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OPTIMIZED HYBRID CNN FOR POTATO DISEASE DETECTION AND CLASSIFICATION

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Abstract

Plant diseases are getting more and more common, seriously threatening world agriculture that leads to enormous crop loss. Major crops that are prone to plant disease are tomato, apple, paddy, potato and cotton. These diseases are caused by a number of pathogen types such as bacteria, fungi, viruses and insects. Conventional methods of detecting diseases are normally time consuming and do not provide the best output. Conversely, artificial intelligence (AI)-driven methods, especially deep learning models, have proved to be more efficient in disease classification and detection. Plant disease diagnosis has extensively utilized deep convolution neural network architectures like Alex-Net, VGG-16, ResNet, and Inception-Net. These pre-trained models are computationally intensive and need high memory, which restricts their use in real-time agricultural environments. To address these concerns, this work introduces a new hybrid deep learning model that harnesses the advantage of Lightweight Convolutional Neural Networks (CNN) and NAS-Net. The presented model is designed to provide effective disease detection while reducing computational complexity and memory requirements. The model is trained on a publicly available potato leaf image dataset with data augmentation, normalization, and scaling techniques to enhance performance. Unlike conventional deep learning models, the new approach supports real-time detection of disease with fewer hardware resources. Experimental validation confirms the efficacy of the model in accurate identification of healthy and infected leaves. This research benefits sustainable agriculture with the capability to diagnose disease early, minimize crop loss, and provide an affordable AI-driven approach for farmers and agriculture researchers.

Keywords: Plant Diseases, CNN, Deep-learning, Lightweight CNN, NASNet, Hybrid model.

1. Introduction

In the last decades, the world's population has been growing gradually, and this has increased the demand for increased agricultural production. Yet, different plant diseases threaten this objective in a significant way by affecting the production of crops [1]. These diseases are a significant contributor to plant death, especially among staple crops such as potatoes. Early detection is key to manage and control such diseases, which can help improve overall agricultural productivity. Conventionally, professionals have relied on manual visual examination to detect and diagnose plant diseases—a process that is time-consuming, error-prone, biased, and inefficient, particularly when there is a shortage of expertise and infrastructure [1].

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Deep learning, which uses deep architectures of artificial neural networks with many layers, has been an effective technique in this field. Deep CNN has brought about significant advances in image classification [3]. Various models as Alex-Net, Google-Net, ResNet and VGG-16 [4], [5], [6], [7] have contributed to making CNNs deeper and more efficient by overcoming issues like vanishing and exploding gradients during backpropagation. Although these models provide robust performance, they tend to have high computational and memory requirements, which render them inappropriate for deployment on low-resource devices. Lightweight models such as MobileNetV2 [8] and Squeeze-Next [9] have been suggested to address this issue. These models significantly decrease the number of parameters, thus making CNNs applicable for deployment on hardware with low processing capabilities.

CNNs [10] have demonstrated outstanding performance for a variety of tasks including segmentation, analysis, object detection, and image classification. Infected crops typically fall short of their optimal yield levels. Viral disease as well as non-infectious issues lead to yield reduction, quality decline, and reduction in economic returns. A significant advance in this field has been the creation of sophisticated classification systems based on computer vision to analyze leaf pictures and identify diseases [11]. Traditionally, diagnosis of such diseases involved human specialists visually examining plants and leaves—a labour-intensive process prone to bias and variability [12]. Today, automated tools that specialize in leaf symptom analysis provide a less laborious and cheaper alternative for disease detection in plants [13].

Manual diagnostic techniques, though historically significant, are constrained by weather, expense, and subjectivity, thus being inefficient and difficult to scale. But with the inclusion of AI, machine learning, and computer vision, disease detection is now much faster and more precise. These technologies are centered on detecting visual signs on plant leaves, significantly reducing diagnosis time and minimizing human error.

Potatoes, prized for their nutritional value and versatility, are a critical world crop in the pursuit of food security [14]. Although they are essential, they are highly vulnerable to diseases like late blight and early blight, which can quickly spread, leading to significant economic losses, higher management costs, and disruption of food supply chains—especially in regions where potatoes are a staple crop.

Such diseases as Early Blight and Late Blight [15], [16], [17] are especially devastating, bringing significant losses to the world potato industry. Early detection and treatment are key to preventing these losses. As a result, the automation of disease detection in plant and fruits became a vital research topic in agricultural monitoring and surveillance systems [20]. The last decade has seen many approaches to leaf disease detection, elevating the innovation and efficiency of sustainable agriculture.

Deep learning has proved particularly potent in surmounting these detection challenges. Advances in CNNs over the past few years have enabled complete automation of plant leaf disease detection, with enhanced accuracy and speed without human intervention. Such advances have revolutionized disease classification, where computer vision is used to analyze leaf images for diagnosis.

There has been a growth in research in this field, with numerous studies using computer vision for agriculture to detect diseases. Examples include the identification of late blight in potatoes [16], citrus canker in orchards [21], and wheat rust [22], enabling earlier and more efficient interventions.

Potatoes are the third most cultivated and consumed plant food crop on the planet after wheat and rice, feeding millions of people across the world in various forms [23]. Classic disease detection means that rely highly on expert subjective vision [24] have rendered themselves impracticable, particularly in remote or resource-poor regions. For comparison, up-to-date technology such as image analysis has also proved to be trustworthy means for early and mass plant disease diagnosis.

To fight potato leaf diseases, scientists have utilized deep architectures such as AlexNet, Inception Net, and ResNet. Though these models are very capable, they tend to be very resource-demanding for implementation in restricted environments. This research introduces the idea of a hybrid approach bringing together a light-weight CNN and NASNet. The light-weight CNN offers the small, computation-efficient design deployable on edge devices, while NASNet refines Batch Normalization in order to accelerate training and enhance model generalizability. The resulting hybrid model is particularly suitable for real-time potato disease detection and classification because it strikes a balance between accuracy and efficiency.

Insect pests or disease agents like bacteria, fungus, or viruses cause plant diseases that have a serious adverse impact on plant functioning and threaten the environment and food supplies. Currently, about 60% of the world's population relies on agriculture as a means of food. To meet future demands, the Food and Agriculture Organization (FAO) puts stress on the fact that world food production will need to increase by 70% [25].

The Lightweight CNN is small, computationally less intensive, and ideal for use in edge devices such as mobile and embedded systems. It consists of three convolutional layers with filter widths of 32, 64, and 128, succeeded by max-pooling and global average pooling layers to simplify complexity and create compact feature representations. Likewise, NASNet utilizes a lightweight design with batch normalization to enhance generalization and convergence. It also employs shared convolutional layers of equal sizes of the filter, with the addition of global average pooling layers and max-pooling layers, rather than using fully connected layers for reasons of efficiency.

The hybrid architecture combines these two models to provide better feature representation A dense layer of 128 neurons activated by ReLU extracts features at a high level, and another dense layer consisting of nine neurons and Softmax activation enables multi-class classification. This light architecture provides efficient feature extraction and classification and is appropriate for real-time agricultural disease monitoring in resource-constrained settings.

This paper comprises our contributions toward this area and include-

1. A pre-processing hybrid approach to remove image outliers and improve the quality of the dataset's input.
2. A effective detection and classification technique that utilizes two pre-trained models, Lightweight CNN and NASNet, and enhanced feature representation.
3. Classification of the hybrid feature vector by the top machine learning classifier.

Plant diseases play a central role in killing plants but can be controlled efficiently if identified early. Rapid and precise detection of crop diseases is essential to enhance productivity. Early detection of disease, however, has previously been hindered by insufficient expertise and infrastructure. The suggested hybrid model resolves these issues through the synergy of efficiency and accuracy in disease detection and thus as a powerful tool for sustainable agriculture.

1.1 Related Work

Current advancements in deep learning have significantly improved precision and effectiveness of classifying plant diseases. Numerous architectures have been created to improve generalization, decrease computing cost, and improve feature extraction. In [1] author introduces a big dataset with over 220,000 photos and 271 disease categories to address the issue of identifying plant diseases using image processing. In order to highlight unhealthy areas, it suggests a technique that reweights picture patches and training loss. To produce a reliable representation for classification, an LSTM is used to process these weighted features. The deep convolutional neural network Alex-Net, greatly enhanced picture classification performance on the ImageNet dataset. It illustrates how well deep learning and GPUs work together for widespread visual recognition. [4] The GoogLeNet design, which effectively deepens convolutional networks while reducing processing costs through the use of Inception modules, is presented in [5]. It combines many filter sizes in tandem within each module to obtain high picture classification accuracy. The VGGNet design, which investigates how network depth affects image recognition performance, is presented in [6]. VGGNet achieves notable accuracy gains by expanding the network depth to 19 layers and employing extremely tiny (3×3) convolution filters. The architecture is straightforward but efficient, demonstrating how feature learning may be improved by deeper networks. It has become a widely used benchmark for image classification within the deep learning community. ResNet, deep cnn architecture that employ residual learning to solve degradation problem in extremely deep networks, is introduced [7]. ResNet facilitates gradient flow during training by introducing shortcut connections, or identity mappings. It increases the accuracy of picture identification by making it possible to train networks with more than 100 layers. In [8], author introduce MobileNetV2, an effective deep learning architecture for embedded and mobile vision applications. Two significant advances are presented, inverted residuals and linear bottlenecks, which enhance model performance while maintaining model portability. MobileNetV2 successfully strikes a compromise between computational efficiency and accuracy. It is often used in resource-constrained environments, such IOT devices smartphones. A lightweight neural network architecture called SqueezeNet is proposed, which is optimized for hardware efficiency, particularly in real-time and embedded applications [9]. It outperforms SqueezeNet by decreasing the computational complexity and model size without compromising accuracy. Better performance on devices with limited resources is ensured by the design's hardware awareness. In order to detect leaf diseases without the need for extensive labeled datasets, author suggests a self-supervised clustering method [12]. It uses clustering to group related illness patterns after using representation learning to extract significant features from unlabeled photos. In [14], a hybrid deep learning architecture that uses digital image processing techniques to classify potato diseases. To use combined advantages and improve classification accuracy, the model combines several deep learning architectures. Feature extraction techniques and image pre-processing are utilized to enhance input quality. A CNN based model is employed for detection of potato leaf diseases in [18]. The model is trained on diseased and healthy leaf images for proper detection. The proposed method indicates high precision and efficiency in disease type identification. Hybrid deep learning algorithm is employed for potato leaf disease prediction that enhances the accuracy of classification and feature extraction by employing various deep learning approaches [20]. It eliminates the requirement for manual pre-processing by processing raw leaf photos immediately.

1.2 Motivation

Plant diseases reduce agricultural yield which causes substantial financial damage and threatens food availability in the population. The worldwide significance of the potato plant as a food crop necessitates an immediate need to control its diseases as they are being grown on an enormous scale for human use all over the world. Human professionals execute disease detection through traditional techniques which are costly and time-consuming in nature and also produce imperfect outputs. Detection of disease in plants has undergone a revolution with the advancement of artificial intelligence (AI) whereby deep learning utilizes convolutional neural networks (CNNs) as immensely successful technology.

The introduction of Optimized Hybrid CNN with NASNet (Neural Architecture Search Network) and a Lightweight CNN aims at delivering accurate potato disease classification and reduced computational complexity. The hybrid model operates efficiently across edge machines but it maintains excellent accuracy levels sufficient for use on mobile platforms and embedded hardware systems.

The proposed solution uses lightweight CNN components to manage overhead costs and achieves optimized feature extraction through NASNet. The proposed model integrates these two methods to achieve superior than 90 percent classification performance with maintainable scalability.

1.3 Research Contribution

The proposed model contributes several ways in the field of identification and classification of potato diseases-

- **Improved Accuracy in Plant Disease Identification-**Combination of light weight CNN and NASNet enhances model accuracy up to 90%.
- **Computational Efficiency-** Lightweight CNN reduces the computational expense, and the model is well-suited to low-power systems like mobile devices and other platforms. The proposed model supports real-time plant disease detection and classification in agricultural fields.
- **Hybrid Model Optimization-** The combination of Lightweight CNN and NASNet optimizes feature extraction and generalization.
- **Contribution to Smart Agriculture-** Suggested model facilitates precision agriculture through early detection of disease, minimizing crop losses.

2. Proposed Approach

The approach utilizing a combination of Lightweight CNN and NASNet has several benefits compared to traditional pre-trained models such as Alex-Net, VGG-16, Res-Net and Inception-Net, primarily in recognizing and classifying plant diseases. One of the main strengths lies in its balance between computational expense and high accuracy. Simplified CNNs lighten the model, they can run on low-resource devices like edge computing platforms and mobile devices. At the same time, NASNet, which is a Neural Architecture Search (NAS)-inspired model, can automatically configure its architecture for learning the most critical features with minimal computational expenses. This way, the hybrid model can make improved classification predictions without the significant parameters and computation expense of deep pre-trained models like VGG and Inception-Net.

In contrast to the fixed layer-based Alex-Net and VGG models, NASNet presents dynamic and optimized feature extraction, thereby allowing improved generalization across a range of plant disease symptoms. While VGG-16 and VGG-19 are powerful and deep networks with a huge number of parameters, they are computationally expensive and susceptible to overfitting with smaller agricultural data. By comparison, the hybrid method utilizes Lightweight CNNs to reduce overfitting while maintaining the ability to capture key features well. In addition, Inception-Net continues to require significant processing even when it employs multiple filter sizes in one layer to extract features of different scales. By comparison, NASNet eliminates redundancy and accelerates inference by automatically selecting the best operations.

In addition, the hybrid model integrates both architectures' strengths to enhance model robustness and flexibility. The most optimal convolutional block architectures are dynamically determined by NASNet to ensure the best performance, while lightweight CNNs retain efficiency and enable real-time disease classification. This renders the hybrid model more preferable for real-world agricultural use, wherein precise and timely disease detection is essential. Finally, by combining Lightweight CNN and NASNet, this hybrid model outperforms conventional pre-trained models by providing a very efficient, scalable, and accurate plant disease classification solution.

Algorithm for the Hybrid Model

- Input Layer:

The model begins with an input layer that takes images of dimensions: 128, 128, and 3 to represent RGB images of 128x128 pixels.

- Lightweight CNN:

For input data, a light weight CNN model is employed. liwg_cnn() function is employed in light weight CNN model to extract features. A feature representation is generated by liwg_cnn function after processing the input data and this feature representation can be similar to a few convolutional layers followed by max pooling layers.

- NAZNet:

A NAZNet architecture has been pre-trained or specially designed and applied to the input data is represented by the naznet() function, which incorporates Batch Normalization to enhance training speed and model generalization.

- Concatenation of Outputs:

The final axis (axis=-1) is used to concatenate the outputs from the lightweight and naznet models. This combines the learnt representations from both models to produce a composite feature map.

- Dense Layers:

After concatenation features are run through a 128-unit, fully linked (dense) layer with a ReLU activation function. This facilitates the process of deriving intricate patterns from the combined feature representation.

The model used for multi-class by pass through a second dense layer with 9 units (for 9 classes) and a Softmax activation function.

- Model Definition:

The last model is created with Keras' Model class where the input layer is an input and the output of the last dense layer is an output.

- Compilation:

The Adam optimizer, a well-known model training optimization algorithm, is utilized to build model. It uses the categorical loss function, which is appropriate for tasks with multi-class classification.

Figure 1. describes a hybrid deep cnn model that merges the Lightweight CNN and NASNet models to predict plant diseases. The model takes an input image (128,128,3) and runs it through the Lightweight CNN and NASNet models simultaneously. ReLU activation function is applied to stack and pass the gathered features from the two networks through a dense layer with 128 neurons that is fully connected. To categorize the input into any of the nine disease categories, the output layer utilizes nine neurons with Softmax activation function. The model is trained for multi-class classification task with Adam optimizer and categorical cross-entropy loss.

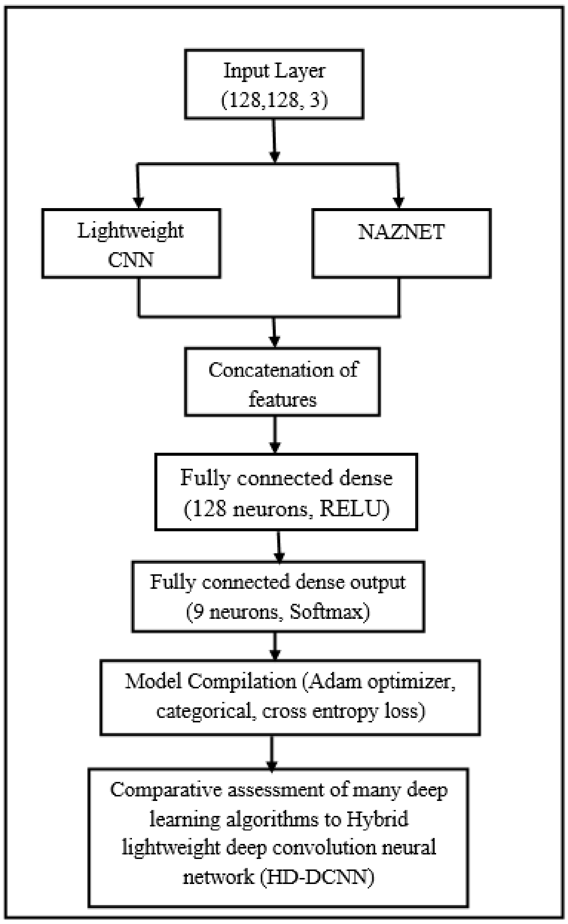


Figure 1: Hybrid CNN Architecture

Table 1: Hybrid CNN Model Summary

Layer (Type)	**Output Shape**	**Parameters**	**Connected to**
input_12 (Input Layer)	[(None, 128, 128, 3)]	0	[]
Sequential_20 (Sequential)	(None, 128)	93248	['input_12[0][0]']
sequential_21 (Sequential)	(None, 128)	94144	['input_12[0][0]']
concatenate_9 (Concatenate)	(None, 256)	0	['sequential_20[0][0]' , 'sequential_21[0][0]']
dense_19 (Dense)	(None, 128)	32896	['concatenate_9[0][0]']
dense_20 (Dense)	(None, 9)	1290	['dense_19[0][0]']

Network' architecture can be described in terms of parameters. Here model has utilized 221578 para meters which contain the number of filters, filter size and bias. Of these, 221,130 parameters are trainable, i.e., are updated during training. Rest 448 parameters are non-trainable parameters as given in Table 1.
Total Parameters: 221578 (865.54 KB)
Trainable Parameters: 221130 (863.79 KB)
Non-trainable Parameters: 448 (1.75 KB)

Figure 2. shows the training procedure for the deep learning approaches used in this work to classify potato illnesses. Pre-processing of the photos begins with the first process of standardization, which ensures uniformity and facilitate subsequent usage of them in future models. The pre-processed images are then fed into hybrid deep learning model for validation and training. The transfer learning method is applied by the proposed strategy to utilize knowledge gained from a pre-trained model to enhance model performance.

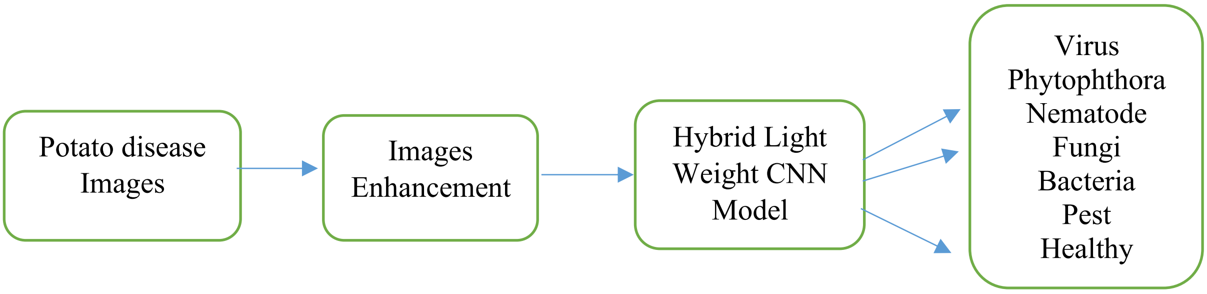


Figure 2: Training process

3. Methodology

3.1 Dataset Acquisition

The dataset employed in this paper was released by the popular data science dataset sharing platform Kaggle.

The specific collection, titled "Potato Plant Diseases," consists of tagged images of potato plants that are both healthy and sick. This information was curated with the intention of identifying and classifying different diseases that affect potato crops.

Source- The Kaggle repository provided the "Potato Plant Disease Dataset" dataset. The dataset is publicly available and free for academic and research purposes.

Number of Images- The dataset has about 3076 pictures in total. Several categories that correspond to various types of diseases are shown in Table2-

Table 2: Summary of Potato Dataset

Types	**No of Pictures**
Nematode	68
Virus	532
Fungi	748
Phytophthora	347
Pest	611

Late-Blight	1000
Bacteria	569
Healthy	201
Early-Blight	1000

Figure 3: Examples of potato leaf diseases

Figure 3. displays a variety of plant leaf diseases labeled as Phytophthora, Bacteria, Virus, Fungi, and Potato Early Blight. Each image displays distinct symptoms like spots or discoloration, which help visually differentiate among disease types.

Image Format- The photos come in different resolutions, often between 1200 × 1200 pixels and 1500 x 1500 pixels, and are supplied in JPEG/PNG format.

3.2 Pre-processing

A critical stage in Deep Convolutional Neural Networks (CNNs) is pre-processing, which improves feature extraction and lowers computational cost to improve model performance. The primary pre-processing actions shown in Figure 4. are as follows-

3.2.1 Image Resizing

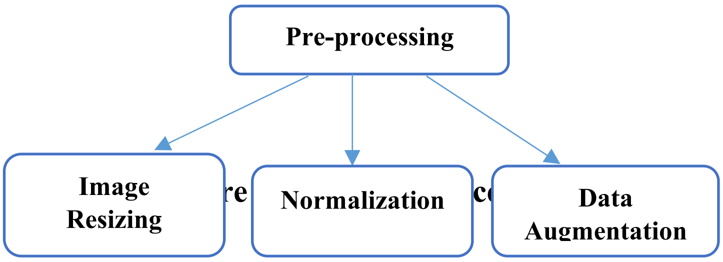
Standardizing image sizes (e.g., 128×128×3) guarantees CNN input layer compatibility and uniformity throughout the dataset.

3.2.2 Normalization

Stability in training and convergence are improved when pixel values are normalized within a specified range, e.g., [0,1] or [-1,1].

3.2.3 Data Augmentation

Methods like flipping, zooming, brightness modifications, and rotation help diversify datasets, which enhances model generalization and decreases overfitting.



3.3 Classification with convolution neural network

A deep CNN's convolutional layer extracts spatial characteristics like edges, textures, and patterns by applying a collection of filters that can learn, or kernels, to an input feature map. An activation map is created by calculating dot product between the input values and filter weights inside its receptive field as each filter moves across the input with a predetermined stride. Filter size, stride, and optional padding used to maintain spatial dimensions and determine the output size. Deeper layers are able to learn complicated representations because several filters catch distinct features. A collection of altered feature maps that are used as inputs to other layers for additional processing is the end result.

3.3.1 Convolutional Layer

The core component of convolutional neural networks (CNNs) is a convolutional layer, which is designed for the feature extraction of input images. It carries out a convolution operation with a set of filters that can learn and can detect edges, texture, and more abstract features as the network goes along in depth. Convolution operation can be shown as-

$$Y(i,j)=m\sum n\sum X(i+m,j+n)\cdot K(m,n) \qquad (1)$$

Where $X(i,j)$ is the input image, $K(m,n)$ is the convolution kernel, $Y(i,j)$ is the output feature map.

3.3.2 Size of the Output of a Convolutional Layer

Convolution's size of the output can be obtained using-

$$O=((I-K+2P) / S) + 1 \qquad (2)$$

Here O represents the output size, I input size, K is kernel size, P Padding and S is Stride.

3.3.3 Max Pooling Layer

Max pooling in deep convolutional neural networks is a down sampling process where the output $Y(i,j)$ is obtained by using the maximum value from a receptive field $R(i,j)$, which is a specified pooling window with its center at location (i,j) within the input feature map $X(m,n)$. Function max picks highest value within $R(i,j)$, minimizing spatial dimensions while maintaining most important features. The operation enhances computational efficiency, decreases overfitting, and increases translation invariance for convolutional neural networks.

$$Y(i,j) =\text{Max}(m,n)\text{€}R(i,j)X(m,n) \qquad (3)$$

3.3.4 Dense Layer

In a dense layer, every neuron in the present layer is connected to every neuron in the previous layer. It accepts high-level features extracted by convolutional and pooling layers and projects them to output classes with weighted connections. Every neuron in a Dense Layer does the following operation-

$$Y=F(WX+B) \qquad (4)$$

Where W = Weights, X = Input features, B = Bias, and f = Activation function (Softmax, ReLU).

3.3.5 Parameter Calculation in Convolutional Layers

Number of parameters in convolution layer is a function of filter size, number of filters used and bias.
Parameters=((n*n*n) +b) *f (5)
where n is the length, width, height of the filter, b is bias and f is the no of filters used.

3.4 Performance Metrics

The n class predictions of the classifier are stored in a confusion matrix, an n × n table. Based on the comparison of actual and expected classes, it gives information regarding the performance of the classifier. False Negative (F_N), False Positive (F_P), True Positive (T_P), and True Negative (T_N) are the elements that constitute the confusion matrix.

We compute the accuracy in order to measure the overall performance of the classifier. Accuracy is the proportion of properly identified samples to total samples. We can calculate it using the formula-
Accuracy = (T_N +T_P) *100/Total samples. (6)
Error Rate= 1- Accuracy (7)
The ratio of truly positive category instances that were expected to be in the positive class is called precision (P). It gives an impression of how well the classifier can detect positive instances.
Precision = (T_P *100) / (T_P + F_P) (8)
Recall is the ratio of samples that actually belong to the positive class and are accurately identified as positive by the classifier.
Recall = (T_P *100) / (T_P + F_N) (9)
Recall and accuracy are combined in a statistic known as the F1-score (F_1). It offers a thorough evaluation by considering recall (the ability to include all positive samples) as well as accuracy (the capacity to accurately identify positive samples). From equation 8 and 9-
F_1 = (2 * Precision * Recall *100) / (Precision + Recall) (10)

3.5 Experiment Result

The training log records validation and training metrics and shows the performance of a hybrid deep cnn model across 50 epochs. At start model's accuracy and loss are poor, but these measures improve during training. As shown in Figure 5. training loss steadily decreases from 1.0917 to 0.3550, accuracy increases from 61.26% to 87.06%. By Epoch 6, validation performance varies to 72.42% with a final validation accuracy of 71.81%. The results demonstrate that while the model does well on training data, it may require additional optimization, such as regularization or fine-tuning, to enhance generalization to validation data.

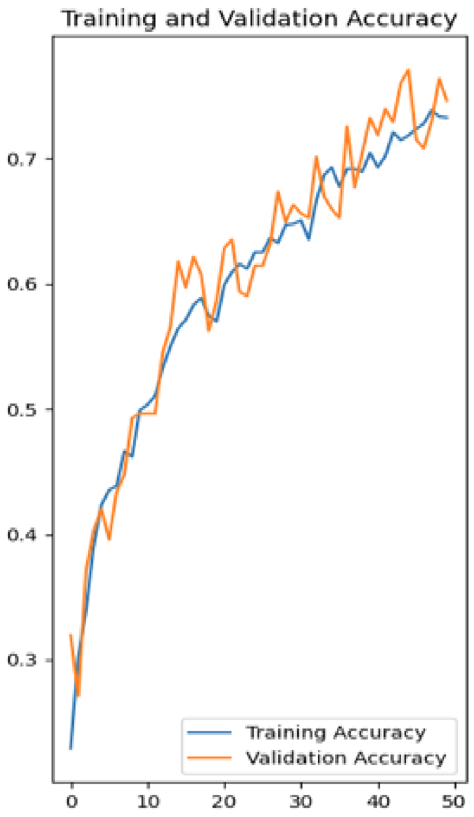


Figure 5: (a) Validation and Training Accuracy

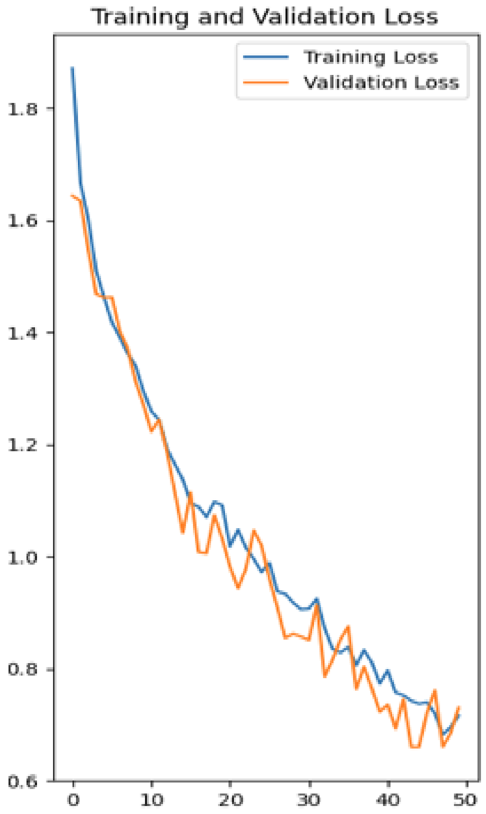
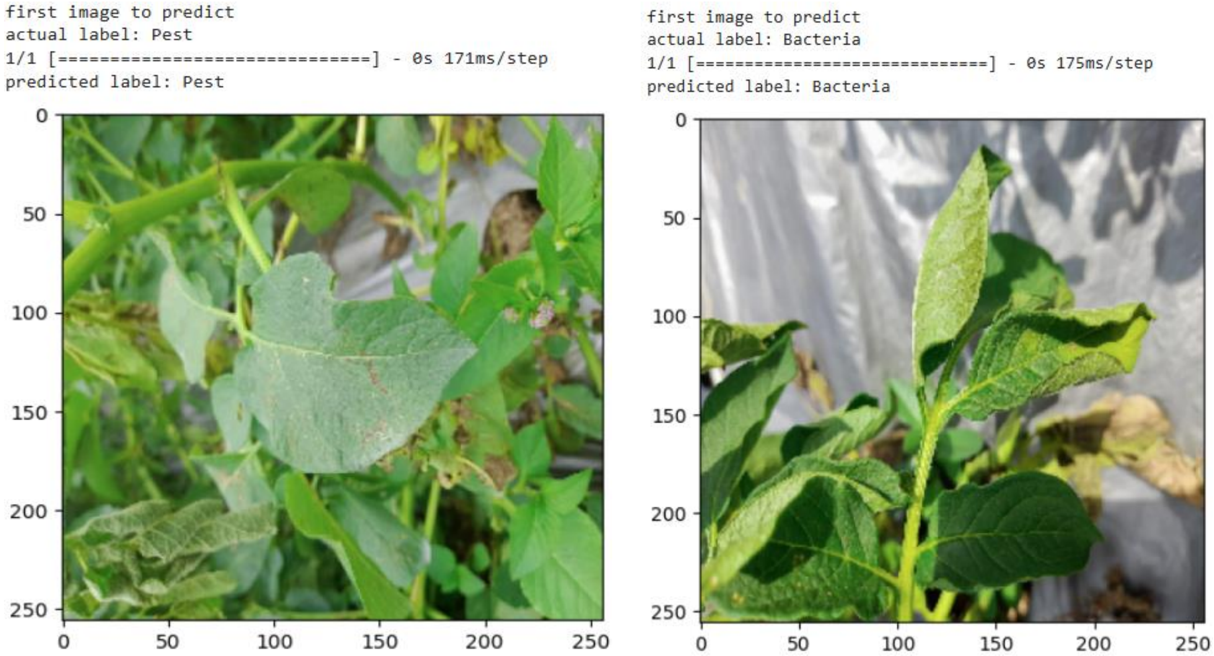


Figure 5: (b) Validation and Training Loss

Figure 6. displays a variety of plant disease classification results, comparing expected and actual labels for various plant states (virus, bacteria, fungi, and healthy) in the figure. For each image, the confidence level of a forecast is shown. Some predictions show misclassifications, such a fungal infection that is incorrectly predicted as bacterial with lower confidence, but some predictions are very accurate, like identifying fungal infections with over 95% confidence. The general layout illustrates the effectiveness of a machine learning model in visual plant disease identification, showcasing both successful and unsuccessful instances that need for accuracy enhancements.

The model accurately identified the label as "Pest," which matches the actual label, and the image depicts a leaf that has been impacted by pests. It takes 171 milliseconds each step to make the prediction, validates the model's performance. The image displays a plant affected by a bacterial disease, and the model correctly classified it as "Bacteria," matching the actual label. It takes 175 milliseconds each step to make the prediction, validates the model's performance. The model probably recognized the leaf's obvious pest damage indicators, like tiny holes and discolouration, as distinctive characteristics. The affected leaves show signs of bacterial infection, such as curling, discoloration. This precise prediction implies that the algorithm is successfully identifying patterns associated with pests in plant photos, which helps to reliably classify plant diseases and pests.



```
first image to predict
actual label: Pest
1/1 [==============================] - 0s 171ms/step
predicted label: Pest
```

```
first image to predict
actual label: Bacteria
1/1 [==============================] - 0s 175ms/step
predicted label: Bacteria
```

Figure 6: Classification of diseased leaf from images

3.6 Classification Report

The categorization report uses precision(P), F1-score(F_1) and recall(R) measures to assess the performance of a model against several categories of plant diseases. Precision is a measurement of the accuracy of positive predictions or ratio of actual labels that were correct and varies from 46% (Pest) to 97% (Late-Blight). Recall, from 15% (Healthy) to 94% (Late-Blight), determines the number of actual positive examples correctly classified by the model. The F1-score shows the better trade-off between recall and precision; more values (for example, 96% for Late-Blight and 23% for Healthy) represent higher performance. The number of actual cases of each class available in the data is called Support and varies from 68 (Nematode) to 1000 (Late-Blight, Early-Blight).

Total accuracy of the model is 72%, i.e., 72% of all the situations were correctly predicted. Although the weighted average (class support-weighted) emphasizes excellent performance on strong classes, macro average (overall average over all classes) exhibits mediocre performance over imbalanced classes. The model needs to be enhanced in some classes, such as Healthy or Pest, despite performing well on others, e.g., Late-Blight.

Table 3: Report of Classification

Classes	**P**	**R**	**F_1**	**Support**
Bacteria	0.74	0.88	0.80	569
Early-Blight	0.96	0.81	0.88	1000
Fungi	0.54	0.56	0.55	748
Healthy	0.49	0.15	0.23	201
Late-Blight	0.97	0.94	0.96	1000
Nematode	0.89	0.57	0.70	68
Pest	0.46	0.59	0.51	611
Phytopthora	0.61	0.50	0.55	347

Virus	0.59	0.70	0.64	523
Accuracy			0.72	5077
macro avg	0.69	0.63	0.65	5077
weighted avg	0.73	0.72	0.72	5077

Figure 7. confusion matrix shows the accuracy of a multi-class classification model in identifying different potato plant diseases. The majority of classes are identified with high accuracy, such as LateBlight with 1000 correct and EarlyBlight with 861. There are, however, significant misclassifications in some classes, such as Fungi being misclassified with Healthy and Pest, and Virus misclassified as Phytophthora and Fungi. These misunderstandings imply similarities in visual symptoms or feature equivalence between some diseases, suggesting that there are areas the model needs better feature discrimination or more training data.

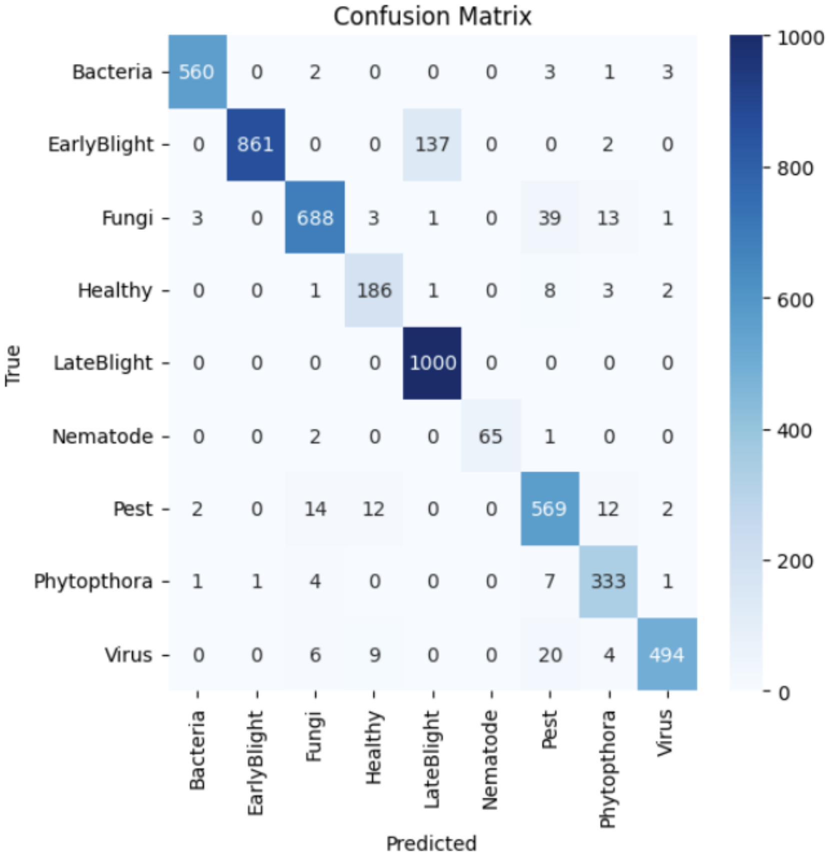


Figure 7: Confusion Matrix

4. Comparison and discussion

If we increase the number of epochs, then models performance can be improved. If we use 80 epochs, then classification report will be-

Table 4: Report of Classification

Classes	**P**	**R**	**F_1**	**Support**
Bacteria	0.99	0.98	0.99	569
Early-Blight	1.00	0.86	0.92	1000
Fungi	0.96	0.92	0.94	748
Healthy	0.89	0.93	0.91	201
Late-Blight	0.88	1.00	0.94	1000
Nematode	1.00	0.96	0.98	68
Pest	0.88	0.93	0.9	611
Phytophthora	0.9	0.96	0.93	347
Virus	0.98	0.93	0.95	533
Accuracy			0.94	5077
Macro Avg	0.94	0.94	0.94	5077
Weighted Avg	0.94	0.94	0.94	5077

The comprehensive analysis of a classification model for the identification of different potato plant diseases based on Recall (R), Precision (P) and F1-score (F_1) can be seen in the above table. All these are significant for assessing how well the model can distinguish between different types of diseases. Accuracy measures the percentage of positive predictions generated by the model that were accurate, while recall measures the proportion of actual occurrences of a disease correctly identified. Support, or the number of test samples in each category, is another component of the model that provides information on disease case distribution within the dataset. At an overall model accuracy of 94%, the classification system is clearly very effective.

It attains close-to-perfect recall and precision for bacterial infections (0.99, 0.98) and nematode detection (1.00, 0.96), i.e., it classifies almost all instances correctly while reducing false positives and false negatives. For early-blight, fungi, and pest detection, F1-scores are greater than 0.90, i.e., there is high reliability. The model also does well in identifying healthy plants (0.89 precision, 0.93 recall), i.e., it does not misclassify healthy crops as diseased. One of the significant cases is late-blight detection, wherein recall achieves 1.00, implying the model is accurate in detecting all cases of late-blight but with slightly decreased precision (0.88), indicating misclassification of other diseases as late-blight.

Generally, the macro average and weighted average scores are both 0.94, which confirms that the model is generally well-balanced across different classes of disease. While the recall for early blight (0.86) is slightly lower than ideal, so some instances were missed, this is a minor issue in an otherwise extremely good system. The weighted average ensures that the model's performance reflects the class distribution of the test set without any bias towards more frequent disease classes. According to these results, the model is suitable for real-world application in potato disease detection, with high accuracy and strong generalization over diseases.

Table 5: Accuracy Precision, Recall and F1-Score of the proposed approach.

Epochs	Accuracy	Precision	Recall	F1-Score
50	72	69	72	65
80	94	94	94	94

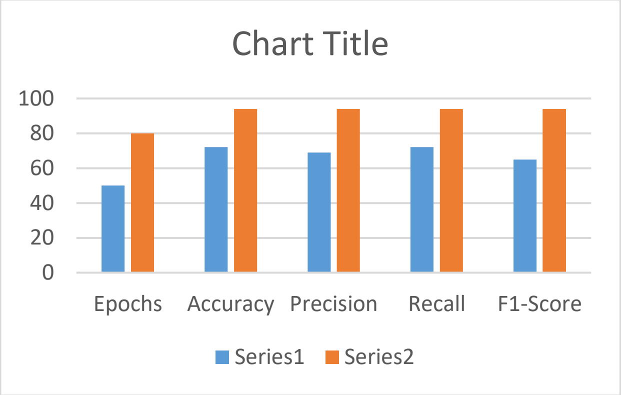


Figure 8. Comparison of Accuracy, Precision, Recall and F1-Score between 50 and 80 epochs

Figure 8. compares the machine learning model performance metrics (Precision, Accuracy, Recall, F1-Score) for training epochs 50 and 80. The number of epochs is marked on the x-axis and percentage values on the y-axis. As the training goes on from 50 to 80 epochs, there is a general trend that all four metrics go up, signifying better performance by the model. While Accuracy is slightly lower but still improving as well, Precision, Recall, and F1-Score graphs all lie very close to one another. This implies that the model is highly balanced and improves progressively in all relevant evaluation metrics. These findings reveal that it is possible to make the model perform better in plant disease classification by having it trained for longer times, and thus more accurate disease detection is possible for agricultural applications.

5. Conclusion and future scope

Plant diseases are a major problem to agriculture since they can destroy crops, cause financial losses, and result in food shortages. Traditional visual and manual inspection techniques are time-consuming procedures and not guarantee to give optimized output. Diseases can be easily detected and classify with the help of Deep CNN. Here a hybrid approach is used that is a combination of light weight cnn and naznet, able to give optimized output. The classification results demonstrate a significant improvement in model performance when increasing training epochs from 50 to 80. The overall accuracy rises from 72% to 94%, with substantial enhancements in precision, recall, and F_1-scores across all classes. Previously weaker categories, such as Fungi (F_1: 0.55 → 0.94), Healthy (F_1: 0.23 → 0.91), and Pest (F_1: 0.51 → 0.90), show remarkable gains, indicating improved feature learning and class differentiation. The macro and weighted average F_1-scores also rise from 0.65 to 0.94, indicating a more generalized and balanced classification of all types of diseases. These findings indicate that the model is able to capture more intricate patterns with an increased number of epochs, resulting in a more accurate and highly efficient plant disease detection system. There will be numerous future opportunities for innovations in plant disease classification with high-tech approaches, especially CNNs. Explainable AI methods could enhance the speed and accuracy of plant disease classifiers, leading to higher agricultural yields and long-term food security.

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