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Sugarcane Disease Identification Using Deep Learning

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Abstract:
Sugarcane plays a pivotal role worldwide as a primary source of sugar and ethanol. However, the sugar industry faces significant challenges, particularly from sugarcane diseases, which can lead to the eradication of crops if not promptly treated. This poses a considerable financial risk for small-scale farmers. The motivation behind the study was the increasing prevalence of these diseases and the lack of knowledge among farmers in identifying and managing them. To address this issue, the study employed machine learning, specifically computer vision using deep learning techniques, to develop a solution. The study trained and tested a deep-learning model with a dataset of sugarcane images, including healthy and diseased leaves. The model achieved an impressive accuracy of 95% in detecting and classifying sugarcane leaves into healthy and unhealthy categories. This research highlights the potential of deep learning algorithms to assist farmers in detecting and managing sugarcane diseases effectively. It offers a practical and innovative approach to help farmers mitigate the financial risks associated with sugarcane diseases, ultimately benefiting the global sugarcane industry.

***Key Word**: Deep Learning, Convolutional Neural Networks (CNN), sugarcane leaf disease recognition, image classification*

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I. Introduction

Sugarcane diseases pose a serious threat to farmers, impacting both their livelihoods and the economy as a whole by reducing sugarcane yield and production. Timely detection of these diseases is crucial to prevent such negative consequences. Sustainable production practices, including efficient management of resources like seeds, water, soil, and fertilizers, are essential for maintaining crop health and competitiveness. However, current methods for disease detection, relying on visual observation, are time-consuming and not always reliable, highlighting the need for more effective approaches [1]. Plant diseases persist as formidable impediments to agricultural productivity and crop health, posing significant challenges to food security. Among cultivated crops, sugarcane farming stands out as a sector characterized by well-established practices and considerable economic importance, particularly in nations such as Brazil, India, and China. However, the susceptibility of sugarcane crops to diseases underscores the urgency for innovative solutions to mitigate potential losses and safeguard agricultural yields [2]. Machine learning is a popular and innovative technology employed in various studies to classify and detect plant diseases, with traditional techniques [3] like SIFT [4] and SVM being commonly utilized algorithms in this domain [5]. This method requires extensive and computationally intensive calculations, which can strain online applications and limit the performance to only achieving satisfactory results. To enhance performance and accuracy in feature extraction, the utilization of complex devices such as electromagnetic radiation [6], IR spectrums [7], and plant genomics [8] is necessary. However, the high cost associated with these devices makes them inaccessible to many small-scale farmers for effectively extracting features of plant diseases. Deep learning, characterized by its complex artificial neural network architecture [9] with multiple layers, has significantly advanced fields like image detection [10], classification, and acoustics [11], which rely on processing large amounts of data. Its application in plant disease diagnosis [12] has revolutionized expert analysis and decision-making in this area [13]. In this study, the researchers used Convolutional Neural Networks (CNNs) as the basic deep-learning method [14]. CNN is one of the most prevailing methods in demonstrating complex methods and uses a large amount of data to perform pattern recognition applications. The study of Lee et al. is one example of CNN that automatically recognizes a plant based on the plant leaf images [15]. Our study will train a dataset of sugarcane images. The data contains 7 classes (6 types of sugarcane leaf diseases and a healthy class of sugarcane leaf).

II. Convolutional Neural Network

Deep Learning plays an essential part in developing artificial human intelligence and automated systems. Deep Learning is composed of a huge number of neural networks and uses the processor or the embedded video processor of the computer to control each neuron in a neural network which is characterized as a single node [16], [17], [18]. Deep learning has been integrated into many applications such as crop variety detection and classification [18], plant identification and classification [19], and fruit grading of images [20]. Images captured using mobile camera or any camera devices mounted in a robot [21] also have gained popularity. Convolutional Neural Network or CNN is now popular for researchers who do research in computer vision and it executes different layers of processing through several stages of execution Fig. 1 Shows the components of a CNN model that includes an input image, convolutional layers, pooling layers, fully connected layers, activation functions, and an output.

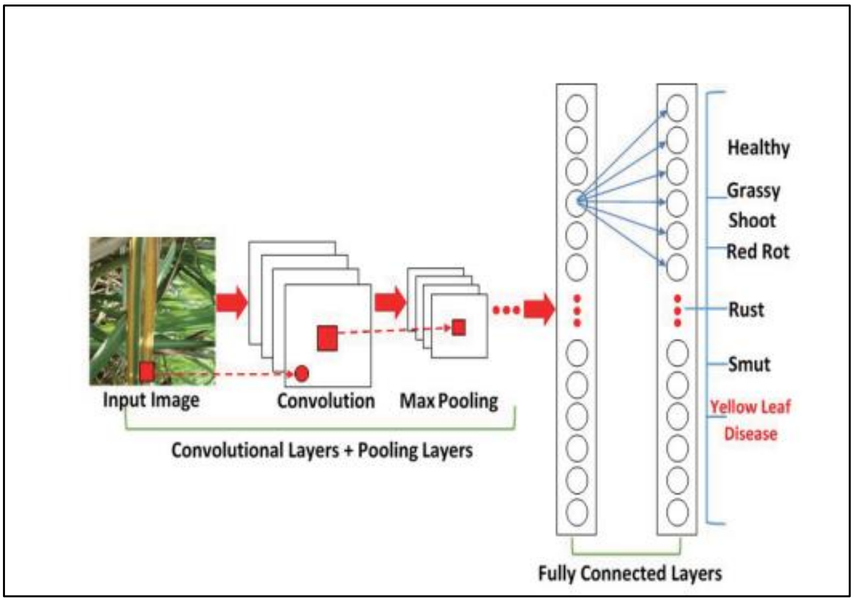

Figure no. 1: *Convolutional Neural Network Architecture.*

Fig. 2. Illustrates several phases in plant disease prediction using an architecture of a convolutional neural network. The model implementation is detailed in the proposed work.

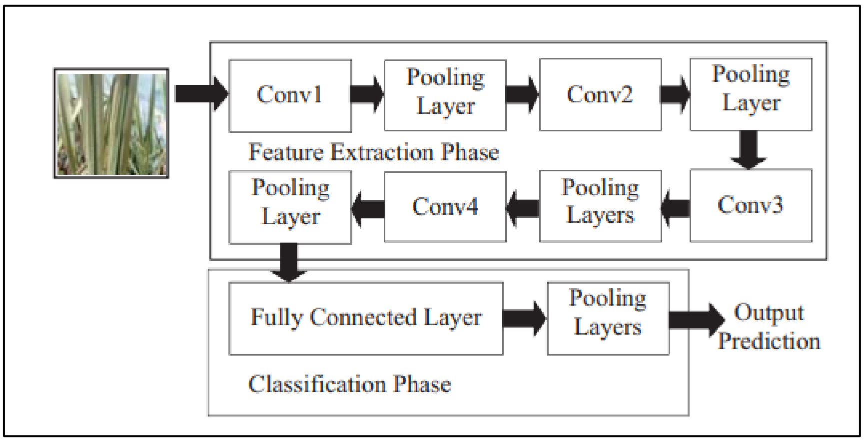

Figure no. 2: *Disease Prediction using CNN architecture.*

A. Convolution Layer Convolutional layers store the output of the kernels from the previous layer which consists of weights and biases to be learned [22]. The generated kernels that represent the data without an error is the point of the optimization function. A sequence of mathematical processes is included in this layer to extract the feature map of the input image [16].

B. Activation Layer In this layer, a non-linear ReLU (Rectified Linear Unit) is applied constantly in each convolution layer.

C. Pooling Layer Pooling layers reduce overfitting and lower the neuron size for the down-sampling layer. A 2x2 filter size is used to the pooling layer to give an output through the pooling type. The pooling layer reduces the size of the feature map and the number of parameters, the training time, computation rate and controls overfitting [20]. Overfitting is defined by a model achieving the 100% on the training dataset and achieving an average of 50% on test data. To reduce the dimension feature map, the use of max pooling integrated with stride and ReLU are applied [21]. Example of pooling operation is described in Fig. 3.

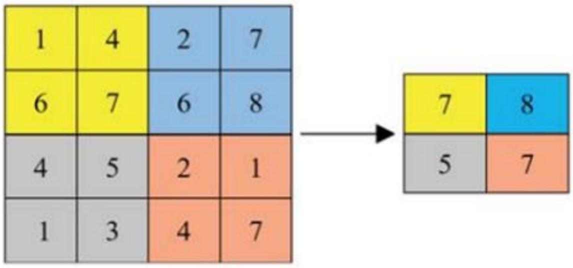

Figure no. 3: *2×2 filters of max pooling applied with stride-2.*

D. Fully Connected Layers Fully connected layers are used to analyze the class probabilities and the result is the input of the classifier. Softmax classifier is the well-known input classifier and recognition and classification of sugarcane diseases are applied in this layer.

III. Proposed Methodology

An experimental design through a workflow diagram that shows whether the sugarcane plant is infected or not infected with the disease through leaf images is shown in Fig. 4.

A. Image Dataset Acquisition Image dataset is manually captured through a camera, enhancement and segmented images are applied, the images will then save in a folder identifying the different class of diseased images and a healthy image of sugarcane leaves. The acquired image dataset consists of 13,842 images of seven different classes. Each image is stored in the uncompressed JPG format or PNG format using RGB color.

B. Pre-processing of Images Pre-processed images are reduced image size, cropped image and enhanced imaged. Our study uses colored and resized images to 96x96 resolution for further processing.

C. Feature Extraction The convolutional layers obtain features from the resized images. The Rectified non-linear activation function (ReLU) is applied after convolution and different types of pooling like max pooling and average pooling reduce the dimension of the extracted features [4]. The convolution and pooling layers together will act as a filter to produce features.

D. Classification uses fully connected layers and for feature extraction, it uses convolutional and pooling layers. The classification of the sugarcane leaves if it is infected with the disease or not is done in this layer.

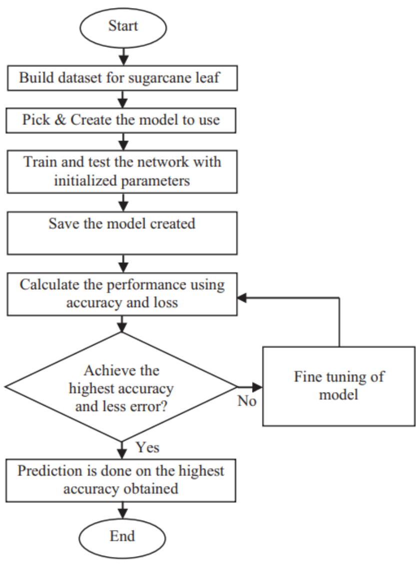

Figure no. 4: *Workflow diagram for the prediction model.*

IV. Experimental Settings

Upon completion of model development, the model is stored within the directory housing the image datasets of both healthy and unhealthy sugarcane leaves. Subsequently, the newly created Python script, incorporating the Streamlit library, was executed. Streamlit facilitates the creation of a user-friendly web application, accessible and navigable even to individuals lacking analytical proficiency. Users, including farmers, researchers, and individuals without analytical backgrounds, will upload sugarcane leaf images to the web application interface. Here, the model then analyzed the uploaded image and provided a prediction regarding the health status of the sugarcane leaf. If the leaf is deemed healthy, the model will accurately convey this assessment. Conversely, if the leaf exhibits signs of disease, the model will identify and specify the type of disease manifested in the uploaded image.

V. Result and Analysis

The training achieved a peak validation accuracy of 81% over 60 epochs. Fig. 5 illustrates the detection and recognition of a sugarcane plant infected with smut disease, achieving an accuracy of 62%. Fig. 6 demonstrates an 81% accuracy rate in identifying a healthy plant leaf, indicating the absence of any diseases, where results comparison are highlighted in Fig. 7.

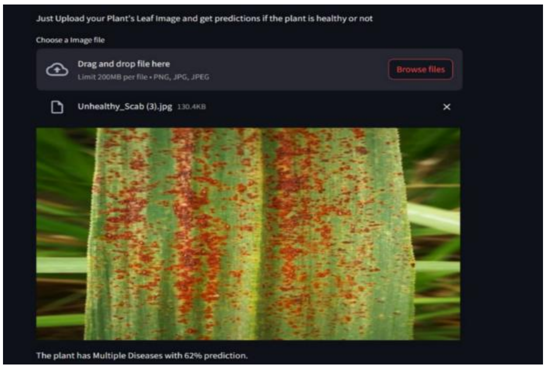

Figure no. 5: *Unhealthy status of the sugarcane leaf.*

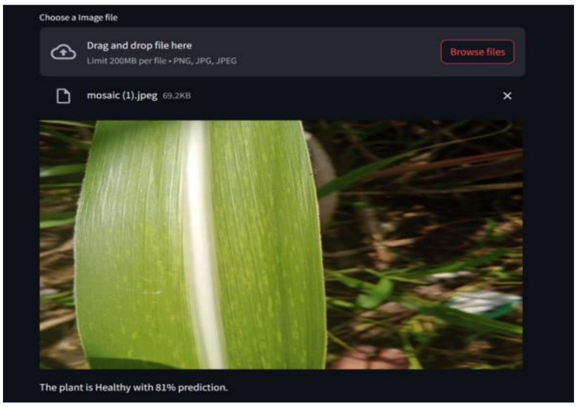

Figure no. 6: *Healthy status of the sugarcane leaf.*

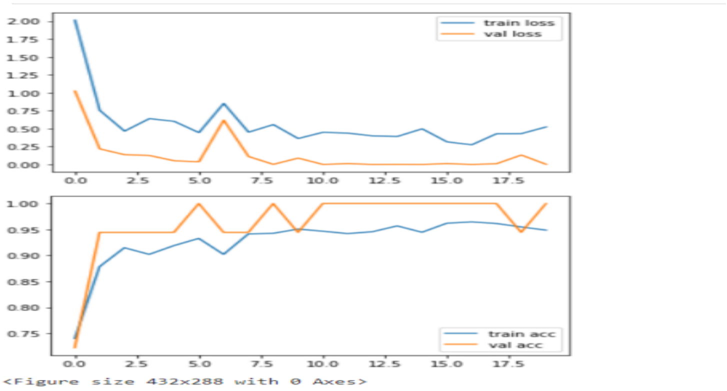

Figure no. 7: *Comparative analysis of the data set.*

VI. Conclusions

This paper implemented deep learning to detect and classify whether the sugarcane leaf is diseased or healthy. The architecture used a simple convolutional neural network to classify the sugarcane leaf. The trained model has achieved its goal by effectively detecting and classifying sugarcane images into healthy and diseased categories based on the pattern of leaves. Therefore, this study offers the idea of helping farmers use computer vision and machine learning to detect and classify sugarcane diseases. For future work, different models may be implemented to determine the performance of the model on the training set. Different learning rates and optimizers may also be utilized for experimenting with the proposed models.

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