

Application of Deep Learning Algorithm for Detection of Pearl Millet Diseases

Johnson I.¹, Karthikeyan M.¹, Paramasivan M.² and Ramjagathesh R.³

¹Department of Plant Pathology, TNAU, Coimbatore – 641003, Tamil Nadu

²Regional Research Station, TNAU, Vridhachalam – 606001, Tamil Nadu

³National Pulses Research Centre, TNAU, Vamban – 622303, Tamil Nadu

Corresponding Author: johnson.i@tnau.ac.in

In agriculture, the production and productivity are influenced by many biotic factors including fungi, bacteria, viruses, and phytoplasma are causing diseases under natural conditions besides the abiotic factors including water stress, nutrient deficiency, extreme weather parameters etc. Of them the fungi are predominant factor and may cause leaf spots, blight, powdery mildew, anthracnose, wilt, and root rots in pearl millet. It would be difficult to diagnose the diseases without an expert support. To achieve this, farmers typically seek guidance from agricultural experts. However, this process can become quite cumbersome, especially in vast farming areas where expert field inspections can be time-intensive. This challenge is particularly pronounced in rural regions, where farmers often face difficulties in accessing expert assistance, sometimes requiring lengthy journeys. This necessitates the development of a user-friendly automatic system that would help the farmers detect plant disease at an early stage without any help from the experts. The detection has to be timely, and thus Artificial Intelligence (AI)-driven farming has gained prominence in recent research.

Initiatives on Pearl millet disease detection



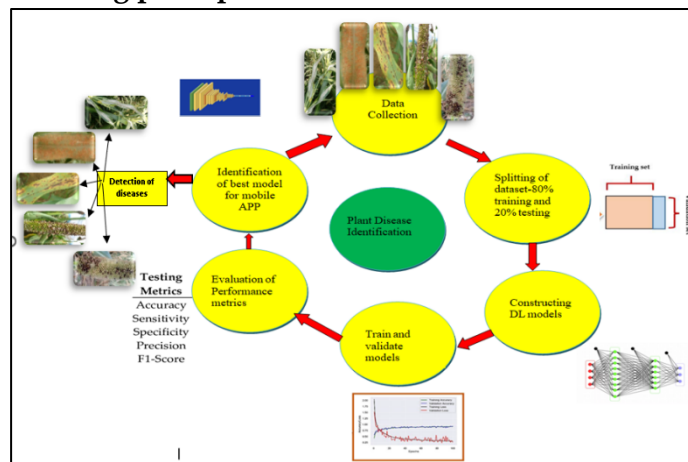
Downy Rust Blast Ergot Smut

Pearl millet is a significant crop in the millet family because this crop can be grown at high temperatures, with less water, and with low soil fertility. Pearl Millet is sown in large quantities as it is the predominant food diet of poor people in the world besides being used as fodder for animals. However, it is affected by diseases such as downy mildew, rust, blast, ergot and smut. AI is one of the best to be used in this system and can also be used in many areas like speech recognition, object detection, object recognition, etc., and could be achieved by training the

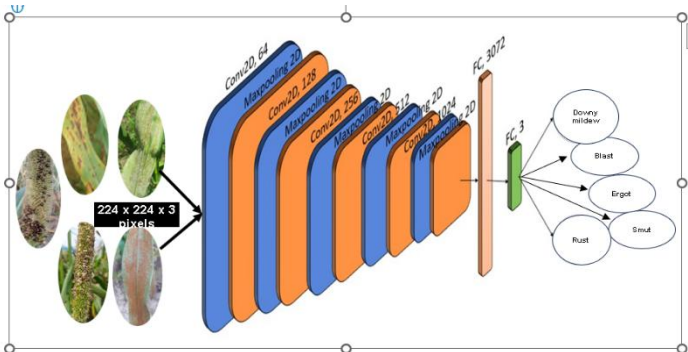
datasets having various data like images/audios/text/video.

Deep learning (DL) has various domains for classifying/detecting different kinds of data. convolutional neural networks are capable of automatically learning features from the input data, they can be trained to recognize complex patterns and variations in leaf images that may not be apparent to the human eye. AlexNet, VGGNet, ResNet 50, Inception, Xception, are some of the CNN states of art models commonly used for extracting relevant features from plant images. They are commonly used as a baseline for comparing the performance of new models in various computer vision tasks. This allows researchers to evaluate the effectiveness of their proposed models and compare their results with the state-of-the-art models in the field.

Working principle of the model



Proposed model for detection of pearl millet diseases



In this study, we have proposed an effective DL framework for the automated identification of Pearl Millet diseases. The Pearl Millet dataset of 5 classes was created through the mobile camera, and the system leveraged computer vision technologies to develop a disease detection model, which used fewer number of hidden layers to classify the plant diseases. The model achieved superior accuracy and reduction in training time compared to state-of-the-art models. The model was trained with 3441 images of diseased pearl millet leaves, along with healthy ones. It has been observed that deep millet achieved better accuracy of 98.66% which is more than other state of art models with less training time of 240 seconds.

The customized CNN model was designed to predict three classes: Downy mildew, Rust, Blast, Ergot and Smut leaf images. The model (Figure.2) consisted of five Convolution2D layers with ReLU activation function and five Maxpooling2D layers in sequential order of three sets after that batch normalization was performed and the flattening method was also applied. After flattening a fully connected (dense) layer followed by a dropout and

classification layer with SoftMax activation function to classify five classes.

The performance of the customized model and all the other six pre-defined CNN classification models were compared with the values of Accuracy, Precision, Recall, and F1-Score and are shown in Table 8. Comparatively, the customized CNN model had yielded a maximum of 98.86 per cent accuracy in detecting downy mildew and rust diseases of pearl millet and hence used in mobile app developed using android studio software.

Display pattern

