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Design of Novel Machine Learning Model for Leaf Disease Detection Using Deep Learning Technique

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Abstract

Plant diseases are one of the main causes of obstruction in plant production, which can lead to the deficiency of food supply worldwide. It is recommended to diagnose plant diseases at their initial phase to reduce agriculture loss. So, there is an urgent need for markedly improved detection, monitoring, and detection of plant diseases. The primary emphasis of this research is to design a novel hybrid model to categorize potato leaf diseases at their earliest with the deep convolutional network by assessing leaf images. This proposed work is based on image feature extraction to train and test the proposed hybrid model. The dataset of 1200 potato leaf images were extracted from the Plant-Village dataset for leaf disease detection. The proposed system for leaf disease detection produced an enhanced training accuracy of 98.60% while training loss reduced to 0.0394 after 25 epochs. The proposed system will be beneficial for the farmers to diagnose leaf diseases at their earliest by evading manual identification which is a very tiresome and labor-intensive task.

***Key words*:** Convolutional neural network, Deep learning, K-Nearest neighbors, Machine learning, Support vector machine

Plant diseases have an impact on the evolution of their species; therefore, their early identification is very much effective [1]. Modern times have seen the most significant evolution in the use of machine learning in farming. The identification of plant diseases from plant images is one custom of machine learning in agricultural research [2]. A diversity of machine learning algorithms like Naive-Bayes, KNN, Decision trees, Support vector machines, fuzzy clustering, neural networks, random forest, logistic regression, and deep learning methods are frequently used for plant disease diagnosis in the agricultural sector [3]. Many machine learning models have been used to detect and categorize plant diseases, but with recent developments in Deep Learning (DL), a subset of machine learning, this field of study seems to offer enormous potential for increased accuracy [4]. Deep learning is an advantageous methodology that can lessen the computation power required to train the models. Batch oriented convolutional and pooling layer in CNN provides improved results for classifying and detecting plant diseases. Therefore, it is crucial to correctly classify plant diseases at initial manifestation to accurately manage plant diseases. The early diagnosis and categorization of damaged leaves is always beneficial to agricultural growth. Identification of plant diseases is imperative to prevent losses within the yield. It's dreadfully troublesome to perceive the plant disease manually as it requires an incredible quantity of labor to detect with extreme time intervals. So, the main purpose of machine learning is to comprehend the training data and fit that training data into models that should be valuable for plant disease detection [5]. Disease on a plant can be recognized by the change of shape, color of the leaf, and damage proportion of the leaf which is used for detecting plant diseases. In order to facilitate early preventative measures and predictive maintenance, the proposed approach sought to anticipate illness detection in its early phases. Convolutional Neural Networks (CNN), an advanced artificial technique, has emerged as a viable means of increasing accuracy, despite their high sample volume need [6]. This research focused on CNN algorithm to formulate hybrid model for identifying and categorizing plant diseases to examine both healthy and diseased potato plant leaves [7-8]. So, recognition of leaf diseases using deep learning at the right time can be enhanced concerning the machine learning approach.

Section II comprises the recent related works in the agriculture sector using machine learning algorithms for crop/leaf detection with significant consequences. Section III of the research depicts the Materials and methods applied for plant diseases using deep learning with Python (Jypyter). Section IV defines the results received from the system with accuracy by implementing the training and testing the data from the Plant Village dataset. The final section determines the conclusion of the research with its future scope.

Machine Learning presents significant outcomes to foretell various leaf diseases by using Machine Learning approach. Various researchers contributed to the detection of leaf diseases by employing a variety of classifiers, algorithms, and models. Some of the related works used by researchers to deal with leaf detection or classification (Table 1).

Sibiya and Sumbwanyambe [9] framed graphical user interface technique using CNN algorithm to detect maize

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diseases. Three different types of maize diseases as grey spot, rust leaf and blight leaf were classified during the study. During the study, 91% accuracy for grey spot, 87% accuracy for rust leaves, and 99% accuracy for blight leaves were indicated in order to diagnose maize disease. Belal and Samy [10] trained DCNN algorithm to identify five different diseases in tomato leaves. The authors applied a convolutional neural network (CNN) algorithm on 9000 images in order to identify various diseases affecting tomato leaves and the data was retrieved from the Kaggle repository. Inception model was also used to attain the accuracy rate up to 99% when training and testing the dataset [11]. The similar representation on tomato leaf disease was provided by Maniyath and Hebbar [12] who proffered plant disease detection using Extreme Learning Machine (ELM) in conjunction with neural network technique. ELM classifier was used to train the model on tomato plant leaves which showed 85% accuracy in comparison with other machine learning models. In continuation, Harakannanavar *et al*. [13] worked on tomato samples to extract quality pictures of healthy and infected leaves using Histogram Equalization. Multiple machine learning approaches were used to identify tomato diseases with 6 different disorders. The model was tested on 600 sample images and approved KNN algorithm attained 97% accuracy while CNN was deemed to have achieved 99.6% accuracy. In addition to the crop disease identification, Mangala *et al*. [14] used support vector machine classification to create a system for detecting paddy crop diseases. Otsu threshold technique was applied to distinguish healthy and unhealthy paddy leaves. The similar approach was accumulated by Shrivastava *et al*. [15] to classify multiple rice diseases based on DCNN learning and SVM classifier. Using the pre-trained data from the existing dataset as a feature extractor, DCNN was able to achieve an accuracy of 91.37%. Through the use of deep convolution neural networks, Park *et al*. [16] devised a deep learning system for disease diagnosis in strawberry leaf pictures. Using acquired images, 92% accuracy was achieved in disease identification, allowing for the categorization of strawberry leaves into healthy and diseased states. Wallelign *et al*. [17] applied a CNN classifier to analyze soybean leaf images from four different classes in the Plant-Village dataset in order to categorize Soybean plant diseases. With an accuracy rate of 99.32%, their model demonstrates that it is possible to extract important features and categorize soybean plant diseases using CNN. Ahmed and Reddy [18] focused to automate detection of plant leaf diseases using mobile based system. The proposed system worked via CNN deep learning approach to classify 38 diseases. More than 96,000 images from various online repositories were used to train and test the proposed model using the Convolutional Neural Networks (CNN) technique. In order to provide plants fertilization possible, an android app was used to automatically captured images of diseased plants and classifies them according to health range. 14 crop species were classified with 94% accuracy by recognizing 38 different diseases.

Table 1 Summary of literature with findings

Authors	Crop / Leaf detection	Methodology and findings
Sibiya and Sumbwanyambe [9]	Maize leaves	CNN algorithm to detect three different diseases in maize leaves with overall 92% accuracy
Belal and Samy [10]	Tomato leaves	DCNN algorithm to diagnose five tomato leaf diseases with 99% accuracy
Mangala *et al*. [14]	Paddy leaves	SVMM classification to identify paddy leaves by using Ostu Threshold approach
Shrivastava *et al*. [15]	Rice plants	DCNN algorithm with SVM classifier to detect unhealthy rice plants with 91.37% accuracy
Park and Kim [16]	Strawberry leaves	92% accuracy with DCNN algorithm and Image Acquisition to identify damaged leaves
Wallelign *et al*. [17]	Soybean plants	CNN classifier to extract unhealthy soybean plants and proved 99.32% accuracy
Ahmed and Reddy [18]	Multiple leaf detection	Identified 14 crop species with 38 different diseases using CNN classifier with an accuracy rate of 94%
Smruti *et al*. [19]	Cotton Leaves	KNN and Transfer learning algorithms to distinguished damaged cotton leaves showed 95% accuracy
Vijay and Misra [21]	Banana and lemon leaves	SVM classifier with genetic algorithm and proved 97% accuracy with multiple disorders
Paymode and Malode [22]	Grape leaves	CNN based VGG-16 model for segmenting grape leaves with 95% accuracy
Ayaz *et al*. [23]	Apple leaves	Deep CNN and Deep NN algorithms for apple disease detection and retrieved 95.6% accuracy

Smruti *et al*. [19] focused on cotton leaf diseases by utilizing KNN and Transfer learning algorithms. KNN algorithm achieved 86% accuracy by distinguish curl and bacterial blight disease on cotton leaves whereas Transfer learning differentiate healthy and unhealthy cotton leaves with 95% accuracy. The similar approach was also presented by Rothe and Kshirsagar [20] targeted cotton leaf disease by extracting different leaf patterns. Snake segmentation was chosen as a key attribute while identify infection area on a leaf. In order to achieve an accuracy of 85%, the classification was carried out using the BPNN classifier. In order to identify diseases using SVM Classifiers, Vijay and Misra [21] concentrated on banana, bean, and lemon plant leaves. The use of a genetic algorithm for segmentation facilitated the extraction of leaves from the samples. Further outputs like early scorch in banana leaves, sun-burn disorder in lemon leaves, and fungal existence in beans led to a 97% accuracy rate. Paymode and Malode [22] emphasized on grapes and tomato leaves detection using CNN based VGG-16 model to classify sick leaves based on visual geometry grouping. Convolutional, flatten and pooling layers were employed for better image processing while training and testing the data samples. 95% accuracy of tomato leaves and 98% accuracy of grape leaves were obtained while performing the sampled data. Ayaz *et al*. [23] conducted deep learning in conjunction with multiple classifiers to investigate apple leaf diseases. The dataset comprises 300 apple leaf images from the Kaggle repository, which were further trained using a deep convolutional layer.

The use of filters allowed for the separation of clear and blurry pictures in the screening for leaf diseases. Deep Neural Network was also implemented on same images with augmentation and pooling layer. 93% accuracy was achieved using deep convolutional approach and 95.6% accuracy was attained using deep neural network approach. So, these are some recent contributions by various researchers in the field of agriculture which proves machine learning a better paradigm for leaf disease detection.

MATERIALS AND METHODS

Deep learning is subset of machine learning consists of multiple layers that produce promising results when dealing with sophisticated problems involving huge datasets such as images and text [24]. The last three decades bestows deep learning a dominant approach to tackle large datasets. Deep neural network comprises several layers of interconnected nodes, each structure be contingent upon the preceding layer to refine the prediction. The agricultural sector frequently uses deep learning for the purpose of making error-free, optimal diagnoses of leaf diseases using plant images [25]. One of the most widely used deep learning techniques, Convolutional neural network (CNN)/ConvNet is primarily used in image classification applications throughout the globe to identify objects, detect features, and identify patterns in images [26]. In a convolutional neural network (CNN), the first layer obtains the most fundamental visual features, such as the edges of the picture, while the subsequent layers identify more complicated elements, such as the corners [27]. Each subsequent layer in batches generates activation functions for image identification. The activation map assigns each image to a distinct class, and the output layer uses this information to generate a confidence score between zero and one. Convolutional neural network (CNN) architecture to detect classification of leaf diseases is represented in the given (Fig 1).

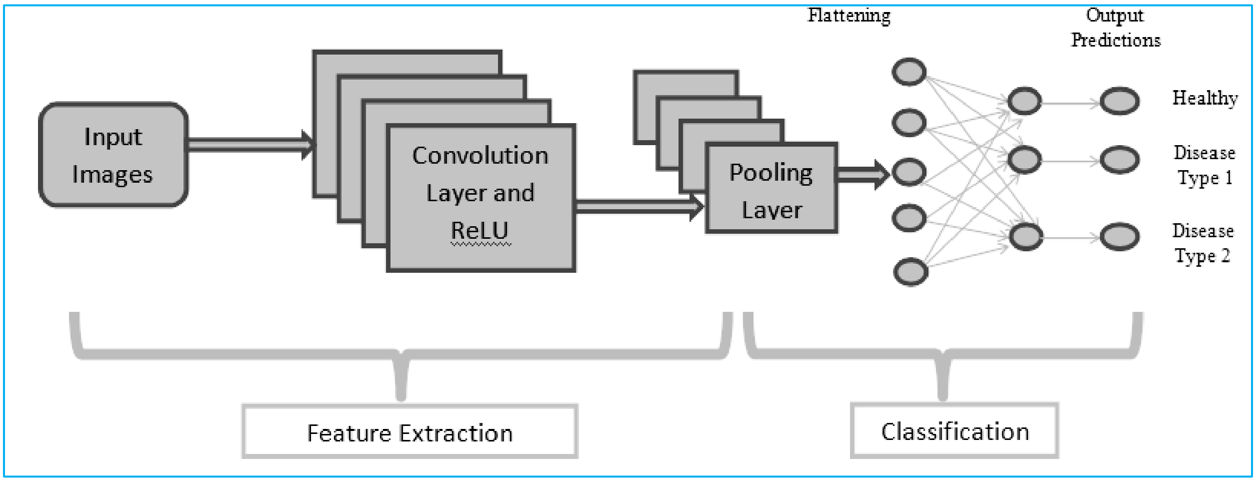

Fig 1 Convolutional neural network architecture for classification of leaf diseases

The suggested hybrid model has several layers, such as a convolutional layer that transforms input data into an output tensor and a pooling layer that maximizes the use of the pool size divided by the window size. The convolutional layer, which takes in two-dimensional convolutional inputs activated by the Rectified Linear Unit (ReLU) function, was used to normalize the images [28]. The role of ReLU is to eliminate –ve values from the filtered images and substitutes them with 0's and provides linear relationship with the dependent variable. In order to save computational processing, the pooling layer's job is to reduce the dimensionality of the convolutional features by making their spatial sizes as small as possible. Noise Suppressant is considered to be valuable in pooling layer as it discards the noisy activations completely [29]. Data is sequentially transmitted from the convolutional layer to the pooling layer until the dropout stage is reached with values of 0.25. An advanced convolutional neural network with many pairs of pooling and convolutional layers is included into the suggested hybrid model in order to achieve the highest level of accuracy [30-31]. Dense layer was also used to flatten feature maps with activation function to produce the multiple classes of leaf diseases. Additional hidden layers can be applied in the hybrid model to enhance the accuracy.

RESULTS AND DISCUSSION

The proposed novel hybrid model was implemented in Jupyter by importing numerous libraries from Keras, Sklearn, tensorflow and represented in (Fig 2) [32-33]. The Plant Village Dataset was used to develop a hybrid model for detecting leaf disease using deep learning.

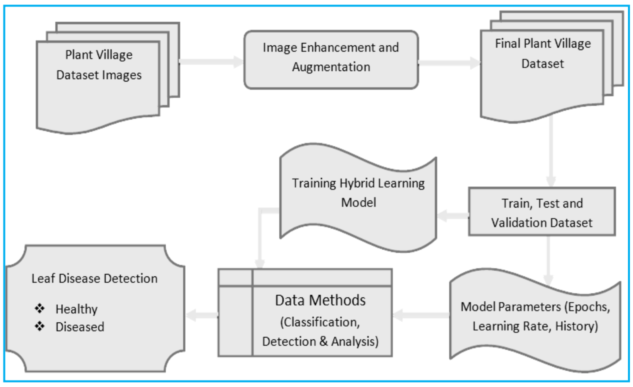

Fig 2 Representation of novel hybrid model

This proposed model will identify any type of crop/leaf classification but this article focused on different forms of potato leaf diseases. Leaf images of Potato Healthy, Early Blight, and Late Blight disease were used in the present implementation, which pertains to diseases that affect the leaves of potatoes. Early blight is basically triggered by fungi whereas Late Blight is initiated by micro-organisms.

Convolutional Neural Networks (CNN), an advanced artificial technique, has emerged as a viable means of increasing accuracy, despite their high sample volume need. library functions were required throughout the implementation as preprocessing of images using binary label binarizer. Activation functions were employed to supplement the images further in order to develop the whole image data for the denser layer. Adam Optimizer was used to get the optimum accuracy among the utilized database. Sklearn was used to implement the novel model and partition the complete dataset into training (consisting of 80% of the data) and testing (20% of the data) images [32]. Matplotlib was also used while depiction of data accuracy and validation loss at the end of implementation.

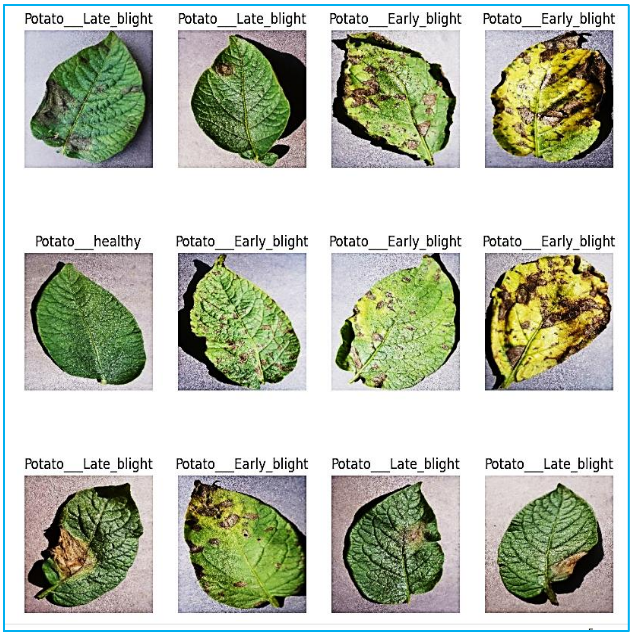

Fig 3 Potato leaves in plant village dataset

The preprocessing of the proposed model was utilized by using data augmentation. The purpose of this strategy was to artificially increase the training dataset, which would ultimately result in a reduction in the amount of over fitting. The purpose of data augmentation is to customize the images by rotating, resizing, and moving their dimensions with varying percentages, and then to generate a training dataset that contains all of these adjusted images. This will be beneficial for the proposed model to provide optimum accuracy with new dataset in future. By using augmentation, the proposed model will detect the disease images that might contain less/bright contrast, horizontal/vertical flipping or varied size images of any crop.

```
aug=ImageDataGenerator(rescale = 1./255,
rotatopn_range = 30, shear_range = 0.2, zoom_range
= 0.2, width_shift_range=0.5,
height_shift_range=0.05, horizontal_flip = True,
fill_mode_mode = 'nearest")
```

For better performance, the data augmentation has done only on training dataset but the proposed model will be able to identify plant diseases in testing dataset due to different data augmentation techniques applied on training dataset based on hybrid model parameters which will be tuned on other adjacent layers. As a result, the proposed novel hybrid model achieves its optimum accuracy on any volume of dataset. The dataset includes images of potatoes, each classified under a separate disease or healthy category; the image size for detecting leaf disorders is 256*256*3, and the number of epochs used to determine accuracy is 25.

The next step is to scale all of the pictures in the dataset and then turn them into array images so that the convolutional layer can access them more easily. For this, the proposed system needs to load all images under one directory with image labels. Additionally, there is a need to transform image labels by using Label Binarizer and identify the total number of used classes and its parameters. The use of image augmentation allowed for the subsequent partitioning of the dataset into train and test sets, with 80% and 20% of the datasets, respectively, being labeled.

```
label_binarizer = LabelBinarizer()
image_labels = label_binarizer.fir_transform(label_list)
pickle.dump(label_binarizer,open('labeltransform.pkl', 'wb'))
n_classes = len(label_binarizer.classes_)
```

After preprocessing steps, the next approach is to build the novel model for leaf disease detection for any type of dataset images. Convolutional Neural Network was further embedded in the proposed hybrid model to attain the maximum accuracy among the dataset with Keras API, which contains multiple pairs of convolutional and pooling layers. Dense layer was also used to flatten feature maps with activation function to produce the multiple class representation of the leaf disease. The subsequent procedure is to load all of the data for training, testing, and validation using data augmentation. To complete this operation, resizing was performed to make the image dimensions equal and batches were formed using RGB color mode.

```
train_generator = train_datagen_from_directory(directory
= '/content/Potato/Train/', target_size = (256, 256),
batch_size = BATCH_SIZE, class_mode = 'categorical',
color_mode="rgb")
validation_generator=validation_datagen.flow_from_direct
ory('/content/Potato/Valid/', target_size = (256, 256),
batch_size = BATCH_SIZE, class_mode = 'categorical',
color_mode="rgb")
test_generator =
test_datagen.flow_from_directory('/content/Potato/Test/',
target_size = (256, 256), batch_size = BATCH_SIZE,
class_mode = 'categorical', color_mode="rgb")
```

The images were normalized using the convolutional layer, which received convolutional two-dimensional inputs with the ReLu activation function, after the image dataset was adjusted. Data from the convolutional layer is passed on to the pooling layer in a chain fashion until the dropout stage is reached with values of 0.25. The role of dense layer is to provide all the classes in fully connected format with an output function. The distribution of images was implemented using Adam Optimizer which reflects the validation loss and value accuracy with 25 Epochs.

```
opt = Adam(lr=INIT_LR, decay=INIT_LR/EPOCHS)
model.compile(loss="binary_crossentropy",
optimizer=opt,metrics=["accuracy"])
Epoch 1/25
73/73 [=======] -43s 583ms/step -loss: 0.2012 – acc:
0.9365 – val_loss: 0.5047 – val_acc: 0.9022
Epoch 2/25
```

Due to multi-class classification among the leaf images, Adam optimizer was also implemented to define the cross-entropy in the loss to compile the proposed model. By utilizing the history parameter to store data for each epoch, training, and validation sets were established to compare the performance of the hybrid model. // was used to round the data to an integer number.

```
Epoch 17/25
73/73 [=======] - 34s 472ms/step -loss: 0.0491 – acc: 0.9820
– val_loss: 0.6471 – val_acc: 0.9195
Epoch 18/25
73/73 [=======] - 35s 484ms/step -loss: 0.0478 – acc: 0.9824
– val_loss: 0.1848 – val_acc: 0.9582
Epoch 19/25
73/73 [=======] - 34s 469ms/step -loss: 0.0443 – acc: 0.9843
– val_loss: 0.1428 – val_acc: 0.9602
Epoch 20/25
73/73 [=======] - 35s 483ms/step -loss: 0.0455 – acc: 0.9832
– val_loss: 0.0754 – val_acc: 0.9755
Epoch 21/25
73/73 [=======] - 35s 476ms/step -loss: 0.0384 – acc: 0.9857
– val_loss: 0.5299 – val_acc: 0.9233
Epoch 22/25
73/73 [=======] - 35s 481ms/step -loss: 0.0463 – acc: 0.9842
– val_loss: 0.0925 – val_acc: 0.9701
Epoch 23/25
73/73 [=======] - 35s 481ms/step -loss: 0.0440 – acc: 0.9844
– val_loss: 0.2281 – val_acc: 0.8855
Epoch 24/25
73/73 [=======] - 34s 472ms/step -loss: 0.0396 – acc: 0.9847
– val_loss: 0.3955 – val_acc: 0.9337
Epoch 25/25
73/73 [=======] - 35s 483ms/step -loss: 0.0394 – acc: 0.9860
– val_loss: 0.1300 – val_acc: 0.9645
```

```
history = model.fit_generator(train_generator,
steps_per_epoch =

train_generator.n//train_generator.batch_size, epoch =
EPOCHS, validation_data = validation_generator,

validation_steps = validation_generator.n //
validation_generator.batch_size)

print("[INFO] Calculating model accuracy")
scores = model.evaluate(x_test, y_test)

print(f"Test Accuracy: {scores[1]*100}")
[INFO] Calculating model accuracy

591/591 [==================================] – 1s
2ms/step

Test Accuracy: 96.44670223221561

plt.figure()

plt.plot(epochs,loss, 'b',label='Training loss')

plt.plot(epochs, val_loss, 'r',label='Validation loss')

plt.title('Training and Validation loss')

plt.legend()

plt.show()
```

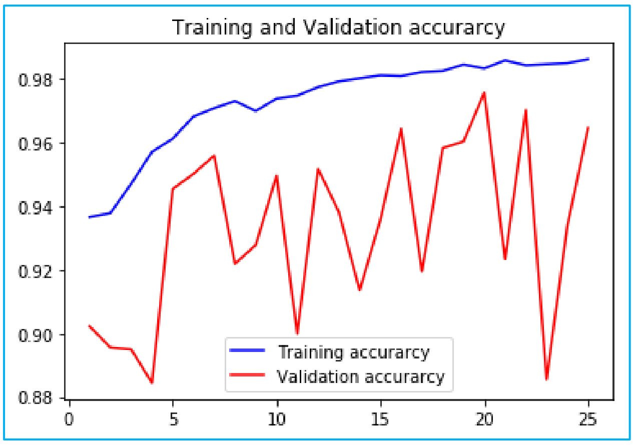

Fig 4(a) Representation of training accuracy

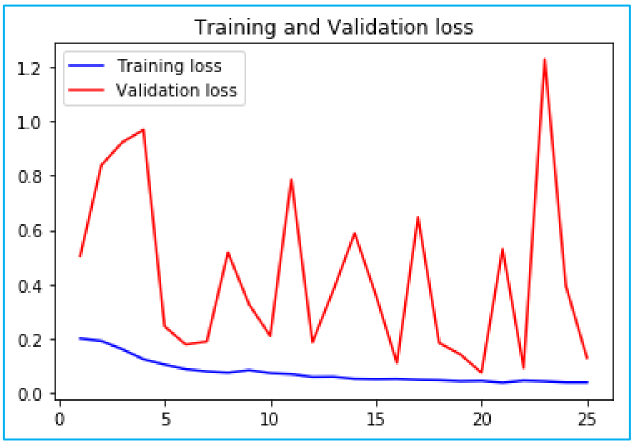

Fig 4(b) Representation of training loss

The training accuracy attained by the system while detecting potato leaf disease is 98.604675012 and test accuracy is 96.446702232 as shown in the (Fig 4a). The training loss reduced to 0.0394 whereas validation loss minimize to 0.1300 as depicted in the (Fig 4b).

CONCLUSION

Detecting leaf diseases using deep learning can assist farmers in minimizing the damage to their crops. In order to increase agricultural output quality and avoid contamination of the entire crop, early identification of plant diseases is crucial. Plant image classification accuracy may be greatly improved using a pre-trained technique with data augmentation through parameter modification. The results revealed that the novel hybrid model for leaf diseases detection outperforms the other suggested and developed plant disease detection models. Therefore, with the proposed model, farmers may benefit from being involved in decision-making processes using this innovative hybrid approach. Models of this kind will be profitable in situations where hand selecting tools are difficult to come by. The proposed hybrid model will be valuable for the farmers to detect this disease at an early stage so that they may take appropriate measures to minimize waste and financial loss. For the future paradigm, this hybrid model can be implemented with other crops diseases with utmost accuracy as the novel model achieves maximum accuracy while identifying leaf diseases.

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