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Advancements in Potato Disease Detection: A Comprehensive Review and a Novel Multi-Model Approach

Abstract

Potatoes play a crucial role in Bangladesh's agricultural landscape, standing as the third most significant crop after rice and wheat, contributing substantially to the country's economic growth. Despite being the seventh largest globally and the fourth in Asia in potato production, Bangladesh faces challenges, particularly from potato leaf diseases impacting season's growth and quality. The early identification of these diseases through automated processes is essential for enhancing productivity and facilitating the digital transformation of the agricultural system. Our primary aim is to leverage machine-learning algorithms on a limited dataset of leaf images to detect potato diseases. Employing deep learning and machine learning techniques, certain methods can categorize potato leaves into two groups, utilizing "The Plant Village Dataset." In this research, we present a novel "MultiNet" infrastructure, leveraging the transfer learning concept to effectively categorize various potato leaf disease types. The framework utilizes three publicly available datasets, each comprising 1000 images of Early Blight Normal, 1000 images of Early Blight Serious, and 1000 Healthy leaves from 'The Plant Village Dataset.' Additionally, the datasets include 302 images of leaves infected by insects, 180 images affected by the LeafRoll virus, and 1000 images infected by a virus. The "MultiNet" infrastructure is specifically designed to deliver rapid and accurate diagnostics for potato disease detection, encompassing two multi-class classifications: (1) Early Blight, Late Blight, and Healthy; and (2) Early Blight Normal, Early Blight Serious, Late Blight, Healthy, Insect infected, LeafRoll Virus infected, and Virus infected. To extract features from images, the proposed framework employs three renowned models that have been pre-trained: ResNet50, DenseNet-201, and VGG16. The educed features are then fed into the concatenate layer and then forming a resilient hybrid model. This envisioned infrastructure demonstrates an impressive accuracy of overall classification is 99.83% when categorizing three classes. Furthermore, it attains a notable 98% accuracy in classifying seven classes. These encouraging outcomes open avenues for the application of the "MultiNet" framework within the agricultural sector, showcasing its potential impact and utility.

Keyword: Potato leaf diseases, ResNet-50, DenseNet-201, VGG16, fine- tuning, Transfer-learning

1 Introduction

The potato, scientifically known as Solanum tuberosum L., holds the distinction of being the most prolific crop globally. It stands as the world's third-largest contributor to our food supply, emphasizing its significant role in sustaining nutritional needs [1, 2]. Bangladesh is known for eating rice; however, it also generates and consumes a substantial quantity of potatoes each year., and their popularity has been constantly increasing. Plant diseases are frequent causes of crop yield loss, which can have a significant negative economic impact by decreasing producer as well as distributor income and increasing prices for consumers. Before they can be harvested, potatoes must be evaluated for diseases at the beginning of their life cycle.

Various ailments can potentially affect potato crops, and the impacts of these diseases are evident in different parts of a potato plant's leaves. Common diseases encompass foliage issues, early blight, and late blight. Early blight is incited by the fungal pathogen Alternaria Solani, while late blight is caused by the bacterium Phytophthora infestans (2002). Both diseases are fungal in nature and pose a significant threat, potentially disrupting potato crop production and impacting the country's budget. Additionally, Potato Leaf Roll (PLR), induced by Polerovirus, leads to the rolling of potato leaves, while other viruses and insects also contribute to leaf damage.

Traditionally, to maximize the use of pesticides and minimize crop production losses, farmers and local experts have visually inspected crops. However, this educational strategy has certain challenges due to the time required, the lack of experience, or a greater chance of accidental mistakes. To address this issue, an automated system that is capable of correctly recognizing and categorizing damaged plant leaves must be created. Plant diseases can be diagnosed using a variety of techniques, one of the most common and simple being visual estimation. The subjective experience of farmers is used in traditional methods of detecting plant diseases, which adds unpredictability and inaccuracy. Unlike these traditional techniques, scientists have developed a tool to identify healthy or diseased plant leaves by measuring the wavelengths of their spectrum of light [28]. Another approach is to use the Polymerase Chain Reaction method to extract the DNA from the leaves [29] or perform Polymerase Chain Reaction in real time [30]. However, implementing these strategies into practice is expensive and time-consuming since they require expert operation, certain experimental settings, and a large-scale application of agricultural safeguards for crops. Developments in algorithms such as machine learning (ML), artificial intelligence (AI), and computational vision (CV) have made possible the ability for scientists to create automated techniques for diagnosing illnesses in plant leaves. Using sophisticated technologies, plant leaf diseases can be identified efficiently and precisely. These solutions work quickly, removing the need for human interaction throughout the process. Notably, Deep Learning (DL) has emerged as a prominent tool in agriculture [31], contributing significantly to efforts in developing, controlling, and enhancing agricultural production. This study introduces an automated system for classifying potato diseases utilizing a 'MultiNet' framework. The framework is designed to classify leaf images into three classes (Early Blight, Late Blight, and Healthy) and seven classes (Early Blight General, Early Blight Serious, Late Blight, Virus Infected, Insect Infected, LeafRollVirus Infected, and Healthy).

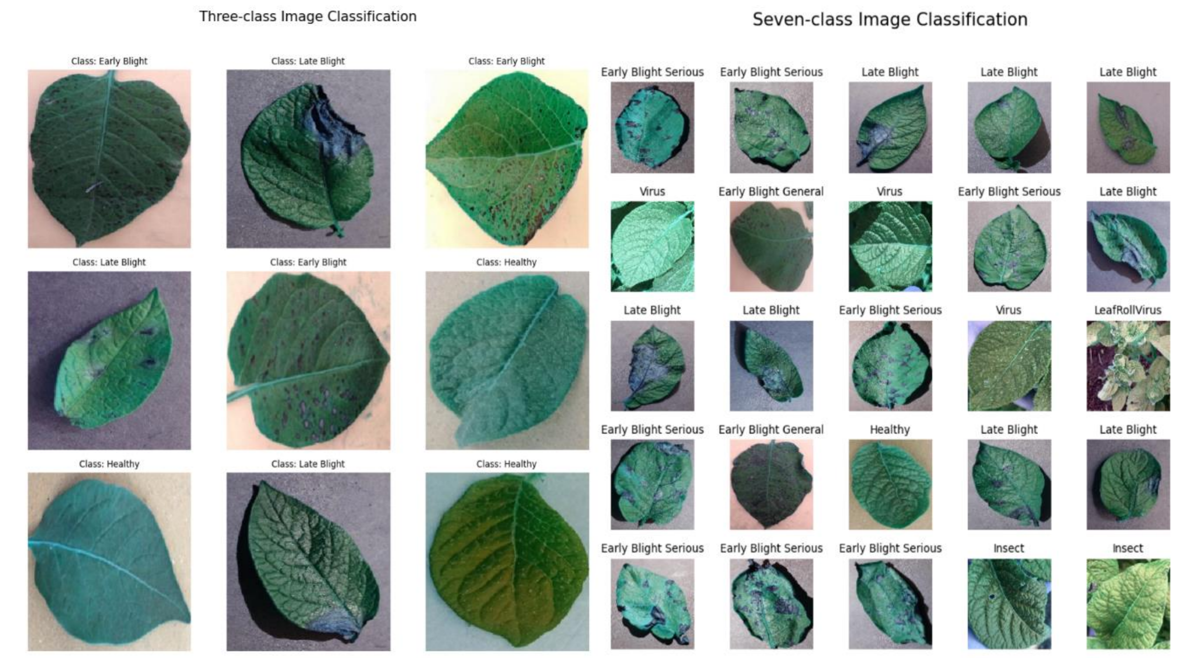


Fig 1: Sample images from three-class and seven-class dataset

To educe features from the images, we utilize three CNN models that have been pre-trained: ResNet-50, DenseNet-201, and VGG16. Subsequently, all extracted features are combined through a concatenation layer. The fused features undergo fine-tuning involves a twofold adjustment for dense layers, batch normalization layers, and dropout layers in the model. For the classification task, the ultimate dense layer is employed, integrating a Softmax Activation Function. This work offers several key advantages, as outlined below:

- The 'MultiNet' framework utilizes methods for feature extraction that do not involve segmentation., eliminating the need for manually crafted feature extraction approaches commonly associated with conventional machine learning methods.
- The proposed infrastructure demonstrates notable performance in both three-class and seven-class classifications of potato leaf images.
- Evaluation of the 'MultiNet' framework's performance extends to both large and small datasets, affirming its competence in achieving high performance across varying data scales.

Structure: The subsequent sections of this paper are organized as follows: Section 2 delves into the literature review. Afterward, Section 3 offers an in-depth elucidation of the suggested 'MultiNet' infrastructure, covering strategies for the pre-processing of data and data augmentation. Section 4 comprehensively details the experimental configuration and outcomes. In Section 5, there is an analysis that compares outcomes and explores potential future operations. Ultimately, Section 6 concludes the paper.

2 Literature Review

Recent research has explored various methodologies for identifying and categorizing potato diseases, each showcasing notable achievements. In a previous study by Islam et al. [3], they utilized the support vector machine (SVM) algorithm for potato leaf segmentation in the potato village dataset. This method achieved a 95% accuracy in categorizing diseases across more than 300 photos. Despite concerns about potential output data loss with RGB imaging, this study focused on SVM and segmentation techniques. In another study by Hu YH et al. [4], Hyperspectral imaging features were applied to analyze potato leaves under late blight stress, using a dataset 60 leaves. Least Squares-Support Vector Machine (LS-SVM) models were developed using both raw and preprocessed data, exhibited optimal performance with a discrimination accuracy of 94.87%. Trishita A. et al. [5] achieved a 98% detection success using "Deep Learning" models, including Support Vector Machine (SVM) and Convolution Neural Network (CNN), on a trained sample dataset of "healthy and unhealthy" plant leaves. Tiwari et al. [6] used a previously trained VGG19 architecture for extracting features and used a variety of classification algorithms for classification, such as neural network models, k-nearest neighbor, and support vector machines. To distinguish between early and late blight illnesses in potato leaves, the model was trained using the Plant Village dataset. Significantly, no testing was done on untested data; instead, the model's performance, which yielded a 97.8% accuracy rate, was assessed only on the training set. Rabbia, M. et al. [7] introduced a system utilizing the efficient pre-trained DenseNet-201 architecture, which tackled class imbalance in the data by adjusting the reweighted cross-entropy loss function. Their model was evaluated on five classes: Early Blight, Late Blight, Healthy, Potato Leaf Roll, and Potato Verticillium_wilt, attaining an impressive accuracy of 97.2%. Meanwhile, Rashid, J. et al. [8] utilized the YOLOv3 image segmentation technique to extract features and developed a CNN model. They achieved a high accuracy of 99.75% in detecting early blight and late blight potato diseases. Chugh, G et al. [9] developed a CNN model utilizing the Inception V3 architecture and Adam Optimizer for the diagnosis and classification of diseases in potato plants, including early and late blight. They attained a classification accuracy of 90% over the test dataset, training the model on 2152 images sourced from the Plant Village Dataset. Iqbal A. et al. [10] conducted segmentation on 450 images depicting both healthy and diseased potato leaves sourced from the Plant Village database. They employed seven classifier algorithms to recognize and classify the leaves based on their health. Notably, the Random Forest classifier achieved an accuracy of 97%. In [11], Tarik M. et al. constructed a CNN model that underwent training on a dataset comprising more than 2034 images depicting unhealthy potatoes and leaves. The training encompassed seven disease types, including Early Blight, Potato Leaf Roll Virus, Hollow heart of potato, Scab of Potato, Soft rot of potato, Potato Tuber Worm, and Virus-related disease. Their findings underscored the effectiveness of CNN for object detection in this context, with the model achieving an impressive accuracy of 99.23%. Geetharamani, G. et al. [20] introduced a deep Convolutional Neural Network (CNN) model designed to distinguish between healthy and diseased leaves across various crops. Their training utilized the Plant Village dataset, encompassing 38 different crop types featuring images of both diseased and healthy leaves, as well as background images. However, the model's emphasis was not specifically on diseases of a single potato crop. Additionally, training on specific regional datasets for the USA and Switzerland proved ineffective in detecting potato leaf diseases in the Pakistani region. In [13], Kamal et al. presented Modified MobileNet and Reduced MobileNet models designed for identifying plant leaf diseases. These models incorporated Depth-wise Separable Convolutional Neural Network instead of the conventional Convolutional Neural Network by modifying the architecture of MobileNet. The models demonstrated an accuracy of 98.34%. In [14], Lee et al. created a Convolutional Neural Network model for identifying Early Blight, Late Blight potato leaves, and healthy potato leaves. The researchers utilized the Plant Village dataset specific to a particular region and did not conduct testing on data not previously encountered, achieving an accuracy of 99%. Barman et al. [15] introduced a Self-Build CNN (SBCNN) model designed for the detection of early blight, late blight, and healthy classes in potato leaf diseases. The model was trained using the Plant Village dataset tailored for a specific region. However, it is important to note that the model was not validated on unseen test data. Despite this, it achieved an accuracy of 96.75%. Lastly, Zhang et al. [16] developed a Faster RCNN model with 97.1% accuracy in detecting tomato diseases, with each technique utilizing the Plant Village dataset and aiming for increased precision in disease identification.

3 Methodology

This section illustrates the classification of potato leaf images through the integration of various multi-scale transfer learning models. Figure 1 showcases the implementation of the suggested 'MultiNet' infrastructure employed for this task of classifying diseases. The infrastructure begins by loading images and fetching corresponding labels from the dataset. Preceding the division of the dataset, multiple preprocessing methods are applied, followed by a comprehensive augmentation of the data, to augment the size of the dataset. Subsequently, the model is trained separately on three classes of potato leaf from Plant Village and seven classes of potato leaf from both Plant Village and different internet source datasets. The evaluation of the proposed 'MultiNet' infrastructure is conducted by testing images. Further information regarding the components of the proposed infrastructure is elaborated on in the subsequent subsections.

3.1 Data Acquisition

In the initial phase, we gathered images of potato leaves from the publicly accessible Plant Village Dataset (Updated), which encompasses over 4000 images related to Potato Leaves diseases. From this dataset, we selected 1000 images each for three classes: Late Blight, Early Blight, and Healthy leaves.

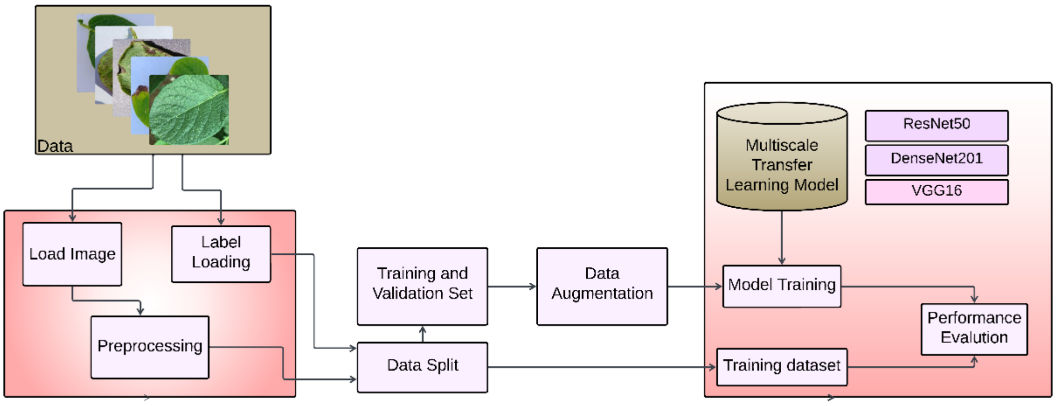


Fig 2: Suggested the "MultiNet" framework for classifying images of potato leaf diseases.

Expanding our dataset to seven classes, we incorporated four additional disease types. Notably, a more severe form of Early Blight, with 1078 images, was distinguished from the regular Early Blight in the Plant Village Dataset (Updated).

Table 1: Further details regarding the two datasets prior to applying data augmentation.

Class	Name of Diseases	No of total Images	No. of train images	No. of test images
Three-class classification	Early Blight	1006	800	206
	Late Blight	1000	800	200
	Healthy	1005	800	205
Seven-class classification	Early Blight Normal	1006	800	206
	Early Blight Serious	1078	800	278
	Late Blight	1000	800	200
	Healthy	1005	800	205
	Insect	1016	810	206
	Potato Leaf Roll Virus	853	653	200
	Potato Leaf Virus	1000	800	200

The remaining three disease types, including 1016 potato leaves affected by insects, 853 potato leaves infected by LeafRollVirus, and 1000 images of potato leaf virus, were manually collected from Google sources. Table 1 provide supplementary information about the three-class and seven-class datasets.

3.2 Preprocessing

Pre-processing refers to the manipulation of raw data before it is input into machine learning or deep learning algorithms. Training a convolutional neural network directly on raw images may result in suboptimal classification performance; however, pre-processing enhances efficiency. It is crucial for accelerating training, incorporating techniques such as centering and scaling. The pre-processing methods employed in this context include the following:

3.2.1 Resizing

Before inputting the images into the fine-tuned multi-scale transfer learning model (refer to Fig. 2), various preprocessing steps were undertaken. The images are in RGB format with three channels. Each channel having an 8-bit depth, underwent adjustments. In the case of the three-class dataset, where the images originally had dimensions of 700 x 460 pixels, we applied a reduction to 224 x 224 pixels, following the principles of transfer learning. Similarly, for the seven-class dataset, the images underwent a transformation adhering to transfer learning principles, ensuring a consistent dimensionality of 224 x 224 pixels. Additionally, to facilitate faster training and minimize memory usage, every image underwent a conversion process to transform it into a NumPy array.

3.2.2 Shuffling

Subsequently, we proceeded to shuffle the images, a step aimed at enabling the model to train effectively on randomly ordered data. This randomization helps prevent the model from learning patterns based on the sequential arrangement of data. By manipulating sensitive data, methods employed are typically well-adapted to mathematical contexts, ensuring the preservation of operational metrics and computer-installed Key Performance Indicators (KPIs) across the database. As every mathematical distribution remains valid after shuffling, this approach facilitates the secure utilization of production data for activities such as testing and training.

3.2.3 Data Splitting:

The datasets are divided into three separate stages. Initial training utilizes 70% of the data, followed by a testing phase, and finally, a validation phase, with the remaining 30% of the data allocated to both testing and validation.

3.2.4 Data augmentation

Various data augmentation techniques are implemented for diverse purposes, such as expanding the dataset size, addressing overfitting concerns, and enhancing the model's overall robustness [26]. Following the application of data augmentation strategies (Table 2), the dataset size for the three-class dataset increased from 3011 to 21077, and for the seven-class dataset, it expanded from 6958 to 48706.

Table 2: Strategies for Augmenting Data with specified parameter values.

Techniques of Data Augmentation	Value of Parameter
Rotation range	90
Zoom range	2
Width shift range	.4
Height shift range	.4
Shearing range	.5
Vertical flip	True
Horizontal flip	True

Table 3: Further details regarding two datasets following the application of data augmentation

Class	Name of Diseases	No of total Images	No. of train images	No. of test images
Three-class classification	Early Blight	7042	5600	1442
	Late Blight	7000	5600	1400
	Healthy	7035	5600	1435
Seven-class classification	Early Blight Normal	7042	5600	1442
	Early Blight Serious	7546	5600	1946
	Late Blight	7000	5600	1400
	Healthy	7035	5600	1435
	Insect	7112	5670	1442
	Potato Leaf Roll Virus	5971	4571	1400
	Potato Leaf Virus	7000	5600	1400

Table 3 provides supplementary details on the datasets following the implementation of the data augmentation technique

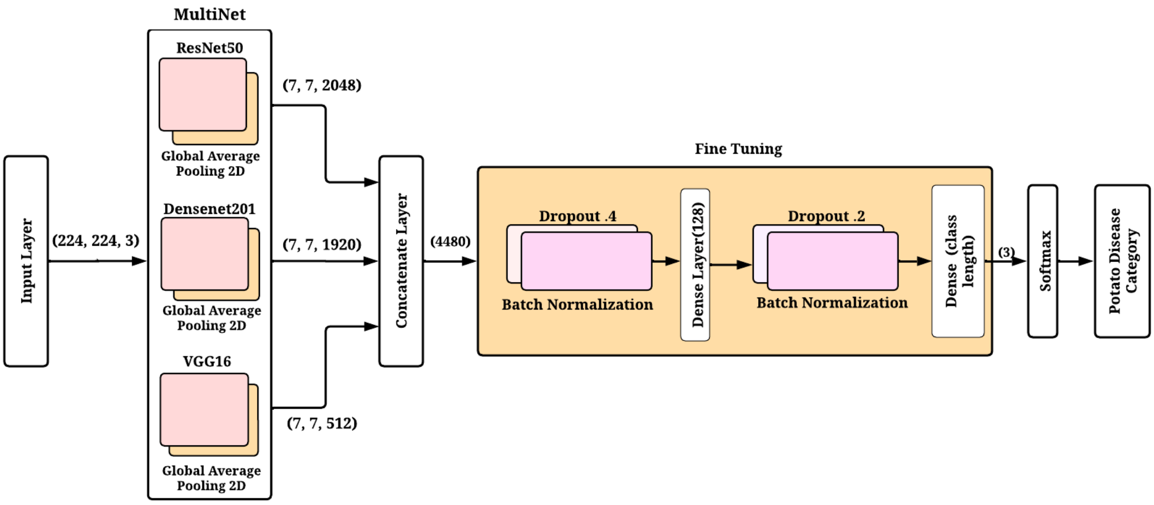


Fig 3: Adapted the "MultiNet" framework through fine-tuning.

3.3 Transfer Learning Model across Multi-Scale

The development of a transfer learning model that incorporates multiple scales involves the integration of three renowned pre-trained CNN models that are ResNet-50, DenseNet-201, and VGG16. This amalgamation forms a comprehensive approach to transfer learning, incorporating the strengths of each individual model for enhanced performance. The models autonomously capture low-level features from images of potato leaves. Subsequently, these features are amalgamated through a fully connected layer to accomplish the task of classification, as depicted in Figure 2. Upon integration of all features, the proposed "MultiNet" framework encompasses 57,217,287 parameters, increasing the parameter count of individual architectures, namely ResNet50, DenseNet-201, and VGG16, by threefold. The subsequent sections offer in-depth explanations of both the foundational formation of every selected CNN model which has been previously trained and the process of fine-tuning.

3.3.1 ResNets - Residual Networks

ResNet50, a variant of the ResNet (Residual Network) architecture, plays a pivotal role as the primary feature extractor in our proposed model. Developed by Kaiming He and his team [20], ResNet50 is renowned for its depth, featuring 50 layers, and over the years, deep convolutional neural networks have made a series of breakthroughs in the field of image recognition and classification. Going deeper to solve more complex tasks and improve classification or recognition accuracy has become a trend.
However, training deeper neural networks has been difficult due to problems such as the vanishing gradient problem [21] and the degradation problem [22]. The goal of residual learning is to solve one

or both of these challenges. Residual connections enable the straightforward transfer of data from one layer to the next, eliminating the difficulties associated with training extremely deep neural networks. This architectural innovation enables The ResNet50 model to effectively capture complicated patterns and hierarchy characteristics in a broad spectrum of datasets. ResNet50, in particular, has shown outstanding efficiency in image categorization tasks, which makes it a popular choice in a wide range of applications related to computer vision. ResNet50 functions as a reliable extracted feature in the model we suggest, removing and encoding important features from input data. The model's ability to acquire intricate representations is facilitated by its comprehensiveness and lack of connections, which additionally enhance the system's general efficiency and resilience. Our dedication to utilizing cutting-edge architectures to obtain improved feature extraction capabilities in our model is demonstrated by the use of ResNet50.

3.3.2 DenseNet - Dense Convolutional Network

Gao Huang, Zhuang Liu, and Laurens van der Maaten have been credited with the preliminary development of the DenseNet model that was previously trained [18]. This model ranked first in 2017 for classification Accuracy among the ImageNet, CIFAR-10, and CIFAR-100 datasets. DenseNet is an innovative method that deviates from the structure of ResNet in that every single layer is linked to every other layer directly. This connectedness makes it easier for important information to be shared within the network, which improves performance generally and training effectiveness [17]. One of the main feature extractors for this investigation is the pre-trained DenseNet-201 model. This model, which has 201 deep Convolutional neural networks, also known as CNN, layers, is designed in an arrangement that seeks to prevent overfitting issues in small datasets. Furthermore, by resolving gradient descent problems, DenseNet-201 significantly enhances the ImageNet database [19]. With multiple advanced CNN layers, the DenseNet-201 model is expected to extract higher-level and important characteristics than designs such as GoogLeNet, AlexNet, and ResNet.

3.3.3 VGGNet - Visual Geometry Group Network

The VGG model was first put forward in 2013 by Andrew Zisserman and Karen Simonyan, who also created a prototype for the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) in 2014. Associated with Oxford's Visual Geometry Group (VGG), their model first gained attention when it achieved the top rank in image-localization. On an individual test scale, VGG demonstrated a top-1 error rate of 25.5% and a top-5 error rate of 8.0%. Across various test scales, VGG exhibited a top-1 error rate of 24.8% and a top-5 error rate of 7.5%. Furthermore, in the 2014 ImageNet competition, VGG secured the second position with a top-5 error rate of 7.3%, subsequently reducing it to 6.8% post-submission [23]. We use the VGG16 variation as our chosen feature extractor in the present study. Thirteen convolution layers and three fully interconnected layers make up the structure of this pre-trained model. A window dimension (3 × 3) is used by all convolution layers. Based on the total amount of number of available filters, there are about 64 filters that can be doubled to make about 128 filters, and eventually up to 256 filters. It is feasible to use 512 filtrations in the final stages. Five max-pooling layers are employed for spatial pooling, positioned after a series of convolutional layers. We use a (2 × 2) pixel window with a stride size of 2 to perform the max-pooling process [24]. In the VGG network, the ReLu activation function is applied to every hidden layer.

3.4 Fine Tuning

After individually extracting features, each pre-trained model employs GlobalAveragePooling2D concurrently to transform all layers into vector forms by calculating the mean value of each input channel. Subsequently, the individual vectors are consolidated into a unified vector using the concatenate layer. Following that, the concatenate layer will be utilized to bring together each of the distinct vectors into one single vector. Six layers are used in the following stage to refine the integrated characteristics for our classification problem, resulting in a Softmax activation function. As mentioned in [25], overfitting is a serious problem for neural networks with deep layers since it occurs when the model overfits to the training set, which negatively affects the performance of the test set. We include two layers for dropouts in our approach to solve the problem of overfitting. During the model development section, 40% of the data has been removed in the first layer of dropouts and 20% of the data is removed in the second layer of dropouts. As noted in [25], for instance, using this approach not only helps to reduce overfitting but also considerably speeds up the training procedure.

Table 4: Summary of the 'MultiNet' Framework.

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 224, 224, 3)]	0	[ ]
resnet50 (Functional)	(None, 7, 7, 2048)	23587712	['input_1[0][0]']
densenet201 (Functional)	(None, 7, 7, 1920)	18321984	['input_1[0][0]']
vgg16 (Functional)	(None, 7, 7, 512)	14714688	['input_1[0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0	['resnet50[0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 1920)	0	['densenet201[0][0]']
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0	['vgg16[0][0]']
concatenate (Concatenate)	(None, 4480)	0	['global_average_pooling2d[0][0]', 'global_average_pooling2d_1[0][0]', 'global_average_pooling2d_2[0][0]']
dropout (Dropout)	(None, 4480)	0	['concatenate[0][0]']
batch_normalization (BatchNormalization)	(None, 4480)	17920	['dropout[0][0]']
dense (Dense)	(None, 128)	573568	['batch_normalization[0][0]']
dropout_1 (Dropout)	(None, 128)	0	['dense[0][0]']
batch_normalization_1 (BatchNormalization)	(None, 128)	512	['dropout_1[0][0]']
dense_1 (Dense)	(None, 3)	387	['batch_normalization_1[0][0]']
Total params: 57216771 (218.26 MB)			
Trainable params: 56925379 (217.15 MB)			
Non-trainable params: 291392 (1.11 MB)			

Batch Normalization and softmax are often used together in deep learning models. BatchNorm can be applied to the input of each layer (except the output layer), improving the training dynamics. The Softmax activation is commonly used in the output layer for multi-class classification tasks, producing class probabilities. We add two batch_normalization layers, which are significant to our classifying approach. These layers are essential for re-scaling all the data and ensuring effective normalization throughout the network. The use of rescaled data markedly accelerates the training process and diminishes susceptibility to the initialization state of the network, providing substantial benefits in enhancing efficiency. A dense layer, which serves as a fully connected layer, establishes dense connections between neurons from both the preceding and current layers. This layer generates an output that corresponds to the input data after thoroughly processing it. Two dense layers are part of our process, with the last dense layer being reserved for the classification goal. To speed up the categorization process, a softmax activation function takes its place. This particular layer estimates the probability of each possible outcome by using the length of the anticipated class. Operating in the range of 0 to 1, the softmax activation function identifies which features are most commonly linked to the anticipated class, enabling neurons to activate in response. The softmax activation function is written as follows in its formulation:

$$\text{softmax}\ (z_i) = \frac{\exp(z_i)}{\sum_{j=1}^{n} \exp(x_j)} \qquad (1)$$

Table 4 displays the results obtained from combining various transfer learning models with fully connected layers. These findings were derived during the development of the "MultiNet" framework, designed for classifying three distinct categories. Consequently, the ultimate layer in the fully connected architecture consists of three neurons. In the context of multiclass classification featuring seven classes, the corresponding dense layer is configured with seven neurons. It is important to highlight that the general structure of the envisioned "MultiNet" framework maintains uniformity and coherence throughout. This consistency is a notable feature of the proposed framework, whether applied to a multiclass (three classes) or a multiclass (seven classes) classification scenario.

4 Setup for Experiments, Evaluation Metrics, and Analysis of Results

This segment presents the experimental configuration, outlines the hyperparameters employed, and showcases the outcomes achieved through the utilization of the "MultiNet" framework sourced from "The Plant Village," along with manually gathered datasets. Furthermore, a thorough comparative examination is conducted between the suggested methodology and the unique pre-trained structures of individual Convolutional Neural Networks (CNNs).

Algorithm 1: Identification and Categorization of Potato Leaf Diseases

Input:

1. Potato Disease Training Set T1, Validation set V1, and Testing set T2
2. Learning rate (a)
3. Number of Epochs (b)
4. Batch size (c)
5. Number of images covered in every batch (d)

Output: w -> CNN pre-trained models' weight.

Start:

6. Transform individual image in the training set into dimensions 224 x 224.
7. Employ a data augmentation technique to increase the size of the dataset.
8. Retrieve features from the images by utilizing pre-existing CNN models such as ResNet50, DenseNet-201, and VGG16.
9. Merge the extracted characteristics by employing concatenate layers.
10. Configure the fine-tuning layers such as dense, batchnormalization, dropout, and softmax.
11. Initialize the parameters of the pre-trained CNN model as a, b, c, d.
12. Assess the proposed framework to determine and confirm the initial weights.
13. for each iteration from 1 to b:
    - Choose a batch of size d from T1.
    - Perform forward propagation and calculate the loss-function.
    - Perform backpropagation to adjust and optimize the weights denoted by 'w.'.
14. end for

4.1 Configuration of Experiments

In line with the proposal, the 'MultiNet' infrastructure was created using Keras, a free software package for integrating neural networks with Python. All of the model's training and testing was done using Google Colab, a free cloud service that makes it possible for users to use a Tesla T4 GPU with 12 GB of GDDR5 Memory.

4.2 Evaluation Criteria

The effectiveness of the suggested framework is evaluated using a variety of statistical measures, including Accuracy, Precision, Recall, False-positive rate (FPR), True negative rate (TNR), F1-Score, Mean Squared Error (MSE), and Mean Absolute Error (MAE). These metrics rely on the values derived from the confusion matrix, which includes True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The formulas for these measurement indicators are presented individually below:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (3)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{FPR} = \frac{FP}{FP+TN} \quad (5)$$

$$\text{TNR} = \frac{TN}{TN+FP} \quad (6)$$

$$\text{F1-Score} = 2 \times \frac{Pr \times Re}{Pr+Re} \quad (7)$$

True Positive (TP) indicates a situation where the 'MultiNet' infrastructure accurately identifies the positive type of Potato disease.

True Negative (TN) indicates a situation where the proposed infrastructure accurately identifies the absence of the negative Potato disease type.

False Positive (FP) indicates a situation where the infrastructure inaccurately identifies the positive type of Potato disease.

False Negative (FN) indicates a situation where the infrastructure mistakenly identifies the absence of the negative Potato disease type.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{i}(Y_i - X_i)^2 \quad (8)$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{i}|Y_i - X_i| \quad (9)$$

Where in equation 8 and 9,
n is the number of data points
Y_i are the observed values
X_i are the predicted values

4.3 Training and Parameter Optimization

Figure 4 illustrates the simulation results during the training of the proposed 'MultiNet' infrastructure for the three potato diseases from the Plant Village dataset. The hyperparameter values employed for training are detailed in Table 5. Significantly, the effectiveness of model training is heavily influenced by the choice of optimizer function and loss function for gradient descent. In this regard, we select Adam as the optimizer function, capitalizing on the advantages of both AdaGrad and RMSProp optimizers. This choice is made to effectively address sparse gradients commonly encountered in large datasets. Categorical cross-entropy is chosen as the loss function, given the binary classification nature of our work on the Plant Village dataset. To optimize the learning process, a learning rate value is crucial, and we address this challenge by selecting a rate of 0.0001 to mitigate undesirable behavior associated with excessively large or small learning rates. Additionally, a small batch size of 32 is utilized, promoting effective model generalization. The suggested framework undergoes 50 training epochs, reaching a training accuracy exceeding 98% and a validation accuracy of 100% by the 21st epoch. The absence of overfitting during training is evident in Fig. 4(a), and the graph for the loss function in Fig. 4(b) illustrates a significant decrease in the loss value. Despite minor fluctuations attributed to the constrained group of 32 images, the training process, on the whole, produces favorable outcomes. Similarly, for the second dataset, encompassing seven diseases, the progression of accuracy and loss during the training of the proposed 'MultiNet' framework is depicted in Fig. 5. The hyperparameter values utilized for training align with those employed for the Plant Village dataset, as detailed in Table 5.

Table 5: The parameter setting employed in the training phase of the 'MultiNet' infrastructure.

Dataset	Parameter	Value
Three-class and seven-class classification	Optimizer	adam
	Learning Rate	.0001
	Loss Function	categorical_crossentropy
	Metrics	accuracy
	Batch Size	32
	Epochs	50

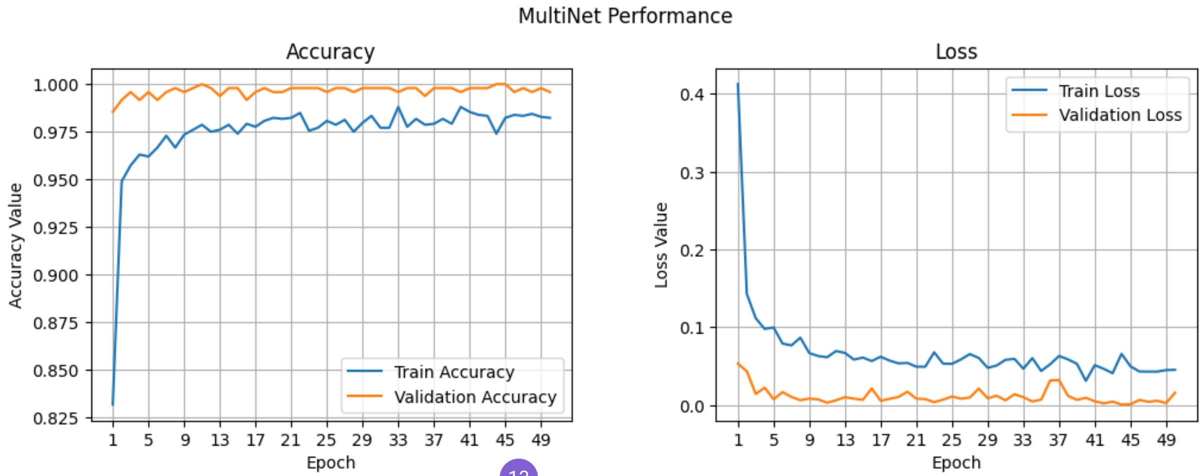


Fig 4: Training advancement for the three-class dataset: (a) accuracy in training and validation (increased values indicate improved performance), and (b) loss in training and validation (decreased values indicate improved performance).

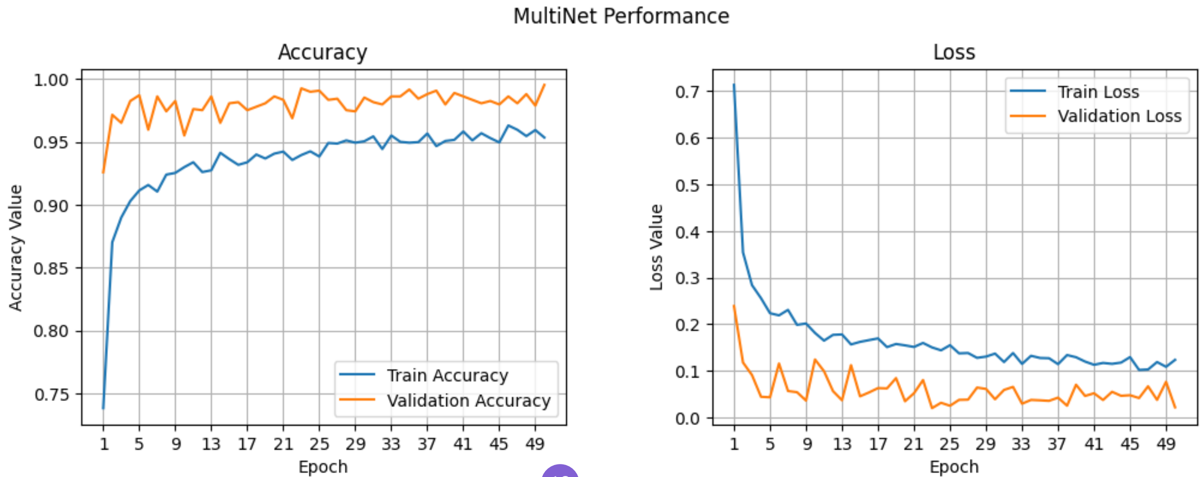


Fig 5: Training advancement for the seven-class dataset: (a) accuracy in training and validation (increased values indicate improved performance), and (b) loss in training and validation (decreased values indicate improved performance).

The 'MultiNet' framework undergoes 50 epochs of training, attaining a training accuracy of 94 percent right after the 24th epoch, with validation accuracy surpassing 97 percent. Fig. 5(b) showcases a loss function curve with minimal fluctuation, indicating that the loss value is nearly zero throughout the training and validation phases. Moreover, Fig. 5(a) provides visual confirmation that the model does not exhibit overfitting during the training process.

4.4 Analysis of Result

The ROC (Receiver Operating Characteristics) curve and confusion matrix for the "MultiNet" framework applied to the Plant Village dataset are shown in Figure 6, which focuses on three-class disease identification. This framework amalgamates ResNet50, DenseNet-201, and VGG16, leveraging their combined features to categorize images of potato leaf into Healthy, Early Blight, or Late Blight classes. As illustrated in Fig. 5(a), the 'MultiNet' framework accurately classifies 205, 200, and 205 leaf images corresponding to Early Blight, Late Blight, and Healthy Potato leaves, respectively. Impressively, only one misclassification occurs for Early Blight leaves, with no errors in classifying Late Blight and Healthy images. The ROC curve in Fig. 5(b) attests to the model's high consistency, achieving an area value of 0.999. Furthermore, individual evaluations of the transfer learning models on the Plant Village datasets are conducted to provide a comprehensive understanding of the 'MultiNet' framework's efficiency.

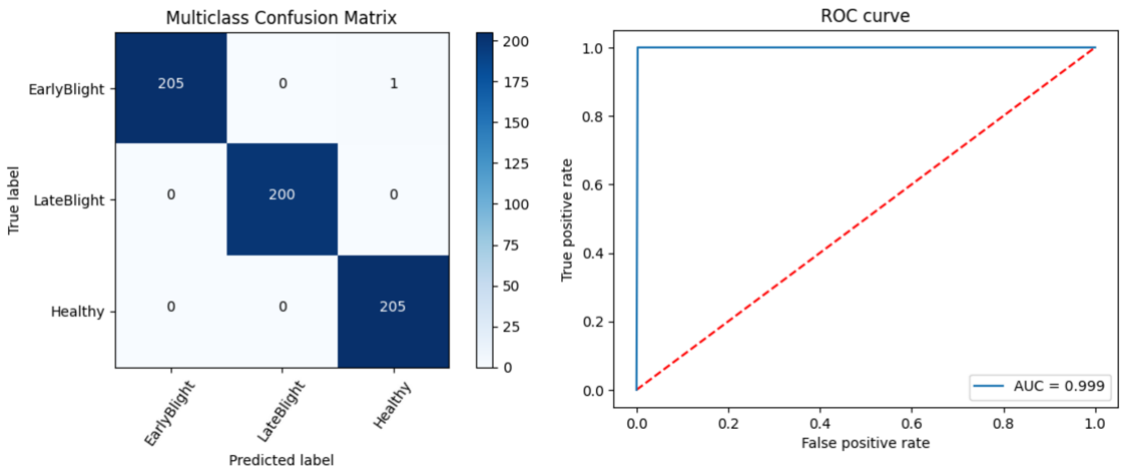


Fig 6: The evaluation of the 'MultiNet' infrastructure on a three-class dataset, including a) Three-class Confusion Matrix and b) ROC curve analyses.

Table 6: Outcomes derived from the utilization of the Proposed 'MultiNet' infrastructure with seven distinct transfer-learning models on datasets pertaining to three-class Potato Diseases.

Model	**Class 3**					
	Accuracy	F1-Score	Precision	Recall	MSE	MAE
VGG16	.995	.995	.995	.995	.015	.008
VGG19	.995	.995	.995	.995	.020	.010
ResNet-50	.961	.961	.961	.961	.152	.077
DenseNet-201	.993	.993	.993	.993	.026	.013
MobileNetV2	.989	.989	.989	.989	.040	.021
NASNetMobile	.980	.980	.980	.980	.069	.036
Xception	.997	.997	.997	.997	.013	.007
Proposed Method	.998	.998	.998	.998	.007	.003

Table 6 provides a comparison between the 'MultiNet' infrastructure and seven additional models based on transfer learning, offering an insightful analysis of their respective performances. Remarkably, the 'MultiNet' framework surpasses all other cutting-edge models, showcasing an exceptional average precision, recall, and F1-score of 0.998. Additionally, it exhibits impressive model efficiency, reflected in MSE and MAE values of 0.007 and 0.003, respectively. Notably, Xception also delivers commendable performance with an F1-score of 0.997, closely trailing the MultiNet Framework. Conversely, VGG16 and VGG19 exhibit comparable F1-scores of 0.995, indicating strong performance. DenseNet201 performs well, achieving an F1-score of 0.993. On the other hand, ResNet50, NASNetMobile, and MobileNetV2 demonstrate F1-scores of 0.961, 0.980, and 0.989, respectively, in the three-class disease detection category.

Using the 'MultiNet' framework, Figure 7 illustrates the ROC curve and confusion matrix for the seven-class dataset. This dataset involves identifying various potato disease categories, namely Early Blight General (EarlyBlightG), Early Blight Serious (EarlyBlightS), Late Blight, Virus infected Leaf, Insect infected Leaf, LeafRollVirus infected Leaf, and Healthy Leaf.

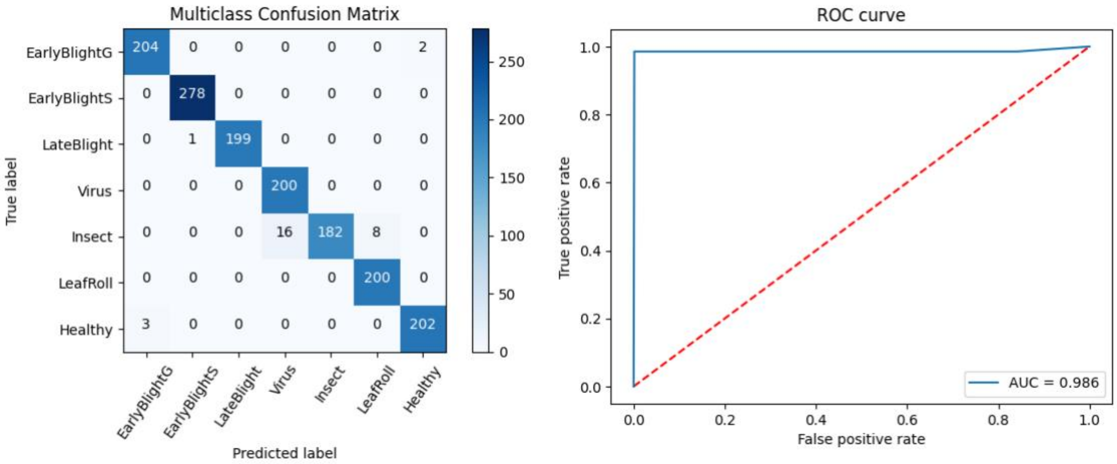


Fig 7: The evaluation of the 'MultiNet' infrastructure on a seven-class dataset, including a) Seven-class Confusion Matrix and b) ROC curve analyses.

Examining Fig. 7(a), the framework correctly classifies 204, 278, 199, 200, 182, 200, and 202 images for Early Blight General, Early Blight Serious, Late Blight, Virus infected Leaf, Insect infected Leaf, LeafRollVirus infected Leaf, and Healthy Leaf, respectively. However, misclassifications occur, notably with two Early Blight General images, one Late Blight image, twenty-four Insect infected leaf images, and three Healthy images. Importantly, the 'MultiNet' framework exhibits no misclassifications for Early Blight Serious, Virus infected, and LeafRollVirus infected images. The model showcases robust consistency and applicability, as evidenced by an area value of 0.986 as depicted in Figure 7(b). This high area value underlines the model's strong performance and versatility across various scenarios.

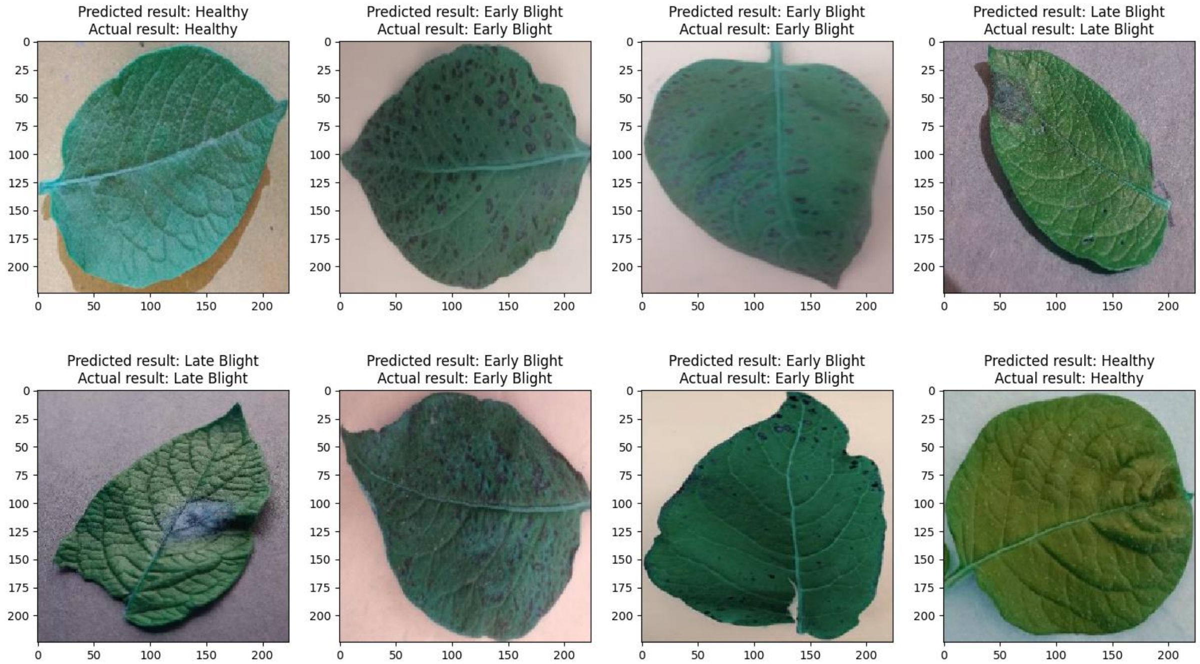
Table 7: Outcomes derived from the utilization of the Proposed 'MultiNet' infrastructure with seven distinct transfer learning models on datasets pertaining to seven-class Potato Diseases

Model	**Class 7**					
	Accuracy	F1-Score	Precision	Recall	MSE	MAE
VGG16	.960	.960	.960	.960	.170	.076
VGG19	.794	.80	.84	.794	1.60	.430
ResNet-50	.978	.978	.978	.978	.075	.036
DenseNet-201	.977	.977	.977	.977	.072	.037
MobileNetV2	.953	.954	.961	.952	.205	.072
NASNetMobile	.978	.978	.979	.978	.119	.039
Xception	.970	.970	.970	.970	.099	.052
Proposed Method	.98	.98	.98	.98	.137	.037

In Table 7, a comparative analysis reveals the 'MultiNet' framework's high performance, boasting an average precision, recall, and f1-score of 0.98, along with MSE of 0.137 and MAE of 0.037. Surprisingly, the system outperforms seven modern models in identifying the presence of potato disease categories. Within this set, DenseNet-201, ResNet50, VGG16, MobileNetV2, NASNetMobile, and Xception achieve classification accuracies surpassing 95%. However, VGG19 exhibits subpar performance specifically in detecting the multiclass potato disease category. This highlights the efficacy of the framework in surpassing its counterparts, especially in comparison to these widely used pre-trained models.

5 Discussion

This paper introduces a novel approach to multiclass classification, specifically targeting three-class and seven-class categorizations, by employing a 'MultiNet' infrastructure on potato leaf images. The evaluation of the 'MultiNet' infrastructure is conducted using two distinct datasets. Table 8 presents a thorough comparison of the performance of the 'MultiNet' infrastructure with prior studies that employed the same dataset. These studies, however, utilized diverse architectures, parameters, and depth sizes, making the comparison comprehensive and encompassing various structural aspects. The aim is to assess how the 'MultiNet' framework fares against existing literature with differences in these critical elements. The results in Table 8 highlight that the proposed framework achieves superior prediction accuracy in identifying multiclass potato diseases compared to previous studies. Remarkably, we have attained an outstanding mean classification accuracy of 99.8% for the three-class dataset through the effective integration of all pre-trained models. Additionally, our approach yielded a commendable mean classification accuracy of 98% for the seven-class dataset, demonstrating the successful integration of pre-trained models. Fig. 8(a) and 8(b) shows the prediction of three-class and seven-class dataset images by our framework.



. **Fig 8: (a)** ''MultiNet'' predicted three-class dataset images.

Our approach exhibits advantages over existing methods in the literature, such as the avoidance of time-consuming and potentially ineffective processes associated with utilizing different feature extractor methods, especially when dealing with a large number of images. The suggested framework offers a segmentation-free methodology that eliminates the need for any manually crafted features. Kamal et al. [13] introduced Modified MobileNet and Reduced MobileNet models for plant leaf disease identification. These models utilized depthwise separable convolution in lieu of the traditional convolution layer, altering the MobileNet architecture. Training sessions involved diverse crops from the Plant Village dataset, encompassing photographs of plant leaves from a specified geographical region. In a related context, Liang et al. [32] introduced a network for plant disease identification and severity approximation, incorporating a residual structure and shuffle units inspired by the architecture of ResNet-50. Bonik, C. et al. [33] presented a CNN model which is trained on potato leaf images from the Plant Village dataset. A CNN model for identifying early blight, late blight, and healthy potato leaves was presented by Khalifa et al. [34]. The model was trained using the region-specific Plant Village dataset. A Convolutional Neural Network (CNN) model developed by Rozaqi and Sunyoto [36] aims to differentiate between early and late blight on the leaves of potatoes as well as healthy leaves. Their model was trained using the region-specific Plant Village dataset. In order to distinguish between healthy potato leaves and two frequent diseases—early and late blight—Sanjeev et al. [35] used a feedforward neural network (FNN). They used the Plant Village dataset to train and test their model. In order to distinguish between potato leaves that have been damaged (by early or late blight) and those that have not, Barman et al. provided a self-constructed CNN framework in [15]. The model was trained using the region-specific Plant Village dataset. Using a previously trained VGG19 framework for the extraction of features, Tiwari et al. [6] classified data from the Plant Village dataset using different classifiers, including SVM, neural, and KNN. Lee et al. [14] built a CNN-based method to differentiate between healthy and diseased (early blight, late blight) potato leaves using the Plant Village dataset. Nevertheless, no data that the model had not seen before was used for testing.

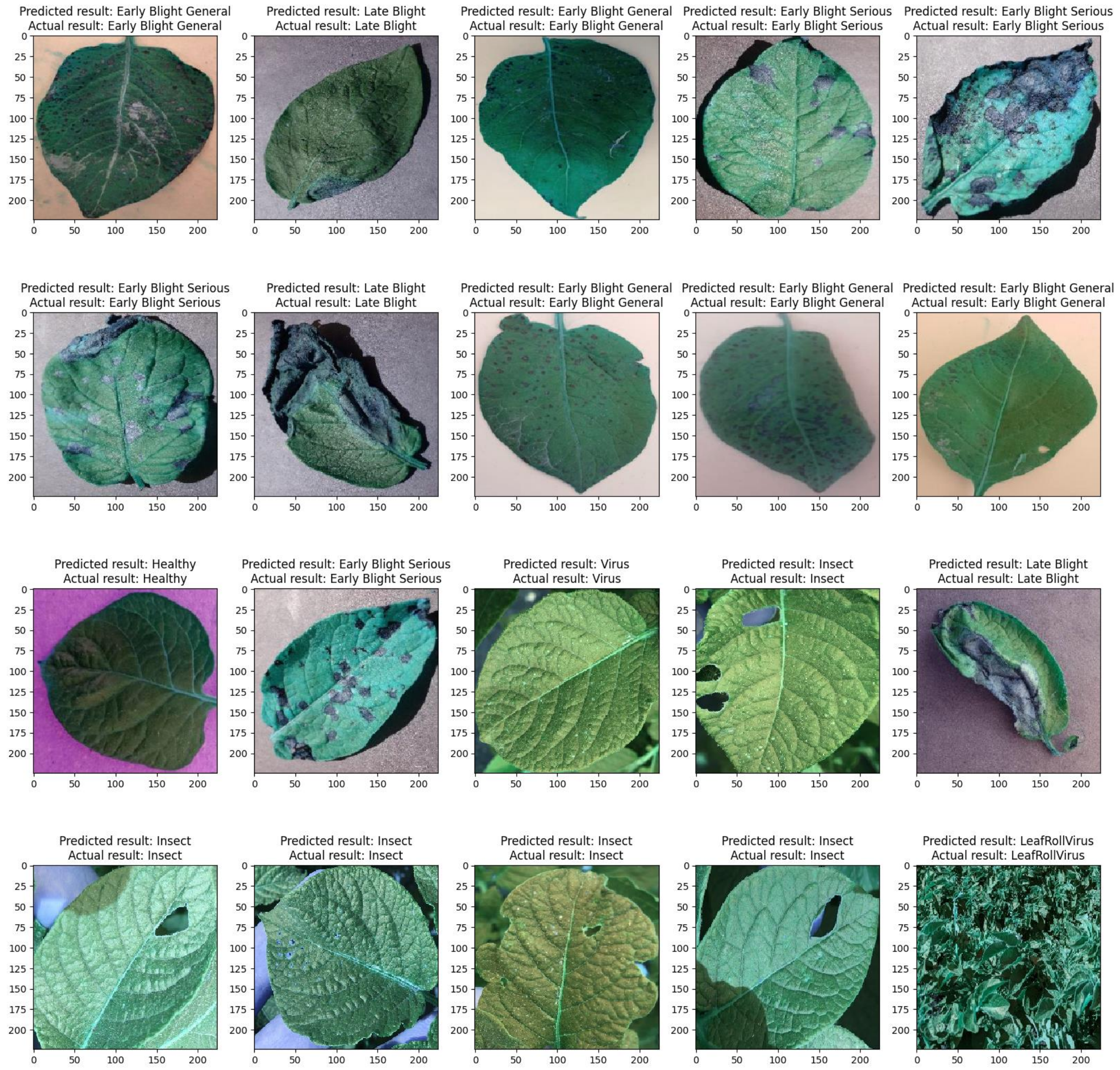


Fig 8: (b) ‘‘MultiNet” predicted seven-class dataset images.

Using the data collected by Plant Village, Islam et al. [3] constructed a multi-support vector machine (SVM) and segment-oriented model for identifying the existence of potato illnesses. Their findings emphasized the potential for accuracy improvement in the model. Rabbia, M. et al. [7] proposed a system utilizing the Efficient DenseNet-201 architecture that has been pre-trained, addressing class imbalance in data through reweighted cross-entropy loss function adjustments.

6 Conclusion

In this study, we present a novel deep learning framework, termed 'MultiNet,' designed to enhance the precision and reliability of the detection of potato leaf disease from images. This 'MultiNet' infrastructure makes use of transfer learning methods. Additionally, it incorporates feature extraction techniques.

Table 8: Assessing the 'MultiNet' framework through comparisons with alternative methods in both binary and multi-class classification scenarios.

Reference	Methodology	Disease	Dataset	Accuracy
1. [37] Chen, J. et al. 2023	MobileNet -V2	3 Classes (Healthy, Late Blight, Early Blight)	PlantVillage	97.73%
2.[13] Kamal, K. et al. 2019	Modified MobileNet	3 Classes (Healthy, Late Blight, Early Blight)	PlantVillage	98.34%
3.[32] Liang, Q. et al. 2019	ResNet50	3 Classes (Healthy, Late Blight, Early Blight)	PlantVillage	98%
4.[33] Bonik, C. et al. 2023	CNN	3 Classes (Healthy, Late Blight, Early Blight)	PlantVillage	94.2%
5. [34] Khalifa, N.E.M. et al. 2021	CNN	Binary (Late Blight and Early Blight)	PlantVillage	98%
6. [35] Sanjeev, K. et al. 2021	FFNN	Binary (Late Blight and Early Blight)	PlantVillage	96.5%
7. [7] Rabbia, M. et al. 2022	DenseNet201	5 classes (Healthy, Late Blight, Early Blight, Leaf Roll, Potato Verticillum_wilt)	PlantVillage, Manual	97.2%
8. [36] Rozaqi, A.J. et al. 2020	CNN	Binary (Late Blight and Early Blight)	PlantVillage	92%
9. [15] Barman, U. et al. 2020	SBCNN	Binary (Late Blight and Early Blight)	PlantVillage	96.75%
10.[6] Tiwari, D. et al. 2020	SVM, KNN and Neural Net	Binary (Late Blight and Early Blight)	PlantVillage	97.8%
11. [14] Lee, T.Y. et al. 2020	CNN	Binary (Late Blight and Early Blight)	PlantVillage	99%
12. [3] Islam, M. et al. 2017	Segment and Multi SVM	Binary (Late Blight and Early Blight)	PlantVillage	95%
13. Proposed Method	ResNet-50+DenseNet-201+VGG16	MultiClass (Early Blight, Late Blight, and Healthy)	PlantVillage	99.84%
14. Proposed Method	ResNet-50+ DenseNet-201+VGG16	MultiClass (Early Blight General, Early Blight Serious, Late Blight, Healthy, Insect infected, LeafRollVirus, and Virus infected)	PlantVillage, Manual	98%

This approach allows multiple CNN models that have been pretrained to retrieve characteristics simultaneously, which are then merged for the classification process. The model is subjected to training and testing on image datasets of varying sizes, showcasing its versatility across diverse datasets. Experimental results showcase the 'MultiNet' framework's exceptional performance, achieving classification accuracy of 99.8% and 98% for three-class and seven-class datasets, respectively. This outperformance extends to individual CNN models that have been pretrained and all other most modern models reported in the literature. The strong experimental outcomes confirm the effectiveness of our suggested strategy. The framework will be used in future developments to automatically track and identify a variety of potato disease data on mobile phones and tablets. Moreover, we are confident that our 'MultiNet' approach could potentially be applicable in other fields, including real-time malfunction evaluation, virtualized rice damage evaluation, and localization for identifying distinct imagery.

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