A Comparative Study on Crop Disease Detection using Deep Learning Techniques

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Abstract - *The crop agriculture industry faces economic losses due to pest infections, bacterial or viral contagions. In India, farmers lose nearly 10-20% of the total annual profit. We propose a solution to the aforementioned agricultural problem by applying deep learning techniques to determine the condition of the crop. Our system extracts features from leaf images, classifies the features into diseases and produces diagnosis to prevent further spread of disease by taking appropriate damage control actions. We have used a dataset of 14 crops and their 26 underlying diseases to help train the model for accurate disease detection. The trained models employing Deep Convolutional Neural Networks, Residual Networks and Recurrent Convolutional Neural Networks provide a performance reaching a 99% success rate in identifying the corresponding crop diseases. Our system also provides relative precautionary information from a sourced database to tackle the diseases that are recognized by the classifier. The application of this system is a useful advisory warning tool for the farmers, agricultural workers and agronomists for the identification of diseases in the early stage so that immediate action can be taken. This can cut down the loss of crops on a large scale, thereby helping the agricultural industry and decreasing economic loss from the same.*

Key Words: Crop Disease Detection, Plant leaf, Convolutional Neural Network, Residual Network, Recurrent CNN, Image processing.

1. INTRODUCTION

Agriculture is the primary occupation in India. Nowadays, a tremendous loss in the quality and quantity of crop yield is observed due to various diseases in the plants. Crop disease classification is a critical step, which can be useful in early detection of pest, insects and diseases and help in disease control and productivity boost, among other examples. In today's times, farmers try to recognize diseases manually with foregoing symptoms of plants, but various diseases are hard to distinguish with naked eye, and it is time-consuming to predict whether the crop is healthy or not. Symptoms of diseases in plants predominantly come out on leaves of the plants. Diagnosing the crop disease symptoms on plant leaves incorporates a high degree of complexity. Due to this complexity, experienced agronomists and plant pathologists often fail to successfully diagnose specific diseases and are consequently led to mistaken conclusions and treatments. The existing techniques for disease detection have utilized various image processing methods followed by a wide variety of classification techniques. Crop Disease Detection has been an area of interest for producers, agricultural-related organizations. Economic and agricultural losses can be minimized by genuine disease detection. We aim to predict crop diseases in plants by processing the images of the crop leaf. For this, Image Processing techniques are used for the quick, accurate and appropriate classification of diseases. The existence of an automated system for the detection and diagnosis of plant diseases would offer a support system to the agronomists who are performing experiments based on diagnosis through observation and farmers who need to prevent infections and diseases in their crop yield.

2. RELATED WORK

Crop Yield Forecasting has been an area of interest for producers, agricultural-related organizations. Timely and accurate crop yield forecasts are essential for crop production. The existing techniques for disease detection have utilized various image processing methods followed by various classification techniques. However, some unconventional approaches have led to classification of diseases using unconventional factors. Chopda et al. [1] proposes a system which can predict the cotton crop diseases using decision tree with the help of the parameters like temperature, soil moisture, etc. based on the previous year data and through sensors. Image classification and regression techniques play a very important role because they allow identifying, grouping, and organizing from a standardized system. In [2], Kamble defines the application of texture analysis for detecting plant diseases with the help of different image processing technique.

Deep learning is a set of learning methods attempting to model data with complex architectures combining multiple non-linear transformations. These techniques have enabled significant progress in the fields of image processing and image classification. Kulkarni [3] formulates an application of Deep Convolutional Neural Network to identify and classify crop disease on images, testing it on five classes of crops and three types of diseases for each class. Mique Jr, Eusebio L [4] proposed an application that will help farmers in detecting rice insect pests and diseases using Convolutional Neural Network (CNN) and image processing.

3. DATASET

The dataset we have used contains a total of 54305 images of 38 different classes of 14 crops. It contains images of 26 diseases and 12 healthy plants. This wide dataset proves significant in training the models properly.

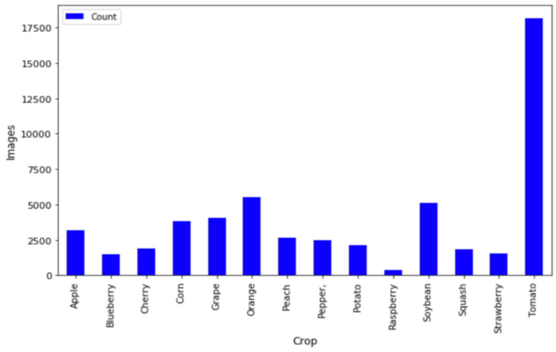


Fig -1: Dataset Distribution

Table -1: Dataset in detail

Plant	Disease	No. of Images
Apple	Apple scab Black rot Cedar apple rust Healthy	630 621 275 1645
Bell Pepper	Bacterial spot Healthy	997 1478
Blueberry	Healthy	1502
Cherry	Powdery mildew Healthy	1052 854
Corn	Common rust Leaf spot Leaf blight Healthy	1192 513 985 1162
Grape	Black Measles Leaf blight Black rot Healthy	1383 1076 1180 423
Orange	Citrus greening	5507
Peach	Bacterial spot Healthy	2297 360
Raspberry	Healthy	371
Potato	Early blight Late blight Healthy	1000 1000 152
Soybean	Healthy	5090
Squash	Powdery mildew	1835
Strawberry	Leaf scorch Healthy	1109 456
Tomato	Bacterial spot Early blight Late blight Leaf mold Leaf spot Spider mites Target spot Yellow leaf curl virus Tomato mosaic virus Healthy	2127 1000 1909 952 1771 1676 1404 5357 373 456

4. METHODOLOGY

4.1 Input Images

For the initial process, images [19] of various image sizes are taken from datasets as input by setting IMGW, IMGH to 224 ppi with 3 channels (RGB), for better visibility, preferred with dimensions greater than 180 in each dimension (i.e. IMGH and IMGW)

4.2 Procedure

- The model architecture is developed using TensorFlow framework.
- The input data for the model is generated using ImageDataGenerator provided by Keras, to preprocess and augment the dataset and is divided into 80:20 training and validation part.
- Parameters such as Validation Spilt size, Normalization Factor, Re-Size range, zoom range are set.
- The model is fitted using Generator object developed by ImageDataGenerator on training data and validation data.

4.3 Classification Models

1) Alexnet:

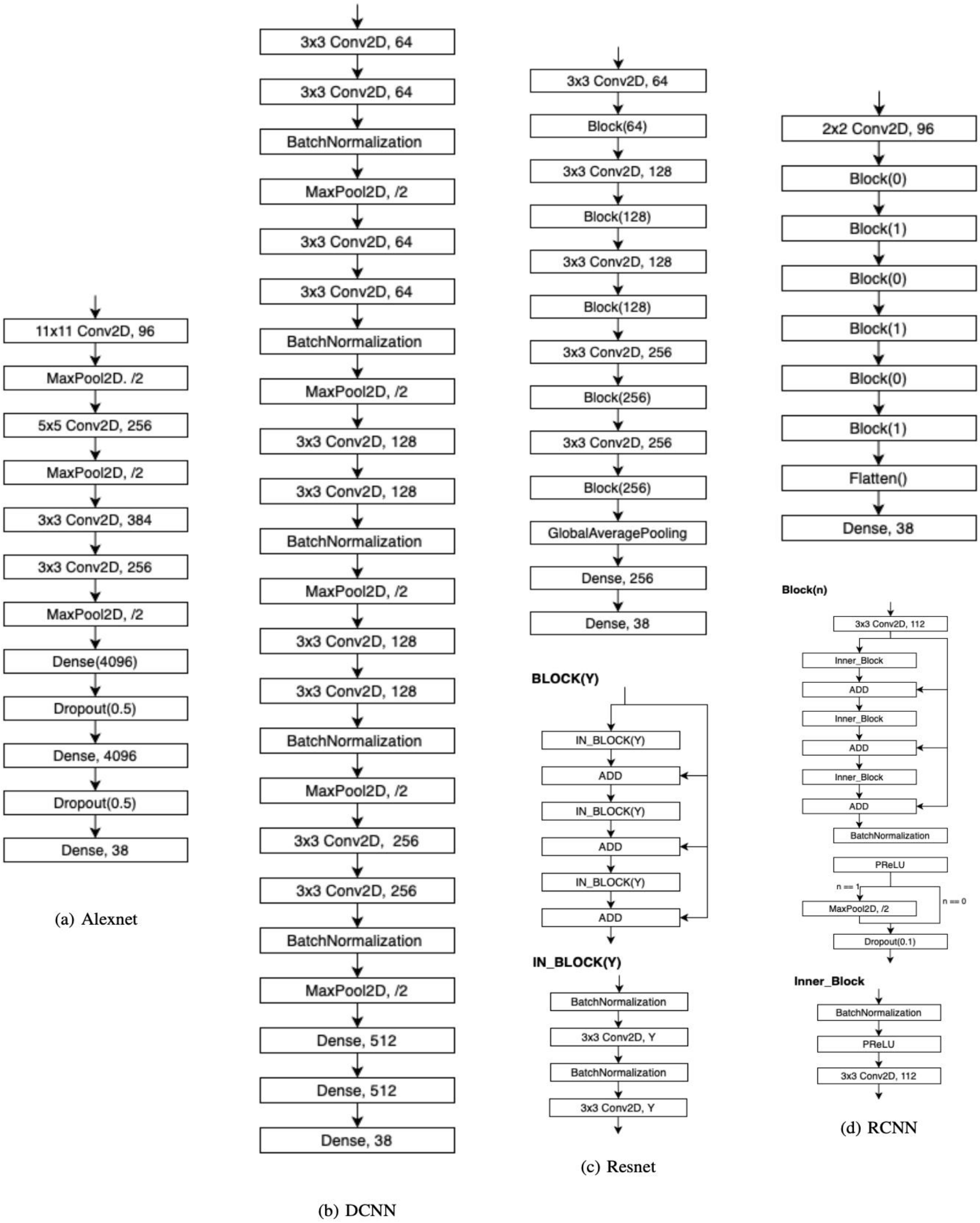
Alexnet is one of the first successful convolutional neural network architecture developed by Krizhevsky et al [20]. We use a similar architecture modified to subjective changes. The architecture is developed with four convolution layers with increasing filter size to extract features from the image followed by three dense layers for classification including output layer. Each dense layer is succeeded by dropout layer with a dropout factor of 0.5. All layers in the architecture use ReLU as an activation function except the output layer that uses SoftMax activation to produce categorical output.

2) Deep Convolutional Neural Network:

Deep Networks have been tested at large scales to provide higher accuracies in image classification tasks. A reason for this is considered to be the extent of features extracted from the image in the deeper layers. Deep networks have been proven efficient in image processing [3]. The deep network developed for the system as shown in Figure 2b utilizes 13 Layers of convolutions, with intermediate Normalization and Max Pooling to reduce over- fitting. The number of kernels in convolution layers increase deeper into network. This is an approach to capture higher details intricacies in the image. Once the features are extracted, they are classified with the help of 2 densely connected layers, followed by prediction layer. Similar to Alexnet, all the layers utilize ReLU activation, with prediction layer using SoftMax function.

3) Recurrent Convolutional Neural Network:

Recurrent Convolutional Neural Network is an experimental architectural setup developed for this project. As described by Liang and Hu in [22], recurrence in CNN allows the network to under- stand the context in the image. The architecture comprises of recurrent convolution layer (RCL), which is depicted as a part of Block in Figure 2d. The RCL is a convolution layer which is superimposed on itself after processing on its copy. This superimposition is achieved by adding the initial layer output with its processed output. This process simulates the recurrence in spatial dimension. Six of such blocks are used to create the network for feature extraction. In alternate blocks, the network uses Max Pooling to drop out irrelevant features. This architecture utilizes Parametric ReLU activation for intermediate layers and SoftMax for the prediction layer.



(a) Alexnet

(b) DCNN

(c) Resnet

(d) RCNN

Fig -2: Architectures

4) Residual Network:

As the depth of a network increases, the difficulty in propagating the error to the initial layers increases and training becomes harder. This is caused due to vanishing gradient, i.e. gradient in back-propagation diminishing to negligible learning at higher layers [21]. Residual Network provides connection links that are made from a higher layer to a deeper layer to reduce the transmission of error and increase the passing of gradient from lower to upper layer by skipping intermediate layers. This provides an effect where a lower layer and an upper layer get similar gradient to learn from. The architecture is comprised of sub-sampling convolution layers, residual blocks and dense classification layers. The residual blocks are a series of Normalization, Pooling and Convolution used thrice, followed by the addition of Identity Output from sub-sampling operation. ReLU and SoftMax Activations are used in each layer.

5. ANALYSIS

The accuracies, losses as well as parameters and epochs for each model during training were comprehensively analyzed. We considered all parameters to determine a best fitting model that provided higher accuracy and good performance for classification of crop leaf images. Each architecture was modified during training to give out its optimal output. Each developed architecture is tested with 15 random images of each class (570 total) to determine the accuracy in prediction. Along with developed Alexnet, DCNN, Residual Network, and Recurrent CNN, the testing is done on Google's MobileNet architecture as well. We have used F1-score as a metric of classification. Upon careful and specific analysis as well as testing of each architecture, we derived that the Deep Convolutional Network was the best architecture for our system. The Deep CNN network provided an accuracy of 97.5% on validation during training and 100% accuracy on testing. Hence, our classification system is equipped with DCNN model trained over 50 epochs.

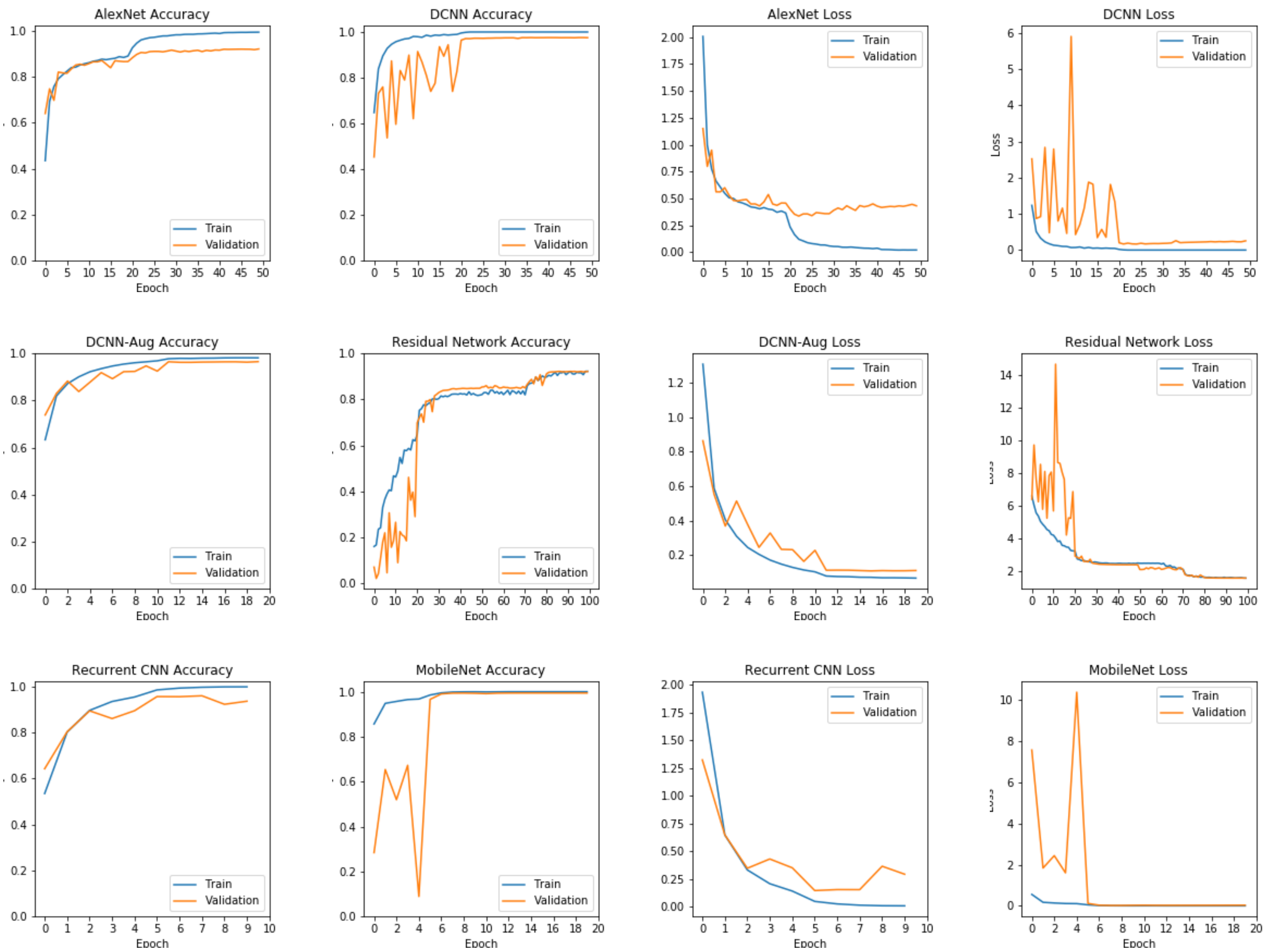


Fig -3: Analysis

Table -2: Training Statistics

Model	Epochs	Accuracy		Loss	
		Train	Val	Train	Val
Alexnet	50	99.35%	92.05%	0.02	0.43
DCNN	50	100%	97.51%	3e-9	0.25
DCNN(Aug)	20	98.13%	96.53%	0.06	0.11
Resnet	100	92.25%	92.18%	1.57	1.57
RCNN	10	99.80%	93.55%	6e-3	0.29
MobileNet	20	100%	99.42%	7e-6	0.03

Table -3: Testing Statistics

Model	True Pred	Accuracy	F1-Score Average	
			Macro	Weighted
Alexnet	556	0.98	0.98	0.98
DCNN	568	1.00	1.00	1.00
DCNN(Aug)	527	0.92	0.92	0.92
Resnet	517	0.91	0.91	0.91
RCNN	545	0.96	0.96	0.96
MobileNet	570	1.00	1.00	1.00

6. CONCLUSION AND FUTURE SCOPE

An operational crop disease detection system that uses neural networks and image processing techniques to recognize underlying diseases in crops based on crop leaf images is developed by us. The proposed system was trained and tested on 6 models to provide basis for our comparative study. The optimal model trained over a Deep Convolution Neural Network (DCNN) on a dataset of over 54000 images labeled in 38 different classes provides a maximum accuracy of 99%. Our study provides an informative detailed comparison of various approaches to crop disease recognition and indicates the contrast between them. Our system could prove useful in aiding to identify underlying diseases in crops for farmers to prevent loss and agronomists to advance scientific research in the respective field.

An extension to this project could be to develop an application compatible with smart mobile devices with features such as displaying recognized diseases in plants based on leaf images captured by the mobile phone camera. A web application could be deployed with a complete system consisting of server-side components containing a trained model with features such as displaying recognized diseases in crops. The application could offer a discussion forum for farmers and agronomists to discuss the treatment and early precautions of diseases that they have encountered. This could be achieved by clustering the users on the basis of their activity on the application.

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