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Disease Identification in Leafy Vegetables Using Transfer Learning

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Abstract: Plants are the major source which gives foods for human to survive. In developing countries like SriLanka agriculture plays a major role in the economic success of people live there and as well as for the whole country's success. In such a situation diseases cause huge losses to farmers. The key concept of maintaining quality and quantity of crops is to detect diseases in earlier stages at the correct time and to take preventive actions against the disease. Usually, farmers recognize diseases through naked eye observation. So, it may not the right caption and it tends to spread wrong pesticides and overdosages of pesticides. Hiring expertise in this area is highly costing and not possible to find that many experts. Here include many techniques used to identify diseases in various types of plants. But those papers do not address the area of Sri Lankan leafy vegetable disease identification. This research work proposed a system with a learning approach for disease identification procedure named transfer learning and fine-tuning, partially tested, and obtain better results. InceptionV3 and VGG16 are the two pre-trained models use to retrain the model. InceptionV3 gain 0.95 training accuracy and 0.79 validation accuracy. VGG16 gain 0.91 training accuracy and 0.86 validation accuracy. At the initial stage the tested system has capable of recognizing brown spot disease at 0.43 and 0.48 testing probabilities in Gotukola, and leaf-spot disease at 0.58 and 0.90 testing probabilities in the Mukunuwanna plant through VGG16 and InceptionV3 respectively.

Keywords: Convolutional Neural Networks, Transfer Learning, Fine-tuning, crop diseases

Introduction

Economic success gain through agriculture highly affects the country's success and for the existence of living beings. Agriculture is the main source that supplies food for us. Plant disease causes huge loss to crops by changing the plant's shape, color, and size. Due to the weather changes from time to time, fertilizer in the soil, bacteria, virus, pests tend to cause plant diseases. For example at the end of 2018, Fall Army worm(FAW) which known asSena Dalambuwa("Protecting crops from invasive species | Sunday Observer," 2019) widely spread throughout the Sri-Lanka. It firstly infects corn yields and loss of 25% cause from each yield due to the damages of the FAW. Then worms infect for paddy fields. Recently yellow-spotted grasshoppers("In Sri Lanka, crop-destroying insects follow the COVID-19 pandemic," 2020) hugely spread with the climate at that time throughout Sri Lanka. Those grasshoppers cause damage mainly to coconut plantations. These types of infections make hesitate in those days by rapidly spreading throughout the country and there was no method to control it. If unable to control disease spreadness finallyit impact on food security."25%-30% losses in agricultural products due to diseases, pest and weeds" . Diseases make whole crop kill and farmers should regrow them again. This financially affect for farmers and the country. So, to maintain the above state real time disease identification should done in early stages. If not, expenditure cost increased, and income cost gets decreased. Then there may not any profit remain for the farmer. To maintain the quantity and quality of the crops it should detect plant disease properly and put suitable pesticides to control it at the correct time.

Farmers identify diseases by their naked eye. It may not be the right recognition. Then adding the wrong pesticide and using overdosage also tend to minimize the quantity and quality of the plant. Identify disease at the correct time and using pesticides at the right time is the main scenario when maintaining crops. Hiring expertise in this area for identifying diseases is a high cost for small scale farmers and that person should do certain procedures to identify the disease and it takes much time to process those data. Also, people who involve newly to the agricultural field cannot recognize these diseases one from another. Those who are growing leafy vegetables in houses for their use haven't any idea about these diseases and chemicals adding procedure. Then it tends to use inappropriate pesticides and sometimes overdose usage. Using chemicals for disease reduction in leafy vegetables not good for the health of farmers who are working and eating these leafy vegetables.

The model present in this paper able to identify brown-spot disease in Gotukola plants and leaf-spot diseases in Mukunuwanna plants. The system going to develop will also provide eco-friendly solutions for the disease reduction process. Also, able to prevent over usage of chemicals by giving the exact amount of pesticides we should use to overcome those threats. And it is more accurate and faster than manual methods. Farmers who doing their cultivation on a small scale as well as in largerscale this automated system will be a solution to identify disease in early stages and to take advice to keep their cultivations in a good state.

The rest parts of the paper organize as follows, section 2 describes an overview of existing systems of disease identification procedure of different kinds of plants.

Section 3 highlights the methodology of the system. Overview of diseases identified by the system depicted in section 4.In section 5 depicts the test results of the model. Finally, the conclusion and further works demonstrate in section 6 and section7.

Literature Review

This section includes researches done throughout the world by various people to identify diseases of plant varieties using different kinds of technologies. And methodologies followed by them to configure diseases. About how much accurate the system they proposed and how much success they are, Azzeddine Elhassouny and Florentin Smarandache(Elhassouny and Smarandache, 2019) proposed a smart mobile application model to identify ten types of most common tomato leaf diseases using 7176 leaf images. That model developed based on

MobileNet(Howard et al., 2017) convolution neural network model. To get classification of diseases, the model is ended by the average Pooling of pooling layers, fully connected and the Softmax function with 10 classes. It obtained 86.7%, 88.9%, and 90.3% overall accuracies by changing learning rates 0.01, 0.005, and 0.001 respectively. Xiaoxiao Sun et, al(SUN et al., 2018)proposed a system used convolution neural network (CNN) for disease detection of tea leaves 15 063 images with 6 types of infected leave types and damaged leaves. Image enhancement is done by rotating, flipping, and adding noises to the images. After that, the total number of images obtained was 25 186. 93.75% of accuracy gained from CNN algorithm at 0.00007 learning rate. Then compare the obtained result using Support Vector Machine (SVM) and Back Propagation (BP) neural network to enhance CNN. Those gained 89.36% and 87.66% accuracies respectively. Omkar Kulkarni(Kulkarni, 2018) used health and infected crop leaves images of five types of crop species to use to retrain CNN MobileNet(Howard et al., 2017) and InceptionV3(Szegedy et al., 2015a) models with 5277 images to detect three types of crop diseases from each class. Images gathered from the public ImageNet(Deng et al., n.d.) data set. In crop disease detection, 99.04% gain by MobileNet(Howard et al., 2017) and 99.54% by Inception V3(Szegedy et al., 2015a) model. Boikobo Tlhobogang and Muhammad Wannous

(Tlhobogang and Wannous, 2018)proposed an android based disease detection system using transfer learning models GoogleNet(Szegedy et al., 2015b) and Inception V3(Szegedy et al., 2015a) models. Used 4306 images of Setsewana herb plants from the PlantVillage(Hughes and Salathe, 2016) dataset to train the models. Sharada Prasanna Mohanty et, al(Mohanty et al., 2016) used a public dataset of 54 306 images with healthy and infected leaves and train those using the deep convolution neural network "Caffe"(Jia et al., 2014) to distinguish 14 types of crop species and 26 diseases. The accuracy obtained was 99.35% and 85.53% from GoogleNet(Szegedy et al., 2015b) and AlexNet(Krizhevsky et al., 2012) respectively. The same Caffee(Jia et al., 2014) framework used by Srdjan Sladojevic et, al(Sladojevic et al., 2016) distinguishes 13 variety of plant diseases.

Neethu K. S and P. Vijay Ganesh. (Ganesh, 2017) This proposed system uses to identify leaf disease of lemon, mango and gives fertilizers to control the diseases. Diseases diagnosis using Artificial Neural Networks (ANN). Namita M. Butale and Dattatraya V. Kodavade(Butale and Kodavade, 2019) proposed a disease detection system that used five different species of plant leaves to detect eight disease types. 63% accuracy obtained by the SVM classifier at last SVM output the infected disease name and the solution to overcome from those diseases.

Varsha P. Gaikwad and Vijaya Musande(Gaikwad and Musande, 2017) proposed a system to identify diseases in the wheat plant. Two classifiers were used in this proposed system. One is a neural network that focuses on color, shape, and texture features. It gave 80.21% of accuracy. The other one is the support vector machine used based on the texture and shape feature of the image. SVM gave 89.23% accuracy.

Chaitali G. Dhaware and K.H. Wanjale(Dhaware and Wanjale, 2017)proposed a system used SVM classifier extract color, texture, and co-relation features and classify whether images of leaves are healthy or infected.

Above research paper publishers address different kinds of disease identification in different plant varieties. There is no such paper for disease classification in leafy vegetables.

Methodology

This section briefly describes the procedures followed to develop a model for disease identification procedure.

A. Image Acquisition

Samsung J7nxt and Huawei y7 smartphones are used to grab images of healthy and infected leafy vegetables. Leafy vegetables hugely growing in the Gampaha district and the climate of the environment is mostly similar to the weather condition of other areas in Sri Lanka. I preferred KalEliya and Pallewela area for picture gathering procedure and some pictures are gathered around my home.

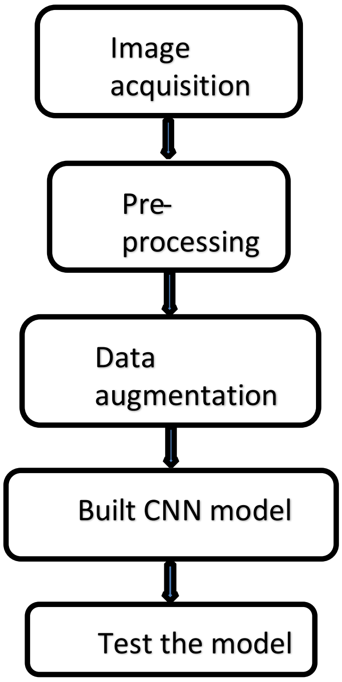

Figure 1: Methodology of the system

B. Image Pre-processing

Go through the collected images to select the ones better in quality and remove unwanted images. Then those good quality images separate into folders by going through each by each according to their disease type and leafy type. Images divide into two sets in 24:1 ratio one for training and another for validating and testing. And rename them according to the numbering procedure applied as in pretrained models.

C. Data Augmentation

Data augmentation techniques apply to enhance the number of images use to train the model by applying position augmentation horizontal flipping and rotation. Those techniques are used to prevent overfitting and to generate models better.

D. CNN Model Build

Retrained the model applying transfer learning and finetuning approaches. InceptionV3(Szegedy et al., 2015a) and VGG16(Simonyan and Zisserman, 2015) are the pretrained models used in here. It's easier to retrain a model than building it from scratch. Model building from scratch is time-consuming and required more data. Segmentation, feature extraction, classification, and prediction are done by CNN itself. In segmentation infected areas are captured from the image. And from that segmented part features are extract and images are classified according to the similarities in extracted features. Layers of the pre-trained model act as feature extractors. The classification layer, the last layer adds when transfer learning. Finetune by freezing the bottom layers and retrain the remaining top layers of the model.Model train using Stochastic Gradient Descent(SGD) optimizer with 0.001 learning rate, 0.9 momentum and 3 epoches.

E. Test the model

Test the developed model using already separated testing data separately for each class. By inputting one image at a time test the model whether predict correctly or not.

Overview of Leafy Vegetable Diseases

Major disease types cause for leafy vegetables used to train disease identification model as follows,

A. Symptoms of brown-spot disease on Gotukola leaves

Figure 2: brown-spot in gotukola

This disease occurs due to Cercospora fungus variety, Purple color rounded spots can be seen in the leaves. At the end leaves turn into yellowish and leaves get to die.

B. Symptoms of leaf-spot disease on Mukunuwanna leaves

Figure 3: leaf-spot in Mukunuwanna

This disease occurs due to Cercospora fungus variety, reddish-brown color spots can be seen in the leaves and spread throughout the leaf and turn it into brownish and dropdown. Mostly can be seen on the matured leaves.

Results and Discussion

The trained model test for three classes healthy Gotukola, the brown spot in Gotukola, and leafspot in Kankun plants. After training the inceptionV3 model it gains 0.95 training accuracy and 0.79 validation accuracy. VGG16 gain 0.91 training accuracy and 0.86 validation accuracy.

A. Prediction results of VGG16 model

Firstly, test the model using an image of brown-spot disease in Gotukola. After inputting an image into the model, it outputs the prediction graph fig.5 and resized image to the target size of 299 x 299 as fig.4.

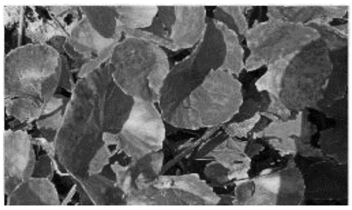

Figure 4: brown-spot in gotukola

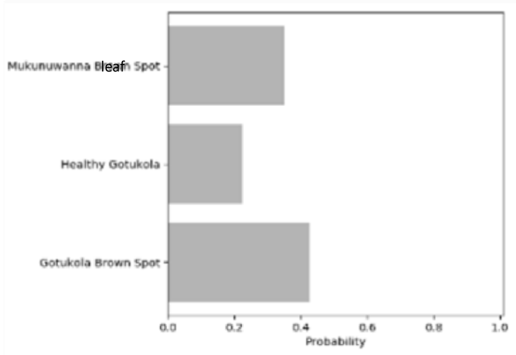

Figure 5: prediction graph

Then test the model using an image of leaf-spot disease in Mukunuwanna. Obtained outputs as the above-tested image depicted using below fig.6 and fig.7

Figure 6: leafspot in Mukunwanna

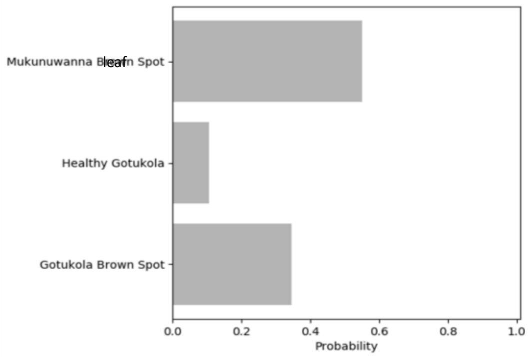

Figure 7: prediction graph

B. Prediction results of INCEPTIONV3 model

Firstly, test the model using an image of brown-spot disease in Gotukola. After inputting the image into the model, it outputs prediction graph fig.9 and resized image to the target size of 299 x 299 as fig.8.

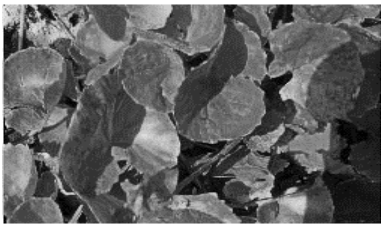

Figure 8: brown-spot in gotukola

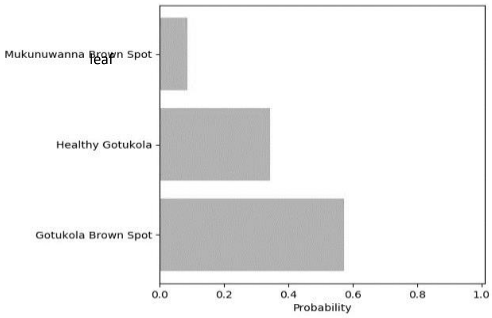

Figure 9: prediction graph

Then test the model using an image of leaf-spot disease in Mukunuwanna. Obtained outputs as the above-tested images depicted using below fig.10 and fig.11.

Figure 10: leafspot in mukunuwanna

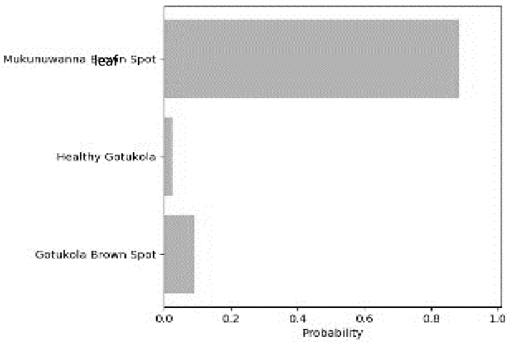

Figure 11: prediction graph

Based on the prediction graph's results in both VGG16 and InceptionV3, better predictive results gained through the inceptionV3 model.

This system further trained for other leafy types Kankun and leafy disease varieties brown spot in Kankun, leaf folding caterpillars in Mukunuwanna, sap-sucking bug infection in Gotukola and for pest infections. Training and testing results obtained for some of these disease types not accurate much as the above results gained model. Currently, I figuring out reasons for this inaccurate results.

Conclusion

To increase the productivity of leafy vegetables it is a must to identify diseases at the right time and take preventive actions against diseases. Hence the above-proposed method is accurate to detect diseases at early stages. In terms of testing and training accuracies, InceptionV3 performs better than the VGG16. Also after train the model for other disease types of leafy varieties, after testing for some images it doesn't predict correctly what disease is. Modle should make as they predict accurately.

Further Works

We are going to develop further this model for other leafy vegetable types Kankun, Niwithi, etc, and for other disease types sap-sucking bug infection, leaf folding caterpillar, and other pest infections by enhancing dataset to get better predictive results. Decided to illustrate this model to the farmers by an android mobile application to view the disease and pesticides or natural methods that should follow to overcome form diseases.

References

Butale, N.M., Kodavade, D.V., (2019). Detection of Plant Leaf Diseases using Image Processing and Soft-Computing Techniques 06, 4.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., Fei-Fei, L., n.d. ImageNet: A Large-Scale Hierarchical Image Database 8.

Dhaware, C.G., Wanjale, K.H., (2017). A modern approach for plant leaf disease classification which depends on leaf image processing, in: 2017 International Conference on Computer Communication and Informatics (ICCCI). Presented at the 2017 International Conference on Computer Communication and Informatics (ICCCI), pp. 1–4. <https://doi.org/10.1109/ICCCI.2017.8117733>

Elhassouny, A., Smarandache, F., (2019). Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks, in: 2019 International Conference of Computer Science and Renewable Energies (ICCSRE). Presented at the 2019 International Conference of Computer Science and Renewable Energies (ICCSRE), pp. 1–4.

<https://doi.org/10.1109/ICCSRE.2019.8807737>

Gaikwad, V.P., Musande, V., (2017). Wheat disease detection using image processing, in: 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM). Presented at the 2017 1st International Conference on Intelligent Systems and Information Management (ICISIM), pp. 110–112. <https://doi.org/10.1109/ICISIM.2017.8122158>

Ganesh, P., (2017). Leaf Disease Detection and Selection of Fertilizers using Artificial Neural Network.

Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., Adam, H., (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv:1704.04861 [cs].

Hughes, D.P., Salathe, M., (2016). An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv:1511.08060 [cs]. In Sri Lanka, crop-destroying insects follow the COVID-19 pandemic, (2020). Mongabay Environmental News. URL <https://news.mongabay.com/2020/06/in-sri-lanka-cropdestroying-insects-follow-the-covid-19-pandemic/> (accessed 7.24.20).

Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., Darrell, T., (2014). Caffe: Convolutional Architecture for Fast Feature Embedding. arXiv:1408.5093 [cs].

Krizhevsky, A., Sutskever, I., Hinton, G.E., (2012). ImageNet Classification with Deep Convolutional Neural Networks, in: Pereira, F., Burges, C.J.C., Bottou, L., Weinberger, K.Q. (Eds.), Advances in Neural Information Processing Systems 25. Curran Associates, Inc., pp. 1097–1105.

Kulkarni, O., 2018. Crop Disease Detection Using Deep Learning, (2018). Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). Presented at the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), pp. 1–4. <https://doi.org/10.1109/ICCUBEA.2018.8697390>

Mohanty, S.P., Hughes, D.P., Salathé, M., (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science 7, 1419. <https://doi.org/10.3389/fpls.2016.01419>

Protecting crops from invasive species | Sunday Observer, (2019). <http://www.sundayobserver.lk/2019/01/27/business/protectingcrops-invasive-species> (accessed 10.21.19).

Simonyan, K., Zisserman, A., 2015. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv:1409.1556 [cs].

Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., Stefanovic, D., (2016). Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification. Computational Intelligence and Neuroscience. <https://doi.org/10.1155/2016/3289801>

SUN, X., MU, S., XU, Y., CAO, Z., SU, T., (2018). Image Recognition of Tea Leaf Diseases Based on Convolutional Neural Network, in: 2018 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC). Presented at the 2018 International Conference on Security, Pattern Analysis, and Cybernetics (SPAC), pp. 304–309. <https://doi.org/10.1109/SPAC46244.2018.8965555>

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z., (2015a). Rethinking the Inception Architecture for Computer Vision. arXiv:1512.00567 [cs].

Szegedy, C., Wei Liu, Yangqing Jia, Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A., (2015b). Going deeper with convolutions, in: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1–9. <https://doi.org/10.1109/CVPR.2015.7298594>

Tlhobogang, B., Wannous, M., 2018. Design of plant disease detection system: A transfer learning approach work in progress, in: 2018 IEEE International Conference on Applied System Invention (ICASI). Presented at the2018 IEEE International Conference on Applied System Invention (ICASI), pp. 158–161. https://doi.org/10.1109/ICASI.2018.8394556

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