

A Cognitive Plant Disease Detector

T. Manjula¹, Prof. T. Sudha²

¹Research Scholar, SPMVV, Tirupathi

²Professor, Department of Computer Science, SPMVV, Tirupathi

Abstract- Agriculture is the major source of food for humanity. Many inventions has taken place in the field of agriculture. Farmers are unable to use these new technologies due to their poor education or less experience with the operation of systems. Plant disease detection is an important agricultural task. The detection of plant diseases in the earlier stages helps the farmer to protect their plants and improves the productivity. The present paper focuses on developing a cognitive agricultural application that enables the farmer to easily communicate with the application even if he or she is a uneducated person, and not able to type. The major goal is to develop an agricultural application which interacts with the farmer to take the symptoms of the plant, process and provide the necessary solutions to the farmers in an efficient and a cost effective manner. This is a novel application which enables the farmer to communicate with the system with voice assistance. Data Processing is performed using Deep Learning Algorithm.

Index terms- Cognitive Computayion, Plant Disease Detector, Machine Learning, Voice Output

I.INTRODUCTION

Agriculture is the major habituate of human beings which is the major source of food. Number of advanced technologies is used in agriculture for the increased productivity and decrease human labor. But these technologies can be used by only by those farmers who are educated or trained with the technology. Unfortunately in most of the developing countries, those who rely on cultivation are far from education. They are unable to use the advanced technologies due to their unawareness or because they are not trained. One major problem in plant cultivation is the detection and diagnosis of diseases. There are so many mobile applications available for the plant disease prediction and analysis. The major problem faced by the farmers in using these applications is the above mentioned problems.

Many plant disease detecting systems are available which are based on image processing techniques. These applications are faced with storage problems in reality due to the large storage requirements of the images. Many text processing applications need the user to type the information. There is a need to develop a Voice based application where the user need not type but can simply tell to system.

The present work focuses on development of an Application which can listen to users voice inputs, analyze users requirements and give possible outputs. There are two ways to implement the system. Either with pure Machine Learning implementation or by just using voice analysis engine. Machine Learning implementation would be quite complex and would take long time to implement whereas voice analysis engine can be done in short time but would not be as effective as Machine learning implementation.

The difference between Machine Learning implementation and Voice analysis is quite subtle. Both require a predefined data samples. Machine learning would require such data samples in large quantity. Machine learning model has to be designed and trained with as many samples as possible. It would then automatically give possible causes and solutions when symptoms queried to the model. Voice analysis on the other side is plain simple. All we need is to store the symptoms, causes and solutions relationships in the database. Read the symptoms and query for the causes and solutions from the database.

Machine Learning is an artificial intelligence subset. It focuses mainly on system design, learning and predicting based on some experience. The learning process starts with the collection of data, like direct experience, to search for data patterns. Machine learning based techniques are recently used for the detection of disease in the plant where images are captured and processed to obtain the necessary information needed for the analysis. Deep Learning is

a special branch in machine learning where we use Artificial Neural Networks for detecting the plant diseases.

II. RELATED RESEARCH WORK

In [23], authors present, review, and recognize the demand for developing a rapid, cost-effective, and reliable health-monitoring sensor that facilitates advancements in agriculture. They described the currently used technologies that include spectroscopic and imaging-based and volatile profiling-based plant disease detection methods for the purpose of developing ground-based sensor system to assist in monitoring health and diseases in plants under field conditions.

After analysis of their work and analysis presented by the authors of [2][19][20][29], it was decided to use image processing disease recognition approach. Among other approaches commonly used for plant disease diagnostics are double-stranded ribonucleic acid (RNA) analysis, nucleic acid probes, and microscopy.

In [19], the authors have presented a method for disease detection by extracting the color feature using computer vision. Numerous procedures are currently in use for plant disease detection applying computer vision.

In [22], plant disease detection could be achieved by extracting shape features method. The authors applied this technique for disease detection in sugarcane leaves where they have used threshold segmentation to determine leaf area and triangle threshold for lesioning area, getting the average accuracy of 98.60% at the final experiments

In [25], the authors have presented a survey of well-known conventional methods of feature extraction. They focused on application of Artificial Intelligence (AI) methodologies and techniques.

In [17], the authors presents models of some approaches which apply the feed-forward back propagation of neural networks consisting of one input, one output, and one hidden layer for the needs of identifying the species of leaf, pest, or disease. They developed a software model, to suggest remedial measures for pest or disease management in agricultural crops.

Another technique proposed by the authors in [8] incorporates the features extracted by Particle Swarm

Optimization (PSO). In [8], authors present the use of forward neural network in direction of determining the injured leaf spot of cotton and improving the accuracy of the system with the final overall accuracy of 95%.

Also, detection and differentiation of plant diseases can be achieved using Support Vector Machine algorithms. This technique was implemented for sugar beet diseases and presented in [26], where, depending on the type and stage of disease, the classification accuracy was between 65% and 90%.

Another approach based on leaf images and using ANNs as a technique for an automatic detection and classification of plant diseases was used in conjunction with -means as a clustering procedure proposed by the authors in [11]. ANN consisted of 10 hidden layers. The number of outputs was 6 which was the number of classes representing five diseases along with the case of a healthy leaf. On average, the accuracy of classification using this approach was 94.67%.

In paper [24], Sunayana Araya and Rajeev Singh, presents how the Deep Learning Technique used to detect plant leaf diseases. A comparative study and analysis of the prominent deep learning techniques were provided by these authors.

In our study, we exploit the deep learning method for plant disease detection, driven by evolvement of deep learning techniques and their application in practice. Extensive search of the state-of-the-art literature survey yielded no evidence that researchers explored deep learning approach for plant diseases detection from the speech to text data.

III. PROPOSED METHOD

The frame work of the present system should support the farmer to interact with the system orally and get the results again by speech. The simple architecture contains three components as given in the figure.1. It gives the sequence in which the various operations will take place in the system.

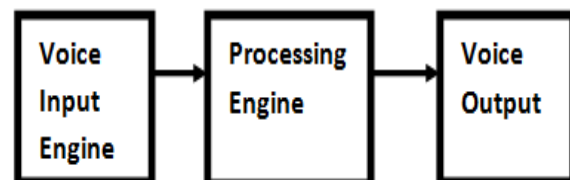


Figure 1

The Voice Input Engine is the first module of the system which receives the human speech (the farmer giving the symptoms of the plant), recognizes the symptoms and sends to the Processing engine. The Processing Engine is the second module which receives the symptoms and finds the related disease and measures to be takes. The Voice Output module conveys the information to the user.

The cloud engines such as Google Speech API or Amazon Alexa can be used as Voice Input Engine which can recognize the voice and performs speech analysis. The Processing engine finds the disease that matches to the given symptoms and also finds the necessary actions to be taken. The Voice output module’s work is to convey the information to the user in voice by converting the text again to speech.

IV. METHODOLOGY

The system has been developed using python. A Multi-Layer perceptron model is built with Keras on the top of Tensor flow. The model of the Neural Network is given in table 1.

The model contains six layers. There are four hidden layers. The data set given to train the model was a simulated CSV file. Rectified Linear Units (ReLU) are used as substitute for saturating nonlinearities. This activation function adaptively learns the parameters of rectifiers and improves accuracy at negligible extra computational cost [5][9].

The model has been trained and tested with different sized data bases, for obtaining the better accuracy, and observed that higher the data size, greater the accuracy of the build model for prediction.

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 50)	550
dense_2 (Dense)	(None, 100)	5100
dense_3 (Dense)	(None, 200)	20200
dense_4 (Dense)	(None, 100)	20100
dense_5 (Dense)	(None, 50)	5050
dense_6 (Dense)	(None, 11)	561
Total params: 51,561		
Trainable params: 51,561		
Non-trainable params: 0		

Table 1

V. EXPERIMENTAL RESULTS

A sample output scenario is given in table 2.

```

device index:1

your plant :Asks the plant name and expects
           :answer from the farmer

you said: rice plant

features: Farmer is supposed to dictate the symptom

you said: red blood

any other features get Y/N/D?:y

features

you said: red blot

any other features get Y/N/D?:n

[[1 0 0 0 0 0 1 0 0 0]]

;Feature Vector Constructed based on the input
    
```

Table 2

Since the constructed system is a voice based one. First it takes the device to be used for recognizing the audio input to the system. The device index specifies the device selected for voice recognition. According to the device selected the system configures itself to recognize the voice of the farmer.

In above scenario, the farmer gives the name of the plant as rice plant and gives one symptom red blot. The system recognized the voice correctly for the second attempt, due to external noise. After getting the option, no features, the system has built a feature vector, which is given as an input to the model for prediction.

The output of the system is the following for the above given input:

```

rice red spot:2.2880213e-05
bloat brown:5.6828352e-08
blue spot:4.9998715e-07
bajra weak:3.504372e-05
fungus:0.00011153096
red brown:0.040031858
brown blue:0.295904
brown weak:0.1570741
blue bloat:0.32166824

The system dictates the predicted disease as blue bloat
    
```

Table 3

In table 3, all the possible diseases for the rice plant, with the given symptoms are listed including the predicted possibilities. The system chooses the one with the highest probability as the disease possible for the rice plant. The list in table 3 shows that the disease named blue blot has the maximum value and hence the system dictates to the farmer that disease is blue blot.

VI. CONCLUSION

A plant disease detecting system which can interact with the farmers would facilitate the farmers to feel free to express their feelings and also to get the quick solutions. A Cognitive Plant Disease Detector thus provides an environment where the farmers can interact with the system orally. It also encourages the youth to perform the cultivation.

The developed system is implemented in a generic way. The present system faces some problems with the ambiguity in speech and implemented in English. In the future, the system can be enhanced to support the regional languages also.

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