Real-Time Plant Leaf Diseases Detection and Identification using a Convolutional Neural Networks on an Embedded Platform

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***Abstract*—Plant diseases cause a major reduction in production and economic losses in agriculture. In the field of agriculture, real-time detection and classification of plant leaf diseases are highly desired. We proposed a real-time plant disease detection and classification system based on machine learning algorithms for disease detection in plants. The first step of the process is to detect leaf, using of single short multi-box detector (SSD) and then to identify plant leaf diseases, using proposed convolutional neural networks (CNNs) architecture. This model was trained using four crops healthy and infected leaves images of the PlantVillage dataset. The proposed system has been achieved higher accuracy comparative to AlexNet. We showcased, the classification and detection model deployed on embedded platforms such as Nvidia Jetson Tx1 and Nvidia Jetson Nano for inference.**

***Index Terms*—Convolutional neural networks (CNNs), Disease classification, Real-time embedded systems, Plant disease.**

I. Introduction

Agriculture is the backbone of every economy. India is well known for agriculture and around sixty percent of the population depend on agriculture. Moreover, agriculture plays a cardinal role in the global economy. Now a Days, Majority plants fail due to diseases because of this problem farmer gets loss every year. Using Machine Learning for plant Diseases Detection is one of the most important research areas in precision agriculture. Because of this technique farmer gets information about plant diseases before plants are fully damaged. Moreover, it also stop a farmer's loss. So, this technique is very beneficial for a farmer.

Crop disease diagnosis is of great significance to prevent the spread of diseases and maintain the sustainable development of the agricultural economy. In general, the crop disease diagnosis is performed manually by visual observation or microscope techniques, which are proven to be time-consuming and have the risk of error due to subjective perception. Many techniques have been applied to identify plant diseases. These include a direct method which is a chemical-based technique and second indirect method which is based on spectroscopy [1]. However, using a machine learning approach in the agriculture sector is a new era. This proposed real-time technique is more efficient than other techniques.

Proposed Real-time machine learning [2] plant disease identification system divided major in two parts namely plant leaves detection and plant disease classification. In this approach rich dataset is needed to train the machine learning model. Moreover, this system firstly detects plant leaves and then identifying the disease of plant leaves. As shown in Figure 1, our proposed system is can estimate the class based on the probability of a plant leaf disease and its location in the image display infected area of the plant. The overall objective of this work is to develop an automatic plant disease diagnosis system to identify Real-time crop leaf disease.

Fig. 1. Flow of Real-time plant leaf disease detection

The main objective of this work are as follows:

- Analysis as well as exploration of different plant disease dataset.
- Real-time detection of crop diseases using trained SSD MobileNet.
- Real-time plant disease classification using proposed trained convolutional neural networks (CNNs).
- Deployment of the developed Machine Learning algorithm on different Embedded platforms for inference.

The remainder of this paper is organized as follows: In Section II, the literature review discusses plant disease detection in brief. In Section III, Describe materials and data which are used in this work. In Section IV, describe the proposed methodology for plant leaves detection and disease classification . In Section V, Discuss experimental results. Finally, this paper is summarized in Section VI.

II. Literature Review

For Centuries food losses due to crop infections from pathogens such as bacteria, viruses and fungi is a vital issue that needs to be addressed across the globe. So, to ensure agricultural sustainability, crop disease detection at an early stage can drastically reduce economic losses. There are several methods to detect disease based on where it has occurred in a plant like Leaf, Node or Stem. To detect diseased plants infected on the leaf there are two methods: Direct and Indirect methods of detection.Direct methods or laboratory-based techniques are Polymerase Chain Reaction (PCR), Immuno Fluorescence (IF), Fluorescence In-Situ Hybridization (FISH), Enzyme-Linked ImmunoSorbent Assay (ELISA), Flow Cytometry (FCM) and Gas Chromatography Mass Spectrometry (GC-MS), they require lager numbers of data set and gives most accurate result. The only limitation while applying this methods are they are time-consuming. With accuracy these methods provide information about the main reason that causes the disease with their concentration and severity. Apart from direct method of detecting the disease, plant stress profiling and volatile profiling can be used for identifying the pathogenic disease as well as the biotic and abiotic stress levels in crops. These methods uses optical sensors that provide a large amount of information in form of electromagnetic spectra which can be processed by various methods to predict plant health. Some of the known indirect methods are thermography, fluorescence imaging, hyperspectral imaging, and gas chromatography [3] .

With rapidly changing technical areas, the involvement of artificial intelligence in agriculture and vegetation can contribute to sustainable development and also efficient uses of the resources are required for the same. The evolution of AI has taken place so rapidly that in less than a century, AI has found its application in almost all fields. There are two methods of detecting disease on leaf namely segmentation [4] and The machine learning. With the popularity of machine learning in every field, and various algorithm namely convolutional neural networks (CNN), Support Vector Machine (SVM), K-means clustering.The machine learning algorithm proves to be an efficient way in the detection of diseases in the plant.

A. Literature Survey on Plant Disease Classification using Machine Learning

Geetharamani G.A and Arun Pandian J. [5] have proposed a model that can achieve 96.46% accuracy in classification for plant leaf disease using deep Convolutional Neural Network (Deep CNN). The proposed model is trained using 39 different classes with six data augmentation method namely: Image Flipping, Gamma Correction, Noise Injection, Principal Component Analysis (PCA) color augmentation, Rotation, and Scaling. This model was also tested concerning its consistency and reliability. It concludes the maximum pooling method is better than the average pooling method. Furthermore, there is an increase in data from 49,598 to 55,636 using data augmentation. Peng Jiang et al. [6] have proposed a new model named INAR-SSD (SSD with Inception module and Rainbow concatenation) that uses deep CNN along with GoogLeNet Inception and Rainbow concatenation to detect apple leaf disease. The proposed model was trained with a data set of 26,377 images of a disease plant leaf. Experimental results showed a high-performance solution with 78.80% mAP and a detection speed of 23.13 FPS. It concludes that the proposed INAR-SSD model provides higher accuracy and faster detection speed when compared to the previous model.

B. Crop disease Classification Detection using Machine Learning Algorithms on Embedded Hardware

This work is also done with the use of embedded hardware. It is used as an inference engine for real-time output. Halil Durmus and Ece Olcay Güne [7] deployed a convolution neural network on hardware successfully. They used two different deep learning architectures: AlexNet and SqueezNet for detecting diseases in tomato plants in fields. This algorithm is implemented on a robot in real-time to detect the diseases on the farm as well as in Greenhouse. The architectures used were trained and tested on the tomato images from the plant village. Using GPU the network was validated on Nvidia Jetson Tx1. The paper compares the architectures AlexNet and SqueeZeNet [8] and concludes AlexNet performed better than SqueeZeNet. It is intelligibly seen that the squeeZeNet model is nearly 80 times smaller than AlexNet [9]. Models Size is taken directly from Cafe model files and the inference time is varying in different tests by only 5 milliseconds. Vittorio mazzia and Aleem khaliq [10] has proposed one real-time embedded system for Apple fruit detection. In this proposed system they used the YOLOv3-tiny algorithm. Moreover, this proposed system deployed on different embedded platforms namely Raspberry Pi 3 B+ in combination with Intel Movidius Neural Computing Stick (NCS), Nvidia's Jetson Nano and Jetson AGX Xavier for inference.The proposed architecture model is capable to detect small objects. In real-time, this deployment model achieved 83.64% average accuracy as well as a frame rate of up to 30 fps even for the difficult scenarios. The proposed system is deployed on Robert vehicle to detect, count, and measure the size of the apples in real-time.

Thus, based on this literature survey, it is observed that Machine Learning algorithms are a convenient method to detect disease in leaf. For the present thesis work CNN algorithm, as well as SSD MobileNet model architecture, is used for detection. Moreover, Tensorflow deep learning library is used for image detection. In addition, the proposed system is deployed on various embedded platforms namely Nvidia Jetson Tx1 and Nvidia Jetson Nano for inference.

III. MATERIALS AND DATA

A. Dataset Description

A big dataset is needed to train the plant leaf detection as well as disease classification models. For training the disease classification model, used around 21,978 healthy and infected leaf images of PlantVillage [11] dataset. Moreover, a total of 500 leaf images were used to train the leaf detection model. Sample images from the dataset are shown in Figure 2.

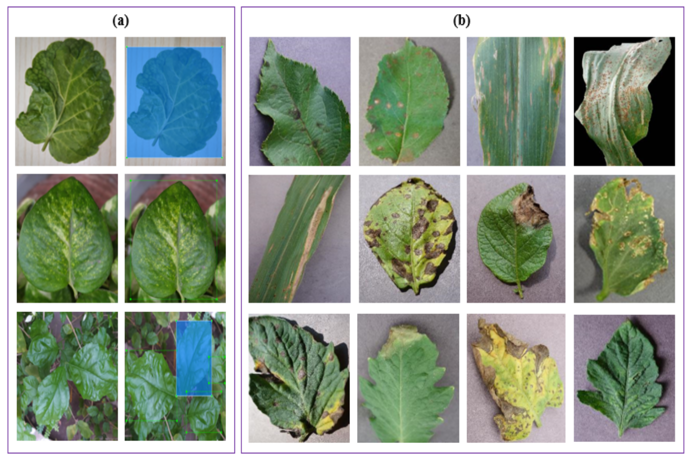

Fig. 2. Sample images of (a) the leaf detection dataset. (b) the healthy and diseased plant leaves from the PlantVillage dataset.

Furthermore, classification dataset split into twenty classes which are shown in Table I.

TABLE I

DETAILS OF HEALTHY AND INFECTED LEAVES [12]

Class label	Class name	No. of Images
0	Apple scab	630
1	Apple black rot	621
2	Cedar Apple rust	275
3	Apple healthy	1645
4	Corn Cercospora gray leaf spot	513
5	Corn common rust	1192
6	Corn healthy	1162
7	Corn northern leaf blight	985
8	Potato early blight	1000
9	Potato healthy	152
10	Potato late blight	1000
11	Tomato bacterial spot	2127
12	Tomato early blight	1000
13	Tomato healthy	1591
14	Tomato late blight	1909
15	Tomato leaf mold	952
16	Tomato Septoria leaf spot	1771
17	Tomato spider mites	1676
18	Tomato target spot	1404
19	Tomato mosaic virus	373

B. Hardware Description

For Real-time plant diseases detection system used two embedded platforms as a inference engine in this work.

NVIDIA Jetson Tx1: For Training and testing purpose used the Nvidia Jetson Tx1. Nvidia Jetson Tx1 has 256 CUDA cores, quad core ARM processor, 4GB RAM, 16 GB eMMC and other peripherals. Jetson Tx1 board is shown at the Figure 3 (a). In Table II shown more specifications of Nvidia Jetson Tx1 [13].

NVIDIA Jetson Nano : For real-time testing also used Jetson Nano embedded platform which is shown in Figure 3 (b) [14]. Nvidia Jetson Tx1 has 128 CUDA cores, quad core ARM processor, 4GB RAM. More specifications are shown in Table II.

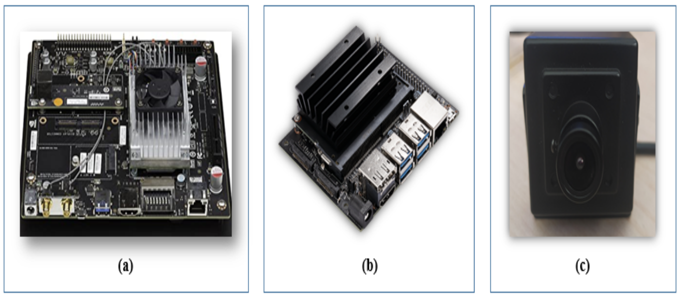

Fig. 3. Embedded Hardware (a) NVIDIA Jetson Tx1 (b) NVIDIA Jetson Nano (c) Intel Up AI Vision Camera

Intel Up AI Vision Camera : For real-time video processing used Intel Up AI Vision Camera connected to embedded platforms. This camera module is shown in Figure 3 (c). Specifications of Intel USB camera with a maximum resolution of 1920p x 1080p at 30 frames per second [15].

TABLE II
MAIN SPECIFICATION OF THE EMBEDDED HARDWARE PLATEFORMS

	Hardware	
	Jetson Tx1	**Jetson Nano**
Memory	4 GB LPDDR4	4 GB LPDDR4
Storage	16 GB eMMC 5.1	MicroSD
CPU (ARM)	4-core ARM Cortex A57	4-core ARM A57
USB	1x USB 3.0, 1x USB 2.0	4 x USB 3.0,USB 2.0
HW Accelerator	256-Cores GPU	128-core GPU
Operating System	Ubuntu 16.04.2	Ubuntu 16.04.2
Nominal Power	10 W	5/10 W
Price	39,675.00	8,799.00

IV. PROPOSED METHOD

A. System Overview

The proposed system is divided into two-part, the first part is crop leaf detection and second part disease identification. In the first part of this system used trained SSD model for plant leaf detection this SSD model was trained using 500 Leaf images. In the second part of the system proposed convolutional neural networks (CNNs) architecture is used for plant disease classification. This classification model was trained using a total of 21,978 healthy and infected leaf images of the PlantVillage dataset. After trained both models combines these two models and make one hybrid model. This hybrid model was deployed on embedded platforms for real-time in filed output. In Figure 4 presents the complete flow of proposed real-time crop leaf detection and disease identification systems.

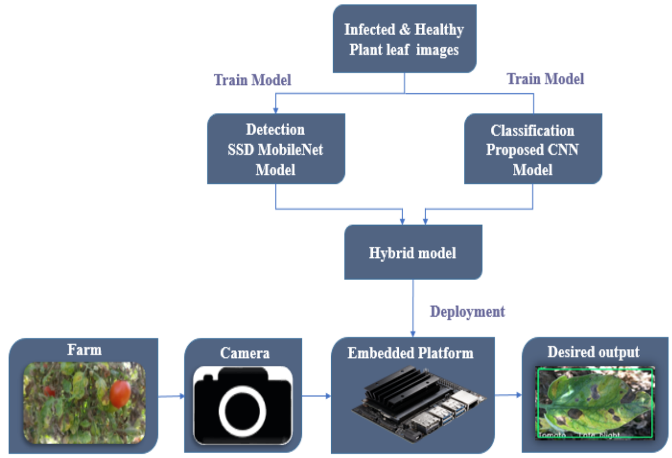

Fig. 4. Illustrates the overall proposed system

B. Single-short Multi-box Detector (SSD)

In the proposed system first part used SSD model for plant leaf detection. SSD [16] is a one-stage object detection method that can predict the types of objects and the coordinates of the corresponding bounding boxes directly, without generating region proposals. The SSD model [17] combines several feature maps with various resolutions to process objects of various sizes. The detection speed of SSD is much faster than that of Faster R-CNN [18], while the detection accuracies of the two methods are approximately the same. Thus, the SSD algorithm is used as the basic object detection algorithm and improved with multi-angle feature fusion.

C. Convolutional Neural Networks

Tensorflow [19], a framework based on python language designed specifically for deep learning and CNNs - related algorithms, has many advantages [20], such as faster updates and flexible expansibility. It provides a complete toolkit for training, testing and fine-tuning. The deployment models can run on both central processing units (CPUs) and graphics processing units (GPUs). For plant diseases classification used proposed Convolutional Neural Networks in model architecture following layers are used:

Convolution: Convolution is the most important operation in CNNs. The convolution calculation of the two - dimensional image can be mapped to the continuous sliding convolution window to obtain the corresponding convolution value.

Activation Function: The Relu activation function is an unsaturated nonlinear function that can receive signals by simulating brain neurons. Saturated nonlinear function, such as Sigmoid and Tanh, have worse performance than unsaturated nonlinear functions when training a network. In this test, the Relu activation function will be added in the Cifar10 model, to prevent the problem of gradient dispersion while accelerating network training and to increase the identification accuracy.

Pooling: As the number of convolutional layers increases, the parameters of the network will increase exponentially. The pooling operation can effectively reduce the number of network parameters. To reduce the parameters in all regions, the pooling operation is performed by calculating the statistical characteristics of a region in order to represent the entire region's characteristics. The effect of different pooling combinations on the identification accuracy of Cifar10 will be explored in this study.

Softmax: Softmax function, a wonderful activation function that turns numbers aka log its into probabilities that sum to one. Softmax function outputs a vector that represents the probability distributions of a list of potential outcomes. This is the last layer of proposed CNNs architecture

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Leaves Detection Results

For leaf detection used SSD model which is give most accurate results.The Plant detector will create the bounding boxes around the leaves which have been detected and crop that part of the leaves as shown in the below Figure 5.

Fig. 5. Leaves detection simulation result

B. Disease Classification Results

For disease classification firstly run onJetson TX1 and then Jetson Nano. This model werecorrectly predicted plant leaf diseases. Below Figure 6 shows a snapshot of the diseases classification simulation result.

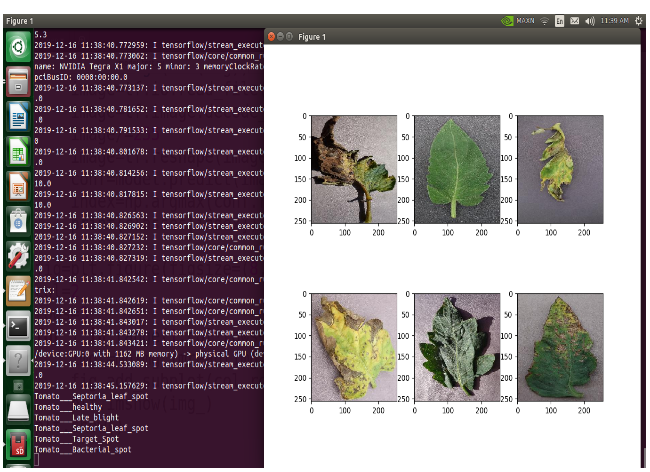

Fig. 6. Disease Classification simulation result

AlexNet model also trained using the same dataset and also this model accuracy result compares with proposed model accuracy which is shown in Table III. This table also shows the proposed model accuracy is better than AlexNet accuracy. Moreover, with fewer epochs and parameters proposed model capable to give higher accuracy.

TABLE III
COMPARISON OF PLANT DISEASE CLASSIFICATION RESULTS

Model	No. of parameters	Epoch	Accuracy
AlexNet	62,378,344	150	95.53%
Proposed model	6,076,980	100	96.88%

C. Real-time disease detection and identification In-field testing results

Nvidia Jetson TX1 and Jetson Nano were used to do field testing of the proposed plant disease identification system. The leaf detection and disease classification models were deployed on Jetson TX1 and Jetson Nano. For Real-time In-field testing visited a tomato farm and test the proposed model work accurately or not. Real-time In-field testing result shown in Figure 7.

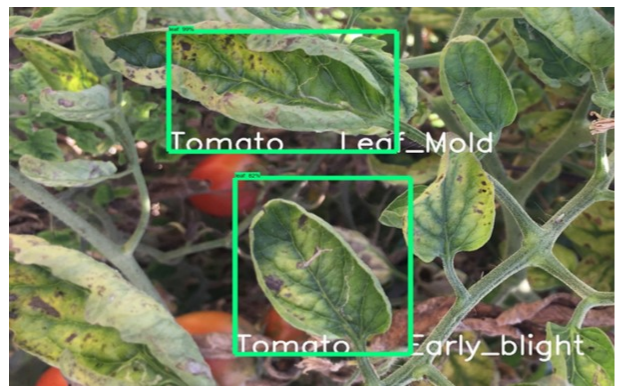

Fig. 7. Real-time In field testing result

VI. CONCLUSION

This proposed method of using machine learning in plant disease detection proves too efficient comparatively. This system detects and identifies disease from plant leaves using CNN architecture proposed in the paper. The proposed architecture model achieved 96.88% classification accuracy, which proves to be higher compare to the AlexNet architecture model. The model also proves to be better when deployed on a field using embedded devices. Moreover, this work highlight performances achieved in terms of power consumption by different embedded solutions used. Finally, the proposed real-time system ensures the capability of the model to detect plant leaf diseases under any conditions of the real field.

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References

[1] S. Sankaran, A. Mishra, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," *Computers and Electronics in Agriculture*, vol. 72, no. 1, pp. 1–13, 2010.

[2] A. Fuentes, S. Yoon, S. C. Kim, and D. S. Park, "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," *Sensors*, vol. 17, no. 9, p. 2022, 2017.

[3] Y. Fang and R. P. Ramasamy, "Current and prospective methods for plant disease detection," *Biosensors*, vol. 5, no. 3, pp. 537–561, 2015.

[4] S. Adhikari, B. Shrestha, B. Baiju, and S. Kumar, "Tomato plant diseases detection system using image processing," in *KEC Conference on Engineering and Technology*, 2018, pp. 1–6.

[5] G. Geetharamani and A. Pandian, "Identification of plant leaf diseases using a nine-layer deep convolutional neural network," *Computers & Electrical Engineering*, vol. 76, pp. 323–338, 2019.

[6] P. Jiang, Y. Chen, B. Liu, D. He, and C. Liang, "Real-time detection of apple leaf diseases using deep learning approach based on improved convolutional neural networks," *IEEE Access*, vol. 7, pp. 59 069–59 080, 2019.

[7] H. Durmuş, E. O. Güneş, and M. Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning," in *2017 6th International Conference on Agro-Geoinformatics*. IEEE, 2017, pp. 1–5.

[8] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "Squeezenet: Alexnet-level accuracy with 50x fewer parameters and¡ 0.5 mb model size," *arXiv preprint arXiv:1602.07360*, 2016.

[9] A. E. Hassanien, T. Gaber, U. Mokhtar, and H. Hefny, "An improved moth flame optimization algorithm based on rough sets for tomato diseases detection," *Computers and Electronics in Agriculture*, vol. 136, pp. 86–96, 2017.

[10] V. Mazzia, A. Khaliq, F. Salvetti, and M. Chiaberge, "Real-time apple detection system using embedded systems with hardware accelerators: An edge ai application," *IEEE Access*, vol. 8, pp. 9102–9114, 2020.

[11] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers in plant science*, vol. 7, p. 1419, 2016.

[12] P. Dataset. Dataset of diseased plant leaf images and corresponding labels. [Online]. Available: https://www.kaggle.com/emmarex/plantdisease

[13] Nvidia. Nvidia jetson tx1 specification details. [Online]. Available: https://developer.nvidia.com/embedded/jetson-tx1

[14] A. N. hardware. Nvidia jetson nano specification details. [Online]. Available: https://developer.nvidia.com/embedded/jetson-nano

[15] I. A. Department. Intel camera module specification details. [Online]. Available: https://software.intel.com/en-us/iot/hardware/up-squared-ai-vision-dev-kit

[16] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, "Ssd: Single shot multibox detector," in *European conference on computer vision*. Springer, 2016, pp. 21–37.

[17] TDS. Ssd single shot detector for object detection. [Online]. Available: https://towardsdatascience.com/ssd-single-shot-detector-for-object-detection-using-multibox-1818603644ca

[18] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," in *Advances in neural information processing systems*, 2015, pp. 91–99.

[19] A. Géron, *Hands-on machine learning with Scikit-Learn and TensorFlow: concepts, tools, and techniques to build intelligent systems*. " O'Reilly Media, Inc.", 2017.

[20] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identification of maize leaf diseases using improved deep convolutional neural networks," *IEEE Access*, vol. 6, pp. 30 370–30 377, 2018.