

Temporal Convolutional Neural Networks for Categorization of Diseases in Rice

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Abstract : Agriculture is one of the most important sectors of the Indian economy. It employs nearly half of the workforce of India, according to a survey conducted in 2018. The techniques of image processing have been extensively applied in various fields to make predictions. Due to its importance, the prevention of diseases in the crops is a major concern that needs to be dealt with to protect the crops from getting destroyed. This paper attempts to apply the techniques image classification using Temporal Convolution Neural Network to classify the diseases found in the rice crops.

The diseases that are taken into consideration in this experiment are Bacterial Leaf Blight, Brown Spots and Rice Blast.

IndexTerms - image processing; machine learning; classification; disease classification; disease detection; rice diseases;

I. INTRODUCTION

Agriculture is one of the major sources of income in India. It accounts for 18% of the country's GDP. India is also the major producer of rice, wheat and barley, among other crops. Rice often gets infected by various kinds of diseases due to the presence of bacteria, virus or fungi. This destroys a major part of the crops that are grown, resulting in a huge loss to the farmers, and to the common people. In the developing world, 40-50 per cent of crops are lost to pests every year. That is an astounding number when solving world hunger is a problem that is trying to be dealt with.

Farmers are usually either unaware of the problems or are unable to pay attention to the crops. Every crop disease has a different remedy. Thus, to treat a plant infected with a certain kind of a disease, one must be able to first identify the kind of the disease. Farmers often rely on their experience to identify the diseases or take help from various books available. But often, these diseases become hard to detect because of similarity in their appearance. Most of them appear initially as spots on the leaves. Since the farmer is unable to classify the disease accurately, the correct treatment cannot be given to the plants. Thus, identification of diseases is an important part to prevent spreading the diseases among the crop.

The increasing popularity of big data and the development of more powerful computers has led to a parallel increase in the ubiquity of artificial intelligence (AI). Machine learning (ML) has gained a wide application in all industries, from banking to sports. Among these applications, the most popular are predictive models that are trained on data of old cases and have to make decisions once the data of a new case is provided to them. ML has been used in past with various different algorithms to detect the diseases in plants.

Support Vector Machines, Neural Networks, Bayesian Classifier, K-nearest methods, are some of the methods that have been used in past for classification of rice diseases.

This paper deals with the classification of diseases in rice crops using Temporal Convolutional Neural Network.

II. THEORY

1. DISEASES IN RICE

This section covers various rice diseases that will be used to train the model in this paper. This section has been put so that different rice diseases and their features can be understood. It also gives an insight into different image processing techniques that can be applied to perform the detection.

1.1 BACTERIAL LEAF BLIGHT

Bacterial Leaf Blight can be identified by wilting and yellowing of leaves. On seedlings, infected leaves turn greyish green and roll up. At a later stage, the entire leaf can turn yellowish colour and dry up, limp and die.

1.2 BROWN SPOTS

In the Brown Spots disease, lesions can be observed on the leaf. The seedlings that have been infected may have small, circular, yellow-brown or brown lesions that may develop over the shoot tip in and damage primary and secondary leaves. Initially they are small, circular or dark brown, but on developing fully, they turn circular with brownish or greyish centre, with a reddish-brown margin around it.

1.3 RICE BLAST

Rice Blast disease is one of the deadliest diseases because of the way it spreads under favourable conditions, destroying all the crops. Its initial symptoms are appearance of white to grey-green spots, with dark green borders. As these lesions become older, they develop an elliptical shape or diamond shape with grey centre and reddish to brownish border. These lesions, when enlarge and get bigger, can kill the entire leaf.



Figure 1.1 Diseases in Rice

2. TEMPORAL CONVOLUTIONAL NEURAL NETWORK

TCNs are basically an architecture for convolutional sequence prediction. They use one dimensional Fully Convolutional Network, containing multiple hidden layers of the length equal to the length the input layer. They also have padding so that the next layer is of the same size as the previous layer. This ensures that the next layer is of the same length as the previous layer. This is useful because this helps TCN produce the output of the same length as the input. Thus, it can map a sequence of any length to the output of same length.

TCNs also have casual convolutions. Dilated Casual convolutions mean that a filter at a certain timestep cannot see the layers at a later timestep. This prevents leakage of information from the future to the past and allows to achieve larger receptive fields with fewer parameters and fewer layers.

$$\text{TCN} = \text{1D Fully Convolutional Network} + \text{casual convolutions} \quad (1.1)$$

TCNs are built up of Residual Blocks. Residual Blocks are stacks of Dilated Casual Convolutional Layers where the inputs of the layer are added back to the inputs to obtain the output of the layer. If there is a difference in the width of the inputs and the width of the second dilated convolution layer, then 1D convolution is applied to match the two widths.

To determine how many layers of residual blocks are to be added to the network, the calculation of the receptive field is necessary. It can be calculated by

$$F(i) = F(i-1) + 2 * [\text{kernel_size}(n)-1] * \text{dilation}(n) \quad (1.2)$$

Where $F(i)$ is the number of dilations i^{th} dilated convolution can see.

The input and output of a residual block can have a different width than the input of another residual block. Thus, a 1x1 convolution layer is added to the network to ensure that the width of the output remains the same as the width of the input.

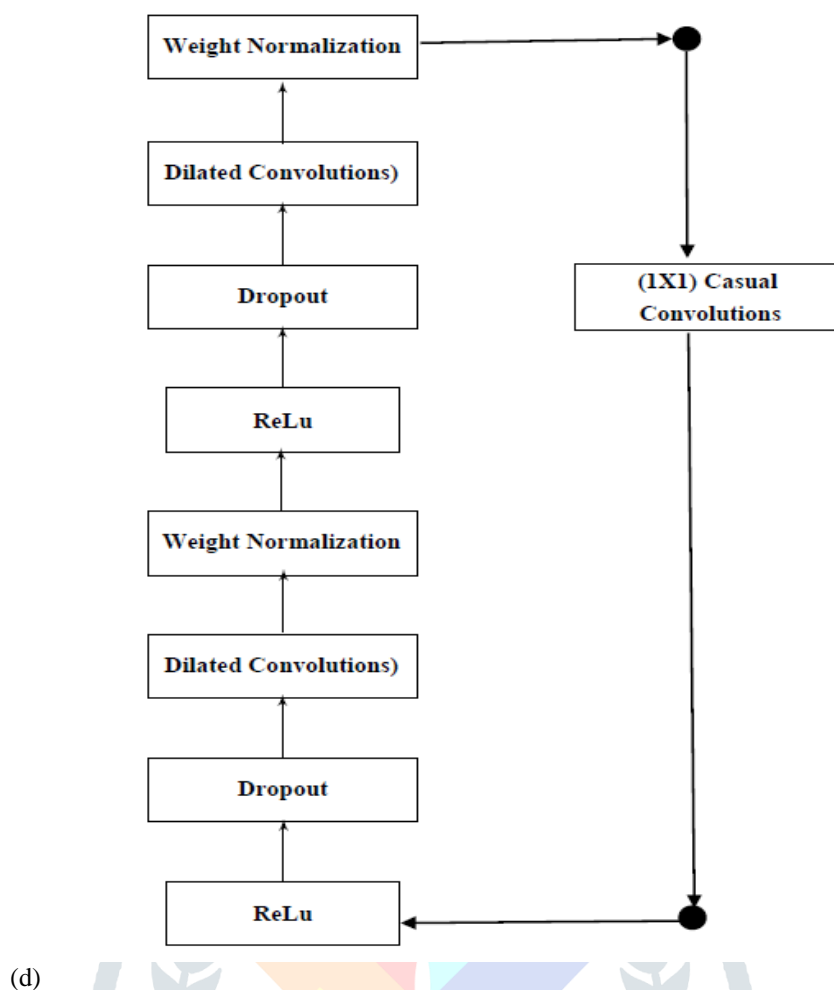


Figure 1.2 Architecture of TCN

III. MATERIALS AND METHODS

This section introduces the proposed work for the detection of diseases in rice leaves by image processing. In the proposed work, the images were pre-processed, and the images were then passed to a classifier to train the model to accurately identify the diseases.

1. IMAGE PRE PROCESSING

Pre-processing is done on the images to remove noise and make the classification algorithm more efficient. The images taken were first cropped, to only contain the image of the leaf. Then Data augmentation was applied to the image, by rotation and enhancement of the image and the new pixels generated due to rotation of the image were filled according to the values closest to them. The images were converted to gray scale by Otsu method. In this method, the lowest class is selected from the histogram by taking the lowest point in the variance of the two classes. The images are converted to gray scale because it makes it easier for the algorithm to classify the images and make the processing faster. Colours can make the detection of edges and the outlines in the image difficult. Converting to gray scale makes the processing of image easier.

2. DETECTION AND CLASSIFICATION OF THE DISEASES

The classification of diseases was done using Temporal Convolution Neural Network(TCN). The TCN consisted of the two residual blocks, each containing a weight normalization layer to stabilize the training, a dilated casual convolution layer allowing for a larger receptive field, a dropout layer to dropout some channels across the timestamp and a ReLu layer. In the end, a 1X1 casual convolution is added to the output to match the width of the input before giving it as an input.

IV. CONCLUSION

Rice is one of the most important crops in India as India is among the major producer of rice. Since the livelihood of a majority of the population depends on agriculture, it is very important to protect the crops from various diseases. These diseases can be prevented by accurate identification and timely remediation. In this paper, one of the methods was discussed to accurately identify the diseases and classify them. The model gave an accuracy of 95.7%. This method can be extended to many other diseases in rice crops and other crops as well

3. ACKNOWLEDGMENT

I would like to express my deepest gratitude to my guide, Mrs. R. Radha her valuable guidance in the completion of this project. I would also like to thank SRM Institute of Science and Technology for giving the opportunity to work in a Research domain.

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