ARABIC DATASET FOR FARMERS' INTENT IDENTIFICATION TOWARD DEVELOPING A CHATBOT

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ABSTRACT

A chatbot is an application of artificial intelligence in natural language processing and speech recognition. It is a computer program that imitates humans in making conversations with other people. Chatbots that specialize in a single topic, such as agriculture, are known as domain-specific chatbots. In this paper, we present a dataset for farmer intents. Intent identification is the first step in building a chatbot. The dataset includes five intents (pest or disease identification, irrigation, fertilization, weed identification, and plantation date). The length of the dataset is 720 records. We applied a Multi-Layers Perceptron (MLP) for intent classification. We tried different numbers of neurons per hidden layer and compared between increasing the number of neurons with the fixed number of epochs. The result shows that as the number of neurons in the hidden layers increases, the introduced MLP achieves high accuracy in a small number of epochs. MLP achieves 97% accuracy on the introduced dataset when the number of neurons in each hidden layer is 256 and the number of epochs is 10.

KEYWORDS

Chatbot, Intent classification, Dataset, Deep neural networks

1. INTRODUCTION

Agriculture helps people to get the foods that are vital to life. Farmers need the information to implement the best agricultural practices. Hence, farmers can increase the yield of their crops and reduce the losses. Extension agents and agricultural experts are a vital source of agricultural information. Furthermore, farmers can get information from the internet and printed agricultural books. A chatbot is a program that can act like a human to make conversation with farmers. A chatbot can immediately answer farmer problems and can also guide farmers to reach the domain expert by availing communication data for farmers. Chatbots are beneficial in applications such as education, information retrieval, business, and e-commerce because they can simulate human speech. Open-domain chatbots can talk about various issues and respond effectively, while domain-specific chatbots are specialized in specific domains such as agriculture [1]. It gets knowledge through a knowledge base or it can learn it using machine learning techniques. In Egypt the number of extension agents has been decreased dramatically so, the main problem that faces the farmers is reaching extension agents or domain experts. Artificial intelligence applications such as Chatbot can mitigate the effect of this problem.

Building an agricultural chatbot requires many steps starting by identifying the farmer’s intent or type of problem and finishing by responding to the farmer. In this paper, we focus on identifying farmers’ intent such as pest or disease identification, and plantation date. Accurately determining the farmer's intent enables the chatbot to engage the farmer in a useful conversation and help the

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farmer find the solution to their problem. In this paper, we will apply Deep Neural Networks (DNNs) in order to classify and detect farmers' intent.

DNNs are a type of advanced machine learning technique. DNNs improved traditional neural network learning algorithms by adding more hidden layers and eliminating the need for human feature extraction. It is applicable to various computer applications such as natural language processing, image classification, and voice recognition [2]. Deep learning was applied widely in agriculture [3]. Examples of applications of deep learning in agricultures are: Classifying leaves of different plant species, Identification of leaf diseases, Classification of different crops based on satellite images, Yield estimation and fruit counting, Weed identifications, and weather prediction.

The main contributions of this paper are introducing Arabic dataset for farmers' intent identification and investigating how to enhance intent identification by applying DNNs to classify the intent of the farmers.

2. EVOLUTION OF CHATBOTS

In 1966, the early chatbot was ELIZA. It uses pattern matching and a response selection scheme based on templates. Its knowledge was limited; it can discuss only a particular domain of topics [4]. In 1972, PARRY was created, it impersonated a paranoid schizophrenic. It defines his responses based on a system of assumptions and ‘‘emotional responses’’ activated by the change of significance in the user's words [5]. In 1988, Jabberwacky was written in CleverScript, it used contextual pattern matching to respond based on previous conversations [6]. In 1992, Dr. Sbaitso was developed to display digitized voices [7]. In 1995, the first online chatbot, ALICE was created, it was written in Artificial Intelligence Markup Language (AIML), and it was based on pattern-matching, without any actual perception of the whole conversation [8]. In 2001, SmarterChild marked a significant evolution in chatbot technology [9]. It was available on Messengers like America Online (AOL) and Microsoft (MSN). It could help people with practical daily tasks as it could retrieve information from databases.

Artificial Intelligence chatbots became another step forward in the creation of smart personal voice assistants; they were built into smartphones or dedicated home speakers that understand voice commands. In 2010, Siri was developed by Apple. Users can interact with it via voice commands, and it offers interaction with audio, video, and image files. Siri is very easy to use, the user speaks naturally, Siri learns the user's preferences over time, and it requires an internet connection [10].

Watson was developed by IBM in 2011, and it was able to interpret natural human language well enough to enable businesses to construct better virtual assistants [11]. Google Now [12] was created in 2012 and was designed to provide information to users based on the time of day, location, and preferences. The next iteration of Google Now is Google Assistant [13], which was released in 2016. It boasts a more advanced artificial intelligence system, as well as a nicer, more conversational interface, and it provides information to the users by anticipating their needs.

In early 2016, an evolution of Artificial Intelligence Technology occurred that changed dramatically the way people communicate with manufacturers. Social media platforms allowed developers to create chatbots for their brand or service to enable customers to perform specific daily actions within their messaging applications. Moreover, the Internet of Things (IoT) introduced a new era of connected smart objects where the use of chatbots improved communication between them [14]. Furthermore, Conversational Agent (CA) was embedded into Government website to help citizens to find the target information or services [15].

3. RELATED WORKS

In agriculture, chatbots can help farmers by providing the answers to their queries quickly and easily when compared to traditional methods. They can access knowledge that necessitates extensive online searches. The chatbot in [16] provides agricultural facts to the farmer. To get an answer, a farmer can send a direct message. This approach would allow a farmer to ask any number of questions at any moment, which would aid in the speedier and more widespread adoption of current farming technology. The Farmbot [17] can help farmers to converse easily with the bot since this system uses the Natural Language Processing technique to parse the user queries, identify the keywords, match them with Knowledge Base and respond with accurate results. This system also uses prediction algorithms to predict the future data like the price of the crops for the upcoming years based on the previous records of data. AgronomoBot [18] is a chatbot that aims at assisting the specialist in the acquisition of data of variables related to soil, plants, and climate, collected by a Wireless Sensor Networks. Also, it helps in decision making based on field reports.

In [19] the authors propose a chatbot named AgroBot to address India's shortage of accurate agricultural information. It attempts to offer advice and important information to farmers, such as irrigation schedules and disease diagnosis and control. Consequently, it raises the productivity of agriculture. Farmers can ask questions, and the chatbot will respond with the most helpful answer by locating the key words and using the knowledge base to provide farmers with the most appropriate answer. Also, the authors of [20] suggested a farmer's assistant they called Agroxpert. It is a smart, portable system that employs Natural Language Processing technique techniques to assist farmers in applying various farming techniques. Additionally, it assists them by responding to their inquiries on agricultural techniques, which enables them to make more money.

Furthermore, chatbots can help customers and farmers in obtaining a fair price for agricultural products. A chatbot was introduced in [21] as an interactive platform that farmers may use to sell their products to potential customers directly. The ability to sell and buy essential agricultural products at a fair and affordable price without the involvement of middlemen benefits both farmers and customers.

A smart chatbot is capable of understanding the user's intentions. To accomplish this, the developer must constantly enhance its ability to classify the user's intents. User intent classification is critical for identifying and analyzing users' intents from short sentences, as well as predicting the intent labels of dialogue sentences, in order to understand what users really want [22].

To classify users' intent, there are some different approaches: rule-based, machine learning, and hybrid approach. The traditional solution is to classify intents based on rules. This approach is to create specific rules, but one of the major problems here is defining too many rules. The machine learning approach is to train a classifier and use the trained classifier to predict the intent. This approach requires a training set of intents, based on which a classifier is built. The hybrid method combines all the previous principles (rule-based and machine learning-based) and comprises the application of the classifier [23, 24].

In [25] the authors presented a hybrid approach for classifying the intent of a dialogue utterance. They combined a convolutional neural network (CNN) and a bidirectional gated recurrent unit neural network (BGRU) to enhance the accuracy of intent classification. In [26] the authors introduced a dataset for predicting out-of-scope and intent classification. They found that recognizing out-of-scope requests was a challenge for all classifier approaches. To increase the prediction accuracy of out-of-scope requests, models require more training data.

4. MATERIAL AND METHODS

To detect or classify intent we used a machine learning approach. Firstly, we prepared a dataset that includes the most common intents of farmers such as plantation data, irrigation, fertilization, pest identification, and weed control. We applied word stemming. Finally, we started applying DNNs to learn and classify farmers' intent as an initial step for building a farmer assistant chatbot.

4.1. Dataset Preparation

In our study we target Egyptian farmers who use the Arabic language so; the language of the data set is Arabic. In the Egyptian agricultural research center there exist many text resources such as the farmer problems system [27] and extension documents for different crops. We focused on the field crops due to its important economic value. Those crops include Maize, barley, wheat, onions, sorghum, soybeans, cotton, peanuts, sugar beets, flax, cowpeas, sesame, and fava beans. The extension document is a manual for farmers to guide them to select suitable varieties and specify plantation date. It is a valuable source for information about diseases, disease control, irrigation, fertilization, and harvesting. For each intent we extracted the text that is related to it, and then we added it to the dataset. Also, we extracted text data from the farmer problems system which are related to different intents.

The data set size is 720 records. Pest and disease identification has 337 records; weed problems include 149 records, plantation date 72 records, fertilizer 84 records, and irrigation 78 records. Figure (1) displays a pie chart that represents all intents.

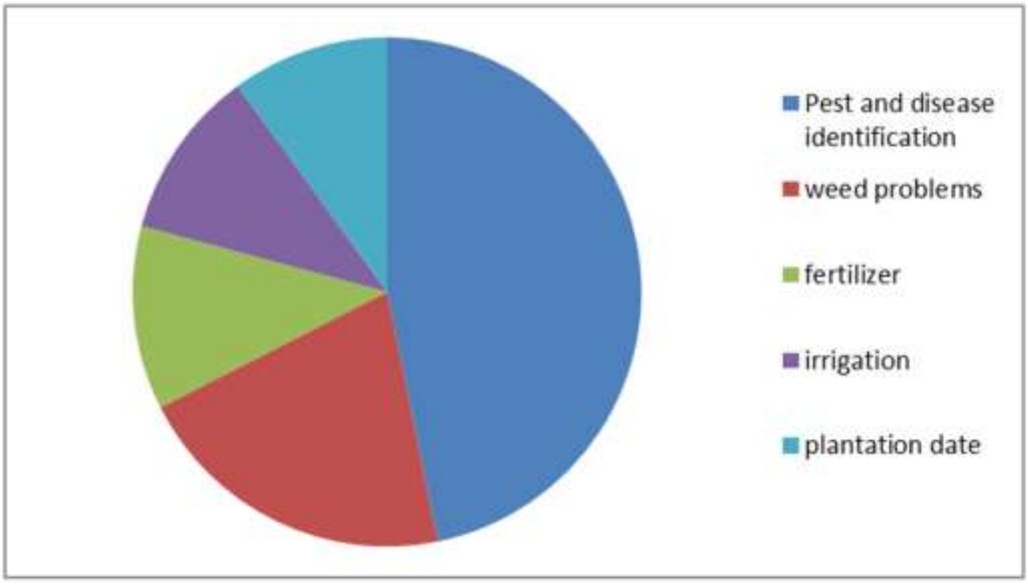


Figure 1. Farmers' intents that exist in the dataset.

The introduced intents in the dataset constitute the primary intents of farmers. We observe that pest and disease identification is the major intent since it is the hot subject for farmers. Pest and disease affect plant and causes many problems that lead to plant damage and decrease yields of crops and causes economic impact on farmers' income. Weed identification and problems occupy the second intent order due to danger effect of weed on plants. Other intents like fertilizers, irrigation and plantation date are close to each other in number of records.

Table (1) shows a sample of the farmers' intents dataset. The data set is stored in an excel file consisting of two columns one for text content and the other for intents. It is available at https://github.com/abdoEgypt/farmers_Intent.

Table 1. Sample of farmers' intents dataset

Text content	**Intent**
. تقرض الأوراق مباشرة والأفرع الثمرية والقرون مباشرة وتعمل ثقوبا بالقرون والقمم النامية	Pest and disease identification
يتغذى الحفار على بذور التقاوى قبل الإنبات وعلى الشعيرات الجذرية فى البادرات الحديثة والنباتات الكبيرة مما يؤدى إلى ذبوله	Pest and disease identification
يظهر قرض تام فى سوق نباتات اللوبيا عند مستوى سطح التربة كما يحدث موت للنباتات المصابة خاصة فى فى طور البادرات	Pest and disease identification
ظهور تقرحات لونها بنى داكن على الجذور تسبب موت البادرات وبتقدم الإصابة تعم التقرحات الجذر كله وموت النبات في النهاية و تؤدى الإصابة إلي سهولة نزع القشرة الخارجية للجذور وظهور نقط سوداء أسفلها ويساعد على انتشار المرض زيادة الرطوبة الأرضية والإفراط في التسميد الآزوتي ويؤدى المرض إلي قلة الجذور الثانوية وتقزم النباتات ثم تموت في النهاية	Pest and disease identification
وجود حشائش نجيلية بكثرة فى ارض الفول البلدى مثل الفلارس وديل القط والصامة	Weed
يشكو من وجود حشائش معمرة مثل السعد والحجنة ويريد علاجها قبل زراعة القمح	Weed
وجود زمير بكثافه عاليه حيث انه قام بالعزيق للتخلص منه فكانت نسبه الحشائش الموجودة عاليه كذلك فما هو المبيدالمفضل لمقاومه هذة الحشيشه الان فى حقل الفول البلدى ؟	Weed
أرض موبوءة بالحشائش (العجيرة - الدنيبة- أبو ركبة) كيفية مكافحتها بإستخدام مبيد الساترين بعد الشتل ؟	Weed
افضل موعد لزراعة شتلة البصل فى الارض المستديمة من ارض المشتل وما هى مميزات الشتلة الجيدة	Plantation date
الميعاد المناسب لزراعة الذرة الشامى الفردى (حقل ارشادى)؟	Plantation date
أنسب ميعاد زراعة الذرة الشامية صنف جيزة10 هجين فردى	Plantation date
ماهو الميعاد المناسب لزراعة الفول البلدى فى الوجه البحرى - وماهى اضرار التاخير او التبكير عن الميعاد المناسب	Plantation date
نتيجة ارتفاع سعر سماد اليوريا .يقوم المزارعين باستخدام سماد النترات فى تسميد محصول الارز .هل هذا ممكن .وهل مفعوله كاليوريا والسلفات	Fertilizier
قيام المزارعيين باضافة الأسمدة الأزوتية بعد الرى بيوم واحد فهل هذه الممارسة صحيحة للقمح .	Fertilizier
يسأل المزارع عن المعدل الامثل من السماد الازوتى لمحصول بنجر السكر وميعاد اضافتة للحصول على اعلى انتاج وزيادة نسبة السكر .	Fertilizier
قمت بزراعة البصل فى اواخر شهر ديسمبر ولم اضف اى اسمدة قبل الزراعة فما هو المعدل المناسب للتسميد من العناصر الكبرى ومواعيد الاضافة	Fertilizier
ما الميعاد المناسب لتوقف الرى فى القمح (تصويم القمح)	Irrigation
ما هى معدلات الرى فى الأراضى الرملية التى تروى بالغمر لمحصول القمح	Irrigation
يجب عدم تعطيش النباتات خلال فترة النمو الثمري نظراً لمواكبتها لتحسين الأحوال الجوية وارتفاع درجات الحرارة للحصول علي محصول عالي من البذور, ويمنع الري قبل الحصاد بأسبوعين.	Irrigation
تقليل مياه الرى بعد الزراعة يمنع إنبات بعض البذور ويسبب وجود مساحات خالية من النباتات	Irrigation

4.2. Deep Neural Networks Implementation

We used Python 3.9 to implement experiments. We used xlrd library to read the dataset from the Excel file. Then we used ARLSTem [28]. The ARLSTem is a simple Arabic stemmer that depends on removing the word's affixes (prefixes, suffixes, and infixes).

We used TFLearn [29] library to facilitate and accelerate building intent classifiers. TFLearn is a deep learning library that is a simple interface for TensorFlow. TensorFlow helps in developing many machines learning applications.

In this paper, we used deep neural networks called Multi-layer Perceptron (MLP) that is consists of an input layer, two hidden layers, and an output layer. We select MLP since it outperforms other classifiers such as KNN and SVM [30]. We used softmax as an activation function since the output has multi classes [31]. It converts the output into probabilities. Dataset was divided into training and testing datasets the size of the test is 33%. Figure (2) shows the python code for the configuration of the used MLP.

```
import tflearn
Input_Layer = tflearn.input_data(shape=[None, len(training[0])])
# Training is an array that represents the dataset , each item in it represented as bag of words
Layer_1 = tflearn.fully_connected(Input_Layer, 256)
# Number of neurons=256 in the first hidden layer
Layer_2 = tflearn.fully_connected(Layer_1, 128)
# Number of neurons=128 in the seond hidden layer
Output_Layer = tflearn.fully_connected(Layer_2, len(output[0]), activation = "softmax")

net = tflearn.regression(Output_Layer)
model = tflearn.DNN(net)
#Split data for training and testing
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(training, output, test_size=0.33,
random_state=80)
#run the model on the training data
model.fit(X_train, y_train, n_epoch=500, show_metric=True)
model.save("model.tflearn")
```

Figure 2. Python code for the configuration of the implemented neural networks.

5. RESULTS AND DISCUSSIONS

We applied MLP in order to classify the farmer’s intent. We ran many experiments to evaluate the results based on tuning parameters for MLP. Firstly, we fixed the number of epochs and changed the number of neurons at each hidden layer. The developed MLP consists of two hidden layers, we started with 32 neurons for each layer, and then we tried different numbers of neurons (64,128, and 265). Also, we ran the experiment with a different number of neurons per hidden layer we set the number of neurons as 64 in the first layer and 32 in the second layer. We repeated each experiment 5 times and took the average of the accuracy results. Also, we used part of dataset for evaluation. The evaluation data set is not used for training to calculate accurate result without overfitting for training data. Table (2) shows the accuracy results with different number of neurons for hidden layers.

From the results, we can conclude that the multi-layer perceptron converged at 256 epochs and the enhancement of the accuracy is trivial when increasing the number of epochs. Also, the accuracy may be decreased by low values when increasing the number of epochs.

Table 2. Accuracy results for number of epoch with number of neurons in hidden layers.

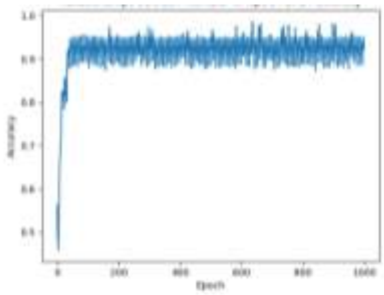
# epochs	***# neurons (layer1)***	***# neurons (layer1)***	***Accuracy***
256	32	32	0.9437
	64	32	0.9487
	64	64	0.9437
	128	128	0.9496
	256	**256**	**0.9504**
512	32	32	0.9437
	64	32	0.9437
	64	64	0.9420
	128	**128**	**0.9513**
	256	256	0.9480
1000	32	32	0.9361
	64	32	0.9445
	64	**64**	**0.9411**
	128	128	0.9403
	256	256	0.9403

We investigated how increasing the number of neurons affects reaching high accuracy with a low number of epochs. Figure (3) shows the relation between increasing number of epochs and the number of neurons. The results show that as the number of neurons in hidden layers increases the MLP reaches a high value of accuracy with a low number of epochs.

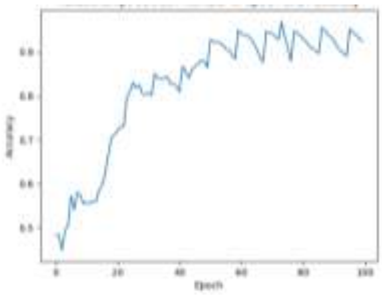
Table (3) displays the accuracy result of MLP when the number of epochs is 10. When the number of neurons per each hidden layer is 256 the MLP achieved a 97.31 % accuracy value, while the accuracy of MLP when the number of neurons in hidden layers is 32 achieved low accuracy (64.7 %). So we can conclude that there is a relation between increasing the number of neurons in the hidden layers and the number of epochs until the MLP converges. MLP achieves high accuracy in case of large number of neurons in hidden layers and a few numbers of epochs. On the other hand, MLP achieves a low accuracy in case of increasing the number of epochs with a low number of neurons per hidden layer.

Table 3. Accuracy results for 10 epochs.

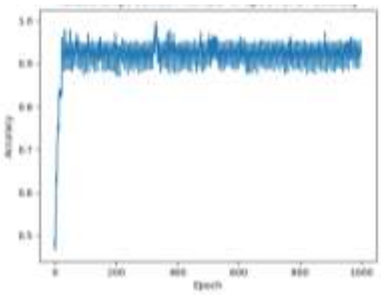
# epochs	***# neurons (layer1)***	***# neurons (layer1)***	***Accuracy***
10	32	32	0.6470
	64	32	0.7118
	64	64	0.7698
	128	128	0.9531
	256	**256**	**0.9731**



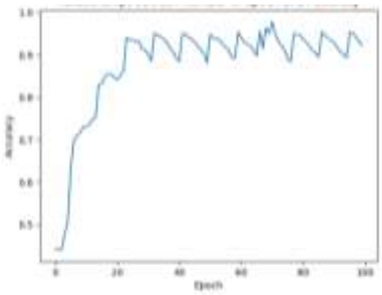
Neurons number Layer1-layer2
(32 -32)



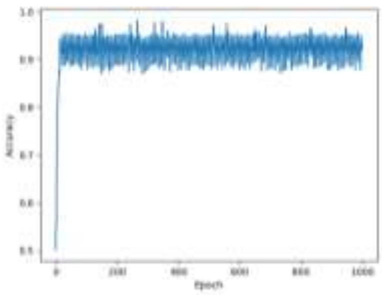
Zoom in the first 100 epochs &
Neurons number Layer1-layer2 (32 -



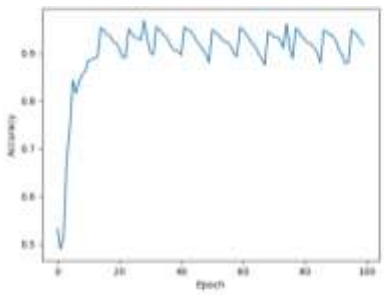
Neurons number Layer1-layer2
(64 -64)



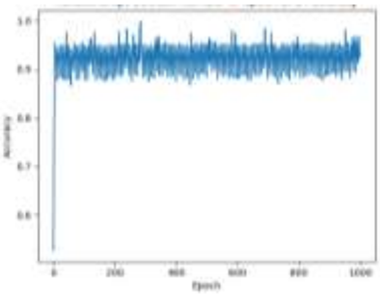
Zoom in the first 100 epochs &
Neurons number Layer1-layer2 (64 -



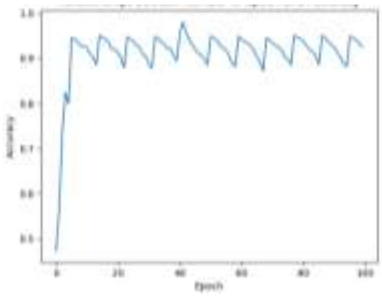
Neurons number Layer1-layer2
(128 -128)



Zoom in the first 100 epochs &
Neurons number Layer1-layer2 (128 -



Neurons number Layer1-layer2
(256 -256)



Zoom in the first 100 epochs &
Neurons number Layer1-layer2 (256 -

Figure 3. Relationship between increasing number of neurons and number of epochss.

6. CONCLUSION

This paper introduced a dataset for classifying farmers' intents as a pre-step for creating a farmer assistant chatbot to help farmers and answer their questions. We applied deep neural networks for intent classification. The multi-layer perceptron converged faster as the number of neurons in hidden layers increased. The proposed system achieves a maximum accuracy when the number of epochs is 10 and the number of neurons is 256 per hidden layer. For future work, the accuracy can be enhanced by increasing the size of the dataset and making balances between numbers of records per intent. Also, the dataset can be extended to include other intents such as prices of crops and weather inquiries.

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