Review Paper on Cassava-Leaf Disease Detection by Convolution Neural Networks

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I. ABSTRACT

Cassava is the third-largest source of carbohydrates in the tropical regions and a major source of carbohydrate for half a billion people. Cassava leaf diseases are the major cause of crop failure in these regions and usually cause 25 to 80% of crop failure yearly. Due to the quantity of the crop grown, it becomes impossible to check each plant for the disease. Recently in many studies related to cassava leaf disease detection, it was found that Convolution Neural Network models were efficient in the detection of the diseases. These models can easily be integrated into mobile applications or drones to easily monitor large areas of the crop. During recent studies, although the accuracy of the model was high many criteria were left unchecked which are discussed in this paper and how can it be improved ahead overall.

II. INTRODUCTION

Cassava also known as *Manihot esculenta* is a rich carbohydrate crop grown throughout tropical and sub-tropical regions. Cassava is one of the largest source of food carbohydrate in the tropics and an essential crop for them. Cassava is considered to be originated from central brazil about 10,000 years ago. As the goods transportation increased the crop entered European countries in 1400 AD. Moving from Europe the crop came to African countries during the 16th century. In Africa cassava is still in the top 3 crops of the country. As the crop emerged so did its various diseases that resulted in crop failures. The four most prevalent cassava infections are listed below. Each illness has its own set of indications that show up on the leaf, which may be utilised to distinguish and categorise diseases both visually and automatically using deep learning algorithms.

1. *Cassava Green Mite (CGM)*

White dots appear on the leaves as a result of it. It begins as tiny patches that grow to cover the entire leaf surface, causing chlorophyll loss and so impairing photosynthesis. In addition to mottling signs that are readily mistaken with cassava mosaic, severe CGM causes the afflicted leaves to dry up, shrivel, and detaches from the plant.

2. *Cassava brown streak virus disease (CBSD)*

Whiteflies are the vectors that spread the disease. Symptoms include a distinctive vein yellow that occasionally enlarges and produces visibly huge yellow patches . CBSD additionally causes dull brown necrotic patches at the tuber root, just as a diminishing in root size.

3. *Cassava Mosaic Disease (CMD)*

The mottling, twisted leaves, and reduced size of leaves, as well as the afflicted plants, are common foliar signs. Spots of green are usually present on leaves, along with various shades of white and yellow patches. Patches reduce most of the possible photosynthetic surface region, consequently, the is lesser development and low yield.

4. Cassava Bacterial Blight (CBB)

Moisture is to blame for this bacterial illness. Cassava plants in wet regions are hence the most vulnerable. Black leaf patches and blights are the most common symptoms. As a result of withering, the damaged leaves dry early and shed.

III. DATA COLLECTION

In CNN models it is crucial to get a trusted and realistic dataset. In early studies, it was seen that the photos taken were for the research, hence the photos were usually of high quality and in a clear background with good lighting. The dataset was also highly imbalanced for a particular class. This makes the model train well and give a better accuracy but fails in real-life situations. To counter these errors there have been many solutions :

1) Getting datasets from reliable institutions that are already researching the topic.
2) Various data-processing methods to improve the images and detect the diseases.
3) For the imbalance of the data there are many pre-existing methods.

In recent studies, the datasets for the model were addressed and were taken from a credible source hence the models were better trained for natural conditions.

IV. DATA PREPROCESSING

Recent Papers are mostly based on the betterment of the data-preprocessing. As the dataset suffers from various errors or imbalances hence an ample amount of changes are required. Usual errors found in datasets are:

1. Data Quality

It is seen that the real-life pictures taken from the field are usually of low contrast or low resolution. One of the successful strategies is to develop brought down the contrast utilising the Gamma remedy procedure and decorrelation extending to improve the shading partition and band-to-band connection of a picture.

The Gamma γ

correction equation is given as [4]:

$$S_L = \frac{1}{\frac{\gamma}{B_p}\left(\frac{1}{\gamma} - 1\right)} - \gamma B_p + B_p$$

$$F_s = \frac{\gamma S_L}{B_p\left(\frac{1}{\gamma} - 1\right)}$$

$$C_o = F_s B_p - S_L B_p$$

$$I = \begin{Bmatrix} S_L I, I \leq B_p \\ F_s I^{\gamma} - C_o, I > B_p \end{Bmatrix}$$

where,

γ is gamma parameter, S_L is the slope of the straight line segment, B_p is the breakpoint of the straight line segment, F_s is the slope matching factor, C_o is the segment offset and is the input image.

Another option is to use the Contrast Limited Adaptive Histogram Equalisation (CLAHE) technique to improve image contrast. CLAHE can aid computer vision algorithms in achieving considerably better results in low-resolution and low-contrast environments.

2. Data Size and Features

Researches have proved that the cropped leaflet dataset shows slightly more accuracy than the original dataset. Although the accuracy is greater it is a tradeoff with the training time. Although the leaflet dataset shows better accuracy overall while individual evaluation of the diseases the leaflet dataset lacks behind the original dataset. Hence, in conclusion, the original dataset is better for the model if the processing power is low. Otherwise, the model can be trained through both datasets to show better accuracy for both.

3. Dataset Imbalance

It is known that finding a perfectly balanced dataset is impossible. An imbalanced dataset often

leads to a biased model. The model trained using these datasets gives an accuracy of 97%-98% but fails to perform in the real world. Hence to train the model better we follow few techniques to counter the
imbalance :

3.1. Synthetic Minority Oversampling Technique(SMOTE):

Its goal is to achieve a more balanced class distribution by replicating minority classes at random.
SMOTE algorithm consists of following steps:

- Selecting the minority class vector.
- Calculation of the number of nearest numbers that is k .
- Draw a line between the minority data points and any of its neighbours and place a synthetic point.
- Repeating the step 3 for all minority data points and their k neighbours, until the data is balanced completely.

Clubbing this technique with class weights, focal loss, and other data augmentation techniques provide a balanced dataset.

3.2. Random Resampling:

Resampling is the way toward delivering a new changed adaptation of the training dataset with an alternate class dispersion for the chose occasions. Irregular resampling is the straightforward method to choose tests for the altered dataset at arbitrary.
There are two approaches to random resampling for imbalanced classification

- *Random Oversampling:* Randomly duplicate examples in the minority class.
- *Random Undersampling:* Randomly delete examples in the majority class.

Random oversampling is the cycle of arbitrarily picking and supplanting tests from the minority class and adding them to the training set. Random under-sampling is the cycle of haphazardly picking and eliminating occurrences from the greater part class from the training dataset.

3.3. Image Generator and Image Flipping:

Picture reversing, random cropping, resizing, zooming, and height and width shift are taken to increase the size of the dataset. It will be more useful in training and testing if the dataset is increased in size using the picture flipping approach, as it will provide greater accuracy.

V. FEATURE EXTRACTION

Every image has some essential part while the rest is not required. Therefore we need to extract those features from the image. To do this for Cassava Leaf images two feature extraction methods have been found useful. These three are

3)1.Speeded Up Robust Features (SURF)

The SURF method is a fast and heart algorithm for close by, similarity invariant depiction, and relationship of pictures. The essential interest of the SURF approach lies in its fast computation of chairmen using box channels, thusly engaging continuous applications, for instance, following an article acknowledgment. A scale and revolution invariant interest direct marker and descriptor toward getting delegate highlights.

3)2.Scale-invariant feature transform(SIFT)

SIFT key characteristics of objects are first isolated from a lot of reference pictures and set aside in a database. An item is seen in another image by independently differentiating every part from the new picture to this informational index and finding contenders planning with features subject to the Euclidean distance of their component vectors

VI. MODEL ARCHITECTURE

The structure of the model has not been changed dramatically in recent studies. The Structure generally categories into two categories as Plain CNN and Deep CNN. They both have a sequence of multiple convolutional, batch normalisation, ReLU layer, and pooling layers only the DCNN has an extra set of layers a shortcut connection which make it simplify to move from the yield layer to the past layers of the association through the limit slants.. Any other change in the model found was to start with a bigger kernel size in the first convolution layer and gradually decreasing the size as the layers increases. This improves the feature detection process. Moreover, it has been found that using transfer learning on a pre-trained model has been successful in achieving sufficient accuracies. This decreases the large amount of time needed to train the model which can be days of work.

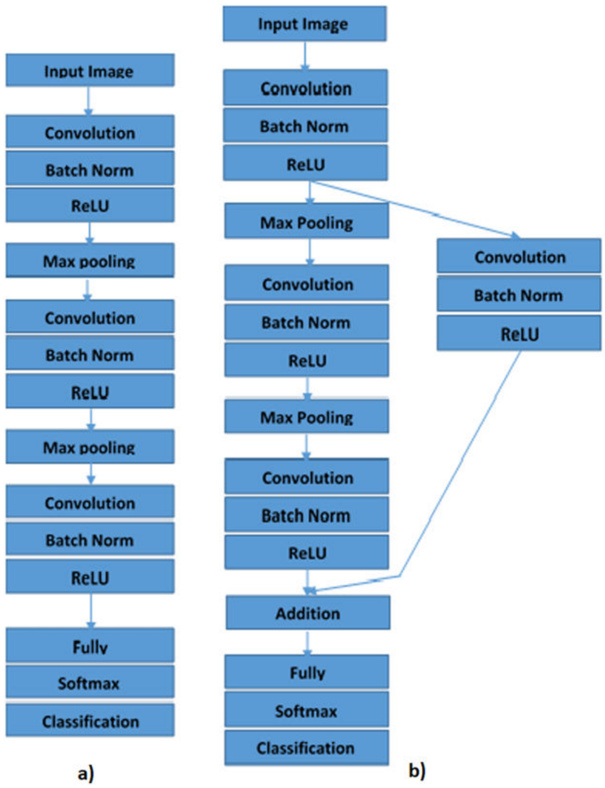

Fig 1 :a) Plain CNN b) Deep CNN [4]

Many studies have been done to derive the best method and algorithm for the detection process. In majority of the studies it was found that Neural Network and Support Vector Classifiers showed the best accuracies and validation amongst all the algorithms considered.

VII. CONCLUSION

It is seen that Cassava Leaf Disease detection has come a long way especially through the CNN method but has various areas to improve. We saw many models achieving high accuracies but still fail in real-life situations. We derived the main reason being the use of a sample dataset with no real-life condition which makes the model somewhat faulty. More reasons that were found were the usage of an imbalanced dataset which makes the model biased. No drastic changes were to be in the area of the model architecture moreover, there is a lot of scope in the area of data-processing and feature extraction and making the model more real-life worthy. The use of various methods as discussed above can be used to counter the challenges that occur in the study and can be used in future models. These models can also be integrated to Mobile devices and drones easily hence making the detection rather easier.

VIII. REFRENCES

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