PLANT DISEASE IDENTIFICATION USING DEEP LEARNING

A Term Paper Report

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In

ELECTRONICS AND COMMUNICATION ENGINEERING

By

K.Santosh Manoj - 150040079

Ch.Naveen Kumar - 150040154

K.V.S.Bhanu Shouri - 150040351

M.Venkata Krishna Prasad - 150040477

Under the supervision of

Mr.K.Sripath Roy

(Asst. Professor)

KONERU LAKSHMAIAH EDUCATIONAL FOUNDATION

Green Fields, Vaddeswaram,Guntur(Dist)- 522502

Andhra Pradesh, India.

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KONERU LAKSHMAIAH EDUCATIONAL FOUNDATION
Green Fields, Vaddeswaram

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

Declaration

The Term Paper Report entitled “**Plant Disease Identification Using Machine Learning**” is a record of bonafide work of K.Santosh Manoj(150040079),Ch.Naveen Kumar(150040154),K.V.S.Bhanu Shouri(150040351),M.Venkata Krishna Prasad(150040477) submitted in partial fulfillment for the award of B.Tech in **Electronics and Communication Engineering** to K L Deemed to be a University. The results embodied in this report have not been copied from any other department/University/Institute.

BY

K.Santosh Manoj - 150040079

Ch.Naveen Kumar - 150040154

K.V.S.Bhanu Shouri - 150040351

M.VenkataKrishnaPrasad-150040477

KONERU LAKSHMAIAH EDUCATIONAL FOUNDATION

Green Fields,Vaddeswaram

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

Certificate

This is to certify that the Term Paper Report entitled "**Plant Disease Identification Using Deep Learning"** is being submitted by K.Santosh Manoj(150040079),Ch.Naveen Kumar(150040154),K.V.S.Bhanu Shouri(150040351),M.Venkata Krishna Prasad(150040477) submitted in partial fulfillment for the award of B.Tech in **Electronics and Communication Engineering** to K L Deemed to be a University is a record of bonafide work carried out under our guidance and supervision.

The results embodied in this report have not been copied from any other department/University/Institute.

Signature of the Supervisor		**Signature of the Research Head**	
Name	: Mr.K.Sripath Roy	Name	: Mr.K.Sripath Roy
Designation	: Assistant Professor	Designation	: Assistant Professor
Affiliation	: KLEF,Vijayawada.	Affiliation	: KLEF,Vijayawada.

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By

1. K.Santosh Manoj - 150040079

2.Ch.Naveen Kumar - 150040154

3.K.V.S.Bhanu Shouri - 150040351

4.M.VenkataKrishnaPrasad-150040477

ABSTRACT

The technology has been increasing day by day, traditional approaches for disease detection requires continues monitoring and observation of farms either by farmers or by experts. Disease infection to agricultural products like plants, fruits and vegetables, results in degradation of quality and quantity of agriculture products. This directly affects the financial source of agriculturists and the human health. Hence, detection of diseases in plants, fruits and vegetables crops at early stages of development leads to reduce loss of yield and quality. Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases (or absence thereof). The trained model achieves an accuracy of 99.35% on a held-out test set, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

Keywords: crop diseases, machine learning, deep learning, digital epidemiology

Contents

Chapter-1

Introduction

1.1 Objetives of the project

- To identify the diseases of the plants using deep learning techniques.
- To perform literature review on our particular base pape and implement it .
- To implement our project using efficient algorithm.
- To create a mobile application so that it might be useful to farmers to detect the disease and can take precautions to cure the disease .

1.2 Motivation of the project

Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure.

The combination of increasing global smartphone penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis.

1.3 Basic theory

Not with standing having seen numerous enhancements in the mass creation and availability of nourishment, sustenance security remains debilitated by an assortment of components, for example, the decrease of pollinators what's more, plant maladies. In the creating scene, more than 80 percent of the agrarian creation is produced by smallholder ranchers, and reports of yield loss of something beyond than half because of irritations and sicknesses are normal. Besides, the lion's share of people experiencing hunger live in smallholder cultivating family units. Luckily, sicknesses can be overseen by recognizing the sicknesses when it shows up on the plant. Also, with the ascent of the web also, portable innovation around the world, it simple to get to conclusion data on a specific sort of sickness. Therefore, the predominance of cell phones with effective cameras can help to scale up an answer that includes edit discovery possible and down to earth. Cell phones specifically offer exceptionally novel methodologies to help recognize maladies due to their processing power, high-determination shows, and broad inherent arrangements of adornments, for example, progressed HD cameras. Indeed, it is assessed that around 6 billion telephones would be accessible around 2050. The contribution to the calculation in this paper will 2D pictures of infected and solid plant takes off. I will utilize a Deep convolutional organize, a generative ill-disposed system, also, a semi administered learning approach that uses a stepping stool arrange. These diverse methodologies will be utilized to yield an anticipated malady write or a kind of solid plant species.

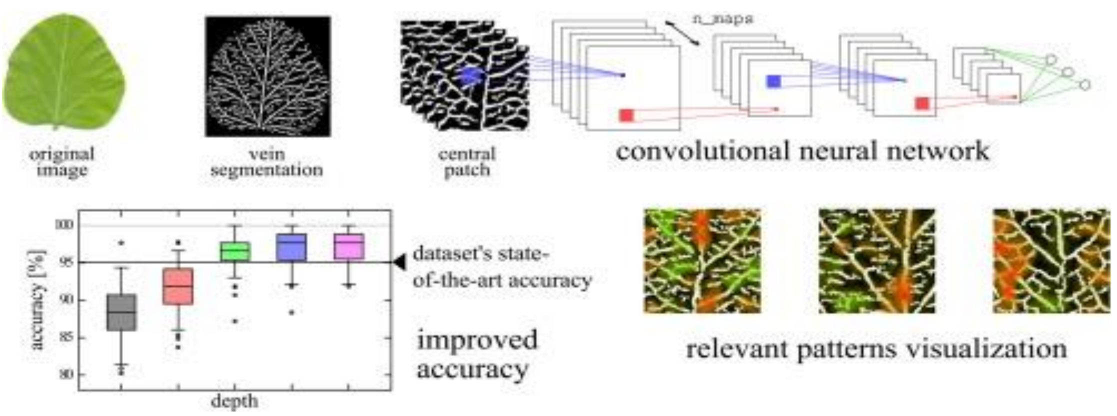
Product infections are a noteworthy risk to nourishment security, however their fast-distinguishing proof stays troublesome in numerous parts of the world because of the absence of the vital framework. The mix of expanding worldwide cell phone entrance and late advances in PC vision made conceivable by Deep learning has made ready for cell phone helped infection determination. Utilizing an open dataset of 54,306 pictures of ailing and sound plant leaves gathered under controlled conditions, we prepare a Deep convolutional neural system to recognize 14 edit species and 26 ailments. The prepared model accomplishes an exactness of 99.35% on a held-out test set, showing the possibility of this approach. In general, the approach of preparing Deep learning models on progressively expansive and freely accessible picture datasets presents a reasonable way toward cell phone helped edit ailment analysis on an enormous worldwide scale.

Introduction to Machine learning:

The various algorithms are directed by the analyst to examine the different variables in the dataset and the output is usually a numerical value like a score or classifications It is essential for associations to plainly comprehend the distinction between machine learning and Deep learning. By definition, machine learning is an idea in which calculations parse the information, gain from it, and after that apply the same to settle on educated choices. A straightforward illustration would be of Netflix, which utilizes a calculation to find out about your inclinations and present you with the decisions that you may get a kick out of the chance to watch.

On account of machine taking in, the calculation should be advised how to make an exact expectation by furnishing it with more data, while, on account of Deep taking in, the calculation can discover that through its own information preparing. It is like how an individual would recognize something, consider it, and after that make any sort of determination.

Deep Learning is a new area of Machine Learning research, which has been introduced with the objective of moving Machine Learning closer to one of its original goals: Artificial Intelligence. See these course notes for a brief introduction to Machine Learning for AI and an introduction to Deep Learning algorithms.



Chapter 2
Literature Review

2.1 Introduction

Deep learning

Deep Learning is tied in with taking in numerous levels of portrayal and deliberation that assistance to comprehend information, for example, pictures, sound, and content. The instructional exercises exhibited here will acquaint you with the absolute most vital deep learning calculations and will likewise demonstrate to your industry standards to run them utilizing Theano. Theano is a python library that makes composing Deep learning models simple and gives the alternative of preparing them on a GPU.

Plant Disease pairs:

Different endeavors have been created to avoid edit misfortune because of ailments. Authentic methodologies of across the board utilization of pesticides have in the previous decade progressively been supplemented by coordinated nuisance administration (IPM) approaches (Ehler, 2006). Autonomous of the approach, recognizing a sickness accurately when it initially shows up is a significant advance for proficient ailment administration. Generally, ailment distinguishing proof has been upheld by rural expansion associations or different organizations, for example, nearby plant centers. In later circumstances, such endeavors have furthermore been upheld by giving data to illness determination web based, utilizing the expanding Internet infiltration around the world. Significantly more as of late, instruments in view of cell phones have multiplied, exploiting the generally unparalleled fast take-up of cell phone innovation in all parts of the world (ITU, 2015).

Cell phones specifically offer extremely novel ways to deal with help distinguish maladies on account of their registering power, high-determination shows, and broad implicit arrangements of extras, for example, progressed HD cameras. It is broadly evaluated that there will be in the vicinity of 5 and 6 billion cell phones on the globe by 2020. Toward the finish of 2015, officially 69% of the total populace approached versatile broadband scope, and portable broadband entrance achieved 47% of every 2015, a 12-overlap increment since 2007 (ITU, 2015). The joined variables of across the board cell phone infiltration, HD cameras, and elite processors in cell phones prompt a circumstance where ailment analysis in view of robotized picture acknowledgment, if in fact doable, can be made accessible at an extraordinary scale. Here, we exhibit the specialized practicality utilizing a Deep learning approach using 54,306 pictures of 14 edit species with 26 illnesses (or solid) made straightforwardly accessible through the venture PlantVillage (Hughes and Salathé), 2015.

Example of leaf images from the Plant Village dataset, representing every crop-disease pair used

Deep neural systems have as of late been effectively connected in numerous differing spaces as cases of end to end learning. Neural systems give a mapping between an information, for example, a picture of an ailing plant—to a yield, for example, a crop-disease combine. The hubs in a neural system are scientific capacities that take numerical contributions from the approaching edges, and give a numerical yield as an active edge. Deep neural systems are basically mapping the info layer to the yield layer over a progression of stacked layers of hubs. The test is to make a Deep system such that both the structure of the system and in addition the capacities (hubs) and edge weights accurately delineate contribution to the yield. Deep neural systems are prepared by tuning the system parameters such that the mapping enhances amid the preparation procedure. This procedure is computationally testing and has as of late been enhanced drastically by various both reasonable and designing leaps forward

So as to create exact picture classifiers for the motivations behind plant infection analysis, we required a huge, checked dataset of pictures of ailing and sound plants. Until as of late, such a dataset did not exist, and significantly littler datasets were not uninhibitedly accessible. To address this issue, the PlantVillage venture has started gathering a huge number of pictures of solid and unhealthy harvest plants (Hughes and Salathé, 2015), and has made them transparently and uninhibitedly accessible. Here, we investigate the order of 26 illnesses in 14 edit species utilizing 54,306 pictures with a convolutional neural system approach. We measure the execution of our models in view of their capacity to anticipate the right product sicknesses combine, given 38 conceivable classes. The best performing model accomplishes a mean F1 score of 0.9934 (general precision of 99.35%), consequently exhibiting the specialized attainability of our approach. Our outcomes are an initial move toward a cell phone helped plant illness analysis framework.

2.2 Existing Methods/Methodologies:

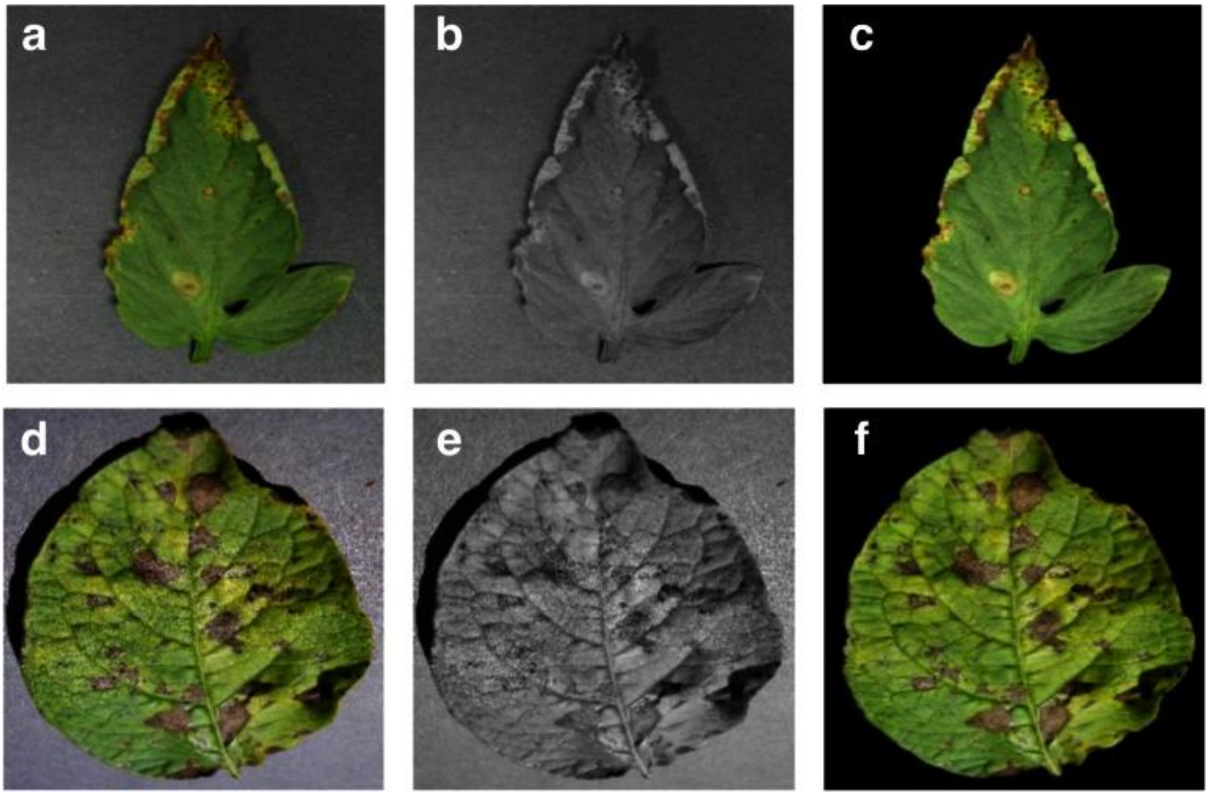
We investigate 54,306 pictures of plant leaves, which have a spread of 38 class marks alloted to them. Each class mark is a product infection combine, and we influence an endeavor to foresee the harvest sickness to match given only the picture of the plant leaf. Figure Figure11 indicates one case each from each product sickness match from the PlantVillage dataset. In all the methodologies portrayed in this paper, we resize the pictures to 256 × 256 pixels, and we perform both the model advancement and forecasts on these downscaled pictures.

Over every one of our tests, we utilize three distinct variants of the entire PlantVillage dataset. We begin with the PlantVillage dataset as it may be, in shading; at that point we try different things with a dim scaled form of the PlantVillage dataset, lastly we run every one of the examinations on an adaptation of the PlantVillage dataset where the leaves were fragmented, henceforth expelling all the additional foundation data which may can possibly present some innate inclination in the dataset due to the regularized procedure of information accumulation in the event of PlantVillage dataset. Division was robotized by the methods for a content tuned to perform well on our specific dataset. We picked a procedure in view of an arrangement of covers created by examination of the shading, delicacy and immersion segments of various parts of the pictures in a few shading spaces (Lab and HSB). One of the means of that preparing likewise enabled us to effectively settle shading throws, which happened to be exceptionally solid in a portion of the subsets of the dataset, hence evacuating another potential predisposition. This arrangement of examinations was intended to comprehend if the neural system really takes in the "idea" of plant infections, or on the off chance that it is simply taking in the inborn inclinations in the dataset. The dataset plants are divided into three kinds :

1.colour

2.gray scale

3.segmented



Estimation of execution:

To get a feeling of how our methodologies will perform on new inconspicuous information, and furthermore to monitor if any of our methodologies are overfitting, we run every one of our analyses over an entire scope of prepare test set parts, in particular 80– 20 (80% of the entire dataset utilized for preparing, and 20% for testing), 60– 40 (60% of the entire dataset utilized for preparing, and 40% for testing), 50– 50 (half of the entire dataset utilized for preparing, and half to test), 40– 60 (40% of the entire dataset utilized for preparing, and 60% for testing) lastly 20– 80 (20% of the entire dataset utilized for preparing, and 80% for testing). It must be noticed that as a rule, the Plant Village dataset has various pictures of a similar leaf (taken from various introductions), and we have the mappings of such cases for 41,112 pictures out of the 54,306 pictures; and amid all these test-prepare parts, we ensure every one of the pictures of a similar leaf goes either in the preparation set or the testing set. Further, for each examination, we process the mean exactness, mean review, mean F1 score, alongside the general precision over the entire time of preparing at consistent interims (toward the finish of each age). We utilize the last mean F1 score for the correlation of results over the majority of the distinctive exploratory designs.

Approach

We assess the relevance of profound convolutional neural systems for the order issue portrayed previously. We center around two well known structures, to be specific AlexNet (Krizhevsky et al., 2012), and GoogLeNet (Szegedy et al., 2015), which were planned with regards to the "Huge Scale Visual Recognition Challenge" (ILSVRC) (Russakovsky et al., 2015) for the ImageNet dataset (Deng et al., 2009).

The AlexNet engineering takes after a similar outline design as the LeNet-5 (LeCun et al., 1989) engineering from the 1990s. The LeNet-5 engineering variations are typically an arrangement of stacked convolution layers took after by at least one completely associated layers. The convolution layers alternatively may have a standardization layer and a pooling layer directly after them, and every one of the layers in the system ordinarily have ReLu non-straight initiation units related with them. AlexNet comprises of 5 convolution layers, trailed by 3 completely associated layers, lastly finishing with a softMax layer. The initial two convolution layers (conv{1, 2}) are each trailed by a standardization and a pooling layer, and the last convolution layer (conv5) is trailed by a solitary pooling layer. The last completely associated layer (fc8) has 38 yields in our adjusted form of AlexNet (paralleling the aggregate number of classes in our dataset), which nourishes the softMax layer. The softMax layer at long last exponentially standardizes the information that it gets from (fc8), subsequently creating a dispersion of qualities over the 38 classes that mean 1. These qualities can be translated as the confidences of the system that a given information picture is spoken to by the relating classes. The majority of the initial 7 layers of AlexNet have a ReLu non-linearity actuation unit related with them, and the initial two completely associated layers (fc{6, 7}) have a dropout layer related with them, with a dropout proportion of 0.5.

The GoogleNet design then again is a significantly more profound and more extensive engineering with 22 layers, while as yet having impressively bring down number of parameters (5 million parameters) in the system than AlexNet (60 million parameters). A use of the "system in organize" design (Lin et al., 2013) as the initiation modules is a key element of the GoogleNet engineering. The commencement module utilizes parallel 1×1, 3×3, and 5×5 convolutions alongside a maximum pooling layer in parallel, consequently empowering it to catch an assortment of highlights in parallel. As far as common sense of the usage, the measure of related calculation should be held in line, which is the reason 1×1 convolutions before the previously mentioned 3×3, 5×5 convolutions (and furthermore after the maximum pooling layer) are included for dimensionality lessening. At long last, a channel connection layer basically links the yields of all these parallel layers. While this structures a solitary initiation module, a sum of 9 beginning modules is utilized as a part of the variant of the GoogLeNet engineering that we use in our analyses. A more nitty gritty review of this engineering can be found for reference in (Szegedy et al., 2015).

We break down the execution of both these structures on the PlantVillage dataset via preparing the model starting with no outside help in one case, and afterward by adjusting effectively prepared models (prepared on the ImageNet dataset) utilizing exchange learning. In the event of exchange learning, we re-introduce the weights of layer fc8 if there should be an occurrence of AlexNet, and of the misfortune {1,2,3}/classifier layers in the event of GoogLeNet. At that point, when preparing the model, we don't restrict the learning of any of the layers, as is in some cases improved the situation exchange learning. As it were, the key contrast between these two learning approaches (exchange versus preparing starting with no outside help) is in the underlying condition of weights of a couple of layers, which lets the exchange learning approach abuse the vast measure of visual information officially learned by the pre-prepared AlexNet and GoogleNet models removed from ImageNet.

All through this paper, we have utilized the documentation of Architecture:TrainingMechanism:DatasetType:Train-Test-Set-Distribution to allude to specific analyses. For example, to allude to the test utilizing the GoogLeNet design, which was prepared utilizing exchange learning on the dark scaled PlantVillage dataset on a prepare—test set dispersion of 60– 40, we will utilize the documentation GoogLeNet:TransferLearning:GrayScale:60– 40. Every one of these 60 tests keeps running for an aggregate of 30 epochs, where one age is characterized as the quantity of preparing emphasess in which the specific neural system has finished a full go of the entire preparing set. The decision of 30 epochs was mentioned in view of the observational objective fact that in these tests, the adapting dependably joined well inside 30 epochs

Chapter 3

Rresults,Conclusion and Future Scope

3.1 Results

At the beginning, we take note of that on a dataset with 38 class marks, arbitrary speculating will just accomplish a general exactness of 2.63% all things considered. Over all our test arrangements, which incorporate three visual portrayals of the picture information (see Figure Figure2),2), the general exactness we got on the Plant Village dataset fluctuated from 85.53% (if there should arise an occurrence of AlexNet::TrainingFromScratch::GrayScale::80– 20) to 99.34% (in the event of GoogLeNet::TransferLearning::Color::80– 20), thus indicating solid guarantee of the profound learning approach for comparable forecast issues. Table Table11 demonstrates the mean F1 score, mean exactness, mean review, and general precision over all our test designs. All the trial arrangements keep running for an aggregate of 30 epochs each, and they reliably focalize after the initial step down in the learning rate. Up until now, the sum total of what comes about have been accounted for under the presumption that the model needs to identify both the yield species and the ailment status. We can confine the test to a more practical situation where the product species is given, as it can be relied upon to be known by those developing the harvests. To survey this the execution of the model under this situation, we restrain ourselves to crops where we have at any rate n > = 2 (to dodge trifling grouping) or n > = 3 classes for every product. In the n > = 2 case, dataset 1 contains 33 classes dispersed among 9 crops. Irregular speculating in such a dataset would accomplish an exactness of 0.225, while our model has a precision of 0.478. In the n > = 3 case, the dataset contains 25 classes conveyed among 5 crops. Arbitrary speculating in such a dataset would accomplish an exactness of 0.179, while our model has a precision of 0.411.

3.2 Conclusion

In this way plant diseases can be identified by using deep learning techniques . Machine learning can also be used for this purpose , Infact with the use of machine learning algorithms it can be done very easily.

3.3 Future scope

We can extend this project by adding virtual reality to it so that It can be very easy to understand by which disease the plants are getting affected and also can provide the information required to cure that disease.

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