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| RESEARCH ARTICLE

Classification of Radish, Radish Leaf and Potato Leaf Disease Using Deep Learning Algorithm: Study and Accuracy Measurement

Md. Abdullah Mandal[1], Sumaiya Siddika Khushi[2], Md. Zahid Hassan[3] ✉ Taher Muhammad Mahdee[4], Engr. Md. Al-Hasan[5], Md Zahim Hassan[6] and Mohammed Sowket Ali[7]
[1234567]*Bangladesh Army University of Science and Technology, Bangladesh*
Corresponding Author: Md. Zahid Hassan, **E-mail**: zahidhassan956@gmail.com

| ABSTRACT
Radish and potato are important root vegetables that are extensively grown for their nutritional and economic importance. However, foliar diseases drastically impair productivity and quality. Early detection of these diseases is crucial for prompt intervention and successful crop management. This study uses Deep Learning based classification approach to automatically detect diseases in radishes, radish leaves and potato leaves using image data. The dataset consists of 9 distinct classes: healthy radish, healthy radish leaves, healthy potato leaves and several diseased categories. The radish leaf diseases include Alternaria brassicae and flea beetle damage, radish diseases include radish scab and white Mold and potato leaf diseases cover nutrient deficiencies and potato late blight fungus. Multiple convolutional neural network (CNN) models were evaluated for classification performance. The tested models and their respective followed with an accuracy of Xception 99.86%, VGG16 at 99.86%, VGG19 at 98.95%, ResNet50V2 at 99.86% and InceptionV3 at 99.51%. Among the models evaluated the Modified DenseNet121 model proposed demonstrated the highest accuracy achieving a score of 99.93 %. Deep Learning (DL) offer precise and well-timed solutions for disease detection, classification and eradication. The results yield significant potential for enhanced crop management methodologies, facilitating a considerable reduction in economic losses linked to radish and potato diseases. Farmers are able to make informed decisions, minimize crop losses and reduce pesticide use by detecting advancements in disease through the targeted application of agrochemicals. This results in a more sustainable agricultural environment, market stability and healthier crops.

| KEYWORDS
Radish Leaf Disease, Potato leaf diseases, Image Classification, CNN, Deep Learning, Agriculture AI Accuracy evaluation.

| ARTICLE INFORMATION
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1. Introduction
Improving agricultural plants development and productivity relies heavily on disease identification and treatment. Early detection, prevention and management of crop infections is crucial as they can significantly reduce yield and quality. Mobile and robotic applications are facilitating solutions for the digital innovation processes essential for environmental protection by aiding in monitoring and treatment operations. The incorporation of Artificial Intelligence [1,2] in these systems is essential to assist the operator in making informed and deliberate decisions regarding the actual condition of a plant's vitality. These tools assist stakeholders in early prediction and diagnosis by identifying symptoms observable to the naked eye. The initial task, diagnosis, primarily involves the analysis of RGB, multispectral, or remote sensing images. In this context, Computer Vision [3] has a pertinent application, by employing suitable networks trained on image samples, it can detect, recognize and identify crop risk situations as well as the various stages of fruit growth, which is advantageous for mechanical harvesting. Recent literature has tackled the issue by employing single output or multi-output convolutional neural networks [3], a methodology referred to as multitask learning. Most successful image classification method available is deep convolutional neural network (DCNN) [4]. For

learning features from the training data, the DCNN consists in several layers including convolutional, pooling and fully connected layers [5]. Artificial intelligence has shown its efficiency and excellent performance in automated image categorization issues via various machine learning methods and is currently being used to automate the diagnosis of various diseases [6] Pre-trained neural network from one task is used in transfer learning to a related new task. Techniques of transfer learning help to reduce the training and model design times.AlexNet, DenseNet, VGG16, Inception-v3, MobileNet and ResNet [7] are the conventional transfer learning methods in image classification. Furthermore, the DCNNs require appropriate hyperparameter values to raise the classification performance. The most important training criteria influencing the performance of deep learning methods are hyperparameters. Most often used hyperparameters in DCNNs are activation function, dropout value, epochs, filter size, learning rate, loss function and mini-batch size. Choosing the appropriate hyperparameter value presents a difficult chore in deep learning problem solving. The most appropriate hyperparameter values for the DCNNs [8] are found by means of hyperparameter tuning methods Two most often used hyperparameter tuning techniques in deep learning are grid search and random search. Training the deep learning algorithm with better efficiency and less training time depends on high-performance computing capability [9].

The representativeness and comprehensiveness of the used dataset for training, the algorithm greatly influences the accuracy and dependability of integrated artificial intelligence system. The generalizability of the model is improved by the development of intelligent neural networks since learning necessary knowledge from known examples depends on large volumes of data. Creating a dataset is a difficult and time-consuming task requiring large resources for the acquisition, annotation and categorization of images, usually carried out by business professionals. Acknowledged as a problem in the literature, the availability of datasets in Digital Agriculture (DA) is stopping scientific progress [10]. Several initiatives aiming at data collecting have been undertaken recently.

There now are several datasets available. The most well known in this field is PlantVillage [11], which features homogeneous background showing 54,000 images on the ventral side of the leaf. Nevertheless, as the literature [12] shows, these setups are not sufficiently representative for the aims of the last application. The datasets produced under controlled conditions that is, those showing the leaf on a homogeneous background do not fairly reflect the possible environmental conditions in which the model will run.

This research proposes a modified DenseNet121 model for diagnosing 9,489 leaf images from two different species radish and potato. The radish part has six classes: two for diseased leaves, two for sick radishes, one for healthy radish and one for healthy radish leaves. A custom dataset was created total of nine different classes. Three classes make up the potato section: one for healthy potatoes, two for sick leaves. To enhance model robustness various preprocessing and image processing techniques such as normalization, contrast enhancement and data augmentation were employed. The deep learning pipeline used pre-trained models, succeeded by hyperparameter adjustment and dense layer optimization to enhance model performance. This works primary contribution encompasses the development of a customized leaf disease dataset and the adaption and fine tuning of a pre-trained Modified DenseNet121 architecture for enhanced classification accuracy. The efficacy of the proposed model was assessed and juxtaposed with other existing deep learning architectures, including Xception, VGG16, VGG19, ResNet50V2 and InceptionV3. Comparative evaluations revealed that the Modified DenseNet121 achieved the maximum classification accuracy while simultaneously preserving competitive training and inference durations.

2. Literature Review

Some writers have discussed how they discovered leaf diseases using different methodologies and advised using different implementations, as seen and described here. The convolutional neural network (CNN), the central component of deep learning methods in image recognition, has advanced rapidly and produced good results in image recognition applications. Many approaches have been employed in the study of Radish and potato disease classification. Still, it is insufficient and remains a topic of active research due to the complexities involved [13]. This demonstrates the novelty and contemporary nature of this technique in the agricultural sector.

The images were normalized to extract enhanced features, which were then fed into image classification algorithms utilizing deep learning techniques. In [14], Three cutting edge CNN systems VGGNet16, ResNet101 and modified AlexNet, on a transfer learning scenario, finds that the modified AlexNet achieves the highest accuracy, with 99.97% training accuracy and 61% testing accuracy, particularly effective at detecting curly leaf disease. The way the experiment was conducted, A total of 5456 photos, 1321 of which are for training and 329 of which are for testing, have been divided into healthy and diseased leaf images. There are 945 early blight training images, 1155 late blight training images, 2044 curly leaf training images and 511 curly leaf training images. They have been split into training and testing in proportions of 80% to 20% respectively. A strategy predicated on deep learning can be designed to learn an efficient feature representation.

In their work, Prajwala and colleagues [15] find and classify using CNN model and LeNet architecture tomato leaf diseases including Septoria Leaf Spot and Yellow Leaf Curl. PlantVillage, an Open Access image repository, provided the data used in the study. The suggested approach produced a degree of accuracy between 94% and 95%. In [16] This research introduces an enhanced ResNet50 model, ECA-ResNet, for the identification of tomato leaf diseases. The integration of a modified Inception module and an attention mechanism improves feature extraction and minimizes misclassification. With an accuracy of 99.24%, it surpasses other models, providing a reliable solution for accurate disease identification in smart agriculture. The subject of this study is the vital element of agriculture that deals with spotting and classifying sick plants in crops. In [17], the research uses transfer learning. approach combining the RMSprop and SGDM algorithms, the Alexnet framework, the ADAM optimiser, Using convolution, max-pooling, normalisation, fully linked, and softmax layers, the 25 layer Alexnet model groups 5300 images into groups comprising healthy, blight, frequent rust, and grey leaf. By fine-tuning hyperparameters including learning rates, epochs, and optimizers, the proposed model achieves an outstanding precision of 99.43% with an unacceptable retention rate of 0.0001. This approach shows the possibilities of automated technology to transform the agricultural sector, including robotic pesticide application and drone-operated devices. In this paper [18], the authors propose order to identify crop diseases and explore the Following Processing Fusion Framework (PFF), which merges prediction matrices from many deep-learning models and achieves an outstanding classification accuracy of 99.33%. Using neural networks, the PFF is applied to five models and evaluated on the 54,305 images distributed among 38 groups in the Plant Village dataset, therefore representing 26 diseases and 14 species. With top-5 quality scores of 99.99%, mean reciprocal rank scores of 99.61% and average accuracy mean scores of 99.42%, the method produces remarkable results. Furthermore, ideal for real-time economic warning systems is its exceptional speed and accuracy, which determines its rate of classification as under a second per sample image. In [19] the author proposes a CNN-SVM hybrid model to exactly identify five radish leaf diseases: Alternaria Blight, White Rust, Root Rot, Radish Mosaic Virus and Radish Phyllody. The model consists of four SVM classifiers after four convolutional layers, four max-pooling layers, one fully connected layer. With an F1 score of 81.45% and 92% accuracy it demonstrated excellent classification skills across several disease categories having been trained on a broad dataset. The early disease detecting ability of the model is underlined in the research which might be very beneficial for farmers in effective disease management and support of sustainable development.

In [20], this chapter offers a careful review of deep learning approaches for plant disease detection. Some of these approaches provide possible solutions to agricultural issues and might help to identify illnesses before they show symptoms. Detecting radish and potato disease requires not only a highly accurate method but a fast and reliable one as well. To address this issue, a modified DenseNet121 model is proposed that provides a higher accuracy rate in the shortest time compared to any existing CNN models. To achieve a large dataset for training and testing the model, images of radishes and potatoes in disease and health were used to create a dataset of 9,489 images.

Table 1. Overview of studies using deep learning approaches with their performance for Radish, potato and plant disease detection.

Specie & Reference	Number of image sample	Class	Architecture	Accuracy(%)
Multiple [21]	240,000	38	custom	98.41
Radish [19]	4975	5	CNN-SVM	92
Potato [22]	2,152	3	Inception V3	98
Potato [23]	5100	5	VGG16	91
Potato [24]	450	3	Random Forest (RF)	97
Potato [25]	2,152	5	DenseNet-201	97.2
Rice [26]	500	10	AlexNet	95.48
Tomato [27]	18,345	10	AlexNet	98
Tomato [28]	3000	10	Custom	98.49
Multiple [29]	46,409	79	GoogLeNet	86.5

3. Methodology

This section provides a complete description of the architecture and training process of the pre-train model and Modified DenseNet121 with the experimental setup and dataset preparation. The Radish and potato leaf disease detection model pipeline starts with dataset preparation and ends with model prediction. Python3.7 programming language and TensorFlow 2.9.1, numpy Version 1.19.2, matplotlib Version 3.5.2 and OpenCV Version 4.5.5 libraries are used for dataset preparation and pre-train model and Modified DenseNet121 implementation. Data preparation, preprocessing, model designing and prediction tasks are performed using an HP 3025 workstation with an Intel Core i5 CPU and sixteen gigabytes of random access memory. The training and testing process of the pre-train model and Modified DenseNet121 and existing state of the art techniques were performed using an Kaggle deep learning server station. The kaggle server includes GPUs for accelerating the training process of deep neural networks. In subsequent subsections, each phase of the radish and potato leaf disease detection pipeline are discussed in detail. First the details of the dataset preparation and preprocess are discussed in the next subsection.

Figure 1. Proposed system diagram.

3.1. Dataset Preparation and processing

Our dataset provides a total of 9,489 images categorized into nine distinct classes. The radish section includes six classes: two for diseased leaves, two for diseased radishes, one for healthy radish and one for healthy radish leaves. The potato section consists of three classes: two for diseased leaves and one for healthy potato leaves. All images are collected from multiple agricultural fields across Bangladesh. The dataset covers specific categories such as Radish Fresh Leaf, Alternaria brassicae, Flea Beetle

Damage, Radish Scab, White Mold, Fresh Radish Leaf and for potatoes: Nutrient Deficiency, Fresh Potato Leaf and Potato Late Blight Fungus. The images are systematically organized into fresh and diseased categories, helping researchers gain clear insights into disease patterns. Table 2 shows the details of the dataset. In, deep learning, data augmentation is a method used to generate artificial expansion of a training datasets size and variety. Random transformations, like rotating, shifting, zooming and flipping, rescale, different copies create new, varied versions of existing images. This helps prevent overfitting by reducing the models dependency on specific features of the training data. All augmentation parameters are shown in Table 3. After, the images were scaled down to the classifier's standard resolution (for instance Densnet121 was 224×224 pixels). After resizing the picture, the deep learning classifier used the enhanced (9,489) images in a ratio of 70% data for training,15%data for validation and whereas 15% was used for testing. Table 4 illustrates the number of images in the training, validation and testing dataset. The development and assessment of deep learning algorithms that will be utilised to categorise and diagnose the various diseases depend on having such a carefully curated dataset.

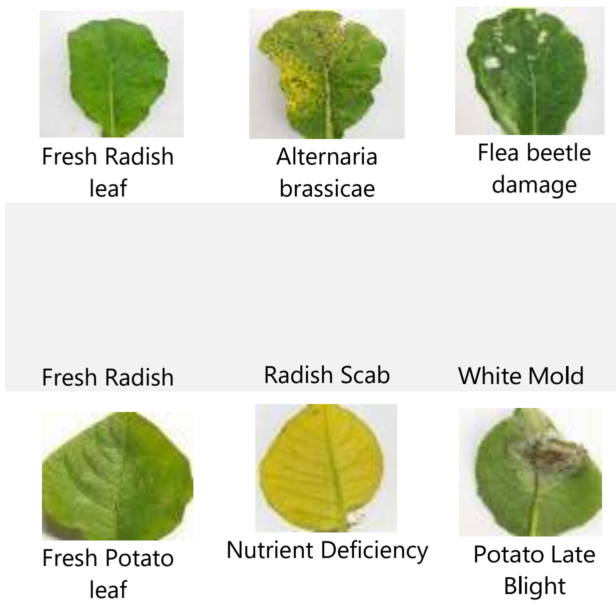

Figure 2. Sample images from Dataset.

Table 2. Dataset Description.

S. No	Plant name	Class name	Number of Image
1	Radish	Alternaria brassicae	1,012
2	Radish	Flea beetle damage	1,091
3	Radish	Radish Scab	1,011
4	Radish	White Mold	1,027
5	Radish	Fresh Radish	1,014
6	Radish	Fresh Radish leaf	1,159
7	Potato	Fresh Potato leaf	1,040
8	potato	Nutrient Deficiency	1,117
9	potato	Potato late blight fungus	1,018

Table 3. Parameters of data augmentation.

Augmentation Technique	Range
Rescale	1./255
Augmentation Technique	Range
Rotation range	20
Width shift range	0.2
Height shift range	0.2
Shear range	0.2
Zoom range	0.2
Horizontal flip	True

Table 4. Training, validation and test dataset size.

Dataset Name (% of data)	Number of images	Classes
Training (70%)	6,636	9
Validation(15%)	1,425	9
Testing (15%)	1,428	9

3.2. Model Selection
The primary objective of this study is to achieve suitable classification outcomes. This study was conducted to select a CNN-based deep learning model suitable for the investigation of Radish and potato disease image classification. The primary aim is to propose a modified novel deep-learning based CNN model to gain the highest accuracy on a large volume of radish and potato disease image data with minimal compilation time and compare the modified novel approach (accuracy, efficiency and compilation time) with existing deep learning models on the same dataset.

3.2.1. VGG19 and VGG16
The Visual Geometry Group is abbreviated as VGG. VGG16 is built using multiple dense layers sequentially. VGG's input is set to a 224 × 244×3 RGB picture. The VGG-19 convolutional neural network was trained using over a million pictures from the ImageNet database. The network has a depth of 19 layers and is capable of classifying images of multiple classes. The VGG architectures primary concept is to keep the convolution size modest and constant while designing an extremely deep network.

3.2.2. InceptionV3
InceptionV3 employs label smoothing, factorized 7 × 7 convolutions, and an auxiliary classifier to convey label information throughout the network, along with batch normalization for sidehead layers. This approach incorporates smaller convolutions to facilitate faster training and reduces grid size to address limitations related to computational costs. A variety of optimization techniques have been introduced for the InceptionV3 model to ease constraints and enhance model flexibility. The methods encompass factorized convolutions, regularization, dimension reduction and parallelized calculations.

3.2.3. ResNet50V2
The architecture of ResNet50V2 is segmented into four distinct stages. The network is designed to accept input images that have dimensions in height and width as multiples of 224×224×3 RGB, along with a specified channel width. The network is designed to accept input images that have dimensions in multiples of 224×224×3 RGB, for both height and width, along with a specified channel width. Every ResNet50V2 architecture performs the initial convolution and max-pooling using a kernel size of 7 × 7 and 3 × 3, respectively. ResNet50V2 employs bottleneck blocks featuring 1×1, 3×3, and 1×1 convolutions, optimizing deep learning processes and enhancing overall performance.

3.2.4. Xception
Xception model design improvement greatly lowers computing complexity while preserving great accuracy. Aimed at gradually collecting information from input photos, the Xception model is structured into three main components: entrance flow, middle flow and exit flow. With an input size of 224×224×3 and around 22.9 million parameters the model shows extraordinary performance in large scale picture recognition challenges such ImageNet outperforming its predecessor InceptionV3 in terms of both speed and accuracy.

3.3. Modified DenseNet121

In a DenseNet121 architecture, every layer is interconnected with all other layers, leading to the designation of Densely Connected Convolutional Network. There exists a total of L(L + 1)/2 direct connections among 'L' levels. The feature maps from earlier layers are concatenated rather than averaged, and these concatenated maps are used as inputs in each layer. Consequently, DenseNet121 require fewer parameters compared to a similar traditional CNN, facilitating feature reuse by eliminating redundant feature maps. Dense Blocks maintain a constant size for the feature maps within a block while allowing the number of filters to vary. The layers situated in between are known as Transition Layers which play a crucial role in down sampling the image through the application of batch normalization, 1 × 1 convolution and 2 × 2 pooling layers.

Modified DenseNet121 is likewise a design suited for mobile as well as computer vision like DenseNet121. To assist with computer vision, deep learning techniques are now being utilized in other areas including robotics, the Internet of Things (IoT), and Natural Language Processing. The modified DenseNet121 model, as well as the CNN layers, are used to predict and categorize diseases in Radish and potato images in this study. The modified DenseNet121 architecture includes a set of hidden layers based on a bottleneck residual block, as well as a depth-wise separable convolution that significantly lowers the number of parameters and results in a lightweight neural network that differs from typical convolution. The standard convolution is substituted with a depth-wise convolution with a single filter, followed by a depth wise severable convolution with a pointwise convolution.

3.4. Modified DenseNet121 Architecture

Proposed Modified DenseNet121 is computationally efficient, which improves performance on both big and small datasets. This work classed leaf diseases in radish and potato plants using a modified DenseNet121 architecture. DenseNet121 the basic model, was pre-trained on ImageNet and used without its top classification layer to maximize its strong feature extracting capacity. To fit the particular categorization work a bespoke classification head was added. Comprising a Global Average Pooling layer followed by three fully linked layers of 1024, 512 and 128 neurons correspondingly, each using the ReLU activation function, the architecture Dropout layers with rates of 0.5, 0.3and 0.2 were included after each Dense layer to reduce overfitting and improve generalization. Nine neurons in the last output layer used a Softmax activation function to classify pictures into nine defined groups. Every layer of the underlying DenseNet121 model was also unfrozen to allow thorough fine-tuning all along the training phase. The model was built with a learning rate of 0.000001 using the Adam optimizer the loss function was categorical crossentropy. This architectural change was meant to increase the model's performance in precisely identifying complex leaf disease patterns.

Algorithm1: Proposed Modified DenseNet121 for Radish and Potato Leaf Disease Classification.

Input: Dataset of 9,489 radish and potato leaf images including healthy and diseased categories.(70%Train,15%validation,15% Test).

Output: Result = Predicted radish and potato class label (1 of 9 categories).

Step 1: Result = Predicted radish and potato class label (1 of 9 categories). Image Size:224×224×3, batch normalization, Processing, Augmentation.

Step 2: ImageNet, excluding the top classification layer (include top=False).

Step 3: Pass the input image through the DenseNet121 base model to extract deep features.

Step 4: Apply Global Average Pooling to reduce feature maps to a single vector per image.

Step 5: Add the first Dense layer: Units: 1024, Activation: ReLU, Apply Dropout with rate = 0.5.

Step 6: Add the second Dense layer: Units: 512, Activation: ReLU, Apply Dropout with rate = 0.3

Step 7: Add the third Dense layer: Units: 128, Activation: ReLU, Apply Dropout with rate = 0.2

Step 8: Add the output classification layer: Units: 9 (number of classes), Activation: SoftMax.

Step 9: Compile the model with: Optimizer: Adam (learning rate = 0.000001), Loss Function: Categorical Crossentropy.

Step10: Finding the accuracy, precision, recall, support, F1-score, confusion metrics, Training and Validation Loss, Training and Validation Accuracy and ROC AUC curve.

3.5. Model Implementation

In order to identify and classify plant diseases, the CNN (Convolutional Neural Network) architecture is crucial in this study. A pre-trained network has been previously trained on a bigger dataset, which is usually adequate to develop a unique hierarchy from which features may be extracted. On tiny datasets, it performs better. Simonyan and Zisserman (2014) [30] created the VGG16 architecture, which is a prime example. The models used and described in the previous section are available as pre-packaged within Keras except for the novel approach. All models are firstly tuned using Keras-tune to determine the optimal hyperparameter ranges. The grid search approach is used, which is a popular method for parameter tuning. Initially, picked the following at random:

Batch size = (16,32,64,128)
Number of epochs = (100, 150, 200)
Learning rate = (0.000001)
Optimizer = (Adam)
Activation=(ReLU(hidden),Sigmoid(final))

Furthermore, the value of parameters using the grid search method for all deep learning models was achieved. The overall data of parameters post tuning is shown in Table 5.

Table 5. Model final parameters.
Table 5.1. Xception Model hyperparameters.

Hyperparameter	Value
Batch Size	16
Dropout Value	0.5(1024)
Learning rate	0.00001(ReduceLROnPlateau)
Loss	categorical crossentropy
Optimizer	Adam

Table 5.2. VGG16 Model hyperparameters.

Hyperparameter	Value
Batch Size	32
Dropout Value	0.4(1024)
Learning rate	0.000001(ReduceLROnPlateau)
Loss	categorical crossentropy
Optimizer	Adam

Table 5.3. VGG19 Model hyperparameters.

Hyperparameter	Value
Batch Size	64
Dropout Value	0.5(1024)
Learning rate	0.000001(ReduceLROnPlateau)
Loss	categorical crossentropy
Optimizer	Adam

Table 5.4. ResNet50V2 Model hyperparameters.

Hyperparameter	Value
Batch Size	32
Dropout Value	0.5(1024)
Learning rate	0.000001(ReduceLROnPlateau)
Loss	categorical crossentropy
Optimizer	Adam

Table 5.5. InceptionV3 Model hyperparameters.

Hyperparameter	Value
Batch Size	32
Dropout Value	0.5(1024)
Learning rate	0.000001(ReduceLROnPlateau)
Loss	categorical crossentropy
Optimizer	Adam

Table 5.6. Optimized hyperparameters of the Modified DenseNet121.

Hyperparameter	Value
Batch Size	32
Dropout Value	0.5 (1024), 0.3 (512), 0.2 (128)
Learning rate	0.000001
Loss	categorical crossentropy
Optimizer	Adam
Activation function	(ReLU(hidden),Sigmoid(final))

For further analysis, every model was trained multiple times over a period of 100 -200 epochs, with precision, recall, F1-score, support and accuracy (training/testing) as well as training validation curves, training validation loss curves and confusion matrices, recorded. The learning rate training pipeline is dynamically adjusted using the ReduceLROnPlateau callback, not manually fixed. The batch size varied between 16 and 128. ImageNet weights were used to train each classifier. To avoid overfitting, the number of dropout sections was adjusted. For enhanced performance, all five models except the model their epochs, optimizers, batch size and learning rate chosen using grid search. Repeated training and testing were conducted with the selected epochs and adjusted parameters to obtain performance scores. Training and testing were performed with a different epoch and optimized hyperparameters in order to get performance scores. According to the testing outcomes exhibited in Table 6, the novel method modified DenseNet121 was more trainable on image classes (Radish and potato, healthy and disease) and provided more reliable highest results when compared to the other models.

Table 6. Model performance summary.

Model	Image model & training record	Accuracy (testing)
Xception	Radish & potato No Overfitting evident (dropout Apply)	99.86%
VGG16	Radish & potato No Overfitting evident (dropout Apply)	99.86%
VGG19	Radish & potato No Overfitting evident (dropout Apply)	98.95%
ResNet50V2	Radish & potato No Overfitting evident (dropout Apply)	99.86%
InceptionV3	Radish & potato No Overfitting evident (dropout Apply)	99.51%
Modified DenseNet121 (proposed method)	Radish & potato No Overfitting evident (dropout Apply)	99.93%

3.6. Performance Evaluation Matrix

A confusion matrix was used to show the performance results [31]. The matrix is composed of the following elements: true positive (TP), true negative (TN), false positive (FP), false negative (FN) . Following the training and testing procedure, performance is evaluate using accuracy, precision, recall, f1-score and specificity. The equations used for the work are Eq. 1, 2, 3, 4 and 5.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F1} - \text{Score} = 2\left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\right) \tag{4}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{5}$$

Finally, the corresponding equations was used to evaluate the validity and reliability of the results.

4. Experimental Result

The proposed study used pre-trained CNN models and compared their performance to a new modified DesnsNet121 technique in order to get the highest performance for radish, radish leaf and potato leaf identification from 9,489 images. Along with the proposed modified DesnsNet121, the VGG16, VGG19, ResNet50V2 and InceptionV3 deep models were assessed in terms of performance and compilation time, since the purpose of the study is to find the most optimal model. The training set reaches the highest accuracy at epoch 18, whereas the test set has the highest accuracy at epoch 15 and Modified DensNet121 proposed in the research achieved the highest accuracy 99.93%, followed by the pre-trained model, Xception, VGG16 and ResNet50V2. The Xception, VGG16 and ResNet50V2 models are achieved an identical test accuracy of 99.86%. Likewise, VGG19 and InceptionV3 models all achieved accuracy of 98.95% and 99.51%. The accuracy and loss values acquired for the training and validation processes from the models were applied to the dataset. The classification training and validation accuracy score were utilized to evaluate the performance of the model and Figure 3 shows the resulting accuracy curve for recorded epochs.

A models loss value indicates how well or badly it performs after each iteration, depending on the model. Less loss means higher performance, unless a model has been over-fitted to its training data. The loss experienced by the model throughout the training and validation processes is shown and quantified in Figure 4. On average, the rate of loss decreased as the number of epochs increased. The average loss varied significantly across models.

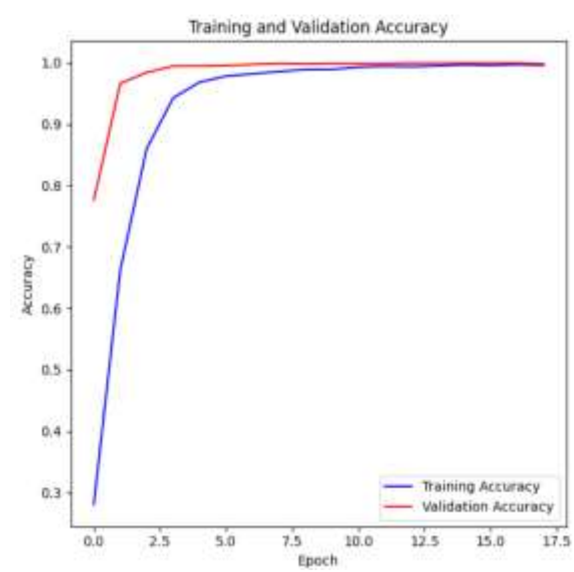

Figure 3. Modified DesnsNet121 Training and validation accuracy curve.

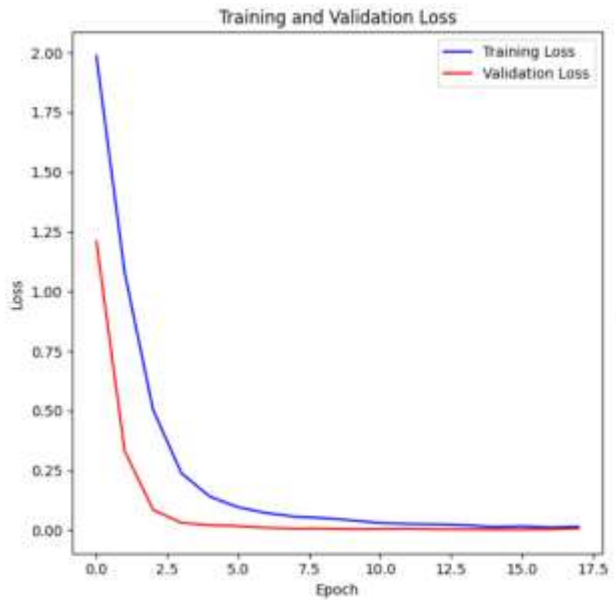

Figure 4. Modified DesnsNet121 Training and validation Loss curve.

The confusion matrix for the models is shown in Figure 5 to aid in visualizing their overall performance. Modified DenseNet121 model achieved near perfect classification across 9 classes. With values between 152 and 174 accurate predictions per class all classes were precisely predicted. One misclassification occurred when an instance of class 8 was mistakenly identified as class 1. With great accuracy, recall and low error this shows outstanding model performance.

Table 7. Modified DenseNet121 classification report.

Classes (dataset folder No)	precision	recall	f1-score	support
Fresh Radish(0)	1.00	1.00	1.00	174
Fresh Radish leaf (1)	0.99	1.00	1.00	157
Nutrient Deficiency(2)	1.00	1.00	1.00	152
Potato late blight(3)	1.00	1.00	1.00	164
Fresh Potato leaf(4)	1.00	1.00	1.00	152
Radish Scab(5)	1.00	1.00	1.00	168
White Mold(6)	1.00	1.00	1.00	153
Alternaria brassicae(7)	1.00	1.00	1.00	155
Flea beetle damage(8)	1.00	0.99	1.00	153
Accuracy	-	-	1.00	1428
macro avg	1.00	1.00	1.00	1428
weighted avg	1.00	1.00	1.00	1428

The confusion matrix was used to assess results, and the outcome represents the model's high accuracy on this dataset.

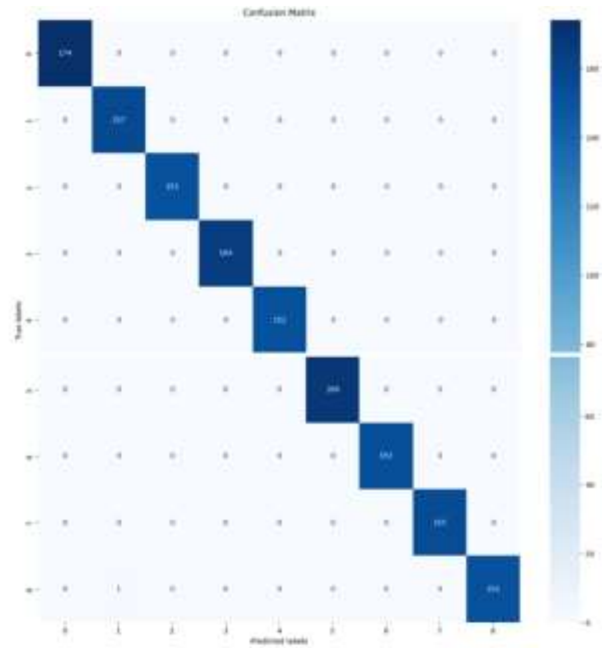

Figure 5. Modified DesnsNet121 confusion matrix.

Therefore, is observed that modified Densenet121 showed better performance than the rest of the models.

5. Conclusion

In conclusion, Deep learning has significantly impacted image processing the agriculture sector and various other applications. The goal of the study is to accurately classify diseases in radish, radish leaf and potato leaf using image data. By employing multiple convolutional neural network models including Xception, VGG16, VGG19, ResNet50V2 and InceptionV3 high classification accuracy was achieved with the proposed Modified DenseNet121 model outperforming all others with an accuracy of 99.93%.Improving crop management techniques greatly depends on the capacity of automated and consistent early stage detection of plant diseases. It helps farmers to make wise judgments, cut the usage of agrochemicals and lower financial losses resulting from plant health problems. Thus, integrating deep learning into agricultural activities helps to create better crop output and more ecologically friendly farming methods.In future work the model can be trained and tested using a more extensive dataset at the same time this model can be tested on other plant disease image datasets for classification and prediction and More investigate real time implementation through mobile apps or drones for field level disease detection and precision agriculture.

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