

Exploiting Deep Learning Architectures for Rice Plant Disease Recognition and Classification

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Abstract:

To detect and classify various diseases of plants, the images of leaves are the main wellspring of information. Misidentifying various diseases in agricultural crops can lead to significant economic loss and environmental impacts. Rice is the most predominant food crop in India. Plant disease is defined as an abnormal physiological process that distorts the plant's normal structure, growth and function. Early diagnosis of rice grain diseases can save tonnes of agricultural products every year. The traditional manual observation of the crop disease is time-consuming and less accurate. For addressing this issue, deep learning architecture which performs well in the disease classification tasks has been analysed in depth in this article on its complex architecture to classify the disease into various categories. It provides overview to model a lightweight efficient automated disease detection system on memory-efficiency. This technique has successfully detected and identified three rice diseases namely rice brown spot, rice bacterial blight, and rice blast. This technique is efficient and faster requires minimum computation time to identify and classify the diseases. Rather than processing the whole leaf, this technique even successfully detects the diseases using only a small sample of leaf containing the affected portion for rice diseased.

Keywords — Rice Disease, Image Segmentation, Deep Learning

I. INTRODUCTION

Rice is the major source of food among the rural population and also it is considered and the second most cereal crop cultivated over the world. Therefore disease free cultivation of rice is very crucial to ensure the economic growth of the country. There are several rice diseases such as viral, bacterial and fungal. These diseases effect the cultivation of rice every year by degrading the quality and quantity which creates major problem for the farmers as well as the country therefore rice disease should be dealt properly and in time. Disease Management which refers to detection, classification and finally treatment of the disease is a very difficult task. To reach the treatment phase of disease management, detection and classification must be done first which is quite challenging.

Diseases are identified based on colored spots or streaks which can be seen on leaves or stem. Different disease has different colored spots and patterns. Though manual observation can identify disease, it becomes obsolete while considering large fields and non-native diseases. In this case, image processing can be used instead of manual observation.

Image processing plays a crucial role in the detection of plant diseases since it provides best results and reduces the human efforts. Image processing techniques helps to identify diseases more accurately and within small period of time. Different image processing techniques have been developed to detect and classify rice diseases using machine learning architectures as rice disease detection technique that was able to detect three rice diseases namely rice blast, rice sheath blight

and brown spot [2]. Several features like shape, texture, and color namely Homogeneity, Correlation, Contrast, Energy and Entropy of the infected regions were computed and used for classifying the diseases. Further Machine learning architectures utilizes the morphological changes for classification and finally vegetation indices based segmentation for detection of two rice diseases namely rice blast and rice brown spot has been employed.

Therefore, these techniques may work very well for the given set of images the models are trained but fail to reach the performance metrics when deployed for images outside the training data. Since advent of deep learning methods, continuous research is being conducted to use deep learning for automating disease detection. The results showed an increase in accuracy in the increasing number of epochs for training and testing modules. The remainder of this paper is organized as follows: We discuss the review of literature in Section 2 and presents deep learning technique for plant disease mining models in Section 3. Section 4 provides finding on diagnosis of the plant disease and section 5 outlines the future directions of proposed methodology.

II. RELATED WORK

In this section, various existing model applied to diagnosis of the plant disease on rice plant by utilizing deep learning model has been detailed as follows

A. Pre-Trained Deep Convolutional Neural Networks for Rice Plant Disease Classification

In this literature, transfer learning of pre-trained deep learning architecture has been analysed for rice plant disease classification. Pre trained deep Convolution layer such as (i) AlexNet; (ii) Vgg16; (iii) ResNet152V2; (iv) InceptionV3; (V) InceptionResNetV2; (vi) Xception; (vii) MobileNet; (viii) DenseNet169; (ix) NasNetMobile; and (x) NasNetLarge has been used for analysis of image

for rice plant disease classification with rice plant diseased images with classes: (i) rice blast; (ii) bacterial leaf blight; (iii) brown spot; (iv) sheath blight; (v) sheath rot; (vi) false smut; (vii) healthy leaves.

Disadvantage of this model

- Pre defined architecture produces less no of epoch value for classification of testing data.

B. Automated Recognition of Rice Grain Diseases Using Deep Learning

In this literature, Convolutional Neural Networks have utilized for disease classification tasks. The model uses many layers, where the input layers are wide but as one moves forward, the layers become deeper. In this architecture, the convolutional layers are followed by pooling layers. Transfer learning was adopted for model stability. The models were first trained on the artificial data set and the weights of the best performing models were stored through checkpoint saving.

Disadvantage of the model

- Setting up and finalizing the model parameters was one of the major complication of the CNN model.

C. A Lightweight CNN Architecture to Identify Various Rice Plant Diseases

In this literature, Deep learning based image processing methods has been employed as a great solution in identifying various rice plant diseases accurately and precisely. The images have been pre-processed and augmented using different algorithms. Along with different state of the art CNN architectures, a lightweight CNN architecture has been proposed for identifying various rice plant diseases for identify 12 different types of rice images.

Disadvantage of the model

- It has difficulties in extracting lesion features from the constant-changing environment

D. Detection of Paddy Crops Diseases and Early Diagnosis Using Faster Regional Convolutional Neural Networks

In this literature, deep learning models were used to detect a rice blast disease such as Brown spot, Sheath blight, Blast and Leaf streak disease at early stage, so we can control disease spread over all plant. The proposed system is applied to identify a various rice plant leaf images disease detection using mask R-CNN, Faster R-CNN algorithms. On analysis mask R-CNN is best suitable for to detect and identify the various rice blast disease such as Blast-96%, Brown spot-95%, and Sheath blight-94.5%.

Disadvantage of the model

- It could not find the similarities on slight illumination changes of the similar features.

E. Genome wide computational identification of regulatory RNAs in rice plant pathogen

In this literature, *Xanthomonas oryzae* is a gram negative bacterial phytopathogen which causes leaf blight disease of rice plant, posing serious threat to the plants and their yield. Regulatory RNAs are heterogeneous functional RNA molecules which modulate/regulate gene expression, thus controlling a wide variety of physiological functions. As an effort to understand the role of regulatory RNAs in the physiology and pathogenesis of *Xanthomonas oryzae*, we identified candidate regulatory RNAs, such as riboswitches (Cobalamin, FMN, Glycine, SAM, TPP, crcB), small RNAs (asX1, asX3, asX4, sX2, sX5, sX6, sX7, sX9, sX11, sX12, sX13, sX14, Xool, Xoo2, Xoo5, Xoo8) and ribozyme (RNaseP_arch), using in silico approach. We also identified the genes regulated by these regulatory RNAs and their role

Disadvantage of the model

- Complication in determining the global minimum easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it.

III. DESIGN OF DEEP LEARNING ARCHITECTURE

In this section, Deep learning architecture has been analysed from dataset collection to disease classification

A. Analysis of Dataset

Artificial Data Artificial rice leaf images were obtained through Kaggle and comprised of a total of 3355 images belonging to four different classes i.e. Healthy, Hispa (pest), Brown Spot and Leaf Blast (diseases). Since these images were captured in the natural fields, a variety of backgrounds could be seen in the images in the figure 1

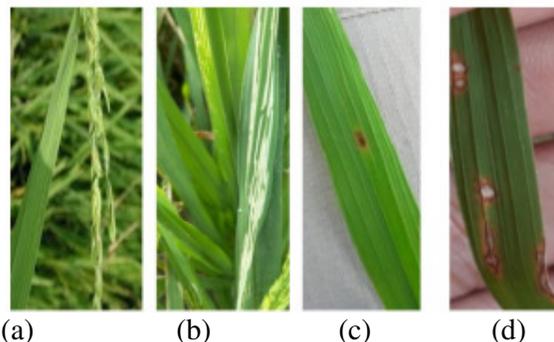


Figure 1: Representation of Rice Plant Disease Image Acquired in Different Background

B. Analysis of Image Pre-processing Techniques

Image processing techniques for leaf segmentation and background and shadow removal were applied to narrow down the region of interest. Intensity Scaling was applied for background removal. However, these techniques were insufficient. In case of the use of Power Law Transform, the entire image would be wiped off. Intensity scaling on the other hand was unable to remove the shadow from the images and also affected the diseased area of the leaf.

Color Thresholding was used to create mask of pixel values of colors we wished to keep. When applied on the images, the mask was able to remove the unwanted background and shadow from

the images. Figure 1 represents the architecture of deep learning models.

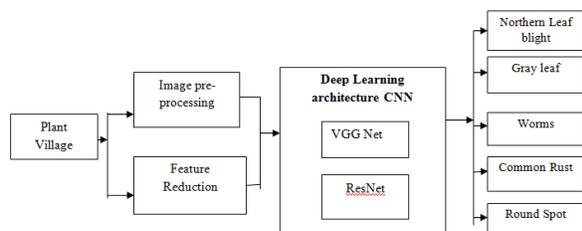


Fig 1 Architecture of Deep Learning models

C. Analysis of Deep Learning Classification models

A comparison between the classification accuracy of two different deep learning models has been analysed. Two main Deep Learning algorithms that have been used in this work are the ResNet and VGGNet.

- **VGGnet Architecture**

The VGGNet has a pyramid like shape where the input layers are wide but as one moves forward, the layers become deeper. In this architecture, the convolutional layers are followed by pooling layers. VGGNet is a great architecture for standardization and since pre-trained VGG Nets are easily accessible online, they can be easily applied for a wide range of problems. But on the downside, training VGG Nets takes a lot of time and is a GPU exhaustive task.

- **ResNet Architecture**

ResNet consists of multiple residual modules which either perform a function on the input or don't. These modules are stacked on top of one another to form connected network architecture. When using ResNet, one is free to add or remove the residual layers as needed, therefore, there is a lot of room for experimentation. But as the network gets deeper, training becomes more complex and time consuming

IV. CONCLUSIONS

In this paper, an extensive study on the deep learning technique to diagnosis of rice plant disease has been presented in detail. It has been analysed on various processing step of the machine learning paradigms on basis of pre-processing, feature extraction and classification against characteristic of plant leaves on various deep learning architectures like VGGNet and ResNet. Especially diagnosis model deals on classifying the disease region accurately on the underlying extracted features. These analyses help to model a new methodology as framework for disease identification and interventions on various characteristics of the plant leaves to numerous kinds of diseases along the identification of mineral deficiency in the plant

REFERENCES

- [1] S. Y. Y. Lu, " Identification of rice diseases using deep convolutional neural networks.," Neurocomputing, pp. 378-384, 2017
- [2] J Pukkela, P. and Borra, S., 2018. Machine Learning Based Plant Leaf Disease Detection and Severity Assessment Techniques: State-of-the-Art. In Classification in BioApps (199-226). Springer, Cham.
- [3] Yao, Q., Xian, D., Liu, Q., Yang, B., Diao, G., & Tang, J., 2014. Automated Counting of Rice Planthoppers in Paddy Fields Based on Image Processing. Journal of Integrative Agriculture, 13(8), 1736–1745
- [4] Phadikar, S. and Goswami, J., 2016. Vegetation indices based segmentation for automatic classification of brown spot and blast diseases of rice, 2016 3rd International Conference on Recent Advances in Information Technology (RAIT), Dhanbad, 284-289.
- [5] X. Pantazi, D. Moshou and A. Tamouridou, "Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers", Computers and Electronics in Agriculture, vol. 156, pp. 96- 104, 2019. Available: 10.1016/j.compag.2018.11.005
- [6] Rahman, C. R., Arko, P. S., Ali, M. E., Khan, M. A. I., Wasif, A., Jani, M., & Kabir, M. (2018). Identification and Recognition of Rice Diseases and Pests Using Deep Convolutional Neural Networks. arXiv preprint arXiv:1812.01043
- [7] B. S. Ghyar and G. K. Birajdar, "Computer vision based on approach to detect rice leaf diseases using texture and color descriptors.", in International Conference on Inventive Computing and Informatics (ICICI), 2017
- [8] Komal Bashir, Maram Rehman, Mehwish Bari, "Detection and Classification of Rice Diseases: An Automated Approach Using Textural Features." Mehran University Engineering Engineering of Engineering and Technology. 2019, vol.38, no.1, pp.239-250 DOI: 10.22581 / muet1982.1901.20
- [9] D. P. R. R. Atole, " A multiclass deep convolutional neural network classifier for detection of commonrice plant anomalies," International Journal Of Advanced Computer Science And Applications, pp. 67-70., 2018
- [10] Sethy, Kumar, P., et al. 2017. Identification of Mineral Deficiency in Rice Crop based on the SVM in Approach of K-Means & Fuzzy C-Means Clustering. HELIX 7.5 1970-1983.