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Semantic Based Answering Technique for Image Query in Mobile Cloud Computing

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Abstract**—** This paper aims an answering technique that identifies the disease name in tomato plants by giving the affected plant's image as input and enables the users to retrieve the preventive and controlling methods of the disease. Classifying an image accurately, takes different forms in different researches. Content Based Image Retrieval and Google's reverse image search are few outcomes of such researches. Still, there is a need for a technique that recognizes images like how humans classify based on their experience. This work comes with a better solution by combining image classification in human's perspective with semantic based answering. TensorFlow is an open source algorithm that is released by Google is an effective tool for classifying images and ontology that gives very accurate answers to the user queries are the technologies that are used in the proposed technique. The images and details of tomato crop diseases are collected from different forums and the glossary terms used in ontology are taken from the web.

Keywords*-Image classification ;TensorFlow; Ontology;Semantic based answering;Question answering technique; Cloud services*

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I. Introduction

Answering to an image based query is a simple task for human, but it is a highly challengeable task for computers. Google's reverse image search allows the users to retrieve the details about an image and retrieves relevant images. TinEye is also a search engine that uses reverse image search. Deep Learning[1][2], Convolutional Neural Network[3], TensorFlow[4][5] are few Machine Learning (ML) algorithms that are used for image recognition. SIFT, PCA-SIFT and SURF are few popular feature detection algorithms that are able to recognize images even in rotation, scale and with illumination changes.

The semantic based answering technique for image query is developed to answer about crop diseases by accepting an image of a diseased crop as input. The Government of India has launched many portals like mkisan.gov.in[5], farmer.gov.in[6], RKVY, Hortnet, Seednet and Extension Reforms for the benefits of farmers. Many mobile applications like Kisan suvidha, Pusa Krishi, MKisan application and Shetkari Masik help the farmers in knowing about weather information, dealer market prices, agro advices and plant protection. These applications assist the farmers to obtain the required information in their languages. Farmers can avail free SMS services, Interactive Voice Response System (IVRS) services and toll-free call services for clarifying their doubts with the experts.

But, all the services need an agriculture expert to be available in fulltime. Apart from phone calls, the farmers have no choice to clarify their doubts. A need for an automated answering technique is mandatory. To identify a disease that is affected a crop, farmers take the crop to an agriculture expert and gets the recommendations and solutions to cure and control the disease. In the proposed automated answering technique, the farmers upload the image of disease affected crop and retrieves the solutions immediately. For image recognition, the proposed technique uses TensorFlow, an open source software library in Machine Learning which is proven as the best till date. As the proposed system is expected to work in mobile phones, TensorFlow is chosen because it runs in mobile platforms like Android and Apple iOS. TensorFlow recognizes the uploaded image and suggests list of names based on the relevance, i.e. Disease names about the image. The top answer from TensorFlow's classification is extracted and fed into the SPARQL query. The query retrieves the causes of disease, preventive and controlling methods of the diseases from the developed ontology. The answer retrieval uses semantic based information retrieval technique. The images used in this work are gathered from many forums and the vocabularies used in the ontology of the proposed technique are taken from plant ontology consortium[8].

II. PREVIOUS WORKS

Image as query is a known term in World Wide Web (WWW) because of Google's images search engine. Google images accepts a single image or multiple images or an image url as input and retrieves relevant images and details about the images. If the uploaded image is from Google, the search engine easily retrieves the details about the image, else, it retrieves the relevant images that resembles the uploaded images in color, texture and pattern. SIFT, PCA-SIFT and SURF algorithms are used in Google images that recognize an

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image in different angles, different scales and even the image is blurred.

Many search engines that allow image as query use Content Based Image Retrieval (CBIR) techniques that retrieve similar pattern images. CBIR focuses part-based object retrieval and low-level visual feature-based information retrieval. In Region Based Information Retrieval (RBIR), texture features are used to classify the images. Gabor feature and Curvelet feature are used to classify and retrieve relevant images. These features are very similar to human's vision identification property. The drawback is, these systems cannot classify the images with irregular shapes. Guang-Hai Liu et.al., [9] proposed an IR technique based on multi-texton histogram that uses edge detection. It differentiates the color, texture and shape features in a noticeable way. ML algorithms play vital role in signature identification, face recognition, food recognition[10] and image recognition. It uses Convolutional Neural Networks[11] and Deep Learning algorithms[12][13] to recognize the images.

Semantic Image Retrieval is an existing work that retrieves similar images based on user's query. Here, user's query can be a text based query or an image as query. In the proposed system, image recognition techniques and ontology are joined together for an automated answering technique. Many Question Answering (QA) techniques are available for farmers. These techniques use semantic-based search. For improving crop productivity, monitoring weather, clarifying the soil types and to know about water resources, much ontology are developed and used. All the QA techniques are with high accuracy because of the semantic-based IR[14]. These ontologies are queried by SPARQL which is not familiar to the farmers. So, Natural Language Processing (NLP) [15] techniques are used to convert the user queries into SPARQL queries. When the query is an image, then NLP is not necessary.

All the techniques can be converted as a web applications or web services that have to be listed in the search engine's display pages. To make it easily available to the users, many Search Engine Optimization (SEO) techniques must be applied. Apple's SIRI, IBM's Watson and GoogleMe are very popular and comprehensive QA techniques. These answering techniques are availed in mobile platforms as a cloud service.

III. SEMANTIC BASED ANSWERING TECHNIQUE FOR IMAGE QUERY

The proposed technique is from farmers' perception. When symptom of a disease is visible in the crop, the farmers don't have any idea about the symptom. Either they call an agriculture expert in person to get suggestion or take a picture of the affected crop, shows and ask suggestion to an expert. But, the lack of agriculture experts and the lack of timely predictions and prevention of diseases cause a big financial loss for farmers. Though our government initiates with many web portals and mobile applications like mKisan, they let the farmers to query through SMS(Short Messaging Service) or make a call and prompts the farmers to explain the symptoms, they are inadequate. Many question answering forums lets the farmers to upload their disease affected image. Farmers are forced to wait for the experts answer. Here an automated answering system is in highly on demand. The proposed technique provides a solution for this problem with an automated answering technique which accepts image as query and responds immediately with the disease name, preventive methods for the disease. Figure 1 presents the steps. The steps are Dataset preparation, Image recognition and Extraction.

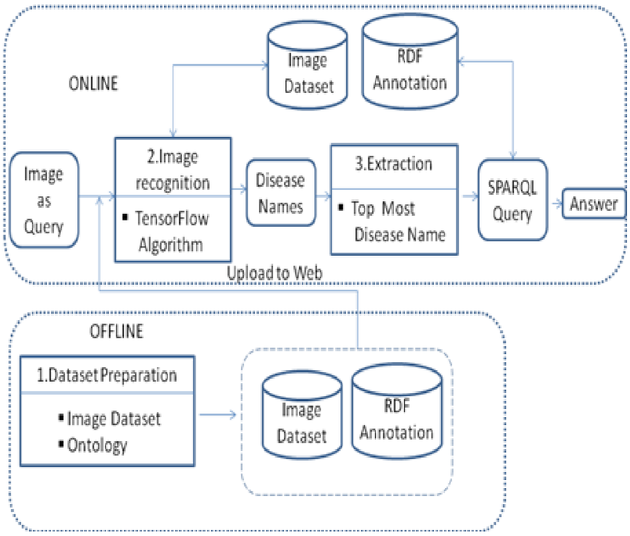

Figure 1. Architecture of Semantic based Answering Technique for Image Query

For understanding image as query, the proposed technique uses neural network's deep learning. To build and train neural networks, google's open source library TensorFlow is used. It automatically creates a neural network for the users, uses an image classifier Inception v3 that automatically does feature extraction and classifies the images. The proposed technique, retrains Inception v3 with bacterial diseases that affect tomatoes. For retraining, the disease affected crops' images are placed inside a folder that is labeled with disease names. In this paper, 5 classes of bacterial diseases are used, namely, bacterial canker, early blight, fusarium wilt, grey leaf spot and pith necrosis. When retraining, bottlenecks are created for each image that helps the classifier to distinguish between image classes. In each training step, 3 outputs are received. They are Training accuracy (Percentage of images used in the current training set that are labeled with correct class), Validation accuracy(Percentage of correctly labeled images from different sets) and Cross entropy (shows the learning process). Then, an image is

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given as query Q and proposed technique recognizes the image and displays a list of disease names D_i where i=1,2,…n along with the probabilities. The disease name with the highest probability D_1 is extracted from the suggestions. Based on the disease name, SPARQL query is framed to retrieve the preventive and controlling methods of the disease as answer A. Thus image query is semantically answered with the use of ontology by combining two huge technologies.

This application is converted as mobile application. Mobile phones has limited processing speed and memory. To optimize the computations and increase the speed in mobile distributions, TensorFlow has a tool “optimize_for_inference” that removes all the nodes that are not needed for the input and output. To reduce the size of Tensorflow’s mobile distribution, it is compressed by quantize the images and network weights by “quatize_graph” script.

The step-by-step procedure is given below.

Input : Image as Query

Output : Disease name and preventive and controlling methods of the disease

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Steps:

1. Upload image as query Q.
2. Query, Q is passed the Image Recognition Algorithm (IRA).
3. IRA identifies and displays the possible names of the diseases, D_i where i=1,2,…n.
4. This technique is optimized and compressed for mobile platforms.
5. Extract the first disease name, D_1 from the result of IRA.
6. Pass D_1 to the SPARQL query editor.
7. Frame the SPARQL query based on D_1 to retrieve the controlling and preventive methods of disease, D_1.
8. Pass this query to the developed ontology.
9. Get the preventive and controlling methods of D_1 as answer A.

IV. SIMULATION RESULTS AND FINDINGS

Semantic based answering technique for image query is developed in Python. Entirely two different datasets are used here. For Image Dataset, the images are downloaded from different web forums and from different web pages and image databases. The images are labeled and organized in a folder named “tomato_diseases”. In this work,5 bacterial diseases of tomatoes are taken. They are, bacterial canker in leaves and stems, bacterial spot, early blight, fusarium wilt, grey leaf spot and pith necrosis. For each disease, a folder is created with the disease name and placed under the “tomato_diseases” folder as shown in Figure 2.

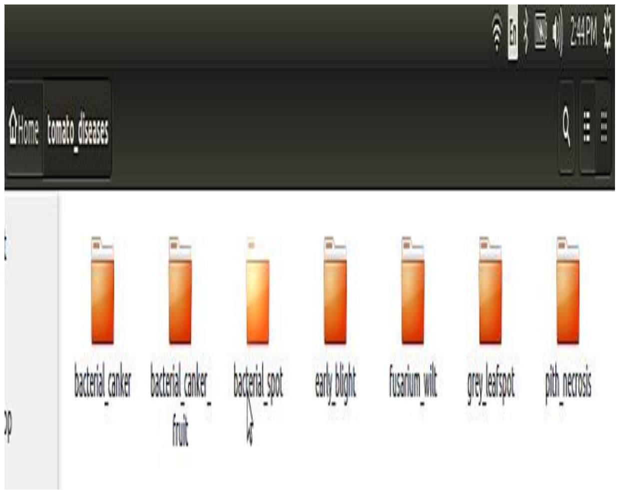

Figure 2. Images to be trained

For each disease, nearly 30-40 images are collected and saved inside the folder as given in Figure 3. The images name can be anything, but the folder name must represent the disease. Because, the proposed answering technique displays the disease name that is named for folders.

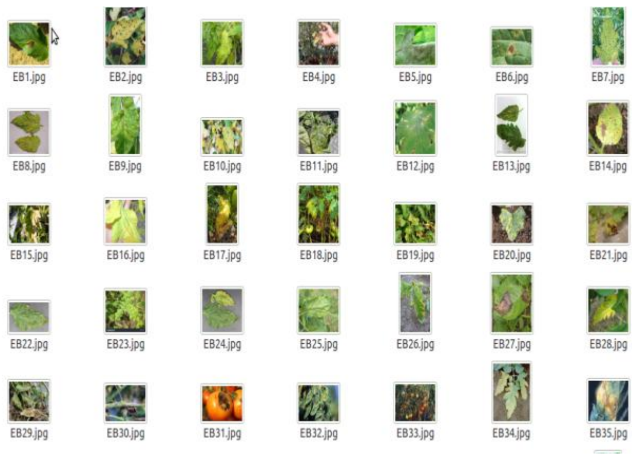

Figure 3. Images collected for Early Blight disease

After preparing the Image dataset, activate Tensorflow by giving source ~/tensorflow/bin/activate in Terminal. To view the training process, Tensorboard is started by issuing the command “tensorboard –logdir training summaries &”. Then the images are retrained in Tensorflow by giving the following command shown in Figure 4. The default number of training steps are 4000. The number of crop diseases going to be trained is 5 classes, So, 500 steps would be enough to get better performance.

```
cynthia@cynthia-Inspiron-N5110: ~
cynthia@cynthia-Inspiron-N5110:~$ source ~/tensorflow/bin/activate
(tensorflow) cynthia@cynthia-Inspiron-N5110:~$ tensorboard --logdir
 training_summaries &
[1] 9718
(tensorflow) cynthia@cynthia-Inspiron-N5110:~$ Starting TensorBoard
 b'54' at http://cynthia-Inspiron-N5110:6006
(Press CTRL+C to quit)
^C
(tensorflow) cynthia@cynthia-Inspiron-N5110:~$ python3 retrain.py \
 --bottleneck_dir=bottlenecks \
>   --how_many_training_steps=500 \
>   --model_dir=inception \
>   --summaries_dir=training_summaries/basic \
>   --output_graph=retrained_graph.pb \
>   --output_labels=retrained_labels.txt \
>   --image_dir=tomato_diseases
```

Figure 4. Command to begin Retraining of neural network

Semantic based answering for image query uses transfer learning, that is, a model already trained for image classification is used here .It could be used in the proposed system by training the final layer. Inception v3 is a pre trained model for image classification that could differentiate 1000 classes of images. It is made up of several layers. The proposed technique uses Inception v3 and trains the final layer to identify the disease by image classification. Every image is used multiple times during training. For every image that is trained, the calculated values are cached in a file called bottleneck and a bottleneck directory is created to store the bottleneck files. The final classification layer takes the values of each image from bottleneck directory for image classification. So, the trained images' values are reused. The bottleneck files for each image is given in Figure 5.

```
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW1.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW7.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW15.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW25.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW19.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW29.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW11.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW6.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW22.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW17.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW8.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW9.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW26.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW10.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW27.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW20.jpg.txt
Creating bottleneck at /tmp/bottleneck/fusarium_wilt/FW14.jpg.txt
```

```
Creating bottleneck at /tmp/bottleneck/pith_necrosis/Pith22.jpg.txt
200 bottleneck files created.
Creating bottleneck at /tmp/bottleneck/pith_necrosis/Pith19.jpg.txt
Creating bottleneck at /tmp/bottleneck/pith_necrosis/Pith5.jpg.txt
```

Figure 5. Bottleneck files creation

After creating bottleneck files, the algorithm classifies images and results with Training accuracy, Validation accuracy and Cross entropy that is shown in Figure 6. To achieve good results, validation accuracy should be high. If the training accuracy is high and validation accuracy is low means, the proposed technique memorizes specific features that couldn't help to classify images accurately. To improve the performance, the training steps are increased and the number of images are increased. The proposed system works fine with high validation accuracy.

```
2017-07-10 14:55:16.440331: Step 0: Train accuracy = 30.0%
2017-07-10 14:55:16.440530: Step 0: Cross entropy = 1.886556
2017-07-10 14:55:16.641913: Step 0: Validation accuracy = 24.0% (N=100)
2017-07-10 14:55:17.975264: Step 10: Train accuracy = 72.0%
2017-07-10 14:55:17.975440: Step 10: Cross entropy = 1.568652
2017-07-10 14:55:18.082168: Step 10: Validation accuracy = 37.0% (N=100)
2017-07-10 14:55:18.922431: Step 20: Train accuracy = 67.0%
2017-07-10 14:55:18.922554: Step 20: Cross entropy = 1.433788
2017-07-10 14:55:18.999707: Step 20: Validation accuracy = 31.0% (N=100)
2017-07-10 14:55:19.847186: Step 30: Train accuracy = 74.0%
2017-07-10 14:55:19.847433: Step 30: Cross entropy = 1.264763
2017-07-10 14:55:19.936542: Step 30: Validation accuracy = 45.0% (N=100)
2017-07-10 14:55:20.892729: Step 40: Train accuracy = 76.0%
2017-07-10 14:55:20.892839: Step 40: Cross entropy = 1.167763
2017-07-10 14:55:20.990290: Step 40: Validation accuracy = 63.0% (N=100)
2017-07-10 14:55:21.826184: Step 50: Train accuracy = 83.0%
2017-07-10 14:55:21.826289: Step 50: Cross entropy = 1.047235
2017-07-10 14:55:21.902468: Step 50: Validation accuracy = 62.0% (N=100)
```

Figure 7. Accuracy in each step

After training is completed, an image is given as query and received the following output shown in Figure 8. The result from TensorFlow shows all the disease names that are trained and the disease name with the higher probability is the answer.

```
(tensorflow) cynthia@cynthia-Inspiron-N5110:~$ python3 label_image.py tomato_diseases/pith_necrosis/Pith8.jpg
pith necrosis (score = 0.84253)
bacterial canker stem (score = 0.09425)
bacterial canker (score = 0.03810)
early blight (score = 0.00919)
fusarium wilt (score = 0.00653)
bacterial spot (score = 0.00579)
grey leafspot (score = 0.00361)
(tensorflow) cynthia@cynthia-Inspiron-N5110:~$
```

Figure 8. Answer retrieved for image as query

After these steps, TensorFlow library is optimized and compressed for mobile distribution. To run this technique in mobile devices, an application is created. Android Studio 3.0.1 is used. When compared with above application, mobile distribution slightly differs in executing the image question answering. The mobile distribution is used as an interface for the mobile applications that needs TensorFlow. The mobile application uses a camera and classifies the image. It uses Google's Pixel Android Virtual Device(AVD) , API level 27 and Oreo operating system in Android. While choosing the AVD, the front camera option is changed as Webcam) to consider the laptop's web camera as it's camera. Sample screenshot is given in Figure 9.

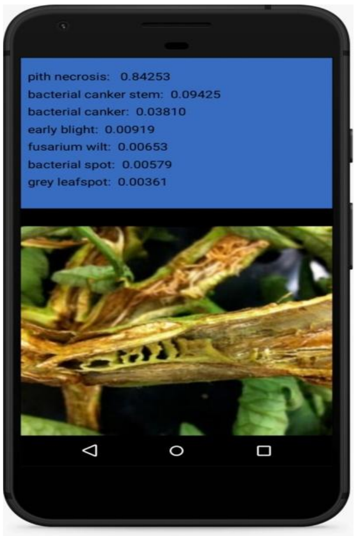

Figure 9. Answer retrieved image as query in mobile devices

The proposed technique is developed to give the disease name along with the preventive and controlling methods of diseases. Using TensorFlow, the disease name of tomato crop is retrieved. To retrieve the preventive and controlling methods of diseases, an ontology has to be created. Before discussing about ontology, having a glimpse about semantic web, helps to understand ontology. Semantic web is an extension of the web that helps to represent web of data through the common standards by World Wide Web Consortium (W3C). Resource Description Framework (RDF), Simple Protocol and RDF Query Language (SPARQL) and Web Ontology Language (OWL) are the W3C standards that allow creating a web of data. Ontology is a model of the world that represents every active element as object. Relationship between objects and the properties of objects are represented by ontology. Ontology is queried using SPARQL queries and answers are retrieved in a semantic way which is more appropriate without any duplication. The proposed work uses the ontology which is our previous work. From the result by TensorFlow, the top answer is extracted and passed to SPARQL query to retrieve the controlling and preventive methods of the identified disease. SPARQL query is

PREFIX:rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>

PREFIX:owl:<http://www.w3.org/2002/07/owl#>

PREFIX:rdfs:<http://www.w3.org/2000/01/rdf-schema#>

PREFIX:xsd:<http://www.w3.org/2001/XMLSchema#>

PREFIX:agris:<http://www.cynthia/agri1.owl#>

SELECT ?subject WHERE { ?subject agris:prevents agris:Disease_Name }

This proposed technique uses minimum number of images. So, a Personal Computer (PC) is enough to store and train the image dataset. In mobile platform, training the dataset is impossible. It needs a powerful machine. For training the dataset, the heavy processing can be offloaded to Amazon Elastic Cloud (EC2) Windows12 server (Virtual Machine) which can be availed from Amazon Web Services (AWS). For storing the image dataset and ontology, AWS's S3 service suits well.

V. CONCLUSION

The proposed semantic based answering technique for image as query is a milestone in information retrieval and image recognition. It helps the farmers to get the answers for their queries by 24 X 7. The simulation and finding results of the proposed technique show that the image classification accuracy is gained semantically and combining this with ontology is a new dimension in answering technique. The proposed technique imitates human beings in recognition of images. When image is a query, there is no need for language processing. The proposed work will be more beneficial if the answer retrieved is in farmer's regional language when ontology is involved.

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