Migration Letters

Volume: 21, No: S5 (2024), pp. 770-783

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

An Improved Deep Residual Convolutional Neural Network For Plant Leaf Disease Detection

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Abstracts

Propose: *When they are growing, plants are vulnerable to an assortment of diseases. One of the trickiest issues in agriculture is the early diagnosis of plant diseases. To raise the standard of crop cultivation, it is crucial for one to identify and diagnose crop leaf diseases. The machine-learning identification of crop disease of leaves using machine learning technology offers outstanding accuracy and no subjective judgement mistake as compared to the traditional human detection strategy.*
Aims: *Compare existing cutting-edge models for the detection of plant leaf disease with the suggested enhanced deep residual CNN.*
Design/Methodology: *ResNet197 was created using six blocks of levels. Using an integrated disease of plants picture dataset, ResNet197 was programmed and evaluated. The added data of the plant's leaf disease picture recuperation was created using the following techniques: expanding, trimming, flipping, cushioning, rotation, quadratic transformation, the saturation point, and hue conversion.*
Results: *The dataset comprised 154,500 photos of both wholesome and ill plant leaves, as well as 103 picture classes of 22 different plants that were simultaneously sick and healthy. The ResNet197 the hyper parameter settings and layers were adjusted using the method of evolutionary search approach.*
Conclusion: *On the test dataset, it yielded an average precision for classification of 99.58 %. The experimental outcomes surpassed both current transfer learning methods and Res Net configurations.*

Keywords: *Plants, Diseases, Image Dataset, CNN Architectures, Resnet197, Learning Techniques, Hyper Parameter, Leaf Disease, Classification Accuracy.*

I. INTRODUCTION

Global food security depends on the prevention of agricultural diseases, and the critical component of disease prevention is early detection of crop diseases. Agricultural technicians are respo[1]nsible for the conventional diagnosis and detection of crop leaf diseases. This approach results in an excessive expenditure of resources and labour force, as well as inadequate identification accuracy [1]. In order to assist in recognising the early indications of crop diseases, more precise automated detection techniques have been created with the advancement of Artificial Intelligence (AI) and processing of images technology. The majority of crop diseases affect the leaves.

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Using maize as a demonstration, leaf spot and wilt are prevalent leaf diseases. The form, colour, texture, and additional traits of leaf images are successfully retrieved using conventional image processing techniques including Support Vector Machines (SVM) [2], and the technique known as K-means clustering. Thus, many illness kinds may be recognised and classified using the image processing approach. All of the common methods for processing and analysing images, however, rely on feature engineering. Furthermore, whereas the deep learning approach considerably increases the identification efficiency by eliminating the need to manually specify picture features, the technique is often not stable in real-life applications and feature extraction is frequently impacted by enlightenment occlusion, and other issues [2, 3].

Plant diseases often lead to epidemics that cause mass death and starvation. The 1943 outbreak of helminthosporiosis in rice is thought to have caused a massive loss of agricultural crops and millions of lives in northeaster India [3, 4]. The typical functioning of the plant is harmed when such diseases proliferate in a region, and the ecosystem is also harmed by the sharp decline in the total number of mature harvests. Crop production often suffers from a variety of illnesses that cause it to operate beneath par, but the damaged region is also hidden from view.

Research on automation plant disease analysis is crucial because it may help monitor major agricultural fields and, therefore, instantly identify diseases based on their symptoms, [5, 6], which constantly manifest as plant leaves. This makes it possible for machine vision to use images to manage processes, guide robots, and perform autonomous inspection. Farmers estimate diseases using their knowledge, but this is sometimes not the best way to take action. Consultant oculus inspection is the most widely used technique for recognising and diagnosing plant diseases. Occasionally, illusions may lead to mistakes [7, 8].

1.1 Crop diseases

The agricultural merchandise's external appearance is its primary quality feature. Their curiosity and behaviour modification consumer purchase patterns are greatly influenced by the external appearance. Thus, the expanding number of reasonable, [8], stable plants in the agricultural sector requires the use of established area units for grading and inspection systems. Plant diseases are starting to cause severe decreases and failures in the quantity and quality of all agricultural goods, which makes them a (serious) disadvantage [9]. The vast bulk of the growing national population is mostly dependent on agricultural production. However, it takes a lot of technical skill to grow certain crops for optimal production and industrial efficiency. Technical assistance and mechanised agriculture often help to improve this. A small number of researchers have looked at automated leaf disease detection and classification using superior-resolution multispectral images, stereo, and hyperspectral pictures. As shown in Fig. 1, the different types of agricultural crop diseases include rust, black identify, green location, powdery mildew, and botrytis blight [10].

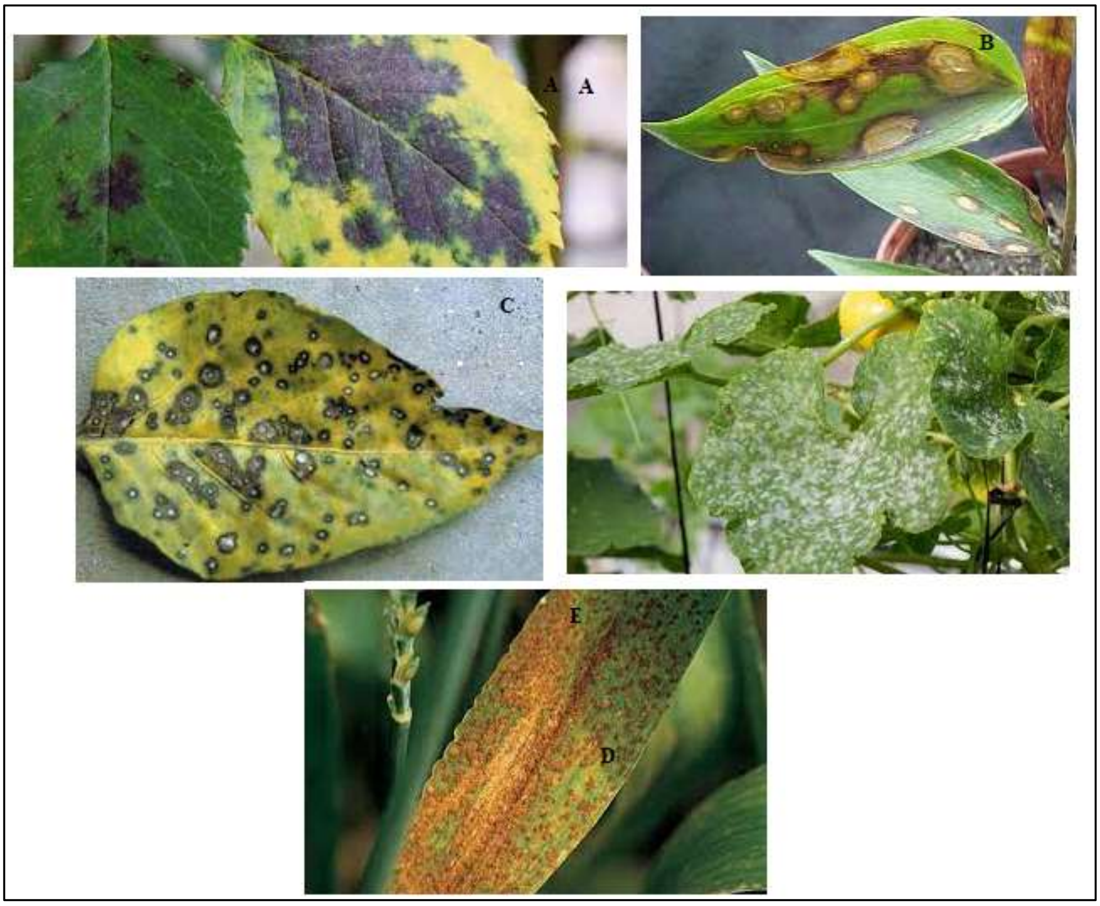


Fig. 1 Crop diseases include: (a) powder fungus; (b) rusty spores; (c) green patch; (d) botrytis withering; and (e) black spot [10].

Fig. 2 Demonstrates the systematic approach used in the plant disease detection system:

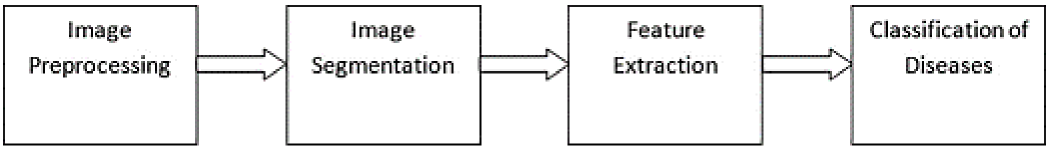


Fig. 2 Plant disease identification system.

- **Image Pre-processing:** Its goal is to further enhance picture data in order to eliminate unintentional distortions and/or improve certain image attributes that are required for additional processing [11]. Transformations of geometric images are within the category of pre-processing methods.
- **Image Segmentation:** It stands for the method of breaking up a digital picture into multiple pieces. This phase's main goal is to identify artefacts or extract additional pertinent information from digital photos. Image segmentation is done using an assortment of techniques, including edge identification, [12], thresholding technique, and K-means clustering. The canny filter is employed for edge detection, while K-means clustering is often used for feature-based approaches segmentation.
- **Feature Extraction:** It is a technique for stressing a number of excellent elements, or picture features, that determine the main element, which, when effectively shown, provides the precise information needed for categorization. The form,

texture, or colour of the item may serve as the basis for the feature extraction technique. The collection of texturing is the most often used technique in this.

- **Classification of diseases:** To decide whether the provided picture is healthy or harmful, the ultimate step is categorization. Classifiers are used to identify photos by extracting their attributes.

Because of the way they perform on image data, Convolutional Neural Networks (CNNs) or Convolutional Auto encoders (CAEs) constitute two Deep Learning approaches that are widely employed in computer vision applications [13]. The convolution process is used in each of these methods to extract multiple temporal and spatial properties in imagine data. While CAEs are employed to effectively decrease an image's dimensionality, CNNs are used to organise input pictures to their appropriate classes.

Considering this paper's imaginative hybrid model to previous state-of-the-art systems in the literature, it offers fewer instructional parameters for autonomous plant disease diagnosis based on CNN and CAE. To their best of our knowledge, [14], no research study has yet presented a hybrid system combining a CNN and CAE for automated plant disease diagnosis, despite the fact that there are several methods available in the literature for this purpose.

One kind of the use of AI approach that builds on artificial neural networks is deep learning. The deep learning method mimics how acquiring data leads to intelligent decision-making in people. It is being used more and more for decision assistance in a variety of applications in industry to boost output, save costs, and cut down on mistakes [15]. When it comes to judgement accuracy and dependability, deep learning approaches outperform conventional AI techniques.

Supervised artificial intelligence methods include the class of convolutional neural networks that are deep or CNNs. Tasks involving object identification and picture categorization are where the DCNNs excel [16, 17]. The DCNN models needed to be trained on a lot of data in order to function effectively in many areas. In order to improve the performance of training of DCNN models, the data augmentation approach was developed to enhance the volume of training data requiring collecting new data [18]. The DCNN model requires a lot of processing power and storage to train. To train models more effectively, Graphics Processing Units, or GPUs, are often used.

The ones that follow are the research's main contributions:

- Extremely deep residual convolutional neural network (CNN) models were used to identify leaf diseases in twenty-two distinct species of plants [19].
- To identify leaf diseases, a unique 197-layer deep residual a convolutional neural called ResNet197 was created.
- To further refine the suggested ResNet197 model, the evolutionary searching approach was used to determine the ideal number of layers and hyper parameter values.
- In a GPU setting, ResNet197 was trained using the plant leaf disease dataset for up to 1000 epochs.
- Standard performance measures were used to determine the trained Resnet197's classification performance on the test dataset.
- Why Without any previous knowledge of plant illnesses, farmers might utilise the model suggested by this study to diagnose different plant diseases from a camera-captured photo.
- The suggested model outperforms previous transfer learning strategies in leaf disease detection tasks, according to a performance comparison with contemporary methodologies.

The manual diagnosis of cauliflower disease is often done by experts using their unassisted eyes, which takes more time and is expensive on large homesteads. It is difficult to quantify, and sometimes it causes an error in determining the kind of sickness. Paddy output has recently declined due to misunderstanding of the proper administration to address paddy plant leaf disease. To combat this, prompt and adequate identification methods for paddy leaf disease diagnosis are needed.

Five of the of the most common paddy leaf diseases—Brown spot, healthful leaf, leaf blast, fungal blight, and plant smut—were the major focus of the present research. Maintaining a level of life has become simpler thanks to the AI revolution. The farming community is benefiting immensely from AI, just as every other sector has. Disease of crops is one of the numerous issues in agriculture that technology has greatly simplified. It can now use deep learning and machine learning to identify a wide range of diseases. It has primarily been successful, despite a few limitations [20]. Therefore, without the assistance of a specialist, the farmer himself may identify paddy illness on his property. In the future, technology will bring about a great deal more improvement in the agricultural industry.

Research on digital plant disease detection is crucial since it may help monitor major agricultural fields and, consequently, instantly identify illnesses by looking for their symptoms, which often manifest as plant leaves. This makes it possible for machine vision to use images to supervise processes, guide robots, and perform autonomous inspection. Farmers estimate diseases applying their knowledge, but this is frequently not the best course of action.

Consultant the cornea assessment is the most widely used technique for identifying and detecting plant diseases. Sometimes, delusions may lead to mistakes. Thus, a computerised procedure and quick approach are used to protect the crop from illness. In the meanwhile, portable imaging equipment (such as cell phones) and nanostructure-supported non-invasive detection methods have enabled long-term plant health status monitoring and quick on-site diagnosis of plant diseases possible, particularly in environments with scarce funds.

1.2 Objectives of the study

- Optimise the design of the model to minimise computing complexity without sacrificing precision.
- Detect plant leaf diseases more accurately overall as compared to current models.
- Optimise the model for real-time detection of plant diseases in the field.
- Assess the effect of dataset augmentation approaches on model performance.

II. LITERATURE REVIEW

[Ahmad, I., Hamid, M., 2020] [21] Vegetables and fruit crops benefit around seven billion individuals worldwide, playing an important part in supporting life on this planet. The fast growth in the usage of chemicals like fungicides and and antibiotics to control plant diseases is having a detrimental impact on the agro-ecosystem. Crop disease incidence has a significant impact on output quantity and quality. Farmers will profit from solving the challenge of early illness detection/diagnosis by using a rapid and consistent reliable procedure. In this regard, our research study focuses on the classification and diagnosis of tomatoes leaf disorders using Convolutional Neural Networks (CNNs).

[Wu, Y., & Xu, L. 2019] [22] In recent years, there has been a lot of study on object categorization and segmentation using Deep Convolutional Neural Networks (DCNN). On one hand, DCNN necessitate enormous knowledge sets and exact labelling, creating significant challenges in execution in practice. On the other hand, it utilises a significant amount of technological resources, making it challenging to adapt to low-cost interface infrastructure. This work offers a technique for agricultural organ division and identifying diseases which employs a poorly supervised DCNN and a lightweight model. When examining the real scenario in the greenhouse, we employ a two-step technique that eliminates the influence of complicated backdrop. To begin, we apply the general neural network architecture—Mask R-CNN collection to implement the particular segmented of tomato organ based on weakly supervised data mining, and then the disease detection of tomato leaves will be realised by depth separable multi-scale convolution.

[Patil, N., Ali, R., Wankhedkar, 2019] [23] The concept focuses on following through information about insecticide recommendations and the quantity of pesticides to be applied on an unhealthy crop. The Farmer takes a picture of his crop and transmits it to the web server using an Android application installed on his mobile device or a website. After uploading the image, the farmer hits the Predict box that appears on screen. Then the uploaded picture undergoes analysis and its characteristics are retrieved. Based on these attributes, the picture is classified using a convolutional neural network, and the classes with the highest probability are chosen. The result is then returned, which includes the illness name. This result is then posted into the message column in the web server and accessed in the application for smartphones or on the internet where associated information such as herbicide name, quantity of pesticide to be used, and organic pesticides are kept.

[Yu, M., Ma, X., Guan, H., 2023] [24] To address the issues of high complexities and large the calculation in current diagnostic models based on machine learning, which are challenging to apply to commonly used portable mobile devices, a lightweight soybeans disease diagnosis model depending on attention mechanisms and residual neural networks was proposed. The Residual Attention Layer (RAL) was built utilising the attention system, continuous processing layer, and shortcut connection from the classic residual neural network, and it was introduced into the Residual Neural Network version 18 (ResNet18) to substitute the residual architectural layer. A new Residual Attentive Network Structure (RANet18) was developed for soybean disease detection. Simulation studies were carried out using 4301 photos of soybeans brown leaf spot, soybeans frogeye leaf spot, and soybean phyllosticta leaf spot that were processed using the RANet18.

[Wu, Y., Xu, L., 2021] [25] The Deep Convolutional Neural Network (DCNN) needs an immense amount of data for training, yet there always has been a data gap in agriculture, making it impossible to appropriately organise all available data. As a result, a lightweight tomato leaf disease monitoring networks powered by Variation Auto-Encoder (VAE) is presented to increase crop leaf disease recognition accuracy. Multi-scale convolution, like deep segmented convolution, may increase networks breadth, enrich retrieved features, and minimise model parameters in a lightweight network. VAE employs a huge quantity of unlabelled data to accomplish unsupervised learning, followed by labelled information for unsupervised illness detection. However, in the real model distribution and production the surroundings, VAE does not need extra computation or storage usage, since it is not employed in the computation part of the application phase.

[Sun, J., Tan, W., Mao, 2017] [26] Plant diseases of leaves are a major problem in the production of crops. Accurate illness classification is critical for resolving this issue and preventing progression of the disease. In this study, we give a Convolutional Neural Network (CNN)-based disease identification model for leaves from plants that employs successive normalisation and worldwide pooling approaches. Traditional CNN algorithms contain enormous parameters that are difficult to converge. The suggested model was adjusted in the typical form of the CNN, which may reduce training time and obtain improved accuracy while also reducing the size of the simulation. To accelerate training convergence, which refers we employed batch normalisation layers. We placed the input of each convolutional layer in a batch, estimated the mean as well as the variance of the batches, and then accepted it.

[ABAWATEW, G. Y., Belay, S., 2021] [27] Deep learning algorithms enable agronomists to quickly detect, assess, and evaluate tomatoes health. The CNN (Convolutional Neural

Network) localization limitation and the current limited training sample hindered disease identification performance. To address these issues, we introduced a prejudiced feature-learning approach to the Awareness Augmentation Recurrent (AAR) networks. The AAR network includes a placed pre-activated residual prevent that acquires deep coarse level characteristics with location context, while the focus block captures prominent set of characteristics while maintaining a worldwide connection in data points. Attention features supplement the statistical learning that occurs in the residual block. We employed the Condition Variational Generalised Adversarial Network (CVGAN) reconstruction of image network and augmenting approaches to increase the example used for training size and enhance feature distribution.

[Zhao, S., Peng, Y., 2021] [28] Crop identification of diseases is very important for the productivity of crops and agricultural output. Deep learning algorithms have emerged as the primary research focus for diagnosing farming diseases. This research presents a deep Convolutional Neural Network (CNN) with an attention mechanism that can better adapt to diagnosing a range of tomato leaf illnesses. The network structure consists mainly of remaining segments and attention extracting modules. The model accurately extracts complicated information from a variety of illnesses. Extensive comparison experiment results reveal that the suggested model achieves an average detection precision of 96.81% on the crop's leaf fungal infection dataset.

[Hassan, S. M., Maji, A. K., 2021] [29] Crop diseases must be identified and prevented as soon as possible in order to improve yield. Deep convolutional neural network (CNN) models are used in this article to recognise and diagnose illnesses in plants based on their branches, since CNNs have shown outstanding results in machine vision. Standard CNN models have an enormous amount of variables and a significant computational cost. In this study, we substituted ordinary combination with depth=separable convolution in order to reduce parameter count and calculation cost. The implemented models had been developed on an open dataset that included 14 distinct plant species, 38 different category disease classes, and healthy plant leaves.

III. METHODOLOGY

The suggested detection of plant leaf diseases model's implementation processes are divided into two parts. The implementation of the suggested ResNet197 model began with data preparation. The data preparations phase focuses on data gathering, augmentation, and pre-processing. The model phase of training consists of ResNet197 design, modification, and instruction on operations [30]. The subsections that follow provide in-depth descriptions of each implementation step.

Scaling, which is cutting, flipping, padding, and rotation, affine alteration, saturation, and hue manipulation methods were employed to create enhanced pictures from the dataset. The data augmentation method equalised the amount of photographs in each class, resulting in 1500. Figure 3 shows the example enhanced photos on the plant leaf-related illness dataset utilising data augmentation methods.

Fig. 3 Sample enhanced photos from the plant disease of the leaves dataset [31].

During the augmentation stage, the dataset was divided for training, validation, and testing. The photos in the collection of images were jumbled and randomly chosen for validation, training, and assessment [32]. Table 1 shows how many photos are in the training, verification, and testing datasets.

Table 1 Size of the training, validation, and test datasets.

Dataset name	Number of images	Number of images in each class
Training set	135,800	1,301
Validation set	15,230	145
Testing set	14,145	455

$$f(x) * g(x) = \int f(x).\, g(x-k)dk \; \ldots .1$$

$$f(x) * g(x) = \sum_{k=-\infty}^{\infty} f(x).\, g(x-k) \; \ldots 2$$

$$m + 2p - k + 1 = m \rightrightarrows p = \frac{k-1}{2} \; \ldots 3$$

IV. RESULTS AND DISCUSSION

The effectiveness of the suggested ResNet197 model for diagnosing plant leaf diseases. Furthermore, it employs typical performance indicators for contrasting the ResNet197 architecture against other ResNet models and cutting-edge transfer learning methods. Current transfer learning approaches, such as VGG-19 Net, ResNet-152, InceptionV3, which Net, Mobile Net, and DenseNet201, have been utilised for the performance comparison.

The most often used statistic for assessing how well categorization methods work is an area Underneath the Curves-Receiver Operating Characteristics (AUC-ROC) curve. Using the class's True-Positive Rate (TPR) and the False Positive Rate (FPR) values from the test data, the ROC of the method of classification for a particular class is computed. The number of properly classified samples that were positive in the test data is represented by the TPR. Comparably, the test data's False Positive Rate (FPR) indicates how many false positive predictions there were among the negative samples. Plotting the ROC curve and determining the Area Under the Curve (AUC) of the model for classification for a particular class requires using the TPR and FPR values. The graph's x- and y-axes stand for the TPR and FPR scales, respectively. The proposed and current models' AUC-ROC curves on two random choices.

The speed of precision gauges are indicated by the Accuracy (CA). It is calculated by taking the total number of accurate forecasts and dividing it by the total number of times the events occurred.

$$CA = \frac{TP+TN}{TP+TN+FP+FN} \ldots .1$$

Accuracy, also known as positive predictive value, is the ability to identify who of the people who were assumed to be positively truly are positive. It is calculated by deducting the total number of real positives from the total number of real positive and fake positive.

$$precision = \frac{TP}{TP+FP} \ldots 2$$

The amount that actually positives that were, as of yet, exactly unbeknownst to consciousness is the true positive rate. It might be calculated by deducting the total amount of positive outcomes from the total number of true positives and deceptive negatives.

$$Sensitivity = \frac{TP}{TP+FN} \ldots 3$$

Explicitness is a defining characteristic of the actual regretful rate. This is the exact amount of real drawbacks that were calculated. To accomplish this action, we divide the total number of false positives by the total number of real negatives and false positives.

$$Specificity = \frac{TN}{TN+FP} \ldots 4$$

The F1-Score indicates the harmonic mean of exactness and review. It provides a more precise indication of the instances that were incorrectly categorised as compared to the CA.

$$F_1 = 2.\frac{precision.sensitivity}{precision+sensitivity} \ldots 5$$

The usual metrics to evaluate the general effectiveness of the classification approaches are F1-score, recall, precision, and the accuracy of classification. Using the measures mentioned above, the effectiveness of ResNet197 and the most current transferable learning approaches was contrasted. Figure 4 shows the performance comparison between the suggested ResNet197 models and learning through transfer techniques.

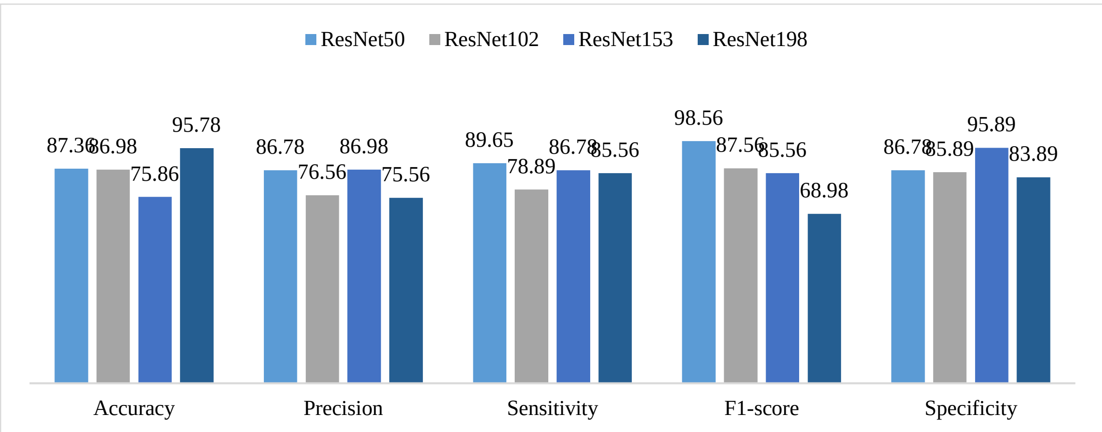


Fig. 4 Comparing the ResNet designs' performances.

Additionally, Table 2 compares the suggested ResNet197 model's performance to those of other ResNet models.

Table 2 Comparing the Resnet models' performances.

Model	Accuracy	Precision	Sensitivity	F1-score	Specificity
ResNet51	86.56	85.45	84.26	97.23	78.25
Resnet 102	86.55	89.56	78.59	86.54	89.44
ResNet153	87.25	88.69	82.36	86.54	78.36
ResNet196	88.25	96.36	88.66	89.36	86.63

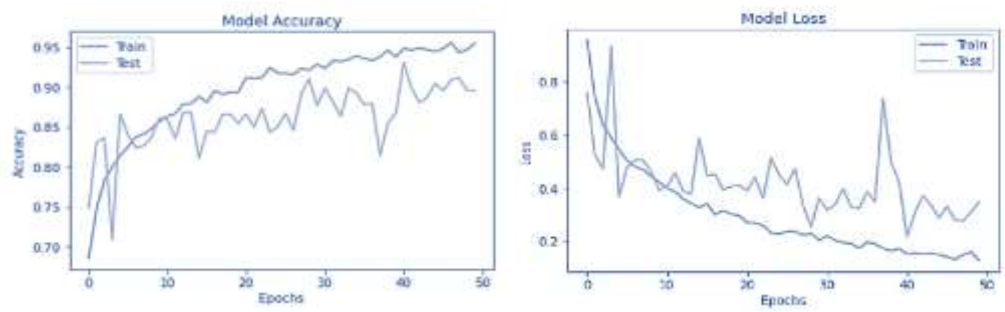
The accuracy score of the suggested and present approaches on a plant's leaf disease information is also shown in Table 3. The comparison result demonstrates that when compared to other transfer learning strategies, [33], the suggested model outperformed them in terms of categorization precision, relevancy, sensitivity, F1-score, and specificity.

Table 3 ResNet 198 and Learning from Transfer Techniques' Performance Comparison.

Model	Accuracy	Precision	Sensitivity	F1-score	Specificity
VCGG19Net	98.59	95.69	89.78	96.49	83.84
ResNet153	98.69	97.58	96.66	95.69	97.54
InceptionV3Net	96.49	97.65	89.65	96.48	89.64
MobileNet	96.48	99.36	89.61	84.98	94.56
DenseNet203	86.69	86.97	86.96	88.59	94.36
Proposed ResNet197	91.69	95.68	86.97	83.96	83.69

When it came to plant diseases of leaves verification, the inceptionV3 network performed better than the other transferred learning approaches. On the test dataset, the suggested ResNet197 the model's average precision in classification was 99.58%, a percentage that is 3.15 per cent more than the inceptionV3 networks [34]. The suggested ResNet197 model outperformed the other transfer strategies for learning in terms of average accuracy for classification, overall precision, overall recall, and averaged F1-score. The indicated ResNet197 model's AUC values and outcome measure results demonstrated that, when it came to plant leaf disease identification, its performance and dependability outperformed those of sophisticated transfer learning strategies.

Comparing deep learning techniques the experimental study carried out in Figs. 5 and 6 is based on CNN-based architecture [35]. The only distinction is that hyper parameter adjustment is required for the outcome shown in Fig. 5. Conversely, the suggested method based on Fig. 6 employs hyper parameter tweaking and dependency-based learning, which efficiently use leaf domain knowledge.



Figures 5 and 6 Current CNN-SoftMax method with model accuracy and loss over epochs.

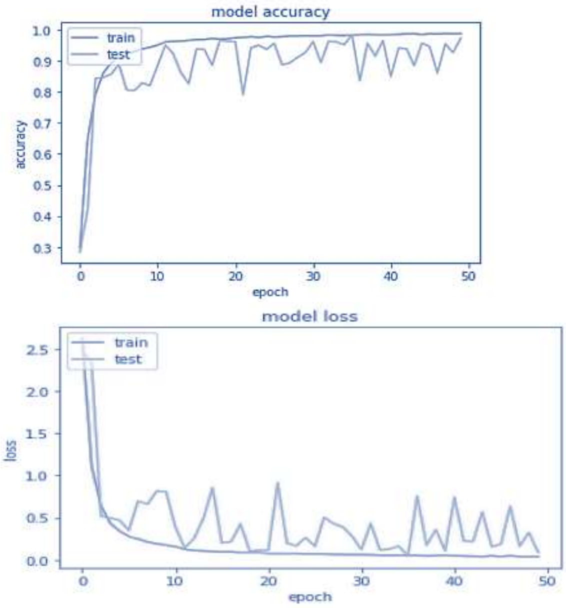


Fig. 7 and 8 Proposed CNN-Bayesian approach with model loss and model accuracy in different epochs.

The results presented in Fig. 7 are predicated on 90% validation accuracy and 90% training accuracy. There are no either under fitting or overfitting issues. Based on instruction and verification accuracy, [36], Fig. 8 shows findings that vary with dropout rate, with an estimated 98.9% accuracy. The outcomes of overfitting and under fitting are absent from the suggested technique [37].

There are two noteworthy use cases for the suggested paradigm [38]. First, on low-processing-power systems, it may be learned and applied for automated plant disease diagnosis with shorter training and forecasting times. Second, smartphones may be utilised to train and use the suggested model [39]. Farmers may benefit from less latency and data privacy by using a Deep Learning model in mobile apps rather than uploading plant leaf photos to a cloud or server.

V. CONCLUSION

One of the most important steps in precision agriculture is automatic identification of plant diseases. A distinctive deep residue convolutional neural networks with 197 layers (ResNet197) was suggested in this research study to identify common diseases of the leaves in 22 distinct plant species. The proposed dataset was prepared for the ResNet197 training using a few contemporary image augmentation methods along with several standard datasets. The enhanced photos were created using the following techniques: scaling, cultivation, flipping it, cushioning, a rotation, affine recombination saturation, and hue transformation.

Early detection of diseases in plants is a difficult and demanding undertaking. Various Machine Learning and Neural Learning methodologies have been used by many researchers to identify plant diseases automatically. Unfortunately, the majority of these methods have poor classification accuracy or need trillions of training parameters. This research established a unique hybrid model for autonomous plant disease diagnosis based on two Deep Learning methods: Convolutional Neural Network (CNN) and Convolutional Auto Encoder (CAE) network. The suggested DCNN and the conventional classifier were compared in terms of accuracy, precision, recall, and the F-score. The outcome revealed the effectiveness of the suggested model as a tool for illness categorization and identification. GPU-enabled workstations were used to train ResNet197 and the current transfer learning models for up to 1000 training epochs. The suggested ResNet197 model's classification accuracy, preciseness, sensibility, F1-score, and specificity were, in that order, 98.58%, 96.36%, 93.42%, 97.39%, and 99.27%. The suggested ResNet197 model outperformed transfer learning methods including VGG19Net, ResNet152, InceptionV3Net, Mobile Net, and DenseNet201 in terms of performance.

Future works

In order to enhance accuracy and guarantee quicker proof of identity, this study might be continued using other kinds of paddy diseases of leaves and more refined CNN models.

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