**Development of Optimized Deep Learning Model for Leaf Disease Detection**

**Abstract**

Plants are a natural source of food and nutrition for mankind, and there has been a long-term dependency of human civilization on agriculture. However, many natural and anthropogenic factors have hindered plant growth. The use of fungicides, insecticides, and other chemicals can lead to many plant disorders. Detection of these diseases at the late stage could severely impact the level of agricultural production by impacting the plant's health. Machine learning applications can reduce the risk of plant damage by detecting the disease at an early stage. This would bring a significant understanding of advanced computational techniques in the agriculture and horticulture domains. This proposal targets the early identification of plant diseases using a convolutional neural network (CNN) algorithm on leaf images. In this investigation, different plants are considered to build a classifier to classify diseased and healthy leaves. Here, binary, and multi-classification modes are proposed to identify various disorders amongst various plants. The proposed CNN method includes image pre-processing in the first phase, where the images are resized to 256 256 pixels and the image quality is improved. The network consisted of multiple softmax classifiers, and various deep learning parameters were needed to optimize to achieve a robust and accurate solution. The performance of the model is proposed to be compared with the state of the art and other existing methods. The datasets proposed for use in this study are obtained from public sources as well as agricultural institutes.

*Keywords: plant leaf disease, deep learning model, optimization algorithm, Convolutional Neural Networks, Mayfly optimization algorithm.*

**INTRODUCTION**

It is anticipated that the global population will reach approximately 10 billion by the year 2050, which will, in turn, put a strain on the available land and water resources. As a result, there will be a need for a 70 percent increase in agricultural production in order to maintain the supply chain and work toward achieving food security. On order for our agricultural practises to be sustainable and resilient to the effects of climate change in our cropping systems, agricultural research needs to adopt methods that are both more intelligent and more up to date. This is especially important for India because the bulk of the country's population relies on agriculture and other linked industries for their primary means of subsistence.

The term "artificial intelligence" (AI) refers to the use of computer programming to mimic the human brain in tasks that were previously performed by humans. Utilizing AI in agricultural and plant science research will make it easier to identify the most suited lines for breeding programmes, candidate genes for stress resistance, and quantitative trait loci (QTL) for trait improvement and ecological sustainability. This offers the farmer significant advantages in terms of crop cycle monitoring and making informed decisions for a range of purposes, such as irrigation management, plant health, detection of pests and diseases, fertiliser use, and weed control. These benefits would make it possible to make timely interventions and allocate resources based on actionable findings. Agriculture and plant science that is powered by AI can be of assistance in the development of new and creative technologies, which can help farm enterprises overcome the obstacles that are being experienced in the conventional ways that are now being used. Detecting the plant disease using the image data is the popular approach in machine learning deployment in agriculture. Plant diseases pose a huge danger to human life since they have the potential to bring about famines and droughts. When farming is done with the intention of making a profit, this circumstance ultimately leads to significant financial losses. In the fight against sickness, the application of technologies such as computer vision and machine learning (ML) are helpful tools.

**KEY RESEARCH CHALLENGES/GAPS:**

1. The PIXEL quality of the leaf image.
2. Publicly available Dataset requirement.
3. Noisy data affecting the leaf samples.
4. Classification is one more challenge, in the stage of detecting the leaf diseases.
5. Color of the leaves may be varied due to environmental effect.
6. Variety of diseases can be seen in various kinds of plants, so detection of disease is quite difficult.
7. Still the tools developed are not deployed on ground and farmers are not using it in their daily routine.

**LITERATURE REVIEW**

Diagnosing plant diseases through the optical inspection of symptoms on the plant's leaves involves a notably high degree of intricacy. The complexity and broader spectrum of the existing phytopathological range have posed a great challenge to experienced agronomists and plant pathologists to successfully diagnose specific diseases. This often led to errors in the final diagnosis and treatments processes1,2. The existence of an automated computational system for the detection and diagnosis of plant diseases, would offer valuable assistance to the agronomist. However, earlier, they were asked to perform plant diagnoses through optical observation of the leaves of infected plants3,4. If the computational driven system were user-friendly and easily accessible via a smartphone application, it may also be a valuable tool for farmers in regions of the world lacking the necessary infrastructure for providing agronomic and phytopathological guidance. In addition, in the case of large-scale cultivations, the system could be combined with autonomous agricultural vehicles, to accurately and timely locate phytopathological problems throughout the cultivation field using continuous image capturing. Image analysis has seen significant progress attributable to the application of DL techniques, most notably CNN. There have been a lot of different studies conducted for the purpose of automatically identifying plant diseases. This particular implementation and interest could pave the way for the development of automatic imaging approaches for plant disease diagnosis and classification, plant recognition, fruit counting, and weed detection, among other applications. These kinds of technology could be of assistance to farmers in terms of adopting more farming methods, as well as excellent agricultural practises and enhancing their ability to provide food security. Within the past five years, the researcher has proposed a number of strategies for the identification of plant leaf diseases based on CNNs. It is remarkable that practically all of the articles were published after 2016, which demonstrates how recent and cutting-edge this technique is in the field of agriculture.

In general, plant leaves are the primary source for identifying most plant illnesses. Earlier study showed that yellow and brown spots, primary and late blister, and other ailments caused by bacteria, virus and fungus can be detected automatically through efficient image processing techniques. Machine learning has been widely applied to diagnose the plant disease. The interaction between fungal infections and their plant hosts involves a unique invasion mechanism. Small secretory proteins, often known as effector proteins, are one of the most important host-manipulation mechanisms. Numerous fungal effectors have been found utilising genomic, transcriptomic, and bioinformatics5,6 techniques7. Plants play a significant role in agriculture and caring for them is crucial. Detecting these diseases is the most difficult aspect of plant disease diagnosis and classification. In recent decades, deep learning (DL) models have shown to be an invaluable asset in agriculture8. Image processing techniques can be utilised to give farmers with improved disease detection help. Most infection symptoms are evident on plant leaves; hence, leaves are often utilised to detect and identify diseases. Deep learning-based feature extraction ha their merits and demerits9. Nondestructive hyperspectral remote sensing has the potential to detect and quantify viral infections. Earlier study employed hyperspectral imaging at the plant level to identify and classify grapevines infected with the newly identified DNA viral grapevine vein-clearing virus (GVCV)10. Paddy crop quality and yield are negatively impacted by leaf diseases. It is necessary to address this problem as soon as possible to decrease its effects. In recent years, deep learning has become indispensable for recognising and categorising leaf diseases. The model proposed in earlier study demonstrated an accuracy rate of 96.4%, which was higher than state of art models11. Owing to the need for professional knowledge and specialised equipment, acquiring data for machine learning applications is a costly endeavour. Previous study demonstrated a novel picture colour histogram transformation technique for generating synthetic images for data enhancement in image classification problems. The findings of the upgraded MobileNetV2 neural network demonstrated a statistically significant improvement in the recognition accuracy of cassava leaf diseases12. In earlier study, authors described an intelligent strategy based on deep learning for recognising nine prevalent tomato illnesses. The proposed method obtained the highest F1 score of 99.5%, outperforming most previous competing methods. However, some of the incorrect predictions involved early blight and late blight13.

Early automated identification and diagnosis of plant diseases are still tough issues in agriculture. In another reported study focuses on the design and implementation of a real-time disease prediction system utilising a convolutional neural network (CNN) on a Platform-as-a-Service (PaaS) cloud14. While minimising chemical inputs, automatic grape disease detection can boost efficiency and adaptability in vineyard crop management. The objective of another study reported was to map unhealthy spots in the vineyard to facilitate rapid and accurate treatment. A fully convolutional neural network technique classifies each pixel according to distinct instances, including shadow, ground, healthy, and ailment. The proposed approach had a detection rate of over 92% at the grapevine level and 87% at the leaf level [83]. Banana (and plantain, Musa spp.) is mostly farmed as a mixed crop by smallholder farmers in their backyards and on their tiny farmlands. Several pests and diseases, especially the invasive banana bunchy top virus, threaten the crop (BBTV, genus Babuvirus). In a study, authors developed an operational banana mapping framework utilising medium-resolution synthetic aperture radar (SAR), Sentinel 2A satellite imagery, and high-resolution RGB and multispectral aerial imagery from an unmanned aerial vehicle (UAV) by combining UAV, SAR, and Sentinel 2A data with the Support Vector Machine (SVM) and Random Forest (RF) machine learning algorithms15. In another study, a deep learning models was proposed to detect lesions on cotton leaves based on photographs of the crop in the field. Using convolutional neural networks, the learning models GoogleNet and Resnet50 achieved an accuracy of 86.6% and 89.2%, respectively. The convolutional neural networks proved to be up to 25 percent more accurate than conventional image processing methods such as support vector machines (SVM), Closest k-neighbors (KNN), artificial neural networks (ANN), and neuro-fuzzy (NFC), suggesting that this method can contribute to a more rapid and accurate inspection of plants growing in the field16. Diseases such as Black Sigatoka/Yellow Sigatoka, Panama, Bunchy top, Moko, chlorosis, etc., impair plantain tree agriculture. Combining RNN with real-time datasets collected in Tamil Nadu, a novel sequential picture classification model for disease detection is presented. Experiments are conducted on these datasets17. The disease-recognition algorithm utilises a convolutional neural network with the EfficientNet architecture. A collection of 2,414 photos of wheat fungal illnesses was collected, and each image was labelled by an expert according to the disease kind. On the Telegram platform, the recognition mechanism was implemented as a bot18.

**OBJECTIVES:**

1. Design and Implementation of binary classification machine learning model on public dataset of leaf images (single disease and healthy) to differentiate the diseased leaf from the healthy.
2. Development of multiclassification machine learning model on public dataset of leaf images (Multiple Diseases) for classifying the multiple diseases from different plant using single model.
3. (a) Optimization of the model and comparison with other existing method (b) Collection of diseased leaf images from agriculture institute/s.
4. Implementation of ML algorithm on real collected dataset (Single/multi-Disease based on available data).

**PROPOSED METHODOLOGY:**

1. **Dataset Collection:** It is proposed to collect data from <https://www.kaggle.com/datasets/dev523/leaf-disease-detection-d> and analyse 70,295 images of plant leaf images, which have a spread of 38 class labels assigned to them diseased and healthy plants for 14 different crop species. The images would be resized to 256 × 256 pixels, and both the model optimization and predictions on these downscaled images would be performed. Here it is proposed to use three different versions of the complete dataset. We would start with the original dataset as it is, in colour. Later, the colour would be tested with a gray-scaled version for the original dataset.
2. **Load Dataset and Data Pre-processing:**  This study will be using TensorFlow and keras for loading the data. TensorFlow contains number of functionalities for loading data. After passing the folder where image data has stored it automatically takes all the class folders and images inside it. It is required to pass some parameters while loading the data including batch size, shuffle, and image-size. Data contains images of leaves of different types of plants, taken with different light settings and rotation. They appear to have been centered in this data set, though this need not be the case. There are a number of pre-processing steps would be followed mainly Data augmentation and Data scaling.
3. **Model Description:** In this project we are using Convolutional Neural Network (CNN). In this network we used three layers a pooling, convolutional layer, and fully connected layer.

Filter

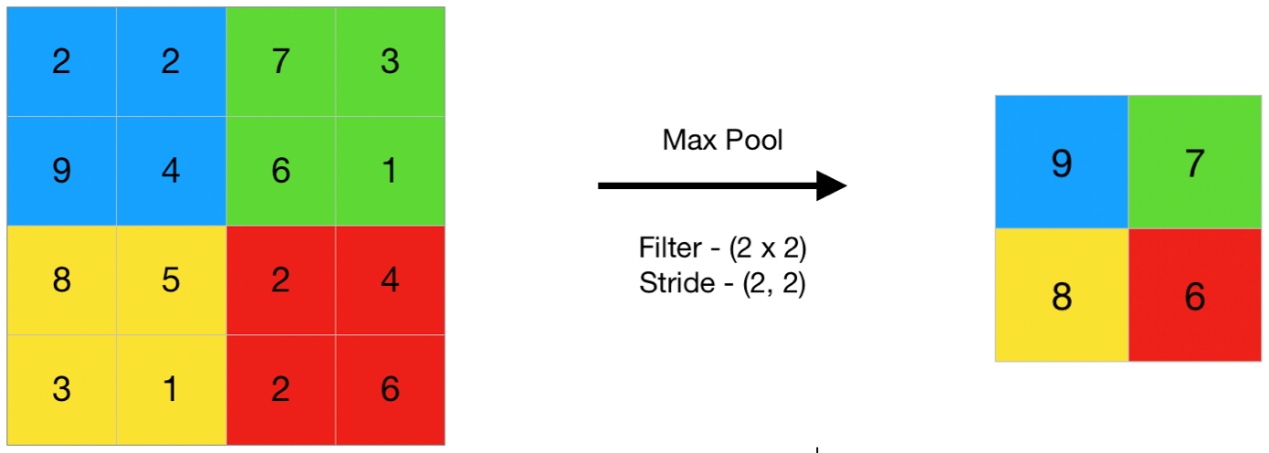
Input

Image Pixels

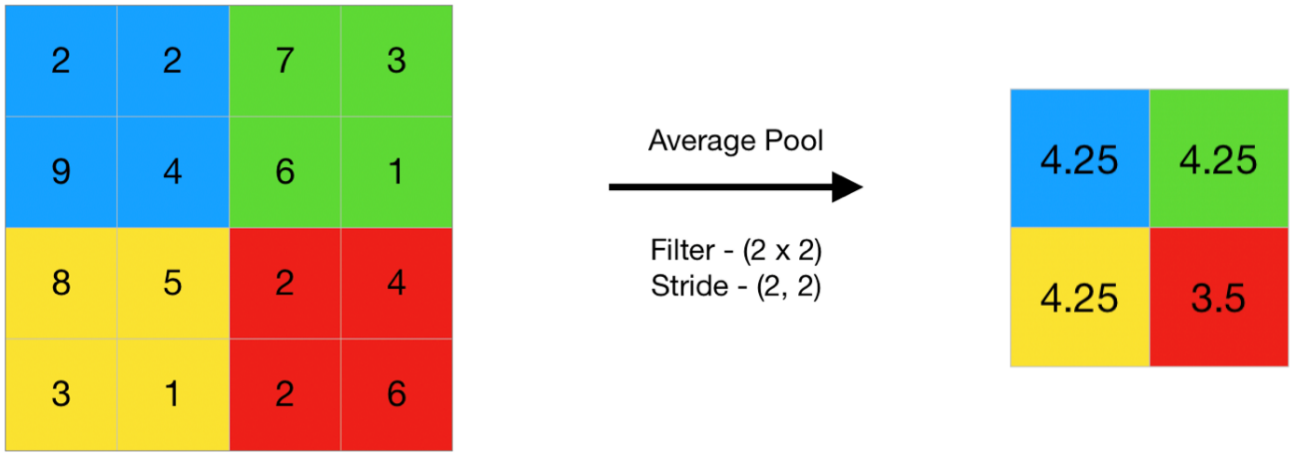
Repetitive Overlapping

Feature Map

We are going to use six layers of max pooling and convolutional layer in the model with 32 and 64 neurons which 32 neurons are used in first layer and then all the five layers are used with 64 neurons. After that the output is “flattened and turned into a single vector which is used as an input for next stage then adds dense layer with 64 neurons with the activation ‘softmax’. The straightforward operation of applying a filter to an input, which then yields an activation, is an example of a convolution layer. A feature map is a map of activations that indicates the positions and strength of a recognised feature in an input such as an image. This map is the result of repeatedly applying the same filter to an input, and its name comes from the term "feature." Pooling layer reduces the data dimension created by the convolution layer so that the features can be used appropriately in the prediction algorithm. (a) Max Pool select the maximum element from the region of filter map covered by filter.



Similalry, average pooling computes the average of the elements present in the region of feature map covered by the filter.



Fully connected layer would be implemented at the end, this layer would have (a) fully connected input layer, (b) fully connected hidden layers and (c) fully connected output layer.

**COMPARATIVE LANDSCAPE**

There are numerous examples of using CNN for plant disease detection using leaf images. These studies reported their accuracy of their respective prediction of the dataset used. Table 1 shows the summary of these methods with the level of accuracy achieved. Two models published in 2021 and 2022 respectively showed 100% accuracy. These models used multiple plant species and potato species collected from plantvillage and Kaggle data set. In 2022, 54 models were proposed as shown in Table 1 that have different level of accuracy. Here, 100 cases are shown in Table 1 where 23 cases were performed on multiple species. Plantvillage dataset is used 52 times that made it most used dataset source. Upon observing the types of models, it was determined that CNN built from scratch was utilised the most (22 times).

**Tables 1.** Comparative analysis of the existing methods for plant disease detection using leaf image in CNN model.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Plant Species** | **Data Source** | **Model** | **Accuracy** | **Year** | **References** |
| chili | self | SECNN | 99.12 | 2022 | 19 |
| chili | plantvillage | SECNN | 99.28 | 2022 | 19 |
| apple | plantvillage | SECNN | 99.78 | 2022 | 19 |
| maize | plantvillage | SECNN | 97.94 | 2022 | 19 |
| pepper | plantvillage | SECNN | 99.19 | 2022 | 19 |
| potato | plantvillage | SECNN | 100 | 2022 | 19 |
| tomato | plantvillage | SECNN | 97.9 | 2022 | 19 |
| soybean | self | R-CNN | 83.84 | 2022 | 20 |
| multiple | self | DADCNN-5 | 99.93 | 2022 | 21 |
| grape | self | InceptionV1 | 96.13 | 2022 | 22 |
| grape | PlantVillage | GoogleNet | 94.05 | 2022 | 23 |
| maize | PlantVillage | GhostNet | 92.9 | 2022 | 24 |
| maize | PlantVillage | LDSNet | 95.4 | 2022 | 24 |
| apple | kaggle | Resnet | 95.8 | 2022 | 25 |
| multiple | kaggle | Resnet | 99.89 | 2022 | 25 |
| multiple | PlantVillage | EfcientNet-B3 | 98.91 | 2022 | 26 |
| cassava | kaggle | CNN | 87 | 2022 | 27 |
| apple | self | ConvVIT | 96.85 | 2022 | 28 |
| multiple | kaggle | EfficientNet | 99.7 | 2022 | 29 |
| wheat | PlantVillage | Inception-v3 | 92.53 | 2022 | 30 |
| cotton | self | CNN | 98.53 | 2022 | 31 |
| cassava | self | ResNet-50 | 89.7 | 2022 | 32 |
| multiple | Plantvillage | CNN | 98.61 | 2022 | 33 |
| multiple | MepcoTropicLeaf | CNN | 90.02 | 2022 | 33 |
| multiple | self | AlexNet | 86.85 | 2022 | 34 |
| mango | self | MobilenetV2 | 99.43 | 2022 | 35 |
| pepper | PlantVillage | CNN | 95.8 | 2022 | 36 |
| potato | PlantVillage | CNN | 94.1 | 2022 | 36 |
| tomato | PlantVillage | CNN | 92.6 | 2022 | 36 |
| grape | PlantVillage | CNN | 98.4 | 2022 | 37 |
| maize | Kaggle | InceptionV3 | 99.66 | 2022 | 38 |
| multiple | self | CNN | 96.88 | 2022 | 39 |
| multiple | PlantVillage | CNN | 99.86 | 2022 | 40 |
| maize | PlantVillage | AlexNet | 99.16 | 2022 | 41 |
| multiple | Kaggle | CNN | 99 | 2022 | 42 |
| multiple | PlantVillage | CNN | 98.41 | 2022 | 43 |
| multiple | PlantVillage | DCNN | 99.79 | 2022 | 44 |
| wheat | PlantVillage | ResNet152 | 95 | 2022 | 45 |
| rice | self | VGG16 | 92.24 | 2022 | 46 |
| potato | PlantVillage | MobileNet V2 | 97.73 | 2022 | 47 |
| cucumber | PlantVillage | DCCNN | 98.23 | 2022 | 48 |
| popato | PlantVillage | DCCNN | 99.83 | 2022 | 48 |
| grape | PlantVillage | DCCNN | 99.78 | 2022 | 48 |
| apple | PlantVillage | DCCNN | 99.78 | 2022 | 48 |
| maize | PlantVillage | DCCNN | 98.85 | 2022 | 48 |
| grape | PlantVillage | VGG16 | 98.4 | 2022 | 49 |
| tomato | PlantVillage | VGG16 | 95.71 | 2022 | 49 |
| multiple | PlantVillage | VGG-ICNN | 99.16 | 2022 | 50 |
| apple | PlantVillage | VGG-ICNN | 94.24 | 2022 | 50 |
| maize | PlantVillage | VGG-ICNN | 91.36 | 2022 | 50 |
| rice | PlantVillage | VGG-ICNN | 96.67 | 2022 | 50 |
| grape | PlantVillage | CNN | 99.34 | 2022 | 51 |
| multiple | PlantVillage | MobileNet | 98.34 | 2022 | 52 |
| bean | Kaggle | MobileNet | 97 | 2022 | 53 |
| cucumber | self | Efficient-B5-SwinT | 99.25 | 2021 | 54 |
| bean | Kaggle | GoogleNet | 93.75 | 2021 | 55 |
| apple | kaggle | VGG19 | 87.7 | 2021 | 56 |
| tomato | PlantVillage | AlexNet | 99.86 | 2021 | 57 |
| multiple | Kaggle | CNN | 100 | 2021 | 58 |
| multiple | PlantVillage | EfficientNetB0 | 99.56 | 2021 | 59 |
| peach | self | CNN | 98.75 | 2021 | 60 |
| multiple | PlantVillage | EfficientNet | 98.42 | 2021 | 61 |
| tomato | self | Inception v3 | 99.6 | 2021 | 62 |
| multiple | PlantVillage | ResNet-50 | 95.61 | 2020 | 63 |
| maize | Kaggle | VGG16 | 98.2 | 2020 | 64 |
| multiple | PlantVillage | DCNN | 88.46 | 2020 | 65 |
| tomato | self | VGG16 | 91.9 | 2020 | 66 |
| soybean | self | CNN | 98.14 | 2020 | 67 |
| grape | self | DICNN | 97.22 | 2020 | 68 |
| plum | self | Inception-v3 | 92 | 2020 | 69 |
| eggplant | self | VGG16 | 99.4 | 2020 | 70 |
| pepper | self | ResNet50 | 88.38 | 2020 | 71 |
| wheat | self | ResNet-50 | 96 | 2019 | 72 |
| multiple | PlantVillage | ResNet50 | 99.8 | 2019 | 73 |
| tea | self | LeafNet | 90.16 | 2019 | 74 |
| rice | self | Lenet5 | 95.83 | 2019 | 75 |
| maize | PlantVillage | CNN | 92.85 | 2019 | 76 |
| guava | self | DCNN | 98.74 | 2019 | 77 |
| mango | self | MCNN | 97.13 | 2019 | 78 |
| multiple | PlantVillage | CNN | 96.46 | 2019 | 79 |
| multiple | PlantVillage | VGG | 99.53 | 2018 | 80 |
| mango | self | CNN | 96.67 | 2018 | 81 |
| tomato | PlantVillage | AlexNet | 97.49 | 2018 | 70 |
| banana | self | CNN | 93.6 | 2018 | 17 |
| wheat | self | VGG-FCN-VD16 | 97.95 | 2017 | 82 |
| rice | self | DCNN | 95.48 | 2017 | 83 |
| tomato | self | GoogLeNet | 99.18 | 2017 | 84 |
| apple | PlantVilage | AlexNet | 97.62 | 2017 | 25 |
| banana | PlantVillage | LeNet | 99 | 2017 | 85 |
| cassava | self | Inception-v3 | 93 | 2017 | 86 |
| apple | PlantVillage | VGG16 | 90.4 | 2017 | 87 |
| olive | PlantVillage | LeNet | 99 | 2017 | 88 |
| potato | PlantVillage | VGG | 96 | 2017 | 89 |
| radish | self | VGG-A | 93.3 | 2017 | 90 |
| radish | self | GoogLeNet | 90 | 2017 | 91 |
| tomato | Plantvillage | AlexNet | 95.6 | 2017 | 92 |
| multiple | PlantVillage | GoogLeNet | 99.35 | 2016 | 3 |
| apple | PlantVillage | AlexNet | 97.3 | 2016 | 93 |
| cucumber | self | CNN | 94.9 | 2015 | 94 |

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