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Research Article

Detection of *Casava Plant* related Diseases using Deep Learning

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Abstract

Cassava plant is known for the high carbohydrate source. But it is vulnerable to various diseases, which sabotage food security in sub-Saharan Africa. Cassava plant related disease identification should be automated to handle the crisis. Disease detection through image classification and recognition is known to be the best and cost-effective method for early detection and prevention of diseases to prevent further damage of a plant. The dataset contains 21,397 labelled images collected from Uganda. The study trains the dataset using three deep convolutional neural networks to identify the diseases and a healthy plant. The four types of diseases are Cassava Mosaic Disease (CMD), Cassava Green Mottle (CGM), Cassava Brown Streak Disease (CBSD), and Cassava Bacterial Blight (CBB). The present study uses Inceptionresnetv2, Inceptionv3, and Resnet50 models and comparing their accuracies. Inceptionresnetv2 is the combination of residual net and inception net, a hybrid of the inception and resnet model. The aim of the paper is to find whether the original models or the hybrid model is efficient in classifying cassava plant disease detection.

Keywords: Image Recognition, Convolution Neural Networks, Inceptionresnetv2, Inceptionv3, Resnet50.

INTRODUCTION

Agriculture is known to be the backbone of every country. Plants are the major source of oxygen. They perform photosynthesis by taking carbon dioxide and releases oxygen. Plants give a lot of benefits to animals as well as human beings in the form of food, medicine, fiber, wood, etc. Plants maintain moisture in the atmosphere by transpiration. Due to deforestation, global warming, industrialization, and pollution, there is a high decline in the plant population. Plant diseases also have a major impact on the decline of the plant population. The global damage of plants is caused by pathogens.

Climatic conditions impact the occurrence of plant diseases. There are diseases like bacteria wilt, late blight, yellow leaf disease, angular leaf spot, leaf curl, etc., that affect the plant's growth. Some plant diseases show very few symptoms and cause high damage to plants. Early identification of such plant diseases helps in the saving of plants before the plant gets damaged irreparably. Various researchers are working on the reduction of the damage due to plant diseases. Some are working on creating hybrid plants having resistant to pathogens whereas some are developing systems that can identify and predict plant diseases based on the leaves images. Precision agriculture has been developed for high crop productivity. Through precision agriculture, farmers can get a good yield from the farm. It consumes a lot of time for farmers to manually identify a disease for each plant in a large plantation. It is efficient to build a plant disease detection system using machine learning classification techniques that are used to recognize and classify plant diseases.

Various deep learning models have been used to develop systems that identify crop disease. Cassava plant is vulnerable to diseases. Early identification of disease can help the farmers to save the plant from irreparable damage. In this paper, we are using Inceptionresnetv2, Inceptionv3, and Resnet50 models and comparing their accuracies. Inceptionresnetv2 is the combination of residual net and inception net, a hybrid of the inception and resnet model. The aim of the paper is to find the whether the original models or the hybrid model is efficient in classifying cassava plant.

LITERATURE REVIEW

Sambasivam & Geoffrey (2021) proposed a CNN model to identify cassava plant disease. The main objective is to identify Cassava Mosaic Disease (CMD), Cassava Brown-Streak Disease (CBSD), Cassava Bacterial Blight (CBB), and Cassava Green Mite (CGM) on cassava plant by applying deep convolution neural networks. Cassava is staple food in sub-Saharan Africa, and it is vulnerable to various types of plant diseases. Cassava brown streak virus disease (CBB) show symptoms of roots rotting and Cassava Mosaic Disease (CMD) show symptoms of wrinkled and yellowing of leaves. There are four common cassava diseases: Cassava Mosaic Disease (CMD), Cassava Green Mite (CGM), Cassava Brown-Streak Disease (CBSD) and Cassava Bacterial Blight (CBB). Deep learning convolution neural networks helps to classify the type of the disease. The proposed method classifies a healthy plant and two types of diseases. The dataset contains 10,000 labeled images collected in Uganda and annotated by National Crops Resources Research Institute. The architecture consists of three convolution layers and four fully connected layers. The first layer consists of max pooling, batch normalization, and kernel for learning features. The convolution layers help in extracting key features from the images. ReLU (Rectifier Linear Unit) and softmax activation functions are used in convolution and hidden layers. The contrast of the image is enhanced through Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm has been used. The model is trained with certain hyper-parameters. Hyper-parameters values are defined using tuning techniques. Cyclic Learning Rate (CLR) and Learning Rate Finder (LRF) are the two techniques used for defining learning rate. The results show that by using Convolution Neural Networks, different diseases are classified accurately.

Bofarhe et al. (2019) proposed a two-tier architecture built using Cubic Support Vector Machine algorithm and Coarse Gaussian Support Vector Machine algorithm to classify whether the disease is Cassava Bacterial Blight or Cassava Mosaic Disease on cassava plant. The first tier is the health diagnosis model developed using the Cubic Support Vector Machine (CSVM) algorithm for classifying whether the leaf contains disease or healthy. The second tier is the disease detection model developed using the Coarse Gaussian Support Vector Machine (CGSVM) algorithm to detect whether the disease is Cassava Bacterial Blight or Cassava Mosaic Disease. The dataset contains 18000 images taken using digital cameras at different times in a day. Some are taken during the morning, afternoon, and evening. The images contain healthy cassava leaves, CMD, and CBB diseased leaves. All the images are normalized and reclassified in the data preprocessing stage. From the cleaned images, features are extracted by creating a bag-of-features, encode images as new features, and create the table using encoded features. For testing the model, five-fold cross-validation has been applied as it performs multiple train-test splits for the better training of the model on unseen data. To calculate the accuracy of the model the predicted and actual values are considered. The results show that the CVSM model gained 83.9% accuracy in classifying healthy and diseased leaf and the CGSVM model gained 61.6% accuracy in classifying whether the disease is bacterial blight or cassava mosaic disease.

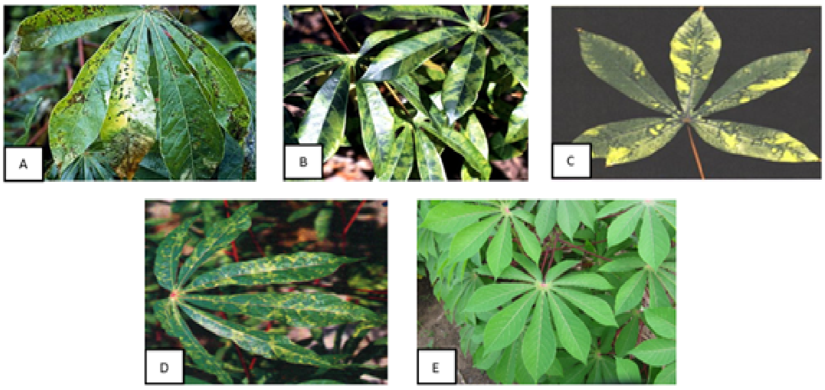
Sangbumrung et al. (2020) proposed the R-CNN model to detect whether the plant is healthy or not and the CNN model to classify the disease type. The cassava leaves images that have five classes i.e., CBSD, CBB. CGM, CMD, and healthy. faster R- CNN and CNN models are used to train the data. The accuracy of the overall system reached 96% by improving the models to classify other cassava diseases such as CBSD, CMD, CBB, CGM, and healthy.

Bin et al. (2017) proposed an automatic system using Convolution Neural Networks to detect the disease on apple leaves to prevent the spreading of the disease. The dataset contains images of four classes: three diseases that are Apple cedar Apple Rust, Apple Black Rot, Apple Sab, and healthy leaves. It is taken from PlantVillage dataset. Convolution Neural Networks model is used to classify images of diseased and healthy. The architecture is implemented using GoogleNet. The GoogleNet is CNN architecture having 22 layers. Each input image is normalized by subtracting mean and dividing by standard deviation. The train and test images are divided into 80 and 20 ratios. Using data generator function, new images are produced by rotating, horizontal and vertical flips, height and width shifts for increasing the dataset and training the model with different angles of the image. It is used when the dataset is limited. The CNN model has four base layers. First convolution layer takes input image followed by another convolution layer. ReLu activation layer and max pool layer are fully connected layers. The output layer has four neurons that represents four categories. The result shows that the model's best accuracy is 98.4%. Each class accuracies are as follows: Apple Scab 97.3%, Apple Cedar Apple Rust 99.2%, Apple Black Rot 98.71%, and Healthy plant 98.7%. This paper concludes that CNN model has higher accuracy in identifying apple plant diseases.

DATASET

The dataset contains 21,397 labeled images. The images are collected from a survey in Uganda. Most of the photos are collected from the farmers who have taken the photos in their gardens. The National Crops Resources Research Institute (NaCRRI) along with the AI lab at Makerere University, Kampala together worked in preparing the dataset. Most of the pictures are realistic which would help to diagnose in real life.

Here we are classifying four diseases and a healthy plant in Figure 1. The four types of diseases are Cassava Mosaic Disease (CMD), Cassava Green Mottle (CGM), Cassava Brown Streak Disease (CBSD), and Cassava Bacterial Blight (CBB). The dataset contains:



(**A**) Cassava Bacterial Blight (CBB), (**B**) Cassava Brown Streak Disease (CBSD), (**C**) Cassava Green Mottle (CGM), (**D**) Cassava Mosaic Disease (CMD), (**E**) Healthy

Figure 1. Images of the five classes in the original dataset

1. 2577 images of a healthy Cassava plant
2. 13158 images of Cassava Mosaic Disease (CMD)
3. 2386 images of Cassava Green Mottle (CGM)
4. 2189 images of Cassava Brown Streak Disease (CBSD)
5. 1087 images of Cassava Bacterial Blight (CBB)

Cassava Bacterial Blight (CBB): Manihotis is the pathogen that causes bacterial blight of cassava. Symptoms include blight, wilting, dieback, and vascular necrosis. Brown lesions form at the bottom of the plant. They enlarge and coalesce causes killing the entire leaf (Fanou et al., 2018).

Cassava Brown Streak Disease (CBSD): It is characterized by severe chlorosis and necrosis on infected leaves, giving a yellowish, mottled appearance. Brown streaks may appear on the stems of the cassava plant (Mohammed et al., 2012).

Cassava Green Mottle (CGM): The leaves contain distinct yellow spots, green patterns(mosaics), and twisted margins. The weight of stems and edible roots of diseased plants reduce to half of the healthy plants (Lennon et al., 2008).

Cassava Mosaic Disease (CMD): Leaves produce misshapen and twisted leaflets with mosaic and mottling. It also causes leaf distortion and stunted growth (Chikoti et al., 2019).

METHODOLOGY

The images in the dataset are in BGR format. Using OpenCV, images are converted to RGB format. The images are split into 80% training images and 20% testing images. The dataset is trained using three models: InceptionResNetV2, InceptionV3, and Resnet50.

InceptionV3 architecture

Szegedy et al. (2016) introduced micro-architecture named Inception. Inception V3 is the third version of Google's Inception CNN. It computes 1x1, 3x3, and 5x5 convolutions and stacks them before sending them to the next layer. It is a CNN used in object detection and image analysis. It acts as a multi-level feature extractor. Figure 2 depicts inception V3 architecture.

ResNet50 architecture

ResNet is known as Residual Networks used in many computer vision tasks. It is a variant of the ResNet model. It is an efficient model to build required number of deeper Convolution Neural Networks without any high accuracy loss. ResNet 50 is the first CNN model to use a special feature namely batch normalization feature. It is a 50-layer network having 48 convolution layers, a max pool layer, and an average pool layer. The input image shape is 224x224x3. It has five stages. It has an identity and convolution block. Both the blocks have three convolution layers (Nan et al., 2019) Figure 3 depicts ResNet50 architecture.

InceptionResNetV2 architecture

Inception-ResNet-v2 is a CNN which is trained on one million images taken from ImageNet database. Inception-ResNet-v2 is a hybrid of the Residual net and Inception net. It can classify images into 1000 different categories and contains 164 layers. The size of the input image is 299 X 299. Average value of all matrix values is calculated by 2d global average pooling layer.The final activation layer is softmax. The model is compiled using adam optimizer (Nguyen et al., 2018) Figure 4 depicts InceptionResNetV2 architecture.

Experimental Results

Figure 5 depicts the training and validation accuracy of Inception V3 model. Training and validation accuracy vary over 10 epochs and at the end of 10^{th} epoch training and validation accuracy are almost same. Overall accuracy is 83.01%.

Figure 6 depicts the training and validation accuracy of ResNet50 model. Training and validation accuracy vary over

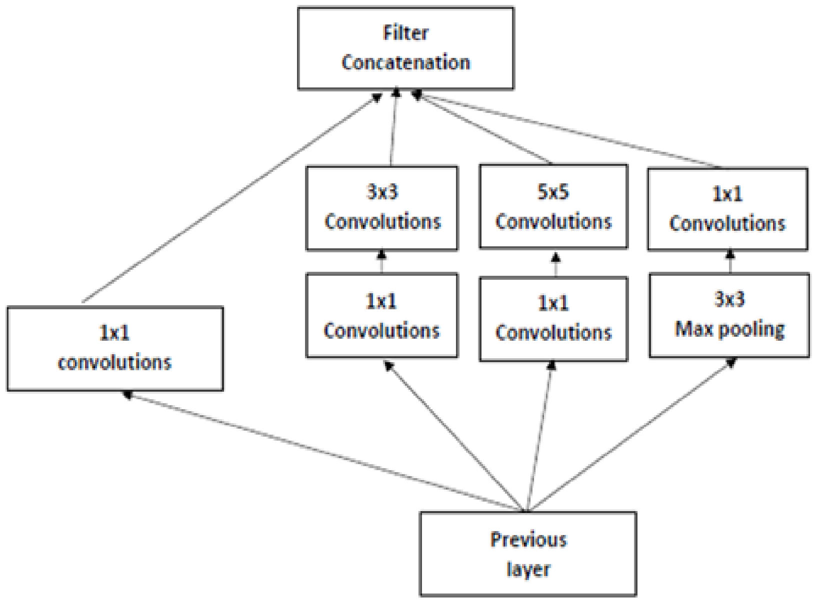


Figure 2. Inception V3 architecture.

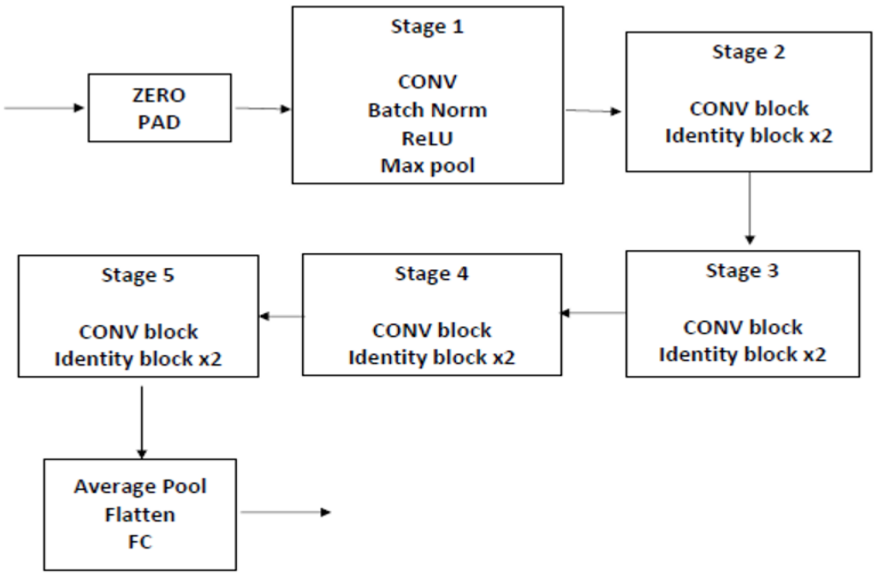


Figure 3. ResNet50 architecture.

10 epochs and at the end of 10th epoch training and validation accuracy has 40% variation. Overall accuracy is 78.29%.

Figure 7 depicts the training and validation accuracy of InceptionResNetV2 model. Training and validation accuracy vary over 10 epochs and at the end of 10th epoch training and validation accuracy has 20% variation. Overall accuracy is 84.77%.

CONCLUSION

Cassava plant is a staple food for many parts in sub urban Africa. Early detection will help to prevent any further damage of the cassava plant. The four major diseases are Cassava Mosaic Disease (CMD), Cassava Green Mottle (CGM), Cassava Brown Streak Disease (CBSD), and Cassava Bacterial Blight (CBB) that cause unrepairable damage to the plant. To protect the plant at an early stage, three deep learning models have been used. The classification and identification of cassava plant diseases have been performed using the above three models. Figure 8 depicts the accuracy of three models. InceptionV3, InceptionResnetV2 and ResNet50 model attained 83.01%, 84.77% and 78.29% accuracies, respectively. InceptionResnetV2 is a hybrid model of Inception and Resnet models. Inception model contains three different convolution layers which act as multi-feature extractor and Resnet has batch normalization feature that is re-centring and re-scaling of the inputs of layers through normalization that results in stable and fast working Convolution Neural Networks. InceptionResnetV2 model has gained the highest accuracy in classifying diseased and healthy leaf and identifying the disease out of four cassava diseases. We can conclude that the hybrid

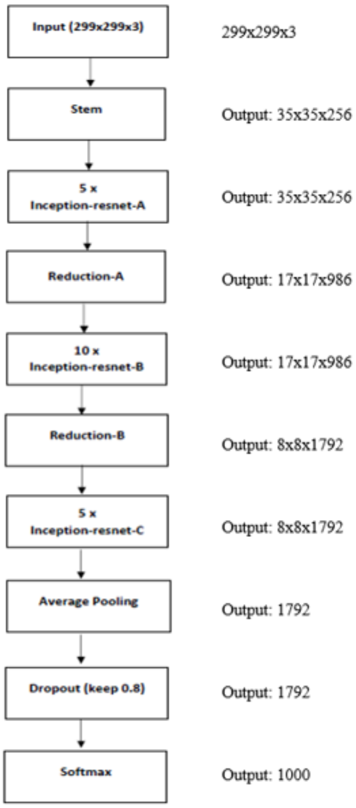


Figure 4. InceptionResNetV2 architecture.

Figure 5. Accuracy of Inception V3.

Figure 6. Accuracy of ResNet50.

Figure 7. Accuracy of InceptionResNetV2.

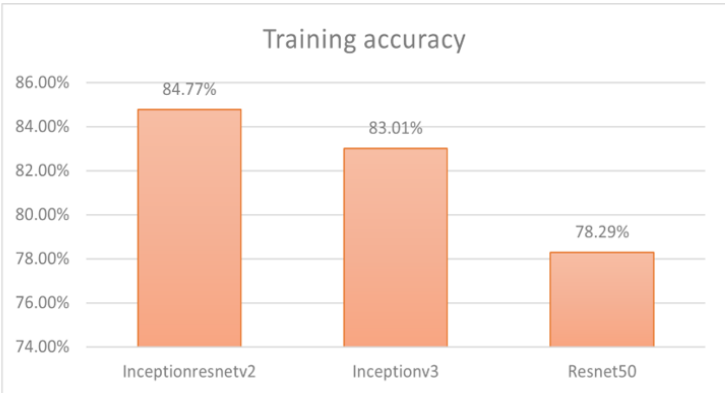


Figure 8. Accuracy comparison of three models.

model has gained more accuracy than the original models working independently.

Hence, using InceptionResnetV2 model we can detect the diseases related to Casava plant with greater accuracy at a very early stage and prevent major damage.

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