

Leaf Disease Detection using Computer Vision

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Abstract - The identification of plant disease is an imperative part of crop monitoring systems. Computer vision and deep learning (DL) techniques have been proven to be state-of-the-art to address various agricultural problems. This research performed the complex tasks of localization and classification of the disease in plant leaves. In this regard, three DL meta-architectures including the Single Shot MultiBox Detector (SSD), Faster Region-based Convolutional Neural Network (RCNN), and Region-based Fully Convolutional Networks (RFCN) were applied by using the TensorFlow object detection framework. All the DL models were trained/tested on a controlled environment dataset to recognize the disease in plant species. Moreover, an improvement in the mean average precision of the best-obtained deep learning architecture was attempted through deferent state-of-the-art deep learning optimizers. The SSD model trained with an Adam optimizer exhibited the highest mean average precision (mAP) of 73.07%. The successful identification of 26 deferent types of defected and 12 types of healthy leaves in a single framework proved the novelty of the work. In the future, the proposed detection methodology can also be adopted for other agricultural applications. Moreover, the generated weights can be reused for future real-time detection of plant disease in a controlled/uncontrolled environment.

Key Words: Deep Learning; Plant Disease Detection; Transfer Learning; Optimization Algorithms; Mean Average Precision

1. INTRODUCTION

In agricultural crops, leaves play a vital role to provide information about the amount and nature of horticultural yield. Several factors affect food production such as climate change, presence of weed, and soil infertility. Apart from that, plant or leaf disease is a global threat to the growth of several agricultural products and a source of economic losses. The failure to diagnose infections/bacteria/virus in plants leads subsequently to insufficient pesticide/fungicide use. Therefore, plant diseases have been largely considered in the scientific community, with a focus on the biological features of diseases. Precision farming uses the most advanced technology for the optimization of decision-making. The visual inspections by experts and biological review are usually carried out through plant diagnosis when required. This method, however, is typically time-consuming and cost ineffective. To address these issues, it is necessary to detect plant diseases by advanced and intelligent techniques.

To address the task of object identification, the classification and localization of objects are performed in a single platform by using deep learning meta-architectures. In this regard, few DL algorithms have been developed. The Region-based Convolution Neural Network (RCNN) was among the first modern techniques towards image detection tasks through CNN. Afterward, the successful implementation of regional proposal methods proved significant developments in object identification. In the context of plant disease recognition, very few studies have been conducted to perform this complex agricultural operation by DL techniques. For example, in the deep learning models were implemented to perform plant disease localization and diagnosis.

From the literature, it can be concluded that most of the recent researches have been focused on the task of plant disease classification (only classify the type of disease among several plant species). However, the complex task of plant disease identification (both localization and classification of the disease in the plant) has been given very little attention. Moreover, none of the previous approaches has performed a comprehensive study regarding the detection/identification of 38 classes of plant disease by advanced DL meta-architectures.

2. LITERATURE REVIEW

Paper [1] Paper Review: S.Phadiar ,J.Sil, Rice Disease Identification using Pattern Recognition Techniques, Proceedings of 11th International Conference on Computer and Information Technology (ICCIT 2008), 25-27 December, pp.420 - 423, 2008.

Objective of the Paper: The aim of this paper is to describe a software prototype system for the detection of disease in rice plant on the basis of various images of the rice plants. Images of the infected part of the rice plant are taken using digital camera. In order to detect the defected part of the plant various techniques like image segmentation, image growing etc. have been used. By using neural network the infected part of the leaf is classified. Image processing and soft computing techniques have been applied on infected rice plant.

Paper [2] Paper Review: A. Meunkaewjinda, P. Kumsawat and K. Attakitmongcol, Grape leaf disease detection from color imagery using hybrid intelligent system, 5th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology, Volume: 1, pp. 513 - 516, 2008

Objective of the Paper: The aim of this paper is to do automatic plant disease diagnosis with the usage of multiple artificial intelligent techniques. In this paper the main focus is on the grape leaf disease. Once the system is trained, it can diagnose the plant leaf disease without doing its maintenance again and again from the beginning

Paper [3] Paper Review: A.Camargo, J.S.Smith, An image-processing based algorithm to automatically identify plant disease visual symptoms, Bio systems Engineering, Volume 102, Issue 1, January 2009, pp. 9-21.

Objective of the Paper: The aim of this paper is to do the automatic identification of the plant disease by image processing from the visual symptoms by analyzing the colored images.

Paper [4] Paper review: S.Bashir, N.Sharma, Remote Area Plant disease detection using Image Processing', IOSR Journal of Electronics and Communication Engineering , Volume 2, Issue 6 , pp.31-34, 2012.

Objective of Paper: Disease can be recognized by using color and texture features. Disease detection in Malus Domestica is using K mean clustering ,color and texture analysis.

Paper [5] Paper review: S.Arivazhagan, R.N.Shebiah, S.Ananthi ,S.V.Varthini ,Using texture detection features, recognizing unhealthy region of plant leaves and classification of plant leaf disease, Agric Eng Int: CIGR Journal, Vol. 15, No. 1, pp.211 - 217, 2013

Objective of Paper: The aim of the paper is to do detection of unhealthy region of plant leaves and classification of plant leaf disease using texture features.

Paper [6] Paper review: E.Omrani, B.Khoshnevisan, S.Shamshirband, H.Saboohi, N.B.Anuar, M.H.N.M.Nasir, 'Potential of radial basis function-based support vector regression for apple disease detection', Department of Bio system Engineering, pp. 2 - 19, 2014.

Objective of the Paper: The aim of this paper is to classify disease using soft computing approaches, Artificial Neural Networks(ANNs) , Support Vector Machines(SVM) in apple.

Paper [7] Paper Review: A.Singh, B.Ganapathysubramanian, A.K.Singh, S.Sarkar, Machine Learning for High-Throughput Stress Phenotyping in Plants, Trends in Plant Science, Volume 21, Issue 2, February 2016, Pages 110-124.

Objective of the Paper: The aim of this paper is to give us an overview regarding the work done in the field of plant stress phenotyping using Machine Learning, classification, quantification and prediction. It will also tell about the general issues in Machine Learning strategy.

3. EXISTING SYSTEM

In existing system leaf disease is predicted using iterative method. The Iterative Method can calculate the threshold in a certain extent automatically. For the iterative process, the Iterative Method includes a prior knowledge concerning the image and noise statistics. And the optimal segmentation threshold can be found by continuously reducing the gray scale meter.

Drawbacks of Existing System

- Its accuracy is below 60%
- There is no suggestion for how to treat that disease

4. PROPOSED SYSTEM

The prevention and control of leaf disease have always been widely discussed because leaves are exposed to outer environment and are highly prone to diseases. Normally, the accurate and rapid diagnosis of disease plays an important role in controlling leaf disease, since useful protection measures are often implemented after correct diagnosis. This system is based on image processing technology and uses python as the main processing tool.

5. APPLICATION

We have analyzed the computer vision based disease detection techniques for detection of leaf diseases from different plants. The techniques utilize two different approaches for disease detection process such as supervised and unsupervised methods. The unsupervised method require less computation time as compared to supervised method. But it cannot be considered that a particular method is applicable for identification of all types of plant diseases. So efforts can be made for effective identification of all leaf diseases using a single approach.

The Uses are:

- Vertical Gardening
- Hydroponics Gardening
- Agriculture Field
- Food Product Industries

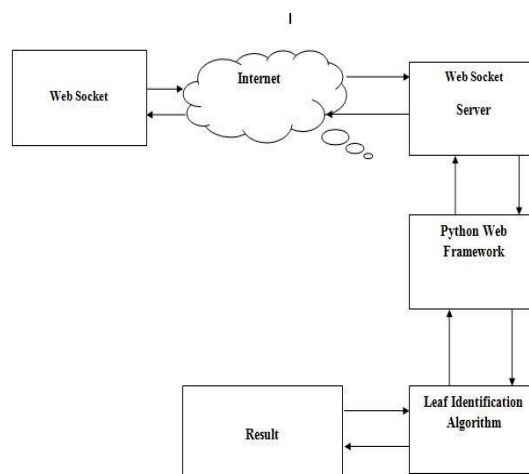


Fig 1 : Block Diagram

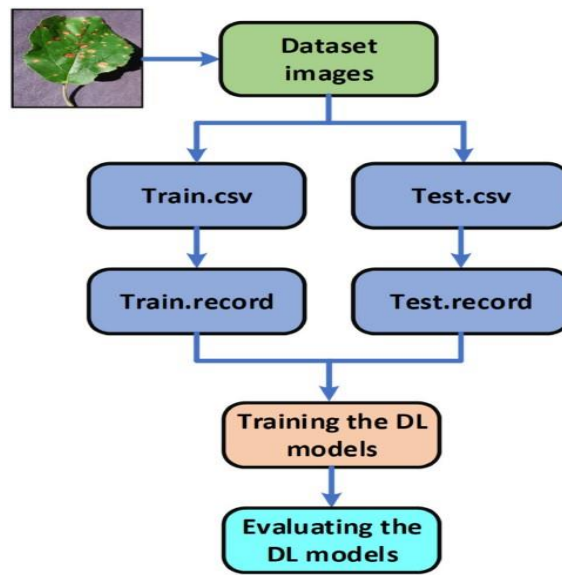


Fig 2 : Flow Chart

6.RESULTS

```

[INFO] Loading images ...
[INFO] Processing Pepper_bell_Bacterial_spot ...
[INFO] Processing Pepper_bell_healthy ...
[INFO] Processing Potato_Early_blight ...
[INFO] Processing Potato_healthy ...
[INFO] Processing Potato_Late_blight ...
[INFO] Processing Tomato_Bacterial_spot ...
[INFO] Processing Tomato_Early_blight ...
[INFO] Processing Tomato_healthy ...
[INFO] Processing Tomato_Late_blight ...
[INFO] Processing Tomato_Leaf_Mold ...
[INFO] Processing Tomato_Septoria_leaf_spot ...
[INFO] Processing Tomato_Spider_mites_Two_spotted_spider_mite ...
[INFO] Processing Tomato_Target_Spot ...
[INFO] Processing Tomato_Tomato_mosaic_virus ...
[INFO] Processing Tomato_Tomato_YellowLeaf_Curl_Virus ...
[INFO] Image loading completed
    
```

Fig 3: Images loading from Dataset

	File	DiseaseID	Disease Type
0	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
1	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
2	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
3	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
4	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot

	File	DiseaseID	Disease Type
1495	Dataset/PlantVillage/Tomato_Tomato_YellowLea...	14	Tomato_Tomato_YellowLeaf_Curl_Virus
1496	Dataset/PlantVillage/Tomato_Tomato_YellowLea...	14	Tomato_Tomato_YellowLeaf_Curl_Virus
1497	Dataset/PlantVillage/Tomato_Tomato_YellowLea...	14	Tomato_Tomato_YellowLeaf_Curl_Virus
1498	Dataset/PlantVillage/Tomato_Tomato_YellowLea...	14	Tomato_Tomato_YellowLeaf_Curl_Virus
1499	Dataset/PlantVillage/Tomato_Tomato_YellowLea...	14	Tomato_Tomato_YellowLeaf_Curl_Virus

	File	DiseaseID	Disease Type
1029	Dataset/PlantVillage/Tomato_Septoria_leaf_spo...	10	Tomato_Septoria_leaf_spot
802	Dataset/PlantVillage/Tomato_Late_blight/005a2...	8	Tomato_Late_blight
74	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
521	Dataset/PlantVillage/Tomato_Bacterial_spot/03...	5	Tomato_Bacterial_spot
336	Dataset/PlantVillage/Potato_healthy/3c0d688...	3	Potato_healthy
107	Dataset/PlantVillage/Pepper_bell_healthy/0...	1	Pepper_bell_healthy
773	Dataset/PlantVillage/Tomato_healthy/0caff918...	7	Tomato_healthy
645	Dataset/PlantVillage/Tomato_Early_blight/0c86...	6	Tomato_Early_blight
77	Dataset/PlantVillage/Pepper_bell_Bacterial...	0	Pepper_bell_Bacterial_spot
910	Dataset/PlantVillage/Tomato_Leaf_Mold/041f3e0...	9	Tomato_Leaf_Mold

Fig 4: Gathered Diseases from Dataset

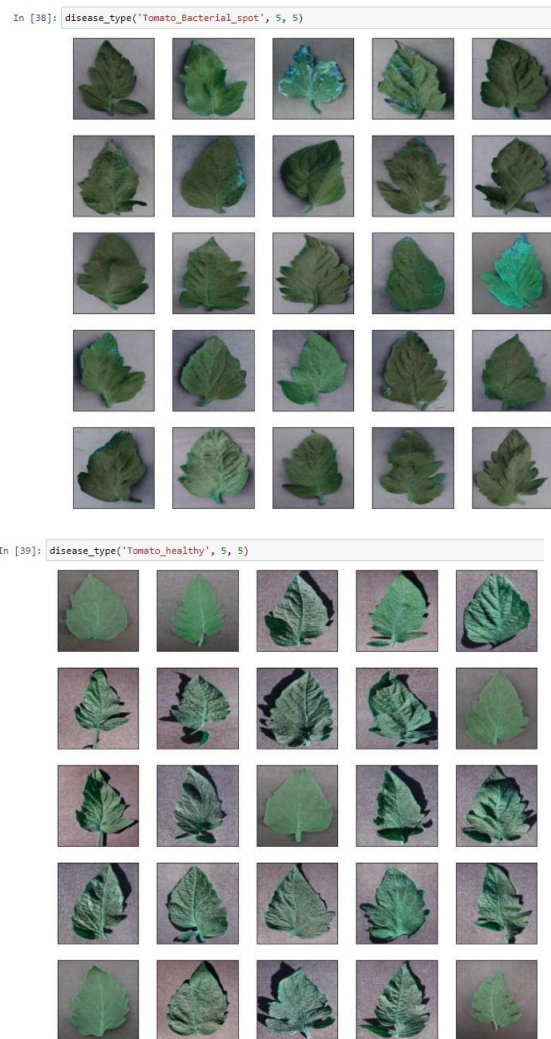


Fig 5: Splited by Diseases

```
In [85]: history = model.fit(
aug.flow(x_train, y_train, batch_size=65),
validation_data=(x_test, y_test),
steps_per_epoch=len(x_train) // 65,
epochs=EPOCHS, verbose=1
)

37/37 [=====] - 534s 14s/step - loss: 0.8710 - accuracy: 0.1669 - val_loss: 0.9321 - val_accuracy: 0.0767
```

Fig6: Calculating Trained Data

```
In [89]: print("[INFO] Calculating model accuracy")
scores = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {scores[1]*100}")

[INFO] Calculating model accuracy
10/10 [=====] - 20s 2s/step - loss: 0.9321 - accuracy: 0.0767
Test Accuracy: 7.666666805744171
```

Fig7: Calculating the Accuracy

7. CONCLUSION

The use of automated monitoring and management systems are gaining increasing demand with technological advancement. In agricultural field loss of yield mainly occurs due to widespread disease. Mostly the detection and identification of the disease are noticed when the disease advances to the severe stage. Therefore, causing the loss in terms of yield, time and money. The proposed system is capable of detecting the disease at the earlier stage as soon as it occurs on the leaf. Hence saving the loss and reducing the dependency on the expert to a certain extent is possible. It can provide help for a person having less knowledge about the disease. Depending on these goals, we have to extract the features corresponding to the disease.

REFERENCES

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- [3] A. Camargo, J. S. Smith, An image-processing based algorithm to automatically identify plant disease visual symptoms, Biosystems Engineering, Volume 102, Issue 1, January 2009, pp. 9-21.
- [4] S. Bashir, N. Sharma, Remote Area Plant disease detection using Image Processing', IOSR Journal of Electronics and Communication Engineering, Volume 2, Issue 6, pp.31-34, 2012.
- [5] S. Arivazhagan, R. N. Shebiah, S. Ananthi, S. V. Varthini, Using texture detection features, recognizing unhealthy region of plant leaves and classification of plant leaf disease, Agric Eng Int: CIGR Journal, Vol. 15, No.1, pp.211-217, 2013
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