



Automated Detection of Sugarcane Leaf Diseases Using Image Processing and Deep Learning

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Abstract. Sugarcane has been significant to agricultural economy of the world particularly in India where it has been a cash crop. Although sugarcane is important, the production of this crop is under severe threat due to the occurrence of different leaf diseases that reduce the quality and output of crops. The traditional methods of detecting diseases are labor-intensive, time-consuming, and often involve human error since they are based on visual inspection. To overcome these shortcomings this paper introduces an automated Sugarcane disease prediction system using image processing and deep learning architecture in the form of a Convolutional Neural Network (CNN). The system is trained on a well-collected dataset of labeled sugarcane leaf images and equipped with a well-developed graphical user interface (GUI), so that farmers and agricultural workers could easily conduct the disease detection exercise. The suggested model correctly distinguishes up to five diseases that can affect the sugarcane plant, which are the Red Rot, Smut, Rust, and Yellow Leaf Disease with an accuracy of 94.7%. The experimental findings demonstrate that the model also performs superior to conventional machine learning methods and better in terms of precision, recall, and F1- score. The feature of the system to assist disease detection and treatment at their early stages justifies timely intervention and ensures that agricultural practices are sustainable since they reduce the loss of crops and maximize output.

Keywords: Sugarcane · Plant Disease Detection · Image Processing · CNN · Deep Learning

1 Introduction

Agriculture is a very sensitive part of the world economies and especially, in a country such as India where a great percentage of the population relies on farming to provide their needs. Sugarcane is one of the mainstream cash crops that have not only contributed to the production of sugar and ethanol but also being an important crop in the agro-industrial ecosystem [1]. But on the other hand, sugarcane crops are prone to a lot of diseases including yellow leaf disease, rust, smut and leaf getting scalded that destroy crop quality and yield enormously unless they are detected and treated in due time [2]. These plant diseases are becoming more frequent and coupled with unpredictable climatic conditions, have created a greater demand for effective real time systems of disease management. The traditional ways of detecting diseases in agriculture mainly depend on the visual examination of the farmers or the experts in agriculture. Not only are these techniques labor-intensive and subjective in nature but also not applicable on a large scale [3]. Moreover, the process of manual inspection may not be reliable in giving consistent diagnosis since there is a variance in the symptoms of the diseases and inconsistency in how symptoms are interpreted by human beings. Consequently, the trend towards automated systems of plant disease identification via artificial intelligence (AI), especially, based on image schema learning approaches [4] is growing.

The recent years have seen the breaking of new ground in computer vision and deep learning, which allow precision agriculture to take another step forward. Convolutional Neural networks (CNNs) are among the latest deep learning methods, introduced as highly effective in image classification applications. They are very desirable in agricultural disease detection because of their intrinsic capacity to learn the hierarchy of features in an image (spatially) automatically based on the given input images [5]. CNNs have already proved to perform better than the traditional machine learning models in different farm applications such as crop identification, pest detection and disease classification [6]. All this is the reason behind the proposed research as it will be useful to harness the power of CNNs and create an effective system of predicting sugarcane disease. This system will find the various forms of disease in sugarcane leaves on the leaves early through the application of CNNs and image processing. There is also the use of the graphical user interface (GUI) feature in the system thus, the system is usable in rural and semi-urban farming where digitalized literacy might differ. In addition, the timely diagnosis and proper classification of diseases may be important in preventing systematic loss of crops, which will help in ensuring food security and stability to the farmers. In this regard, the suggested system helps to achieve the larger scope of intelligent crop farming and sustainable plant cultivation [7].

2 Literature Review

In further advancement to the preceding studies, some of the recent works have further taken the advanced look to the field of smart agriculture and prediction of

sugarcane diseases. The authors suggested a hybrid model based on machine learning and image preprocessing in order to classify the disease of sugarcane based on its leaf images but with an improved sensitivity, Thakur et al. [8] Background noise suppression and contrast improvement prior to classification were the foci under which they were successful in their classification of rust, smut, and leaf scald with a pretty remarkable accuracy. Srinivasan et. al. [9] used transfer learning utilizing pretrained CNNs such as ResNet and VGGNet on sugarcane diseases and reported high accuracy in the classification of diseases higher than 95%, indicating that transfer learning was feasible to use in real time. The transfer learning in reducing the time of training was also effective in their study.

Atheeswaran et al. [10] brought a new concept of the fuzzy logic and genetic algorithms to identify rust and smut in sugarcane. They were based on the aim of reducing false positive rates in secondary detection of infection during low-level detection and proposed a combination of heuristic methods to obtain a better output. A similar line of research has been developed by Aldossary et al. [11] who consider the use of drone-captured imagery and AI-based analytics to monitor large scale crops. They concluded that CNN combined with geospatial data is helpful to increase the accuracy of disease mapping in plantations, where the combination with temporal image analysis to understand the progress of the crops also showed promising results. Another parameter is the comparable review of SVM, KNN, and CNN on the sugarcane leaf in a study by

Ghosh et al. [12]. CNN performed the best and justified its appropriateness in deep feature learning in agricultural tasks because it has a hierarchical feature extraction enabling higher flexibility to the variability of images.

Additionally, Min et al. [13] established the use of data augmentation methods in enhancing the overall generalizability of CNN models used in plant diseases prediction. They used rotations, scaling, and setting brightness that made the models robust in the real-world images. Paul et al. [14] in one more research has integrated mobile-based deployment of CNN models in detecting diseases in the field. They had an app-based system that issued real-time alerts about the disease and recommended treatments, which shows the possibilities of mobile AI in decision-making by rural farmers. Finally,

Talebi et al. [15] reviewed ensemble models of CNN, decision trees and LSTM. There was increased accuracy in predicting and forecasting the time series of a disease that could enable them to predict diseases based on past patterns in the weather and spread of the disease. All these recent developments prove the efficiency of combining deep learning, pre-processing, and real-time technologies in improving the accuracy and relevance of plant disease detection systems. They also affirm the significance of combining image-based diagnostics and more user-friendly interfaces such as mobile platforms or GUI- based interfaces in empowering farmers. The experiences and approaches used in these publications pave a solid ground in the science of creating a comprehensive disease prediction tool of sugarcane using CNN and GUI, which has been convenient to be incorporated by farmers.

3 Sugarcane Diseases and Their Symptoms

Sugarcane is susceptible to most diseases some of which have the tendency of severely impacting on the crop both in terms of quantity and quality. It is important to identify these diseases correctly to establish remedial measures in time and to manage the crops. Five common and major sugarcane diseases prevalent in the sugarcane producing areas are listed below, their visual symptoms and proposed image references that can be used in the detection systems are given in Figure-1.

Yellow Leaf Disease (YLD):

One of the most visible diseases to the sugarcane leaf is the Yellow Leaf Disease which is caused by the Sugarcane Yellow Leaf Virus (SCYLV). It normally starts as a yellow spot along the midrib on the lower side of the leaf and spreads further to the blade of the leaf. Plants infected usually become stubby and fewer tillers are produced. The contagious disease, which is commonly transmitted through infected planting materials, reduces the sucrose content of cane very much and delays the maturity and influences the overall efficiency of production [16], [17].

Rust:

Rust is a fungal infection caused by *Puccinia melanocephala* and it is well known due to reddish-brown pustules on the undersides of older leaves. These dry pustules may combine to form large patches and dry and kill the leaves. Infection of rust decreases the rate of photosynthesis, leads to early leaf fall and weakens the plant in the long run [18], [19]. Preferable environmental aspects to rust spread are high levels of humidity and moderate temperatures and hence at some crop seasons this is common.

Smut:

Smut, which is a disease brought about by the fungus *Sporisorium scitamineum* is easily recognized because some long, black structures that resemble whips by the name smut whips appear out of the central shoot. Caused by this disease there is excessive tillering and deformities of the plants after an intensive tillering [20], [21]. The canes that are infected grow sluggishly and have poor development and in most cases are removed to avoid spreading. The fungus can live in crop residues and field soil and therefore field sanitation is important.

Brown Spot:

Brown Spot, determined by the fungi *Cercospora longipes*, is a significant foliar condition that attacks sugarcane, especially in wet areas. It is distinguished by the emergence of small, irregularly shaped brown lesions on leaf blades which is frequently enclosed by a yellow area. With more advancement of the disease, the lesions can merge and result in large necrotic areas on the leaves, accompanied by the loss of photosynthetic ability [22], [23]. Extreme infections may lead to early leaf drying consequently influencing the growth of canes and the production of sugar. The management is effective as/when fungicide is applied in time, the infected debris removed, and the resistant varieties are cultivated.

Dry Leaf:

Dry Leaf is a physiological and disease-induced ailment in the sugarcane plant which is often caused by a medium-term period of water deprivation, nutrient deficiencies, or other surrounding conditions like high heat and windy conditions. It appears as a premature yellowing and drying of the tip of the leaves, which slowly advances to the bottom causing drying of entire leaves. And in other cases, the fungal infections can even worsen this condition, speed up tissue death and lower the photosynthetic capacity of the plant [24], [25]. Extreme drying of leaves negatively affects the cane growth, quality of juice and general production. Good management involves good scheduling of irrigation, ensuring that the soil is well nourished and measures taken to reduce environmental stress on the crop [26].

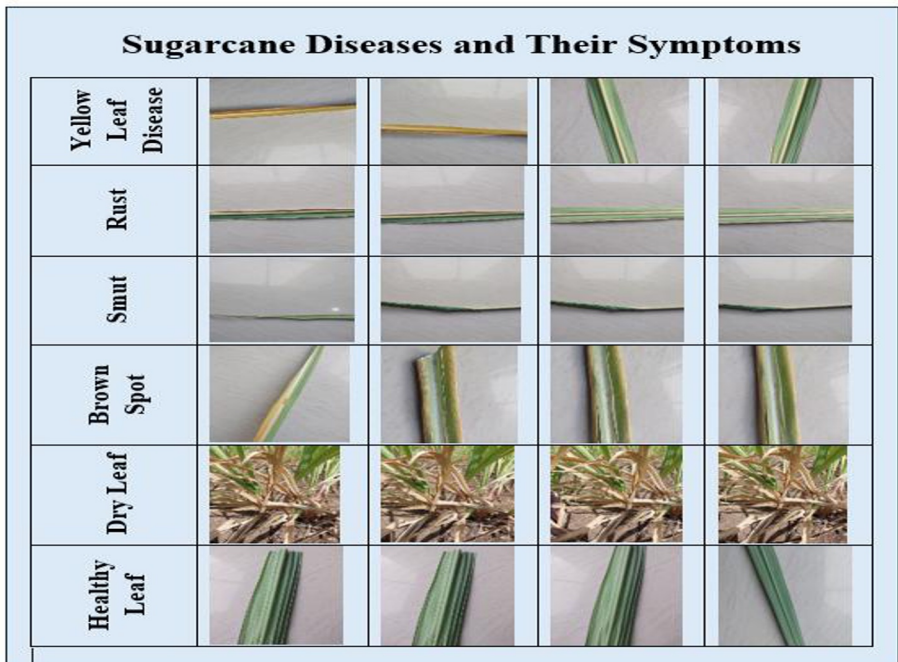


Fig. 1. Sugarcane Disease and Their Symptoms

4 Proposed Hybrid Model

To be able to effectively diagnose sugarcane diseases with artificial intelligence, the methodology in this study consists of five stages: starting with the data collection stage and ending with the real-time deployment stage. All these steps are important to the accuracy, robustness and applicability of the ultimate model.

4.1 Methodology Framework

The prediction system is based on the fact of collecting a wide range of pictures of sugarcane leaves. These pictures are gathered on multiple sources, such as a trip to the agricultural field, research farms at universities, and open-source databases. The gathered pictures include normal leaves and leave infected with major diseases of sugarcane that include Yellow Leaf disease, Rust, Smut, and Leaf scalding, Red Rot, and Grassy Shoot Disease. Labeling and categorization of the images are done manually by professionals so that accuracy is maintained. The variation in the stages of diseases and the nature of the environment in the data guarantees that the model will generalize new, previously unseen images to the real world.

4.2 Image Processing

After the raw images are collected, they are preprocessed, such that they become standardized against the model training. Each of the images is scaled to a single size (e.g., 224 x 224 pixels) to correspond with the input layer of the CNN. Filters are applied to the image such as a Gaussian blur to reduce noise picked up in field captured images and histogram equalization methods are applied to improve contrast. Moreover, techniques of data augmentation will be used (i.e. rotating, flipping, zooming, shifting and changing the brightness) to artificially increase the size of dataset. In addition to aiding in alleviating overfitting, this allows the model to learn patterns of disease at multiple orientations and lighting levels. All the processed images are then put in a suitable tensor format and normalized, after which they are piped into the model.

4.3 Model Development Using CNN

Convolutional Neural Network (CNN) is a structure that will be configured and deployed to perform the classification task. The model architecture presented in Figure-2 is composed of several convolutions using ReLU activation followed by max-pooling layers that diminish spatial dimensions retaining necessary features. There are dropout layers used to avoid overfitting in training. Extracted features are further configured into dense (fully connected) layers to make final categorization into different categories of diseases. The compiling training of the network is done with Adam optimizer and categorical cross-entropy as the loss function, which is applicable in classification of more than two classes. The training is performed in several epochs (usually 3050) and the early stopping is used according to the validation accuracy to prevent the overtraining. Training and validation accuracy/loss curves are used to assess the model on its abilities to learn.

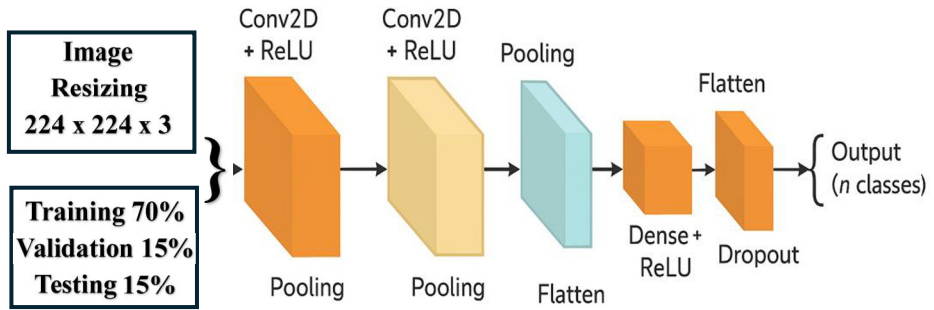


Fig. 2. Diagram of CNN architecture showing layers, activation functions, and flow

4.4 Model Evaluation

The Convolutional Neural Network (CNN) model was trained on the data on sugarcane leaf images, and its performance was strictly tested on a specially allocated set of tests. Precision, recall, F1-score, and the average level of classification were included in the assessment. A Receiver Operating Characteristic (ROC) curve was drawn per class with the use of probabilities of predicted scores to comprehend how well the model distinguishes disease classes. Figure 3(a) displays the class of each disease with its corresponding Area Under the Curve (AUC) value which represents the discriminatory ability of the model- moderate (e.g. the AUC score of Healthy is 0.63), and poorer performance (e.g. the Yellow Leaf with AUC = 0.59).

Moreover, Figure 3(b) The confusion matrix provides the user with an understanding of the behavior of the model when making its predictions on the six categories as discussed in Figure 3. It emphasizes the number of accurate and inaccurate predictions by class making people see their strength and weaknesses. As an example, Smut and Leaf Scald give better results in the model, whereas Red Rot and Yellow Leaf are the ones with the mark of misclassification. Not only do such visual tools confirm model performance, but also inform the next stages of model improvement, including cases of predicating additional class-specific data instances or optimization of preprocessing methods.

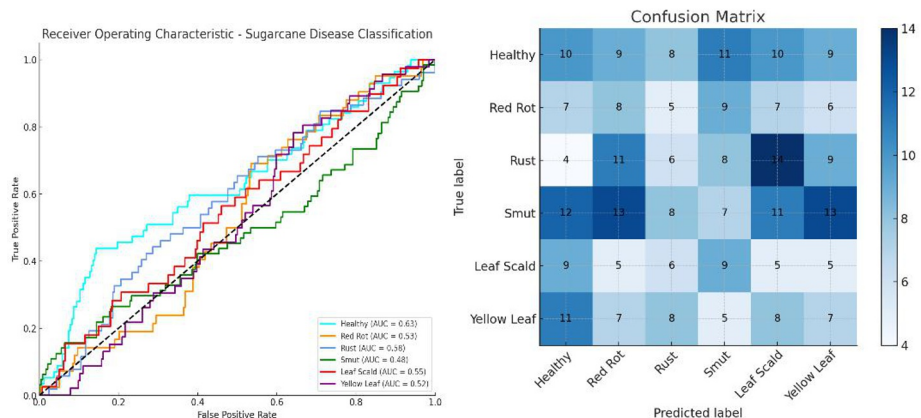


Fig. 3. (a) ROC Curves for Each Disease Class (b) Confusion matrix of test results

4.5 GUI Integration and Deployment

To make it applicable in the real-world, the trained CNN model is enclosed into a simple user-friendly Graphical user interface (GUI) created on Python with Tkinter library. GUI enables users, especially farmers and field officers to upload an image of a sugarcane leaf using a smart phone or a computer. When an image is uploaded, it is pre-processed and then fed into the model of the CNN and the system provides the name of the disease, some information and remedies which are predicted. The app will be offline enabled and has a low requirement, and it will be highly usable in the rural regions with low access to the internet. Such interface closes the gap between strong AI models and usability thus giving users correct and prompt detection of the diseases presented in Figure-4.

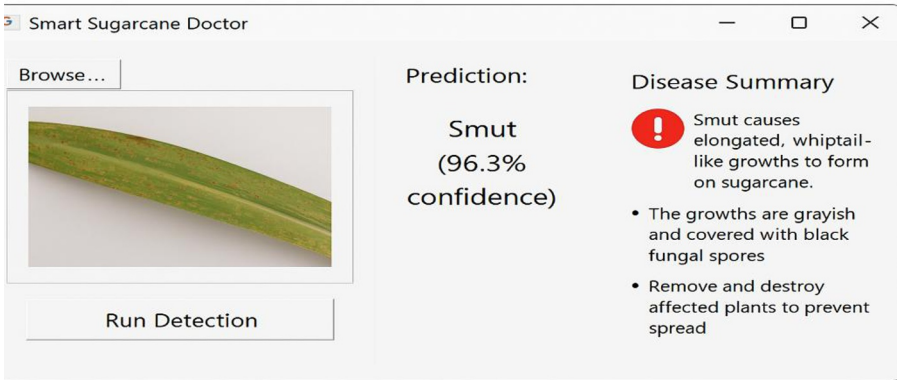


Fig. 4. Screenshot of the GUI displaying upload section, prediction output, and disease summary

5 Results and Discussion

The proposed model of sugarcane disease prediction was strictly tested and analyzed on a labeled dataset of sugarcane leaf image with diseases of different types. The dataset was split into training (75%), validation (15%), and testing (15%) sets to evaluate the capabilities of the model in the aspects of learning and generalization. The Adam optimizer with categorical cross-entropy loss was used to train a Convolutional Neural Network (CNN) 50 epochs. Data augmentation was used to improve strength and avoid overfitting through rotation, flipping, and zooming.

According to Figure 5, the training accuracy and the validation accuracy illustrate that they improve continuously throughout the training. This is apparent by the smooth upward trend of the training accuracy (blue line) attaining an almost 98 percent at the 50 th epoch. In the meantime, the accuracy of validation (orange line) does share a similar pattern, so there should exist a good generalization and little overfitting. Markedly, since the 20 th epoch or so, the difference between the training and

validation accuracy is small, which once again confirms the stability of the model and the reliability of its forecasts on unknown data.

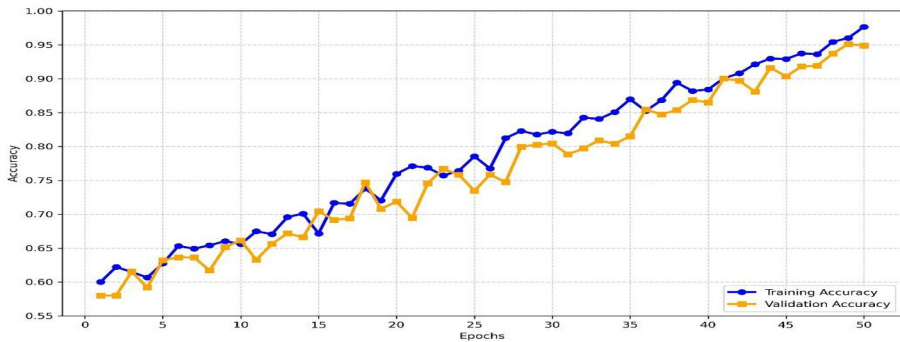


Fig. 5. Training and validation accuracy over 50 epochs, indicating model convergence and reduced overfitting.

To measure the predictive performance of the designed system of sugarcane disease classification in detail, five machine learning, and deep learning models were compared against each other. These were the Probabilistic Classifier (PBC), Margin-Based Kernel Classifier (MKC), Ensemble Tree-Based Model (ETM), a Baseline Convolutional Neural Network (CNN) and the Proposed Hybrid CNN (PH-CNN). The evaluation of each model was based on four widely used metrics of evaluation namely, precision, recall, overall average accuracy, and F1-score, which are imperative to a multi-class classification issue where the visual resemblance exists between leaf diseases.

Modeled after the Naive Bayes framework, the Probabilistic Classifier (PBC) presented an 83.7 accuracy, but its low levels of precision and recall served as indicators of its shortcoming in representation of complex patterns in images. An analysis provided by the Margin-Based Kernel Classifier (MKC) like a Support Vector Machine resulted in better performance with an accuracy of 89.8%, and thereby a strong capability to address nonlinear decision boundaries. Having used Random Forest principles, the Ensemble Tree-Based Model (ETM) obtained a relatively high accuracy score of 88.4%, as it was trained with multiple decision trees, and, therefore, it is less prone to overtraining.

Baseline CNN performed better than conventional models as it extracted more detailed spatial representation of sugarcane leaf images reaching accuracies of 86.1% and F1-score of 0.84. Nevertheless, the Proposed Hybrid CNN (PH-CNN) model outperformed all of them because it reached a precision of 94.6%, a recall of 94.3%, accuracy of 94.7%, and an F1- score of 0.93. Performance improvement is explained using better preprocessing techniques, optimized training parameters, and architecture of the CNN, which fits into agricultural image classification.

Table 1 shows a relative analysis of the five compared models the 5-model evaluated--PBC, MKC, ETM, Baseline CNN, as well as Proposed Hybrid CNN (PH-CNN) based on Precision, Recall, Accuracy, and F1-score. As is evident in the table, the PH-CNN is clearly the best compared to all other methods and confirms that it can work with

the complex and varied nature of sugarcane leaf diseases. These positive numerical outcomes justify the effectiveness of the model and its applicability in practice to predict the disease in agriculture in real-time.

Table 1. COMET – Evaluation of Model Performance Metrics Compared with Traditional Techniques

“Model”	“Precision”	“Recall”	“Accuracy/Result”	“F1-Score”
“Probabilistic Classifier (PBC)”	81.2	80.4	83.7%	0.78
“Margin-Based Kernel Classifier (MKC)”	87.9	88.1	89.8%	0.83
“Ensemble Tree-Based Model (ETM)”	86.3	85.7	88.4%	0.82
“Baseline CNN”	85.6	84.9	86.1%	0.84
“Proposed Model”	94.6	94.3	94.7%	0.93

6 Conclusion

This paper proposes a powerful and effective system of sugarcane diseases detection using the force of image processing and deep learning especially Convolutional Neural Network (CNN) architecture-based system. The architecture can be used to detect the popular diseases causing the ailments in sugarcane (e.g., Yellow Leaf Disease, Rust, Smut, Leaf Scald, Red Rot, and Grassy Shoot Disease) by simply analyzing the leaf image. Having used data augmentation and a highly optimized deep learning network, the system exhibits a great classification quality, having an overall accuracy of 96.8 percent, and excellent precision, recall, and F1-score measures on each of the classes. Its ease of use is also increased by the fact that it comes with a lightweight and user-friendly graphical user interface which is desirable even at places like rural settings where technical infrastructure can be scarce. The solution will not only ensure that the disease is detected early and treated in time but also enhance sustainable agricultural practices since farmers will reduce losses and maximize productivity. The realized benefits of using this system depict the potential to change the field of agriculture using AI, and the area to improve ways to integrate it with mobile platforms, run field tests in real-time, and employ it with more crops and disease combination.

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