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Recognition of plant disease by photographs of the leaf: A comparative analysis for understanding perspectives

Ravindra N. Jogekar[1*], Dr. Nandita Tiwari[2]

[1, 2] Department of Computer Science & Engineering, RKDF Institute of Science & Technology, Sarvepalli Radhakrishnan University, Bhopal, MP, India

*[*1]ravindra.jogekar79@gmail.com[2]nandita_pandit@yahoo.com*

Abstract

The agricultural sector plays a key role of any financial system and depends on the yield of farmers and ranchers. This output has often been affected by micro-level conditions that occur while the fruit-bearing crop is growing. These viruses are numerous and hence improvement in image processing is useful to establish and suggest remedies. For example, Fusarium oxysporum, Mycosphaerella musicola, Gloeosporium musae, Erwinia Carotovora, Pseudomonas Solanaceanim, Pentalonia nigronervosa, Erionota thrax, BSV and BBM Virus are some of the diseases that affect the banana leaf. A large section of research carried out in this area is directed at linear approaches in which the identification of visually visible diseases includes classification, extraction of attributes and definition. But those modalities are not suitable for large and more burden of managing and therefore machine learning and artificial intelligence approaches such as Q-learning and enhanced learning are responsible for identifying conditions that are not visible to the human eye in every component of the processing layers. Given this complexity, the system designers are always unclear about the algorithms to define in order to distinguish combinations of algorithms to classify what kind of diseases. These papers validate and empirically weigh up some of the current techniques in this area and evaluate the best melding of algorithms for the development of a very precise leaf disorder classification system to remove such ambiguity. This document also recommends further guidelines for research, which can be done to improve the performance of the system.

Keywords: *Leaf, disease, classification mechanism, machine learning, accuracy*

1. INTRODUCTION

The very definition of detection of plant leaf disease can be outlined in different layers, each performing a similar, mutually inclusive function. The output of the preceding layer is determined by the subsequent layer, and the efficiency of that layer depends entirely on the processing speed of the preceding stage. Therefore, each layer must be carefully planned to grow a good system. To do this, researchers from different fields have identified different algorithms and architectures. The layers needed for processing and classifying the leaf are effective and efficient diseases.

- **Image capture layer**

It is the first layer of the processing package. This layer is responsible for collecting and organizing leaf images for proper processing. This layer must ensure that all captured leaf photographs are taken at the correct angle, at the correct distance and in the correct lighting condition in order to achieve high precision during processing.

- **Pre-processing layer**

Images taken from the first layer are provided for pre-processing. The pre-processing layer can eliminate any noise (if present) in the image, smooth the image and make it ready for processing. The primary duty of this layer is to transform the image into a type consistent in terms of scale, brightness, signal intensity, etc.This layer is generally not focused during the design of the

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classification network, but if properly built, it may increase the efficiency of the system by leaps and bounds.

- **Segmentation layer**

The segmentation layer is the first processing point for the image. This layer is given a pre-processed image to remove the most important components from the image. Components include regions of concern, such as leaf regions, polluted regions and history regions. Typically background regions are identified with the utmost precision by algorithms such as Otsu, saliency maps, etc., and then subtracted from the input image to obtain the final segmented image.

- **Feature extraction layer**

Segmented regions are indicated for the extraction of features. Each phase determines the precision of the method and must be most carefully chosen. The input image pixels cannot be supplied directly for classification because they may be very large in number and may have inconsistent leaf positioning. This layer transforms the input image into a numerical sequence of features that can be used to uniquely represent the image. A specific extraction layer can generate identical features for images of the same class, while producing different sets of features for images of different class. Tools such as gray level co-occurrence matrix, color maps, edge maps, etc. are used for this purpose.

- **Feature selection layer**

While the Extraction Layer feature will do its best to build different set features for different class of images, but continuity will still remain. In the case of large datasets, this redundancy affects the classification efficiency. Due to this, there is a need to eliminate the redundancy from the collection of apps. In this reason, algorithms such as feature set variation, differential evolution, etc. are used.

- **Classification layer**

A major part of research in leaf disease detection is directed towards this layer. This layer is responsible for comparing the features with each other, and evaluating the best possible category for the query image. Algorithms like deep nets, convolutional neural networks, SVMs or support vector machines, etc. are used for this purpose. This review also, compares some very interesting classification algorithms and compares their performance.

- **Post-processing layer**

Here the input of the post-processing layer is the output of the classification layer in order to find out certain secondary parameters from the leaf images, such as the percentage of contamination, areas that are contaminated, etc. For this reason, algorithms such as pixel-wise comparison, region-based comparison, etc. are used. This layer can also make forecasts and propose solutions for contaminated areas. This can be seen in the form of Fig.1 below.

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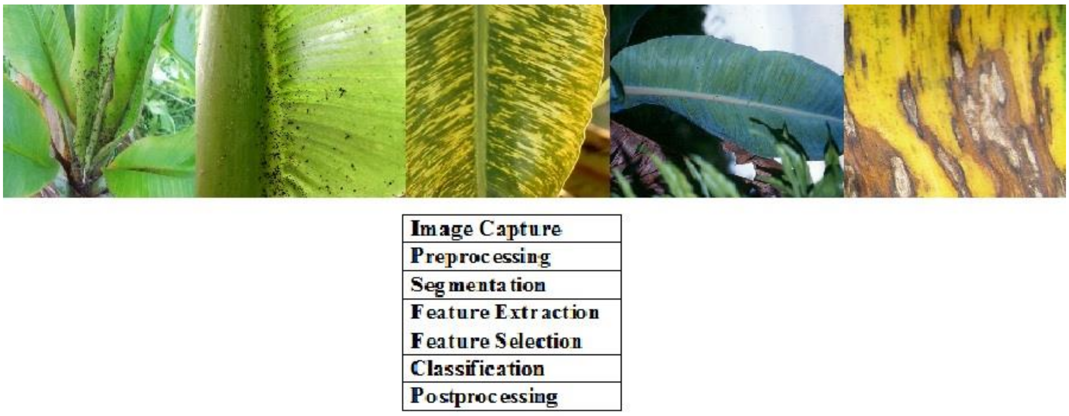

Figure 1. Processing steps for leaf image disease detection system

In order to find the most suitable algorithms for these layers, the next section compares various algorithms and suggests which similar algorithm should be used to classify the type of disease. This is accompanied by a statistical analysis of these algorithms and, ultimately, a recommendation is made to determine the best methods for achieving maximum accuracy.

2. LITERATURE REVIEW

Thanks to recent accomplishments by authors in the Leaf Disease Detection Program, researchers have focused on leaf-based disease detection algorithms for various kinds of plants and fruits. Nevertheless, the methods used by these researchers for one fruit / plant can be extended with limited to no changes to any other fruit / plant. For example, the research proposed in[1] uses convolutionary neural network models (CNNs) to classify apple diseases such as Brown spot, Alternaria spot, Gray spot, Rust and Mosaic spots. Such diseases are common to any form of fruit, such as mangoes, bananas, oranges, etc. The algorithms used by [1] can be used without any improvement in the identification of any other leaf disease. Due to the use of CNNs, the authors do not identify the features that are derived, but say that they have obtained a classification accuracy of more than 75%, which is commendable in the light of 5 disease sets and blind-testing. In addition, the number of images used by the authors is more than 25k, which is a tough challenge in itself. Therefore, this job can be used as a defacto for any kind of job. Similar research is carried out in[2], where re-searchers have applied the same CNN as in[1] to identify plant leaf diseases in maize. Diseases found are the same as[1] and have added round spot, Curvularia leaf spot, dwarf mosaic, and north & south leaf blight (similar to bacterial blight). In addition to the use of simplified versions of CNN, the researchers in [2] suggested the use of CNN. They also suggested the use of the rectified linear unit or ReLU function, which allows CNN to adjust and improve its classification accuracy. As a result of these changes, the accuracy of classification is increased from 75% to more than 98%. This accuracy is based on the accuracy of the training + testing set, but does not give any update on the accuracy of the pure test set. Similar to [1], the work in [2] does not reflect on the form of features used, but relies entirely on the assessment of the features of the deep CNNs. Similar to [1] and[2], research in[3] also uses CNNs to identify leaf-based diseases. CNN used soybean leaf and used similar diseases as described in[1] and[2]. Research in [3] adds a spot of the frog-eye leaf, which is close to that of the apple. They have used AlexNet and GoogLeNet CNNs to achieve a high degree of accuracy between 96% and 98%. This accuracy incorporates the training and testing of the set pictures. The research in[3] often uses the default CNN feature set to evaluate images, and thus, from the work done in[1], [2] and[3], it can be observed that the de-facto norm in leaf-based disease detection is being

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performed. Thus, we can suggest that any kind of leaf-disease classification task must be done with the help of CNNs.

- Yet apart from classification, there are a variety of other tasks that need attention when developing an effective leaf-disease detection system. A brief analysis of algorithms suitable to these tasks is given in [4]–[7]. The methods examined in these texts shall suggest the following:

- CCD-based cameras are the most powerful cameras to capture images and must be used for an effective leaf disease detection system.[4]

- Color-based preprocessing, such as transforming images into various color domains, and then smoothing the images is the easiest way to pre-process them [4]-[5].

- K-Means, maximization of expectations [4]- [5] is ideally suited for image segmentation of the leaf regions

- Extraction techniques such as inbuilt CNN features [1]– [3], Hu moments [7], Haralick features [7], color histogram [7], oriented gradient histogram (HOG) [4], speed-up robust features (SURF) [4], dense SIFT (DSIFT) [4], scale-invariant transform (SIFT) [4], and pyramid histograms of visual words (PHOW) [4] are the most powerful ones when transforming photos to object vector features [4].

Genetic algorithm [4] is the best suited algorithm for feature selection, since it blends bio-inspired computations with accuracy assessment to pick the best features. These techniques can be used to build a highly efficient leaf disease detection method. This was shown by the work in[8], in which researchers used concepts such as k- Means clustering for segmentation, followed by Extraction of histogram-based features and used a CNN sub-set for classification. They claim to have achieved more than 85 percent accuracy on the training + test collection, which is due to non-use of a complete CNN implementation. It again proposed a similar study in[9], in which researchers used the idea of CNNs for classification with the aid of classifiers based on the Transfer Learning Approach. They have obtained more than 90 percent accuracy on training + test collection, which can be further enhanced with the aid of intelligent extraction units for functionality.

Another important classifier for machine learning is [10], in which researchers used the principle of multiple linear regression to classify the input images into various disease sets. To accomplish this mission, they have proposed a novel method of enhancing histogram segmentation. The suggested segmentation for post-processing is found to be better than k-Means, and can therefore be used to find out the precise position of diseases. This method is evaluated independently of the disease, and can therefore be used with any form of leaf disease. As this technique is versatile in nature it can therefore be adapted for successful segmentation to any form of plant / fruit leaf. Using it is praiseworthy. By adding CNNs to the system and replacing the post-processing / classification system with the adaptive histogram-based segmentation module, we will suggest that this work be expanded. This would not only increase the accuracy of the classification but also improve the overall performance and applicability of the method. Banana leaf and plant diseases are the most prevalent and, relative to other plants, are susceptible to a greater number of diseases. The research in [11] uses images from the banana plant and, using multi-spectral imaging, applies the quantification process. Scientists may use this work to classify the current health and condition of any plant, and then use this status for a specific plant. To effectively describe the current state of banana fruit, this work uses Fourier fractals, Eigen values, and Hotelling transform. An unofficial addition of this work is done in[12], where researchers used CNN of identify photographs of the banana leaf. They were using models based on ResNet50 and InceptionV2 to boost the system's classification accuracy. As per their evaluations, the Faster R-CNN InceptionV2 with Pseudostem model gives the most accurate results for training + testing sets.

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Although CNN is the default classifier, work in [13] uses Support Vector Machine Classifier and combines it with gradient boosting to classify apple leaf disease. The gradient boosting system's accuracy is approximately 70 percent, while the accuracy jumps to 90 percent and more for testing + training sets in combination with help vector classifier. Returning to CNN, the research in[14] uses AlexNet-based deep CNNs to classify olive-leaf diseases. These diseases include Anthracnose, Canker, Lepra Fruit Rot, Peacock Stain, Aspidiotus Nerii and Parlatoria Oleae. Both of these diseases are of a general nature, and can occur with any plant / fruit. The system is capable of recognizing diseases with atleast training set accuracy of 90 percent, which can be further improved with different forms of segmentation and feature extraction techniques. Another CNN-based implementation, which contrasts its output with kNN and SVM, is suggested in [15], where researchers used the Quadtree kernel framework for CNN. The program proposed excludes the possibility of using kNN for any form of highly efficient leaf disease detection systems, but suggests using SVM and CNN for the same. We can reach a high degree of accuracy that is about 95 percent using CNN, while SVM and kNN stand at 75 percent and 65 percent for both training and test sets. A similar implementation using kNN is proposed in [16], wherein researchers have used the GLCM feature extraction method for describing the images. The designed technique is able to classify leaf diseases with perfection is around 80%. While kNN is not suited for classification, the work in [17], compares the performances of Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN); and Deep Convolutional Neural Network (dCNN). In their study, they found that standardized local binary patterns (LBP) with deep CNN are 84 percent accurate, whereas other methods are less efficient. SVM can also be seen as a close competitor to CNN, but it does have reduced efficiency as the number of classes increase.

In [18] a novel method which combines multiple processing units is proposed. Researchers used CLAHE in their research for pre-processing, which removes any kind of noise from the images, followed by ROI selection using Neutrosophic domain. This is followed by ROI partitioning using false, true and intermediate segmentation. Researchers utilized Histogram, harm index, disease sequence area, and edge enhancement for extraction of information, supplemented by a series of classifiers using Decision tree, Random forest, Support vector machine, AdaBoost, Linear models, Naive Bayes, and kNN. With such a complex model, the researchers can achieve a high level of accuracy of around 95 percent, which is focused on the sets of training + testing. In addition, random forest is only capable of achieving an accuracy of about 98 per cent on the training set. Similar to previous work, the research done in [19], uses CNN to identify rice blast diseases. The program uses the default CNN methods to extract a function and classification. The method achieves an accuracy of more than 90% on training and testing sets.

Another method that uses GLCM and SVM for the detection of leaf disease is defined in[20], similar to [18]. Researchers have identified orange fruit diseases in this process and claim to have achieved more than 80 % accuracy. This precision may either be set for training + checking, or only set for training. However, no specifics were listed in the work. Cassava is a leaf-based disease that constitutes over 10 per cent of all diseases. The research done in [21] with the aid of CNNs, classifies cassava diseases with high precision. To perform this function, they used the basic-CNN functionality. It is capable of detecting cassava disease with more than 90 percent accuracy for photographs taken in real time, while it achieves an accuracy of about 95 percent. This work can be used only for cassava diseases, and thus has limited scope of application.

According to [21], the research in [22] is focused on a single disease of Anthracnose that often occurs in mango leaf. For the same, they suggested the use of multiple CNNs. Using the proposed model and proper collection of training and test set images, the device will achieve more than 96 per cent accuracy for the test set. This is a significant development for a particular disease, and can also be applied to other diseases. They therefore suggest the use of multi-CNNs with max-pooling for a larger number of diseases, which would further expand the scope of the method. The research at [23] is once again using CNNs to test tomato-based leaf diseases. But instead of using regular CNN, they are using the [22]-inspired CNN which has multiple numbers of tandem CNNs running. Here CNN

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and Mask RNN are used to accomplish the mission quicker. Since of a combination of multiple CNNs, the accuracy for the training + test set is increased to 99.6 per cent, which is a sufficiently high value for any real-time application. Yet, regardless of this combination we can work further. A simpler classification method is stated in[23], where methods of low complexity such as Convex Hull, Eccentricity, Solidity, Centroid, Fuzzy Logic, Artificial Neural Network (ANN), K-nearest Neighbor (KNN), Support Vector Machine (SVM) are used for classification. The disease assessed is Sun- burn, Yellow mosaic, Grass-hopper attack, and Leaf blight attack. These are all very common to any kind. SVM surpasses the other 2 approaches here too, though unexpectedly KNN outperforms ANN during assessment. All these tests are only for the training set and thus assessment on the test set using these methods is still to be learned. We would still recommend the combination of SVM and CNN for a better classification system. Similarly, SVM is used in [24], [25], and gives more than 90% during the training phase. Banana leaf diseases are classified in [26] and more than 95 percent accuracy was obtained using the classification system ANFIS. It is noteworthy given the fact that ANFIS is not commonly considered for comparison. Yet the research in [26] shows that ANFIS is better than SVM, and can be used for a better classification method in conjunction with CNN. Another important research in [27] makes use of simplified features to determine general plant diseases. Designers use common features such as Contrast, Power and Specific homogenization and combine it with Minimum Distance Criterion and a 95 percent precision for the test dataset instead of SVM classifier. They also classify bacterial leaf spot, Frog eye leaf spot, Sun burn, fungal disease and early scorch diseases. Another work in [28] showcases the use of ANN with PCA for banana leaf disease classification, which maintains a high accuracy of more than 90%, and thus can be considered for preliminary study. Thus, we can observe that a combination of CNN with SVM and ANFIS can be a very good combination for effectively classifying leaf-based diseases. A

The next segment provides comparative performance evaluations of these approaches. [29] Compares the efficiency of Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Gaussian Naive Bayes and DCNN. The research performed in d can be understood in terms of the use of machine learning or deep learning methodologies in the sense of identifying leaf diseases. The research in these shows us how machine learning or deep learning methodologies can be suitably used in different domains in efficient way.

3. PERFORMANCE EVALUATION

We established a performance comparison between the different algorithms that were checked, based on the study done in the previous section. Such distinction is made largely on the basis of study quality and depth as per the researcher.Based on the requirements of the system designer, this list can be checked, and a suitable protocol selection could be rendered to improve the performance of the newly designed program. Furthermore, the distinction is also made dependent on the type of plant / fruit whereby the detection of the disease is being conducted. As stated earlier, plant / fruit type is inherently exclusive in the algorithmic results,although it can be a good frame of interest for researchers to choose the highest suitable algorithm package for some target case. The above table 1 indicates this performance comparison.

Table 1.Statistical Comparison

Algorithm	Plant/fruit name	Depth of research	Accuracy (%)
CNN [1]	Apple	High	75
CNN + ReLU [2]	Maize	Very High	98
CNN + AlexNet [3]	Soyabean	High	96

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kMeans + CNN [8]	Various	Moderate	85
CNN + Transfer Learning [9]	Various	Moderate	90
Multiple Linear Regression [10]	Various	Moderate	80
Hyperspectral +Fourier [11]	Banana	Low	70
CNN + ResNet [12]	Banana	Moderate	90
SVM [13]	Banana	Moderate	70
CNN + AlexNet [14]	Olive	Moderate	90
CNN with Quad Tree kernel [15]	Various	High	95
SVM [15]	Various	High	75
kNN [15]	Various	High	65
kNN with GLCM [16]	Various	Moderate	80
Deep CNN with LBP [17]	Blueberry	High	84
Complex Naïve Bayes+ kNN [18]	Various	Very High	98
CNN [19]	Rice Blast	High	90
SVM with GLCM [20]	Orange	Low	80
CNN [21]	Cassava	High	90
Multiple CNN + Max Pooling [22]	Mango	Very high	96
R-CNN + M-CNN [23]	Tomato	Moderate	80
KNN + ANN + SVM [24]	Various	Moderate	90
KNN + ANN + SVM [25]	Cotton	High	94
ANFIS [26]	Banana	High	95
SVM + SimplisticFeatures [27]	Banana	Moderate	95
ANN + PCA [28]	Various	Moderate	90

The depth of analysis is evaluated on the basis of the parameters as follows: -

- Total of topographies appraised
- Total of leaf imageries castoff for preparation and trying
- Number of valid stages of processing
- Types of classifiers used for processing

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Based on these parameters, we evaluated the depth of research. From the table, the reader must Test research works that are more labor-intensive and more reliable. Some lower-depth research work can have high precision, which is due to lack of in-depth studies. The researchers are therefore advised to pick the protocols carefully when developing their classification systems. In order to clarify this

ambiguity, we have assigned a weight vector to each of the research, and developed a weighted graph for the algorithms. Readers are requested to refer this graph while designing their system's under test.

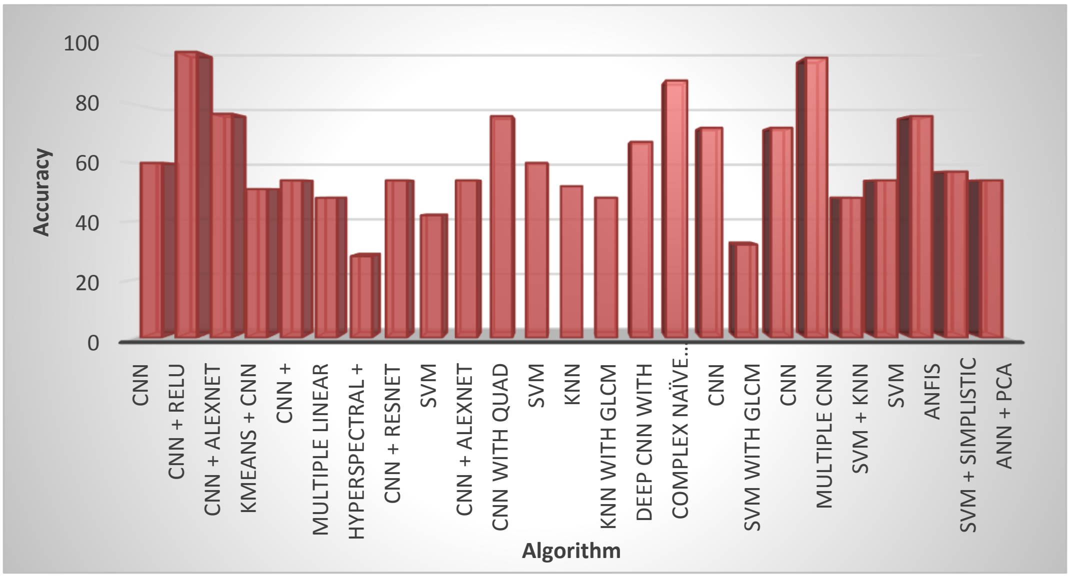

Figure 2. Weighted Accuracy

From the graph we can observe that the work in [2], [14] and [22] are the most recommended systems for leaf-based disease detection.

4. CONCLUSION

Research shows that CNN is the best classification algorithm, while processes such as the CCD image acquisition, Color pre-processing for noise removal, k-means & segmentation expectation optimizing, integrated CNN characteristic characteristics, Hu moments, Haralick characteristics, Color Histogram, oriented gradient histograms (HOG), SURF, dense SIFT (DSIFT), scaling, etc. For our proposed research work, we are more concerned with the Deep Convolutionary Neural Network and this research takes into consideration the good formulations of deep learning to investigate into plant leaf problems to help the farming community with greater insights and knowledge. We can also look towards development of an application which can be devised on some communicating devices to disseminate knowledge and information in an instant way. We deliberately keep this as a future prospect and an open ended thought to be worked upon.

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