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Page 33:37

Detection of Various Plant Disease Stages and Its Prevention Method Based on Deep Learning Technique

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Abstract

About 70% of India's rural population relies mostly on agriculture for their income. There are many different crops grown in India. In India, more than 500 different crop kinds are grown. This research propose novel technique in detection of various plant disease stages using feature extraction and classification using deep learning techniques. here the input data has been collected from tomato and grape leafs. This data has been processed for noise removal, image resize and normalization. Then this image features has been extracted using graph Convolutional networks and classification of extracted features has been done using ResNet-50. The suggested model offers a high-performance remedy for crop diagnosis in the actual farming setting.

Keywords: plant disease, tomato, grapes, feature extraction, classification, deep learning

1 Introduction:

In India, agriculture is a significant source of income. Majority of the population of the nation is either directly or indirectly involved in the agriculture industry. As a result, maintaining the nation's economic prosperity depends on delivering high-quality agricultural production [1]. Use of image processing in conjunction with a ML strategy might assist farmers identify plant diseases early on as a result of technological advancements [2]. A significant quantity of data is now being captured in real-time thanks to the development of digital methods, and this data is then used to create ML-based approaches that help people make better decisions [3]. The effectiveness of these methods, such as decision trees (DT), support vector machines (SVM), K-nearest neighbours (KNN), and Gaussian frameworks, etc., for detecting agricultural diseases has also been well investigated [4].

2 Related works:

Through early illness identification and subsequent disease control, DL technology has been used in many studies to increase the survival rate of fruits, vegetables, and field crops [5]. The average recognition rate of 10 categories of tomato leaves is higher thanks to Work [6]'s application of transfer learning to initial Alex Net network. Work [7] uses migration learning in conjunction with the original AlexNet, VGG16 network structure to achieve an accuracy of roughly 97% on seven segmented tomato sick leaves. Work [8] uses Faster RCNN, R-FCN, and SSD for training to capture images of 9 tomato illnesses and insect pests using cameras with varying resolutions. Using transfer learning technology, work [9] trained the AlexNet and GoogleNet networks to recognise illnesses of the Camellia oleifera plant. A pre-trained ResNet network is used in Work [10] to accurately classify 7 tomato illnesses with a 98.8% accuracy rate.

3 System model:

Figure 1 displays the entire methodology for this study. The initial phase was choosing the datasets. One dataset was sizable and was used to obtain pre-trained weights for transfer learning. Second dataset dealt with several kinds of plant leaf diseases. The training dataset was then annotated using a free online application called LabelImg. The development and training of the DL architectures resulted from this.

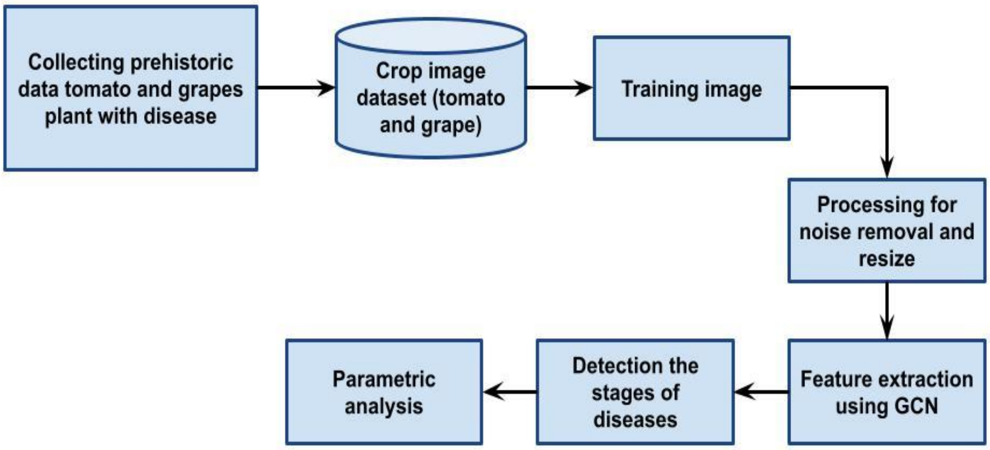


Figure- 1 Overall Proposed architecture

4 Dataset Selection

A small number of datasets with a large number of classes have been produced and utilised for diverse real-life processes. For instance, major advances in object categorization and detection studies have been made using the ImageNet dataset, which contains an unparalleled number of photos. Similar to this, there are 91 common object classes in the MS COCO dataset, with 82 of them having more than 5k tagged instances. In 328k images, there are 2500k data instances in total that include labels. Comparing the MS COCO dataset to ImageNet (3.0) and PASCAL (2.3), there are noticeably more object instances per image (7.7) in MS COCO dataset. Therefore, for purpose of transfer learning, we employed training weights from MS COCO dataset. Plant Village dataset was then chosen because it has pictures related to the research area. This collection includes pictures of 14 different plant species. The dataset displays 4 bacterial diseases, 2 fungal illnesses, 17 fungi infections, 2 infectious disorders, and 1 mite-related ailment. Images of healthy leaves from 12 different plant types are also displayed.

5 Graph Convolutional network-based Feature extraction:

Convolutional layer: **M**ultiplication of a signal$x\epsilon\mathbb{R}^N$ (a scalar for each node) with a filter $g^\theta = diag(\theta)$parameterized by $\theta\epsilon\mathbb{R}^N$ N in the Fourier domain, i.e., a precise formulation of spectral convolution on graph in eq. (1)- (3).

$$g\theta * x = Ug\theta(\Lambda)U^T x \quad (1)$$

$$g\theta(\Lambda) = \sum_{k=0}^{K} \theta_k T_k(\Lambda) \quad (2)$$

$$g\theta * x = \sum_{k=0}^{K} \theta_k T_k(\mathrm{L}')x \quad (3)$$

With $L' = \frac{2}{\lambda_{max}} L - I_N$ as can easily be verified by noticing that $(U\Lambda U^T)^k = U\Lambda^k U^T$.

Thus, a multi-layer Graph Convolutional Network with subsequent layer-wise propagation rule is obtained as eq. (4):

$$H^{(l+1)} = \sigma(\sum_{k=0}^{K} T_k(L')H^{(l)}W^{(l)} \quad (4)$$

Here,$W^{(l)} = \theta_k, (k\epsilon[0, K]\Lambda k\epsilon\mathbb{Z})$is a layer-specific trainable weight matrix. σ(·) denotes an activation function.$H^{(l)}\epsilon\mathbb{R}^{N\times D}$is matrix of activations in l^{th} layer;$H^{(0)} = X$

Pooling layer: Reducing the graph scale while keeping local geometry as well as connection details of the original graph is key to quick pooling of graph signal. The Metis graph partitioning algorithm's coarsening step reveals the fundamentals of quick pooling of graph signals. The original graph $G_0 = (V_0, E_0)$ can be broken down into a collection of smaller graphs $G_i = (V_i, E_i)$ during the coarsening phase by fusing nodes, where $V_i \Big| < \Big| V_{i-1} \Big|$ A group of nodes in the graphG i are often consolidated into a single node in next-level roughening graphG_{i+1}during the coarsening process. A group of nodes in graph G it that are combined to form a node in graph $G_{i+1}$are referred to as V ivis.

The most used optimization approach for neural networks is gradient descent [35]. In comparison to the normal approach, its momentum variant can reach convergence more quickly. The fundamental concept is to compute gradients' exponentially weighted average and then utilise the to adjust the weights. However, using a higher learning rate could lead to issues like overshooting and divergent output. Equations (5) and (6) take exponentially weighted averages of dw and db for momentum method.

$$Vdw = \beta * Vdw + (1 - \beta) * dw \quad (5)$$

$$Vdb = \beta * Vdb + (1 - \beta) * db \quad (6)$$

Performance analysis:

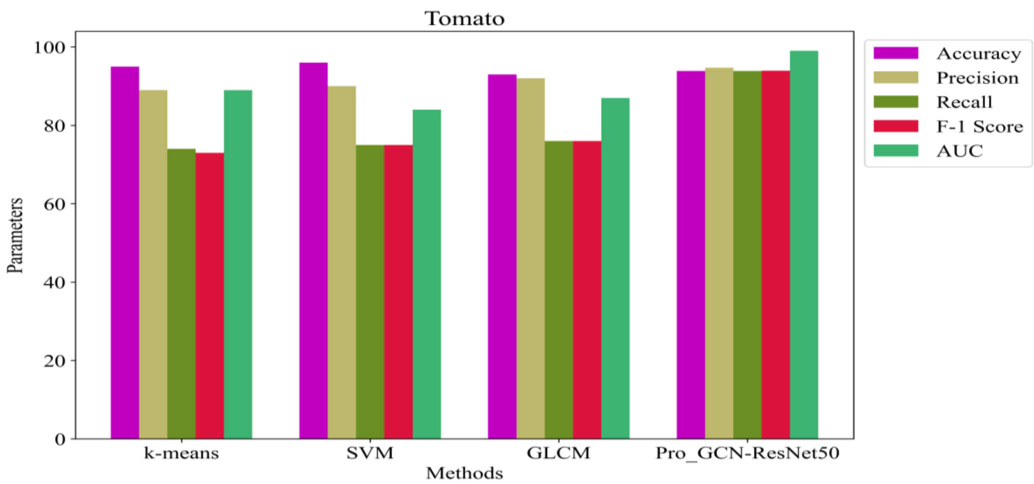
On Windows 10, we run the simulations using the PyTorch deep learning framework. The PC used for the tests has an AMD Ryzen 5 1600X Six-Core Processor and an 8GB GeForce GTX 1070Ti GPU. Programming is carried out using the Python language.

Dataset description:

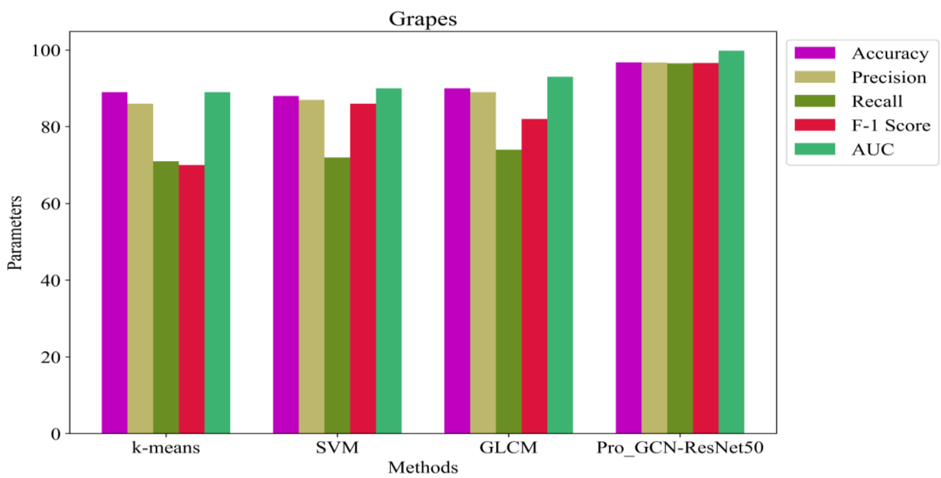
The open dataset Plant Village is what was used in this study's trials. For disease detection, we use 1,180 photos of black rot on grapevine leaves. For annotating the sick leaf portions, we employ LabelImg. Around 15 different diseases are often visible in an image, and there are more than 17,000 different detection targets overall. We split the 1,180 photos into training and test sets before we begin the training procedure.the overall comparative analysis of proposed technique is shown in table-1 and figure-2 (a), (b).

Table-1 Comparative Analysis in crop disease detection

Crop	Parameter	k-means	SVM	GLCM	Pro_GCN
Tomato	Accuracy	95	96	93	93.86
	Precision	89	90	92	94.70
	Recall	74	75	76	93.86
	F-1 score	73	75	76	93.94
	AUC	89	84	87	99.01
Grapes	Accuracy	89	88	90	96.78
	Precision	86	87	89	96.73
	Recall	71	72	74	96.52
	F-1 score	70	86	82	96.60
	AUC				99.80



(a) Tomato stages of disease detection



(b) Grapes stages of disease detection

Figure-2 Comparative analysis of (a) Tomato and (b) Grapes stages of disease detection

6 Conclusion:

This research proposes novel technique in detection of various plant disease stages using feature extraction and classification using deep learning techniques. here the input data has been collected from tomato and grape leafs. This data has been processed for noise removal, image resize and normalization. Then this image features has been extracted using graph Convolutional networks and classification of extracted features has been done using ResNet-50. Furthermore, the suggested model also obtains better results, with an average detection accuracy of 94%, in the model comparison experiment conducted on the publicly available dataset for grape leaf diseases. It is proven that adding the attention module has fewer parameters and can extract complicated aspects of a range of diseases with greater accuracy.

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