An Enhanced Faster-RCNN Based Deep Learning Model for Crop Diseases Detection and Classification

Mallarapu Harish, A V L N Sujith, K. Santhi

***Abstract*:** **Recently Plant phenotyping has gained the attention of many researchers such that it plays a vital role in the context of enhancing agricultural productivity. Indian economy highly depends on agriculture and this factor elevates the importance of early disease detection of the crops within the agricultural fields. Addressing this problem several researchers have proposed Computer Vision and Pattern recognition based mechanisms through which they have attempted to identify the infected crops in the early stages.in this scenario, CNN convolution neural network-based architecture has demonstrated exceptional performance when compared with state-of-art mechanisms. This paper introduces an enhanced RCNN recurrent convolution neural network-based architecture that enhances the prediction accuracy while detecting the crop diseases in early stages. Based on the simulative studies is observed that the proposed model outperforms when compared with CNN and other state-of-art mechanisms**.

Keywords: CNN, RCNN, Deep Learning, Plant diseases

I. INTRODUCTION

Nowadays technology adoption in farming has demonstrated quantitative results in the agricultural productivity in terms of monitoring the crops of big farms with minimal manpower. With the advent of technologies viz. IoT(Internet of Things), Cloud Computing, Artificial Intelligence, and Computer Vision have revolutionized the agricultural sector to progressively improve productivity with low investments. The major concern that affects the productivity of the crops is the failure of detecting crop diseases in the early stages. In general context, the detection of crop diseases is performed through manual inception, besides it is not possible to identify the crop diseases without the intervention of expert opinions having accumulated knowledge regarding the symptoms and the cause of the diseases. From the literature studies, it has been observed that several ways methodologies could be adopted to identified plant pathology. Symptoms associated with few types of crops diseases will not be visible to naked I could be identified thorough electromagnetic spectrum [1]. Most of the crop diseases exhibit their symptoms on the different areas of plants that includes stem, leaf, fruits, root, and seeds. This research mainly focuses on the development of an automated model based on artificial neural networks to classify and predict the crop diseases in the early stage. Previously diagnosis of crop diseases was made directly by the formers with the suggestions of domain experts based on their past experiences, from 1970's adaption of technology in agricultural engineering enabled a prevalent practice to attain maximized performance in terms of agricultural productivity. Design and development an automated crop diseases detection model improves the prediction accuracy with minimal effort and time. Several studies have proposed a vast range of algorithms that enables the classification of plant diseases using image processing based on the infected crop image dataset. The pattern of diseases within the image plays a vital role in identifying the accurate symptom of the diseases. Image segmentation is the most profound methodology that is utilized in the process of separating and grouping different parts of the image. Deep learning is considered to be the next generation study for developing prediction models based on learning the past patterns of any phenomenon. It constitutes to be a modern technology that enhances the performance of image processing and data analysis. Machine learning techniques like K nearest neighbor (KNN), decision tree, k-means, and support vector machines (SVM) are widely used mechanisms in applied agricultural research [2].

CNN's are considered to be a widely used class of deep neural networks which is generally applied in the context to visually analyze the crop images. It consists of multilayer perceptions that are fully connected to each neuron across the layers and this makes CNN more efficient to analyze feature of every neuron within the network. Several CNN architectures that include AlexNet, GoogleNet and several states of art mechanism have been utilized for saliency Map visualization and detection of plant diseases in the past studies. Further, it is observed that it is a lack of evaluation in quantitative visualization of diseases crop images. From the motivation gained from the scenario, this study mainly focuses on the application of modified RCNN in developing diseases detection model for the agricultural sector.

RCNN is a most prominent artificial neural network when compared to CNN such that, CNN is considered to be a feed-forward neural network-based architecture in which the recurrent connections are abundant.

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But in the context of RCNN, the object recognition could be made by recurrent connections in is the conventional layer. As it is known that the feed-forward architecture could only able to identify the higher layers but neglect the connectivity of the sub-layers, RCNN overcomes this phenomenon with the help on recurrent connections.

Based on this property RCNN has been chosen over CNN for crop diseases detection in this article. The contribution of the article includes a hybrid RCNN model for crop diseases classification and detection along with performance evaluation using real-world dataset.

The rest of the article is organized as follows: section1 provide introduction for the problem statement and provide motivation for choosing RCNN, Section 2 provides the analysis of literature study that includes various techniques and algorithms implemented on crop diseases detection and classification, Section 3 illustrates the proposed extended RCNN model to analyze various crop image dataset, Section 4 enables with the details regarding to the performance evaluation metrics and case study of crop diseases detection and classification, Section 5 describe the limitations of the proposed work and provides conclusion along with future enhancement.

II. LITERATURE REVIEW

Arivazhagan [3] addressing the problem of predicting plant diseases presented a technique based on classification and identification of crop diseases. This model automatically detects and classify plant disease appear on plant leaves. The proposed model consists of four main steps, in the first step to get the input RGB image it uses the color transformation process, further the green pixels are eliminated based on the unique threshold value and the process is continued to segmentation. For useful segments, the texture statistics are computed. The proposed model extracted features passed through the classifier. In this model successfully detect and classify the plant diseases up to the accuracy of 94%.

Muhammad Attique Khan [4] while addressing the problem of detecting and classification of apple crop diseases proposed a model based on strength and co-relation and genetic algorithm. The main objective of this approach is to detect is apple crop diseases at early stages. This model is based on a three-level pipeline procedure which includes pre-processing of diseases data set, the pattern of spots accord on apple crop and feature extraction. Initially, during the first level model have utilized a hybrid method that includes three-dimensional box and median filtering technique coupled with De-correlation. In the second phase lesion spots segmented based on fusion exportation maximization, further using

local binary patterns the feature extraction has been processed. The experimental results depicted in this article shows that this technique optimizes the rate of detection and classification of apple crop diseases.

Zhongqi Lin[5] starting stage of classification fine-grained image classification face many challenges. The crop diseases classification is affected by various visual interference, including uneven illumination, dew, and equipment jitter. This poses work include algorithm to complete the process of classification. In that article, they used CNN for it denoted the matrix-based CNN, and is proposed for the classification process. In this CNN all the layer are arranged parallel and staring layer 16,652 images arranged, and finally, this process gets particularly affected leaf images. In this process of MBCNN possible to classify the fine-grained image.

Xihai Zhang[6]In this paper improved GoogLeNet and Cifar10 models based on deep learning are used for identification and diagnosis of maize leaf diseases. To test and train purpose some different types of maize leaves are used in this model. By adjusting the parameters, changing the combination, adding dropout operations and rectified linear unit function, and reducing the number of classifiers. VGG and AlexNet structures are bigger then parameters improved models. In the process of identification of maize leaf diseases, GoogLeNet finds more then CIfar10 model. By improved methods are reduce the maize leaf diseases.

Siddharth Sign Chouhan [7] In this model introduced Bacterial Foraging Optimization-based Radial basic Function Neural Network (BRBFNN) for automatic classification and identification of plant leaf diseases. The main objective is to asses optimal weight to radial basis function neural network and further bacterial foraging optimization by network speed is increase identify and classify the diseases on different types of leaf and diseases

Neha G. Kurale[8] In this article Support Vector Machine(SVM), K-nearest neighbor and neural Network are used for detection and classification of crop diseases. Here, the diseases are classified and identified by using four types of leaf images, early blight, Late blight, Black rot and Healthy. By using this leaf images it is possible to calculate the percentage of the affected leaf and simply classify the crop diseases. The simulation result includes the verification of the data that consist of 5000 infected crop images using SVM and KNN classifiers to analyze the accuracy of prediction.

Leninisha Shanmugam [9] In this model described that detect the effected leaf at the early stage by using remote sensing images. Here, they have used two phases for detection, in the first phase deal with healthy and effected leaves and the second phase by using canny edge detection algorithm and histogram analysis to classify and detect the particular diseases.

III. PROPOSED MODEL

The main objective of the proposed model is to design an enhanced Faster-RCNN model that integrates with ResNet CNN for the detection and classification of plant diseases. In this context it is intended to build a RCNN model in which ReSNet CNN is implemented on the top of each region for the classification of images. Further the output of the model is processed through SVM classifier for the process of classification and recognition. IN the context of Faster-RCNN [15], the features of the image are extracted before identifying the regions and further the entire image is processed through ReSNet CNN to improve the performance of the process. Region sampling the context of RCNN is adopted as Ren et al [16].
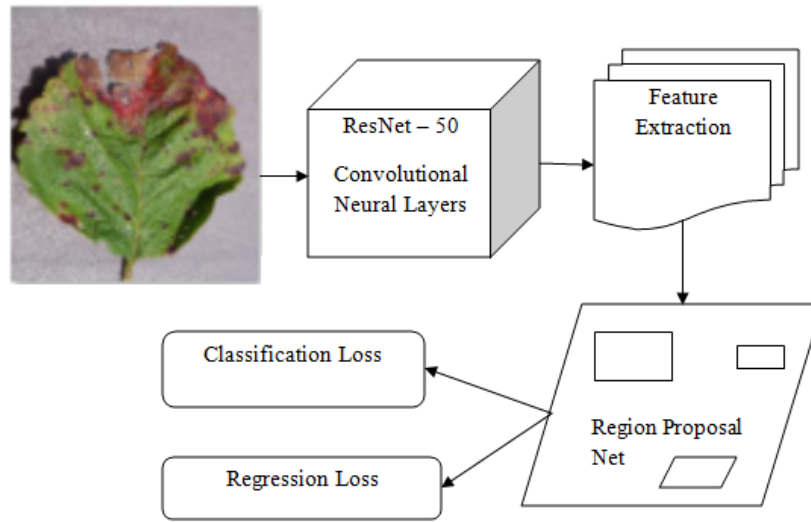
Figure 1. Proposed ResNet based Faster- RCNN

Focal loss is a dynamically scaled version of cross-entropy (CE) loss. As shown in Figure 2, we set xt as the input of the tth node on the last layer. By using a sigmoid activation function, the CE loss for the tth node can be given by

$$CE(y, xt) = -\log(pt) \qquad (1)$$

where $y \in \{-1, 1\}$ specifies the ground-truth class, and pt satisfies

Thus, the total loss can be obtained by summing the CE loss at each node, i.e., $CE = -\sum t \log(pt)$. As mentioned above, a traditional method for addressing class imbalance in the dataset is to introduce a weighting factor $\alpha \in [0, 1]$ for class 1 and $1 - \alpha$ for class -1 in the loss function. We define αt as α for $y = 1$ and $1 - \alpha$ for $y = -1$. Thus, the CE loss can be written as

$$CE = -\sum t \quad \alpha t \log(pt) \qquad (2)$$

Similar with the sampling techniques, the factor αt is usually set by inverse class frequency in practice. However, in focal loss (FL), αt is chosen to be a modulating factor

$$\alpha t = (1 - pt)\gamma, \qquad (3)$$

where γ is a tunable parameter and satisfies $\gamma > 0$. Thus, the focal loss can be given by

$$FL = \sum t\, FL(pt) = -\sum t\, (1 - pt)\gamma\, \log(pt). \qquad (4)$$

As shown in Figure 2b, for different $\gamma \in [0, 5]$, it can be found that $FL(pt)$ reduces the relative loss for well-classified examples. That is, when training with the FL instead of CE, the algorithm would focus training on hard negatives, thereby theoretically improving the predicting performance on minority classes. In addition, the derivative of FL can be written as

$$dFL(pt) / dxt = (1 - pt)\gamma\, (\gamma pt \log(pt) + pt - 1), \qquad (5)$$

Plots for selected γ are shown in Figure 2c, where the derivative is small as soon as $xt > 0$.
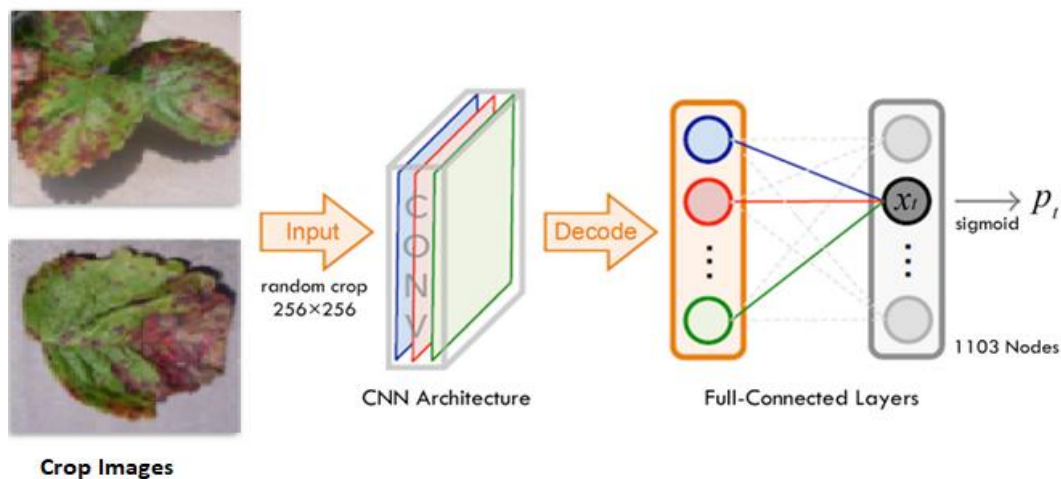

Crop Images

Figure. 2. Schematic diagram of the CNN model, where the CNN architectures used in this work are ResNet-50, ResNet-101, and SE-ResNeXt-101 (32×4d) respectively.

The schematic diagram of the CNN model in our works is shown in Figure 2a. Randomly cropped 256×256 patches from the original images are used as the input.

After passing through a CNN network, the input is decoded and flattened as a feature vector, which is classified

by the following full-connected layers. The last layer has 1103 nodes with sigmoid activation functions, where the outputs are used to calculate the loss. The model is trained by implementing the back-propagation algorithm using a single RTX 2080 Ti. The CNN architectures used in this work are ResNet-50, ResNet-101, and SE-ResNeXt-101 (32×4d) with ImageNet weights. In the following part, we will briefly introduce the network structures of ResNet and SE-ResNeXt respectively, as well as the training schedule.

3.1 ResNet

ResNet (residual neural network) was arguably the most groundbreaking CNN network in the deep learning community in the last few years [10]. By reusing activations from a previous layer until the adjacent layer learns its weights, the problem of vanishing gradients can be effectively avoided. The residual module of ResNet can be mathematically expressed as

$$\mathbf{y} = F(\mathbf{x}, \{Wi\}) + \mathbf{x}. \quad (7)$$

Here $\mathbf{x}$ and $\mathbf{y}$ are the input and output vectors of the residual module. The function F is the residual mapping to be learned, and the operation $F + \mathbf{x}$ is performed by element-wise addition. Based on Eq. (7), the gradient of the ith element in output $\mathbf{y}$ can be written as

$$\nabla yi = 1 + \nabla Fi(\mathbf{x}, \{Wi\}) \quad (8)$$

SE block transformation is taken to be the non-identity branch of a residual module

As mentioned above, the CNN architectures are initialized with the ImageNet weights, while the full-connected layers are initialized using the He initialization. Loss functions are chosen to be the focal loss with $\gamma = 2$ and cross-entropy loss respectively. The model is trained by the back-propagation algorithm with batch gradient descent and Adam optimizer. Learning rate (LR) at the very beginning is set as $10-4$. We reduce the LR with a factor 0.2 (LR = LR × factor) when the valid loss doesn't improve ve after 2 epochs. The training process is early stopped when the number of LR changes exceeds 3. In this work, 5-Fold cross-validation is used to improve model performance. For this purpose, the dataset is split by multi-label iterative stratification [14], where the folds are made by preserving the percentage of samples for each class.
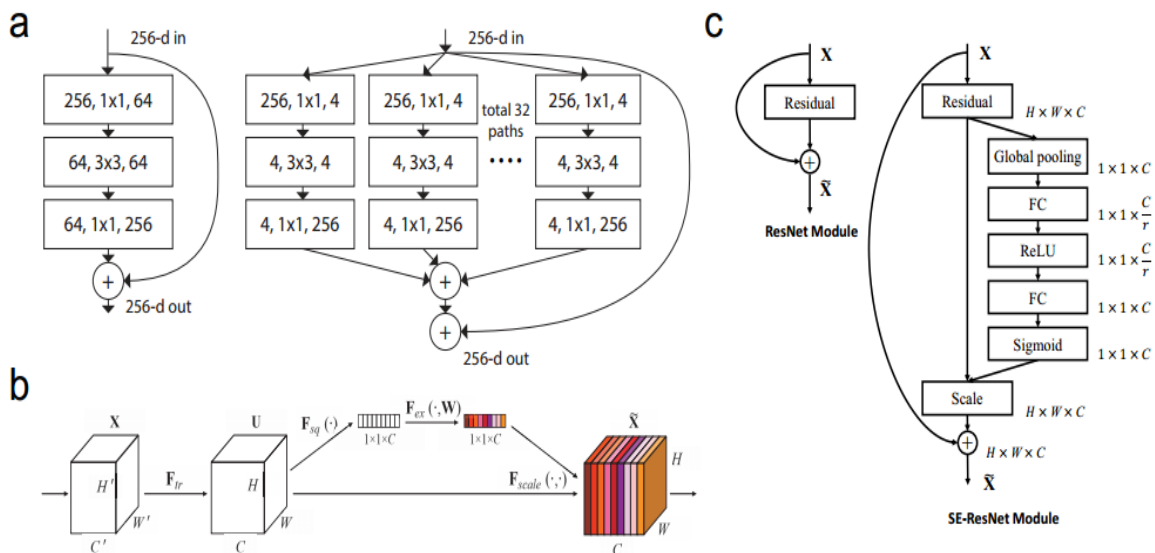

Figure. 3. (a) The block of ResNet (left) and the block of ResNeXt with cardinality = 32 (right) [11]. (b) The squeeze-and-excitation block. (c) Schematic diagram of the SE-ResNet module, where the SE block transformation is taken to be the non-identity branch of a residual module [12].

IV. Performance evaluation of the Proposed Model

4.1 Crop Dataset

In the process of evaluating the performance of the proposed model comparative analysis of different CNN, architectures are evaluated in the context of training the data set. To ensure the evaluation process and to compare the results of the existing work with the proposed model a dataset of 44055 images of different plants along with the 32 classes of the diseases are considered. During the process of training the model, only color images were considered for better accuracy.

4.2 Training Proposed model for Disease Classification

A Python platform based deep learning framework PyTorch is adopted for the purpose of evaluating and training the state of art mechanisms along with the proposed mechanism. The accomplishment of the training process includes three different levels in which two levels that are based on the concept of transfer learning and further the process is evaluated based on scratch starting in which the random weighting configuration is processed.

In the context of transfer learning, the features of images are pre-trained to the model in which the layers are optimized through backpropagation and the analysis of the process is accomplished. The training time and accuracy of the proposed model along with the state of art mechanism are depicted in figure 4 as shown below. It is observed from the figure that the proposed CNN

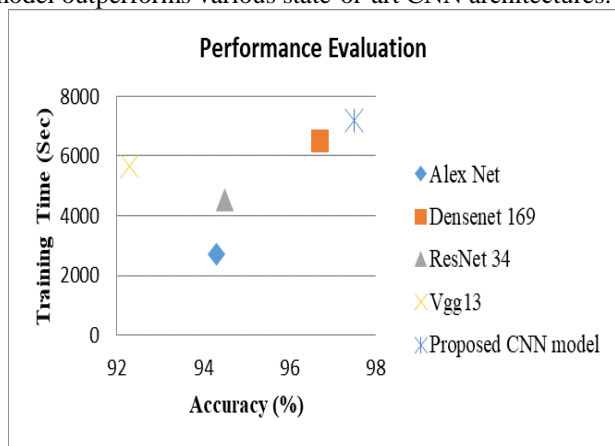model outperforms various state-or-art CNN architectures.

Figure 4. Comparative analysis of State-of-art mechanisms with Proposed CNN model

4.3 Results

The visualization of the output in the context of identifying the disease of the plant is depicted in figure5. The process includes the intermediate images that are generated when a diseased crop leaf is given as an input and the model is trained over the convolutional layers. Initially, the feature vectors are obtained based on the global average pooling where the spatial information is eliminated

Since the residual mapping F is small, ∇yi should be far from 0. That is, the effects of vanishing gradients can be significantly decreased by using the residual module. Therefore, ResNet makes it possible to train up to hundreds or even thousands of layers and still achieves a compelling performance.

4.2 SE-ResNeXt

SE-ResNext is the combination of ResNeXt [11] and squeeze-and-excitation (SE) network [12]. Comparing with ResNet, ResNeXt performs aggregated transformations in the residual module when calculating the residual mapping F. The aggregated transformations can be mathematically presented as

$$F(\mathbf{x}) = C\sum_{I=1} Ti(\mathbf{x}), \quad (9)$$

where $Ti(\mathbf{x})$ can be an arbitrary function. C is the size of the set of transformations to be aggregated and usually referred to as cardinality. Figure 3a shows a representative block of ResNeXt with cardinality = 32. On the other hand, the structure of the SE building block is shown in Figure 3b. The squeeze operator is for global information embedding, which utilizes the global average pooling to generate channel-wise statistics. Excitation is the operator for adaptive recalibration, expressed as

$$\mathbf{s} = \mathbf{F}ex(\mathbf{z}, \mathbf{W}) = \sigma(g(\mathbf{z}, \mathbf{W})) = \sigma(\mathbf{W}2\delta(\mathbf{W}1\mathbf{z})) \quad (10)$$

for $\mathbf{z} \in \mathbb{R}n$. That is, this operator forms a bottleneck with two fully-connected layers with ReLU (δ) [13] and sigmoid (σ) activation functions respectively. In particular, the schematic diagram of the SE-ResNet is given in Figure 3c, where the in which the next layer of CNN will be able to identify the diseased region of the crop.
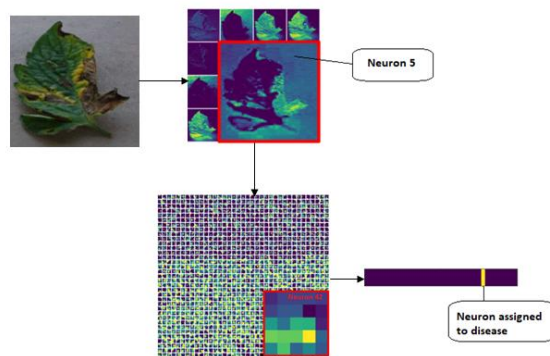

Figure 5: Intermediate layers of Evaluating Proposed RCNN

V. CONCLUSION AND FUTURE WORK

This main contribution of this article is developing an enhanced RCNN model that is integrated with ResNet CNN based on which an attempt is made to detect and classify the crop diseases at the early stages and enhance the productivity of the crop. Several state-of-art CNN architectures like Alexnet, ResNet34, Vgg13 are evaluated over the proposed models in which it is observed that the proposed model outperforms the architecture in terms of accuracy. The major observation is that the proposed model requires a slight higher training time when compared to the various state of art mechanism that could be resolved in the future based on the usage of fast and hybrid deep neural networks.

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