Corn Leaf Disease Identification with Improved Accuracy

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Abstract

The corn is a major food crops in many countries along with rice and wheat. It is one that is produced easily and used to feed millions of hungry stomachs. The production of corn is always affected by various diseases that might have different treatments. So incorrect classification of diseases may lead to incorrect remedial measures and reduced production efficiency also. The proposed model is formed with various convolutional layers and fully connected layers and predicts corn leaf disease correctly. This work utilizes corn leaf images from Mendeley dataset for all four health conditions of leaves like; Gray Leaf Spot, Common Rust, Blight, Healthy and contains 3852 images in all. After exhaustive iterations, the proposed work classifies corn disease with 95.60% training and 97.60% validation accuracy. All the performance metrics are presented and discussed here for a clear understanding. The F1-score calculated for each disease shows the strength of this work.

Keywords

Corn leaf disease, deep learning, convolution layers

1. Introduction

In recent years, the world has witnessed the utilization of machine learning applications; starting from Chatbot to critical biological and medical data analysis. All these things became possible due to the introduction of more learnable layers and sophisticated deep learning models. The conventional neural networks and underlying algorithms underperform due to the huge amount of data and underlying huge computations. The deep learning model learns features itself from the input sample [1]. Here, with the use of a set of algorithms, it provides a high level of abstract model to produce faster and more accurate results [2].The Convolutional neural network (CNN) is a combination of one or more convolutional layers, followed by an activation function and pooling layers. Actually, all these three-layered arrangements can be seen as one convolutional layer. CNN uses kernels or masks which are matrices that move over the image to extract the feature while maintaining the spatial relation between the pixels. The role of activation functions is very important. It adds non-linearity to CNN; since most of the data in the real world is non-linear. After convolutional layers flattening layer is applied to convert data into a long vector which is followed by a fully connected feed-forward neural network. The activation function in deep learning plays a very important role. It decides whether a neuron will fire or not. A detailed discussion on activation functions is given in [3, 4]. The Rectified Linear Unit (ReLU) is very useful to add non linearity in deep learning [5]. It returns 0 for negative input, but for positive input *x*, it returns the same value back. Mathematically it is given in Eq. 1 and plotted in Figure 1.

$$f(x) = \max(0, \mathrm{x}) Where, \mathrm{x} = \sum_{i=1}^{m} \mathrm{w_i x_i} \; and\ w\ represents\ weights \tag{1}$$

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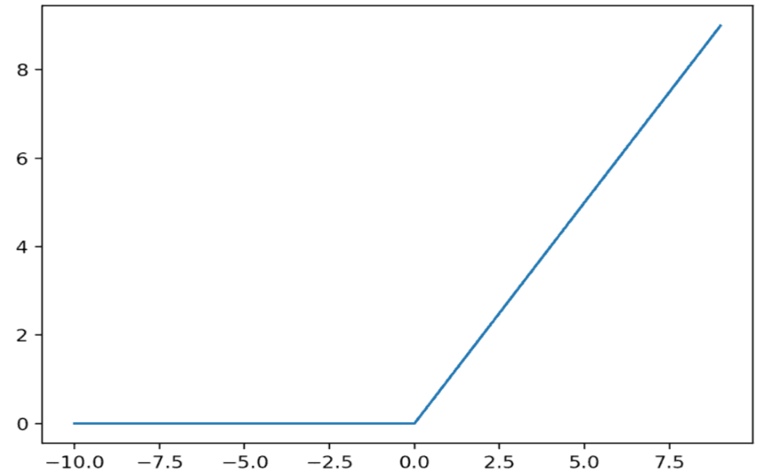

Figure 1: ReLU

The following Eq. 2 describes Softmax activation method mathematically.

$$\sigma(z)_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}} \quad (2)$$

Where $\sigma =$ Softmax, $z =$ Input Vector, $e^{z_i} =$ standard exponential function for input vector,
$k =$ number of classes in the multi − class classifier,
$e^{z_j} =$ standard exponential function for output vector and
$e^{z_j} =$ standard exponential function for output vector

The Softmax will produce a vector having probabilities of each class. Using agrmax() method of NumPy library, an index value of the highest probability class can be found.

2. Related work

The research presented in [6] classifies rice plant disease by using colour features with an accuracy of 94.65% and SVM is considered as a classifier. A model is proposed in [7] for automatic grape leaf disease identification with a validation accuracy of 99.17%. The model presented in [8], is based on deep forest that predicts maize leaf disease with an accuracy of 96.25%. In this model three disease classes and one healthy class with 100 images for each were considered. The research outlined in [9], investigates a real time method based on deep convolutional neural network for identification of corn leaf with an accuracy of 88.46%. The model proposed in [10] uses K-Mean clustering and deep learning to predict corn leaf diseases with an average accuracy of 93%. The work given in [11] proposes a model using CNN and AlexNet architecture to identify maize leaf diseases. The CNN model achieved an accuracy of 87%. The model given in [12] identifies maize diseases using support vector machine and achieves 95.63% as average accuracy. The article outlined in [13] detects and classifies groundnut leaf diseases using KNN classifier with an accuracy of 75%. The literatures given in [14, 15, 16] justify the use of deep learning for the detection of diseases. The model presented in [17] classifies plant disease using neural network and hyperspectral images. The work given is [18] classifies 26 diseases among 14 crops. Here, Alexnet and Googlenet pre-trained models are used and achieve an accuracy of 99.35%. And the model presented in [19]) classifies leaf disease using leaf image processing.

3. Dataset and preprocessing

This work utilizes images from the Mendeley dataset (Pandian et al. 2019[20]) for four health conditions like Gray Spot, Common Rust, Blight, and Healthy with 513, 1192, 985, and 1162 corresponding images. To enrich the dataset with a variety of images, a data augmentation technique with various parameters is applied here to generate images. The Figure 2, shows the four classes of the images that are considered here. Before feeding to the convolutional layer the images are reshaped as (160,160) by data augmentation.

(i) (ii) (iii) (iv)

Figure 2: Images from the Mendeley dataset. (i) Gray Leaf Spot (ii) Common Rust (iii) Blight (iv) Healthy

4. The proposed model

The overall process for creating a trained model is given in Figure 3. The total size of dataset including all classes is 3852. Here, 985 images belong to Blight class, 1192 images belong to Common Rust class, 513 images belong to Gray Leaf Spot class and rest 1162 images belong to Healthy class. The ImageDataGenerator library is used for data augmentation.

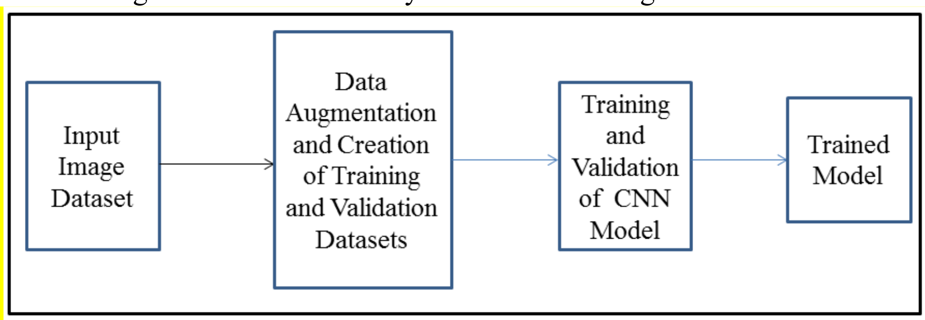

Figure 3: Training of model

At first, a dataset will be provided for augmentation for more quantity and variety of images. During augmentation with the use of the validation_split attribute of ImageDataGenerator, the training and validation sets will be specified. In this model, 50 images in one batch are considered. So, during the training of the model, 50 images will be provided in the each iteration. After the completion of all the iterations in each epoch, the validation process will be started. Here 50 images are considered in each batch; hence, in the each iteration 50 images will be provided by ImageDataGenerator for validation of the model. Figure 4, demonstrates the model testing process, where a corn leave image will be provided to classify.

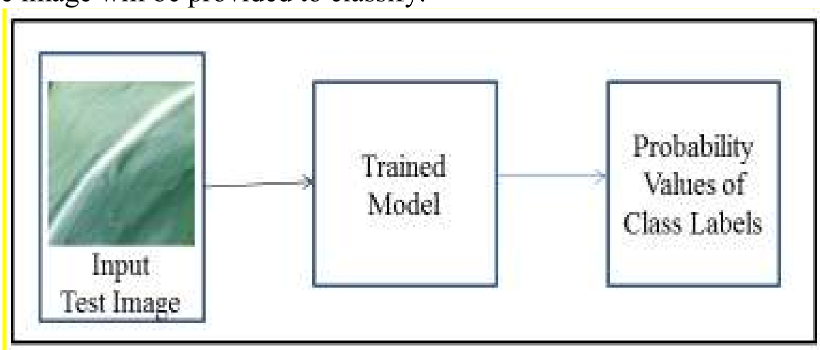

Figure 4: Model Testing

5. Model Description

In this model three convolutional layers are considered with the different numbers of kernels (or masks). The first, second, and third layers consist of 32, 64, and 128 kernels with sizes (3,3), (2,2), and (2,2) respectively. The image shape is considered as (160,160). To add non-linearity, the ReLU activation function is used. At the first layer batch normalization is applied. To downsample the inputs along height and width Maxpool2D class is used after each convolutional layer.
After convolutional layers, a flattening layer is applied to create a long vector of feature values and then a fully connected layer is applied. The fully connected neural network is composed of two layers. The first layer consists of 64 neurons, ReLU as an activation function and to regulate the overfitting, dropout (with 50%) and L2 regularization techniques (with regularization parameter=0.01) are applied. Regularization also controls the model complexity. The second (or last) layer consists of 4 neurons that represent the 4 class labels. In this layer, the Softmax activation function is used that ensures the sum of output probabilities is 1. At the time of model training and validation, ImageDataGenerator plays an important role. It creates a batch (here batch = 50) of augmented images and provides to model for training and validation for the first iteration. In second (or other) iteration again creates a new batch of augmented images and provides for training and validation. The same batch will be created for each iteration until the whole training dataset is exhausted. In this way, the trained model becomes very robust and accurate. Here 70% of data is considered for training and the remaining 30% of data is considered for validation. During compilation of model, Adam optimizer (Learning_rate=1e-03 and Decay= learning_rate /1000) is used. This model is trained for 50 epochs. The early stopping callback is used to stop the model training when no improvement in validation accuracy is observed in later epochs. Hence it saves the model from overfitting. Here early stopping is used with patience point=2. Figure 5, presents that model training stops at epoch 5 since after epoch 3 the validation loss increases continuously.

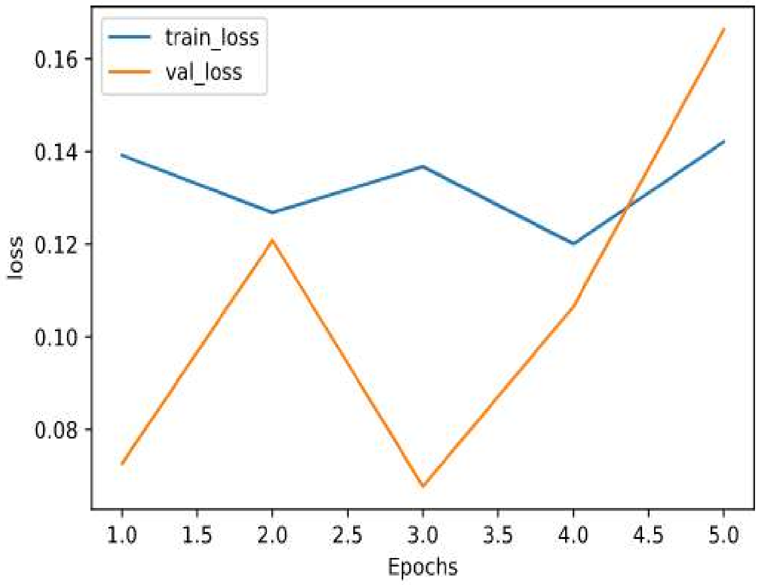

Figure 5: Training and validation loss

6. Result discussion and comparison

Table 1 presents a complete view of performance matrices. The overall validation accuracy is 97.60%. The confusion matrix represents the accuracy and correctness of any model (Sammut et al. 2011[21]). It gives a tabular representation of actual labels versus predicted labels on horizontal and vertical axes respectively. The confusion matrix for this model is given in Figure 6.

Table 1
Classification Report

	Precision	Recall	F1-Score	Support
Gray_leaf_spot	1.00	0.90	0.95	10
Common_rust	1.00	1.00	1.00	10
Blight	0.91	1.00	0.95	10
Healthy	1.00	1.00	1.00	10
Accuracy		0.9760		40
macro avg	0.98	0.97	0.97	40
weighted avg	0.98	0.97	0.97	40

Actual Labels	Predicted Labels			
0	9	0	1	0
1	0	10	0	0
2	0	0	10	0
3	0	0	0	10

Figure 6: Confusion Matrix

Here, 40 images are considered for testing where 10 images belong to each class. This matrix shows 9 correct predictions of Gray leaf spot disease (Class 0), 10 correct predictions of Common Rust disease (Class 1), 10 correct predictions of Blight disease (Class 2), and 10 correct predictions of healthy leaves (Class 3). There are various models that are already given for the classification of corn leaf diseases. Table 2 presents a comparison between different given models and the proposed model. The proposed model performs well and achieves an accuracy of 97.60%.

Table 2
Comparison of various models

Models	Technique used	Accuracy (%)
Model given in [8]	Deep Forest	96.25
CNN model presented in[9]	Deep CNN	88.46
Model outlined in [10]	K-Mean Clustering and Deep Learning	93.00
CNN model given in[11]	Convolutional neural network	87.00
CNN model presented in [22]	CNN Based on Multi-Pathway Activation Function Module	97.41
The Proposed Model	Convolutional neural network	97.60

7. Conclusion

The proposed model achieves a training accuracy of 95.60% and validation accuracy of 97.60%. This model is trained for 50 epochs with early stopping and patience point is 2. The training gets terminated at epoch 5 due to a continuous increase in validation loss (at epoch 4 and 5) after the 3rd epoch. However, there is the scope for further enhancement of training and validation accuracy with the help of pretrained networks and may be considered as future work.

8. References

[1] Kumar V., Garg M. L. : Deep Learning Techniques and Their Applications: A Short Review. Biosc.Biotech.Res.Comm. 11(4) (2018).

[2] Deng L., Yu D. : Deep Learning: Methods and Applications in Fundamentals and Trends in Signal Processing, 7(3), 197-387 (2014).

[3] Ding B., Qian H., Zhou J. : Activation functions and their characteristics in deep neural networks. Chinese Control and Decision Conference (CCDC). 1836-1841 (2018).

[4] Apicella A., Donnarumma F., Isgrò F., Prevete R.: A survey on modern trainable activation functions. Neural Networks. (138), 14-32 (2021).

[5] Jason BB. 2019. A Gentle Introduction to the Rectified Linear Unit (ReLU). Machine Learning Mastery. https://machinelearningmastery.com/rectified-linear-activation-function-for-deep-learning-neural-networks/, last accessed 09/04/2021.

[6] Shrivastava V. K., Pradhan M. K. : Rice plant disease classification using color features: a machine learning paradigm. Journal of Plant Pathology. 103(1), 17–26 (2021).

[7] Ji M., Zhang L., Wu Q. : Automatic grape leaf diseases identification via united model based on multiple convolutional neural networks. Information Processing in Agriculture, 7(3), 418–426 (2020).

[8] Arora J., Agrawal U., Sharma P. : Classification of Maize leaf diseases from healthy leaves using Deep Forest. Journal of Artificial Intelligence and Systems, 2, 14–26 (2020).

[9] Mishra S., Sachan R., Rajpal D. : Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition, Procedia Computer Science, (167), 2003-2010, ISSN 1877-0509 (2020).

[10] Yu H., Liu J., Chen C., Heidari A. A., Zhang Q., Chen H. : Corn Leaf Diseases Diagnosis Based on K-Means Clustering and Deep Learning. in IEEE Access, (9), 143824-143835 (2021).

[11] Malliga S., Nandhini P. S., Kogilavani S. V., Harini R.J., Shree S.J., Jeeva G. : Maize leaf disease classification using convolutional neural network. AIP Conference Proceedings 2387, 040001 (2021).

[12] Alehegn E. 2019. Ethiopian maize diseases recognition and classification using support vector machine. International Journal of Computational Vision and Robotics, 9(1): 90–109 (2019).

[13] Vaishnnave M. P., Devi K. S., Srinivasan P., Jothi G. A. P. : Detection and classification of groundnut leaf diseases using KNN classifier. Proceedings of the IEEE International Conference on System, Computation, Automation and Networking (ICSCAN). pp. 1–5, Pondicherry, India (2019).

[14] Gupta D., Arora J., Agrawal U., Khanna A., Albuquerque H. C. V. Optimized Binary Bat algorithm for classification of white blood cells, Measurement. (143), 180-190 (2019).

[15] Arora J., Agrawal U., Tiwari P., Gupta D., Khanna A. Ensemble Feature Selection Method based on recently developed Nature-inspired algorithms, Proceedings of ICICC (2019).

[16] Shankar K., Prabu S.K. L., Gupta D., Maseleno A., Albuquerque H. C. V. : Optimal features-based multi kernel SVM approach for thyroid disease classification, Journal of Supercomputing (Springer), (2018).

[17] Golhani K., Siva B., Ganesan V., Biswajeet P. : A Review of Neural Networks in Plant Disease Detection using hyper-spectral data. Information Processing in Agriculture. Goodfellow I, Bengio Y., Courville.. Deep Learning. MIT Press, Online (2018).

[18] Mohanty S., David H., Marcel S. : Using Deep Learning for Image-Based Plant Disease Detection. Frontiers in Plant Science (2016).

[19] Khirade S. D., Patil A. B. : Plant Disease Detection Using Image Processing, 2015 International Conference on Computing Communication Control and Automation, pp. 768-771. Pune (2015).

[20] Pandian J. A., Geetharamani G. : Data for: Identification of Plant Leaf Diseases Using a 9-layer Deep Convolutional Neural Network, Mendeley Data, V1 (2019).

[21] Sammut C., Webb G. I. : Encyclopedia of machine learning: Springer Science & Business Media (2011).

[22] Zhang Y., Wa S., Liu, Y., Zhou, X., Sun, P., Ma, Q. : High-Accuracy Detection of Maize Leaf Diseases CNN Based on Multi-Pathway Activation Function Module. Remote Sens. 13, 4218 (2021).