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Identification of Foliar Diseases in Apple Trees

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Abstract: *In agriculture, detecting illnesses in plants is a critical responsibility. This is something that the economy is extremely reliant on. In the agribusiness area, infection detection in plants is a crucial task since plant illnesses are quite prevalent. Continuous inspection of the plants is necessary to detect illnesses in leaves. This constant observation or monitoring of the plants necessitates a significant amount of human work and is also time demanding. To put it another way, seeing the plants requires some type of pre-programmed approach. The use of a programme to identify illnesses in plants makes it easier to spot damaged leaves, reducing human effort and saving time. In comparison with existing methodologies, the presented method identifies illness in plants and categorize them more efficiently.*

Keywords: Foliar Diseases, Apple Tree

I. Introduction

India is primarily an agricultural country, with agriculture providing employment to the majority of the population. Agriculture serves as a source of energy and a solution to the problem of global warming, in addition to feeding an ever-increasing population. Agriculture research aims to boost production and food quality while lowering costs and increasing profits, and it has gotten a lot of attention recently. Apple tree leaf diseases such as scab and rust are widespread. Apple tree leaf diseases can be efficiently controlled, losses reduced, and the apple industry's healthy growth ensured by early diagnosis and correct identification. Traditional plant leaf disease detection methods rely on expert knowledge to manually extract disease leaf colour, texture, and shape traits.

II. Literature Survey

Chowdhury, Dhruba K. Bhattacharyya, Jugal K. Kalita propose an Co-Expression Analysis of Gene Expression: A Survey of Best Practices. It presented an overview of best practices in the analysis of (differential) co- expression, coexpression networks, differential networking, and differential connectivity that can be discovered in microarrays and RNA-seq data, and shed some light on the analysis of scRNA-seq data as well.

XiaoyanGuo, MingZhang, Yongqiang Dai proposed Image of pant disease segmentation model based on pulse coupled neural Network with shuffle frog leap algorithm. A novel image segmentation model SFLA-PCNN for plant diseases based on hybrid frog-hopping algorithm is proposed. Using the weighted sum of cross entropy and image segmentation compactness as the fitness function of SFLA, the image of potato late blight disease is taken as a trial segmentation image to find the optimal configuration parameters of PCNN neural. Image segmentation is a key step in feature extraction and disease recognition of plant diseases images.

Chit Su Hlaing, Sai MaungMaung Zaw proposed Plant Diseases Recognition for Smart Farming Using b Model- based Statistical Features. Ithas shown the advantages of GP distribution model for SIFT descriptor and successfully applied in plant disease classification. Furthermore, it proposed feature achieves a good tradeoff between performance and classification accuracy. Although it proposed feature can successfully model the SIFT feature and applied in plant diseases recognition, it need to try to improve our proposed feature by considering and cooperation with other image processing methods

III. Existing System

Plants are thought to be a source of energy for humans. Plant diseases can have a negative impact on agriculture, resulting in a significant reduction in agricultural output. As a result, detecting leaf diseases is critical in the agricultural industry. However, it necessitates a big workforce, more processing time, and considerable knowledge and expertise in plant diseases. As a result, machine learning plays a role in the identification of illnesses in plant leaves by evaluating data from multiple sources and categorising it into one of a number of predetermined classes. The various types of plant diseases and various classification techniques in machine learning that are used for identifying diseases in wild varieties leaf are considered major assertions for classification, as are the features and properties of the plant leaves like colour, intensity, and dimensions.

IV. Proposed System

To build the module in such a way that it could be used and obtained by someone who had no prior understanding of programming. It suggested a technique for forecasting the occurrence of leaf diseases. It illustrates how our methodology's experimental analysis works. Apple Leaves samples were gathered from over 1000 photos. For each illness, a different number of photos were gathered and categorised as database images and input images. The form and texture-oriented aspects of the picture are the image's major qualities.

V. System Architecture

5.1 Architecture of System

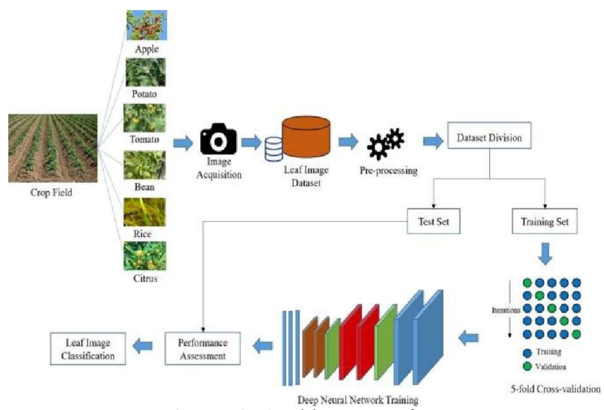

Figure 1: Architecture of system

As shown in figure 1 there is a database which consist of all the apple plant leaf diseases which we have taken into account. The module is trained repetitively to attain the maximum accuracy. If a new image is given to the module its features get compared with the features that are already trained in the database. It then provides the appropriate result.

5.2 Use Case Diagram

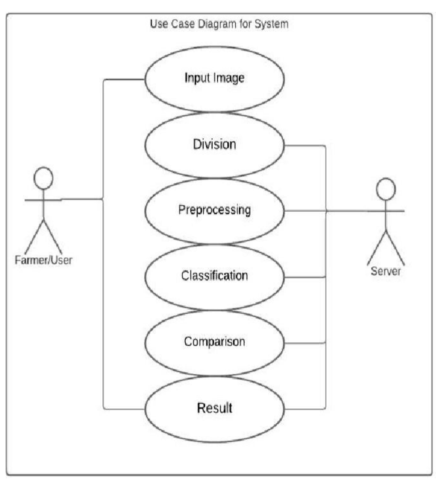

Figure 2: Use Case Diagram

As shown in figure 2. When we give a new input image first the module extracts the leaf features. Then it goes through the CNN model. It then compares the features with already trained dataset. Then it goes through dense CNN and the leaf features are extracted separately. Then the module will predict whether the plant leaf is affected by any disease or not. It shows the output from one of the 4 types which are predetermined and trained. Then the output will be in a textual format.

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5.3 Data Flow Diagram Level 0

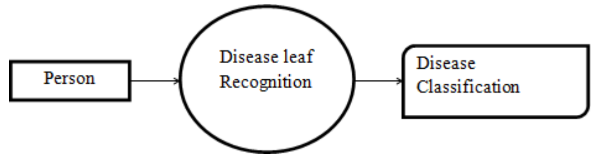

Figure 3: Data flow diagram level 0

As shown in figure 3, at level 0, the person recognizes the plant leaves disease and able to classify it.

5.4 Data Flow Diagram Level 1

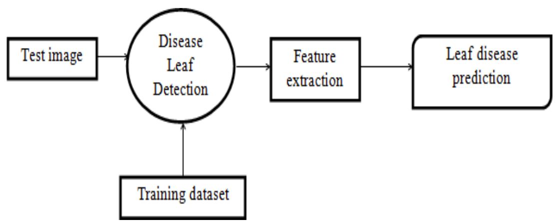

Figure 4: Data flow diagram level 1

As shown in figure 4, at level 1, a test image is given and it is tested with using the trained dataset. The features are extracted and gets compared. Then we can able to predict the leaf disease.

5.5 Data Flow Diagram Level 2

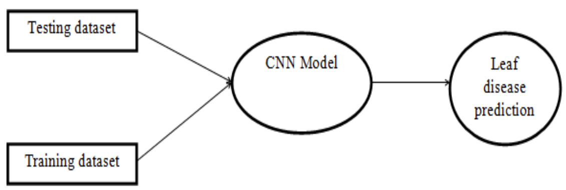

Figure 5: Data flow diagram level 2

As shown in figure 5, at level 2, the testing and training dataset are used in CNN model to predict the leaf disease.

5.6 Data Flow Diagram Level 3

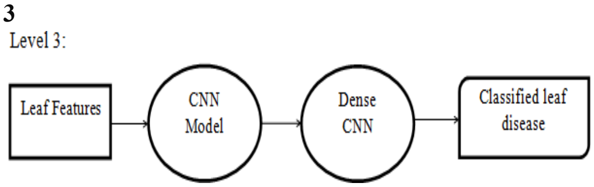

Figure 6: Data flow diagram level 3

As shown in figure 6, at level 3, The last level comprises of both CNN model. It is used to gain more accuracy.

VI. CNN Model

- Conv2D: The layer that convolves the picture into several images. Activation is the function that activates the image. MaxPooling2D: This function is used to max pool the value from a particular size matrix, and it is repeated for the following two levels.
- Flatten: This command is used to flatten the dimensions of a picture after it has been convolved.
- Dense: This is the hidden state that is developed to generate this a fully linked model.

Dropout is employed to avoid overfitting on the dataset, and dense means that the output layer only has one neuron that determines which category each picture belongs to.

- Image Data Generator: It rescales the image, adds compression in a certain range, zooms the image, and flips it horizontally.

- Training Process: Train_datagen. Flow_from_directory is the function that is used to prepare data from the train_dataset directory Target_size specifies the target size of the image. test_datagen. flow_from_directory is used to prepare test data for the model and all is similar as above. fit_generator is used to fit the data into the model made above, other factors used are steps_per_epochs tells us about the number of times the model will execute for the training data.
- Epochs: It tells us the number of times model will be trained in forward and backward pass.
- Validation process: validation_data is used to feed the validation/test data into the model. validation_steps denote the number of validation/test samples.

6.1 Training and Testing Model

The dataset is preprocessed such as Image reshaping, resizing and conversion to an array form. Similar processing is also done on the test image. A dataset consisting of about 1000 different plant leaf diseases is obtained, out of which any image can be used as a test image for the software.

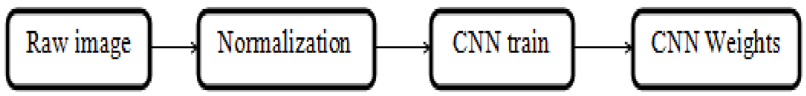

Figure 7: Training Model

The train dataset is used to train the model (CNN) so that it can identify the test image and the disease it has CNN has different layers that are Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D. After the model is trained successfully, the software can identify the disease if the plant species is contained in the dataset. After successful training and preprocessing, comparison of the test image and trained model takes place to predict the disease.

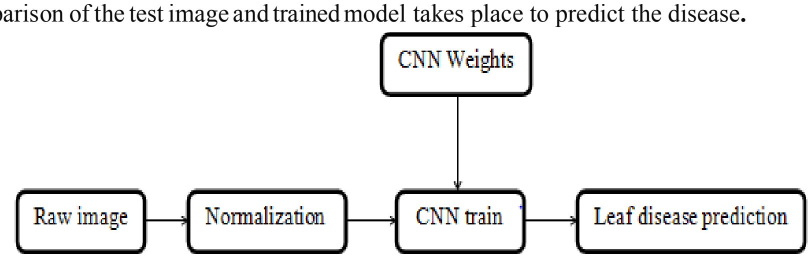

Figure 8: Testing Model

VII. Conclusion

It looked at how images from a particular dataset in the field and previous data sets were utilized to forecast plant disease patterns using a CNN model. This leads to some of the following conclusions concerning the forecasting of plant leaf disease. Because this system will cover the most varieties of plant leaves, farmers will be able to learn about leaves that have never been grown and will be able to see a list of all conceivable plant leaves, which will aid them in deciding which crop to produce.

VIII. Future Scope

The agricultural department seeks to automate the process of recognizing high-yield crops. This method can be automated by displaying the prediction result in a web or desktop application.

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