International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

A Robust Restructured LeNet (RR LeNet) for Plant Leaf Disease Recognition

S. Janes Pushparani[1] and PL. Chithra*[2]

Submitted: 14/03/2024 **Revised:** 30/04/2024 **Accepted :** 07/05-2024

Abstract: Convolution Neural Networks (CNN) with Deep learning has attained remarkable achievement in categorizing major diseases in plants. The objective of this study is to identify diseases in Tomato, Corn and Apple plants using CNN. There are several popular Convolutional Neural Networks for object detection and object categorization from leaf images. In this work, Robust Restructured LeNet architecture is applied to the Plant Village data set. It has been exhibited that neural networks could detect the colors as well as the quality of lesions attributed to corresponding ailments that are similar to man-made confirmatory diagnosis. The database contains 18789 imageries. Out of these images, 20% of the imageries were kept apart for testing and 80% imageries were utilized for training. A maximum validation accuracy of 96.64%, 96.23%, and 96.85% was achieved over 30 epochs of testing, whereas a maximum of 98.46%, 96.79%, and 97.28% of accuracy were obtained over 30 epochs while training for tomato, corn, and apple respectively.

Keywords: *Convolutional Neural Networks, Deep Learning, Plant Disease Recognition, Object Categorization, Object Detection.*

1. Introduction

India mainly depends on the agricultural industry to take care of the needs of its population. In our country, being tropical in nature, the crops are worst threatened by numerous diseases and pests. Agricultural produce is affected both in quality and quantity due to plant diseases. The main task is to recognize and detect the plant diseases correctly. The practice of detection of diseases was earlier done through visual examination. Because of the multifaceted nature and time duration, analyzing the plants manually is a difficult task. Hence, there is a necessity to avoid manual procedures for precise diagnosis and safeguarding the farmers' lives.

Moreover, there are chances of wrong predictions while detecting plant diseases manually, which eventually leads to faulty preventive steps. Farmers often tend to apply the same solution as a group as they are not supported with an expert's opinion. In addition, because of insufficient knowledge as well as misapprehension pertaining to the quantum of the disease, there is a possibility of over-treatment or under-treatment with the pesticides resulting in the destruction of crops.

Considering the above facts, deep learning is the best-suited method as the system automatically identifies the most relevant feature without manual intervention. Amongst numerous network architectures utilized in deep learning, Convolutional Neural Networks was preferably applied for image recognition. Currently, it is upgraded with various technologies.

[1] Department of Computer Applications, Ethiraj College for Women Chennai, Tamil Nadu, India
ORCID ID: 0000-0003-1590-5104
[2]Department of Computer Science, University of Madras, Chennai, Tamil Nadu, India
ORCID ID : 0000-0001-7450-4170
** Corresponding Author Email: chitrasp2001@yahoo.com*

The planned and pre-conditioned LeNet Convolutional Neural Network (CNN) prototype is utilized for categorization of most afflicted diseases because precise diagnosis and documentation of diseases are essential for profitable harvest. Traditionally, using the naked eye is generally favouring the pathology experts for spotting plant diseases. However, bias can arise because of the subjective decision grounded on the expertise and skill of specialists.

To acquire correct diagnosis and outcomes, numerous investigators have considered computerized disease diagnosis grounded on the following techniques, namely digital image processing, pattern recognition, and computer vision.

This paper is organised as follows. Section 2 discusses the related methodologies in this domain. Section 3 explains the suggested Robust Restructured LeNet system. Section 4 shows the experimental results for the deep learning model, the outcome of the suggested system is analyzed in Section 5. Lastly the proposed model is compared with existing methods in Section 6 and Section 7 yields the inference.

2. Related Work

One of the approaches details about an aggregate scheme grounded by Convolutional Neural Networks. Moreover, to that, the amplification procedures were utilized to build the system arrangement further vigorous and precise. Arithmetic experimentation executed by means of the planned scheme utilizing the ResNet50 structural design achieved a precision of 95.24% for the biological strain categorization and 86.51% for rigorousness assessment. In addition, one could observe that if they were categorized based on indication, the inference would be enhanced to more than 97%. The interim inferences point to the fact that they facilitate the planned scheme, which might be an appropriate instrument to support mutually specialist and cultivators for the recognition as well as quantitatively of biological strain in coffee plantations [1].

Another efficient rapid R-CNN structural design that was executed through altering the parameters of a CNN model as well as rapid R-CNN plan for impulsive detection of a leaf spot disease ---Cercospora beticola Sacc, in sugar beet. The method detects severity of the malady by tomography specialist schemes that were trained and evaluated using 155 imageries. Based on the experiments, it was inferred that accurate categorization percentage was recorded as 95.48% [2].

A trial based on the manifestation of signs to recognize diseases in cucumber was attempted. The imageries of manifested signs were divided in cucumber foliage imageries that were collected in field-like circumstances through picture division method followed by execution of authoritative recognition of maladies and its signs including clutter environment. Considering the pictures from manifestation of signs, information set consisting four maladies aimed at foliage spots was created that was again amplified by information amplification technique. Perceptible testing established that the DCNN accomplished outstanding identification outcomes. The accurateness of the DCNN on the unequal data set and fair data set was 93.4 % and 92.2 % respectively. Qualified experiments have shown that AlexNet outplayed the DCNN because of its dominant characteristic arrangement. DCNN and AlexNet mutually exhibited results greater than that of the conservative identifiers [3].

One more small blast experimental technique for identification of tea leaf's disease in order to timely avert and resist maladies in tea foliage was carried out. The complexion and character topographies were mined concerning malady specks on tea foliage illness imageries which was then subdivided by means of support vector machine (SVM) technique. The subdivided malady speck imageries were delivered in the form of data subsequently through specimens for novel training that were fashioned by the enriched conditional deep convolutional generative adversarial networks (C-DCGAN) for information augmentation, which were deployed to formulate VGG16 deep learning model for identification of maladies in tea foliage. Investigational outcomes exhibited that SVM could subdivide diseased and its speck imageries based on the state of low shot training though recalling the edge info correctly. Enhanced C-DCGAN can produce amplified pictures incorporating the similar information as well as scattering with respect to actual malady speck imageries. VGG16 deep learning model prepared by amplified malady speck imageries could recognize tea foliage maladies precisely, as well as the regular recognition and precision of the projected technique was 90%, which exceeded traditional low shot learning techniques [4].

A different method by utilizing transfer learning associated with characteristic features mined to construct a recognition scheme for mildew ailment in pearl millet was performed. The deep learning simplifies an essentially rapid as well as remarkable information investigation in meticulous farming. The benefit will offer sustenance to all stakeholders concerned such as scientists and agriculturalists by the facts and information created through the rational procedure. The outcome of the trial provided a promising presentation with a precision of 95.00 %, accuracy of 90.50%, recall of 94.50% as well as the f1-score of 91.75% [5].

Moreover, to extract inequitable topographies from foliage pictures by training as well as spreading over them as classifiers for herbal recognition was tested. The outcomes of the investigation reveal that training the topographies utilizing CNN scan could deliver improved characteristics that signifies the foliage images as equated while utilizing hand-made feature. In addition, the characteristic features were also evaluated which effectively characterize the foliage to determine the species recognition by means of Deconvolutional Network (DN) method. During prior experimentation, it was revealed that stratum arrangement was a significant characteristic for identification particularly when contour details single-handedly were insufficient. Then it was checked by scrutiny through over-all reaction of the filters individually by intricacy coating by means of the V1 scheme [6].

3. I In addition, the transfer learning advances the enactment of deep learning prototypes and particularly, prototypes that put on a by small topographies as well as refinement deliver healthier presentation equated to various transfer learning approaches was implemented. The outcome suggests that in the place of merely utilizing an end-to-end CNN prototype to categorize the herbs, the supplementary transfer learning methodologies should be taken into account when there is less precision and poor presentation [7].

3. Materials and Methods

Flow diagram that describes the main processes of the disease recognition structure is displayed in Fig. 1. The methodology comprises of 3 major steps:

1. Data Acquisition:

2.

It deals with obtaining the high quality images of the plant leaf. The imageries utilized for carrying out the suggested procedure were learned from a publicly available dataset termed as Plant village Dataset.

3. Pre-processing:

4.

The attained dataset comprised of imageries by means of insignificant noise and therefore noise elimination was not a mandatory pre-treatment phase. The imageries in the dataset were rescaled to 60 × 60 tenacity so as to hasten the training procedure and create the training prototype through computer-intensive method that is achievable.

5. Classification:

6.

Finally, Convolutional Neural Networks (CNN) could be utilized for the conception of a computing prototype which deals with inputs from amorphous imageries, then transform them to equivalent classification output tags. It is said to be considered under the classification of multi-layer neural networks, which could then be prepared to acquire the essential topographies for cataloguing determinations. Classifiers were used for the training and testing of the datasets. This leads to classify and detect leaf diseases.

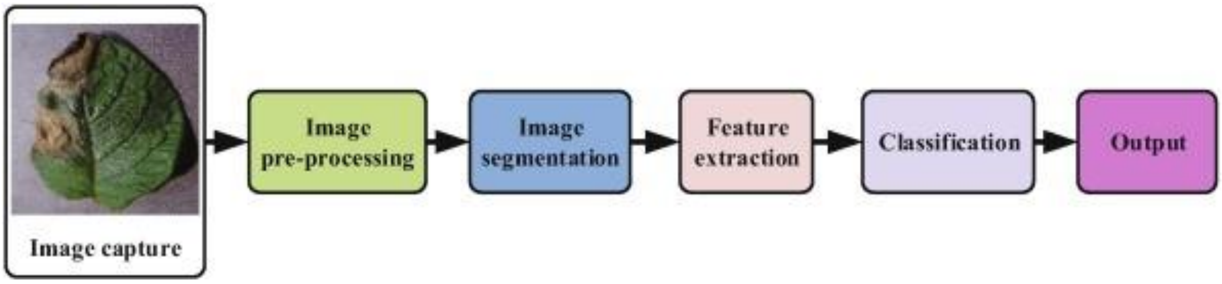


Fig. 1. Flow Diagram

3.1. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is one of the deep learning networks that can identify and categorize topographies in imageries for computer vision. It is a multi-layer neural network intended to analyze graphical inputs as well a complement works namely image classification, segmentation, and object detection. CNN architecture was stimulated by the arrangement and processing of the optical cortex which is developed to imitate the connectivity configuration of neurons inside the human brain. The neurons inside CNN are divided into a three-dimensional configuration, utilizing an individual set of neurons analyzing a minor portion or characteristic of the imageries. CNNs utilize the calculations from the layers to obtain an outcome.

3.2. Training and Testing Datasets

The Plant Village dataset [8] is an open-access repository containing 54,306 labeled images of both healthy and diseased plants, covering 14 different plant varieties. For this study, 18,789 images of healthy and diseased foliage were used to train and test CNN prototypes. The dataset was split into training and testing sets, with 80% of the images (15,031) used for training and 20% (3,758) for testing, following the commonly used 80/20 training/testing ratio in neural network applications [9].

A Python script was developed to randomly select images for the two datasets. Table 1 provides details on the 15 classes, including the number of images per class. The dataset was employed to recognize tomato diseases such as Tomato Bacterial Leaf Spot, Tomato Early Blight, Tomato Late Blight, Tomato Leaf Mold, Tomato Septoria Leaf Spot, Tomato Yellow Leaf Curl, and Healthy Tomato, with sample images shown in Fig. 2. For corn, diseases like Corn Cercospora, Corn Common Rust, Corn Northern Leaf Blight, and Corn Healthy were identified, with sample images in Fig. 3. For apple, the diseases included Apple Scab, Apple Black Rot, Apple Cedar Rust, and Healthy Apple, with sample images in Fig. 4.

Experiments with typical deep learning models such as LeNet, AlexNet, and VGG-16 were conducted to identify and classify diseases in foliage, revealing that better outcomes can be achieved using the Robust Restructured LeNet architecture

Table 1: Information and Quantifiable Data of Database Images

Class	*Plant Common Name*	*Plant Scientific Name*	*Disease Common Name*	*Disease Scientific Name*	*No. of Images*
C_0	Tomato	Lycopersicum esculentum	Bacterial leaf spot	Xanthomonas campestris pv. Vesicatoria	1702
C_1	Tomato	Lycopersicum esculentum	Early Blight	Alternaria solani	800
C_2	Tomato	Lycopersicum esculentum	Late Blight	Phytophthora infestans	1527
C_3	Tomato	Lycopersicum esculentum	Leaf Mold	Fulvia fulva	761
C_4	Tomato	Lycopersicum esculentum	Septoria leaf spot	Septoria lycopersici	1417
C_5	Tomato	Lycopersicum esculentum	Yellow Leaf Curl	Begomovirus	4286
C_6	Tomato	Lycopersicum esculentum	Healthy Tomato	Lycopersicum esculentum	1273
C_7	Corn	Zea mays	Cercospora leaf spot	Cercospora zeae-maydis	513
C_8	Corn	Zea mays	Common Rust	Puccinia sorghi	1192
C_9	Corn	Zea mays	Northern Leaf Blight	Exserohilum turcicum	985
C_10	Corn	Zea mays	Healthy Corn	Zea mays	1162
C_12	Apple	Malus domestica	Scab	Venturia inaequalis	630
C_13	Apple	Malus domestica	Black Rot	Botryosphaeria obtusa	621
C_14	Apple	Malus domestica	Cedar Rust	Gymnosporangium juniperivirginianae	275
C_15	Apple	Malus domestica	Healthy Apple	Malus domestica	1645
			Total		18789

(a)Bacterial leaf spot (b) Early Blight (c) Late Blight

(d)Leaf Mold (e) Septoria leaf spot (f)Yellow Leaf Curl (g) Tomato Healthy

Fig. 2. Images of 7 Tomato Diseases

(a) Cercospora (b) Common Rust (c)Northern Leaf (d) Corn Healthy

Fig. 3. Images of 4 Corn Diseases

(a) Scab (b) Black Rot (c) Cedar Rust (d) Apple Healthy

Fig. 4. Images of 4 Apple Diseases

3.3. Deep Learning Models

3.3.1. LeNet

Yann LeCun suggested the famous LeNet-5 grounded on CNN in 1998, that were effectively useful to character recognition. It is a fundamental CNN model that contains convolution layer, activation layer, pooling layer in addition to fully connected layers. It comprises of 7 layers, i.e. an input layer, two convolution layers, two pooling layers, two fully connected layers plus an output layer [10]. It conglomerates characteristic extraction as well as image identification. LeNet-5 CNN mines topographies, by various convolution kernels, converts the original data into higher-level, more abstract expressions through some simple nonlinear models, and finally uses high-level features for classification and identification [11].

3.3.2. Alex Net

AlexNet architecture was proposed by Alex Krishevesky in the year 2012. It comprises of 5 convolutional layers, 3 pooling layers that was followed by three fully connected (FC) layers. In order to decrease the over fitting - difficulty, these fully connected layers were utilized by means of the dropout layer. Convolution layer then utilizes many numbers of filters to convolve the imageries, and generate characteristic maps. Rectified Linear Unit (ReLU) layer was utilized alongside with convolutional layer as it executes non-linear operation as well as transforms all negative values to zero.

The work of pooling layer was to minimize the feature map that was obtained from previous layer [12].

3.3.3. VGG–16

The VGG network was first described by Simonyan and Zisserman in 2014. VGG-16 is abysmal and extensive than the previous CNN structure. It contains 5groups of convolution operations; each group contains 2 to 3 neighbouring convolution layers. Neighbouring convolution groups were linked via max-pooling layers. The magnitude of kernels in all convolutional layers is 3×3. The quantum of kernels inside each group was the same [13].

3.3.4. Proposed Model RR LeNet

LeNet is said to be one of the modest CNN prototypes that comprises of convolution layer, activation layer, pooling layer and fully connected layers. The proposed prototype utilized for the detection of foliage maladies is a modified version of the above said architecture. It comprises of four sets of convolution layers, activation layers and pooling layers followed by a fully-connected layer, activation layer, another fully-connected layer, and lastly a classifier. The proposed prototype is shown in Fig. 5

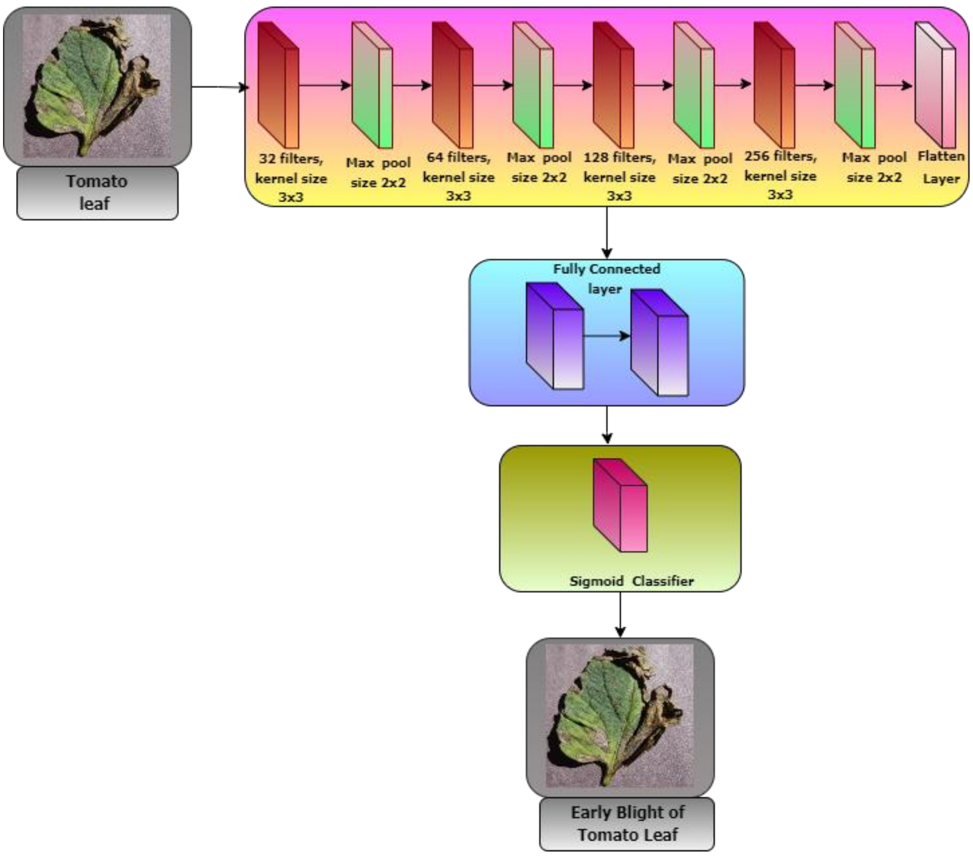


Fig 5. RR LeNet Architecture

Convolutional layer relates to convolution operation for the abstraction of topographies. Using the escalation in deepness, the intricacy of the abstracted topographies will be enhanced. The dimension of the filter is taken as 5×5, while the quantum of filters is amplified gradually when moving from one group to the successive group. The quantum of filters is 20 in the preliminary convolutional group whereas it is raised to 50 during the second followed by 80 in the third group and finally 120 in the last group. The change in the quantum of filters is mandatory to reimburse for the decrease in the dimension of the characteristic maps triggered using pooling layers in individual groups. The topography records were furthermore zero-padded so that the dimension of the pictograph is conserved afterwards the submission of the convolution procedure.

The Max pooling layer is utilized for the decline in dimension of the characteristic maps, hastening up the training process, and producing the prototype with minimal variation to slight changes in input. The kernel dimension for max pooling is 2×2. The ReLU activation layer is utilized in individual chunks to introduce non-linearity. In addition, the dropout regularization method has been utilized using the probability of 0.5 to eliminate overfitting.

It occurs arbitrarily so that neurons descend in the network in the course of individual repetition of training so as to decrease the inconsistency of the prototype and abridge the network.
The advantages of the proposed architecture RR LeNet are as follows:

- This architecture uses morphologic, textural, and time-based herbal characteristics through a computer optical system for automatic non-contact observation of herbal well-being and development.

- The present work extends to cover more diseases in three plant species such as tomato, corn, and apple.

- The validation accuracy is enhanced with the implementation of RR LeNet while existing architectures lack in accuracy of results.

4. Results

In this research, three popular CNN (LeNet, Alex Net and VGG – 16) architectures have been evaluated. After appropriate experimentation, LeNet has been selected as the target model because this model showed the highest accuracy in training. But the validation accuracy has been decreased. The values are presented in Table 2 (LeNet), Table 3 (Alex Net) and Table 4 (VGG – 16).

Table 2: Classification Accuracy using LeNet

Plant Name	Total Images	Training Images (80%)	Test Images (20%)	Training Accuracy (%)	Validation Accuracy (%)
Tomato	11766	9415	2351	98.63	93.70
Corn	3852	3083	769	99.71	94.15
Apple	3171	2537	634	99.21	94.95

Table 3: Classification Accuracy using AlexNet

Plant Name	Total Images	Training Images (80%)	Test Images (20%)	Training Accuracy (%)	Validation Accuracy (%)
Tomato	11766	9415	2351	97.71	94.05
Corn	3852	3083	769	92.47	90.38
Apple	3171	2537	634	96.85	88.80

Table 4: Classification Accuracy using VGG – 16

Plant Name	Total Images	Training Images (80%)	Test Images (20%)	Training Accuracy (%)	Validation Accuracy (%)
Tomato	11766	9415	2351	96.66	92.05
Corn	3852	3083	769	97.83	95.97
Apple	3171	2537	634	98.82	97.00

To improve the validation accuracy, the existing architecture of LeNet is restructured and the proposed model is implemented using Python. Then the outcomes are assessed. Table 5 shows the accuracy using RR LeNet. As seen in the table, there is not much difference in the accuracy values of training and validation.

Table 5: Classification Accuracy using RR LeNet

Plant Name	Total Images	Training Images (80%)	Test Images (20%)	Training Accuracy (%)	Validation Accuracy (%)
Tomato	11766	9415	2351	98.46	96.64
Corn	3852	3083	769	96.79	96.23
Apple	3171	2537	634	97.28	96.85

5. Performance Analysis

Figure 6, Figure 7, and Figure 8 illustrate that the RR LeNet achieves higher accuracy and more robust compare to the current models (LeNet, Alex Net and VGG – 16).

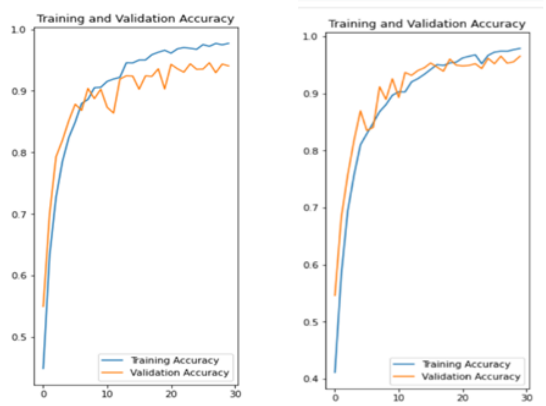


Fig.6. Accuracy obtained on the training and validation set by LeNet and RR LeNet for Tomato

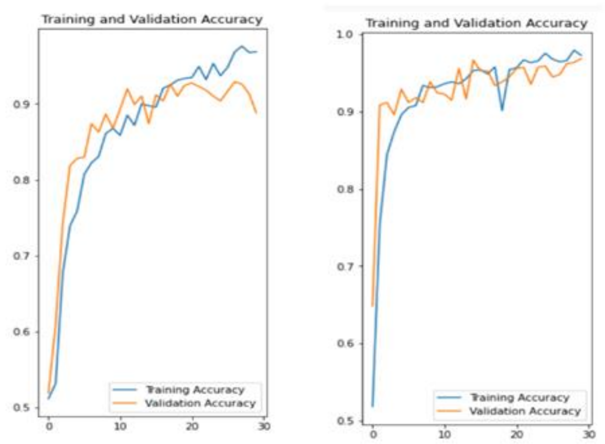


Fig. 7. Accuracy obtained on the training and validation set by AlexNet and RR LeNet for Apple

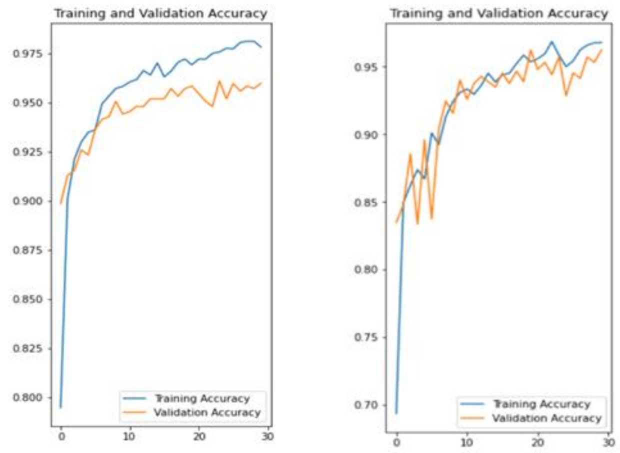


Fig. 8. Accuracy obtained on the training and validation set by VGG 16 and RR LeNet for C

Table 6: Performance Analysis

Architecture/Plant Leaf	LeNet		Alex Net		VGG16		RR LeNet	
	Training Accuracy (%)	Validation Accuracy (%)	Training Accuracy (%)	Validation Accuracy (%)	Training Accuracy (%)	Validation Accuracy (%)	Training Accuracy (%)	Validation Accuracy (%)
Tomato (7)	98.63	93.70	97.71	94.05	96.66	92.05	98.46	96.64
Corn (4)	99.71	94.15	92.47	90.38	97.83	95.97	96.79	96.23
Apple (4)	99.21	94.95	96.85	88.80	98.82	97.00	97.28	96.85

Table 6 demonstrates the comparison performance between the existing models and the proposed RR LeNet model. When considering the results of training, LeNet has performed the best with 98.63% with tomato, 99.71% with corn and 99.21% with apple. But it is reduced in testing as 93.7% with tomato, 94.15% with corn and 94.95% with apple. Furthermore, while equating the variations in testing and training, it is seen that the proposed RR LeNet has noticeably caused in maximum values pertaining to validation accuracy.

The highest validation accuracy of 96.64% with tomato, 96.23% with corn and 96.85% with apple were obtained over 30 epochs, while high 98.46%, 96.79% and 97.28% of training accuracy with tomato, corn, and apple respectively were reported. The results presented in Table 6 indicate that RR LeNet achieved better performances than the other architectures. In Fig. 9, all the results are displayed with a bar graph. It shows that, compared to all other methods, the recognition of various diseases can be effectively improved through RR LeNet.

6. DISCUSSION

In the recent past, CNN models are being utilized to identify different maladies in crops/herbs that would be helpful to the farmers/agriculturalists in obtaining fruitful yield [14]. In this context, a maiden attempt has been put forth to recognize tomato, corn and apple maladies Numerous CNN models were established to categorize plant maladies from plant leaf imageries. The most common models are LeNet, AlexNet, GoogLeNet and VGG16 [15].

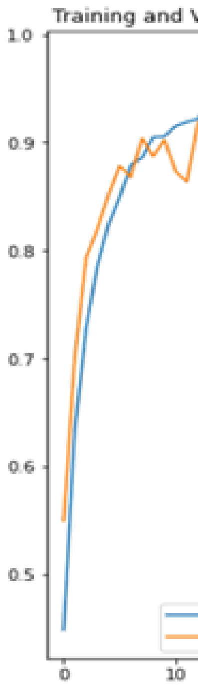
In previous studies, two deep convolutional neural network models namely AlexNet and SqueezeNet were established to identify maladies in tomato [16]. The accuracy for AlexNet is 95.65% and SqueezeNet is 94.3%. There was a notable difference in accuracy when compared with the proposed work in terms of accuracy. The RR LeNet achieved the accuracy of 96.64% which is 0.99% higher than AlexNet and 2.34% than SqueezeNet.

Furthermore, CNN based architecture to automatically detect plant maladies and resulted in an average accuracy of 96.3% [17].However, it is 0.34% lesser than RR LeNet. A model using VGG 16 is built for extraction of features from the fully connected layer, that shows an accuracy of 88% whereas using the proposed model RR LeNet an accuracy of 96.64% which is 8.64% higher over VGG 16 could be obtained [18].

Another CNN model which is capable of classifying the corn maladies at an overall accuracy of 92.85% was demonstrated [19]. In comparison, the experimental results could establish the RR LeNet produces better accuracy of 96.23%. An additional method had obtained 93% of accuracy in maize leaf maladies recognition [20] while proposed method has obtained the accuracy of 96.23% which is 3.23% higher than that of the existing model.A different method was suggested using neural network classifier to identify the maize maladies at an accuracy of 95.3% [21] which is 0.93% lower than the proposed model.

73.50% accuracy was achieved using MobileNet deep learning model for identifying maladies in apple [22].

But the proposed model achieves the accuracy of which is 23.35% greater than the MobileNet. By co the proposed RR LeNet with Yu and Son (201 observed that the proposed method increas recognition accuracy by 12.55%. A newly suggeste R – CNN for the detection of apple leaf maladies an accuracy of 84.5% while the proposed RR LeN 96.85% accuracy which is 12.35% more.



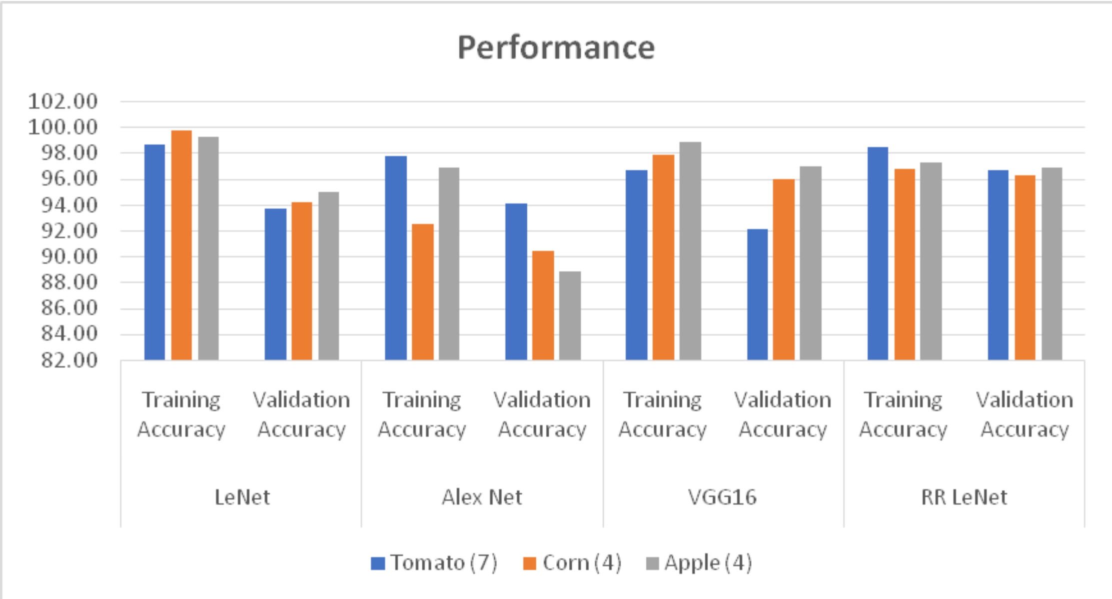


Fig 9. Comparative Analysis of LeNet, AlexNet and VGG 16 with RR LeNet

7. CONCLUSION

The Robust Restructured LeNet (RR LeNet) prototype, which modifies elements of the CNN architecture, is designed to automatically identify disease in foliage. The model utilized three sets of leaves, totaling 18,789 images for both training and testing. Achieving an accuracy of 98.46% in validation and 96.64% in training, RR LeNet outperformed contemporary methods from previous studies. The findings suggest that the RR LeNet model can be reliably employed for disease detection in plant leaves. It is recommended that future studies involve different deep learning architectures and large datasets to enhance disease detection accuracy

References

[1] Esgario JGM, Krohling RA, Ventura JA, “Deep learning for classification and severity estimation of coffee leaf biotic stress”. Comput. Electron. Agric 169, (2020) https://doi.org/10.1016/j.compag.2019.105162

[2] M. M. Ozguven and K. Adem, "Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms," Phys. A Stat. Mech. its Appl., vol. 535, pp. 1-12, 2019, doi: 10.1016/j.physa.2019.122537.

[3] Ma J, Du K, Zheng F, Zhang L, Gong Z, Sun Z, “A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network”. Comput. Electron. Agric 154 : 18 – 24,(2018) https://doi.org/10.1016/j.compag.2018.08.048

[4] Gensheng H, Haoyu W, Yan Z, Mingzhu W, “A low shot learning method for tea leaf’s disease identification”. Comput. Electron. Agric 158 : 151–158, (2019). https://doi.org/10.1016/j.compag.2019.104852

[5] Coulibaly S, Kamsu-Foguem B, Kamissoko D, Traore D, “Deep neural networks with transfer learning in millet crop images”. Comput. Ind 108 : 115–120, (2019). https://doi.org/10.1016/j.compind.2019.02.003

[6] Lee SH, Chan CS, Mayo SJ, Remagnino P, “How deep learning extracts and learns leaf features for plant classification”. Pattern Recognit 71 : 1–13, (2017). https://doi.org/10.1016/j.patcog.2017.05.015

[7] Kaya A, Keceli AS, Catal C, Yalic HY, Temucin H, Tekinerdogan B, “Analysis of transfer learning for deep neural network based plant classification models”. Comput. Electron. Agric 158 : 20–29, (2019) https://doi.org/10.1016/j.compag.2019.01.041.

[8] Hughes DP, Salathe M, “An open access repository of images on plant health to enable the development of mobile

disease diagnostics"(2015).

[9] Fine TL Feedforward Neural Network Methodology. Springer Science Business Media, New York, (1999).

[10] Ma M, Gao Z, Wu J, Chen Y, Zheng X, "A smile detection method based on improved LeNet-5 and support vector machine". Proc. IEEE SmartWorld, Ubiquitous Intell. Comput. Adv. Trust. Comput. Scalable Comput. Commun. Cloud Big Data Comput. Internet People Smart City Innov. SmartWorld/UIC/ATC/ScalCom/CBDCo : 446–451,(2018). https://doi.org/10.1109/SmartWorld.2018.00104

[11] Wang G, Gong J, "Facial Expression Recognition Based on Improved LeNet-5 CNN". Proc. 31st Chinese Control Decis. Conf. CCDC : 5655–5660, (2019). https://doi.org/10.1109/CCDC.2019.8832535

[12] Arya S, Singh R, "A Comparative Study of CNN and AlexNet for Detection of Disease in Potato and Mango leaf". IEEE Int. Conf. Issues Challenges Intell. Comput. Tech. ICICT : 1-6, (2019). https://doi.org/10.1109/ICICT46931.2019.8977648

[13] Taheri S, Toygar Ö, "On the use of DAG-CNN architecture for age estimation with multi-stage features fusion". Neurocomputing 329 : 300–310, (2019). https://doi.org/10.1016/j.neucom.2018.10.071

[14] Boulent J, Foucher S, Théau J, St-Charles P, "Convolutional neural networks for the automatic identification of plant diseases". Front. Plant Sci. 10:941, (2019). https://10.3389/fpls.2019.00941

[15] Saleem, M. H., Potgieter, J., & Arif, K. M, "Plant Disease Classification: A Comparative Evaluation of Convolutional Neural Networks and Deep Learning Optimizers. Plants", 9(10), 1319, (2020). https://doi:10.3390/plants9101319

[16] Durmuş H, Guneş EO, Kırcı M, "Disease detection on the leaves of the tomato plants by using deep learning". In: 6th IEEE International Conference on Agro-Geoinformatics (2017) 1–5. https://doi:10.1109/Agro-Geoinformatics.2017.80470 16.

[17] Sladojevic S, Arsenovic M, Anderla A, Culibrk D, Stefanovic D,"Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification". Comput Intell Neurosci. 1 – 11(2016). https://doi.org/10.1155/2016/3289801

[18] Shijie, J., Peiyi, J., Siping, H., Haibo, L, "Automatic detection of tomato disease and pests based on leaf images", Chinese Automation Congress, 3507-3510, (2017). https://doi:10.1109/CAC.2017.8243388

[19] Sibiya, M.; Sumbwanyambe, M, A "Computational Procedure for the Recognition and Classification of Maize Leaf Diseases Out of Healthy Leaves Using Convolutional Neural Networks". AgriEngineering , 1, 119-131, (2019). https://doi.org/10.3390/agriengineering1010009

[20] Syarief, Mohammad, and Wahyudi Setiawan,"Convolutional neural network for maize leaf disease image classification",TELKOMNIKA Telecommunication, Computing, Electronics and Control. (2020). https://DOI:10.12928/TELKOMNIKA.v18i3.14840

[21] Ibrahim M. Adekunle, "Implementation of Improved Machine Learning Techniques for Plant Disease Detection and Classification". International Journal of Research and Innovation in Applied Science (IJRIAS) | Volume V, Issue VI, 136 – 140 ISSN 2454-6194 (2020)

[22] Bi C, Wang J, Duan Y, Fu B, Kang J, Shi Y, "Mobilenet based apple leaf diseases identification". Mobile Netw Appl.,(2020). https://doi.org/10.1007/s11036-020-01640-1

[23] Melike SARDOGAN , Yunus OZEN , Adem TUNCER, "Detection of Apple Leaf Diseases using Faster R-CNN". Düzce University Journal of Science & Technology 1110-1117 (2020). https://doi.org/10.29130/dubited.648387