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Machine Learning Technique for Crop Disease Prediction Through Crop Leaf Image

S. Nandhini * *and K. Ashokkumar*

Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai, India

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Abstract: Plant diseases are a huge danger to food security, yet owing to the lack of infrastructure in several regions of the world, timely detection is challenging. Smartphone-assisted detection of disease is now achievable thanks to a combination of rising global smartphone usage & recent advancements in machine vision facilitated by depth learning. They trained a depth convolutional neural network to detect 16 crops & 25 diseases utilizing a public dataset for 64,412 pictures of damaged & normal leaf tissue taken under controlled settings (absence thereof). On the held-out testing set, the training set achieved an accuracy of 99.35 percent, showing the practicality of this strategy. The method of training deep learning techniques increasingly vast & available to the public specific sequence points to a clear route to widespread global smartphone assisted plant disease detection.

Keywords: Crop diseases; Machine learning; CNN; Smartphone device

1 Introduction

Human civilization now can produce sufficient food to sustain and over 8 billion people [1] thanks modern technology. However, several variables, such as the changing climate, pollinator decrease, crop diseases, & others, continue to pose a danger to food security. Crop diseases are a global hazard to food safety, but they could also be devastating for small-scale farmers whose livelihoods were dependent upon healthy crops [2,3,4,5]. Small-scale farmers provide more than 85 percent of agricultural production in developing countries, & estimates of yield losses of more than 60 percent owing to pests & illnesses were typical. Moreover, small-scale farming households account for the majority of hungry individuals, rendering small-scale farmers, particularly sensitive to pathogen-related disruptions of food supply [6].

To prevent yield losses owing to diseases, many attempts had been established [7,8,9]. Integrated pest management tactics had progressively augmented historical methods of broad pesticide use in the last decade. Regardless of the method, appropriately recognizing a disease since it first arises is critical for effective illness management. Extension groups of agricultural/other organizations, like local plant nurseries, have always assisted disease diagnosis. In past years, such initiatives had been aided by giving disease diagnosis info online, utilizing the growing Internet penetration around the globe [10,11,12]. Much more lately, cell phone tools have emerged, capitalizing on the historically unprecedented quick adoption of cellular phone technology in all corners of the globe.

Since of their computer, energy, high-resolution screens, & comprehensive built-in accessory sets, such as sophisticated High definition cameras, cell phones at particular offer very unique techniques to help detect disorders. Around 2020, it is expected there would be between 5 and 6 billion cell phones around the world [13]. Because of the ubiquitous use of smartphones, high-definition cameras, & high-performance CPUs in smartphones, diagnosis of disease based on automatic picture identification might be made accessible at an unimaginable level if theoretically possible [14]. They use 64,412 photos of 16 crop species with 28 illnesses provided publically available through a Crop Village initiative to show technical viability utilizing a deep learning technique.

During the last few years, machine learning, & specific object identification, had made great progress. The PASCAL VOC Competition, as well as more major Recent Size Visual Recognition Challenge based on the

* Corresponding author e-mail: nandhiniseec@gmail.com

imagined set of data, had been widely utilized as benchmarks for a variety of visualization-related computer vision tasks, including item categorization. Around 2020, a massive, deep convolutional neural network classified pictures into 1000 potential classes with an error of 10.4 percent [15]. Several breakthroughs in convolutional neural networks dropped the failure rate to 2.57 percent during the next 3 years. Although training big neural networks could take a long time, the learned networks could swiftly classify photos, making them acceptable for consumer smartphone applications.

2 Related Works

As an example of end-to-end training, deep neural networks had lately been effectively deployed in a variety of disciplines. Neural network map input, including a photo of a damaged plant, to a result, including a crop disease pairing [16]. A neural network's nodes are mathematical that accept numeric inputs from incoming edges & output numeric values as an outbound edge. Deep learning models are just a sequence of stacking interconnected nodes that map the input layer to an output layer. The goal is to build a deep network in a way in which the network's architecture, including its functions (nodes) & edge strengths, accurately map the inputs to outputs [17]. Deep neural networks are educated by adjusting network variables in such a manner that the mapping develops over time. This technique is computationally intensive, but it has recently been much simplified by a variety of theoretical & engineering advancements [18].

They required a bigger, validated collection of photos of damaged & healthy crops to create accurate picture classifiers for crop diagnosis of diseases [19]. Such a dataset didn't even exist until later, or even smaller datasets just weren't openly available [20]. To address this problem, the PlantVillage project has begun collecting tens of thousands of images of healthy and diseased crop plants and has made them openly and freely available. Utilizing a convolutional neural network technique, they were able to classify 28 illnesses in 16 plant species utilizing 64,412 photos. As a result, we've demonstrated the technological viability of their strategy. Their findings pave the way for a smartphone-based crop diseases diagnosis process.

3 Materials and Methods

They look at the 64,412 photos of leaf tissue that have been allocated 38 different class designations. Every class label represents a plant disease pair, and they are trying to predict the plant disease couple using only the plant leaves in the picture. Every plant disease pair from the Plant Village set of data is represented in Figure.1. They resize the photos to 256 $\times$ 256 PX in all of the methodologies outlined in this research, & they perform model improvement & prediction on such down-scaled pictures.

They utilize 3 multiple variations of the PlantVillage set of data in all of their tests. We begin with the PlantVillage set of data in its original colors; then they experiment with such a gray-scaled over on the PlantVillage set of data; & eventually, they run all the experimentations on a ver of the PlantVillage set of data in which the leaf had been fragmented, thus removing all the additional background info that could initiate a few obvious biases in the set of data owing to the regularized process of data collection in the scenario of the PlantVillage set of data. The classification was automated using a script that's been adjusted to work well with this dataset. They used a masking technique based on an examination of the color, brightness, & saturation elements of distinct regions of the photographs in several color spaces (Lab & HSB) [21]. One of the phases in that processing also enabled us to readily repair color casts, which were particularly strong in certain dataset's subgroups, eliminating still another potential for bias.

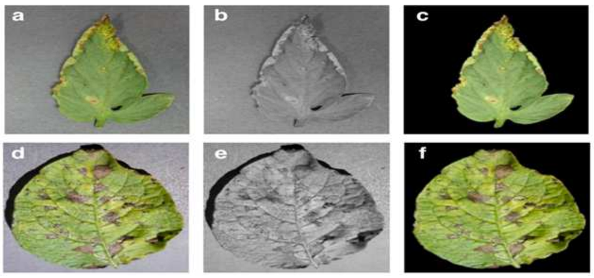

Fig. 1: Pictures from the three various variants of the PlantVillage dataset that were utilized in different testing setups. (A) Leaves 1 color, (B) Leaves 1 grayscale, (C) Leaves 1 segmented, (D) Leaves 2 color, (E) Leaves 2 grayscale, (F) Leaves 2 segmented.

4 Analysis

They conduct all of their tests across a variety of train, test batch divides, notably 80-20, 60-40, 50-50, 40-60, & eventually 20-80, to obtain a feel of how their techniques would behave on new unknown information as well as to keep track of if some of their methods were overfitting. It should be emphasized that the PlantVillage dataset had numerous photographs of the same leaves in several cases, and we also have mappings of 43,1293 of 64,412 pictures; and throughout all tests, trains divide, they ensure that all pictures of the same leaves are placed either in learning/testing group. They also calculate the average accuracy, average recall, average F1 rating, and accuracy rate for each test at periodic intervals throughout the training phase. For comparability of outcomes across whole various experimental setups, they utilize the final median F1 rating.

The Alex Net structure, as seen in Fig.2, was based on the LeNet-5 architectural style from the 1990s. A pair of layered activation functions were constantly influenced through one or perhaps more fully linked stages in the LeNet-5 architectural versions. That after fully connected layers, there could be a standardization phase as well as a hidden state, but all of the fully connected layers were sort of benefit to Rely non-linear activated elements [22]. Alex Net was made up of five activation functions, three highly interconnected strands, as well as a max-pooling layer at the conclusion. A normalization, as well as a cooler layer, precedes the very first 2 fully connected, as well as only one coolest layer, following the final fully connected layers. In their new variant of Alex Net, the total convolution layer (fc8), that supplies the retrained network, contains 38 outlets. Lastly, the learning algorithm gradually normalizes the data input (fc8), culminating in a group of numbers throughout the 38 categories which sum to only one. Those results could be read as the channel's trust in the representation of a reference picture by the categorical attributes. A Rely quasi activated component was linked to each of Alex Net's initial seven layers, and the very first 2 convolution layers get a washout stratum with such a loss frequency of 0.5.

The Google Net design, but at the other end, was substantially bigger and longer than Alex Net [23], including 22 stages as well as a significantly less amount of components in the connection. A fundamental component of the Google Net structure was the use of the "internet within system" structure in the shape activation functions. The convolution layer captures a range of characteristics simultaneously by using concurrent 1, 1, 3, 3, as well as 5 fully connected layers, as well as an at the very most surface concurrently. The quantity of related processing must be reduced to a minimum for simplicity of execution, and that was why 1 fully connected layer was included just before previously specified 3, 5 convolutions to image compression. Eventually, the outcomes of each of these adjacent layers were concatenated by a filtration system synthesis stage. Although this was one genesis component, the Google Net design which they employ current research uses a minimum of seven activation functions. Mostly on Plant Village collection, they examine the effectiveness of each of these structures by supervised learning from fresh for one scenario and afterward adjusting previously taught systems via word embedding in the other. They do not restrict the training of some of the stages while learning was taking place, as has been normally accepted for action recognition. To put it another way, the main variations between these two instructional methods would be in the original conditions of a very few formations' strength training, that also allows the transmission active learning to take advantage of the huge quantity of variable indicating already knowledge gained by the pre-trained AlexNet as well as Google Net designs derived from Deep learning [24,25,26]. Every one of those 60 operations lasts 30 eras, including one period equaling the variety of research iterations wherein the human brain had got an entire sweep of the entire sequence. Its decision of 30 periods was supported by the research finding that training consistently ended nicely inside the 30 periods represented in Figure 3 in most of these studies.

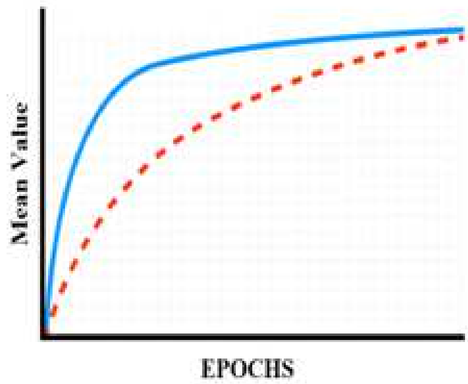

Fig. 2: Evaluation metrics

Figure 2 shows the evolution of average Evaluation metrics as well as attrition throughout all trials throughout a 30-epoch initial training, sorted by research configuration settings. They have sought to standardize the high energy across several trials to allow for a valid assessment something like the findings of all the research procedures. Every one of the following studies has been carried out by our branch of Cappuccino, a quick, free software computational intelligence platform. A typical example of cafe [27] could be used to duplicate the rapid early, including such great certainty.

5 Discussions and Findings

To begin, they should point out that randomized estimating would only attain an accuracy level of 2.63 percent on a collection containing 38 target classes. Figure 2 depicts the whole of their research procedures, which would include 3 graphical images of the picture information. With the Plant Village collection, they received a total efficiency of 85.53 percent, indicating that the machine learning approach has a great promise regarding comparable forecasting issues. Table 1 displays the average Highest accuracy, clarity, memory, as well as total correctness for the whole of their test settings. Every one of the research procedures executes for a minimum of 10 periods, and they kind of always converge during the first training tax reduction.

To handle the problem of more than, they change its assessment based on training, group proportion as well as find that throughout the instance of Google Net in 20-80, the method achieved an overall accuracy rate of 98.21 percent, although when learning on just 20 percent of the information and testing the learning algorithm just on remaining 80 percentage of the information. Picture 3D shows that, as anticipated, the total performance, including both AlexNet as well as Google Net degrades as the exam required to train set ratio was increased, but the decline was not as extreme because they would assume if the system were truly too much. Figure 3 further demonstrates that perhaps the confirmation, as well as learning losses, would not vary, indicating were over was not a factor in the outcomes they acquire throughout their studies. Therefore, as seen in Figures 3A and 3B, Google Net regularly outperforms AlexNet, because the actual training approach, deep learning usually produces improved levels, which had been hoped.

Whenever they maintain the remainder of the research arrangement same, the three phases of the information (color, colored, as well as divided) exhibit a consistent fluctuation in efficiency throughout all trials. The colored form of the information performs best to the programs. Researchers were worried while constructing these studies that perhaps the human brains would only train to detect the intrinsic biases connected with the varying illumination, data analysis method, as well as equipment. They tested the designer's flexibility in the lack of color channels, as well as its capacity to study better cognitive knowledge structures specific to crop production as well as illnesses, using a colored rendition with the same information. The damage or disruption, as anticipated, especially contrasted to the studies on the instead of the information, although the reported average Classification performance was 0.8524 in bad condition. The fragmented editions of the entire information have also been created to analyze the impact of the source picture in actual quality. As can be seen in Figure 3E, the achievement of the framework utilizing selected features would be notably better than just the prototype utilizing colored pictures, and though lower than the prototype that used the colored edition of the pictures. Whereas these methods add value to the organization on the Plant Village information, which had been gathered in a safe setting, they further tested the quality of the system on photos from reputable internet sources, including such university government agricultural agencies. They generated 2 minor, validated collections of 121 (dataset 1) as well as 119 photos (dataset 2), correspondingly, utilizing a mix of automatic acquisition using the Google Integra Picture as well as IPM Pictures with such a human authentication process (see Supplementary Material for a detailed description of the process). To use the right design on each of this information, researchers were able to correctly identify the actual target class (i.e., agricultural as well as illness data) among the 38 potential target classes with high accuracy of 31.40 percent in information 1 as well as 31.69 percent in the information 2. A randomized classification would only achieve good efficiency of 2.63 percent. In collection 1, the correct class had been in the top-5 forecasts in 52.89 percent of those surveyed, while in information 2, it would be in the top-5 forecasts in 65.61 percent of those surveyed. Google Net: Sectioned: Learning Approach: 80-20 for various datasets, as well as Google Net: Shades: Learning Approaches: 80-20 for dataset 2 have been the perfect candidates for both experiments. An instance picture for either of these collections, including its activity visualization in most previous findings, has indeed been predicated on the presumption that perhaps the system must identify combined crops as well as clinical manifestations. They may make the problem extra genuine by providing the type of crop, which could be assumed to be recognized by individuals who produce the products. They restrict themselves to plants with at most n > 2 (to avoid trivial categorization) or n $>$ three students every harvest to evaluate the effectiveness of the algorithm within that situation. In the situation of n $> = 2$, collection essentially comprises 33 categories spread across 9 harvests. With this information, the uncontrolled prediction would have had an efficiency of 0.225, whereas your system does have an efficiency of 0.478. The information is then $> = 3$ instances, has 25 categories spread across 5 harvests. In this sample, chance prediction might have an efficiency of 0.179, whereas the system does have an efficiency of 0.179. Likewise, in the situation of n > 2, collection 2 comprises 13 categories spread across four harvests. With this information, chance prediction might have an efficiency of 0.316, whereas the system does have an efficiency of 0.545. In the event of n $>= 3$, the information comprises 11 classifications spread across three harvests. In this sample, chance prediction might have an efficiency of 0.288, whereas the system does have an efficiency of 0.485.

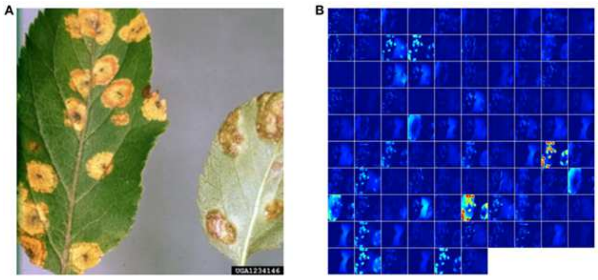

Fig. 3: Visualizing action potentials in the earliest layers of an Alex Net architecture

Table 1: The average score after 30 periods for different testing settings

Training	AlexNet		GoogleNet	
	Learning for Transfer	Scratch for Training	Learning for Transfer	Scratch for Training
1	52	42	17.08	12.54
2	30	27	4.25	4.32
3	25	27	5.03	5.04
4	32	17	19	5.02
5	45	59	59	12.5
6	34	34	34	6.25
7	81	81	87	32.6
8	39	39	35	6.05
9	504	555	34.9	34.8
10	84	84	8.93	9.83
11	115	114	12.3	12.22
12	27	28	5.26	5.62
13	18	18	5.66	5.66
14	175	175	14.3	14.32
15	45	45	6.32	6.23

As a result, the efficiency among those methods was strongly reliant on the fundamental preset characteristics. Learning algorithms would be a time-consuming as well as difficult procedure that must be addressed whenever the situation at the side of the accompanying information shifts significantly. This challenge arises in all previous machine vision efforts to identify crop diseases since they rely primarily on hand-engineered characteristics, picture augmentation techniques, as well as a variety of other complicated & labor-intensive techniques.

Furthermore, classic machine learning techniques to disease categorization usually focus on a restricted number of courses, typically within a single plant. To evaluate tomatoes downy mildew versus healthy tomato leaves, one example is a characteristic extraction & classification pipeline that uses thermal & stereo pictures. In out method is based on current research that demonstrated for the first moment that end to end monitored learning utilizing a depth convolutional neural network structure is a viable option may be for picture classification issues with a wide range of courses, outperforming conventional method utilizing hand-engineered characteristics in benchmark datasets by a significant margin. They are a very attractive choice for a realistic & scaleable technique for computer diagnosis of crop diseases due to the absence of a labor-intensive stage of feature engineering as well as the generalization of the answer.

They educated a system on photos of leaf tissue utilizing the depth convolutional neural network structure, to distinguish both different crops as well as the presence & identification of illness on pictures that the system had never seen previously. Such goal was accomplished within the PlantVillage set of data of 64,412 photos encompassing 38 categories of 16 different crops and 25 diseases (or lack thereof), as seen by the top reliability of 99.35 percent. Therefore, in 993 out of 1000 photos, the model properly identifies yield & disease from 38 potential classes without any feature extraction. Significantly, whereas the model's learning takes time (several hours on a high-performance Graphics processing unit cluster system), the categorization is quick (less than a second on a Central processing unit), and thus could be simply deployed on a cellphone. This paves the way for widespread use of smartphone-assisted crop disease diagnostics on a worldwide scale. Therefore, there are several restrictions at this time that will need to be considered in future research. Initially, whenever the model is evaluated on a batch of photographs collected under settings other than those utilized for learning, the model's reliability drops to slightly over 31 percentage. Although this reliability is significantly greater than the one based on an arbitrary choice of 38 categories (2.6 percent), a more diversified training set of data is required to increase accuracy. Their current findings suggest that simply collecting more (and much more variable) information would be sufficient to significantly improve reliability, & data gathering initiatives are now ongoing.

The second constraint is that they are now limited to classifying individual leaves that are looking ahead against a uniform background. Since these are simple settings, in the actual world, an application should be able to recognize photographs of the disease as it appears on the crop. Numerous diseases do not just affect the upper surface of leaves but could affect other areas of the crop. As a result, future picture gathering operations should aim to acquire pictures from a variety of perspectives, preferably in as real a situation as feasible. Around the same hand, by selecting 38 groups that include both different crops & disease states, we've made the problem more difficult than it needed to be from a practical standpoint because farmers were supposed to know which plants they're planting. Reducing the classification task to disease state would have no discernible impact owing to the great reliability of the PlantVillage database. On a real-world set of data, therefore, they could see significant improvements in reliability. However, the proposed method performs admirably with a wide range of different crops & diseases, and it's projected to massively improve with the further training dataset.

6 The Proposed System's Implementation

6.1 Design phases

They develop processes, as stated in the Design content, comprise of basic picture Processing phases paired with a classification algorithm, in this case, a Multiple-Class Support vector machine, to recognize the disease & determine the percentage of the affected region.

The International Commission of Illumination developed the CIELAB color system (also referred to as CIE ($L^*a^*b^*$) / frequently shortened as 'Labs' color space) around 1976. For color, 3 calculated values were utilized: L^* for lightness, a^* & b^* for green red & blue yellow elements, respectively. CIELAB was created to be intuitive in terms of human color perception. At some period, a numeric shift in such numbers correlates to a visibly seen shift of the same quantity.

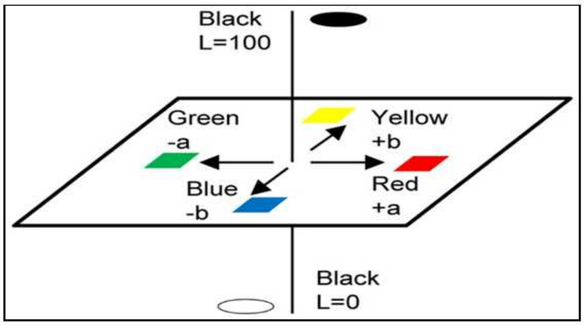

Fig. 4: Lab-space color system

($L^*a^*b^*$) is made up of 3 levels: an L^* radiance level, aa^* chromaticity level that indicates at which color falls along the red-green line, & a' b^*' chromaticity level that indicates at which color falls along the blue-yellow line. The color model for the laboratory room is shown in the diagram ahead. Most of the color details as displayed in Fig.4's levels a^* & b^*.

Following that, they employ Otsu's predictor in image analysis. It's a technique for performing picture-based filter grouping. Nobuyuki-Otsu performs the gray-level picture reduction to the binary picture. In each method, the picture is made up of two types of pixels. To do so, a bimodal distribution is being utilized (front & background px). In separating 2 classes, they can determine the ideal threshold as well as the combination distribution (intraclass variance) which is negligible/similar. This classification is responsible for the enhanced leaf picture. Fig 5 (a) & (b) indicates the common leaves picture as well as the improved picture (b).

(a)

(b)

Fig. 5: (a): Normal leave (b): Enhanced leave

Furthermore, K-means grouping separates the leaves into 3 groups, i.e., three parts: healthy, diseased, & background. Fig.6 illustrates this. The sick area then is chosen from the 3 groups to be processed further.

6.2 Extraction of Feature

Estimating the affected areas is the most crucial factor herein. The Gray Layer Co-Occurrence Matrix extracts structure & textural features. It depicts the brightness of a single picture px. s seen in Fig 7, it was built as arcs in degree at a distance of d=1 (0, 45, 90, 135). The various

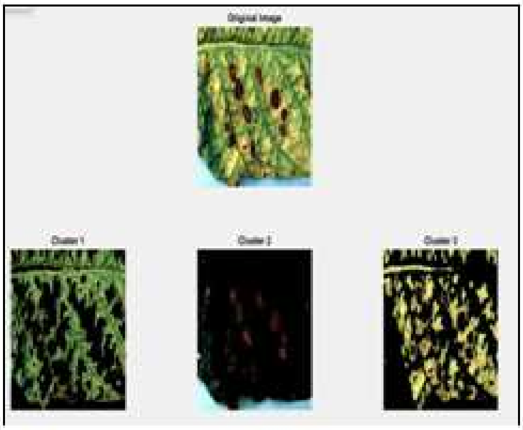

Fig. 6: Following segmentation, clusters are formed.

measurements available include entropy, power, brightness, correlation, and so on. These assessments are taken from various angles.

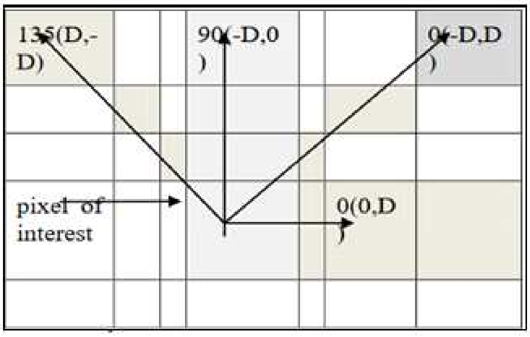

Fig. 7: Construction of GLCM

Fetchangle horizontal at zero initially. Because there is 1 opulence inside the input picture where 2 horizontal pictures were identical to a 1-px gap & had values of 1 & 1, component(1,1) has value 1 inside the outcome. Because there is 2 opulence in the source images with values of 1 & 2 near to range 1 horizontal, GLCM (1,2) had a value for 2. GLCM (1,3) has a range of zero since there is no opulence inside the source images, although 2 horizontal comparable px at range 1 had values of 1 & 3. The method is then repeated of the entire GLCM matrix at different angles. Figs 8(a) & 8(b) depict the aforesaid implications (b).

Contrast: Contrast is abbreviated as Conc. Intensity is also known as Total of Square Variance. By comparing the concentration contrast which connects each px to its neighbor, the entire picture is stretched.

Connection: The linear grayscale dependency is evaluated also on nearby px while determining the

1	1	5	6	8
2	3	5	7	1
4	5	1	1	2
8	5	1	2	5

(a) LCM-1

1	2	0	0	1	0	0	0
0	0	1	0	1	0	0	0
0	0	0	0	1	0	0	0
0	0	0	0	1	0	0	0
1	0	0	0	0	1	2	0
0	0	0	0	0	0	0	1
2	0	0	0	0	0		0
0	0	0	0	1	0	0	0

(b) GLCM-2

Fig. 8: Levels of GLCM matrix

obtaining accuracy of the picture among a px and its neighbor. Power: Since power is consumed to complete the task, it is ordered. This allows the material to be utilized in a picture that determines the ordering. The amount of square pieces is shown in GLCM. It is utilized as power & is assumed to become the square root of an Angular Second Moment.

Similitude: HOM was the moniker given to it. Components were transported diagonally from across GLCM to determine the value which quantifies leakage inside the distributing GLCM.

Slanted: It was an asymmetrical assessment. The set of data is symmetrical & identical to the right & left of the center dot.

Kurtosis: It was a metric for comparing information to a normally distributed, regardless of how light or heavy this is. Sets of data with high kurtosis tend to have heavy tails/outliers, whereas those with a small kurtosis tend to have light tails / no outliers.

Average: Mean pixel intensity data were used to calculate the average px intensity.

Deviation Standard: The deviation/variance of the source frame in px is represented by this function.

Entropy: The grayscale distribution's randomness is described here. Entropy is large when a picture's grey layers are good dispersion.

IDM: The picture texture is measured by the reversed moment of a discrepancy, which is commonly referred to as homogeneity. The IDM features are used to determine the proximity of a component dispersion at the diagonal of GLCM.

Variance: Variability is a metric for estimating how each px differs from the next (central) px and categorizing it into distinct regions.

Smoothing: Smoothing is indeed the technique of taking comparative measurements of proxies & distortions in addition to making a picture ready for processing.

Support vector machines of various sorts were evaluated, but it was determined that a Support vector machine Multiple-Class would be the best fit for the platform in terms of velocity & accuracy. An all-in-one Classifier is a Support vector machine design that solves the multiple-class problem with one optimization process. An all at ounce strategy is what it's termed. It creates k binary classification processes, with gi(X) classification processes separating a Ci group's drive pieces of data from the rest of the data pieces. Utilizing the all-in-one Support vector machine, we can find the decision limit of 3 classification issues.

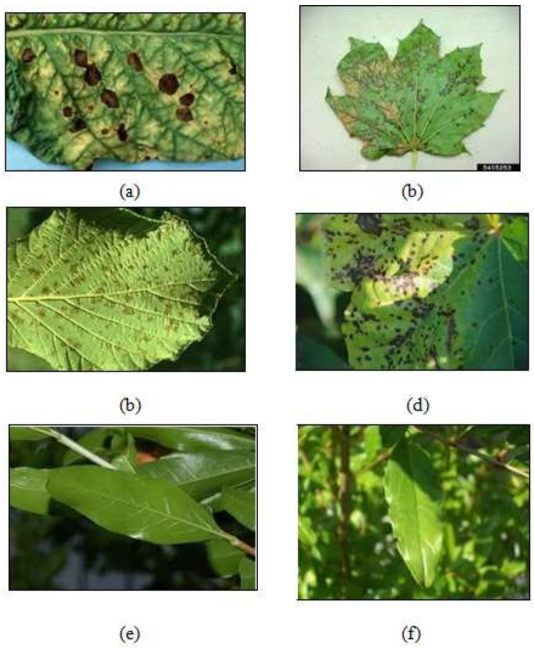

Fig. 9: (a):Alternaria-Alternate (b):Anthracnose (c):Bacterial-Blight (d):Cercospora Leave Spot (e):Healthy Leave 1 (f):Healthy leaves 2

6.3 Set of Data Definition

Data Class: JPEG File (.jpeg)
Amount of Pictures: 4000
There are healthy & sick leaves inside the group of ailments. Alternaria Variant, Anthracnose, Bacterial-Blight, and Cercospora Leave Spot are a few of these diseases. Fig.9 a-d shows the sample information, while Fig 9 (e) & (f) show healthy leaves (f).

The number of different classifiers utilizing Support vector machines & Artificial neural network classifiers include combined features is shown in the Performance Review Graph below in terms of True Positive Rate, False Positive Rate, efficiency, recall, F measure, & ACA. The graph illustrates that the Support vector machine classifier outperformed the Artificial neural network in identifying & classifying crop illnesses that impact agricultural & horticultural plants. This analysis was performed on the same set of data. Fig.10 shows the results of the performance assessment graphic.

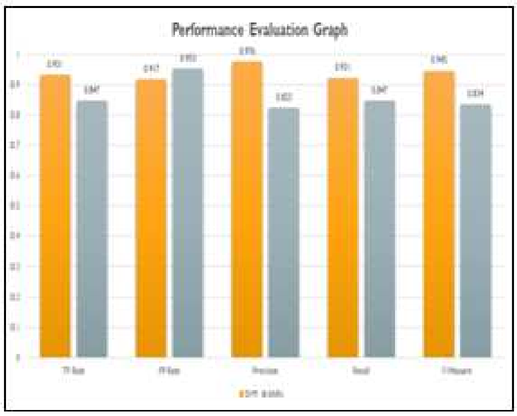

Fig. 10: (a):Alternaria-Alternate (b):Anthracnose (c):Bacterial-Blight (d):Cercospora Leave Spot (e):Healthy Leave 1 (f):Healthy leaves 2

7 Conclusion

It's important to note that perhaps the method given here would be meant to complement instead of upgrade current diagnostic options. Extensive testing is so much more accurate than judgments depending purely on eye strain, although correct detection by thorough observation was typically difficult. Pictures from the Smartphone may well be augmented using time and geographical data in the area to enhance reliability even further. Finally but just not less, it seems to be important to remember the incredible rate during which digital phones have advanced over recent times, and therefore will likely do that in the future. Researchers believe high accuracy diagnostics through smartphones are almost a matter of time, due to the sheer number and efficiency of detectors on smartphones.

Conflict of interests:

The author declare that there is no conflict of interest regarding the publication of this paper.

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S Nandhini obtained her Bachelor's degree in Computer Science and Engineering from Periyar Maniammai University, Tanjore, Tamilnadu, India in 2012. Then She obtained her Master's degree in Computer Science and Engineering in Easwari Engineering College, Anna University, Chennai, Tamilnadu, India in 2014 and pursuing Ph.D in the field of Deep Learning On Agriculture in Sathyabama Institute of Science and Technology. Currently, she is an Assistant Professor in Department of Computer Science and Engineering at SRM Institute of Science and Technology. She has published more than 15+research papers in reputed journals and conference proceedings. Her specializations include Cloud Computing, Algorithm Design and Analysis, Networking, Theory of Computation, Machine Learning. Her current research interests is in Deep Learning on Agriculture. She has guided more than 15+ Undergraduate projects till date.

K. Ashokkumar received his Masters's Degree in Computer Technology -Applied Science and Engineering from KSR college of Technology, Thiruchengode, Namakkal, Tamilnadu, India in 2002 and Master's Degree in Computer Science and Engineering from Sathyabama University,Chennai, Tamilnadu, India in 2005 and Ph.D from Sathyabama University, Chennai, Tamilnadu, India in 2016. He is currently an Associate Professor in the Department of Computer Science & Engineering in Sathyabama Institute of Science & Technology. His research interests are in Grid Computing, Cloud Computing, Data Analytics and Web Services. Dr. K.Ashokkumar is an editor in NCABC 2019 for special Issue and Reviewer in Computers and Electronics in Agriculture(Elsevier), Journal of Computer Science, Journal Of Agricultural Science and Technology. He is a Life member of Indian Society for Tech-nical Education.He has published more than 60+ research papers in reputed journals and conference proceedings. He is presently teaching a wide variety of courses at both under-graduate and postgraduate levels and has 16 years of teaching experience. He has guided more than 25 Undergraduate and Postgraduate students' projects and 5 Ph.D research scholars till date.