Cassava leaf disease classification in realtime and GUI using CNN

Nguyen Ba Huy-19146194
University of Technology and Education, Thu duc district,Ho Chi Minh city

Abstract: Cassava cultivation associated with a wide range of diseases and insect pests, which have seriously affected the yield and quality of cassava leaf, restricting the sustainable development of agriculture. To tackled this problem,many potential methods have been proprosed to identify the symptoms appearing on Cassava leaves. In reccent years, the diagnoses of Cassava diseases could become more easier with the support of Computer vision,which can identify,track and measure targets for further image processing using a camera and a computer as an image to the human eye [6]. Deep learning approaches have made significant contributions to computer vision applications such as classification, object detection, and image segmentation [7].In this paper, I applied CNN to classify image of four types of diseases and one healthy image.

1. Introduction:

Cassava (Manihot esculenta Crantz) is the most widely grown root crop in the world and a major source of calories for roughly two out of every five Africans (Nweke et al., 2002) In 2014, over 145 million tonnes of cassava were harvested on 17 million hectares of land on the African continent (FAOSTAT, 2017)It is considered a food security crop for smallholder farms, especially in low-income, food-deficit areas (Bellotti et al., 1999) as it provides sufficient yields in low soil fertility conditions and where there are irregular rainfall patterns(De Bruijn and Fresco, 1989).

Data competition provide four types of Cassava diseases such as Cassava Bacterial Blight (CBB),Cassava Brown Streak Disease(CBSD), Cassava Green Mottle (CGM) and Cassava Mosaic Disease (CMD), labeled from 0 to 3 and the healthy one labeled 4.Before diving into further study, it is important to have a great understanding of the characterization of the Cassava disease.

Cassava brown streak disease (CBSD) was first reported in Eastern Africa during the 1930s and causes up to 70% losses in cassava root yields [1]. Typical CBSD symptoms are leaf chlorosis, brown streaks on stems and dry hard rot in roots thus affecting both the quality and quantity of edible storage roots .CBSD is caused by cassava brown streak (+)-ssRNA viruses (CBSVs) (genus Ipomovirus; family Potyviridae) comprised of the two phylogenetically distinct species CBSV and Ugandan CBSV (UCBSV) [1].

Cassava bacterial blight (CBB) caused by Xanthomonas axonopodis pv. manihotis is the most important bacterial disease of cassava, a major root crop widely grown in the tropics. Typical symptoms of CBB include watersoaked angular leaf spots, blighting, wilting, defoliation, vascular necrosis of the stem, production of exudates on leaves, petioles or stems, and stem dieback[3][4].

Cassava Green Mottle (CGM) is caused by Cassava green mottle nepovirus.These are viruses,which can be transmitted by nematodes.Some typical symptoms of CGM nepovirus can be identified by looking for yellow patterns on leaves,ranging from small dots to irregular patches of yellow and green.Others symptoms can be noticed is that the margins of leaves are distorted and the plants may be stunned [2].

Cassava mosaic disease(CMD) is characterized by lightgreen,yellow or white spots formed on the leaves. In addition, farmers can easily find discoloration,puckering appear on the leaf blade.Another symptoms of Cassava mosaic virus is that the entire plant becomes stunned and show vein clearing, vein banding and vein thickening[5].

To determine the incidence of Cassava diseases, It is important to have a comprehensive knowledge and deep understanding of how the pathogen spreads between fields as a function of distance.This requires more work to investigate and obtain more information related to cassava pathogens[8].However,with the wide spread of deeplearning and computer vision,reseachers do not have to be an expert to detect cassava disease.They can develop a more robust and reliable Cassava leaf diseases detection[9].

The state of art of using deep learning algorithms in general and convolution neural network has lead to many breakthroughs in not only computer vision tasks ,but also in recognition and object detection .CNNs can learn feature hierarchy from pixels to classifier and train layers jointly.Hence, CNNs can learn the feature representation form of an object in an image.

Because this competition is an object detection tasks ,so it is reasonable to focus on building an CNN architecture to extract useful features from four types of Cassava disease and healthy leaves to categorise them. As you can see the characterization of disease leaves and healthy ones just by eyes. See pictures below

(a) Healthy (b) CBB (c) CGM (d) CMD (e) CBSD

2. Related Work:

In this section, I described about previous works ,which inspired my investigation.

2.1. CNN architecture

There are 3 types of layers in CNN architecture.These are convolutional layers, pooling layers and fully connected layers .

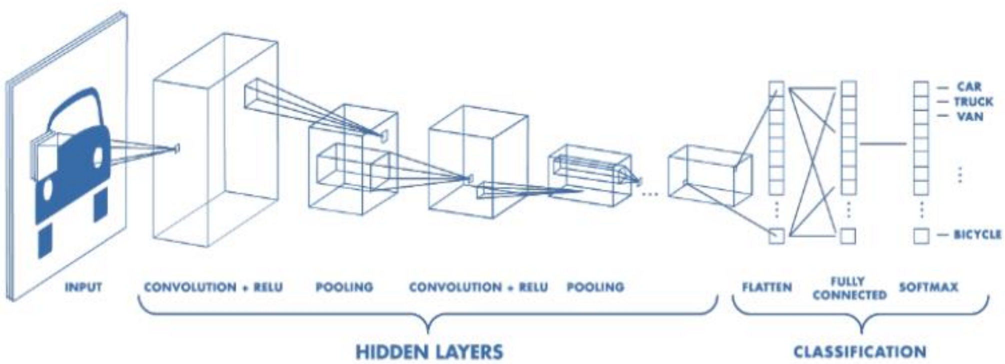

Fig.1: Convolutional neural network

Input layer :The input layer will hold pixels values of the image and feed these pixels into convolutional layer.

Convolutional layer: in the convolutional layer, filters will stride on image from input layer to make input for next layer. Basic features of image like edges and form of images will be learned.The main purpose of this layer is to extract features.

Pooling layer : when extracting features,we will need a large amount of parameters.The more parameters we have, the more complexity our model have to compute.To reduce computing time, we often reduce the dimension of input matrix.

Fully connected layer : After reduce the dimension at the pooling layers, matrix was flatten into vector and then we apply softmax activation function to compute probalities of output classes.

3. Materials and Methods:

In this section, I outline the proposed technique, describe the CNN architecture and experiments conducted.

3.1. Datasets

The Cassava dataset includes 21.367 images,provided by farmer owners in Uganda

3.2. Kaggle Challenge Dataset

When exploring the datasets, I make some observations.Firstly, the data includes wrong label images.For instance, image with characterization of Cassava bacterial blight mislabeled as “healthy” image.

Fig. 2 .Wrong label image

Secondly, dataset is heavily noisy. As we can see in picture below. Some pictures are taken far apart,which might not display details on the leaves.This is hard for the model to focus on interesting features in an image .As we

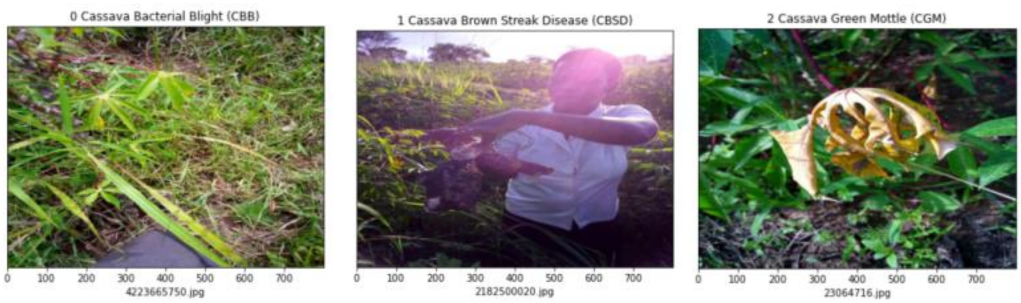

Fig. 3.Noisy data

Another problem shows in pictures above is that the brightness and contrast of pictures result in bad resolution of images.

3.3. Data Pre-Processing

In the Cassava competition, the resolution of the images is originally 600 × 800.However, i resized into 300x300 to decrease computing costs. I am awared of a smaller number of images might lead to overfitting, a common phenomenon where model performs very well on training data but performs poorly on new test data.This is why I applied augmentation techniques included random rotation, zoom range, height and width shift range to enrich my training data.

To deal with noisy data problem,some images do not contains information about diseases are removed. I only keep images which contains a lot of information about a disease.For instance, Healthy cassava image show green and no brown spot on leaves will be kept for training procedures.If leaves show both healthy and diseases , I crop these features and drop them into 2 different folders.

Fig. 4.New image after cleaning

3.4. Proposed CNN model

The preprocessed images jointed the convolutional network as an input .The convolution layers extract features map of images data to learn basic features of leaves.Here I used image with resolution 300x300,which contains detail characterization of Cassava disease.

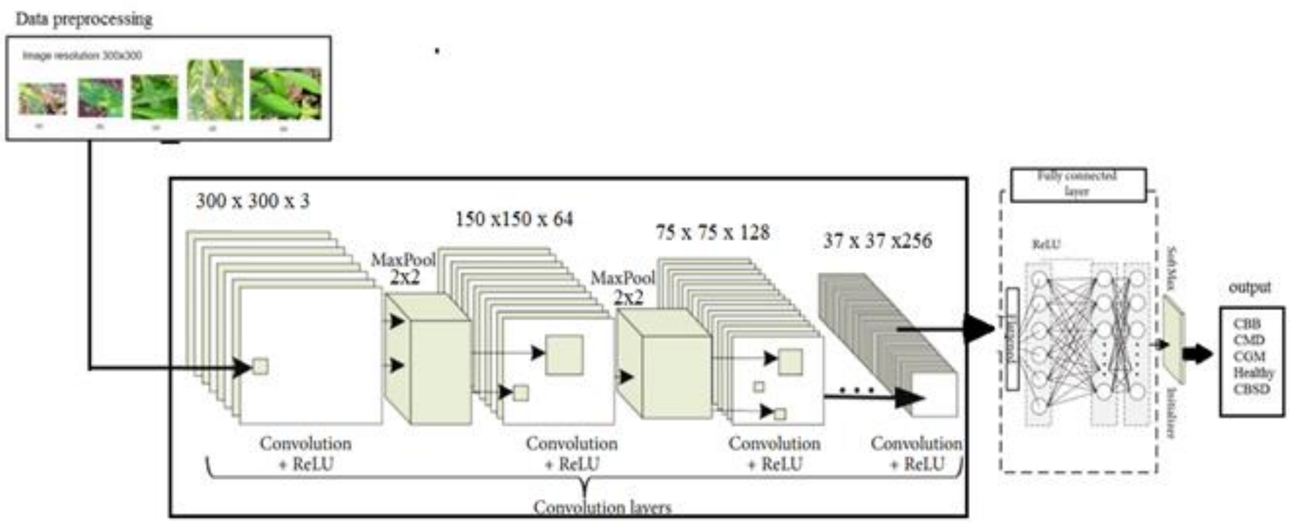

Fig.5 : Proposed CNN model[11]

The output layers of convolutional layers are used as an input for maxpooling layers with stride 2 x 2 to reduce dimension of image .The output from the last maxpooling layer was flatten to transform 1D vector to predict output classes. Specifically,The layer after flatten is fed into dense layer with softmax activation to predict the probalities of classes.Since an input image of 300 x 300 x 3 is transformed ino feature map of 150 x 150 x64 [11].Each feature map is converted into vectors by appling maxpooling layer.These vectors aree used to predict output classes.

4. Results

I experiment proposed model with adam optimizer, to compute loss I used categorical crossentropy loss .I trained 80 epochs with 16 batch size.

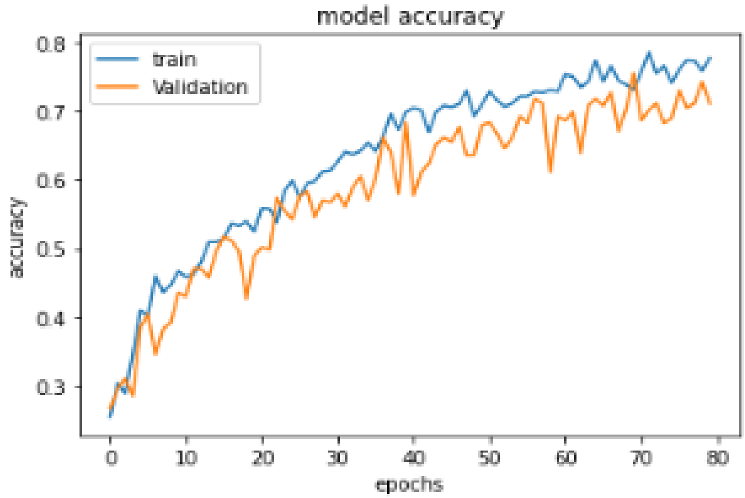

Fig.6 : Training accuracy and validation accuracy

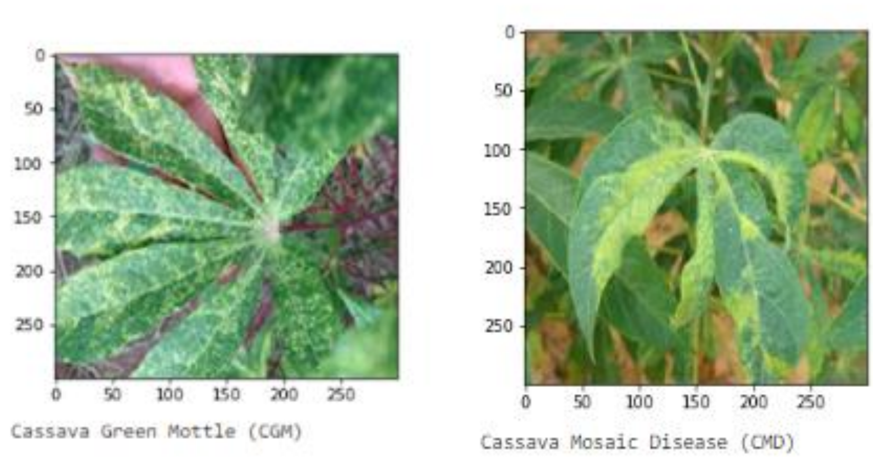

Fig.7 : Predict result

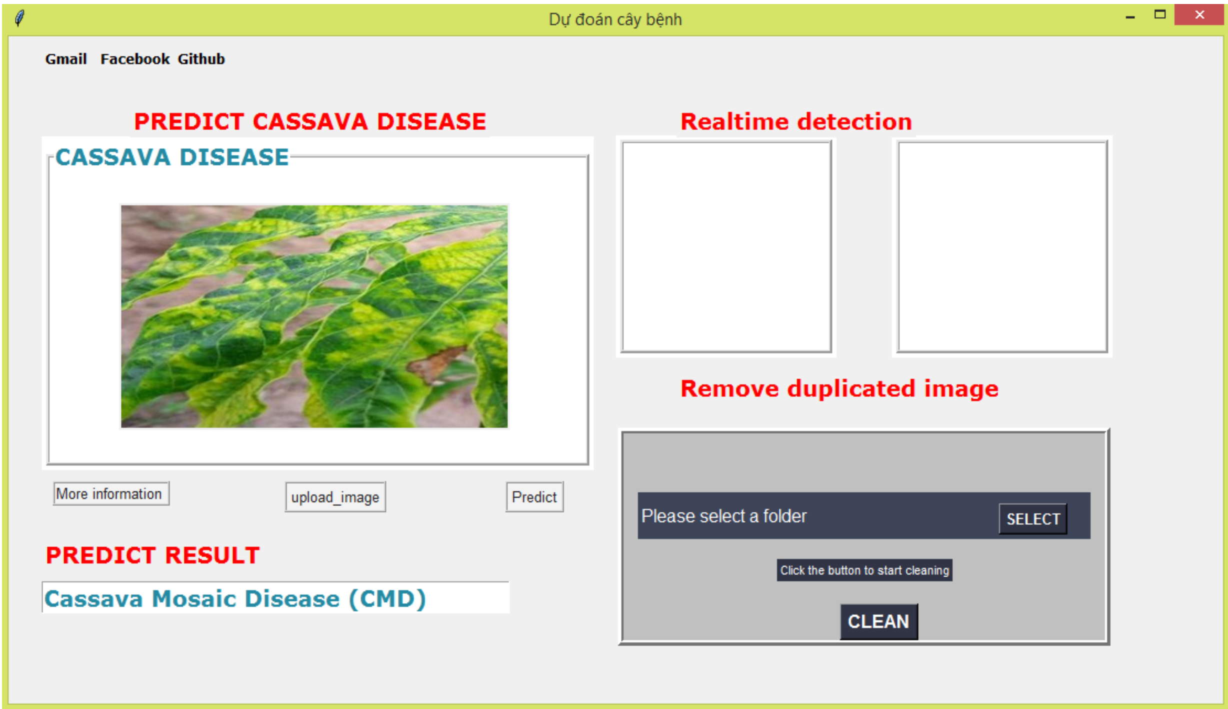

Fig.8 : Predict result in GUI

Fig.9 Real time prediction

4. Conclusion and future work

In this paper, I have so the challenges of this dataset, inluding noisy label and data.I proprosed an CNN architecture to investigate the datasets. I proposed CNN architecture with simple design ,but the accuracy.of model is outperformed VGG16 ,Vgg19 architecture . Because this study only focus on the application of CNN so that I do not experiment with difference backbone .

Acknowledgement

Author would like to thank professional Nguyen Truong Thinh for teaching us for 15 week.

Conflicts of Interest: The author declare no conflict of interest.

References:

1. Cassava brown streak virus,sciencedirect.com,https://www.sciencedirect.com/topics/agricultural-and-biological-sciences/cassava-brown-streak-virus
2. Chiu, M. T. et al. (2020) 'Agriculture-Vision: A Large Aerial Image Database for Agricultural Pattern Analysis', in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
3. Lozano, J.C. and Sequeira, L. (1974) Bacterial Blight of Cassava in Colombia—Epidemiology and Control. Phytopathology, 64, 83-88. http://dx.doi.org/10.1094/Phyto-64-83
4. Maraite, H. and Meyer, J.A. (1975) Xanthomonas manihotis (Arthaud-Berthet) Starr, Causal Agent of Bacterial Wilt, Blight and Leaf Spots of Cassava in Zaire. PANS Pest Articles & News Summaries, 21, 27-37.
5. Mosaic disease of tapioca symptoms and control measures , easybiologyclass.com, https://www.easybiologyclass.com/mosaic-disease-of-tapioca-symptoms-and-control-measures/.
6. H. Tian, T. Wang, Y. Liu, X. Qiao, and Y. Li, "Computer vision technology in agricultural automation -A review," Information Processing in Agriculture, China Agricultural University, vol. 7, no. 1, pp. 1–19, 2020.
7. X. Feng, Y. Jiang, X. Yang, M. Du, and X. Li, "Computer vision algorithms and hardware implementations: a survey," Integration, vol. 69, pp. 309–320, 2019
8. K.Simonyan and A.Zisserman , Very deep Convolution Networks for Large-Scale Image Recognition.2015
9. Loey, M.; ElSawy, A.; Afify, M. Deep learning in plant diseases detection for agricultural crops: A survey. Int. J. Serv. Sci. Manag.Eng. Technol. 2020, 11, 41–58. [CrossRef].
10. Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, Hartwig Adam, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications" arXiv preprint arXiv: 1704.04861,2017.
11. Ho Nguyen Anh Tuan, Nguyen Dao Xuan Hai, Nguyen Truong Thinh, "Shape Prediction of Nasal Bones by Digital 2D Photogrammetry of the Nose Based on Convolution and BackPropagation Neural Network" Volume 2022, Article ID 5938493