ability to maintain contextual awareness during conversations. Additionally, the inclusion of different wildcards enables the bot to capture and respond to various user queries effectively. Furthermore, AIML features a 'learn' tag that allows the chatbot to acquire new information from user inputs, facilitating incremental learning. Though these AI-related components enhance the bot's performance, it is essential to emphasize that the core of AIML remains rooted in rule-based pattern matching. Figure 4 illustrates the workflow of the approach utilized by our proposed bot.

1) Preprocessing: Before comparing the user input to patterns, the input is usually preprocessed to remove any irrelevant characters, punctuation, or special symbols. The text is converted to lowercase to make the matching case-insensitive.

2) Pattern Matching: Once the input is preprocessed, the chatbot goes through its database of AIML categories and checks each category's pattern to see if it matches the user's preprocessed input. The matching is usually done on a one-to-one basis, meaning the entire input should match the pattern exactly.

3) Selecting the Best Match: If multiple AIML categories have patterns that match the user input, the chatbot may prioritize them based on predefined rules. For example, the chatbot might consider the category with the highest priority, the most recent interaction, or other context-specific criteria.

4) Generating Response: Once the best-matching pattern is identified, the chatbot uses the corresponding template from that category to generate the response. The template may contain placeholders or variables that are filled with specific information from the user input, making the response more personalized.

5) Sending Response: Finally, the chatbot sends the generated response back to the user.

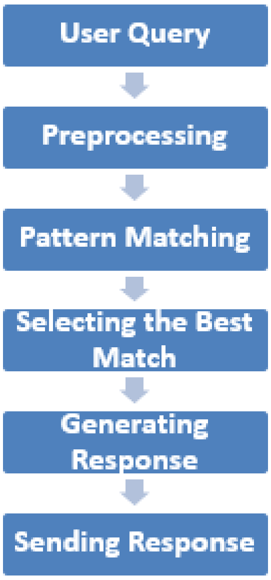

Fig.(4):-: Pattern Matching Algorithm Workflow

4.4 Evaluation

Once the model has been created and executed, its effectiveness has been measured through an assessment process. Generally, the evaluation is divided into two types: automatic and manual [21]. Despite the lack of a specific automated metric for evaluating chatbots, machine translation automatic tools, such as BLEU, METEOR, and ROUGH, can be utilized instead. Regarding manual evaluation, there is no standard framework to be followed. The proposed model has been evaluated manually based on some factors such as user satisfaction, accuracy, error rate, and response type.

5. RESULT AND ANALYSIS

After developing and putting the preliminary version on a trial website, 23 individuals engaged with it. Table-2 outlines the queries made by the users when using the prototype. Accuracy is determined by taking the number of accurate queries and dividing it by the total number of queries asked. Overall, the users made 109 queries across various subjects within the dataset. The bot performed best (with 76.1% accuracy) in responding to greeting-related queries and performed worst (with 17.6% accuracy) in responding to cross-domain queries (queries that fall outside the dataset's scope).

Table(2):-: Accuracy scores for the prototype.

Topics	No. of queries	Score
Greeting	21	16/21 = 76.1%
Hotel	18	11/18 = 61.1 %
Restaurant	19	10/19 = 52.6 %
Park	11	6/11 = 54.5 %
Museum	6	4/6 = 66.6 %
other	34	6/34 =17.6 %
Overall queries including cross-domain	109	53/124 = 48.6 %
Overall queries excluding cross-domain	75	47/75 = 62.6 %

After revising all the conversations between the prototype and the users, the knowledgebase has been updated in such a way that all required categories have been added to bridge the gaps found in the prototype. Once the modifications were completed, the bot was deployed as final production. To observe the result of the modifications, 30 users were asked to utilize the bot. Revising the interactions made with the prototype led to adding two new topics, shopping mall and resort that asked by some of the users. Table-3 presents a summary of the improvements that were identified during the conversations conducted with the final product, these enhancements were observed in various topics, such as greetings, hotels, restaurants, and parks by 6, 10.3, 8.5, and 6.3 points, respectively. The only subject that experienced a decrease of 6.6 points after the modifications was the Museum topic.

Table(3):- Accuracy scores for the bot.

Topics	No. of queries	Score
Greeting	84	69/84 = 82.1%
Hotel	42	30/42 = 71.4 %
Restaurant	54	33/54 = 61.1 %
Park	23	14/23 = 60.8 %
Museum	10	6/10 = 60.0 %
Shopping mall	37	26/37 = 70.2 %
Resort	20	15/20 = 75.0 %
other	68	19/68 = 27.9 %
Overall queries including cross-domain	338	212/338 = 62.7 %
Overall queries excluding cross-domain	270	193/270 = 71.4 %

The proposed model has been evaluated for user satisfaction by asking the three questions listed in Table-4 to all 30 users who interacted with the bot. The results of the survey, which are displayed in Table-4, indicate the satisfaction scores of the users.

Table(4):- User satisfaction scores

Queries	Score (out of 10)
Could you rate your level of satisfaction with the chatbot?	7.16
To what extent the chatbot had a human-like conversation?	6.22
could you prefer chatbot-based over traditional tourist guides?	7.65
Overall score	7.01

Regarding the response types, Precision, Recall, and F-score have been utilized. precision measures the quality of positive predictions, recall measures the coverage of positive instances, and the F-score is a combination of precision and recall that is useful when both metrics are important. The formulas for calculating Precision, Recall, and F-Measure were applied using the responses presented in Table-5.

$$Precision = \frac{\text{True Positives}}{True\ Positives + False\ Positives} \quad (1)$$

$$Recall = \frac{\text{True Positives}}{True\ Positives + False\ Negative} \quad (2)$$

$$F - score = \frac{1}{\frac{\beta}{precision} + \frac{\beta}{recall}} \quad (3)$$

Table(5):- Response types

Response type	Description
True Positive	The chatbot provided a correct response to the user's correct message.
False Positive	The chatbot provided an incorrect response to the user's correct message.
True Negative	The chatbot provided a correct response to the user's incorrect message.

False Negative	The chatbot provided incorrect response to the user's incorrect message.

Table(6):- Precision, Recall, and F-measure scores

Response type	No. of responses
True Positive	161
False Positive	102
True Negative	43
False Negative	32
Precision	0.612
Recall	0.834
F-score	0.674

6. LIMITATIONS

Limitations were identified after creating and executing the model. These limitations can be condensed into a few key points. Firstly, One notable limitation of this research is the usage of a small-scale dataset, which may restrict the full potential and generalizability of the chatbot's performance in real-world scenarios.. Secondly, the proposed model should be integrated into a real website to allow it to interact with a larger number of users and tackle more complex queries. Thirdly, additional functionality needs to be added for cross-domain questions as the model was unsuccessful in answering these. Currently, the knowledgebase needs to be monitored and updated manually, this additional functionality can forward any cross-domain questions to the admin and return the response back to the user.

7. CONCLUSION AND FUTURE WORKS

This work aimed to facilitate tourist guiding through an automatic tool named chatbots. A rule-based approach called AIML was chosen to implement the chatbot as it's a good promise for close-domain problems. The model has been set in a test website to be available for the users to interact with. To identify its effectiveness, the model has been evaluated based on user satisfaction, accuracy, task completion rate, and response type factors. The findings indicated that the proposed model received a high level of user satisfaction compared to traditional web-based tourist guides. In the future, addressing the limitation of the limited-size dataset can be achieved through extensive data collection efforts, data augmentation techniques, and transfer learning approaches. These steps will enable the development of more robust and effective chatbot-based tourist guide systems with broader real-world applicability. A hybrid approach that combines both rule-based and generative approaches could be used to create more advanced chatbots. Additionally, voice functionality could be integrated into the chatbot.

Acknowledgements

We express our gratitude for the collaboration of the Sulaimani Tourism General Directorate in supplying us with information regarding the city of Sulaimani.

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