INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 17, Issue: 2, Month: April, Year: 2022
Article Number: 4356, https://doi.org/10.15837/ijccc.2022.2.4356

CCC Publications

Cassava Leaf Disease Identification and Detection Using Deep Learning Approach

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Abstract

Agriculture is the primary source of livelihood for about 60% of the world's total population according to the Food and Agricultural Organization (FAO). The economy of the developing countries is solely dependent on agriculture commodities. As the world population is increasing at faster pace, the demand for food is also escalating tremendously. In recent days, agriculture is experiencing an automation revolution. Hence the introduction of disruptive technologies like Artificial Intelligence plays a major role in increasing agricultural productivity. AI enabled approaches would help in overcoming the traditional challenges faced in agriculture practices, by automating various agriculture related tasks. Nowadays, farmers adopt precision farming which uses AI techniques namely in crop health monitoring, weed detection, plant disease identification and detection, and forecast weather, commodity prices to increase the yield. As there is scarcity of manpower in agriculture sector, AI based equipment like bots and drones are used widely. Crop diseases are a major threat to food security and the manual identification of the diseases with the help of experts will incur more cost and time, especially for larger farms. The machine-vision based techniques provide image based automatic process control, inspection, and robot guidance for pest and disease control. It provides automated process in agriculture, paving way for improved efficiency and profitability. Various factors contribute for plant diseases, which includes soil health, climatic conditions, species and pests. The proposed chapter elaborates on the use of deep learning techniques in the leaf disease detection of Cassava plants. The chapter initially describes the evolution of various neural network techniques used in classification and prediction. It describes the significance of using Convolutional Neural Network (CNN) over deep neural networks. The chapter focuses on classification of leaf disease in Cassava plants using images acquired real time and from Kaggle dataset. In the final part of the chapter, the results of the models with original and augmented data were illustrated considering accuracy as performance metric.

Keywords: Cassava leaf diseases, Deep learning, Convolutional Neural Network (CNN).

1 Introduction

Cassava (Manihot esculenta Crantz) or Tapioca is one of the significant staple crops grown in most of the tropical countries in Africa, Asia, and Latin America. Cassava is a

perennial crop and cultivated under rain-fed or irrigated conditions for its tubers. It is one of the most drought-tolerant crops and can grow in less fertile soil. Other than Cassava being used as a staple food, it is processed for various products namely starch, ethanol, glucose, and Cassava hey is used as animal feed and also used in the production of adhesives, textile, and cosmetics. In 2019, the global cassava market increased by 0.4In India, Cassava is cultivated in 13 states with major production in the southern states, namely Kerala and Tamil Nadu. It is grown for both food and industrial purposes. Among various diseases that curb the production, Indian Cassava mosaic diseases, root rot, and brown leaf spot are the significant contributors [3]. It is also evident that viral diseases like Cassava Mosaic disease are predominantly affecting Cassava production in many countries of the world. The identification of Cassava disease could be done only by trained experts as many of the types of diseases show similar symptoms and crops could be infected by multiple diseases. Due to this, it comes very difficult for the farmers to choose pesticides or nutrients to treat the disease as it becomes a complex task. In such tasks, deep learning techniques will provide a solution for better decision making to identify the type of diseases and to treat the diseases, and improve productivity [4].

2 Literature survey / Related works

Ozichi Emuoyibofarhe et.al [5] has proposed machine learning models for detection and classification of Cassava leaf diseases as blight or mosaic disease. The Cubic Support Vector Machine (CSVM) model is used to classify whether the leaf is healthy or not and the Coarse Gaussian Support Vector Machine (CGSVM) algorithm is used to classify the type of the disease and the accuracy obtained with the deployment of cubic support vector machine model is 83.9% predicting the leaf is healthy or not and the Coarse Gaussian Support Vector Machine with an accuracy of 61.6% in classifying the disease as either Blight or Mosaic. Gnanasekaran, Sambasivam and Opiyo, Geoffrey[6] proposed a predictive machine learning model for Cassava disease detection and classification in imbalanced datasets using SMOTE E (Synthetic Minority Over-sampling Technique) to avoid over fitting and provide better accuracy. In the work proposed by Amanda Ramcharan et.al [7], transfer learning is applied to train a deep neural network for classifying three types of leaf diseases and pest damage in Cassava plants and the model is deployed in mobile devices. P. B. Padol and A. A. Yadav [8] proposed a machine learning model which uses a SVM- based classifier to detect the leaf diseases in grape leaves and the model has achieved an accuracy of 88.89

Sharada P et.al [9] proposed deep learning based mobile application for plant species identification and disease detection. It uses plant village dataset and identifies the plant species. Deep learning models like GoogleNet and AlexNet were used for identification of plant species and disease detection. Through training the network from scratch, the system can able to achieve accuracy of 99.35Omkar Kulkarni [10] done transfer learning using MobileNet and InceptionV3 pre- trained models to identify 13 types of crop species and 26 types of diseases. The system can able to achieve accuracy of 99.45%. It also makes use of plant village dataset. In all these works, the dataset used was a single leaf image with plain background. So, the system can able to achieve reliable classification accuracy. The dataset used in our work is a real time dataset captured directly through smart phone in the cassava plant field. Dataset with noisy background, image quality and unbalanced dataset remains challenging part in the cassava plant disease identification.

3 Description about the datase

For prediction of any type of plant disease when human experts are involved, it is expensive and time consuming. This process can be automated with the help of computer vision along with deep learning techniques. Computer vision-based systems are widely used in the applications which involves image recognition and identification and has tremendous scope in large scale agricultural process. Disease categorization that is done by human through naked eyes which can be modelled using computer vision. Cassava plant is cultivated widely throughout the world and is one of the staple foods in developing countries. Disease identification in these plants at the earliest helps to improve the food productivity. The major types of disease like Cassava Bacterial Blight (CBB), Cassava Brown Streak Disease (CBSD), Cassava Green Mite (CGM) and Cassava Mosaic Disease (CMD) were considered for classification process. Along with these disease varieties healthy leaf images were also included. In this proposed system, totally five categories have been considered. Cassava dataset has been downloaded from Kaggle repository. The dataset has been divided into training and validation data in the percentage split of 70-30. The distribution of original dataset has been provided in the Fig. 1. Sample images of five different categories of image has been provided in the Fig. 2

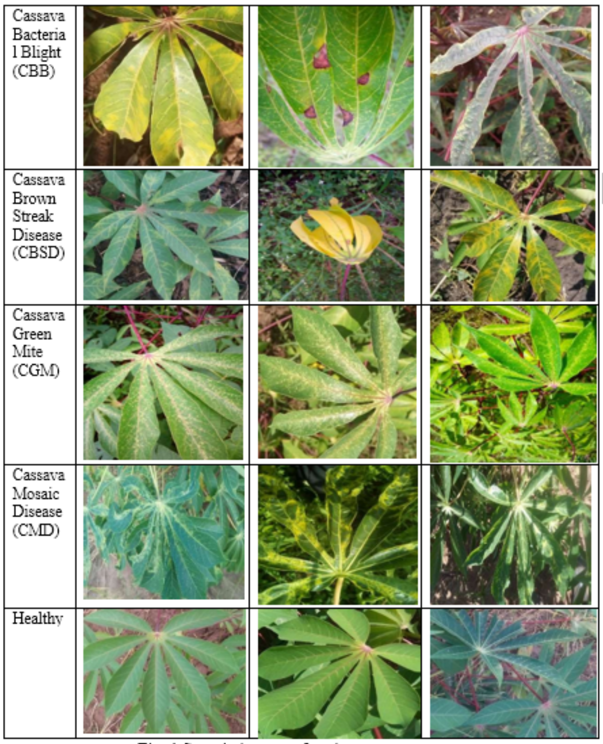

Figure 1: Sample images of each category

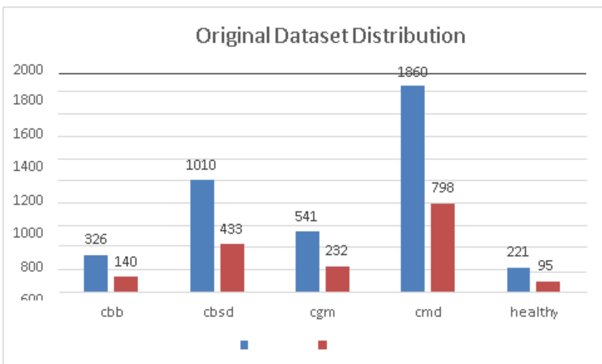

Figure 2: Original Data Distribution

4 Experiment & Result discussion

The proposed method makes use of CNN model to identify the type of disease. The model consists of convolutional layer, maxpooling layer, batch normalization, dropout layer, flatten and dense layer arranged in sequential order. Fig. 3 shows the order in which layers has been arranged. Number of trainable parameters can be identified using the model summary report provided in Fig. 4. Convolutional layer is used extract features based on the filters across the image. Feature map is created as an output of convolutional layer. Activation functions are is used to convert the net input into activations. Most used activation function in CNN are ReLU(Rectified Linear Unit) at hidden layer and softmax at fully connected layer. The dataset considered for experimentation is highly imbalanced.

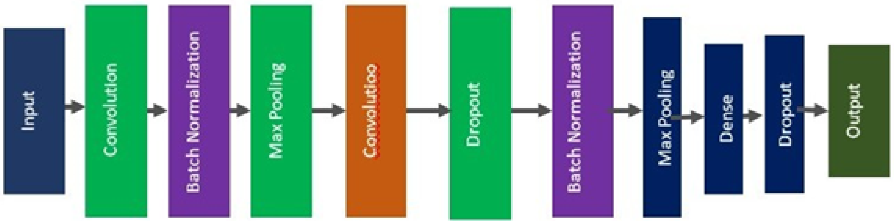

Figure 3: CNN Model representation

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 120, 120, 32)	2432
batch_normalization_1 (Batch	(None, 120, 120, 32)	128
max_pooling2d_1 (MaxPooling2	(None, 60, 60, 32)	0
conv2d_5 (Conv2D)	(None, 28, 28, 16)	12816
dropout_2 (Dropout)	(None, 28, 28, 16)	0
batch_normalization_2 (Batch	(None, 28, 28, 16)	64
max_pooling2d_2 (MaxPooling2	(None, 14, 14, 16)	0
flatten_1 (Flatten)	(None, 3136)	0
dense_2 (Dense)	(None, 32)	100384
dropout_3 (Dropout)	(None, 32)	0
dense 3 (Dense)	(None, 5)	165

Total params: 115,989
Trainable params: 115,893
Non-trainable params: 96

Figure 4: Model Summary

The number of images in CMD category is high rather than other categories. The number of images in healthy category is also very low. Initial experimentation was done with the actual dataset using simple CNN model. The model is able to achieve a training accuracy of 98.9% but the validation accuracy 54.35%.

The results in Fig. 5 shows that model is overfitting due to biased data. The confusion matrix Table 1. obtained for that model shows that high misclassification in CBB, CBSD, CGM and Healthy categories. Table 2 shows the classification report of the model and its precision, recall, f1-score and support values.

	cbb	cbsd	cgm	cmd	healthy
cbb	18	55	12	45	10
cbsd	31	238	33	120	11
cgm	13	35	23	156	5
cmd	9	96	52	634	7
healthy	5	18	12	50	10

Table 1: Confusion Matrix for Actual dataset

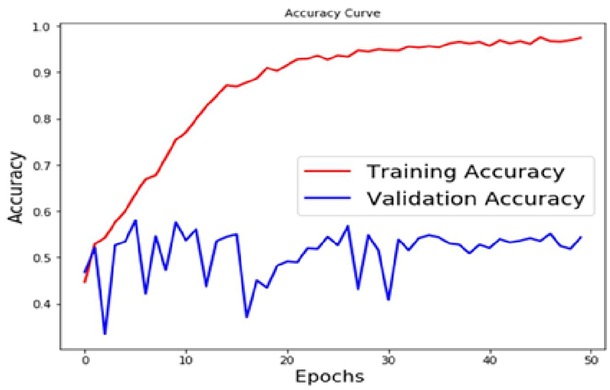

Figure 5: Accuracy curve over original dataset

	precision	recall	f1-score	support
cbb	0.24	0.13	0.17	140
cbsd	0.54	0.55	0.54	433
cgm	0.17	0.10	0.13	232
cmd	0.63	0.79	0.70	798
healthy	0.23	0.11	0.14	95

Table 2: Classification Report

The dataset unbalancing and model overfitting can be reduced using data augmentation techniques. Fig. 6 shows sample augmented data of a healthy image after rotating it in the r angle of 90 degrees.

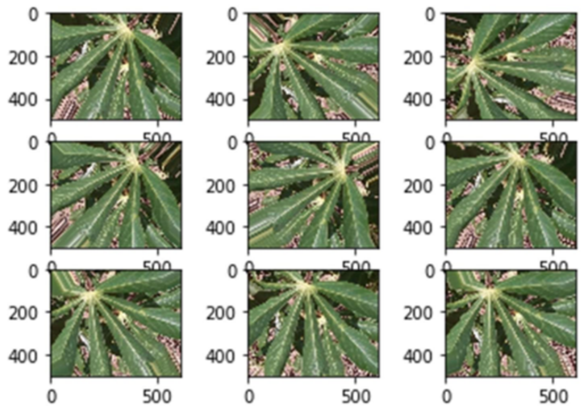

Figure 6: Accuracy curve over augmented dataset

5 Conclusion

Deep learning-based architecture was designed with minimum number of parameters to classify Cassava plant diseases. Initially the model was trained using original dataset after converting the images to the size 244X244. With this the system can able to achieve the validation accuracy of only 54%. Data augmentation techniques were used to increase the number of images in the dataset. After augmentation system can able to achieve validation accuracy of 90%.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Conflict of interest

The authors declare no conflict of interest.

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Cite this paper as:
Anitha J.; Saranya N. (2022). Cassava Leaf Disease Identification and Detection Using Deep Learning Approach, *International Journal of Computers Communications & Control*, 17(2), 4356, 2022.
https://doi.org/10.15837/ijccc.2022.2.4356