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TOMATO PLANT DISEASES DETECTION SYSTEM USING IMAGE PROCESSING

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ABSTRACT- In the agriculture sector, one of the major problems in the plants is its diseases. The plant diseases can be caused by various factors such as viruses, bacteria, fungus etc. Most of the farmers are unaware of such diseases. That's why the detection of various diseases of plants is very essential to prevent the damages that it can make to the plants itself as well as to the farmers and the whole agriculture ecosystem. Regarding this practical issues, this research aimed to classify and detect the plant's diseases automatically especially for the tomato plant. As per the hardware requirement, Raspberry Pi is the major computing unit. Image processing is the key process of the project which includes image acquisition, adjusting image ROI, feature extraction and convolution neural network (CNN) based classification. Here, Python programming language, OPENCV library is used to manipulate raw input image. To train on CNN architecture and creating a machine learning model that can predict the type of diseases, image data is collected from the authenticated online source. As the result , few diseases that usually occurs in tomato plants such as Late blight (training 100, test 21), Gray spot (training 95, test 18) and bacterial canker (training 90, test 21) are detected.

Keywords: Convolution Neural Network (CNN), Image Processing, Raspberry-Pi, YOLO

I. INTRODUCTION

Agriculture is the mainstay of the Nepalese people living. Still, two-third of the population relies upon agriculture directly or indirectly. Majority of Nepalese people depend on agriculture for their livelihoods and has contributed about 32.6% of nation's GDP alone by the agricultural sector in the year 2015/16. In the year 2014/15, the average economic growth was confined to 0.77%. Tomato is one of the major cash crops cultivated in Nepal. Throughout the year the tomatos are cultivated in 25.49 hectors of area and harvesting rate is about 13419 KG/Hac [1]. In desease recognition in such plants , the current system relies on visual observation which is a time consuming process.

Image processing in agriculture has been applied in the areas of sorting, grading of fresh products, detection of defects such as dark spots, cracks and bruises on fresh fruits and seeds, etc. Recent advances in hardware technology have allowed the evolution of deep Convolution Neural Networks (CNN) and their number of applications, including complex tasks such as object recognition and image classification also smart phone based applications for shape and disease identification in plant leaves have been developed.

In this scenario, this research is focused on collecting the data of diseases in tomato plants and train a model for diseases detection.

II. LITERATURE REVIEW

Qin et al. proposed a feasible solution for lesion image segmentation and image recognition of alfalfa leaf disease. The Relief method was first used to extract a total of 129 features, and then an SVM model was trained with the most important features. The results indicated that image recognition of the four alfalfa leaf diseases can be implemented and obtained an average accuracy of 94.74% [2]. These approaches have been applied for classification of tomato powdery mildew against healthy leaves using thermal and stereo images [3].

Rothe et al. presented a pattern recognition system for identifying and classifying three cotton leaf diseases. Using the captured dataset of natural images, an active contour model was used for image segmentation and Hu's moments were extracted as features for the training of an adaptive neuro-fuzzy inference system [4].

The pattern recognition system achieved an average accuracy of 85%. Islam et al. presented an approach that integrated image processing and machine learning to allow the diagnosis of diseases from leaf images. This automated method classifies diseases on potato plants from 'Plant Village', which is a publicly available plant image database.

The segmentation approach and utilization of an SVM demonstrated disease classification in over 300 images, and obtained an average accuracy of 95% [5].

Authors discussed convolutional neural networks models were developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants. Training of the models was performed with the use of an open database of 87,848 images containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations including healthy plants [6].

Rathod et al., have discussed different machine learning methods for disease detection of plant leaf anomalies. The

systems utilized plant image disease classification, boundary division, feature extraction, which give quick and exact discovery of plant leaf infection have been engaged [7].
Sladojevic et al. proposed a novel approach based on deep convolutional networks to detect plant disease. By discriminating the plant leaves from their surroundings, 13 common different types of plant diseases were recognized by the proposed CNN-based model. The experimental results showed that the proposed CNN-based model can reach a good recognition performance, and obtained an average accuracy of 96.3% [8].
Lu et al. proposed a novel identification approach for rice diseases based on deep convolutional neural networks. Using a dataset of 500 natural images of diseased and healthy rice leaves and stems, CNNs were trained to identify 10 common rice diseases. The experimental results showed that the proposed model achieved an average accuracy of 95.48% [9].
Mohanty et al. developed a CNN-based model to detect 26 diseases and 14 crop species. Using a public dataset of 54,306 images of diseased and healthy plant leaves, the proposed model was trained and achieved an accuracy of 99.35% [10].
Tan et al. presented an approach based on CNN to recognize apple pathologic images, and employed a self-adaptive momentum rule to update CNN parameters. The results demonstrated that the recognition accuracy of the proposal was up to 96.08%, with a fairly quick convergence [11].
The novel cucumber leaf disease detection system was presented based on convolutional neural networks. Under the fourfold cross-validation strategy, the proposed CNN-based system achieved an average accuracy of 94.9% in classifying cucumbers into two typical disease classes and a healthy class [12].

III. METHODOLOGY

A. System Overview

A general overview of the system is presented in the block diagram of the system as follows:

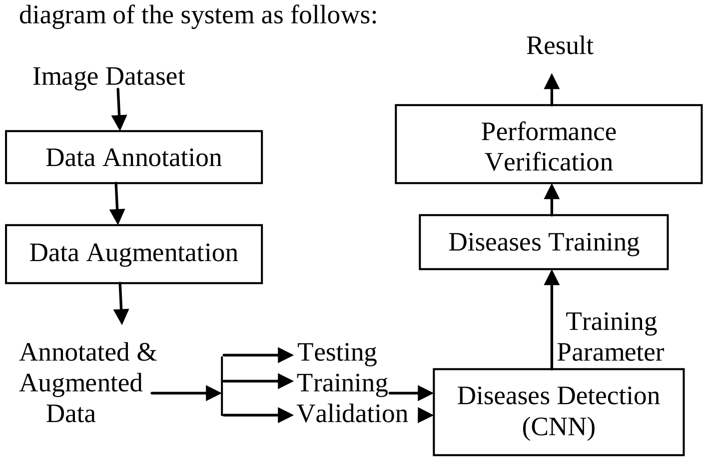

Figure 1: System overview

B. Data Collection and Annotation

The dataset contains images with several diseases in tomato plants. Some of the images are extracted from the internet and some are captured from the farm using a camera device. The image was collected at different time and orientation (e.g. illumination, different light intensity, placement, different rotation, scales). Images consist of different infected areas in the plant (e.g. stem, leaves, fruits ,etc).
Starting with the dataset of images, the areas of every image containing the disease with bounding box and class were annoteded manually. Some diseases might look similar depending on the infection status . Therefore, the knowledge for identifying the type of disease has been provided by experts in the area that has helped us to visibly identify the categories in the images and infected areas of the plant.
This annotation process aims to label the class and location of the infected areas in the image. The output of this step is the coordinates of the bounding boxes of different sizes with their corresponding class of disease which will be evaluated as the Intersection Over Union (IOU) with the predicted results in the network during testing.

C. Designing Convolution Neural Network (CNN)

Inspired by the classical Alexnet [13], YOLO [14] and their performance improvements, a deep convolution neural network is designed to identify tomato plant diseases. The designed network has 24 convolution layers followed by 2 fully connected layers.
First of all, a structure is designed, which is based on standard YOLO model. For the perception of the convolution kernel, A larger sized the convolution kernel has a stronger ability to extract the macro information of the image, and vice versa. A Layer grid is smaller than the whole image. And other information of the image can be understood as "noise" which needs to be filtered. As a consequence, the first convolution layer is designed to be 64 kernels of size 7*7*2.

Table 1: CNN Network Filter

Type	Filter	Size/Stride	Output
Convolutional	32	3*3	224*224
Maxpool		2*2/2	112*112
Convolutional	64	3*3	112*112
Maxpool		2*2/2	56*56
Convolutional	128	3*3	56*56
Convolutional	64	1*1	56*56
Convolutional	128	3*3	56*56
Maxpool		2*2/2	28*28

Convolutional	256	3*3	28*28
Convolutional	128	1*1	28*28
Convolutional	256	3*3	28*28
Maxpool		2*2/2	14*14
Convolutional	512	3*3	14*14
Convolutional	256	1*1	14*14
Convolutional	512	3*3	14*14
Convolutional	256	1*1	14*14
Convolutional	512	3*3	14*14
Maxpool		2*2/2	7*7
Convolutional	1024	3*3	7*7
Convolutional	512	1*1	7*7
Convolutional	1024	3*3	7*7
Convolutional	512	1*1	7*7
Convolutional	1024	3*3	7*7
Convolutional	1000	1*1	7*7
Avgpool		Global	1000

D. Training Model

The input image is collected from internet and annotated to label region of the area. An object with a different background, light intensity, orientation and different shapes and sizes is collected to increase accuracy and minimize false detection. This model has trained with the 4 class classification dataset in 2000 iterations: using stochastic gradient descent with a starting learning rate of 0.1, polynomial rate decay with a power of 4, weight decay of 0.0005 and momentum of 0.9. In the initial training, input image is 580* 580 resolution then it is scaled down to 448*448 and for 10 epochs at a 10^{-3} learning rate. After the training, the classifier achieves a top-1 accuracy of 76.5% and a top-5 accuracy of 93.3%.

After removing the fully connected layers, Classifier can take images of different sizes. If the width and height are doubled, we are just making 4x output grid cells and therefore 4x predictions. Since the CNN network down samples the input by 32, we just need to make sure the width and height is a multiple of 32. During training, Classifier takes images of size 320×320, 352×352, and 608×608 (with a step of 32). For every 10 batches, Classifier randomly selects another image size to train the model. This acts as data augmentation and forces the network to predict well for different input image dimension and scale. In additional, we can use lower resolution images for object detection at the cost of accuracy. This can be a good tradeoff for speed on low GPU power devices. At 288 × 288 algorithm runs at more than 90 FPS with mAP almost as good as Fast R-CNN. Batch normalization leads to significant improvements in convergence while eliminating the need for other forms of regularization. By adding batch normalization on all of the convolutional layers in detection we get more than 2% improvement in mAP. Batch normalization also helps regularize the model. With batch normalization 4%. Then the fully connected layers and the last convolution layer is removed for a detector. Detection algorithm adds three 3 × 3 convolutional layers with 1024 filters each followed by a final 1 × 1 convolutional layer with 125 output channels. (5 box predictions each with 25 parameters) Classifier also add a passthrough layer. CNN trains the network for 160 epochs with a starting learning rate of 10^{-3}, dividing it by 10 at 60 and 90 epochs. Input image is annotated where annotated file contain region of area of infected plant parts. Over 500 images per class are trained. Here class represents the type of diseases Training was done on Nvidia 1080 Ti.

E. Detection

Detection algorithm divides the input image into an **S×S** grid. Each grid cell predicts only one object. Each grid cell predicts a fixed number of boundary boxes. Each boundary box contains 5 elements: (*x, y, w, h*) and a box confidence score. The confidence score reflects how likely the box contains an object (objectne**ss**) and how accurate is the boundary box. The bounding box width *w* and height *h* by the image width and height. *x* and *y* are offsets to the corresponding cell is normalized. Hence, *x*, *y*, *w* and *h* are all between 0 and 1. Each cell has n conditional class probabilities. The conditional class probability is the probability that the detected object belongs to a particular class (one probability per category for each cell).

The major concept of this algorithm is to build a CNN network to predict a (7, 7, 30) tensor. It uses a CNN network to reduce the spatial dimension to 7×7 with 1024 output channels at each location. Detection performs a linear regression using two fully connected layers to make 7×7×2 boundary box predictions (the middle picture below). To make a final prediction, we keep those with high box confidence scores (greater than 0.25) as our final predictions (the right picture). The class confidence score for each prediction box is computed as:

It measures the confidence on both the classification and the localization (where an object is located). In the real-life domain, the boundary boxes are not arbitrary. Gray spot have very similar shapes and leaf mold have an approximate aspect ratio of 0.41.

Since we only need one guess to be right, the initial training will be more stable if we start with diverse guesses that are common for real-life objects. Instead of predicting 5 arbitrary boundary boxes, we predict offsets to each of the anchor boxes above. If we constrain the offset values, we can maintain the diversity of the predictions and have each prediction focuses on a specific shape. So the initial training will be more stable.

IV. Results

The CNN-based classifiers are tested on a subset of the diseases dataset, including tomato plant leaf diseases. The dataset consists of 3 leaf diseases of the tomato plant, including Gray spot (113 samples), Late Blight (121 samples), Bacterial Canker (111 samples). Adding healthy tomato leaf images, the used dataset contains 520 images in 3 categories. The preliminary preparation and augmentation are applied to the dataset. The images of the dataset are resized to fit into 412×412 dimensions which are chosen to be relatively small and close to a fraction of the average size of all images. After excluding 10% of the images as test set, the remaining images as training set are augmented, in order to reduce over fitting, by adding horizontally flipped copy of the images, then a portion of these images is further separated as the validation set pre-trained on Image-Net and fine-tuned on the dataset, and the proposed CNN architecture with and without residual learning. Firstly, the pre-trained YOLO models, are fine-tuned on the dataset to be considered as a baseline for comparison. Then a simplified CNN architecture is proposed and trained with and without the residual learning framework (residual and plain CNN) to compare the results. All the diseases which may affect the growth of tomato plant has been analyzed. Different diseases has different features and symptoms, by classifying these visual symptoms of diseases data is trained on convolution neural network (CNN).after training model is created which can detect all the diseases. After testing trained model on Pascal voc. Format, Mean Average Precision (MAP) is found to be 0.76.

System can predict diseases on different scales and resolution of images. Size , orientation, light intensity does not affect the output result. However on high resolution image detection accuracy will be high. System resize the input image into 412*412 (width * Height) and scales pixel value at this ratio.

A. *Training Model on CNN*

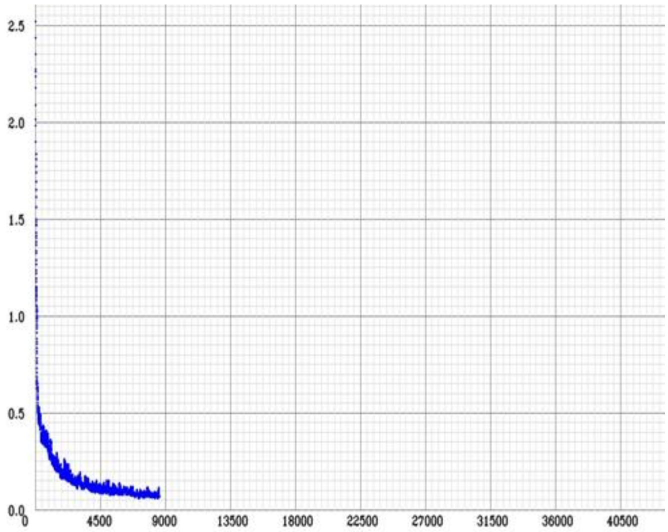

Figure 2: Iteration vs. loss function

Above graph shows the relation between number of iteration and average loss of training. Y-axis represents average loss and X-axis represents number of iterations. The model is trained upto 8000 iterations with average loss of 0.0634 and Mean Average Precision (MAP) is found to be 0.76.

B. *Detection of diseases*

Figure 3: Detection of late blight (accuracy: 95%)

Figure 4: Detection of bacterial Canker (accuracy: 89%)

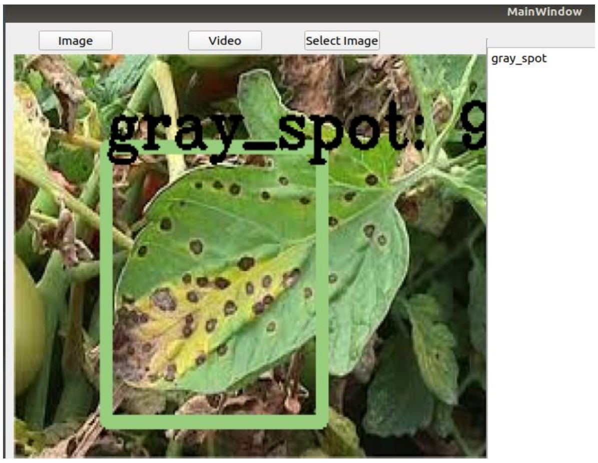

Figure 5: Detection of Gray-Spot (accuracy: 92%)

Figure 6: Detection of Healthy Plant

Regarding accuracy of the system during training, it is 0.76 MAP. An overall accuracy of the system is found to be 89 % based on plant village dataset. System failure or predicting false positive on those images which have similar pattern of diseases were caused due to the mud, insects waste such as white moth , pest and eggs.

V. CONCLUSION

In this way by collecting data of various diseases of tomato plants and process them to train on CNN architecturte to create a machine learning model, Late blight (training 100, test 21), Gray spot (training 95, test 18), bacterial canker (training 90, test 21) are the detected diseases.

For detection purpose YOLO object detection algorithm build in darknet framework is used to train a model and predict diseases in tomato plant. Python programming language, OPENCV library is used to manipulate raw input image. Model is trained on Nvidia 1080 gpu. This system is implemented in Raspberry pi, desktop based Graphical User Interface (GUI) is developed to capture image or video.

In addition, It is found that using technique based data annotation and augmentation results in better performance.

As a limitation; this system is only capable of detecting three classes of diseases and healthy plant. In order to detect other class of diseases data has to be trained on current model. Algorithm will use transfer learning method to classify other class of diseases.

The main challenge while developing object detection model on machine learning was to collect large number of train images with different shapes, sizes, with different background, light intensity, orientation and aspect ratio.

As per the recommendation; the further study can be done to detect all types of plant diseases, not only detection but also suggesting remedies for diseases. Finally, this system can be integrated with IOT server to implement system on rural and remote area.

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REFERENCES

[1] N. Ghimire, M. Kandel, M. Aryal and D. Bhattarai, "Assessment of tomato consumption and demand in Nepal," *The Journal of Agriculture and Environment*, vol. 18, p. 83, Jun. 2017.

[2] F. Qin, D. Liu, B. Sun, L. Ruan, Z. Ma and H. Wang, "Identification of alfalfa leaf diseases using image," 2016.

[3] G. Prince, J.P. Clarkson, N.M. Rajpoot, “Automatic detection of diseased tomato plants using thermal and stereo visible light images,” *PloS one*, Vol. 10 No. 4, 2015, pp. e0123262.

[4] P. Rothe and R. Kshirsagar, "Cotton leaf disease identification using pattern recognition techniques," in *International Conference on Pervasive Computing, Pune,India,* 2015.

[5] Islam, A. Dinh, K. Wahid and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," *Canadian Conference on Electrical and Computer Engineering, Canada*, 30 April–3 May 2017.

[6] K. P. Ferentinos, "Deep Learning models for plant disease detection and diagnosis," 2018.

[7] P. Rothe and R. Kshirsagar, "Cotton leaf disease identification using pattern recognition techniques," in *International Conference on Pervasive Computing, Pune,India,* 2015.

[8] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," 2016.

[9] Y. Lu, S. Yi, N. Zeng, Y. Liu and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks," 2017.

[10] S. Mohanty, D. Hughes and S. Marcel, "Using deep learning for image-based plant disease detection," 2016.

[11] W. Tan, C. Zhao and H. Wu, "CNN intelligent early warning for apple skin lesion image acquired by infrared video sensors," 2016.

[12] Y. Kawasaki, H. Uga, S. Kagiwada and H. Iyatomi, "Basic study of automated diagnosis of viral plant diseases using convolutional neural networks," in *12th International Symposium on Visual Computing, Las Vegas*, 2015.

[13] A. krizheysky and G. Hinton, "ImageNet classification with deep convolution neural networks," in *25th International Conference on Neural Information Processing Systems*, Lake Tahoe, USA, 3 Dec. 2012.

[14] J. Redmon, S. Divvala, R. Girshick and A. Farhadi, "You only look once: Unified, real-time object detection," in *IEEE conference on computer vision and pattern recognition* , 2016.