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Fungal and Bacteria Disease Detection Using Feature Extraction with Classification Based on Deep Learning Architectures

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Abstract

In India, agriculture provides a living for half the population. Food security is significantly threatened by microbial infections, however due to inadequate infrastructure, it is still difficult to identify them quickly. This paper propose novel technique in Fungal and bacteria disease detection of tomato and grapes plant using deep learning based on feature extraction and classification. Here the input images of tomato and grapes has been collected and processed for noise removal and image resize. This processed image features have been extracted using scale-invariant feature transform (SIFT) and classified using Convolutional neural network-based Alex Net architecture. The suggested model has attained the highest testing accuracy. The deep learning model utilised in this study aims to identify disease in plant leaves. However, in the future, the model can be combined with a drone or any other technology to identify plant diseases in real time and inform people of the locations of the afflicted plants so that they can be treated appropriately.
Keywords: plant diseases, Fungal disease, bacterial disease, deep learning, feature extraction, classification.

1 Introduction:

Climate change and the economy both heavily rely on plants. Due to the fact that it has become a worldwide concern, the 2019 UN General Assembly will also address Future climate change is expected to occur at a rate that is 10–100 times greater than that of DE glacial warming [1]. According to estimates in the hundreds of billions of dollars [2], plant pests and diseases generate annual losses in food, fibre, and decorative production systems.Finding illness in plants at an early stage is a very difficult task [3]. Common plant disease symptoms include Powdery mildew, Sclerotinia (white mould), Leaf rust (common leaf rust in maize), Stem rust (wheat stem rust), Anthracnose, seedling damping off, leaf spot (septoria brown spot), and chlorosis (leaf yellowing) are some of the diseases that can affect plants [4].

2 Related works:

Researchers have come up with numerous strategies to solve the aforementioned issues. Machine learning can classify plant diseases using many different kinds of feature sets. The classic handcrafted and deep learning (DL)-based feature sets among them are the most well-liked feature sets. Before effectively extracting features, preprocessing, such as picture enhancement, colour modification, and segmentation [5], is necessary.Following feature extraction, various classifiers may be employed. K-nearest neighbour (KNN), support vector machine (SVM), decision tree, random forest, naïve bayes (NB), logistic regression (LR), rule generation, artificial neural networks (ANNs), and Deep CNN are some examples of well-liked classifiers [6,7].KNN is a straightforward supervised machine learning technique that uses similarity measurements (i.e., distance, proximity, or closeness) to solve classification problems [8,9]. Another well-liked supervised machine learning method for classification is SVM. Finding a hyperplane between data classes that splits each class is the goal of SVM. Network depth, width, and resolution may improve performance accuracy with fewer parameters, claims [10].

3 System model:

This section discuss novel technique in Fungal and bacteria disease detection of tomato and grapes plant using deep learning based on feature extraction and classification. Here the input images of tomato and grapes has been collected and processed for noise removal and image resize. This processed image features has been extracted using scale-invariant feature transform (SIFT) and classified using Convolutional neural network based AlexNet architecture.The overall proposed architecture is shown in figure-1.

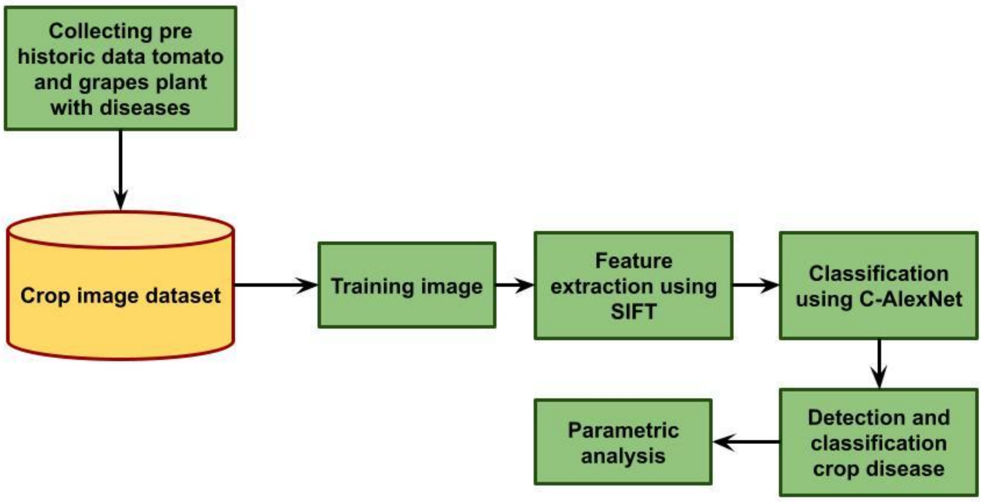


Figure-1 Overall Proposed architecture

4 SIFT based feature extraction:

Features that are invariant to scale, rotation, and translation are produced by the SIFT algorithm. Computing a Gaussian scale-space out of the source image is the first step in the SIFT feature extraction process. The initial image is divided into 5 octaves, each of which comprises variations of the original image with a lower samplerate. There are 5 photos in each octave, all with the same sample rate but varying degrees of blur (Gaussian blur is used).The information regarding the local spatial distribution of the gradient orientation on a specific neighbourhood must be encoded in order to compute the descriptor. There have been publications that have used the complete image as a neighbourhood. The original SIFT approach, in contrast, uses a square normalised patch aligned with the point's orientation to create scale, rotation, and translation invariance by eq. (1).

$$\min_{ye,ze} \prod_{i\in e} ((yeIi + ze - qi)^2 + y_e^2)$$
$$ye = \frac{H_e(I_q) - H_e(I)H_e(q)}{J_e(I) + \epsilon'}$$
$$ze = H_e(q) - yeH_e(I) \quad (1)$$
$$gi = H_e i(fi0) = H_e i(y)Ii + H_e i(z)$$

5 C-Alex Net based Classification:

A feature extractor, which consists of a convolutional layer and a pooling layer and can efficiently recombine extracted low-level features to extract higher-level features as illustrated in figure 2, was introduced for convolutional neural networks, which are feedforward neural networks. Due to the sharing of weights, automatic feature extraction significantly reduces the amount of manual work required, making it quicker and more effective.

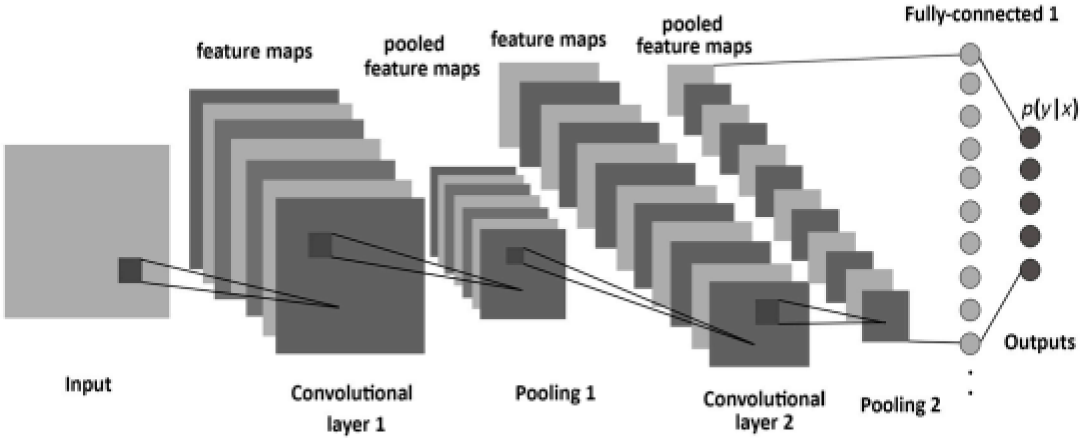


Figure 2 structure of a CNN, consisting of convolutional, pooling, and fully-connected layers.

Convolutional, pooling, full connection, and output layers are the typical components of a convolutional neural network. Softmax classifier, which is suitable for solving multi-classification issues, has a minimal computation amount and quick training times, and it is typically used in the output layer. Assuming that equation (2) accurately describes the function:

$$\mathbf{h}_\theta(x^{(i)}) = \begin{bmatrix} p(y^{(i)} = 1 \mid x^{(i)}; \theta) \\ p(y^{(i)} = 2 \mid x^{(i)}; \theta) \\ \vdots \\ p(y^{(i)} = \mathrm{K} \mid x^{(i)}; \theta) \end{bmatrix} = \frac{1}{\sum_{j=1}^{K} e^{\theta_j^T x^{(i)}}} \begin{bmatrix} e^{\theta_1^T x^{(i)}} \\ e^{\theta_2^T x^{(i)}} \\ \vdots \\ e^{\theta_K^T x^{(i)}} \end{bmatrix} \quad (2)$$

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k} l\{y^{(i)} = j\}\right]\log\frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k} e^{\theta_l^T x^{(i)}}}$$
$$f(x) = \max(x, 0)$$

First, second, and fifth convolutional layers are followed by three max-pooling layers. AlexNet has eight weight levels total, including three fully connected layers and five convolutional layers. In conclusion, pre-trained AlexNet architecture with SS strategy functions in a way that allows for the output performance of complete network to be attained with "satisfactory" performance from the hidden layer classifiers. Similar to the original AlexNet architecture, pre-trained AlexNet architecture with SS strategy uses SGD algorithm and gradient functions for the optimization process.

6 Performance analysis:

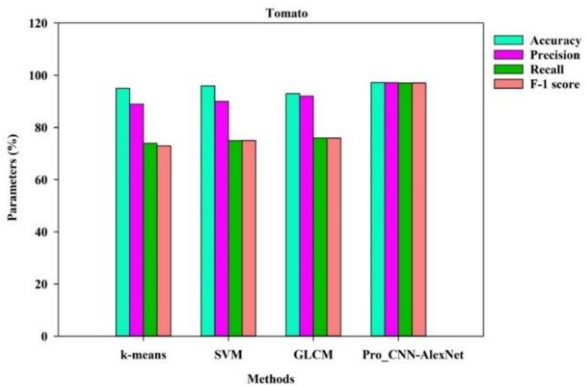
On Windows 10, we run the simulations using the PyTorch deep learning framework. The PC used for the tests has an AMD Ryzen 5 1600X Six-Core Processor and an 8GB GeForce GTX 1070Ti GPU. Programming is carried out using the Python language.

7 Dataset description:

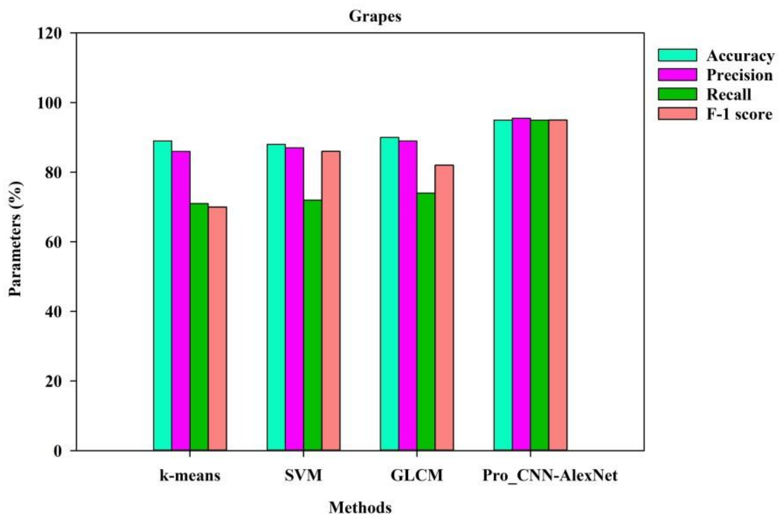
The open dataset Plant Village is what was used in this study's trials. For disease detection, we use 1,180 photos of black rot on grapevine leaves. For annotating the sick leaf portions, we employ LabelImg. The dataset utilised in this experiment is in the coco dataset format. To hasten convergence, we employ the model weights that have already been trained.
Though, maximum iteration number is 60, this has the development certainly in terms of accuracy for various classes of prediction because of the errors in loss and training. Though being the trained model which is appropriate in terms of statistics, then this model do not possess the efficient capacity in prediction. Because of this regularization the simulation has been maximized when the simulation for enhanced test among them ranges between the values for regularization parameter. Hence from above confusion matrix the prediction class has been validated along with the parameters of precision and recall of a deep neural network classification model.the overall comparative analysis of proposed technique is shown in table-1 and figure-3 (a), (b).

Table-1 Comparative Analysis in crop disease detection

Crop	Parameter	k-means	SVM	GLCM	Pro_C-AlexNet
Tomato	Accuracy	95	96	93	97.25
	Precision	89	90	92	97.18
	Recall	74	75	76	97.05
	F-1 score	73	75	76	97.10
Grapes	Accuracy	89	88	90	94.93
	Precision	86	87	89	95.50
	Recall	71	72	74	94.93
	F-1 score	70	86	82	94.99



(a) Tomato Fungal and bacteria disease detection



(a) Grapes Fungal and bacteria disease detection
Figure-3 Comparative analysis of (a) Tomato and (b) Grapes disease detection

8 Conclusion:

This research propose novel technique in Fungal and bacteria disease detection of tomato and grapes plant using deep learning based on feature extraction and classification. Here the input images of tomato and grapes has been collected and processed for noise removal and image resize. This processed image features has been extracted using scale-invariant feature transform (SIFT) and classified using Convolutional neural network based AlexNet architecture.In this study, we also put up the idea of using occlusion techniques to pinpoint the disease-affected areas and aid in human disease comprehension. Our long-term goal is to make deep models smaller and less computationally intensive for mobile devices and other small computers. In addition, feature visualisation is a popular area in deep learning and could be applied to comprehend plant illnesses.

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