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A Smart Advisor for Pregnancy Healthcare Using Chatbot Approach Based on Decision Tree Methods

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***Abstract*—With the technological progress in the current era, artificial intelligence has gained significant popularity in all applicable fields. Indeed, one of these important fields is automated chat systems or so-called smart conversation chatbots. In this study, we introduce a mobile application for automated chat with pregnant women. We have employed this technology in providing a healthcare assistant. As bringing a new life into the world is the wish of every mother, it proposed health care system helps the pregnant mother by discussing some symptoms with the pregnant mother, diagnosing diseases, and predicting the mode of delivery. It is used for providing guidance regarding nutrition, healthy exercises, safe medications, and many different functions pregnant mother needs. The proposed chatbot system is not based only on rules, rather, it has been built based on the machine learning (ML) method; i.e., decision trees (DT) model. ML methods help process user inputs, which are not previously entered during training, and then answer them in a good level of correctness. Besides, the system overcomes most spelling and linguistic errors, accepts words with diacritics, and many other features. After training the smart advisor several times, it was tested by introducing several different conversational formulas. The evaluation accuracy results reached 85.45%.**

***Keywords*: —Healthcare System; Chatbot Technology; RASA; Pregnant Mother Healthcare; Machine Learning; NLP; Decision Tree (DT); Random Tree DT; J48 DT.**

I. INTRODUCTION

Recently, artificial intelligence (AI) has developed the healthcare fields through a qualitative shift that has affected diagnostic techniques, drug discovery, health analyses, etc. With time, some services have become managed automatically through new and innovative technologies, including “chat bot” technology. Chatbot technology has gained popularity over the years and can be seen on several websites. Business companies for customer support and other services are increasingly using chatbots. Of course, with the presence of artificial intelligence, we expect the chatbot to be developed rapidly over the coming years [1] [2].

Chatbot is a kind of simulation that can understand human language, process it, and interact with humans to perform several tasks. For example, a chatbot can be used as an executive for help and consulting offices. According to our knowledge, the first known chatbot was named (Elisa), and it was proposed by Joseph Weizenbau in 1966 [1]. Some studies consider the idea of chatbots started after Alan Turing published his rules about distinguishing between AI systems against human-based systems. As time passed, conversations with the chatbot became natural and even very natural, as is the case with conversations with another person [1].

Nowadays, many services websites, and/or applications include chatbot technology to answer user-specific inquiries to realize and respond to his service. Among these chatbot applications, there are the apps that respond to questions from pregnant mothers, who face concerns during and after pregnancy, as a healthcare-oriented system. Such chatbots would give the experiences that pregnant mothers face vary. Every mother has questions during and after pregnancy. In many places around the world, mothers contact and counseling medical services for this goal. They search the Internet for these answers, but there is a huge amount of information available on the Internet that is very complex or very long, and very few applications provide information specifically for pregnant mothers, especially in the Arabic language as our system does. Reducing anxiety is extremely important for the child’s health during pregnancy [2].

Pregnant women often feel anxious and become curious about many questions and concerns. Chatbot technology can be used to address these concerns and help them obtain advice that will help them pass the pregnancy phase. Pregnant women are among the most vulnerable patients because they are more susceptible to infection and have limited mobility. Due to their condition medical; every mother has many questions during and after pregnancy. In many places around the world, mothers communicate with their doctors or search the Internet for answers to these questions, but what about the mother who lives in a rural community, or in a place that may be far from any center? How does she ask for healthcare? While the mother looking for an instant specialized answer and advice, in its language [1].

This study confronted the problem of fast information availability to the mother pregnant. The type of smart interface-based information exchange and the environment-based medical problems that assisted the patient with close cases to her need. Therefore, this study focuses on local conditions to develop an Arabic language user interface system, which

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consists of local-specific medical information, extracted from doctors who worked in the same region. Collected information has been ordered for chatbot purposes. Using a reliable ML method, i.e., Decision trees (DT). DT is designed with a chatbot for providing appropriate answers to pregnant women and inquiries during pregnancy, where the mother can obtain all the answers to her inquiries, namely at her home using such a chatbot.

The remainder of this paper is organized as follows: section II presents previous related work, section III presents the paper's methodology, section IV illustrates experiments and results, and section V finalizes the paper by the conclusions.

II. Related work

Maduwantha et al developed a phone application to help pregnant mothers. This study includes an artificial intelligence-based chatbot that guides the mother in a very user-friendly way, chatting with her as her unborn child. The application provides a personalized service that meets the individual needs of mothers and helps reduce depression associated with the pregnancy period. It aims to inform mothers of the changes that occur during pregnancy and take appropriate steps to prevent unwanted problems Intended to use pop-up notifications, daily reminders, an emergency call feature, a kick counter, and daily tips along with mothers engaging in small activities like mind relaxation games to improve the mental health of the mother. This study has been implemented using a spiral methodology, which will certainly lead to release through potential implementation across four phases: Planning, risk analysis, engineering, evaluation, and identification including In-project threats and post-release mitigation [2].

Matteo Conte et al proposed a system based on ML and NLP, to support mothers during pregnancy (Mamabot). The chatbot MamaBot is a regular contact in Telegram and patients can see a description of the contact to decide to start using. It is designed to help patients understand that they will be speaking to a chatbot It is one of the most important messages. Upon first arrival, Mamabot asks a series of questions about the patient's name, age, and lifestyle. So the system builds a patient profile, which can be very useful in emergencies allowing time to be saved for future requests. MamaBot was developed with five use cases: find nearby pharmacies, search for nearby hospitals, symptoms and diseases, and tips on feeding children. Pediatric emergency management. They used tools such as open source Framework Bot 6 of Microsoft. They used the Intelligent Language Understanding Service (LUIS) which allows the generated language model to be trained with a series of example utterances (messages that a real user would typically say) via an easy-to-use online graphical user interface. Telegram is selected because it encrypts messages and is safe. They added the Google Maps API to get the patient's location [3].

Al-Hajri et al designed a smart system to facilitate the diagnosis of gynecological diseases during pregnancy. The primary purpose of this research work is to build a regular Android application. It gives a thoughtful approach to providing the best diagnosis for pregnancy. So as not to Women fall into complications during pregnancy. During data collection, they determined an appointment was made to conduct interviews with 60 pregnant women from a health center in IBB City in Yemen, through interviews, they appointed some doctors to examine these women, and some diagnostic tests were done. They used some tools for the Android application. They use algorithms of the decision tree algorithm to predict pregnancies; this algorithm performs better and is more powerful than other models. Pregnant women interact with the system Proposed via the mobile interface of the Android application, The system's response depends on data input that is processed according to pre-defined variables and results decision tree [4].

Jeewon Choi and others designed Bonobot as a case study aimed at designing a conversation sequence for a brief motivational interview (MI). It is delivered via a web-based text messaging application (chatbot). They apply the experience in conversation with graduate students coping with stress, tension, depression, and serious risks related to a mental health crisis. The research questions were as follows: How do users perceive threaded conversation regarding MI components? What aspects of conversation can help graduate students cope with stress? In what ways can the conversation be improved to better support mental health? Bonobot provides brief introductions to the user and gives instructions for using a chatbot. Bonobot asks the user to detail his problem, making him recognize an internal conflict [5].

Hunar et al have introduced a personal healthcare chatbot, that takes into account the needs and understanding of the rural Indian population. It provides general healthcare information with preventive measures for prevalent diseases and indigenous ailments in India in simple user language. It gives a particular focus on interactive prenatal and postnatal healthcare for women. It contains additional features including home remedies, and location- and age-based diet recommendations. Sex-specific health screening tips, emergency helpline numbers, and can be linked to real-time messaging apps such as WhatsApp [6].

Rohit et al introduced Chatbot LL to Predict, treat, and recommend diseases using Machine Learning. They designed a medical chatbot to be a conversational agent that motivates users to discuss their health issues constructively. On the symptoms they present restores chatbot. The system can diagnose using a chatbot. This is from identifying symptoms from the user interaction and using these extracted symptoms, the chatbot predicts the disease and recommends treatment. The used machine-learning algorithm, here, is the Nearest Neighbor (KNN) algorithm. This shows that the medical chatbot can to some extent accurately diagnose patients through simple symptom analysis and approach. Conversation that takes place with the help of natural language processing. In addition, they used Natural Language Processing (NLP) and Neuro-Linguistic Programming, which makes the human communicate with the machine easily, as it understands the natural language spoken by humans, classifies it, analyzes it as well, and responds to it when a question is received. Chatbot approximates what is available in the dataset it was already trained on and will be one of the nearest neighbors. When a user asks a question, the question will go through a series of scripting operations and finally it will be converted into a vector (bag of words). The chatbot will predict the disease for the user and will also provide a link where the user can search for the necessary treatment for the expected disease [7].

Based on the presented studies. We haven't implemented a specific paper. Rather, we have taken various ideas and collected them to implement what benefited our current study. We have analyzed the tools used in all studies. We chose what is compatible with our study. We have noted that there are previous studies that focused on general diagnosis, whether they were automated chats or regular applications. Other studies focused on pregnant mothers, but no application combines the functions of diagnosis, providing advice and recommendations, and predicting the situation with each other. This confirms the importance of this research. The proposed work is focused on the Arabic language; in addition to using local-specific problems of pregnant women, which were collected from three local doctor specialists in women and pregnancy medication.

III. METHODOLOGY

For this study, we utilized the RASA framework [8]. It is used to build chatbots. RASA basics, which are presented in the first two sections. Then the basic system diagrams and the DT algorithms are explained in distinctive two subsections.

A. *RASA framework*

The RASA framework provides a flexible and customizable framework for building conversational AI chatbots that can be tailored to specific use cases and applications. RASA is an open-source chatbot framework based on machine learning and the libraries that help to apply ML techniques. With RASA, you create chatbot heads and can easily integrate these chatbots with your system, website, Facebook, WhatsApp, etc. [9].

RASA contains two main components: RASA Natural Language Understanding (NLU) and RASA CORE. RASA NLU is an interpreter that processes user input, determines intents, and extracts entities from it. The RASA CORE receives the output from the RASA NLU (which is a dictionary that defines intents, entities, and other information). It based on these details, the RASA Core part selects the appropriate response and sends it back to the user as the bot's answer. RASA architecture is illustrated in Figure (1), it starts with a message from the user. The chatbot receives the message and passes it to the interpreter. Then, converts the message into a dictionary including the original text with the target, and any entities found. This part is handled by (NLU). The message is passed from the Interpreter to the tracker. The tracker trails the state of the conversation. The current state of the tracker is sent to each policy. Each policy chooses what action to take next. The chosen action is recorded by the tracker. A response is sent to the user [10].

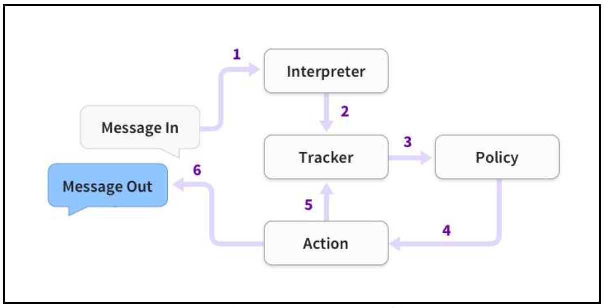

Figure 1. RASA architecture

The mechanism of RASA action starts with training data. The first step is to provide the RASA framework with training data, which includes examples of user input and the corresponding responses that the chatbot should provide. This data is used to train NLP and ML models. The NLU model is responsible for understanding user input and extracting relevant information from it. It uses techniques like entity recognition, intent classification, and sentiment analysis to understand what the user is saying. Once the NLU model understands the user's input, the dialogue management component decides how the chatbot will respond based on its training data, using a combination of rule-based systems and ML algorithms to generate appropriate responses. The action server performs actions based on the Chabot's response, such as sending an email or making an API call. When users interact with the chatbot, their feedback is used to improve its performance over time. This feedback loop helps improve NLP models and ML, so they can better understand user input and create more accurate responses [8].

B. *Algorithms and diagrams:*

The user response mechanism is shown in the Figure (2) diagram. The chatbot works according to a set of steps to achieve the fastest response to user inquiries. These steps consist of receiving data or inputs, analyzing them, and then providing the answer or submitting an inquiring question to verify the request. Before starting these steps, you must first prepare a question and answer list, by setting the questions expected from pregnant mothers, with a set of responses stored.

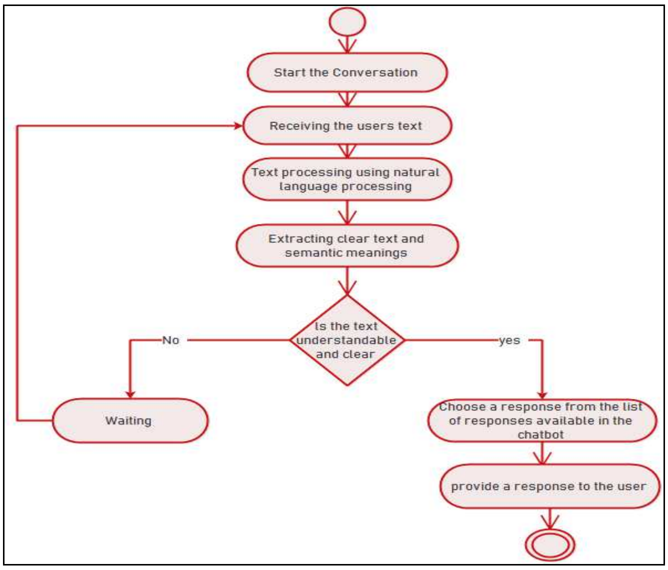

Figure 2. Activity diagram of the response process

C. *Text pre-processing*

The text preprocessing steps are very important for any chatbot system. Text preprocessing helps the smart chatbot to understand and generate human language. It also attempts to improve the communication that takes place between humans and machines, making it similar to what happens between humans, and extracting meaning from unstructured text by extracting keywords, intents, and entities. Text preprocessing steps are depicted in Figure (3).

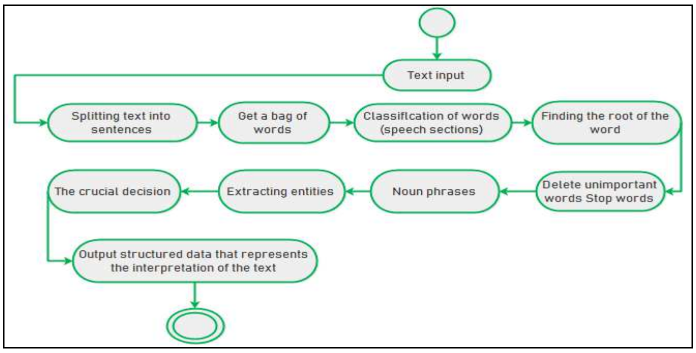

Figure 3. Steps of text pre-processing

D. Decision tree algorithm (DT):

In this study, the decision tree algorithm is used for the functions of diagnosing diseases. Thus, it produces predictions for the condition in the smart advisor application, which is used for pregnant mother care. The prediction is made according to the rules that were configured during the construction of the tree. The steps of the decision tree algorithm are started by posting the best-obtained feature of the dataset at the root of the tree. Then, the training is set into subsets. Subsets should be made in such a way that each subset contains data with the same attribute value. Then repeat step 1 and step 2 on each subset until finding the leaf nodes in all branches of the tree [4]. Figure (4) shows the mechanism of building a decision tree for disease diagnosis purposes.

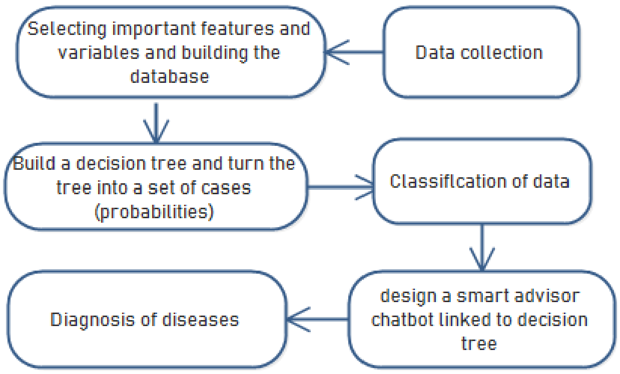

Figure 4. A diagram of the decision tree mechanism

Figure (5) illustrates a sample of DT that is used for disease diagnosis, related to any pregnant woman. As illustrated above, it begins with a root, diced the path based on a root field value, and then branches a new root of a subset of branches. Until reaching the final decision that should be relied on all preceded node values.

J48, a Decision tree algorithm, employs a top-down approach and a divide and conquer strategy to accomplish classification. Unlike traditional trees, the root node is positioned at the top of the tree. Each branch and node within the tree represents a potential attribute value. Instances are then divided into subsets, with each subset corresponding to a branch extending from the root node [11].

A sample of converting a DT sample to a conversation in a chatbot is illustrated in Figure (6) as a diagram of DT. Since, you review the process of predicting of DT method of decision delivery, take into account the most prominent symptoms to predict the process. Although there are many symptoms, we show only the most notable ones [10].

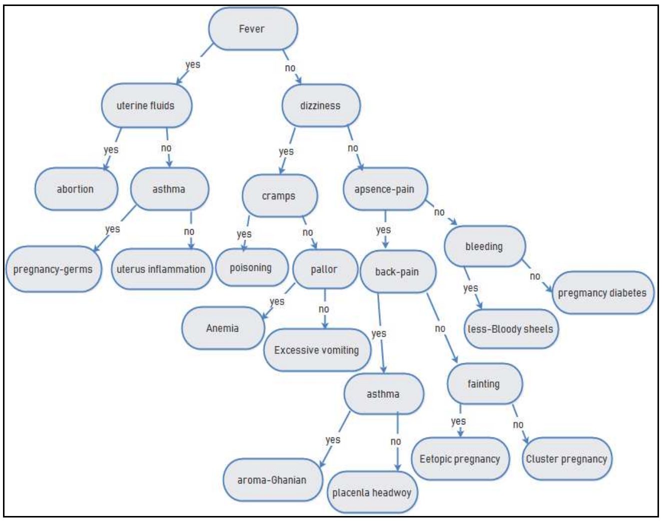

Figure 5. Disease diagnosis diagram in the decision tree

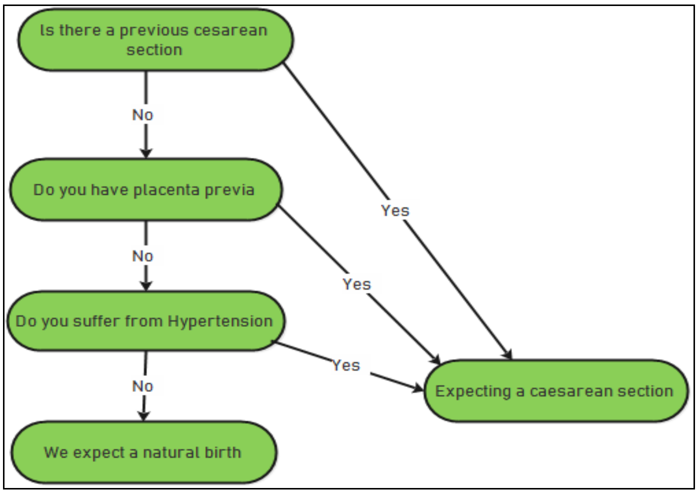

Figure 6. Chatbot conversation based on DT

IV. IMPLEMENTATION AND RESUTLS

In the implementation phase, the process parts sub-components are assembled and formed into integrated units, in a way, that leads to achieving the system goals. Therefore, THE RASA components process includes all collected pregnancy cases and trained decisions. The implementation process includes all practical procedures for building the system in terms of taking all inputs and achieving all outputs in a way that ensures this from various processes. These operations are integrated with developed the mobile application. It takes user input and sends it to the RASA engine, which processes it based on pre-trained information and makes a suitable decision that has been transformed into an understandable sentence. The sentence is the generated answer that is sent back to the user, as an output.

In this section, we presented samples of the application user interface (UI), to show how the system finally works. Then we presented the experiment evaluation results.

A. Samples of App User Iinterface

The first UI is a greeting and welcome interface. In it, the functions of the smart advisor are presented. If it is the first user's session, the advisor begins by requesting the user's first and second names and age, as well as the phone number. Session input information is recorded in chatbot slots. These slots are the advisor's private memory and are deleted after the end of the session. These slots can also be used as variables and included in the advisor's responses. Figure (7) displays the greeting UI. It is in the Arabic language.

Figure 7. The Greeting User Interface

Figure (8) displays the process of user profile gathering by the chatbot in the first session. It shows how the name was used within the conversation, and thus the flow of the conversation can be customized according to the user's input.

Figure 8. User profile gathering UI

An example conversation of the natural symptoms associated with each month of pregnancy is shown in Figure (9). The symptoms may differ according to each pregnancy month. It shows several forms of asking about symptoms, whether normal or colloquial, some of which have been trained on, and some of which the chatbot has understood correctly on its own. The response is determined based on the previously entered rules.

Figure 9. Normal symptoms UI

We show how to diagnose the type of disease that the pregnant mother suffers from in Figure (10). The results are output based on the answers that the mother gives to the advisor's questions; the chatbot then makes a diagnosis based on the dialogue or story followed during the mother's response.

Figure 10. Diagnosis of uterine symptoms

B. Results and discussion

The Smart Advisor for Pregnant Mother healthcare chatbot was trained on 42 intents. Each intent is defined by several phrases that we assume are input from the user. Each intention was provided with more than 10 phrases that are widely used in society. The model is trained within several functions that include diagnosing, predicting, the method of delivery, reviewing normal symptoms, responding to the mother's inquiries about the shape and movement, knowing the sex of the fetus, psychologically calming the mother, and providing advice on nutrition, exercise, and healthy behaviors. Some samples of these intents are shown in Table (1) with some explanation.

TABLE1: SAMPLE OF RASA INPUT INTENTS

Intent	Explain
greet	It indicates that the user exchanges greetings with a chatbot.
goodbye	It indicates that the user wants to end the conversation with a chatbot.
affirm	It indicates that the user affirms something.
deny	It indicates that the user denies something.
bot_challenge	It indicates that the user says something unknown to the chatbot.
symptoms_first _month	It indicates that the user talks about pregnancy symptoms in the first month.
safe_medicine	It indicates that the user requests medications that are safe during pregnancy.
headache	It indicates that the user suffers from headaches.
classify	It indicates that the user asking for a diagnosis.
diabetes	It indicates that the user requests medications for diabetes that are safe during pregnancy
foods	It indicates that the user asking for healthy food during pregnancy.
teeth	It indicates that the user suffers from tooth pain.
move_baby	It indicates that the user asking for baby movement.

The advisor was trained on specific responses collected manually from the internet, related work, and from doctors specializing in obstetrics and gynecology: Dr. Aisha Mujalli, Dr. Faten Al-Wisabi, and Dr. Malikat Al-Shafaq. The number of types of these responses reached 82 different responses, then we linked the target intents to the answers through rules or scenarios in 38 rules and 20 scenarios, and all of these files are utilized by the RASA framework. In the practical evaluation, we tried 110 different formula inputs related to the smart advisor's functions. 94 of them were correct and 16 were incorrect, meaning that the smart advisor's answers were correct at a rate of 85.45%.

The data training phase was repeated several times, and then we conducted a test and evaluation of the system. Figure (11) shows the confusion matrix for classifying intentions, where the horizontal axis refers to the process of predicting intentions and the vertical axis refers to the actual intentions (true intentions). The appearance of these colors in this way means that every intention prediction (intent) matches the actual intention.

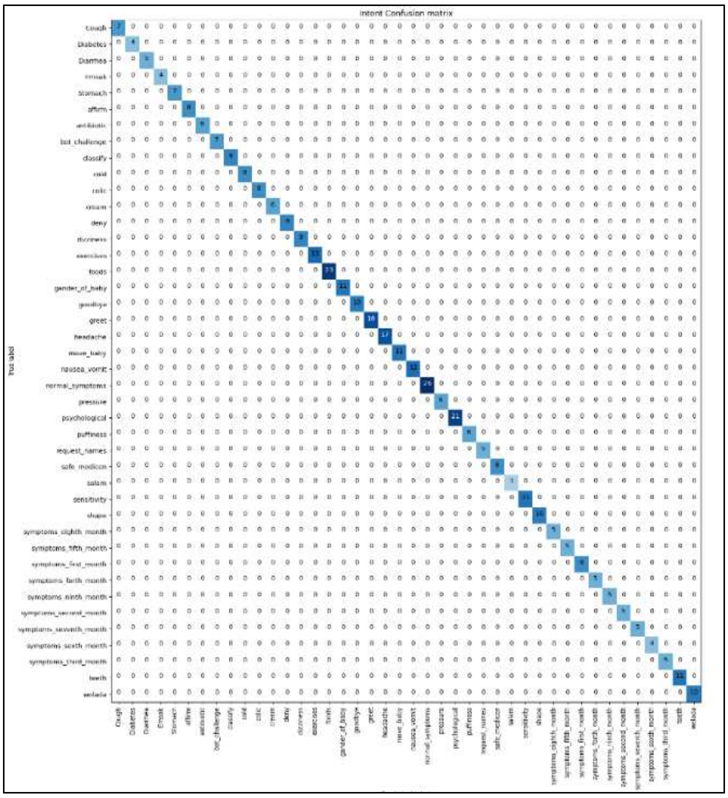

Figure 11. Confusion matrix to classify intentions

Chatbot decisions are produced based on the output of decision tree classification, using collected data. Decision tree experiments are implemented using Weka software. It was used to train the decision tree on the data. Two types of decision tree methods were tried, and the one that included the most symptoms was applied. The two DT methods are Random Tree and J48. Table (2) displays the accuracy of both DT methods in addition to the manual test.

TABLE (2) EVALUATION RESULTS ACCURACY

Method	Accuracy	Error Rate
J48	83 %	0.379
Random Tree	83 %	0.455
System eval.	85.45%	-

There is no distinction between using any one of the two DT methods. They have obtained the same accuracy. However, they are varied in the error rate. Eventually, we applied the decision tree output of J48 DT, although, it has an error rate greater than the error rate of Random Tree DT, our decision was based on the logic of J48 output. J48 DT output generated more comprehensive symptoms than the Random Tree DT output. Moreover, the manual evaluation outperformed DT evaluation, regarding the human testing achieved with an empirical or practical perspective.

V. CONCLUSIONS

This study presented a very important healthcare field. The pregnant women expert advisor is used via a mobile application system. This system is built using ML methods together with NLP methods, incorporated in a chatbot framework. An advisor of pregnant women's healthcare was designed using RASA and the decision tree model. It is built based on customized information gathered manually, with specialist doctors' supervision. It allows chatting with users in the Arabic language. The model of the chatbot is trained within several functions that are possibly required from pregnant women. The advisor's performance was promised in the task of answering the questions professionally. Accuracy results reached 85.45%. This level of accuracy does not prevent the system from making many improvements. We recommended future studies focus on increasing the size of training data, by digging deeper into the field of pregnancy-required information. Besides increasing the accuracy of involved models, more training and testing to gain more valid and accurate answers.

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