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PLANT DISEASE DETECTION USING DEEP MACHINE LEARNING ALGORITHM

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ABSTRACT

The world population is increasing rapidly. In order to cater the daily needs of an individual, grains and vegetable production are imperative. This paper is focused to establish a technology support to formers and to minimize the deceases in plant. Tomato and pepper bell leaves are considered to detect the deceases. Contrast limited adaptive histogram equalization (CLAHE) is applied to improve the contrast of the leaf image before processing with machine learning algorithm. The contrast limiting is considered with clip limit 40. Bi- cubic interpolation is applied to minimize the false edge of the leaf with neighbouring tails of the leaf. The qualitative parameters like absolute mean brightness error (AMBE), mean square error (MSE), peak signal to noise ratio, mean average error (MAE) and maximum deviation (MD) are analysed. MSE values achieved less than '1' indicates contrast adjustment is good. CNN Classification is applied. The decease detection accuracy with CNN is increased to 95.6 percent with increasing epochs. The accuracy Vs epoch and Loss Vs Epoch analysis is done. Optimum Tunning of hyperparameters (β1), and (β2) is done in this study. The results achieved with this approach are best fit for plant decease finding to improve the yielding rate the crop.
Keywords: *Plant leaf, CLAHE, CNN*

1. INTRODUCTION

With increasing population and descending resources, crop yielding rate improvement is significant. The impact of environment conditions on the yielding rate also needs to be considered to improve the yielding rate of the crop. The yield rate is to be improved with the advancement of technology, specifically, Machine learning based leaf disease detection mechanisms[1]. This system adds supporting diagnosing tool to formers and to interpret the rate of disease growth and to add needed pesticides at right pace. Crop diagnosis with Leaf monitoring certainly enhance the quality of precision agriculture[2]. This paper used a neural network with filly connected layers to implement plant leaf disease classification. The collection of data, data processing, feature extraction and specifically the disease classification and performance evaluation of the proposed model is considered. Particularly in deep learning approach, convolution neural network is weighted method for classification of leaf diseases. Better accuracy is achieved with CNN with 95%. Contrast limited adaptive histogram equalization (CLAHE) is applied before classification[3]. The leaf image contrast enhancement impacted by the image distortion. Absolute mean brightness error (AMBE) is considered. The contrast enhancement quality is estimated with absolute mean brightness error (AMBE). Mean square error (MSE), Peak signal to noise ratio (PSNR), maximum deviation (MD), mean absolute error (MAE) metric parameters[4]. Adaptive movement estimation is applied to reduce the loss function during training process of CNN. For optimization, the hyper parameters learning rate of proportion (β1), rms proportional term (β2) and learning rate decay (ε) are considered[5].

2. METHODOLOGY

The plant disease classification procedure using CNN is composing of various significant stages. Stage1. Keras libraries are used to build CNN. Stage 2 is the convolution layer. Stage 3 is the pooling layer[6]. Stage 4 is the batch normalization layer. Stage 5 is the dense layer. Stage 6 is the dropout layer. Stage 7 is the CNN compiling layer using loss parameters. Stage 8 is the data training and validation layer leaf[10]. Re-scaling and re-cantering and batch norm function is considered to improve the training speed of the plant leaf images. The accuracy is subsequently enhanced with batch normalization function[11]. Overfitting is minimized by eliminating the co-dependent of each other node. The dropout layer supresses the noise to improve the accuracy of the output and improves the performance of the training process.

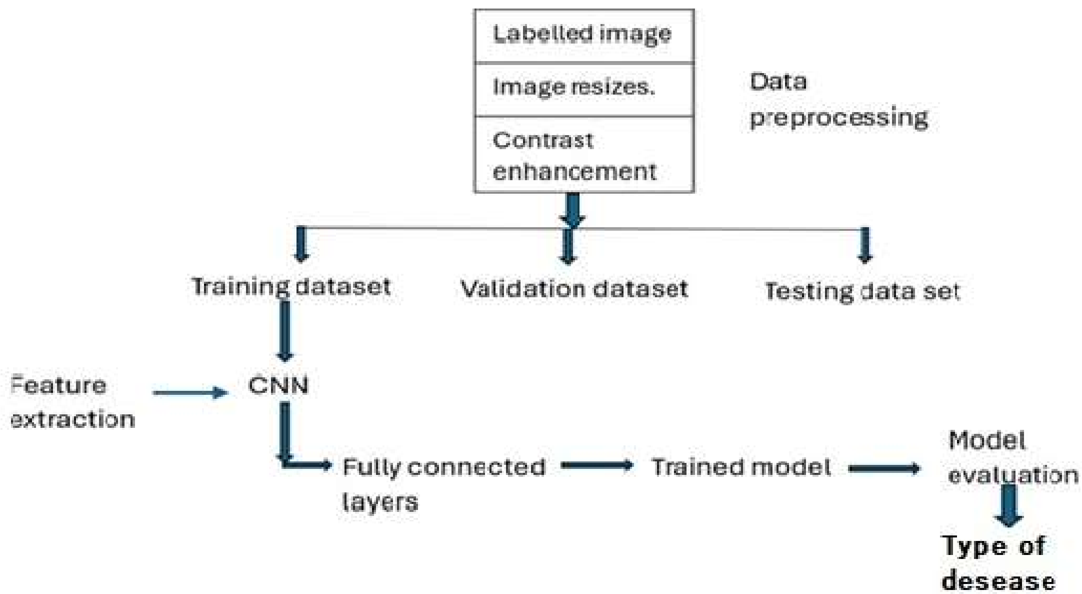

Fig.2.1. Disease CLASSIFICATION MODEL

The Plant leaf image size is reduced to improve the processing speed with CNN. The size of the image is reduced by safeguarding the actual features of the image[7]. The fully connected dense layers are the end layers of the CNN methodology. Multilayer perceptron in CNN is created using fully connected dense layers. High dimensionality of Plant leaf image is reduced without losing the original information using convolution layer[8]. Convolution operators are applied to convolute the original image. The convoluted information is fed to different channels of the convolution layer. Max pooling layer is applied to elect the maximum value from each pool. The max pooling improves sharpness of the original image[9]. Flattening is used to convert the two-dimensional arrays of the image from the pooled feature maps into a continuous linear vector. So, the classification of the infected leaf image is used with flattened matrix. The dense layer is used to classify the diseases of a The image texture, edges of the image are extracted as features. This featured image is considered as an input data set. Then the CNN model is applied to validate the data sets.

Algorithm:
Step1: The size of the image is resized to 255 pixels.
Step2: consider trained data is 75% and test data is 25%.
Step3: classify the image using trained CNN model using 75% data.
Step4: Tune the hyperparameter apply the validation.
Step5: estimate the validation accuracy.
Step6: Test 25% data with trained model
Step7: detect the desease with 75% trained data using CNN.
Step8: Tune the hyper parameter and apply the validation.
Step9: Apply the activation function and SoftMax.

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Step10: Determine the test data is healthy or deseased.
Step11: Estimate the validation accuracy.
Step12: classify the desease using CNN
Step13: Repeat step 8 and step 9
Step14: Repeat step11
Step 15: end

Contrast limited Adaptive Histogram Equalization (CLAHE) is used to improve the contrast levels of the plant leaf image. The image is decomposed into tiles. CLAHE works on each tile of the image to stabilize the over amplification[12]. The false edges of the leaf image are minimized with Bi-Cubic Interpolation in association with neighbourhood tails of the leaf image. Contrast limiting is considered with clip limit 40.

The contrast enhancement quality is estimated with absolute mean brightness error (AMBE). MSE, PSNR, MD, MAE, and CT values. Brightness average is estimated for two images. Difference of average is considered as AMBE. Input image is denoted as 'X' and the output image is denoted as 'Y'. Average brightness of the input image is labelled as X_i and Average brightness of the output image is represented as Y_0

$$AMBE(x,y)=|X_i-Y_0|$$

The input image brightness is safeguarded during enhancement process by keeping the AMBE value is low. The input image and output image consist of 'K' number of levels and p×q pixels i. j is considered as spatial location of each pixel value. The mean square error (MSE) is calculated as

$$MSE(x,y)=\left(\sum_{i=1}^{p}\sum_{j=1}^{q}|x(i,j)-y(i,j)|^2\right)/(p\times q)$$

Mean square error is estimated between input and output images of leaf. MSE is labelled as mean square deviation. The quality of the output image is determined with a low value of MSE. i,j represents ith and jth pixel of the leaf images.

$$PSNR(X,Y)=1-\operatorname{Log} 10(K-1)2\ MSE(X,Y)$$

The quality of contrast image is also determined with peak signal to noise ratio (PSNR). High value of PSNR represents the quality of contrast enhancement. PSNR is estimated using the following equation.

$$PSNR(x,y)=10\operatorname{Log}_{10}\left((K-1)\right)/MSE(x,y)$$

The Maximum difference among same pixel of X, Y images determines maximum deviation (MD). The lowest value of MD i.e. approximately equal to zero considered as the best quality parameter for contrast enhancement. The MD value is estimated using the following equation[13].

$$MD(x,y)=Max|x(i,j)-y(i,j)|$$

Similarity index value between images X, Y is labeled as maximum absolute error value (MAE)[14]. The resultant output image Y is compared with input image X. A High Value of MAE is the indication of better similarity between the input and output images. Eventually the distortion between the images X and Y is negligible[15].

$$MAE(x,y)=\left(\sum_{i=1}^{p}\sum_{j=1}^{q}|x(i,j)-y(i,j)|\right)/(p\times q)$$

3. RESULTS AND DISCUSSION

The leaf desease input image is transformed into grey level image. Contrast limit adaptive histogram equalization is applied to improve the contrast of the image. The contrast limiting threshold value is adjusted by tuning the clip limit to 43. The image is decomposed into tiles. The grid size is adjusted to 91. The leaf image contrast enhancement impacted by the image distortion. Absolute mean brightness error (AMBE) is considered. This low value of AMBE represents the enhancement quality of leaf image. The peak signal to noise ratio (PSNR) is estimated. Significantly good PSNR value is achieved during contrast enhancement of the image represented in table 3.1. Mean square error (MSE) value is estimated for each image. MSE values are less than '1' show the contrast adjustment is significantly good shown in Table 3.1. Maximum difference (MD) and mean absolute error (MAE) values are estimated. Table.3.1. shows MSE values are less than 1, which represents the contrast adjustment is good

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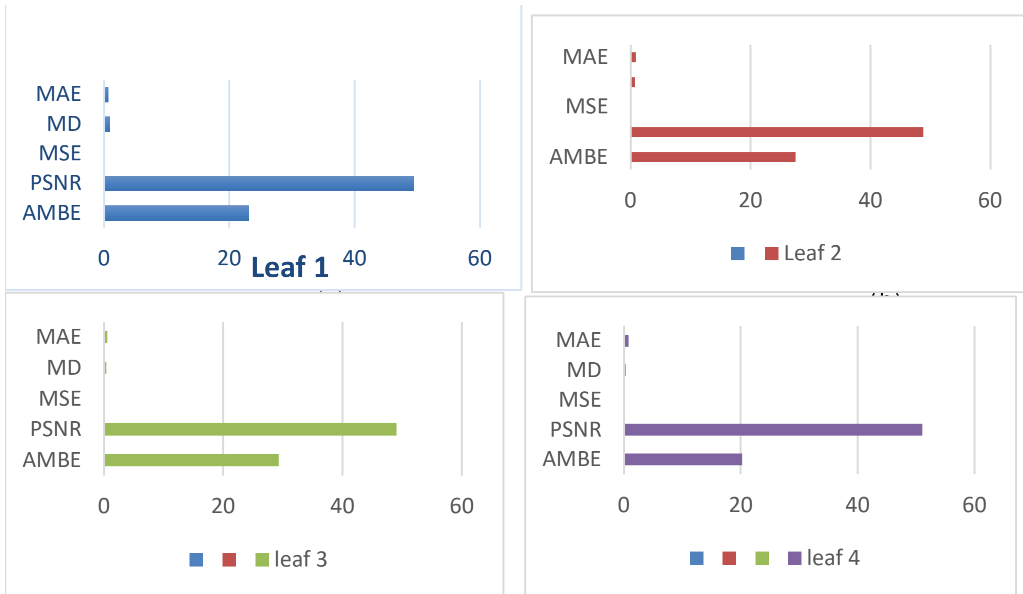
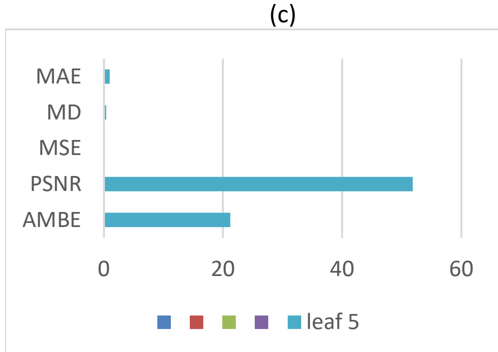


(c) (d)



(e)

Fig. 3.1. Plots of the Qualitative parameters of the images

(a) Leaf 1
(b) Leaf 2
(c) Leaf 3
(d) Leaf 4
(e) Leaf 5

Set 1. Input images. output

Set 2. Input images. output

Fig.3.2 Input images showing 15 class labels

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Table.3.1. CLAHE Qualitative Parameters Of The Images

Image	AMBE	PSNR	MSE	MD	MAE
Leaf1	23.057	49.43	0.0246	0.9	0.6549
Leaf 2	27.532	48.81	0.0198	0.7	0.8742
atient3	29.341	49.09	0.0167	0.4	0.5789
Patient4	20.252	51.08	0.0194	0.3	0.7989
Patient5	21.231	51.84	0.0207	0.4	0.9859

A CNN model is built and trained to detect plant diseases for potato, tomato and Pepper. The CNN algorithm is chosen over other algorithms due to its high accuracy in results. This accuracy may vary contingent upon the quantity of pictures given. It can be increased by increasing the number of epochs. The number of epochs used are 10

```
hist = model.fit(X_train, y_train,
          batch_size = batch_size, epochs = nb_epochs,
          verbose = 1, validation_data = (X_test, y_test))
```

```
Epoch 1/10
452/452 [==============================] - 17s 13ms/step - loss: 1.3312 - accuracy: 0.5780 - val_loss: 0.7809 - val_accuracy: 0.7492
Epoch 2/10
452/452 [==============================] - 6s 13ms/step - loss: 0.6273 - accuracy: 0.7910 - val_loss: 0.6011 - val_accuracy: 0.8018
Epoch 3/10
452/452 [==============================] - 5s 11ms/step - loss: 0.4369 - accuracy: 0.8518 - val_loss: 0.5789 - val_accuracy: 0.8029
Epoch 4/10
452/452 [==============================] - 4s 9ms/step - loss: 0.3493 - accuracy: 0.8827 - val_loss: 0.4519 - val_accuracy: 0.8499
Epoch 5/10
452/452 [==============================] - 5s 11ms/step - loss: 0.2900 - accuracy: 0.9007 - val_loss: 0.3181 - val_accuracy: 0.8939
Epoch 6/10
452/452 [==============================] - 5s 11ms/step - loss: 0.2311 - accuracy: 0.9222 - val_loss: 0.3690 - val_accuracy: 0.8826
Epoch 7/10
452/452 [==============================] - 4s 9ms/step - loss: 0.2016 - accuracy: 0.9310 - val_loss: 0.4238 - val_accuracy: 0.8695
Epoch 8/10
452/452 [==============================] - 4s 9ms/step - loss: 0.1776 - accuracy: 0.9391 - val_loss: 0.3322 - val_accuracy: 0.8916
Epoch 9/10
452/452 [==============================] - 4s 9ms/step - loss: 0.1471 - accuracy: 0.9487 - val_loss: 0.3974 - val_accuracy: 0.8738
Epoch 10/10
452/452 [==============================] - 4s 9ms/step - loss: 0.1393 - accuracy: 0.9528 - val_loss: 0.2869 - val_accuracy: 0.9116
```

Fig 3.3 Accuracy for 15 class labels combined.

The images in Fig. 3.2 represent 15 class labels which are used in this project and each label refers to different crops like Pepper Bell , Potato and Tomato . Giving the data/image to "Choose File" option and upon submitting the trained model , it will be able to detect the disease and predict the pesticide along with the precaution as shown below in Fig.3.3

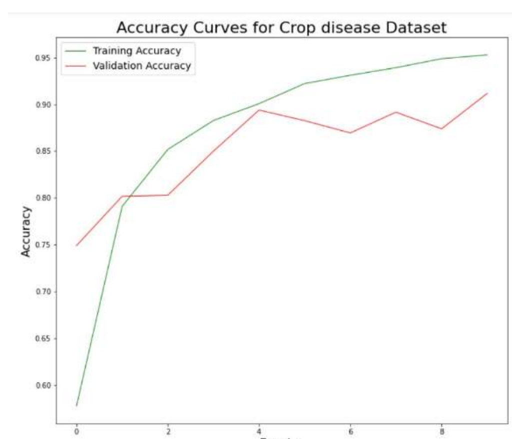

Fig 4.5 Accuracy Vs Epochs

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The test data sets are given to the model, The accuracy is increased to 95% with 15 class labels. The number of epochs is increased to 10. The accuracy will be further increased with increasing the number of epochs. Fig.4.2. represents the training accuracy, (i.e. the similar set of images are used for training and testing) is increased to 95 with increasing the epochs. The validation accuracy (i.e. is effective learning rate and generalising is good) is at 91% with increasing the epochs. The validation accuracy was significantly better with increasing the number of epochs and optimally tuned hyper parameters,

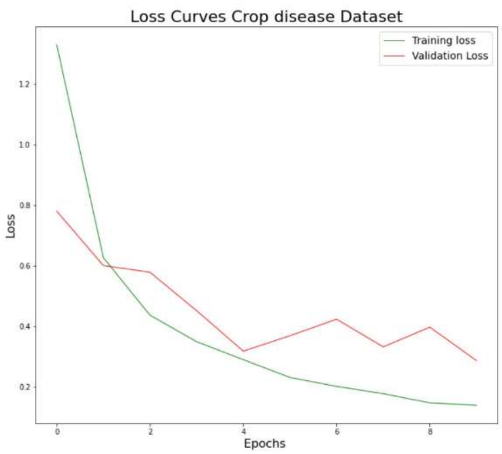

Fig 4.6. Loss Vs Epochs

The Accuracy Vs Epoch graph represents the validation accuracy and training accuracy where accuracy increases by increasing the epochs. The Loss Vs Epoch graph represents the validation loss and training loss where loss decreases from first epoch to last epoch. Adaptive movement estimation is applied to reduce the loss function during training process of CNN. The minimum learning rate of 0.007 is considered as good fir for optimiser. For optimization, the hyper parameters learning rate of proportion (β1), RMS proportional term (β2) and learning rate decay (ε) are considered as β_1=0.89, β_2=0.989 and $\varepsilon = 1e^{-8}$. The exponential decay rate of the first momentum is estimated with β_1. Initially the training loss is elevated to maximum value. With increasing the epochs, the training loss is minimized to a negligible value. The validation loss is at maximum value, i.e., 08. With increasing epochs, this loss is minimized to 03.

Evaluation of leaf disease is estimated using the parameters, precision, recall and f1 measure. F1 score is estimated to interpret the statistical measure of accuracy. The f1 score is closely equal to the value '1' represent exact precision and recall. True positive rate is estimated as recall which represents the positive class of the plant leaf trained with CNN. 92.6% true positive rate is achieved with healthy leaf and 84.5% achieved with diseased leaf.

Eq1

$$Recall\ messure\ (\%) = \frac{True\ positives}{True\ positives + false\ negetives} \times 100$$

Eq.2

$$F\ messure\ (\%)= \frac{True \times Precission \times recall}{precision+recall} \times 100$$

Eq3

$$precision\ mesure\ (\%)= \frac{True\ positives}{True\ positives+false\ positives} \times 100$$

Table2: CNN Performance Metrics To Interpret The Crop Leaf.

Methodology	Type of leaf	Precision	Recall	F1-Score	Accuracy %
CNN	Healthy	0.986	0.926	0.943	95.6
	deceased	0.923	0.845	0.910	94.1

4. CONCLUSIONS

This paper aimed to detect the deficiencies of the plant and specifically interpreted to detect the abnormality using conventional neural networks. The decease of the plant is analysed by addressing the quality of the leaf image, and the Classification. CLAHE is applied to enhance the contrast level of the image. The contrast limiting is considered with clip limit 40. Bi- cubic interpolation is applied to minimize the false edge of the leaf with neighbouring tails of the leaf. The quality parameters are investigated to determine the enhancement of the image quality. AMBE, PSNR, MSE, MD and AME values are investigated to determine the contrast quality of the image. The AMBE values for five set of test images are below 30. Leaf 1 leaf4 and leaf 5 AMBE values are 23.057, 20.252, 21.231 respectively these values are much lower than leaf 2, leaf 3 which are 27.532 and 29.341 respectively. These low AMBE values represent enhanced preservation of the test leaf brightness. The PSNR values for all the test leaves are greater than 48.81. The value above 40 dB is significantly a good value. Less than 20 dB are reasonably not acceptable PSNR levels of the image. The MSE values are less than '1' represents the image brightness level is optimally adjusted. The training and validation accuracy against increasing epochs are plotted. With increasing epochs, the validation accuracy is almost closely matching the testing accuracy. The accuracy level is increased to 95.6 percentage. Loss function during training is reduced using adaptive movement optimization. The learning rate of proportion and rms proportional terms are optimally tunned to 0.89 and 0.989 respectively. The validation loss is reduced to 03 with increasing epochs. The F1 score is the indication of better accuracy. With CNN 94.3 percent F1 Score is achieved, which represents the accuracy of the classification with CNN is much reliable for agricultural applications.

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