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ABSTRACT

Potato disease management plays a valuable role in the agriculture field as it might cause a significant loss in crops production. Therefore, timely recognition and classification of potato leaves diseases are necessary to minimize the loss, however, it is time taking task and requires human efforts. Thus, an accurate automated technique for timely detection and classification is needed to cope with the aforementioned challenges.There exist techniques grounded on machine learning and deep learning procedures that use the existing dataset i.e., 'The Plant Village Dataset' and perform classification into only two classes in potato leaves. Therefore, this article proposes a technique based on an improved deep learning algorithm that uses the potato leaf visual features to classify them into five classes i.e., Potato Late Blight (PLB), Potato Early Blight (PEB), Potato Leaf Roll (PLR), Potato Verticillium_wilt (PVw) and Potato Healthy (PH) class. The propose model is trained on the existing dataset i.e., "The Plant Village" that comprises of images having two ailments such as Early Blight (EB) and Late Blight (LB), and a Healthy class for potato leaves. Additionally, we have gathered the data for classes i.e., Potato Leaf Roll (PLR), Potato Verticillium_wilt (PVw) and Potato Healthy (PH) manually. A pre-trained Efficient DenseNet model has been employed utilizing an extra transition layer in DenseNet-201 to classify the potato leave diseases efficiently. Moreover, the usage of the reweighted cross-entropy loss function makes our proposed algorithm more robust as the training data is highly imbalanced. The dense connections with regularization power help to minimize the overfitting during the training of small training sets of potato leaves samples. The proposed algorithm is a novel and first technique to address and report the successful implementation for the detection and classification of four diseases in potato leaves. The algorithm's performance was evaluated on the testing set and gave an accuracy of 97.2%. Various experiments have been performed to confirm that our proposed algorithm is more consistent and proficient to detect and classify potato leaves diseases than existing models.

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Introduction

The economic development of any country greatly relies upon its agricultural sector. Production of Potato crops has helped in the uprising of the economy of many developed countries. Fields Security is one of the most basic challenges for any country as almost all of the developing countries face problems of malnourishment which is directly related to fields security (Oppenheim et al. 2019). Moreover, it is also the 4^{th} largest crop being cultivated in Pakistan. The latest stats depicted that potato is grown on 170,300 hectares with a total production of 4 million tones and the annual per capita intake graph is showing an upward trend. Hence, being such an integral part of the economy, farmers must pay attention to the healthy growth of potato crops (2005).

Several ailments can outbreak potato crops and the effects of all these diseases are prominent in various parts of a potato's leave. Some of the common diseases include foliage, early blight, and late blight. Early blight is triggered due to the fungal pathogen (*Alternaria Solani*) and the bacterium that is the cause of late blight in leaves of potato is *phytophthora infestans* (2002). Both diseases are fungal and fatal that can greatly influence the production of potato crops affecting the budget of the country. Moreover, Potato Leaf Roll (PLR) is caused by *Polerovirus* and makes the leaves of the potato to be rolled, whereas Potato Verticillium_wilt (PVw) is triggered through the fungal infection and transforms the color of the leaf yellow. Consequently, for optimal use of insect killers and to reduce the loss in crop production, examination of crops by the naked eye should be performed by the farmers and the local experts. However, this approach is unfeasible due to unnecessary execution time and insufficiency of experts or a greater chance of human error. Henceforth, to overcome this situation, an automated system should be designed that can detect and classify the diseases on the leaves of the plant with greater accuracy.

There exist various automated techniques for the recognition of diseases in potato plants. Islam et al. (2017) has proposed a machine learning-based algorithm i.e., SVM for disease classification for potato plants. They used the dataset namely "plant village" and trained the method for 300 samples. The proposed algorithm attained an accuracy of 95%. Sandika Biswas et al. (2014) developed a system for the detection of the ruthlessness of potato disease i.e., late blight in leaves of potatoes. They employed Fuzzy C-mean clustering and convolutional neural network for the disease detection and categorization attaining 93% accuracy. Aparajita used dynamic thresholding to detect the late blight disease of potatoes using leaf images. The threshold value was computed from the image statistical features. They trained the model on 100 images from both categories using a dataset of "Plant village" attaining an accuracy of 96%.

Thus, according to our finest knowledge, the present techniques for the disease recognition of potato leaves consider only the two main diseases i.e., late blight and early blight. Moreover, it is worth mentioning that other than these diseases, the public dataset is not available for other diseases in potato leaves for the experiments. Therefore, in this study, we are considering four diseases such as early blight, late blight, Verticillium wilt, and leaf roll utilizing our customized dataset alongwith The Plant Village dataset. Additionally, our proposed procedure is grounded on an improved architecture of the existing deep learning model i.e., DenseNet. The dense layers of the proposed technique help to mine the most representative features from the potato leave images obtained after preprocessing. Moreover, an additional transition layer after the fourth dense block reduces the feature map size consequently decreasing the computational complexity. In addition, DenseNet employs a fewer number of parameters for training than existing deep learning models i.e., ResNet, which makes it more efficient. The dataset we used has a class imbalance challenge, however, we cope with this issue using the reweighted class balance cross-entropy loss function.

The key contributions of this study are below:

- To recommend a novel and vigorous algorithm that can classify the potato leaves diseases into five classes such as Potato Late Blight (PLB), Potato Early Blight (PEB), Potato Leaf Roll (PLR), Potato Verticillium_wilt (PVw), and Potato Healthy (PH). According to the best of our knowledge, our proposed algorithm is the first successful implementation for the identification and classification of four ailments of potato leaves as most of the existing techniques classify only two diseases such as Potato Late Blight (PLB), and Potato Early Blight (PEB).
- The algorithm is a modified form of pre-trained Densely Connected Convolutional Network i.e. DenseNet-201. We have added an extra transition layer after fourth dense block of the network that increases the compactness of the network. The DenseNet's architecture allows the concatenation of features and uses a lesser parameters than other DL models. This mechanism makes possible effective detection through DenseNet layers. Moreover, the dense connections have regularization properties help to minimize overfitting during the training of small training sets of potato leaves.
- The imbalance problem in the potato leave dataset is dealt with using the reweighted class well-adjusted cross-entropy loss function during the softmax layer processing.
- To analyze the performance of the suggested system, the datasets i.e. The Plant Village Dataset and our customized dataset comprising of 1700 images have been distributed into training, validation, and testing sets. The algorithm attained 97.2% accuracy for the detection of four diseases and outperforms the existing algorithms of leaves disease detection.

Related work

The cultivating land is adequate as needed for crop sourcing nowadays. The economic growth of any under developing country is mostly relying upon the Agricultural sector. There exist various methods based on deep learning for the disease detection (Mahum et al. 2021, Mahum et al. 2021) and various mechanisms (Gul et al. 2021) have been used for the fields analysis. The early detection of diseases based upon plant leaves in 1993 results in sustaining the economy. Islam et al. (2017) employed the support vector machine (SVM) algorithm on extracted features of potato leaves using the potato village dataset. Sharma et al. (2017) has employed the adaptive thresholding method for the identification of disease using statistical features of potato leaves on plant village dataset. Hu et al. (2016) collected the dataset manually and trained the SVM classifier for the classification. Tiwari et al. (2020) has used VGG 19 with the Convolutional Neural

Network (CNN) for the classification of the leaves into diseased and healthy classes. Butte et al. (2021) has used Faster R-CNN for the detection and classification and collected the dataset using the solo unmanned aerial vehicle. Pavel (2020) has utilized Resnet 34 on the plant village dataset for the classification of potato leaf images. Ranjan et al. (2015) has proposed a methodology for the cotton plants disease detection using leaf images. Images of damaged areas are captured and after image preprocessing, Neural Network is employed over healthy and unhealthy samples attaining accuracy of 80%. Libo has employed a method to classify healthy and unhealthy plants of rice employing the Back Propagation NN (BPNN). He trained the model on 400 images of affected area of rice leaves attaining accuracy of 90%. Pinki et al. (2017) proposed the model of disease detection considering three diseases. The K-mean clustering algorithm has been utilized for the classification of the diseased part analyzing the visual features such as texture, shape, and color. The Support Vector Machine (SVM) is employed for the categorization of disease attaining accuracy of 92.06%.

Aparajita has proposed a methodology to recognize the late blight disease in the potato leaf images. This method uses segmentation to employ a statistical features-adaptive thresholding (SFAT) in leaf images. Yanikoglu et al. (Yanikoglu et al. 2014) has proposed an automated plant recognition system to detect the plant assortment among various samples. An Imaginarium pattern recognition model to identify plant diseases as (IRPD) has been developed in Sabrol and Satish (2016). Sabrol et al. has performed the categorization using color, shape along texture characteristics to recognize the non-diseased and diseased leaf images. Monzurul developed a plant ailment identification technique based on ML SVM classifier has been employed for the categorization of segmented images into healthy and unhealthy plants. Patil et al. (Patil et al. 2017) has proposed an autonomous disease management technique (ADMT) in potato plants. Gayathri Devi and Neelamegam (2019) used the wavelet transform and Scale-invariant feature transform (SIFT) along with grayscale matrix based procedure encountering the co-occurrence to investigate the diseases present in leaves of rice, and further it uses multiclass SVM and Naïve Bayes classifiers for the categorization of the images of leaves. Krishnaswamy Rangarajan and Purushothaman (2020) employed the pre-trained networks technique using VGG16 network for eggplant disease detection.

Wang et al. (Wang et al. 2017) has developed a deep CNN-based flora disease intensity detection model. Kaur et al. (Kaur et al. 2018) proposed the k-means congregation based on semi-autonomous mechanism (KCM) to segregate the leaves diseases. Sladojevic et al. (2016) proposed a deep learning-based system to recognize the disease in the samples of leaf of the plant. Brahimi et al. (2017) worked on an algorithm (SDCT) that is based on CNN for warning signs recognition and categorization in tomato leaves. The most important advantage of CNN is the autonomous feature mining from the input images. Similarly, Ferentinos (2018) has done work on the CNN model to identify leaves disease identification using the samples of plants images. Bharali et al. (Bharali et al. 2019) have done work using DL technique on leaf samples such as (DLLA) to recognize the plant diseases. Hang et al. (2019) proposed DL model for disease recognition and categorization (DLDIC) using samples plant leaves. Thus, most of the prevailing techniques depends upon only the existing "The Plant Village" dataset. Moreover, the dataset has large imbalance which significantly affects the

Table 1. Related work for the potato leaves disease detection.

Reference	Algorithms	Dataset	Accuracy	Task Type
(Islam et al. 2017)	GLCM (Feature Extraction) SVM (Classification)	Plant Village Dataset	95%	Classification
(Biswas et al. 2014)	Fuzzy C-means Neural Network	Plant Village Dataset	93%	Classification
(Sharma et al. 2017)	GFD(Feature Extraction) Random Forest (Classification)	Plant Village Dataset	97%	Classification
(2016)	LS-SVM	Manually Collected	94.87%	Classification
(2020)	VGG 19 + CNN	Plant Village Dataset	97.8%	Classification
(2014)	Fuzzy C-Means + Back Propagation Neural Network	Manually Collected	93%	Clustering
(Bharali et al. 2019)	CNN-F	Manually Collected	95.8%	Classification
(2021)	Faster R-CNN	Data collected by Solo unmanned aerial vehicle	89%	Classification
(2020)	Resnet 34	Plant Village Dataset	97.03%	Classification
(2019)	MCD + TTF	Plant Village Dataet	91.67%	Classification
(Lee et al. 2021)	CNN	Plant Village Dataset	99%	Classification
(Khalifa et al. 2021)	Deep CNN	9822 (Augmented Data)	98%	Classification

performance of the model. Furthermore, only two diseases i.e., early blight, and late blight have been detected in the discussed work. Therefore, to overcome the issue of class imbalance and to detect two more diseases, our proposed algorithm is trained using five classes of potato leaves employing an improved deep learning model. However, due to unavailability of datasets of maximum diseases in potato leaves, fields images can be captured employing various mechanisms such as satellite Khan et al. (2022) and mobile devices (Mahmood et al. 2021). Therefore, we collected our customized dataset for potato leaves disease using a camera device. The summary of existing techniques is reported in Table 1.

Methodology

In this study, a robust framework for the recognition of diseases in potato leaves is proposed. The deep and high dimensional features play a major role in the detection and characterization of disease in plants leaf. Deep learning models are famous for the mining of key features that distinguish the images and classify them in various classes. Therefore, a technique for the recognition of potato leaves disease is employed using modified DenseNet-201 architecture. The proposed model comprises of four phases such as 1) Data Gathering, 2) Preprocessing, 3) Training, and 4) Classification. After data collection preprocessing is performed using operations such as i.e., normalization, CLAHE, binary file conversion, and resizing. Normalization and CLAHE operations improve image visibility. Furthermore, binary files are formed and then resized for training and classification. More precisely, to reduce the computational cost of our model we have converted the RGB images into binary files and then stored them as RGB channels. In the end, features have been extracted and classified using modified trained DenseNet-201. Moreover, we have employed a reweighted cross-entropy loss function to minimize the effects of class imbalance in our training data. The various field's images are shown in Figure 1. The flow illustration of the projected system is presented in Figure 2.

Figure 1. Potato Field's Images captured while collecting customized data.

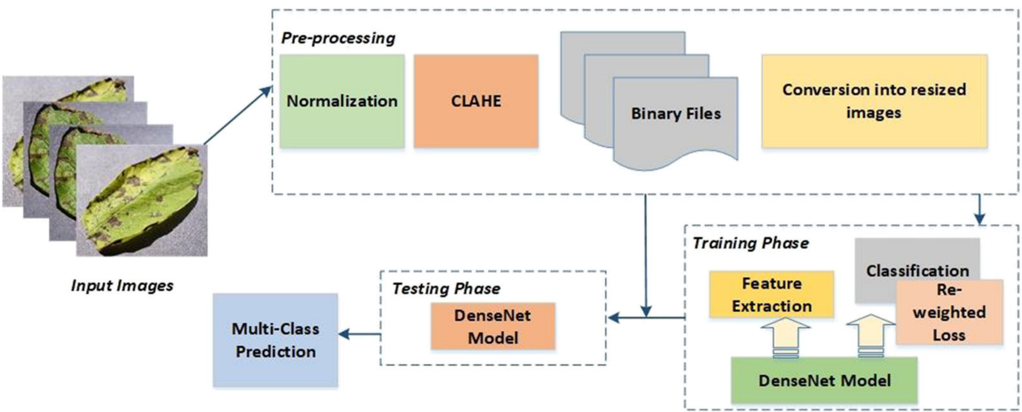

Figure 2. Flow diagram for the proposed model.

Data collection

In the initial stage, the potato leaves images have been collected from an openly accessible dataset namely Plant Village Dataset that contains a total of 2,152 images for Potato Leaves diseases among which 1000 of "Late Blight", 1000 of "Early Blight" and 152 of "Healthy Plants" are included. Other than existing dataset, 1700 images have been captured using a camera device of potato leaves having the disease Verticillium_wilt and leaf roll from various fields.

Preprocessing

After the data acquisition, preprocessing is employed to prepare the samples for the training and classification. First, image normalization is applied to change the series of original pixel values to improve the contrast of samples increasing the visibility. The equation of normalization is given in below in equation 1.

$$Norm = (I - Minimum) * \frac{NMaximum - NMinimum}{Maximum - Minimum} + NMinimum, \quad (1)$$

Where an image is denoted by I, Maximum and Minimum represent the pixel values and the difference between them depicts the range i.e., between 0 and 255. Moreover, the contrast limited adaptive histogram equalization (CLAHE) (Reza 2004) improves the prominence of the samples. The samples are divided into numerous separated regions of having the same size. However, the results are better when the original size of the image is 1024×1024, and images are divided with 8 in all directions. The output image after CLAHE is shown mathematically in equation 2.

$$CL = \{f(Z_m(x, y)) | \forall Z_m(x, y) € Z_m\}, \quad (2)$$

Where, (x,y) refers the coordinates of the pixel of an image, and $f(Z_m)$ represents the function for transformation based on density function.

In addition, the binary files are formed from the original images read in bytes that range from 0 to 255 to minimize the size of files and increase the model's efficiency. These files are stored in form of a one-dimensional array of the vector. It consists of unsigned 8-bit integers which depict the intensity level of pixel i.e., 0 refers to a black color and 1 to white color. Thus, binary files size is of varying length whereas CNN's accept images having the same size because of the fully connected layers that have a constant parameters' count. Therefore, the sample images are required to resize into a size of 128×128. The nearest interpolation technique has been used for the resampling as it keeps the image data the same. The pixel value is selected from the nearest neighbors of the specific interpolated value. This technique is better than bilinear and bicubic, as it is more simple and takes less computational time. This technique is selected for the potato leaves as each pixel value from the diseased part is crucial for the recognition of disease. Finally images are stored as RGB channels to train the model, however these images require the less storage making our model more efficient.

Efficient DenseNet

DenseNet (Huang et al. 2017) is based on deeply layered architecture having direct connections hence attaining a good flow of information. At each layer, the information increases and flows to all subsequent layers in form of maps of features. All the feature maps of the current layer are combines with the previous layers' feature maps. This fully connected layered architecture is called DenseNet which employs a fewer parameters count than classical convolutional neural networks. The motivation for using Efficient DenseNet instead of the original DenseNet is that the proposed architecture is more efficient than the original DenseNet due to an extra transition layer after the fourth Dense Block. Moreover, transition layers down-sample the representations received from the dense block, which reduces the required computational power by improving the compactness of the model.

Let suppose, we have an input image I_0, that is provided to the input layer. The architecture has total N layers that have non-linear functions for transformation individually i.e., $F_n(.)$. If n^{th} layer comprises of feature maps from previous layers i.e., $I_0, I_1, I_2, \dots \dots, I_{n-1}$ the network comprises of $N(N+1)/2$ number of layers. The output at the n^{th} layer refers by:

$$I_n = F_n([I_0, I_1, \dots\dots, I_{n-1}]), \tag{3}$$

Where I_n refers to the n^{th} layer, $I_0, I_1, I_2, \dots \dots, I_{n-1}$ represent all the feature maps of layers from 0 to n-1, whereas $F_n(.)$ represents the transformation function for ReLU.

In the transition layer there exist three operations i.e., Batch Normalization (BN), convolution of 3×3 filter, and Rectified Linear Units (ReLU). These operations do not give proper output if the feature maps have variations in size. Therefore, the layers having variations in feature maps sizes are downsampled. The transition layers having 1×1 convolution and 2×2 average pooling are fed into the mid of Dense convolutional blocks. The primary convolutional layer comprises 7×7 blocks of convolution and a stride of 2. Later the last Dense convolutional block and transition layer, and the output layer consists of average global pooling along with the softmax classifier. The precise classification is performed utilizing all feature maps. Therefore, the classification layer having Z neurons gives the correct correspondence with Z diseases.

Pooling reduces the dimensionality of feature maps in output. There exist two ways for pooling i.e., max and average. First takes the highest value from the enhanced feature map. While average divides the input among the area and takes the average value from each area. A convolutional function deals with sample matrix and filter. At each conv layer, there exists a BN-ReLU convolutional sequence. When the convolution is achieved on the feature map, ReLU is applied for the output. Hence, the nonlinear ReLU function is represented in equation 4.

$$f(I_0) = max(0, I_0) \tag{4}$$

The algorithm for the proposed system is given below.

Algorithm 1. Efficient DenseNet-201

Input: Potato leaves images (Healthy and Diseased)

Output: Classified Images as C_i

START:

1. Preprocess images to improve visibility (Normalization and CLAHE)
2. Transform to binaries arrays of images *I*, where I $\in$ {x0, x1, . . . , xn},
3. Resize images to 128 x 128 square and save as RGB channels
4. Start Training of model for all images *I:*
5. Extraction of raw features from the preprocessed images.
6. Start convolution and feature maps generation.
7. Concatenate the feature maps of a present layer with all preceding layers.
8. In the 1st Dense block I x I and III $\times$ III convolutions 6 times.
9. In the 1st transition layer I $\times$ I convolution having II $\times$ II average pooling.
10. In the 2nd Dense Conv block I $\times$ I and III $\times$ III convolutions 12 times.
11. In the 2nd transition layer I $\times$ I convolution having II $\times$ II average pooling
12. In the 3rd Dense Conv block I $\times$ I and III $\times$ III convolutions 48 times.

13. In the 3rd transition layer I × I convolution having II × II average pooling.
14. In the 4th Dense Conv block I × I and III × III convolutions 32 times.
15. In the 4th transition layer I × I convolution having II × II average pooling.
16. Global average pooling.
17. Classification through softmax classifier as C_i belonging to i classes of disease.

END

Training

To train the proposed model for the potato leaves disease detection, an adaptive optimization algorithm for learning rate is employed. It is known as Adam, used for the modification of the weights for potato leaves samples. It depicts the discrete learning rate for each parameter. It evaluates the 1st and 2nd moments of gradient for the modification of weights in a neural network. Moreover, moving averages are used for the current mini-batch based on the gradient. The mathematical notations for the 1st and 2nd moments of the gradient are represented in equations 5 and 6. The detailed architecture of modified DenseNet is shown in Figure 3.

$$a_i = \beta_1 a_{i=1} + (1 - \beta_1) g_i, \tag{5}$$

$$b_i = \beta_2 b_{i-1} + (1 - \beta_2) g_i^2, \tag{6}$$

Where a represents the moving average, β refers to the decay value, and g is the current mini-batch gradient.

To analyze the efficiency of the proposed model's classification, cross-entropy (CE) loss is computed. Its probability value ranges between 0 and 1. When the predicted class has a difference from the real class label, loss rises. The equation of cross-entropy is provided below:

$$CE = -\sum_{k}^{c} i_k log(S_k), \tag{7}$$

Where c refers to all diseased and healthy classes, i_k refers to the ground truth, and S_k represents the convolutional neural network scores for each individual class i of c.

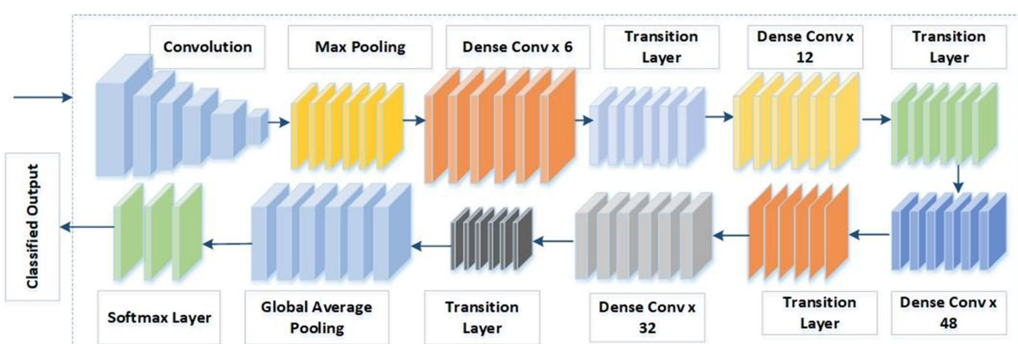

Figure 3. Detailed architecture of an Efficient DenseNet-201.

CE is the categorical loss that consists of softmax activation function and CE loss is called softmax loss. It is employed for multiple classifications and gives a computed probability of each image within a class c.

The categorical class entropy (CCE) loss for sample s according to labels of class y is represented as:

$$CE(f, y) = -log\left(\frac{\exp(f_y)}{\sum_{l=1}^{c}\exp(f_l)}\right), \tag{8}$$

The balanced cross-entropy of class (BCEC) loss for class y and n_k samples of training is represented as in equation 9.

$$BCEC = \frac{1-b}{1-b^{n_k}}\log\left(\frac{\exp(f_y)}{\sum_{j=1}^{c}\exp(f_j)}\right), \tag{9}$$

Classification

The potato leaves are classified into five classes such as leaf roll, early blight, late blight, verticillium wilt, and healthy. The final classification layer consists of the fully connected layer with the softmax function. In this layer, the number of neurons is constant conferring to the classes in the dataset. Therefore, the softmax function has been employed here for the multi-class cataloguing. The function computes the possibility distribution for individual class i. The Mathematical notation of function is given in equation 10.

$$S(y_i) = \frac{e^{j_i}}{\sum_k e^{j_k}}, \tag{10}$$

Where j_i refers to the input value and j_k belongs to all values for the image I. This formula computes the fraction of the exponential of the specific input value and the sum of all input values.

There exists a challenge i.e., the class imbalance problem that occurs in the training dataset due to uneven distribution of classes. Class imbalance is difference in the number of training samples for each class, and a significant imbalance is a challenging problem and needs an advanced method to deal with. Thus, the plant village dataset has more samples for diseased classes and fewer for healthy classes. Moreover, the self-captured images for three classes has also variations in numbers. Hence, a model that is required to be trained on these samples behaves abnormally. There exist some solutions such as data augmentation and oversampling the minority classes or down-sampling of majority classes to overcome this issue of data imbalance. However, these solutions are not suitable for potato leaves disease detection because the oversampling does not generate realistic images for potato leaves. On the other side, through down-sampling, the potato images might be overlooked.

The proposed system utilizes class-balanced loss (Cui et al. 2019) that uses a weight parameter w_i, it employs the inverse of the total samples for i^{th} class. The equation is given below:

$$w_i \alpha \frac{1}{S_{n_i}}, \tag{11}$$

Where S_{n_i} represents the number of samples referring to i^{th} class. It is represented as:

$$S_{n_i} = \frac{\left(1 - b_i^{n_i}\right)}{\left(1 - b_i\right)}, \tag{12}$$

Where *b=(I-1)/I* and *I* refers to the all probable instances for a class. It can be represented mathematically as below:

$$I = \lim_{n \to \infty} \sum_{i=1}^{n} b^{i-1} = 1/(1 - b), \tag{13}$$

Experimental evaluation

This section reports the evaluation details and results of the proposed model. In section 4.1 dataset detail is discussed, and in 4.2 employed experimental setup is represented. In sections $4.3 - 4.7$ the various experiments have been reported that we utilized to assess the performance of the proposed technique.

Dataset

For the training and testing of the proposed model for potato leaves disease detection, the data has been attained from a publically available dataset called *The Plant Village* Dataset (Hughes and Salathé 2015) that contains a total of 2,152 images for Potato Leaves diseases. However, there exist only healthy leaves images and two diseased classes' images i.e., early blight and late blight. Therefore, we have created our own dataset using a camera device for three classes such as 200 images for potato healthy (PH), 750 images for Potato Verticillium_wilt (PVw), and 750 for Potato Leaf Roll (PLR). The total number of potato leaves images of the plant village dataset and our customized dataset are 3852, among which 1326 images are carefully chosen for testing belonging to all classes. The images have been preprocessed and resized to 128×128 for the training and classification. In addition, we have divided the images of the dataset into training, validation, and testing sets considering that there should not be overlapping among these sets. The training data and validation data has been used while training the model, and the testing data has been applied for the performance evaluation of the proposed model. The detail of class wise distributed samples of The Plant Village dataset and own created dataset is shown in Table 2. We have also depicted the short abbreviations used for class names as reported in Table 2.

Table 2. Class-wise distribution of the datasets (The Plant Village, Customized).

Class/Category	No. of Images	No. of Training Images	No. of Testing Images
Potato Late Blight (PLB)	1000	500	500
Potato Early Blight (PEB)	1000	500	500
Potato Leaf Roll (PLR)	750	625	125
Potato Verticillium_wilt (PVw)	750	625	125
Potato Healthy (PH)	352	276	76

Evaluation setup and metrics

To evaluate the performance of the proposed method, we divided the plant village data randomly into testing and training sets. Moreover, we also utilized the customized images of potato leaves for the training. The experiment was performed using an NVIDIA GM107GL Quadro on a windows system having Intel® Xeon(R) CPU E3-1226 v3 at 4 GHz x 4, 32 GB RAM. The hyperparameters values were as: 100 epochs with a learning rate of 0.001, and the batch size as 32. All the experiments were performed on the Python framework with Keras v0.1.1 library. We analyzed the performance of the proposed model using an image size of 256×256 and 64×64 as well. However, it is considered that results are better in accuracy for the image size of 128×128. The training and testing accuracies plot is shown over the number of epochs using the dataset for the proposed model in Figure 4. It is depicted that the accuracy is rising as the number of epochs is increasing.

Metrics: The metrics utilized for the assessment of the proposed model are True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP is the percentage of the prediction that an image is from a specific class and it belongs to that class in actuality, i.e., if a leaf has the disease of leafroll and it is predicted as PLR. TN is the percentage of the prediction of an observation that an image doesn't belong to a class and it doesn't belong to that class in actuality. For example, if a leaf is healthy and it is not predicted as any diseased image by the proposed system. FP is the prediction of observation that an image is from a negative class and it is predicted as it doesn't belong to that class, i.e., if an image does not have any disease and it is predicted as potato late blight. FN is the prediction of an image that if it is not from a negative class and it is predicted as it does belong to that class, i.e., a leaf has a disease and it is predicted as negative such as potato healthy (PH).

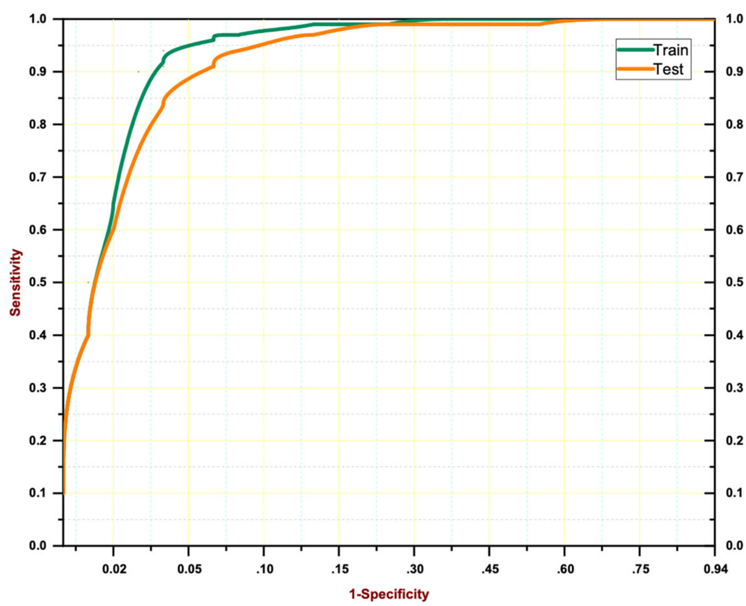

Figure 4. Training and testing accuracies of proposed model over The Plant Village dataset.

These four metrics have been used to build the confusion matrix to present the analysis of the result. The order of matrix depends upon the number of classes such as if classes are N then the confusion matrix will have N x N matrix, having true class on the left axis and the predicted class to an image on the top axis. Let suppose x represents the actual class and y represents the predicted class. Confusion metrics elements for the individual class are shown below, where M represents the matrix.

$$TP_x = M_{xx}, \tag{14}$$

$$FP_x = \sum_{i=1}^{n} M_{ix} - TP_x, \tag{15}$$

$$FN_x = \sum_{i=1}^{n} M_{xi} - TP_x, \tag{16}$$

$$TN_x = \sum_{i=1}^{n} \sum_{j=1}^{n} M_{ij} - TP_x - FP_x - FN_x, \tag{17}$$

In addition, the four metrics i.e., accuracy, precision, recall, and F1 score are used for the evaluation of classification performance. Accuracy represents that how many correct predictions have been made using the proposed model. It is computed as the number of correct predictions divided by the total number of predictions made using the proposed system. The equation of accuracy is given below.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{18}$$

Precision is the percentage of those images that are accurately classified by the proposed system. It is computed as the number of actual positive class images divided by the total number of positive class images predicted by the proposed model. The mathematical form is given in equation 19.

$$Precision = \frac{TP}{TP + FP}, \tag{19}$$

The recall is the percentage of images that were Non-Healthy that the system recalled. It is computed as the fraction of the correctly classified positive instances to all the positive class images.

$$Recall = \frac{TP}{TP + FN}, \tag{20}$$

F1 score represents the accuracy of the proposed model on the dataset. It is computed as the harmonic mean of precision and recall. It depicts the robustness of the classifier. The performance results of the proposed model are reported in Table 3 for the disease detection in potato leaves. Equation 21 shows the mathematical formula for the F1 score.

$$F1score = 2* \frac{Precision*Recall}{Precision + Recall}, \tag{21}$$

Table 3. Performance evaluation of the proposed Deep Learning model on the testing data.

Class	TP	TN	FP	FN	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Potato Late Blight(PLB)	489	0	3	8	97.8	99.4	98.4	98.89
Potato Early Blight(PEB)	493	0	5	2	97.6	99	99.6	99.3
Potato Leaf Roll(PLR)	121	0	3	1	96.8	97.6	99.2	98.4
Potato Verticillium_ Wilt(PVw)	122	0	2	1	97.6	98.4	99.2	98.8
Potato Healthy(PH)	73	0	3	0	96.1	96.05	100	98
Average					97.2	98.09	99.28	98.67

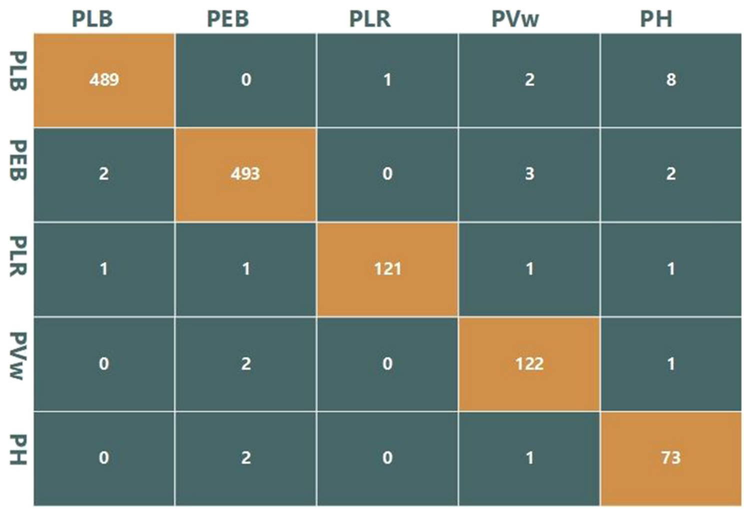

Figure 5. Confusion matrix for the proposed classifier.

Therefore, it is depicted in Table 3 that the proposed system attained 97.2% accuracy overall to classify the potato plants into five classes such as PLB, PEB, PLR, PVw, and PH. Moreover, the individual binary classification results of the classifier are also shown in Table 3. The precision of the proposed system is 98.09% and the F1 Score is 98.67%. Furthermore, in Figure 5, a detailed confusion matrix for multi-classification has been represented. It can be seen that 489 PLB test images have been correctly classified through our proposed model, however, 1 image has been incorrectly classified as PLR, 2 images have been incorrectly classified as PVw, and 8 images have been incorrectly classified as PH class. Similarly, 493, 121, 122, and 73 images have been correctly classified as PEB, PLR, PVw, and PH class respectively. Whereas, 7, 4, 3, and 3 images have been falsely classified as either positive (diseased class) or negative (healthy class) for PEB, PLR, PVw, and PH class. The visualization of the performance for the proposed system is shown in Figure 6. Some of the samples from the dataset are shown in Figure 7.

Comparative analysis with CNN-based existing techniques

There exist various techniques for disease detection specifically in potato leaves. The convolutional neural networks perform better than traditional machine learning based algorithms for the classification due to the back progpagation strategy to reduce the cost. Thus, the existing proposed techniques for the potato leaves disease detection

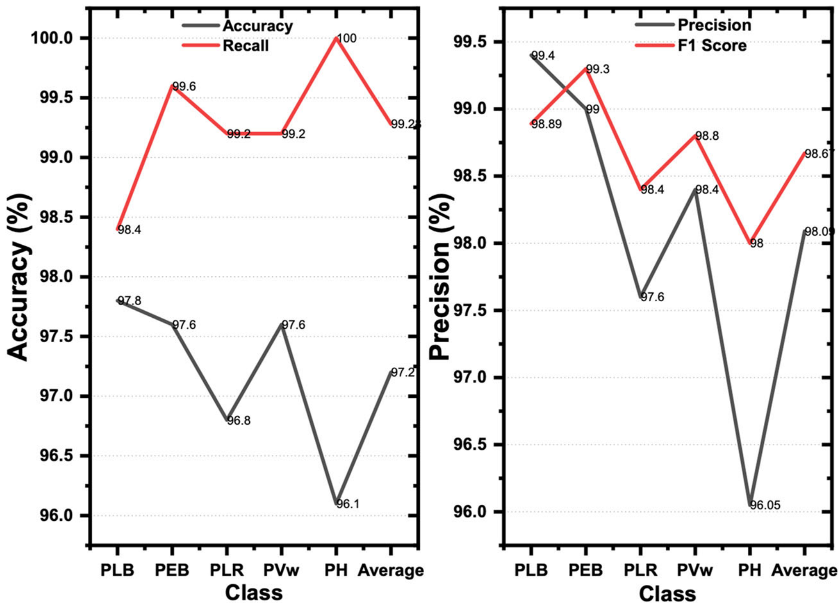

Figure 6. Plot for performance of the proposed model.

employed The Plant Village dataset. To assess the performance comparison of the proposed system with existing CNN-based techniques is presented in Table 4. We employed DenseNet-201 and the proposed Efficient DenseNet model to assess the performance for potato leave detection using The Plant Village Dataset. The DenseNet-201 consists of four dense blocks and the information flows from input layers to the output layer without any loss. Moreover, the dataset consists of leaf images of three classes' namely early blight, late blight, and health class. Therefore, existing techniques detect and classify only two diseases such as Early Blight, and Late Blight. Therefore, we proposed a model which detects and classifies the diseases of potato leaves into four classes i.e., leaf roll, early blight, late blight, and verticillium wilt. In Tiwari and Ashish (2020), the algorithm is proposed based on VGG19 with CNN for the recognition and categorization of potato diseases into early blight, late blight, and healthy. Although they have achieved an accuracy of 97.8%, however, our proposed algorithm achieves an accuracy of 97.2% detecting the four diseases. In Butte et al. (2021), the deep learning-based algorithm has been proposed for the detection of stress in aerial images of potato crops. In Biswas et al. (2014), the proposed algorithm detects the severity level of one disease i.e., late blight achieving an accuracy of 93%. In addition, our proposed algorithm is based on one stage network while (Tiwari et al. 2020) employed two architectures. The performance of DenseNet-201 is significant i.e., 96.03% accuracy, whereas an Efficient DenseNet gives 97.2% accuracy. More precisely, our algorithm is robust and extracts the most representative features from the images. Thus, due to its improved architecture, the complexity of the model was reduced to a minimum by decreasing the number of parameters.

Comparison with existing plant disease detection models

Here, we discuss the evaluation procedure of the proposed model with existing techniques of the plant leaf disease detection employing binary classification i.e., Healthy and

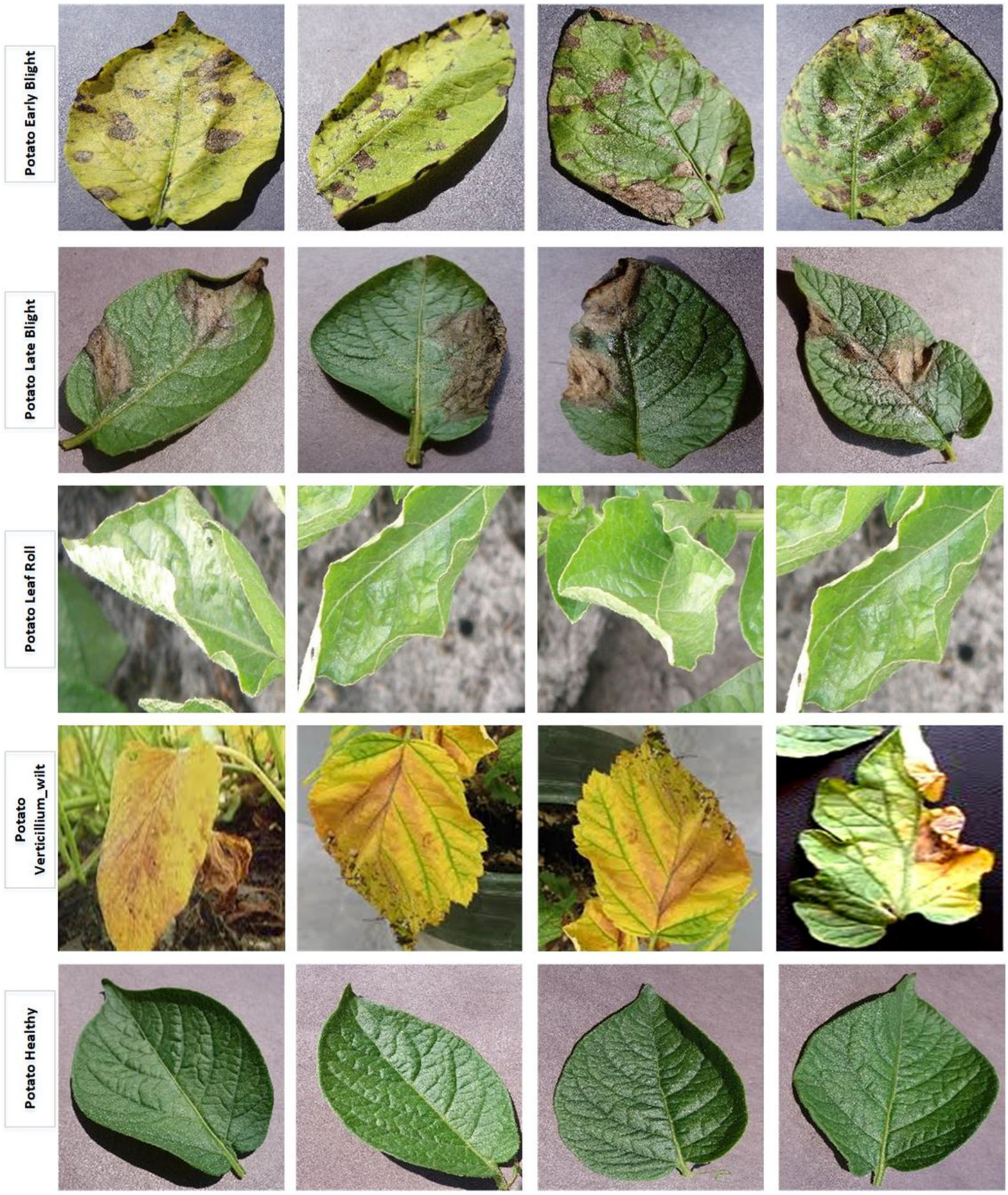

Figure 7. Potato leaves samples from the dataset.

Table 4. Comparative analysis of the proposed model with CNN-based existing techniques.

Authors	Their Proposed Models	Accuracy (%)
(Tiwari et al. 2020)	VGG 19 + CNN	97.8
(Biswas et al. 2014)	Fuzzy C-Means + Back Propagation Neural Network	93
(Athanikar and Badar 2016)	segmentation + backpropagation neural network	92
(Islam et al. 2017)	Image segmentation + Support Vector Machine	95
(Oppenheim and Shani 2017)	CNN-F	95.8
(Butte et al. 2021)	Faster R-CNN	89
(Pavel 2020)	Resnet-34	97.03
The Proposed Technique	**DenseNet-201**	**96.03**
	Efficient DenseNet	**97.2**

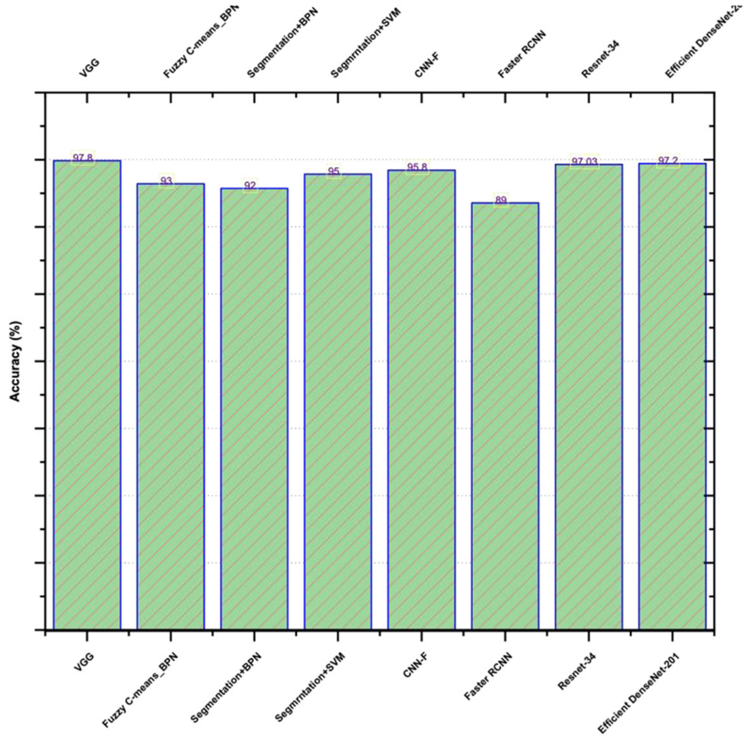

Figure 8. Comparison of the proposed model with existing CNN based disease detection techniques.

Table 5. Comparison of the proposed model with existing plant disease detection models.

Reference	Year	Aim	No. of Images	Algorithm	TCC (%)
(Mohanty et al. 2016)	2016	Plant Disease Detection	54306	AlexNet	93.88
(Sladojevic et al. 2016)	2016	Plant Disease Detection	2589	CNN	96.3
(Amara et al. 2017)	2017	Banana Leaves Disease Detection	3700	CNN	92.88
(Ashqar and Abu-Naser 2018)	2018	Tomato Leaf Disease Detection	9000	CNN	95.54
(Geetharamani and Pandian 2019)	2019	Plant Leaves Disease Identification	54305	CNN	96.46
(Hu et al. 2019)	2019	Tea Leaves Disease Identification	4980	VGG16	90
(Ozguven and Adem 2019)	2019	Sugar Beet Leaves Disease Detection	155	Faster RCNN	92.89
The Proposed Model	2022	Potato Leaf Disease Detection	3852	Efficient DenseNet	97.2

Diseased. The comparison plot is shown in Figure 8. As shown in Table 5, significant accuracy as two-class classification (TCC) has been attained using CNN and DL techniques (Mohanty et al. 2016), (Ashqar and Abu-Naser 2018), (Geetharamani and Pandian 2019), (Hu et al. 2019)), however, the number of images were also huge than our proposed method during the training phase. Ozguven and Adem (2019), Sladojevic et al. (2016) and Amara et al. (2017) employed less number of images than our proposed model, however the accuracy of the models are not comparable with the proposed system. Moreover, in the proposed system, we fine tune the parameters well and use dense architecture to give a high accuracy. The proposed efficient DenseNet-201 employs four dense blocks separated through transition layers. We have added an extra transition layer after fourth dense block to make our classifier more efficient and compact. Additionally, Efficient DenseNet utilized lesser number of features than other existing

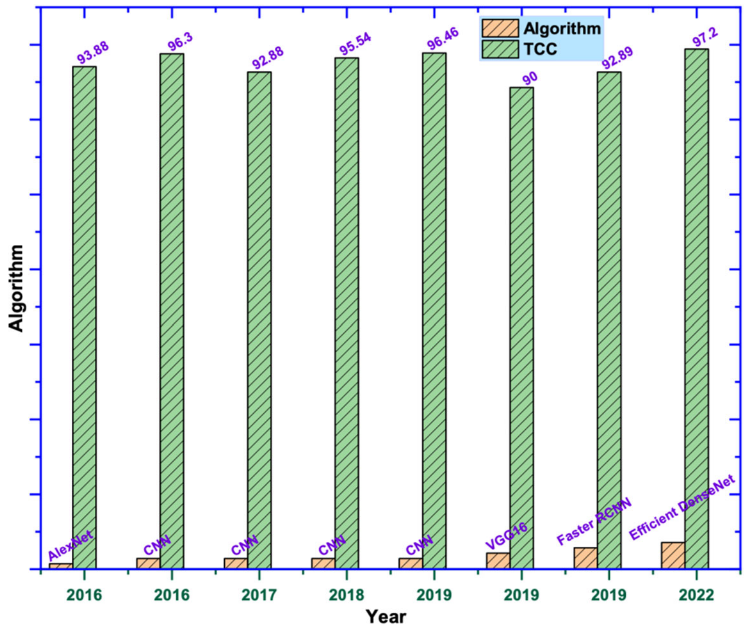

Figure 9. Performance comparison with existing plant leaf disease detection techniques.

Table 6. Comparative analysis of the proposed model with ML-based eechniques.

Reference	Year	Algorithm	Plant Type	No. of Diseases	Total Images	Training Images	Testing Images	Accuracy (%)
(Singh and Misra 2017)	2017	SVM	Banana	5	106	60	46	95.7
(Zhang et al. 2015)	2015	KNN	Corn	5	100	90	10	90
(Mondal et al. 2015)	2015	NB	Okra	2	79	40	39	87
(Mohan et al. 2016)	2017	KNN	Paddy	2	330	198	132	76.5
(Tian et al. 2011)	2010	SVM	Wheat	4	200	150	50	95.1
The Proposed Model	2021	Efficient-DenseNet	Potato	4	3852	2526	1326	97.2

DL models such as Resnet. On the other side, it is known that the variations in light during the leaf image caption, the accuracy of the model is affected negatively. Therefore, our proposed model is designed to detect leaf diseases in real-time scenarios due to usage of our customized dataset during training phase. As various deep learning models have been employed for plant disease detection such as AlexNet, GoogleNet, CNN, VGG16, and Faster RCNN however they were unable to achieve such a better accuracy than our proposed model as shown in Figure 9.

Comparison of ML-based techniques for leaf disease detection

Here, we discuss the various existing techniques for leaf disease detection grounded on machine learning algorithms. The traditional machine learning algorithms require hand-crafted feature extraction for the detection and classification, whereas our proposed algorithm grounded on DNN generates the feature maps automatically. Furthermore,

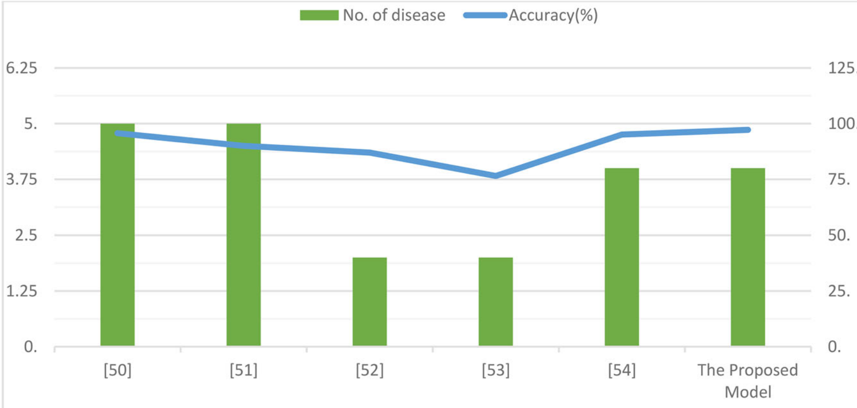

Figure 10. Plot for comparison of the proposed model with ML-based techniques.

machine learning based methods utilize small size of dataset for training, whereas deep learning based models require large dataset size for training. However, the machine learning based algorithms face the issue of generalization. As in (Singh and Misra 2017) five banana leave diseased have been detected by the authors. They employed the SVM classifier and trained it over 60 images collected using the digital camera. Moreover, the accuracy of the algorithm was 95.7%. The authors of (Zhang et al. 2015), employed k-Nearest Neighbor (KNN) algorithm to detect the five diseases of corn leaves, using the images taken by the camera. They attained 90% accuracy. The Naïve Bayes (NB) algorithm has been used by (Mondal et al. 2015) to classify the leaves of okra into healthy and diseased classes. They employed 79 images, however used 49 images to train and 30 to test the model. The algorithm classified the leaves with an accuracy of 87%. Furthermore, two techniques i.e., SVM and KNN has been employed by (Mohan et al. 2016) to classify paddy leaf into two diseases achieving an accuracy of 93.3% and 91.10% respectively. They used 120 samples among which 90 samples were utilized for training and the remaining 30 utilized for testing. In (Tian et al. 2011), four diseases of wheat leaves have been classified using 150 images for training and 50 images for testing. They proposed the multiple classifier systems (MCS) for the classification and attained 95.1% accuracy. Thus, the detailed analysis is reported in Table 6. It is depicted that our proposed algorithm based on a very deep network effectively classifies four plant diseases i.e., potato leave diseases. Our proposed algorithm utilizes greater number of images for training, however it is based on deep learning architecture that extracts the features automatically. In addition, our proposed algorithm is able to tackle the overfitting in training data. Graph of comparative analysis is shown in Figure 10.

Comparison with segmentation-based techniques for leaf disease detection

In this unit, we compare the suggested method with existing segmentation-based techniques to examine the performance of our technique for leaf disease detection. Segmentation is the procedure to divide the sample into numerous segments and mine the affected part from the image. There exist several segmentation-based techniques for leaf disease recognition. In (Soni and Chahar 2016), the authors proposed the two-stage technique for disease detection, Firstly, the segmentation algorithm based on the ring has been employed to mine the color intensity features from the images. Secondly, they employed Probabilistic Neural Network (PNN) classifier for the binary classification of plants leaf achieving 90% accuracy. In (Rothe and Rothe 2019), cotton plants have been categorized using the dataset collected from Nagpur's fields. They employed a filter to improve the edges of leaves at the initial phase. Furthermore, they applied the Otsu segmentation mechanism to extract the affected part from the images. After that, nine color, 22 texture, and 4 shape features were extracted and fed to Feed Forward Neural Network. The model achieved 95.48% accuracy. A novel model has been proposed in (Sun et al. 2018) based on Multiple Linear Regression (MLR) to detect the number of plants diseases. After preprocessing, an improved histogram approach has been introduced to calculate the threshold value automatically. Then the affected part was subtracted and later features were extracted based on texture, color, and shape. In the end, MLR was employed to classify the leaves giving 90% accuracy. The pea plants have been assessed for classification into healthy and diseased classes (Singh et al. 2019). Firstly, preprocessing is performed using Gaussian filters to remove noise from images. In addition, a log transform was applied to enhance the images. In the end, binary threshold techniques were used for the segmentation. In the end, the SVM classifier has been applied on extracted wavelet features of segmented images achieving 89.6% accuracy. Moreover, palm oil leaves have been classified using a Multi-class SVM classifier into diseased and healthy images (Masazhar and Kamal 2017). Then k-means segmentation algorithm was employed to separate the unhealthy part of the leaf. Later, 13 features including shape, color, and texture have been used for the classification attaining an accuracy of 95%. In (Iqbal and Talukder 2020), three ailments of potato leaves have been classified employing seven different ML algorithms. Firstly, 450 images have been preprocessed and segmented using the color threshold segmentation method. Later, features were extracted using Humoment, Histogram, and Haralic methods and classified using seven algorithms. The highest accuracy of 97% was attained by RF.

Therefore, the analysis clearly shows that our proposed algorithm outperformed the existing segmentation-based techniques which require more processing time. Our algorithm extracts features automatically and easily encounter the challenge of over-fitting extracting more representative features. The existing techniques are computationally less efficient than the proposed algorithm. The detailed analysis is reported in Table 7 and the plot is shown in Figure 11.

Conclusion

In this study, an automated technique for disease detection and classification for potato leaves is proposed. The proposed model is trained for the five classes such as Potato Healthy (PH) and four diseased classes i.e., Potato Late Blight (PLB), Potato Early Blight (PEB), Potato Leaf Roll (PLR), and Potato Verticillium_wilt (PVw). Moreover, due to limited datasets, the 1700 leave images for the PLR (750), PVw (750) and PH (200) have been captured under a normal environment to make the proposed algorithm more robust and contextual independent. The dataset is distributed into two parts i.e.,

Table 7. Comparison of the proposed model with segmentation-based techniques.

Reference	Year	Segmentation	Features	Training and Testing	No. of Disease	Classifier	Accuracy (%)
(Soni and Chahar 2016)	2017	Ring	Color and Intensity	NA	NA	Neural Network	90
(Rothe and Rothe 2019)	2019	Ostu	Color, Shape, and Texture	70,30	3	Neural Network	95.48
(Sun et al. 2018)	2018	Improved Histogram	Color, Texture, and Shape	NA	NA	Multiple Linear Regression	90
(Singh et al. 2019)	2018	Binary Threshold	Wavelet	NA,500	1	SVM	89.6
(Masazhar and Kamal 2017)	2018	K-means	Color, Texture, and Shape	NA	2	SVM	95
(Iqbal and Talukder 2020)	2020	Color Threshold Method	Humoment, Histogram, and Haralic	450-100	3	RF	97
The Proposed model	2021	NA	Automatic	3852-1326	4	Efficient DenseNet	97.2

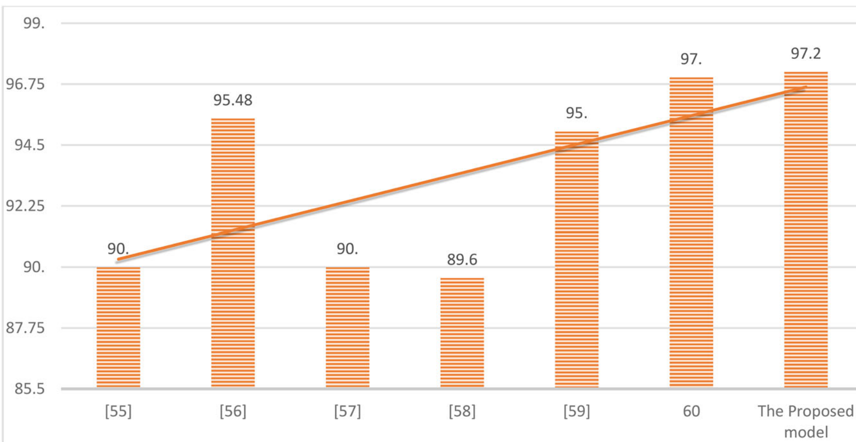

Figure 11. Comparative plot of the proposed model with segmentation-based techniques.

2526 for training and validation and the other 1326 for testing. The proposed system is based on an efficient pre-trained DenseNet-201 architecture that reweights the cross-entropy loss function to cope with the challenge of class imbalance in the dataset. The model effectively and efficiently identifies the diseases in potato leaves due to the small size of training and testing images. Furthermore, the algorithm achieves 97.2% accuracy and is computationally fast due to usage of preprocessed images and an additional transition layer.

Although, our proposed algorithm attained significant results, however, we aim to use it in future after some modifications in its architecture for various fields such as human disease detection, activity recognition in surveillance systems, and other plants disease detection problems. We also aim to reduce its training time and adjust the parameters so that a minimum number of images should be required for the training phase giving significant results. Additionally, our proposed model is flexible enough and easily fine-tuned to be utilized as base network in object detection techniques such as Centernet, and YOLO. Therefore, we will be performing experiments to use our proposed model in these algorithms after some modifications.

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Disclsoure statement

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