Plant Disease Detection Using CNN – A Review

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Abstract— The distinguishing proof and location of sicknesses of plants is one of the essential concerns which decide the deficiency of the yield of harvest creation and agribusiness. The examinations of plant sickness are the investigation of any noticeable places in any piece of the plant which assists us with separating between two plants, any spots or shading conceals. The manageability of the plant is one of the central issues that are for agrarian turn of events. The ID of plant illnesses is extremely challenging to get right. The recognizable proof of the affliction requires bunches of work and ability, loads of information in the field of plants and the examinations of the acknowledgment of those illnesses. Hence, picture taking care of is used for the location of plant ailments. The Detection of illnesses follows the techniques for picture obtaining, picture extraction, picture division, and picture pre-handling.

Keywords - Disease detection, Convolutional Neural Networks, Image Classification, Transfer Learning.

I. INTRODUCTION

Horticultural yield is powerless against different biotic burdens which cause huge misfortunes as far as diminished creation. In many immature nations, significant harvest yield is delivered by little ranchers for instance, just in Africa, 80% of yields are created by little ranchers. It is a disturbing circumstance as lesser assets are accessible for smallholder ranchers, which suggests that most of rural creation of immature nations is in harm's way. Overall yearly harvest misfortunes because of plant infections are assessed to be $60 billion annually [1]. Plant illnesses are analyzed dependent on their visual indications which as a rule appear on various locales of the plant like leaf, stem, and mash. Nonetheless, master information is needed to effectively analyze infection classes. It is hard to connect the provincial regions particularly in immature nations where the greater part of the yield is created by smallholder ranchers. With the utilization of trend setting innovation, it is feasible to get a specialist level determination. For example, cell phones are presently unfathomably accessible at reasonable costs; this alongside boundless inclusion of the web can be an appropriate stage for a cell phone-based help for sickness analysis.

The event of plant illnesses adversely affects farming creation. In the occasion that plant sicknesses are not found in time, food uncertainty will increment. Early location is the reason for viable avoidance and control of plant diseases, furthermore they expect to be a fundamental part in the administration and decision making of agrarian creation. Lately, plant infection recognizable proof has been a vital issue. Illness tainted plants ordinarily show clear checks or sores on leaves, stems, blossoms, or organic products. By and large, each sickness or vermin condition presents an interesting apparent example that can be used to remarkably analyze irregularities.

Ordinarily, the leaves of plants are the essential hotspot for distinguishing plant diseases, and the greater part of the manifestations of sicknesses may start to appear on the leaves. By and large, farming and ranger service specialists are used to recognize nearby or ranchers distinguish natural product tree infections and bothers considering involvement. This technique isn't just abstract, yet in addition tedious, arduous, and wasteful. Ranchers with less experience may misconception also use drugs aimlessly during the recognizable proof interaction. Quality and result will likewise bring ecological contamination, which will cause pointless monetary misfortunes. To counter these difficulties, investigation into the utilization of picture handling strategies for plant contamination acknowledgment has turned into a hot exploration subject.

A mechanized framework intended to help distinguish plant sicknesses by the plant's appearance and visual side effects could be of extraordinary assistance to beginners in the cultivating process and furthermore prepared experts as a confirmation framework in sickness diagnostics. Progresses in PC vision present a potential chance to grow furthermore work on the act of exact plant insurance and broaden the market of PC vision applications in the field of accuracy farming.

The overall course of utilizing customary picture acknowledgment handling innovation to distinguish plant illnesses is displayed in Fig 1.

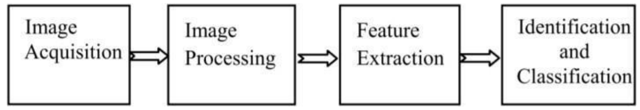

Fig 1. Flow of work in recognition using images

The mechanized recognizable proof of plant infections in light of plant leaves is a significant milestone in the field of farming. Additionally, the early and ideal distinguishing proof of plant infections decidedly impacts crop yield and quality. Because of the improvement of countless yield items, even an agriculturist and pathologist may frequently neglect to recognize the infections in plants by envisioning sickness impacted leaves. Regardless, in the provincial areas ofemerging nations, visual perception is as yet the essential methodology of illness distinguishing proof. It likewiserequires persistent observing by specialists. In far off regions, ranchers might have to make a trip far to counsel a specialist, which is tedious and costly. Computerized computational frameworks for the identification and determination of plant infections help ranchers and agronomists with their high throughput and accuracy. To conquer the above issues, analysts have thought about a few arrangements. Different sorts of capabilities can be utilized in AI for the characterization of plant illnesses. Among these, the most well known capabilities are conventional carefully assembled and profound deep learning based elements. Preprocessing, like picture improvement, shading change, and division, is an essential before productively separating highlights. Afterinclude extraction, various classifiers can be utilized.

Motivation

Plants and harvests harm from microorganisms and vermin is an overall issue. Farming harvest efficiency has beenseriously impacted by different irritations. This harm for the most part prompts a colossal yield misfortune that would ultimately influence food security. This additionally influences a yearly, overall yield misfortunes to be about worth $60 billion. There are assorted justifications for why we want to gauge or quantify the illness of plants. Information on thesickness presence and its seriousness is fundamental for fast administration choices, particularly since infection is firmlyconnected with yield misfortune. Besides, the early location and avoidance of sickness are likewise essential to shield crops from harm. Accordingly, it is basic to screen sicknesses from the beginning phase of their life cycle.

Much research is being actively pursued in this area. Disease detection using image processing, CNN, deep learning, machine learning are some of the proposed ideas. Hence we have done detailed review on Convolutional Neural Network along with transfer learning approach to detect disease in plants.

CNN for Deep Learning

In profound learning, a convolutional neural network (CNN/ConvNet) could be a lesson of profound neural systems, most connected to analyze visual symbolism. Presently when we think of a neural network we think approximately network increases but that's not the case with ConvNet. It uses a special method called Convolution.Presently in science convolution could be a numerical operation on two capacities that produces a third work that communicates how the state of one is adjusted by the other.

Convolutional neural systems are composed of different layers of counterfeit neurons. Manufactured neurons, a unpleasantimpersonation of their natural partners, are numerical capacities that calculate the weighted whole of numerous inputs and yields an enactment esteem. After you input a picture in a Convul.Net, each layer produces a few actuation capacities that are given to the following layer. Then to begin with layer, as a rule extricates fundamental highlights such as even or inclining edges. This yield is passed on to the following layer which identifies more complex highlights such as corners or combinational edges. As we move more profound into the layer, we organize it can recognize indeed more complex highlights such as objects, features, etc.

Image Classification

Picture or Image classification is the assignment of allotting an input picture one name from a settled set of categories. This is often one of the center issues in Computer Vision that, in spite of its effortlessness, includes a huge assortment of commonsense applications. It alludes to the labeling of pictures into one of a number of predefined classes. There are possibly n numbers of classes in which a givenpicture can be classified.

The rest of this paper is coordinated as follows. First, we audit some essential information including profound learning idea, establishment, system, the plant leaves illness datasets, etc. Then, we survey research work done as such far towards the use of profound gaining in crop leaves sickness acknowledgment from certain viewpoints. Then, by then, plant sickness discovery in view of little example informational index is examined. Then, a few utilizations of hyper-phantom imaging in plant infection location are talked about.

II. LITERATURE SURVEY

Liu, Bin, [2] in "Identification of apple leaf diseases based on deep convolutional neural networks." In this paper, Liu proposes another model of profound convolution networks for exact expectation and recognizable proof in apple leaves. Model Proposed in the Paper can naturally perceive the diverse person exchanges with an extraordinarily huge level of precision. An aggregate of 13,689 pictures were made with the assistance of picture handling innovations like PCA swaying. Aside from this new Alex-Net based neural organization was additionally proposed by carrying out the NAG Algorithm to advance the organization. In future work to anticipate the apple leaf illness, different Models of Profound Learning like F-CNN, R-CNN, and SSD can be carried out.

The article [3] proposes a better approach to arrange leave utilizing the CNN model and assembles two models by changing organization profundity utilizing Google Net. We evaluated the adequacy of each model in view of staining or leaf harm. The acknowledgment rate accomplished is over 94%, regardless of whether 30% of the leaves are harmed. In future exploration, we will look to distinguish leaves appended to branches to foster a visual framework that can emulate the techniques people use to recognize plant species.

The paper [4] likewise portrays different procedures for extracting the idea of tainted leaves and arranging plants Disease. Here we are utilizing a Convolution Neural Network (CNN), which comprises of different levels that are utilized for anticipating. The total strategy is depicted in view of the pictures utilized for preparing and pretreatment testing and Image improvement and afterward a preparation technique for CNN profound and analyzers. Utilizing these pictures we can exactly decide the handling strategy and separate between various plant sicknesses. The justification behind this paper [5] is to audit proof of foliar sickness, warm, computerized and hyper-spectral imaging review with different grouping strategies. The division techniqueis applied to distinguish the necessary regions. The strategydetaches the ideal region from the foundation. In light of the edge Value, grayscale picture, shading picture division technique unique. Used to remove highlights just as different techniques, for example, grayscale the grid is utilized for related qualities, histogram force, and so forth To classification of illness propagation from occasions, counterfeit neurons Maintenance vector organizations and machines are utilized in upkeep the vector motor gives the most palatable outcomes to each kind picture.

On paper [4], RGB pictures are changed over to grayscale pictures utilizing shading transformation. Different upgrade strategies, for example, histogram arrangement and difference change are utilized to further develop picture quality. Various kinds of order attributes are utilized here, for example B. Arrangement as indicated by SVM, ANN, and FUZZY. When separating capacities, various kinds of trademark esteems are utilized like surfaces, structures, and mathematical components. The ANN and FUZZY orders can be utilized to distinguish sicknesses in unpeeled plants.

In [6], the creators utilized a shallow CNN with SVM and RF classifiers to group three particular kinds of plant contaminations. In their work, they essentially analyzed their results with those of profound learning strategies and showed that grouping utilizing SVM and RF classifiers with extricated highlights from the shallow CNN outflanked pre-trained deep learning models. A self-consideration convolutional neural organization (SACNN) was utilized in [7] to distinguish a few yield infections. To inspect the power of the model, the creators added distinctive commotion levels in the test-picture set.

Transfer learning [8] intends to improve the learning execution of a model in an objective space by moving information from source areas. It has been widely concentrated in tending to target undertakings that have scanty or no named information. In the previous many years, endeavors have been paid to work on the exhibition of move learning along two angles: 1) helping positive information move; and 2) keeping away from negative information move. Due to inconsistencies between the source and target areas, ways to deal with improve helpful information move center around limiting the space inconsistency across the source and target spaces, for example, example re-weighting, and element coordinating. Then again, procedures for diminishing negative information move frequently attempt to debilitate the impact of immaterial source information through diminishing their loads.

Ahmad et al. [9] utilized four different pre-training convolution neural organizations VGG19, VGG16, Res-Net, and Beginning V3, and the models were prepared by adjusting boundaries. The trial results showed that the Origin V3 haddataset and the field dataset). What's more the normal execution better than 10% to 15% on the research facility dataset thought about with on the field dataset.

Bi et al. [10] showed that the acknowledgment exactness paces of apple leaf spot and rust models gathered by agrarian specialists were 77.65%, 75.59%, and 73.50%, by utilizing ResNet152, Commencement V3, and Mobile-Net, separately.

Jiang et al. [11] utilized the Mean Shift calculation to portion four sorts of rice illness spot (red scourge stripe sickness to rice impact and sheath scourge) from the outset, and afterward extricate shape include by counterfeit computation (set forward three new shape trademark sores number N, S injury region, number of sores proportion R) and CNN removes shading highlight, finally, the SVM classifier was utilized to recognize the illnesses, what's more the outcomes showed that the CNN utilized division calculation precision was 92.75%, the exactnesswas 82.26% without the division calculation.

Liang et al. [12] set up a dataset contains 2906 of the positive examples also 2902 of the negative examples to distinguish rice impacts. Furthermore the test results showed that the senior qualities separated from CNN than the customary manual extraction of nearby parallel example histogram (LBPH) what's more wavelet change would do well to ID what's more adequacy.

Huang et al. [13] set forward a sort of plant leaf picture illness acknowledgment strategy in view of the neural construction search calculation; the strategy can become familiarwith the design of the neural organization to the fitting profundity on the PlantVillage, consequently. As indicated bythe consequences of the concentrated on strategies on the datasetof imbalanced and adjusted looked out a appropriate organization structure, and the acknowledgment exactness of themodel was 98.96% and 99.01% individually. Regardless, if the equilibrium of the dim pictures was not improved, the precision tumbled to 95.40%.

Long et al. [14] involved Alex-Net for 2 sorts of preparing, that is, preparing without any preparation and move gaining from the Image-Net to recognize the camellia leaf sicknesses (4 sorts of illnesses and solid). The outcomes showed that move learning can fundamentally further develop the assembly speed and grouping execution of the models, and the characterization precision as high as 96.53%.

Xu et al. [15] to acknowledge picture acknowledgment of corn leaf illness (sound, leaf curse, rust) in complex field foundation with little examples, proposed a convolutional neuralorganization model (VGG16) in view of move learning. The weight boundaries of the VGG16 model were prepared on Image-Net and moved to the model, and the normal acknowledgment precision was 95.33%.

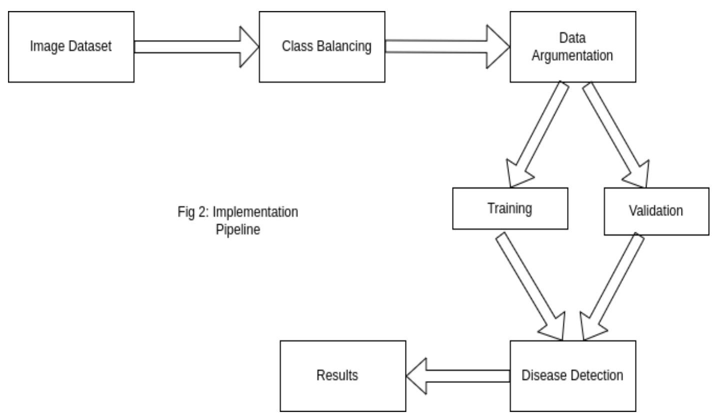

Fig 2. Implementation and Methodology

Implementation pipeline used for the proposed methodology

A complex procedure is proposed by fusing different set up cycles to work with the course of grouping and ID of sicknesses in crops. The grouping pipeline comprises of different strides as displayed in figure 2, which is started by first physically breaking down the dataset for class irregular characteristics. Class unevenness happens at the point when a few classes are under-addressed when contrasted with others. This can make themodel foresee one-sided outcomes. This issue is destroyed by utilizing information expansion methods for under-addressed classes just as eliminating a few examples from the over-addressed classes. Later class-adjusting next urgent advance is model determination.

Due to fast progression in AI, a few state-of the- craftsmanship Convolutional Neural Organizations (CNNs) are accessible which make it hard to pick the most proper model for the main pressing issue. We chose three distinct kinds of CNNs which are known to perform well on the Image-Net dataset and benchmarked them on plant sickness datasets. This way model choice advance can be systemized rather than the hit and- preliminary strategy. After the underlying benchmarking andmodel determination, we train our dataset without any preparation i.e., without involving move learning procedures to understand the model limit when contrasted with the given information. A harmony between the limit of the CNN model being utilized and the intricacy of preparing information is significant. Any awkwardness can prompt the over-fitting orunder-fitting of a model. Afterward, the fundamental portrayals gained from Image-Net dataset are progressively moved to our model. The exchange learning tests are additionally clarified in the examination segment. An outline of the grouping pipeline is in Fig 2.

Data Set

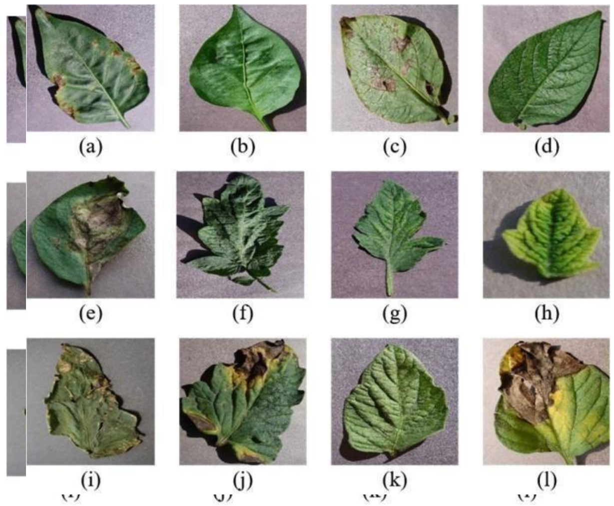

Fig 3. *Some sample images from PlantVillage dataset. (a) Pepper bell _ bacterial spot, (b) Pepper bell _ healthy, (c) Potato _ Early blight, (d) Potato _ healthy, (e) Potato _ late blight, (f) Tomato _ target spot, (g) Tomato _ tomato mosaic virus, (h) Tomato _ tomato yellow leaf curl virus, (i) Tomato _ bacterial spot, (j) Tomato _ early blight, (k) Tomato _ healthy, (l) Tomato _ late blight.*

Plant Village dataset (Fig 3) comprises of 54,306 pictures ofdifferent plant leaves which are separated into 18 classes. The dataset comprises of 14 kinds of plant species and 26 kinds of plant contaminations. The dataset contains both sound and sick crop pictures .The pictures cover 14 types of yields, including: apple, blueberry, cherry, grape, orange, peach, pepper, potato, raspberry, soy, squash, strawberry and tomato. Each class comprises of two fields for example name of the plant and name of the infections .Every one of the pictures are resized andportioned for preprocessing and further arrangement.

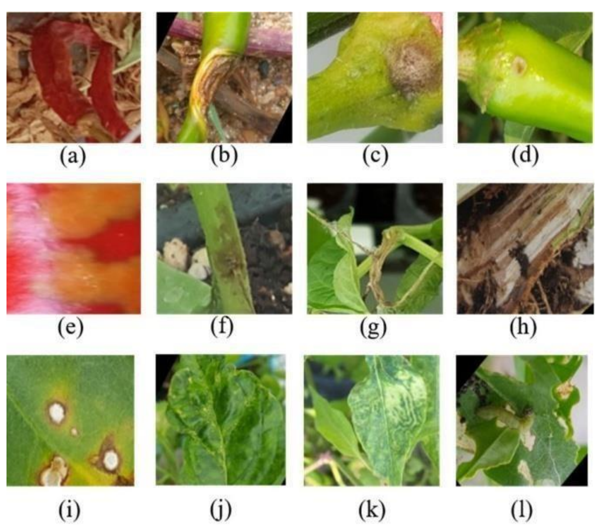

Fig. 4 Some sample images from our pepper dataset. *(a)Phytophthora blight (pulp), (b) Biter rot (pulp), (c) Gray mold (pulp), (d) Moth damage (pulp), (e) Tomato spotted wilt virus (pulp), (f) Tomato spotted wilt virus (stem), (g) Gray mold (stem), (h) Bacterial wilt (stem), (i) Bacterial leaf spot, (j) Damping off (leaf), (k) Tomato spotted wilt virus(leaf), (l) Gray mold (leaf).*

The Pepper dataset (fig 4) is worked to help the preparation for the visual indications of the depicted sicknesses which present weakness towards pepper plants. It incorporates a sum of 99,507 pictures having a spot with 24 classes of sicknesses definitively explained with the help of specialists and the help given by the Public Foundation of Plant and Natural Science, Republic of Korea. Since the application is focused on at normal clients and handheld gadgets, the pictures are caught utilizing normal advanced cameras under shifting sunlight conditions. The dataset covers the extent of plant ailments even more exhaustively as it highlights infections on the different bits of the plants, e.g., stem, leaf, and mash. Among 24 classifications, 6 infections are connected with the mash, 6 are connected with stem, 9 are connected with leaf, 2 are hatchling based, and 1 class joins solid plant pictures from each of thethree sections i.e., leaf, mash, and stem.

This dataset is difficult especially a direct result of two differentiating reasons: (I) Outwardly recognizable indications of certain infections are altogether similar to those of different sicknesses. For example, bacterial spot, severe decay, and dark form show fundamentally the same as visual side effects on the leaf. (II) Some diseases show different visual symptoms on different plants and crops.

Table 1. Categorization of each plant as healthy/unhealthy in Plant Village dataset.

Plant Name	**Healthy/Un-healthy**	**No. of images**
Apple	Healthy	1645
Blueberry	Healthy	1502
Cherry	Healthy	854
Corn	Healthy	1162
Grape	Healthy	423
Orange	Healthy	5507
Peach	Healthy	360
Bell-Pepper	Healthy	1478
Potato	Healthy	152
Raspberry	Healthy	371
Soybean	Healthy	5090
Strawberry	Healthy	456
Tomato	Healthy	1591
Apple	Un-healthy	1526
Cherry	Un-healthy	1052
Corn	Un-healthy	2690
Grape	Un-healthy	3639
Peach	Un-healthy	2297
Bell-Pepper	Un-healthy	997
Potato	Un-healthy	2001
Squash	Un-healthy	1835
Strawberry	Un-healthy	1109
Tomato	Un-healthy	16569
Total	**14 (Species)**	**54306**

Class Balancing

Perhaps the greatest test for grouping models is an unevenness of classes in the preparation information. Serious class uneven characters might be veiled by generally great F1 and precision scores - the classifier is essentially speculating the larger part class and not making any assessment on the underrepresented class. There are a few methods for managing class unevenness like defined testing, down inspecting the greater part class, weighting, and so forth However, before these moves can be made, it is essential to get what the class balance is in the preparation information.

As we know,– unbalanced dataset can prompt one-sided preparing, so the info dataset is broke down for class lopsided characteristics. Any lopsided characteristics in class dissemination can make the model 6 one-sided towards a particular class which can present a lack in model correctness and subsequently, debasing the generally execution of the model. For instance, for the situation of our Pepper crop dataset; damping off, bacterial wither, and southern curse are under-addressed when contrasted with different classes as displayed in figure 10, so it is normal for the prepared model to get one-sidedtowards other classes.

Data Augmentation

Other than involving further developed procedures for information expansion, a few fundamental increase strategies were applied to all of the classes to build the quantity of tests and vigor towards inconspicuous information. Pictures were scaled to consolidate the indications in various goals. Further expansion steps incorporate flipping, turn, interpretation, adding commotion, changing lighting conditions.

The exhibition of profound learning neural organizations frequently improves with how much information accessible. Information expansion is a method to misleadingly make new preparation information from existing preparation information. This is finished by applying area explicit methods to models from the preparation information that make new and different preparation models.

Picture information increase is maybe the most notable kind of information expansion and includes making changed forms of pictures in the preparation dataset that have a spot with a similar class as the first picture.

Changes incorporate a scope of tasks from the field of picture control, like movements, flips, zooms, and substantially more. The plan is to extend the preparation dataset with new, conceivable models. This implies, varieties of the preparation setpictures that are probably going to be seen by the model. For instance, an even flip of a picture of a feline might check out, considering the way that the photograph might have been taken from the left or right. An upward flip of the photograph of a feline doesn't seem OK and would undoubtedly not be proper given that the model is probably not going to see a photograph.

All things considered, obviously the decision of theparticular information increase techniques used for a preparation dataset should be picked cautiously and inside the setting of the preparation dataset and information on the issue area. Moreover,it might be helpful to explore different avenues regarding information increase techniques in confinement and in show to really take a look at whether they bring about a quantifiable improvement to demonstrate execution, maybe with a little model dataset, model, and preparing run.

Present day profound learning calculations, for example, the convolutional neural association, or CNN, can learn highlights that are invariant to their area in the picture. By the by, expansion can additionally support this change invariant way to deal with learning and can help the model in learning highlights that are likewise invariant to changes, for example, left-to-right to beginning to end requesting, light levels in photos, and that's only the tip of the iceberg.

Picture information expansion is ordinarily simply appliedto the preparation dataset, and not to the approval or test dataset. This is not equivalent to information readiness, for example, picture resizing and pixel scaling; they should be performed reliably across all datasets that connect with the model.

Mobile-Net Model

It is such a model may adequately come out as comfortable with the elements in our information and accomplish great order results because of its special construction and profound design while having few teachable boundaries. Having fewer boundaries makes a model less inclined to over-fitting, which isa main issue while learning portrayals on limited scope datasets. The architecture of Mobile-Net can be elaborated as in Table 2.

Mobile-Net is a proficient and versatile CNN engineering that is utilized in genuine applications. Mobile-Nets fundamentally use depth-wise separable convolutions instead of the standard convolutions utilized in before designs to fabricate lighter models. Mobile-Nets present two new worldwide hyper parameters (width multiplier and goal multiplier) that permitmodel engineers to compromise idleness or precision for speed and low size contingent upon their necessities.

Transfer Learning

In profound learning, move learning is the reuse of a pre- trained network on another undertaking. Move learning is extremely well known in profound learning since it can prepare the organization with a modest quantity of information and high exactness. In move learning, a machine takes advantage of information acquired from a past assignment to further develop speculation about another. In move learning, the last couple of layers of the prepared organization are supplanted with newlayers, for example, a completely associated layer and delicate max arrangement layer, with number of classes, which is 38 in our paper. In each model, we unfroze the layer and added a heap of one initiation layer, one clump standardization layer, and one dropout layer. All models were tried with various dropout esteems, learning rates, and cluster sizes.

The essential reason of move learning is basic: take a model prepared on a huge dataset and move its insight to a more modest dataset. For object acknowledgment with a CNN, we freeze the early convolutional layers of the organization and just train the last couple of layers which make an expectation. The thought is the convolutional layers extricate general, low-level elements that are relevant across pictures - like edges, designs, slopes - and the later layers distinguish explicit elements inside apicture like eyes or wheels.

In this way, we can involve an organization prepared on irrelevant classes in a monstrous dataset (generally Image-Net) and apply it to our own concern since there are widespread, low- level elements divided among pictures. The pictures in the Plant Town Dataset and Chime Pepper Dataset are basically the same as those in the Image-Net dataset and the information a model learns on Image-Net ought to handily move to this errand.

This approach has demonstrated fruitful for a wide scope of areas. It's an incredible device to have in your armory and byand large the primary methodology that ought to be attempted when faced with another picture acknowledgment issue.

Table 2. Mobile Net Architecture

MobileNet				
Input size	*Layer Type*	*Size Of filter*	*Number of filters*	*Stride*
224x224x3	Conv	3x3	32	2
112x112x32	DW Conv	3x3	32	1
112x112x64	Conv	1x1	64	1
112x112x64	DW Conv	3x3	64	2
56x56x64	Conv	1x1	128	1
56x56x128	DW Conv	3x3	128	1
56x56x128	Conv	1x1	128	1
56x56x128	DW Conv	3x3	128	2
28x28x128	Conv	1x1	256	1
28x28x256	DW Conv	3x3	256	1
28x28x256	Conv	1x1	256	1
28x28x256	DW Conv	3x3	256	2
14x14x256	Conv	1x1	512	1
14x14x512 14x14x512	DW Conv Conv	3x3 1x1	512 512	1 1
14x14x512	DW Conv	3x3	512	2
7x7x512	Conv	1x1	1024	1
7x7x1024	DW Conv	3x3	1024	1
7x7x1024	Conv	1x1	1024	1
7x7x1024	Pool	7x7		
1x1x1000	FC	1024x1000		
1x1x1000	Softmax	Classifier		

V. CONCLUSION

There are many developed methods in the discovering and grouping of plant illnesses utilizing diseased leaves of plants. However, there is still no efficient and effective commercial solution that can be utilized to recognize the diseases. Thus, we say that Plant Disease Detection has seen a lot of improvement through the various CNN and DL models, but none of them can help recognize diseases in parts of plants other than the leaf. Also the utilization of Mobile-Net and the proposed Mobile application will be able to help remote area farmers by providing immediate assistance for diseases caused in plants eventually reducing losses just as increase in overall crop production, and also achieve a better profit to investment ratio.

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