Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 167 (2020) 2003–2010

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

Deep Convolutional Neural Network based Detection System for Real-time Corn Plant Disease Recognition

Sumita Mishra[a,*], Rishabh Sachan[a], Diksha Rajpal[a]

[a] *Amity University, Lucknow Campus, India*

Abstract

Corn is one of the most popular food grains in the India and crop loss due to diseases substantially affects the Indian economy and threatens the food availability. Recent access of smart devices can be utilized to provide automatic diagnosis of corn diseases and prevent severe crop losses. This paper presents a real time method based on deep convolutional neural network for corn leaf disease recognition. Deep neural network performance is improved by tuning the hyper-parameters and adjusting the pooling combinations on a system with GPU. Further, the number of parameters of the developed model is optimized to make it suitable for real time inference. The pre-trained deep CNN model was deployed onto raspberry pi 3 using Intel Movidius Neural Compute Stick consisting dedicated CNN hardware blocks. During the recognition of corn leaf diseases, the deep learning model achieves an accuracy of 88.46% demonstrating the feasibility of this method. The presented corn plant disease recognition model is capable of running on standalone smart devices like raspberry-pi or smart-phone and drones.

Keywords: Image Processing; Precision agriculture ; Corn disease; Deep Learning ; CNN; NCS

1. Introduction

In India, maize is the third important food crop after rice and wheat. Leaf blight and rust are two of most prevalent diseases causing substantial economic losses to maize crop in India[1]. If these diseases are identified at an initial stage and remedial measures are taken then crop yield, and grain quality may be preserved. Corn disease symptoms at very early stage, manifest on different parts of infected plants, particularly leaves present symptoms of detectable change in colour, spots and blight. Machine learning techniques have been successful in identification and classification of wide variety of maize diseases from images of plant leaves [2]. Improvements in deep learning techniques in recent years have made them the state of the art among various computer vision approaches for image classification. Traditional computer vision approach for plant disease detection requires manual selection of features in making classification decisions [3],[4]. In contrast, deep convolutional neural networks automatically learn most important features by multilayer processing of visual input. Early stages of such network focus on basic visual elements and higher-level layers respond to more complicated visual concepts. Deep learning based automated detection techniques provides an opportunity in the field of precision agriculture to

*Sumita Mishra. Email : mishra.sumita@gmail.com

1877-0509 © 2020 The Authors. Published by Elsevier B.V.

10.1016/j.procs.2020.03.236

Fig. 1. Proposed framework for deployment of trained Deep CNN for corn disease detection

expand the computer version scope. Training a deep convolution neural network requires huge amount of data and high performance computing resources. To meet these stringent requirements on a mobile device, one of the most successful approach is cloud based solution, to transfer input data and subsequently obtain inference results using computing resources at the cloud platform. However, vast majority of population in rural area still does not have Internet connectivity. Thus in order to bring the benefit of artificial intelligence based plant disease identification system to the remote regions with limited or no access to internet, it is imperative to devise a method that is not only cost-effective and accurate but also deployable in rural area. This paper proposes a deep learning based corn plant disease recognition system that works in a standalone mobile device (Raspberry pi , smart phone)without requiring internet access. The proposed framework is shown in Fig 1 where deep neural network is first trained on computer with GPU using keras API[5]and trained model is migrated from high-performance GPU to mobile device with limited computational capability. mobile device is reserved for image preprocessing when new plant leaf images are captured. The trained DNN model is deployed on to the Intel Movidius NCS [6], a system on chip (SoC) using NSDSK toolkit.

This paper is organized as follows: Section II provides an overview of the basic components of proposed system , Section III describes the results and section IV compares the presented system with other related work finally section V concludes the paper.

2. Materials and Methods

2.1. System Architecture

The Corn disease identification system using deep learning has two main hardware units namely NCS and Raspberry pi 3b+ module equipped with 1.4GHz 64-bit quad-core processor, 1GB LPDDR2 SDRAM, Full-size HDMI, 4 USB 2.0 ports, BCM43438 highly integrated single chip which includes 2.4GHz WLAN, Bluetooth.

Neural computing framework including a comprehensive network layer topology and associated hyper parameters proposed in this work may be deployed on mobile device as shown in Fig 2.

Smartphone camera captures the live image from the infected or healthy corn plant and these images are forwarded over Wi-Fi network for further processing to Raspberry pi 3b+ module. NCSDK on Raspberry Pi 3 b+ is used by the classifier to carry out inference on received images and classifier output is displayed on LCD screen via HDMI cable. In the process of performing the inference on NCS, a modified CNN model is trained and deployed since NCS supports tensor flow framework, Keras binding was removed and model was compiled to create NCS graph.

2.2. Dataset

An appropriate dataset is was created from some images captured from corn plantations in Raebareli and Sultanpur district but bulk of the images were obtained from plant village dataset originally hosted at Plant-Village Disease Classification Challenge [7]. Images are divided into 3 different categories namely: rust, Northern leaf blight and Healthy. Agriculture Scientist from G. B. Pant Univ. of Agriculture and Technology, India was consulted to label the captured images into suitable disease class. Table 1 shows the division of dataset in train

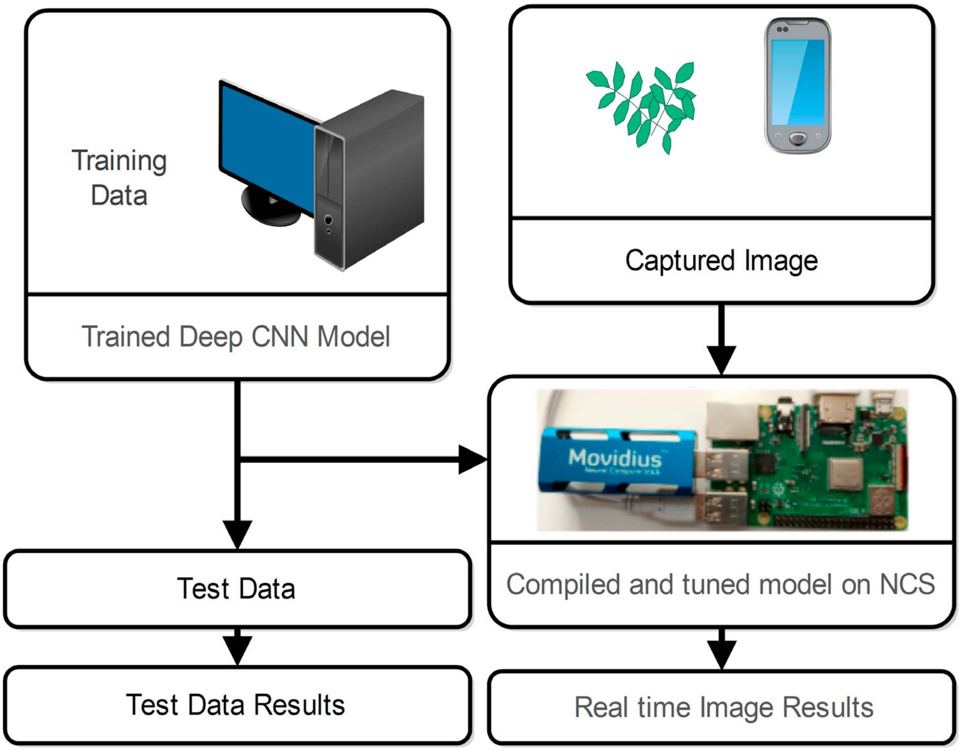

Fig. 2. Schematic Representation of Block Diagram of the System

Table 1. Dataset for corn leaf disease classification.

Class	Common Rust	Northern Leaf Blight	Healthy
No.of Train Images	1192	986	1162
No.of Test Images	139	100	124
No.of Validation Images	227	291	161

Fig. 3. Common Rust infected corn leaf .

Fig. 4. Northern Leaf Blight infected corn leaf .

Fig. 5. Healthy Corn Plant.

, test and validation data with the ratio of 70,10 and 20 percent respectively. Typical images from all the three classes of dataset are shown in Fig 3, 4 and 5. Fig 3 depicts corn plant leaf infected from rust disease.

General symptoms that manifest on leaves of plants infected with common rust are brown pustules on both leaf surfaces. Further in severe cases, infection spreads to sheaths and other plant parts. Northern Leaf Blight effect on corn leaf is shown in Fig 4. Northern corn leaf blight lesions appear on lower parts of plant first and then as it spreads to leaves of whole plant turn pale gray as blight lesions enlarge. One to six inches distinct cigar-shaped lesions are major distinguishing characteristic of northern corn leaf blight. Healthy corn leaf is shown in Fig 5.

2.3. Deep convolutional neural network Implementation

The following section presents the working principle and the complete architecture of developed Deep Convolutional Neural Network. As shown in Fig. 6, Convolutional neural network is created by stacking a sequence of layers; namely: Convolutional Layers, Max- Pooling Layers , activation layers and dropout layers. These operations are discussed below:

2.3.1. Convolution Layer

Convolution is the primary operation in extraction of features from input images. In 2-dimensional convolution calculation a 2-D image can be mapped into a convolution window which gets sliding continuously in order to obtain corresponding value of convolution. Convolution operation on an input x_i of i_{th} convolution layer, may be represented as (1).

$$x_{i+1} = f(W_{i+1} * x_i) \tag{1}$$

Where convolution operation is represented by *, W_i is a linear operator and f represents non linear activation function[7].

Activation function does the non-linear mapping between layers of the network making it capable to learn and perform more complex tasks. We have chosen Rectified Linear Unit (RELU) as activation function in each layer except at output layer where, softmax activation is used [8].

2.3.2. Max-Pooling Layer

Convolution layers extract features from the image , the pooling layer is placed after the convolution layer to aggregate the statistics of feature map. Fundamental pooling process involves down sampling of feature map resulting in reduced trainable parameters. Two pooling hyper-parameters, namely stride and filter size define pooling characteristics. We have used max pooling; i.e. the maximum value of a particular feature over a region of the image is computed and retained in pooling operation.

2.3.3. Drop out Layer

Main purpose of using dropout layer is to improve generalization capability of trained model. Drop out layer with hyper-parameter p randomly ignores activation by probability p during the training phase. This provides regularization and effectively prevents over-fitting by reducing correlation between neurons. During testing phase all activations are used but are scaled by factor p.

2.3.4. Flatten Layer

Flattening collapses the spatial dimensions of the pooled feature map but retains channel dimension. Even If inputs are shaped without a channel dimension, then flatten layer adds an extra dimension.After flattening operation feature matrix is transformed into a vector that can be fed into a fully connected neural network known as dense layer in Keras .

2.3.5. Dense Layer

Dense layers are used to perform linear operation on input. These fully connected layers multiply the input by a weight matrix and output is produced after addition of a bias vector.

3. Results and Discussion

Input images of size 150X150 are fed to the network. Batch size of 32 and Gloret uniform initialization was chosen for all weights. Model uses max-pooling operation in all pooling layers with 2x2 pool size and relu activation function except at the last layer of network. Output of the last layer is corn leaf diseased prediction which utilizes softmax activation function. During the training phase of the network hyper-parameters like learning rate, maximum epoch are changed to achieve accuracies above 96%.Optimized value of learning rate is .0004. After that feature visualization was used to create a lighter model for real time data inference. Total 679 images from the database are used for validation task.

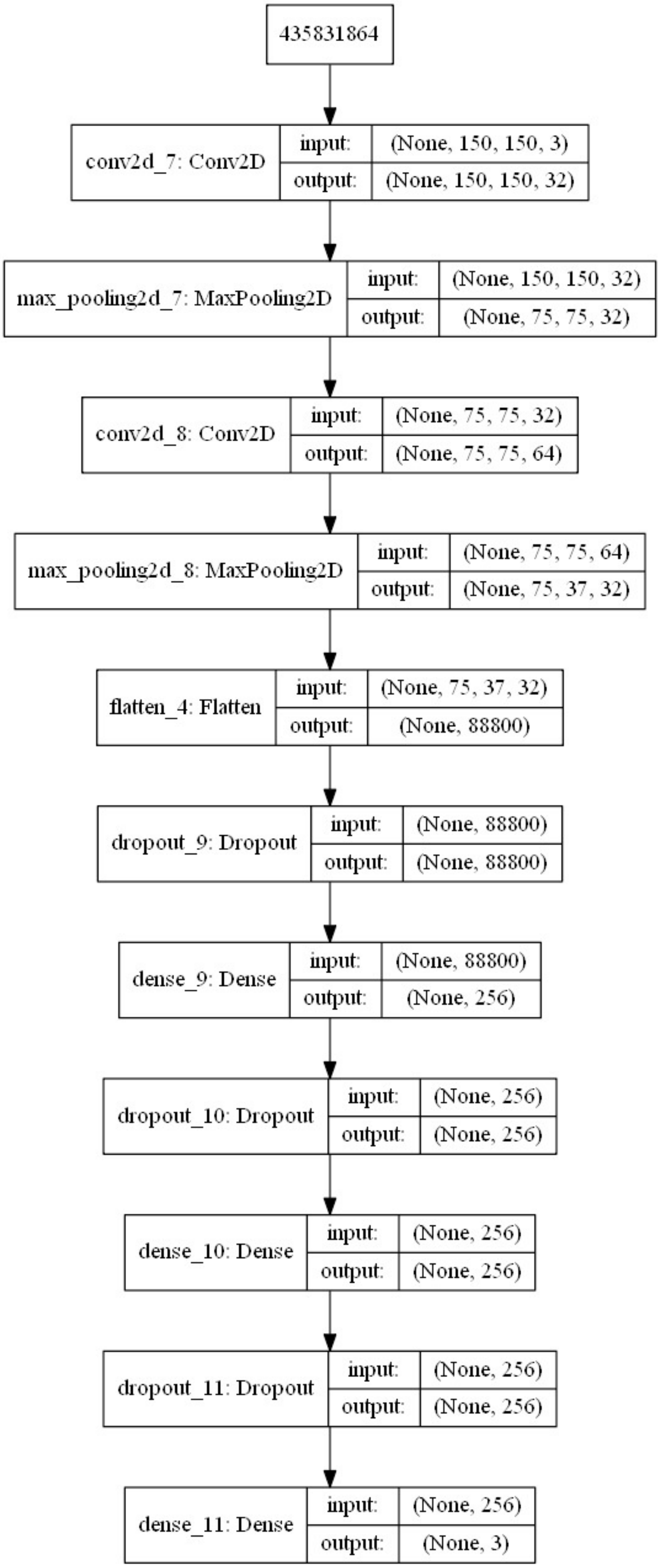

Fig. 6. Architecture of DNN trained on GPU

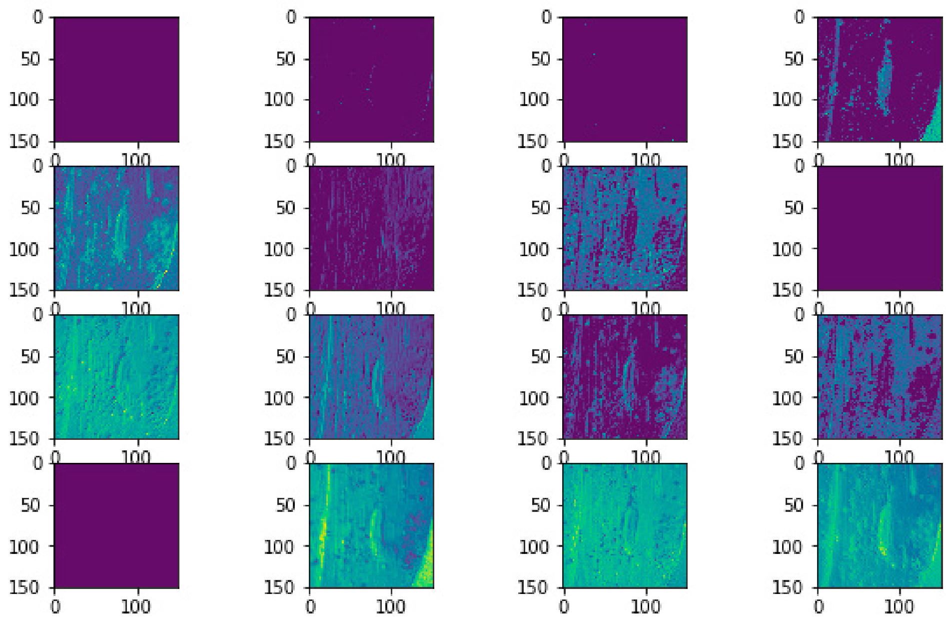

Fig. 7. Visual Representation of result for each convolution layers

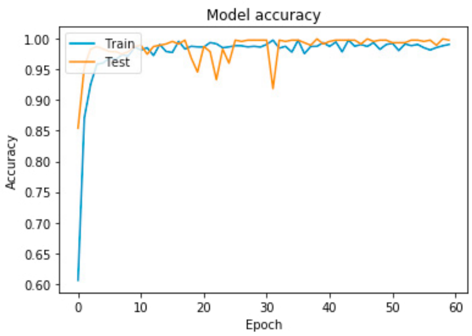

Fig. 8. Accuracy of model trained on system with GPU.

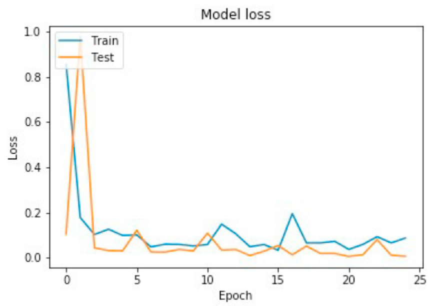

Fig. 9. Loss Curve.

3.1. Feature Visualization

Next step is layer-wise feature visualization to modify the DNN for deployment on NCS. Fig 7 visualizes the hidden layer outputs when an input image of blight infected corn leaf is fed to the trained network. Optimal number of feature extraction layers were determined after feature visualization to reduce the number of trainable parameters. It was observed during feature visualization process that neurons in the shallow layers (Conv1, Conv2), recognize simple patterns and textures.

Fig 8 shows the model accuracy that stabilizes to 99 percent after 24 epochs. This trend conforms with loss curve as depicted in Fig 9, which starts to stabilize after 18 iterations. Trained model was evaluated on test data and accuracy of 98.40% was obtained. The system proposed in this paper can directly take the image of the diseased or healthy corn plant leaf as the input of the convolutional neural network and identify the plant as healthy or suffering from rust or blight. After deep learning model is trained , Movidius NCS is interfaced with OpenCV software installed on the Raspberry Pi to process live images fed by smartphone camera. OpenCV was chosen for this paper since DNN module of OpenCV is optimized by Intel to support deep learning . The Movidius/Myriad coprocessor performs the actual deep learning inference, reducing the load on the Pis CPU. Various steps involved to achieve this are listed below:

Table 2. Classification Accuracy for each class .

Class	Common Rust	Northern Leaf Blight	Healthy
Accuracy of NCS Model	77.26%	88.42%	100%
Accuracy of Deep Learning model trained on GPU	96.32%	98.88%	100%

Step 1: First step is to interface NCS with Raspberry Pi in desktop mode.
Step 2: Install Debian and Python dependencies.
Step 3: Download NCSDK on Raspberry Pi 3b+ from [9].
Step 4: Compile and install NCSDKs API framework.
Step 5: Test installation using sample code.
Step 6 : Install OpenCV module in Raspberry pi.
Accuracy of Deep CNN model deployed using NCS on the captured images is also calculated as the percent of the images the model correctly detects. Captured images are labeled by a corn disease expert Accuracy results for the mobile CNN model run on 30 images of the field experimental leaves with 10 images belonging to each class is listed in table 2.

4. Related Work

Significant prior work in the relevant area include field imagery based deep neural network by De Chant et al for northern leaf blight detection. Authors have trained several CNNs to classify small region of images into infected and healthy classes and then these small regions are fed into final CNN that classifies the whole image as diseased or healthy [10] .Proposed system achieved an accuracy of 96.7% on test data. Some researchers [11],[12] applied transfer learning on preexisting models trained on different data to improve the classification accuracy of plant diseases. These studies have obtained noteworthy results, but to obtain a feasible solution for precision corn crop monitoring it is highly desirable to design plant disease identification methods that can provide reasonable accuracy on standalone mobile device without the requirement of Internet access. It will enable farmers to make quick and accurate decisions about crop disease.

5. Conclusion

Agriculture forms the backbone of our country and crop loss due to plant disease is a major factor contributing to reduction in crop yield. Artificial Neural Network (ANN) methods with smart algorithms for plant disease identification are the need of hour to reduce severity of losses and minimize crop health problems. This Paper presents a real time deep learning based model for identification and classification of major corn diseases without the requirement of Internet. Performance analysis of designed Deep CNN has shown the average accuracy of 98.40%. In addition, a modified version of designed CNN model with optimized trainable parameters is deployed on NCS to perform inference on live images captured from smart phone with average accuracy of 88.66%. While the results achieved are promising; recognition accuracy on NCS may be further improved by tuning and optimization of hyper parameters and increasing the diversity of pooling operation, furthermore data augmentation may be used. In future research, we plan to diversify dataset by including additional maize diseases for enhancing the efficacy of method.

References

[1] https://farmer.gov.in/Micropstaticsmaize.aspx accessed on 2 January 2019.
[2] I. K. Das; P. Rajendrakumar (2016) Biotic Stress Resistance in Millets, Academic Press, , 23-67
[3] Deshapande, Anupama S., Shantala G. Giraddi, K. G. Karibasappa, and Shrinivas D. Desai (2019) "Fungal Disease Detection in Maize Leaves Using Haar Wavelet Features." In Information and Communication Technology for Intelligent Systems, pp. 275-286. Springer, Singapore.
[4] Kumar, Sachin, Sumita Mishra, and Pooja Khanna (2017) "Precision Sugarcane Monitoring Using SVM Classifier." Procedia Computer Science, Vol.122: 881-887.

[5] Francois Chollet (2018) ”Keras Documentation”. keras.io. Deep learning. 2.2.4 / 3 October.
[6] https://github.com/movidius/ncsdk accessed on 2 January 2019.
[7] Agarap, Abien Fred (2018) ”Deep learning using rectified linear units (relu).” arXiv preprint arXiv:1803.08375.
[8] Dunne, Rob A., and Norm A. Campbell (1997) ”On the pairing of the softmax activation and cross-entropy penalty functions and the derivation of the softmax activation function.” Proc. 8th Aust. Conf. on the Neural Networks, Melbourne. Vol. 181.
[9] https://movidius.github.io/ncsdk/install.html accessed on 29 January 2019
[10] DeChant, Chad, Tyr Wiesner-Hanks, Siyuan Chen, Ethan L. Stewart, Jason Yosinski, Michael A. Gore, Rebecca J. Nelson, and Hod Lipson (2017) ”Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning.” Phytopathology ,Vol.107, no. 11,pp.1426-1432
[11] QI, Zhao, Zhaohui JIANG, Chunhe YANG, Lianzhong LIU, and Yuan RAO (2016) ”Identification of maize leaf diseases based on image technology.” Journal of Anhui Agricultural University,Vol.43, no. 2 :pp.325-330.
[12] Jayme Garcia Arnal Barbedo (2019) ”Plant disease identification from individual lesions and spots using deep learning”, Biosystems Engineering, Volume 180, Pages 96-107