STM JOURNALS
Scientific Technical Medical

International Journal of
Advance in Molecular Engineering

Volume 1, Issue 2, 2023
July-December
DOI (Journal): 10.37591/IJAME

https://journals.stmjournals.com/ijame/

Review IJAME

Revolutionizing Plant Disease Detection: A Comprehensive Review

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Abstract

Rise in population demands more food production but the diseases in plants contribute to loss. The advancement in agricultural field has a remarkable effect in detecting plant diseases. These diseases will have a major impact on the quality of plant and yield and hence can destroy the entire plant if they are not controlled on time. To reduce disease-related losses, it is necessary to identify different types of diseases and control the diseases in the early stages. Subjective audit by farmers or agricultural experts across vast plant fields consumes much time and is impractical thus minimize crop production. Therefore, many agricultural procedures and practices are adapted to control plant diseases. Existing systems have adapted various image processing techniques, computer vision, machine learning techniques, deep learning techniques and deep transfer learning technique for diseases detection. Artificial Intelligence (AI) plays a crucial role in addressing many challenges faced. It is integrated with other technologies for efficient farming. This review helps the researcher to know the existing methods applied for the detection of plant diseases and also the research gaps and future exploration in the field of deep learning to improve the model accuracy for better detection.

Keywords: Machine Learning models, Precision Agriculture, Deep Learning models, Deep Transfer Learning models, Pretrained models, Quantitative Metrics.

INTRODUCTION

Traditional methods for plant disease detection often involve manual observation and visual inspection by agricultural experts or farmers. Here are some of the common traditional methods such as Visual Inspection, Symptom-Based Diagnosis, Sample Collection and Laboratory Testing, Field Tests and Kits, Consultation with Experts, Weather and Environmental Monitoring and Crop Rotation and Cultural Practices. Farmers or agricultural experts visually inspect plants for symptoms such as discoloration, lesions, wilting, deformities, or unusual growth patterns. They rely on their experience and knowledge of common plant diseases to identify potential issues. This method involves matching observed symptoms on the plant with known symptoms of various diseases. Agricultural experts use field guides, manuals, or reference materials to identify diseases based on symptom. In cases where visual inspection is inconclusive, samples of diseased plant tissue (leaves, stems, fruits) may be collected and sent to laboratories for further analysis. Laboratory tests may include culturing pathogens, microscopic examination, serological tests (ELISA), or molecular techniques (PCR) to identify the causal agent. Some simple diagnostic kits or tools are available for on-site testing. These kits often involve antigen-antibody reactions or biochemical assays to detect specific pathogens or disease markers. They provide rapid results without the need for specialized laboratory equipment. Farmers may consult with agricultural extension officers, plant pathologists, or experts in the field to

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Received Date: May 08, 2024
Accepted Date: May 15, 2024
Published Date: August 29, 2024

Citation: Shruthi T.V., Suresh M.B. Revolutionizing Plant Disease Detection: A Comprehensive Review. International Journal of Advance in Molecular Engineering. 2023; 1(2): 44–55p.

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get advice on disease diagnosis and management strategies. These experts can provide guidance based on their knowledge and experience. Monitoring weather conditions and environmental factors ca provide insights into disease development and spread. Certain diseases are favoured by specific weather conditions or environmental factors, so tracking these parameters can help predict disease outbreaks. Traditional farming practices such as crop rotation, intercropping, sanitation, and proper field management can help prevent the occurrence and spread of diseases by reducing pathogen buildup and creating unfavourable conditions for disease development.

A major threat to the world's ability to feed itself is posed by plant diseases, which makes the agriculture industry crucial to economic growth. Precision agriculture demands sophisticated methods to tackle this problem, and deep learning has become a vital tool in this regard. This review involves papers from 2018 to till date which gives overview of different pre-processing techniques, data augmentation techniques, segmentation and classification techniques. Some of the observations from existing papers to perform the segmentation and classification are:

i. Only image processing techniques implemented,
ii. Both image processing techniques and machine learning model deployed,
iii. Combination of image processing techniques and deep learning models implemented,
iv. Only deep learning model applied and
v. Only a deep transfer learning techniques being used.

LITERATURE SURVEY

In this research the new dataset FieldPlant consist of 5,170 images of plant leaves were taken straight from plantations. Individual leaves of the dataset were manually annotated under the guidance of plant pathologists. 8,629 distinct annotated leaves for each of the 27 disease types were produced as a consequence. CNN models were assessed using this dataset through a variety of benchmarks, and the results showed that FieldPlant gives better on classification tasks than PlantDoc [1].

The research focuses on comprehensive computational analysis of five cutting-edge object detection algorithms on the PlantDoc dataset to identify diseases on the leaves, and 18 cutting-edge classification algorithms on the PlantDoc dataset to determine if a leaf has a disease or not. According to computational results, YOLOv5 has a high accuracy of object detection. The neural network model MobileNetv2and ResNet50 exhibit the better accuracy and training time trade-off for the image classification task [2].

In the first step of the research Super Resolution Generative Adversarial Network (SRGAN) was used to acquire suitable 256*256 mages to expand the size of the unbalanced dataset in stage 2. Lastly, compared to pictures produced using a “Deep Convolution Generative Adversarial Network” (DCGAN). DoubleGAN enhanced accuracy to 99.80 and 99.53 percent, respectively, and enabled the dataset to be expanded. It also yielded crisper images than DCGAN. The identification results are superior than those of the first dataset [3].

The study in the paper involves a comprehensive analysis of the literature, focusing on various crops such as grapes. The primary focus of our research has been on hyperspectral images and vision-cantered approaches. In comparison to conventional classifiers, ―Support Vector Machines‖ (SVMs) and ―Logistic Regression‖ (LR) classifiers showed improved accuracy in trials. There is no set method for evaluating the performance of a model; nevertheless, most people utilize the confusion matrix, accuracy, recall, precision, and F1 Score. Eleven datasets considered are based in laboratories and fields, and nine of them are openly accessible. Some datasets from laboratories are quite small, which makes using them in experiments problematic. In order to create robust models, it is necessary to have models that have fewer parameters, can be used with small devices, and can be applied to big datasets that include a variety of crops and illnesses [4].

The study proposes an approach for recognizing cardamom plant diseases using the EfficientNetV2 model. The experiments carried out to ascertain the efficacy of the proposed technique and is compare with other models such as EfficientNet and Convolutional Neural Networks (CNN). The experimental results showed that the proposed technique has a better detection accuracy of 98.26% [5].

This work focused on position-sensitive score maps and anchor box parameters empirically, which increased performance. Furthermore, a stratified k-fold cross-validation process and testing on an external dataset are employed to demonstrate robustness and feasibility with proposed method. The mean average precision of the RFCN model was 93.80%, which is 19.33% better than the default settings. As a result, the work could be used as template for further investigations into the automated control of illness in other plant species [6].

The primary goal of the paper is to determine which deep transfer learning model is appropriate for the specific dataset on plant diseases. To obtain the best classification accuracy, 38 deep transfer learning models are used in this work. For the Agri-ImageNet, sunflower and cauliflower datasets, the EfficientNetV2B2 and EfficientNetV2B3 models accuracy is higher when compared to other deep transfer learning models [7].

The suggested approach, through training on a customized dataset and cascading Symmetric Autoencoders with Attention Residual U-Net model, it outperformed previous techniques in detecting four illness classifications. With a weighted mean intersection over union of 0.7451 and a mean pixel accuracy of 95.26%, the model exhibits impressive precision in collecting individual pixels and demarcating borders between illness classes. This strategy has a lot of potential to help with early plant disease diagnosis and enhance crop management techniques. Its implementation could close a crucial gap in the agricultural industry and have a substantial impact on global food security. The outcomes demonstrate the plant disease management strategy's efficacy and pave the way for additional study in this area [8].

This research develops a ―convolutional neural network‖ (CNN) with fewer layers, which results in a reduced computational load. Without really taking new pictures, some augmentation techniques like scaling, zooming, and flipping are used to provide extra samples and expand the training set. The thorough experimental results showed that the suggested model achieves 98% classification accuracy and is well-fit to diagnose illnesses of apple leaves. Additionally, the results show that compared to various other deep CNN models currently in use, it requires less storage and executes faster. While other CNN models can detect crop diseases with a similar level of accuracy, the suggested model requires less computing power and storage. It is very well suited for use in portable electronics [9].

In this paper model performance proposed is assessed in terms of quantitative metrics such as sensitivity, accuracy, F1-score, precision and ROC curve, where the proposed framework outperforms the previous efforts. The proposed MULTINET framework is implemented in the MATLAB R2020a simulation tool. Comparing the suggested work to the existing work, there’s increase in accuracy from 19% to 29%, increase in precision from 19% to 28%, increase in sensitivity from 31% to 38%, increase in F1-score increases from 31% to 38%, and improvement in ROC curve increases by around 0.15 to 0.22 [10].

This work aims to classify 14 classes (two healthy and 12 diseased) for tomato and cotton crops by using a lightweight 2D CNN architecture based on deep learning. This model is implemented for a smartphone-assisted plant disease diagnosis system in an Android application called “Plant Disease Classifier”. The experiment findings show that, despite having fewer parameters, the models suggested performs better than the pre-trained models VGG16, VGG19, and InceptionV3. The model suggested achieves a significantly higher accuracy than MobileNet and MobileNetV2 with slightly more parameters. The suggested model's average accuracy of 97.36% indicates the model's excellent performance, while the classification accuracy of these models ranges from 57% to 92% [11].

An extensive study of the pepper bell leaf disease dataset is the first step in this research project. The dataset is normalized by a number of painstakingly crafted image processing techniques, improving its consistency and quality. Using the InceptionV3 transfer learning model in conjunction with the UNET segmentation technique builds upon this preprocessing. This innovative method produces remarkable outcomes, with 99.48%. The suggested model's relevance is unbiasedly evaluated by comparing its performance to that of current cutting-edge models. Obtained results show that the suggested method is best in the field of plant disease identification. This research potentially helps the agricultural sector detect crop disease and manage it effectively by automating its detection process, which improves efficiency and allows for early disease identification [12].

In this paper a large range of disease photos with trustworthy label information in order to develop a workable image-based automatic plant detection system. It does need a lot of labor, though. The diagnosis performance of conventional systems has been reported to be quite high; nevertheless, the genuine diagnosis capabilities of these systems were significantly lower than promised, as the scores were biased due to the “latent similarity” between the training and test images. In order to solve this problem, they presented LeafGAN, which produces an enormous amount of training images and serves as a productive data augmentation technique. The performance of the systems used to diagnose cucumber diseases can be enhanced by the use of such generated images as valuable resources [13].

In this research Inception module was improved by replacing depth-wise and point-wise convolutions for the original convolutions. Then, behind the foundation network for crop disease classification and detection, the SSD block and the fully linked Softmax layer with the actual number of categories were added independently. During the model training process two-stage transfer learning was used in order to create an effective model. According to experimental results, the suggested approach may achieve the required results with an accuracy of 99.21% [14].

This study used a spectroradiometer to examine the reflectance spectra of diseased leaves with varying symptom fractions and DS levels in order to construct a “spectral disease index” (SDI) that can identify the phases of wheat leaf rust disease at different DS levels. Next, a new function was created to identify the wavelengths most sensitive to the fraction of disease symptoms by analysing pure spectra of the various disease indicators at the leaf scale. Ultimately, a new SDI was developed to distinguish between three distinct disease stage levels at the canopy level using the normalized difference of DS and the ratio ρ 675/ρ 775 [15].

In this study, a powerful new deep ensemble model called PlantDet—which draws inspiration from InceptionResNetV2, EfficientNetV2L, and Xception—has been presented. In addition to addressing underfitting issues, PlantDet simultaneously leverages superior performances for sparse datasets with a variety of background picture datasets. In comparison to all previous models, PlantDet incorporates effective data augmentation, preprocessing, a Global Average Pooling layer, a Dropout mechanism, and more Dense layers. These features increase the model's robustness and enable it to manage issues like underfitting and overfitting while maintaining better performance [16].

This paper is based on eight refined deep learning models, the paper's experimental results demonstrate that, with testing accuracy of 0.9580 and 0.9464, respectively, the models Xception and MobileNet outperformed the others in the recognition of maize leaf illnesses. Similarly, with testing accuracy of 0.9632 and 0.9628, respectively, the models MobileNetV2 and MobileNet fared best in identifying the wheat leaf illnesses. In terms of identifying rice leaf illnesses, the Xception and Inception V3 models outperformed, with testing accuracy of 0.9728 and 0.9620, respectively [17].

According to the paper's experimental result, the Inception_v3 model's minimal number of parameters and great computational efficiency allow it to achieve 74.38% accuracy for severity detection, which is higher than other models. The Inception_v3 model was trained on a new training dataset including 14,056 leaf images made up of the primary training images and the augmented ones, with the goal of assessing whether GANs-based data augmentation can help boost model learning performance [18].

In this work, the fusion not only raises the bar on previous models' performance but also improves the accuracy of disease diagnosis. In terms of accurately detecting diseases, our hybrid model achieves an astounding 99.54% training accuracy while maintaining a validation accuracy of 98.67%. It also does remarkably well in F1 score values when compared to its peers, demonstrating its outstanding ability in agricultural technology. This study offers a ground-breaking technique for identifying diseases in palm leaves. It will transform the agricultural industry [19].

In this study, a step-by-step strategy to transfer learning is given, which can aid in rapid convergence, minimize overfitting, and avoid negative transfer learning when transferring information between domains. Two plant disease datasets—PotVillage, a publicly accessible dataset, and the pepper disease dataset from Korea—are used to train and assess the system. The pepper database is especially challenging because it includes images of many plant parts, such as the leaf, pulp, and stem. With accuracy scores of 99% on the Pepper dataset and 99.69% on the PlantVillage dataset, respectively, the proposed approach outperforms previous studies on the PlantVillage dataset [20].

The study involves three sensor nodes, each containing temperature, humidity, and LWSs, provide the data needed to train the model. The network that was constructed is a collection of several submodels that were each trained independently utilizing data from distinct sensor nodes. The final output is then obtained by combining the results of these independently trained networks. By utilizing the attention mechanism, the network is engineered to attain superior outcomes by strengthening the impact of the most significant feature on the anticipated outcomes. It was discovered that the model's average accuracy was almost 94%. The model demonstrated an excellent recall rate of 97% and a high precision of 96% on average [21].

According to the lab measurement data reported in the research, when LWS is exposed to water compared to air, the manufactured LWS on the flexible substrates responds by roughly 36000%. The manufactured LWS exhibits an observed reaction time of around 10 seconds and a hysteresis of approximately ± 4%. Furthermore, spanning a temperature range of 20 °C to 65 °C, the sensor capacitance barely varies by 6%. On the Ocimum tenuiflorum (Tulsi) medicinal plant, three manufactured sensors LWS and internally created internet of things (IoT) enabled equipment are also installed [22].

The paper goal is to categorize illnesses that fall under PA. Using RL-block and PL-blocks to integrate multi-contextual features, MMF-Net efficiently combines various model streams trained on heterogeneous data. While PL-block 1 extracts fine-grained global context by enlarging the perceptual region of images, the RL-block processes coarse-grained images to convolve the local context using spatial range. Real-world environmental conditions are the focus of PL-block 2. Following fusion, it adaptively employs the majority voting procedure to produce the base model's ultimate decision probability score. A real-world numerical dataset and the maize leaf diseases dataset are used in multiple studies to get an amazing 99.23% precision in the categorization of corn leaf diseases [23].

This study examines four machine learning techniques, all of these classifiers have balanced accuracy of less than 65%, and the use of features transform based upon Modified Lemurs Optimization enhances their performance. In particular, applying the suggested feature transform for the K-Nearest Neighbour classifier allows for a balanced accuracy of 90% [24].

In this work, a technique that enables quick cytohisto chemical identification of “tobacco mosaic virus” (TMV) in tobacco plant leaves. The time needed to prepare the leaf samples was cut down to 90 minutes with the use of microwave irradiation. Following sample sectioning, the viral coat protein was immunogold labelled to stain the virus particles on the sections, a process that took one hour. It took roughly thirty minutes to visualize TMV in tobacco cells after using the TEM for study. This study unequivocally shows that TEM can quickly diagnose plant virus infections in around 30 minutes when microwave-assisted plant sample preparation is combined with cytohistochemical localization of the viral coat protein [25].

The tests conducted in this research obtained the leaf images of peach plants from Plant Village. With just 9,914 training parameters, the suggested system attains 99.35% precision for training and 98.38% testing accuracy. The suggested hybrid model needs less training parameters. It reduces the amount of time required for training a model for automatic detection of plant diseases and the amount of time needed to use the trained model to identify the illness in plants [26].

This paper's fluorescence-based approach had a lower overall discrimination error of roughly 16.5%, making it less accurate. However, utilizing QDA, combining the values from the two methods enabled for 94.5% total illness from healthy discrimination. A “Self-Organizing Map” (SOM) neural network was also used for data fusion, resulting in a 1% reduction in overall classification error. It is discussed if the SOM-based illness classifier may be used for quick retraining in the field. Additionally covered are the real-time elements of spectral and fluorescence picture processing and acquisition. The multi-sensor fusion disease detection system can be used to detect plant diseases in the field in real-time with the suggested modifications [27].

In the paper when compared to other cutting-edge techniques, the suggested method performs noticeably better; on the public dataset, it attains an accuracy rate for validation of at least 91.83%. The suggested method's average accuracy for classifying rice plant photos is 92.00%, even with complicated background conditions. According to experimental data, the suggested technique is valid and effective for detecting plant diseases [28].

The paper proposes a “deep convolutional neural network” (Deep CNN) based innovative plant leaf disease diagnosis model. An open dataset comprising 39 different kinds of plant leaves and backdrop images are used to train the Deep CNN model. The following six categories of data augmentation techniques are applied: rotation, scaling, principal component analysis (PCA), noise injection, gamma correction, image flipping, and rotation. Implementing data augmentation can improve the model's performance. The suggested model was trained with varying batch sizes, dropout rates, and training epochs. When employing the validation data, the suggested model performs better than well-known transfer learning techniques. Following simulation, the model's classification accuracy is 96.46%. The suggested work's accuracy surpasses the accuracy of traditional machine learning approaches [29].

In this study, features for an automatic classification, nine spectral vegetation indices that are connected to physiological factors were employed. A Support Vector Machine using a radial basis function as kernel may distinguish between infected and healthy plants as well as between particular diseases early on. Upto 97% of the time, the leaves of sugar beets could be distinguished between healthy and unhealthy. Even yet, the accuracy of the multiple categorizations between leaves that were healthy and leaves that had indications of the three diseases was higher than 86% [30].

Early diagnosis of plant diseases is essential to avert epidemics and lessen their impact on crops. Deep learning-based automatic algorithms are the most accurate for identifying plant diseases from plant field images. Large image datasets must be acquired and annotated to use these methods, which is frequently not possible from a technical or financial standpoint. In this work, deep learning with limited datasets is used to introduce Few-Shot Learning (FSL) methods for plant leaf categorization.38 plant leaf and/or disease kinds (classes) were represented in the 54,303 annotated photos from the PlantVillage dataset that was used for the study [31].

In this paper the capacity of the improved disease indicators to differentiate between healthy and diseased sugar beet leaves was put to the test. Sugar beet leaves with excellent accuracy and sensitivity were used to classify leaves with sugar beet rust, Cercospora leaf spot, and powdery mildew. Additionally, spectral disease indices have been effectively applied to non-imaging and hyperspectral imaging data from a sugar beet field. In precision agriculture applications, specific disease indices will enhance disease detection, identification, and monitoring [32].

MobileNet-V2 model and already trained ImageNet is used in this study in order to improve the capacity for learning for minute lesion information. The author has incorporated an attention mechanism to help the network understand the significance of spatial points and inter-channel relationships for input features. Meanwhile, two transfers of learning were carried out to train the model, and the loss function was optimized. The performance of the suggested procedure is better than that of other cutting-edge techniques. On the public dataset, it attains an average identification accuracy of 99.67%. The average accuracy for detecting rice plant illnesses is 98.48%, even with complex background conditions. Findings from experiments support the validity of the suggested method, which is successfully used to identify rice diseases [33].

The innovative ResTS architecture for plant disease diagnostics is different from the previously proposed Teacher/Student architecture in that it does batch normalization following each convolution operation and considers the residual connections in all constituents. Residual connections help prevent vanishing or growing gradients in ResTS by helping to sustain gradients. Moreover, batch normalization is performed after every convolution operation to encourage quicker convergence and greater dependability. Based on 54 306 images of 14, each test result is derived from the PlantVillage dataset [34].

It was looked into how the spectral reflectance of wheat plants sick with Puccinia striiformis differed between diseased and healthy plants. A spectrograph installed at the height of the spray boom was used to capture spectral images in the field. A normalization technique based on modifications to light and reflectance was used. A complete canopy reflection was taken into account by introducing a spatially shifting average. A quadratic discrimination-based classification model was constructed using a subset of wavebands that were acquired by progressive variable selection. Based on four distinct wavebands, the proposed approach reduced confusion rates between 12 to 4% erroneous classifications. The findings are highly encouraging for the creation of an affordable optical tool for early spring disease detection in the field, such as yellow rust detection [35].

The data base for the research can be used in two ways of which first way is by using the pre-recorded database available related to the diseases and second way is collecting the live data of the plants for a few time (about 5-10 min of plant video data/month) for a longer duration.

OVERVIEW OF INFECTIOUS DISEASES IN PLANTS

An overview of plant diseases based on the survey papers are mentioned below:

Plant diseases is broadly classified into several types, including fungal diseases, bacterial diseases, viral diseases, and other types caused by environmental factors or pests (Figure 1). Fungal diseases are among the most common and devastating, affecting a wide range of crops such as wheat, rice, and maize. Examples include powdery mildew, rusts, and blights.

Bacterial diseases also pose significant threats to plant health, leading to symptoms like wilting, leaf spots, and rotting of plant tissues. Some well-known bacterial diseases include bacterial blight, bacterial wilt, and fire blight.

Viral diseases are caused by various types of viruses and can result in symptoms such as leaf discoloration, stunted growth, and deformities in plant structures. Examples of viral diseases include mosaic viruses, leaf curl viruses, and necrosis viruses.

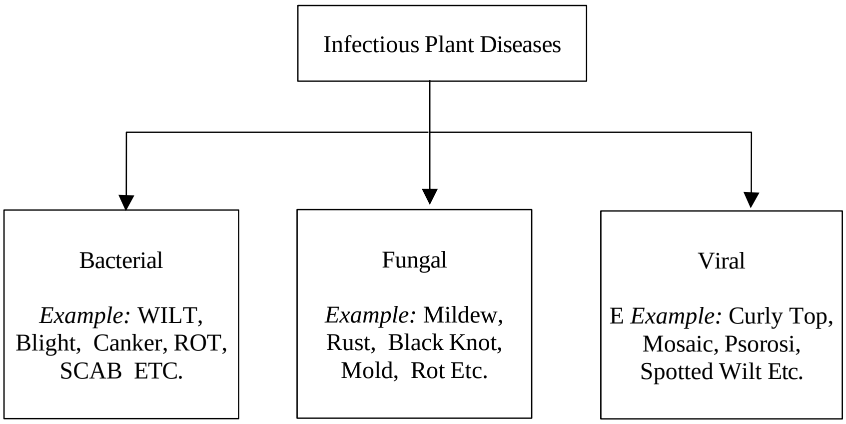

Figure 1. Types of Plant Diseases.

In addition to these major categories, plants can also suffer from diseases caused by environmental factors like nutrient deficiencies, water stress, and extreme temperatures. Pests such as insects, mites, and nematodes can also contribute to plant health problems.

Early detection of the disease is of prime importance for effective management and mitigation of their impact on agricultural productivity. Timely identification allows for prompt intervention strategies such as the application of fungicides, antibiotics, or cultural practices to prevent disease spread and minimize yield losses.

The importance of current reviews and advancements in plant disease detection cannot be overstated. With the rapid development of technologies such as deep learning models, sensor-based systems, and data augmentation techniques, there is a growing potential to revolutionize the way plant diseases are diagnosed and managed. These advancements enable farmers to detect diseases at early stages, thereby educating them to make informed decisions and implement proactive measures to protect their crops.

In conclusion, a panoramic understanding of the types of plant diseases and the need for early detection underscores the significance of ongoing research and advancements in this domain. By leveraging innovative techniques and technologies, we can enhance our ability to safeguard global food security and sustainably manage plant health in agricultural systems.

QUANTITATIVE METRICS

a. Accuracy

$$\text{Accuracy} = \frac{(\text{True Negative Ratio} + \text{True Positive Ratio})}{\text{Total number of samples}}$$

b. Precision

$$\text{Precision} = \frac{\text{True Positive Ratio}}{\text{True Positive Ratio} + \text{False Positive Ratio}}$$

c. Recall (Sensitivity)

$$\text{Recall} = \frac{\text{True Positive Ratio}}{\text{False Negative Ratio} + \text{True Positive Ratio}}$$

d. F1-Score

$$\text{F1} - \text{Score} = \frac{2 * (\text{Recall} * \text{Precision})}{\text{Recall} * \text{Precision}}$$

e. Specificity (SPE)

$$\text{Specificity} = \frac{\text{True Negative Ratio}}{\text{False Positive Ratio} + \text{True Negative Ratio}}$$

f. Average Accuracy (mAP)

$$\text{mMAP} = \frac{\sum \text{N (Precision.Recall.100\%)}}{\text{N}}$$

g Intersection Over Union (IoU) or Jaccard Index

$$\text{IoU} = \frac{\text{True Positive Ratio}}{\text{True Positive Ratio} + \text{False Positive Ratio} + \text{False Negative Ratio}}$$

h dice Coefficient (DC)

$$\text{DC} = \frac{2 * \text{True Positive Ratio}}{2 * \text{True Positive Ratio} + \text{False Positive Ratio} + \text{False Negative Ratio}}$$

i Receiver Operating Characteristic (ROC)

$$\text{TPR} = \frac{\text{True Positive Ratio}}{\text{True Positive Ratio} + \text{False Negative Ratio}}$$

$$\text{FPR} = \frac{\text{False Positive Ratio}}{\text{False Positive Ratio} + \text{True Negative Ratio}}$$

j Area Under the Curve

It is a measure of the classifier's performance.

$0.5<\text{AUC}<1$ specify higher chance that the classifier will be able to differentiate the positive class values from the negative ones (1-indicates an ideal classification and 0.5-indicates a random classification). A larger AUC value indicates higher the ability of classifier.

RESEARCH GAP AND FUTURE ASPECTS IN DEEP LEARNING

1. *Early Detection:* Detect before the symptoms appear to the human eye or before they manifest visually, which enables early intervention in diseases detection**.**
2. *Generalizability:* models behavior with real world variations in lighting, weather, and plant growth stages.
3. *Multi-disease detection:* Difficulties in differentiating between co-occurring diseases or those with similar symptoms.
4. *Transparency and explainability:* Need for AI model that can explain the reason behind diseases detection for better decision making.
5. *Image recognition:* Pattern-based identification eases visual recognition of symptoms on leaves, fruits or stems.
6. *Accuracy and Efficiency:* DL models give better accuracy in detection and efficiently analyses large datasets.
7. *Different approaches:* DL can be used for various tasks – classification (specific disease identification), detection (locating diseased areas) and segmentation (for separating healthy and unhealthy part)
8. *Advance Deep Learning Techniques:* Improve diseases detection accuracy and robustness using novel Deep Learning Approaches.
9. *Disease Progression Monitoring:* Need of a system to track disease progression over time using image analysis, assisting in tailored treatment decision.

Plant diseases detection using deep learning is an exciting and rapidly evolving field. Here are few aspects to explore:

1. *Convolutional Neural Networks (CNNs):* Investigate the effectiveness of CNN architectures for identifying specific plant diseases from images. Pretrained CNN models on plant datasets can be fine-tuned to explore transfer learning.
2. *Multi-Modal Diseases Detection Approaches:* Combine visual data (images) with other modalities such as hyperspectral imaging or volatile organic compound (VOC) sensors, thermal imaging, or even audio signals to improve disease detection accuracy.

3. *Data Augmentation Techniques:* Develop novel data augmentation methods to enhance the diversity of training data, especially for limited plant disease datasets.
4. *Anomaly Detection:* Explore deep learning models for detecting rare or novel plant diseases that may not be well-represented in existing datasets.
5. *Interpretable Deep Learning:* Investigate techniques to make deep learning models more interpretable, allowing researchers and farmers to understand the decision-making process behind disease predictions.
6. *Transfer Learning Across Crops:* Study the transferability of deep learning models trained on one crop to detect diseases in other crops. Can knowledge learned from one domain be effectively applied to another?
7. *Real-Time Detection:* Develop efficient deep learning models suitable for real-time disease detection in the field using edge devices or drones.
8. *Uncertainty Estimation:* Investigate uncertainty estimation methods for deep learning models to quantify the confidence of disease predictions.
9. *Semi-Supervised and Self-Supervised Learning:* Explore techniques that leverage unlabeled data to improve disease detection performance.
10. *Robustness to Environmental Variability:* Study how deep learning models can handle variations in lighting conditions, weather, and other environmental factors.

CONCLUSION

Different models applied for detecting plant diseases are analysed. Many challenges that have to be considered is listed to overcome the problems of existing techniques. In the existing papers, the researchers have considered many features for classification purposes. Multiple features can be extracted to enhance the performance or accuracy of classification. From the study its inferred that the deep learning and deep transfer learning techniques applied gives more accurate result compared to image processing technique. The techniques applied can be improvised for obtaining better accuracy in locating the plant diseases. Finally, the paper concludes that even though there is advancement in the evolution of various deep learning techniques, improvement in the disease recognition and classification approaches is required which aids the early diagnosis.

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