KeepItGreen – Plant Leaf Disease Detection App

A Project Work Synopsis

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Learning

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1. INTRODUCTION

1.1 Problem Definition

Agricultural production is something on which Indian economy highly depends. This is one of the reasons that disease detection in plants plays an important role in agricultural field, as having disease in plants is quite natural. If proper care is not taken in this area then it can be very dangerous and can effect on crops and consequently the relevant product quality. Detection of plant disease through some automatic technique is beneficial as it reduces a large work of monitoring in big farms of crops, and at very early stage itself it detects the symptoms of diseases i.e. when they appear on plant leaves. Farmers experience great difficulties in switching from one disease control policy to another. The naked eye observation of experts is the traditional approach adopted in practice for detection and identification of plant diseases. Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure, with increased profit.

1.2 Project Overview/Specifications

KeepItGreen – Plant Leaf Disease Detection App project is about collecting images of various infected, good and seemingly infected plant leafs. Then apply image processing on the images and predict the infected plant's leaf using Deep Learning and Image Processing. The main purpose is to detect the diseased part of the leaf. Using python, Convolutional neural network are implemented in order to classify the diseased part. Aim is to detect the diseased part by finding the optimum way with minimum cost. Especially CNNs, they are the majority a promising way to automatically learn the decisive and discriminatory aspects.Deep learning (DL) consists of different layers representing the learning features from data Diagnosis of plant diseases can be made through in-depth study model In-depth reading also has its drawbacks, as it requires a large amount of data network training. If the available data set does not have enough images, it works too bad. Transfer learning has several benefits; for example , it does not require a large the amount of network training data. Passing on learning improves learning a new job by transferring information to the same function that has already been studied. Many studies have used transmission studies in their pathology. CNN-based reading transfer is used on MobileNetV2 and EfficientNetB0model. In each model, we freeze the layer weight before the fully connected layer and removed all layers after that. Add a layer of activation layer, batch normalization layer, and dense layer. After each layer of batch-normalization, we applied a drop-off layer with different stopping values, which prevents the formation from excess. Since a large number of features were available, we used L1 and L2 techniques to accentuate the dense layer of all models, making the models simpler. We configured the network with different parameters to get the best results. We perform a comprehensive test by adjusting the different parameters. We used a different one cluster sizes 32–180, with different values dropping in the range of 0.2–0.8.In order to prepare the model, we have tested it with different reading values in that grade 0.01–0.0001. Models trained for different eras.

1.3 Hardware Specification

1.3.1 Processor - Minimum 1 GHz; Recommended 2GHz or more
1.3.2 Windows 7 or newer
1.3.3 MAC: OS X v10.7 or higher or
1.3.4 Linux: Ubuntu

1.4 Software Specification

1.4.1 Jupyter Notebook
1.4.2 Python Libraries - TensorFlow , Pandas, NumPy, Matplotlib, Scikit-learn, Keras
1.4.3 Frontend – Android Studio

2. LITERATURE REVIEW

Disease Detection in plant's leaf has always been vital subject since the beginning of human life. There has been a lot of changes in the methods of detection of leaf disease over the centuries . Earlier it was done by just looking at the leaf by naked eyes by some experts [1] , but this method is always not very convenient and not very easily approachable to everyone. Implementing appropriate techniques to identify healthy leaves helps to control crop losses and increase productivity. Here is some of Existing Systems to detect disease in plant's leaf -

2.1. Shape-Based and Text-Based Identification

In [2], authors identified diseases using images of tomato leaf. They use something different geometric features and histogram from different parts of the disease and used is SVM section with different configuration kernels. S.Kaur et al. [3] identified three different soybean diseases use different colors and texture features. In [4] P Babu et al. use the feed-forward neural network and backpropagation to identify plant leaves as well diseases. S. S. Chouhan et al. [5] used a neural-based radial-base function neural network (BRBFNN) to identify leaves and fungal infections. on plants. On their way, they use a regional algorithm to extract features from the leaf on the basis of seed points with similar properties. Bacterial-fogging efficiency is used to speed up the network and improve the accuracy of the sections.

2.2. Deep-Learning-Based Identification

Mohanty et al. [6] used AlexNet and GoogleNet CNN architectures in the identification of 26 different plant diseases. Ferentinos et al. [25] used different CNN architectures to identify 58 different plant diseases, achieving high levels of classification accuracy. In their approach, they also tested the CNN architecture with real-time images. Sladojevic et al. [7] designed a DL architecture to identify 13 different plant diseases. They used the Caffe DL framework to perform CNN training. Kamilaris et al. [8] exhaustively researched different DL approaches and their drawbacks in the field of agriculture. In [9], the authors proposed a nine-layer CNN model to identify plant diseases. For experimentation purposes, they used the PlantVillage dataset and data-augmentation techniques to increase the data size, and analyzed performance. The authors reported better accuracy than that of a traditional machine-learning-based approach. Pretrained AlexNet and GoogleNet were used in [10] to detect 3 different soybean diseases from healthy-leaf images with modified hyperparameters such as minibatch size, max epoch, and bias learning rate. Six different pre-trained network(AlexNet, VGG16, VGG19, GoogLeNet, ResNet101 and DenseNet201) used by KR Aravind et al. [8] to identify 10 different diseases in plants, and they achieved the highest accuracy rate of 97.3% using GoogleNet. A pretrained VGG16 as the feature extractor and multiclass SVM were used in [38] to classify different eggplant diseases. Different color spaces (RGB, HSV, YCbCr, and grayscale) were used to evaluate performance; using RGB images, the highest classification accuracy of 99.4% was achieved. In [12], the authors classified maizeleaf diseases from healthy leaves using deep-forest techniques. In their approach, they varied the deep-forest hyperparameters regarding number of trees, forests, and grains, and compared their results with those of traditional machine-learning models such as SVM, RF, LR, and KNN. Lee et al. compared different deep-learning architectures in the identification of plant diseases [12]. To improve the accuracy of the model, Ghazi et al. used a transfer-learning-based approach on pretrained deep-learning models [40]. In [41], the authors used a shallow CNN with SVM and RF classifiers to classify three different types of plant diseases. In their work, they mainly compared their results with those of deep-learning methods and showed that classification using SVM and RF classifiers with extracted features from the shallow CNN outperformed pretrained deeplearning models. A self-attention convolutional neural network (SACNN) was used in [14] to identify several crop diseases. To examine the robustness of the model, the authors added different noise levels in the test-image set.

Oyewola et al. [16] identified 5 different cassava-plant diseases using plain convolutional neural network (PCNN) and deep residual network (DRNN), and found that DRNN outperformed PCNN by a margin of 9.25%. Ramacharan et al. [4] used a transfer-learning approach in the identification of three diseases and two pest-damage types in cassava plants. The authors then extended their work on the identification of cassava plant diseases using a smartphone-based CNN model and achieved accuracy of 80.6% [44]. A NASNet-based deep CNN architecture was used in [8] to identify leaf diseases in plants, and an accuracy rate of 93.82% was achieved. Rice- and maize-leaf diseases were identified by Chen et al. [2] using the INC-VGGN method. In their approach, they replaced the last convolutional layer of VGG19 with two inception layers and one global average pooling layer. A shallow CNN (SCNN) was used by Yang Li et al. [12] in the identification of maize, apple, and grape diseases. First, they extracted CNN features and classified them using SVM and RF classifiers. Sethy et al. [1] used different deep-learning models to extract features and classify them using an SVM classifier. Using ResNet50 with SVM, they achieved the highest performance accuracy. A VGG16, ResNet, and DenseNet model was used by Yafeng Zhao et al. [16] to identify plant diseases from the plant village dataset. To increase the dataset size, they used a double generative adversarial network (DoubleGAN), which improved the performance.

Literature Review Summary

Table 2.1: Literature review summary

Year and citation	Article By	Purpose of the study	Tools/ Softwareused	Findings	Data set (if used)	Evaluation parameters
2016	Mohanty et al.	Research	Python- AlexNet and GoogleNet	lexNet 99.34% in	Not Provided	Accuracy
2016	Sladojevic et al.	Research	Python- Finetuned CNN architecture	racy	Not Provided	Accuracy
2020	Chen et al.	Research	Python - INC VGGN	cy	Not Provided	Accuracy
2020	Li et al.	Research	Python - Shallow CNN with SVM and RF	94% accuracy	Not Provided	Accuracy
2021	Oyewola et al.	Research	Python - Deep residual neural network (DRNN)	96.75% accuracy	Not Provided	Accuracy

3. PROBLEM FORMULATION

Identification of the plant diseases is the key to preventing the losses in the yield and quantity of the agricultural product. It requires a tremendous amount of work, expertise in plant diseases, and also requires excessive processing time. Hence, image processing is used for the detection of plant diseases. Disease detection involves the steps like image acquisition, image pre-processing, image segmentation, feature extraction and classification. This paper discussed various techniques to segment the disease part of the plant. This paper also discussed some Feature extraction and classification techniques to extract the features of infected leaves and the classification of plant diseases. The use of CNN methods for classification of disease in plants such as self- organizing feature maps can be efficiently used. From these methods, we can accurately identify and classify various plant diseases using image processing techniques.

It is hard to determine the factors that lead to the diseases unless they are detected on time. In other words, if a disease is detected on time, it is easy to relate it to the possible factors that lead to its occurrence. For example, scientists could determine if there was a change in weather or climate that could have led to the occurrence of the disease.

Inadequate database that could be used to provide background knowledge for comparing the images taken. The other challenge is that the symptoms and characteristics of the diseases are diverse and could be similar to a certain degree.

The other challenge is the lack of suitable instruments for use in the work of image detection. Most of the experts in the field do not have the equipment they require to analyze the images they get from the field, and this makes it hard for them to acquire accurate data and identify the diseases. The other one is that there is a low rate of implementation in some areas due to the regulations put in place to ensure the credibility and reliability of the data from these analyses. The rules discourage some of the results from the ML functions from being applied in practice because they do not meet the required parameters.

The technology has been in existence for several years now. However, there are still many issues that have not been clarified about its application. The other challenge is related to this fact. Some of the important images that could help determine if disease exists have not been captured. The other one is that the future perspectives of the research are not clear, and this is because of the increased diversity in the diseases that affect both humans and animals. The application of image-based detection is also affected by the increased diversity in the way the diseases appear. Some of the diseases that used to affect the plants a few years ago have evolved into new forms, and they have different impacts and outcomes. It is difficult for the images to be used alone to conclude the diseases and choose a solution. Some of the solutions used in the past have also become ineffective, reducing the effectiveness of the technology.

The aforementioned challenges show that there are many possible ways in which the image-based detection could be applied, but the challenges reduce its usability. The first solution is to provide adequate data that can be used to identify the diseases accurately without confusing the ones that are closely related. The changes in weather, global warming, and other impacts have led to many diseases that have not been documented. The solution is to increase scientists' coverage and promote a better way of collecting information . The other solution would be to offer training to the scientists in this field to ensure that they are equipped to collect the data. Yet another solution is to create better ways of capturing the data collected about the diseases. The challenge of inadequate information about the diseases can be solved if there is an improved data-captioning process that involves fine details of the images taken and the differences that define them. The images should be analyzed keenly to determine the ones that are affected or infected.

Another solution would be to focus on using the latest technology that is reliable and valid. The confusion that comes with the inadequate database for use in detecting the diseases results from inferior technology and low storage abilities of the existing systems. Most of the images are not stored correctly, which affects the accessibility of the information. It could be solved by the use of modern methods of storing information. For example, the use of cloud computing could help increase the accuracy of storage and accessibility. The other solution is training the people in charge of the research and analysis of the information. A trained DL algorithm increases the accuracy of the technology. The other solution would be to update the systems to ensure the data captured is up to date. The high level of uncertainty in the detection of diseases affects the way the technology is implemented.

4. OBJECTIVES

The existing method for plant disease detection is simply naked eye observation by experts through which identification and detection of plant diseases is done. For doing so, a large team of experts as well as continuous monitoring of plant is required, which costs very high when we do with large farms. At the same time, in some countries, farmers do not have proper facilities or even idea that they can contact to experts. Due to which consulting experts even cost high as well as time consuming too. In such conditions, the suggested technique proves to be beneficial in monitoring large fields of crops. Automatic detection of the diseases by just seeing the symptoms on the plant leaves makes it easier as well as cheaper. So, Plant Leaf Disease Detection App project is about collecting images of various infected, good and seemingly infected plant leaf which we get from kaggle PlantVillage Dataset dataset. Then apply image processing on the images and predict the infected plant's leaf using Deep Learning and Image Processing. The main purpose is to detect the diseased part of the leaf. Using python, Convolutional neural network and various deep learning techniques are implemented in order to classify the diseased part. The objective of our project is to develop a system that capable to detect and identify the type of disease that too at an early stage or the initial stage i.e. when they appear on plant leaves. It will be less laborious task and at the same time, more accurate than the visual way of plant disease identification.

5.METHODOLOGY

The following methodology will be followed to achieve the objectives defined for proposed research work:

Deep learning is powerful machine learning approach which have mitigated the traditional machine learning headache of feature engineering. It doesn't need any domain expertise now and all credit goes to deep learning. The core of deep learning is artificial neural network (ANN).
Artificial neural networks are mathematical models that replicate with their neurons and synapses interconnecting them the general principles of brain function. To implement neural network one of the most standard library is Tensor flow. It provides all libraries related to artificial neural network. With the help of Tensor flow one can perform classification tasks on text as well as images.

- **Convolution Neural Network (CNN)**

  Convolution Neural Networks (CNNs) are used to detect the disease in plant's leaves. CNN is an evolution of simple ANN that gives better result on images. Because images contains repeating patterns of particular thing (any image). Two important functions of CNN are convolution and pooling. Convolution is used to detect edges of patterns in an image and pooling is used to reduce the size of an image. CNN architectures that were applied on a problem are following:

  (a) Simple CNN.
  (b) VGG.
  (c) InceptionV3.

  Moreover training of these models are done using Jupyter notebook and Keras API of Tensor flow. Keras is tensor flow's high level API for building and training deep learning models.

- **Dataset Discussion**

  Two datasets are used to perform plant disease detection. First dataset consists of 15 classes and second one consists of 38 classes. Both databases have number of images of each plant. First dataset have total 2952 images. Final findings of this work is on Plant Village dataset which contains 38 classes of different plants. It is also openly available on internet. Description of these classes and dataset is given in following Table- I (a) and (b).

Class	Plant Name	Healthy or Diseased	Disease Name	Images (Number)
C_0	Apple	Diseased	Apple_scab	2016
C_1	Apple	Diseased	Black_rot	1987
C_2	Apple	Diseased	Cedar_apple_rust	1760
C_3	Apple	Healthy	-	2008
C_4	Blueberry	Diseased	-	1816
C_5	Cherry_(including_sour)	Diseased	Powdery_mildew	1683
C_6	Cherry_(including_sour)	Healthy	-	1826
C_7	Corn_(maize)	Diseased	Cercospora_leaf_spotGray_leaf_spot	1642
C_8	Corn_(maize)	Diseased	Common_rust	1907
C_9	Corn_(maize)	Diseased	Northern_Leaf_Blight	1908
C_10	Corn_(maize)	Healthy	-	1859
C_11	Grape	Diseased	Black_rot	1888
C_12	Grape	Diseased	Esca_(Black_Measles)	1920
C_13	Grape	Diseased	Leaf_blight (Isariopsis_Leaf_Spot)	1722
C_14	Grape	Healthy	-	1692
C_15	Orange	Diseased	Haunglongbing (Citrus_greening)	2010
C_16	Peach	Diseased	Bacterial_spot	1838
C_17	Peach	Healthy	-	1728
C_18	Pepper_bell	Diseased	Bacterial_spot	1913
C_19	Pepper_bell	Healthy	-	1988
C_20	Potato	Diseased	Early_blight	1939
C_21	Potato	Diseased	Late_blight	1939
C_22	Potato	Healthy	-	1824
C_23	Raspberry	Healthy	-	1781
C_24	Soybean	Healthy	-	2022
C_25	Squash	Diseased	Powdery_mildew	1736
C_26	Strawberry	Diseased	Leaf_scorch	1774
C_27	Strawberry	Healthy	-	1824
C_28	Tomato	Diseased	Bacterial_spot	1702

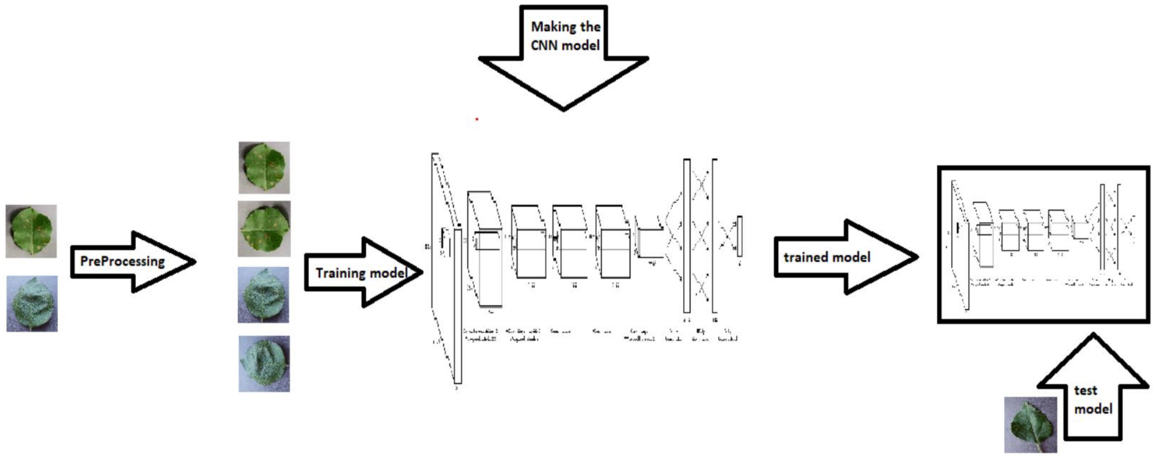
Class	Plant Name	Healthy or Diseased	Disease Name	Images (Number)
C_29	Tomato	Diseased	Early_blight	1920
C_30	Tomato	Diseased	Late_blight	1851
C_31	Tomato	Diseased	Leaf_Mold	1882
C_32	Tomato	Diseased	Septoria_leaf_spot	1745
C_33	Tomato	Diseased	Spider_mites Two-spotted_spider_mite	1741
C_34	Tomato	Diseased	Target_Spot	1827
C_35	Tomato	Diseased	Tomato_Yellow_Leaf_Curl_Virus	1961
C_36	Tomato	Diseased	Tomato_mosaic_virus	1790
C_37	Tomato	Healthy	-	1926
Total				**70295**

By using this table you can come to know number of images in each class. Each class contains approximately 2000 images. Fourteen different plants are available in this dataset. For every plant healthy as well as diseased images of leaves are available. Most of the images belongs to Tomato and Apple plants. Least images are from Raspberry, Soybean, and Squash class. Below image show some images of different leaves which are available in dataset.

Dataset is divided into two parts one for training and other for Testing. Splitting of dataset is 80/20 ratio randomly. 80% for the training dataset and rest 20% for testing dataset. Training dataset consists 56,236 image and testing consists 14,059 images. Training of model is done using 56,236 images and 14,056 images were kept unseen by model so that accuracy of model can be checked.

- **Model Description**

First some preprocessing is applied on dataset in form of augmentation to increase size of dataset in order to achieve better accuracy. Then images size are reduced by 256x256 pixels. After that a convolution neural network based model will be created with multiple pooling and convolution layers and a dense layer for prediction. Five convolution layers with 3x3 filter are used and five MaxPooling2D layers with 2x2 filter. Batch Normalization is also used in this model. Batch normalization is used to scale data on particular scale but the difference is that it not just does it on input layer but it also do it at other hidden layers. At last model is trained on Plant Village dataset.



6. TENTATIVE CHAPTER PLAN FOR THE PROPOSED WORK

CHAPTER 1: INTRODUCTION

KeepItGreen – Plant Leaf Disease Detection App project is about collecting images of various infected, good and seemingly infected plant leafs. Then apply image processing on the images and predict the infected plant's leaf using Deep Learning and Image Processing. The main purpose is to detect the diseased part of the leaf. Using python, Convolutional neural network are implemented in order to classify the diseased part. Aim is to detect the diseased part by finding the optimum way with minimum cost.

CHAPTER 2: LITERATURE REVIEW

Mohanty et al. [6] used AlexNet and GoogleNet CNN architectures in the identification of 26 different plant diseases. Ferentinos et al. [25] used different CNN architectures to identify 58 different plant diseases, achieving high levels of classification accuracy. In their approach, they also tested the CNN architecture with real-time images. Sladojevic et al. [7] designed a DL architecture to identify 13 different plant diseases. They used the Caffe DL framework to perform CNN training.

CHAPTER 2: BACKGROUND OF PROPOSED METHOD

The importance of plants in the world has increased over time. The discoveries about the critical roles that plants could play in medicine, energy production, and the recent concerns about the reduction of global warming have for long been a significant part of science and technology. A reduction in the plant cover in the world increases the risk of higher global warming and an increase in the related challenges. The need to build a state-of-the-art convolutional system that supports the image detection technology and classification of plant diseases has led to many research programs to provide the scientists with the required knowledge. Image detection could be applied when necessary to differentiate healthy leaves from those that are not healthy. The convolutional neural networks (CNNs) provide the differences among plant images that help determine the abnormalities that could exist in the plants in the natural environment. The background study shows that the scanning of the images that show the healthy and unhealthy plants forms a basis for comparison by the scientists in this field.

CHAPTER 4: METHODOLOGY

1. Convolution Neural Networks (CNNs) are used to detect the disease in plant's leaves.
2. CNN is an evolution of simple ANN that gives better result on images.
3. Two datasets are used to perform plant disease detection. First dataset consists of 15 classes and second one consists of 38 classes.
4. Some preprocessing is applied on dataset in form of augmentation to increase size of dataset in order to achieve better accuracy.
5. Batch normalization is used to scale data on particular scale.

CHAPTER 5: EXPERIMENTAL SETUP

1. Python Libraries - TensorFlow , Pandas, NumPy, Matplotlib, Scikit-learn, Keras
2. Frontend – Android Studio

CHAPTER 6: RESULTS AND DISCUSSION

Five convolution layers with 3x3 filter are used and five MaxPooling2D layers with 2x2 filter. Batch Normalization is also used in this model. Batch normalization is used to scale data on particular scale but the difference is that it not just does it on input layer but it also do it at other hidden layers. At last model is trained on Plant Village dataset. And finally an android app will be made to directly scan the diseased leaf.

CHAPTER 7: CONCLUSION AND FUTURE SCOPE

Many visualization techniques/mappings were summarized to recognize the symptoms of diseases. Although much significant progress was observed during the last three to four years, there are still some research gaps which are described below:
1. In most of the researches, the PlantVillage dataset was used to evaluate the accuracy and performance of the respective DL models/architectures. Although this dataset has a lot of images of several plant species with their diseases, it has a simple/plain background. However, for a practical scenario, the real environment should be considered.
2. Hyperspectral/multispectral imaging is an emerging technology and has been used in many areas of research. Therefore, it should be used with the efficient DL architectures to detect the plants' diseases even before their symptoms are clearly apparent.
A more efficient way of visualizing the spots of disease in plants should be introduced as it will save costs by avoiding the unnecessary application of fungicide/pesticide/herbicide.
3. A comprehensive study is required to understand the factors affecting the detection of plant diseases, like the classes and size of datasets, learning rate, illumination, and the like.

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