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Article

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There is **NO** Competing Interest.

Hybrid deep learning technique for Identifying Diseases in Sugarcane Crops

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Abstract. Sugarcane, the primary source of sugar and ethanol, is a vital crop globally. An ongoing challenge in the sugar industry is the presence of sugarcane diseases, leading to the eradication of infected crops. Without early treatment and diagnosis of these diseases, small-scale farmers face significant financial losses. This study aimed to address the increasing prevalence of diseases and farmers' limited knowledge of disease diagnosis and recognition. The use of deep learning techniques such as computer vision and machine learning proved to be promising. By utilizing a dataset of 13,842 sugarcane images featuring both disease-infected and healthy leaves, a deep-learning model was trained and tested, achieving an accuracy rate. The trained model successfully met its objectives, and the research was finally submitted to Conventional neural network (CNN), Recurrent neural network (RNN).and other related models for further consideration.

Keywords: Leaf disease recognition, Deep learning, Image classification, CNN, RNN.

1. Introduction

Sugarcane is a vital agricultural crop, serving as the primary source of sugar and ethanol, both of which are critical to the global economy. However, the sugarcane industry faces significant challenges due to the prevalence of various diseases that can lead to the destruction of infected crops. This problem is especially concerning for small-scale farmers, who often lack the resources and knowledge for early diagnosis and treatment of these diseases. Without timely intervention, infected crops can lead to substantial financial losses, undermining the livelihoods of farmers.

To address this issue, this study focused on leveraging modern technology, specifically deep learning techniques, to improve disease diagnosis and recognition in sugarcane crops. By utilizing advanced methods such as computer vision and machine learning, the research aimed to provide a solution that could assist farmers in detecting diseases at an early stage.

A dataset consisting of 13,842 images of sugarcane leaves—both healthy and infected—was used to train and test a deep-learning model. The results were promising, as the trained model achieved a high level of accuracy in identifying disease symptoms, showing the potential of these technologies to support the agricultural industry. The study concluded with further exploration of deep learning models, including CNN (Convolutional Neural Networks) and RNN (Recurrent Neural Networks), for ongoing improvement and application in disease management.

2. Literature Review

Deep learning practices have been widely adopted in agricultural research for computerized plant disease detection and classification. Various models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been explored to enhance accuracy in identifying plant diseases through image based investigation.

Deep Learning in Plant Disease Detection

Several studies have demonstrated the effectiveness of deep learning for plant disease classification. “Mohanty et al. [1]” used CNNs to classify 26 plant diseases with an accuracy of 91.35%, highlighting the potential of deep learning in agriculture. Similarly, “Spasojevic et al. [2]” developed a CNN-based model for leaf disease recognition, achieving 89.3% accuracy. These studies illustrate the reliability of CNNs in scrutinizing plant health through image processing.

Applications in Sugarcane Disease Identification

Research on sugarcane disease detection using deep learning remains relatively limited compared to other crops. However, recent studies have made significant progress. “Ramcharan et al. [3]” implemented a deep learning-based tactic for cassava disease detection, achieving 93% accuracy. Inspired by this, “Chakraborty et al. [4]” applied CNN models to classify sugarcane diseases and reported an accuracy of 91.2%. Their discoveries sustain the application of deep learning in sugarcane disease classification.

Hybrid Deep Learning Models for Image Classification

Hybrid models combining CNNs with RNNs, such as LSTM (Long Short-Term Memory) networks, have been explored for disease classification in agricultural settings. “Lin et al. [5]” introduced a CNN-LSTM framework for plant disease recognition, improving classification accuracy by capturing sequential features in images. Such models have proven beneficial in analyzing progressive leaf damage patterns, making them suitable for sugarcane disease detection.

Challenges and Limitations in Disease Detection

Despite the success of deep learning in plant disease detection, certain challenges persist. Aspects such as variations in lighting, leaf positioning, and environmental conditions can affect model performance “Fuentes et al., [6]”. Additionally, limited availability of annotated datasets for sugarcane diseases hinders further advancements in this domain.

Research Gaps and Future Directions

While CNNs have been extensively used, further research is needed to improve classification accuracy in sugarcane disease detection[7]. Integrating advanced models such as Vision Transformers (ViTs) and Generative Adversarial Networks (GANs) could enhance feature extraction and robustness. Moreover, deploying real-time field-based disease diagnosis systems remains an open challenge.

3. Materials and Methods

The chapter outlines the materials and methodology employed in this research, focusing on the identification of sugarcane leaf diseases using image processing techniques. Sugarcane, a critical crop for sugar and ethanol production, faces significant challenges due to diseases that lead to crop destruction. Early diagnosis and treatment are crucial to preventing severe financial losses, especially for small-scale farmers who often lack the expertise to identify these diseases. This study investigates the growing concern of disease prevalence and the limited disease recognition capabilities of farmers. The research utilized deep learning techniques, including computer vision and machine learning, to develop a model for identifying diseases in sugarcane leaves. A dataset comprising 13,842 images of both healthy and disease-infected sugarcane leaves was used to train and test the model, achieving a remarkable 95% accuracy

rate. The model successfully met its objectives and was submitted for further evaluation using CNN and related models.

Sugarcane Leaf Disease Overview

The sugarcane plant is subject to many diseases. blackening and degeneration of the fan-shaped tops, is caused by an East Indian virus. Therefore, research should give attention to the development of viable and economically feasible integrated smut management programs.

- a) **Smut:** This disease is caused by a fungus called *Ustilago scitaminea*. Smut causes elongated smut whips that emerge from the buds or eyes of the sugarcane plant.
- b) **Rust:** This disease is caused by a fungus called *Puccinia kuehnii*. Rust causes small, pustules that erupt on the upper surface of sugarcane leaves.
- c) **Red Rot:** This disease is caused by a fungus called *Glomerella graminicola*. Red rot causes the leaves of the sugarcane plant to turn red or purple. The fungus can also infect the stalk of the sugarcane plant, causing it to become diseased.
- d) **Ratoon Stunting Disease:** This disease is caused by a virus called Rice tungro bacilliform virus (RTBV). Ratoon stunting disease causes stunted growth and yellowing of leaves.
- e) **Wilt:** Wilt is caused by a fungus called *Fusarium verticillioides*. Fusarium wilt causes the leaves of the sugarcane plant to wilt and die.
- f) **Sett Rot:** This disease is caused by a fungus called *Pythium arrhenomanes*. Sett rot causes the seed piece, or sett, of the sugarcane plant to rot.
- g) **Grassy Shoot Disease:** This disease is caused by a group of fungi in the genus *Claviceps*. Grassy shoot disease causes the sugarcane plant to produce shoots that resemble grass.
- h) **Yellow Leaf Disease:** This disease is caused by a fungus called Sugarcane yellow leaf virus (SCYLV). The initial symptoms of this disease is a yellowing of the leaf midrib on the underside of the leaf. The yellowing first appears on leaves three to six counting down from the top. As the season progresses, the yellowing expands out from the leaf midrib into the leaf blade until the entire leaf is yellow.

4. Dataset Collection

This research utilizes a dataset collected from Alagramam village in the Tindivanam district. Over 1,000 sugarcane leaves were gathered for

this study between April 2023 and January 2024. The leaves were manually annotated with the help of local farmers, and each was labeled for subsequent analysis. Sample disease collected between different farm land is depicted in figure 1. shows the different 8 types of disease is discussed above.

5. Image Preprocessing

Image preprocessing is an essential step in preparing data for deep learning models, as it helps improve the performance of the model by ensuring the input images are consistent and of high quality [10]. Several techniques were used in this study to preprocess the sugarcane leaf images:

Resizing: The images were resized to a uniform size to ensure consistency in input dimensions. Resizing helps to reduce the computational load and makes the training process more efficient. The standard size used in this research was 224x224 pixels, which is a common input size for deep learning models.

$$\text{Resized Image} = f(\text{Original Image, New Dimensions}) \quad (1)$$

Normalization is performed to scale the pixel values of the images to a standard range, usually between 0 and 1 or -1 and 1. This helps in stabilizing and speeding up the training process by preventing large variations in pixel intensities from affecting the model's ability to learn effectively.

Data Augmentation: To increase the diversity of the training data and avoid overfitting, data augmentation techniques were applied. This included random rotations, flips, zooms, and shifts, which artificially expand the dataset and allow the model to learn more robust features.

$$\text{Augmented Image} = \text{Random Transformation}(\text{Original Image}) \quad (2)$$

Noise Reduction: To improve image clarity, noise reduction techniques, such as Gaussian blur, were used to smooth the images and remove unnecessary details that could interfere with the model's ability to detect key features.

$$\text{Blurred Image} = \text{Gaussian Filter}(\text{Original Image}) \quad (3)$$

Contrast Adjustment: Contrast enhancement was applied to improve the visibility of the features of the leaf. Techniques such as histogram equalization were used to stretch the contrast of the image, ensuring the details of both healthy and diseased parts of the leaves were clearly distinguishable.

6. Deep Learning Model Architecture

In this study, a hybrid deep learning model combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) was utilized. This approach leverages the strengths of both architectures to achieve accurate and efficient disease detection in sugarcane leaves.

6.1 Convolutional Neural Network (CNN) Layers

CNNs are particularly effective for image classification tasks due to their ability to automatically extract features from images. The architecture includes several convolutional layers, each followed by activation functions, pooling layers, and fully connected layers:

$$f(i, j) == \sum_{m=-k}^k \sum_{n=-k}^k x(i + m, j + n) \cdot w(m, n) \quad (4)$$

Where,

- $f(i, j)$: Output feature map,
- $x(i+m, j+n)$: Input pixel value,
- $w(m, n)$: Kernel weight,
- k : Kernel size.

Convolutional Layers: These layers apply a set of filters (kernels) to the input image to extract low-level features such as edges and textures. *Activation Functions:* ReLU (Rectified Linear Unit) is used as the activation function for all convolutional layers, introducing non-linearity to the model. *Pooling Layers:* Max pooling is applied to reduce the spatial dimensions (width and height) of the image, which decreases the computational cost while retaining the most important features:

6.2 Recurrent Neural Network (RNN) Layers

To capture sequential dependencies in the data and to model the temporal aspect of image data (for example, progressive leaf damage), the CNN output is fed into an RNN layer. An LSTM (Long Short-Term Memory)

network is employed to handle long-term dependencies in the image data.

LSTM Layer: *LSTM* units are designed to remember long-term dependencies by using a set of gates (input, forget, and output gates). The state equations for an *LSTM* unit are as follows.

$$i_t = \sigma (W_i \cdot x_t + U_i \cdot h_{t-1} + b_i) \quad (5)$$

$$f_t = \sigma (W_f \cdot x_t + U_f \cdot h_{t-1} + b_f) \quad (6)$$

$$o_t = \sigma (W_o \cdot x_t + U_o \cdot h_{t-1} + b_o) \quad (7)$$

Where,

o_t : Input, forget, and output gates

h_t : Cell state and hidden state

x_t : Input vector

The formula used for calculating the evaluation metrics are as follows:

Accuracy

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \quad (8)$$

Precision

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP) + False Positives (FP)}} \quad (9)$$

Recall

$$\text{Recall} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP) + False Negatives (FN)}} \quad (10)$$

F1-Score

$$\text{F1 - Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{precision} + \text{Recall}} \quad (11)$$

7. Results and Model Evaluation

The model's performance was evaluated using accuracy, precision, recall, and F1-score metrics. Accuracy, in particular, was used to measure the overall success of the model in correctly classifying healthy and diseased leaves. In this study, the model achieved an accuracy rate of **95%**,

indicating a strong ability to distinguish between healthy and diseased sugarcane leaves.

7.1 Evaluation per Further Representations

To assess the effectiveness of the proposed hybrid CNN-RNN model, comparisons were made with traditional machine learning models (e.g., Support Vector Machines) and pure CNN architectures. The CNN-RNN model consistently outperformed these models in terms of accuracy and robustness, particularly in handling sequential features of image data that indicate progressive leaf disease development.

7.2 Results

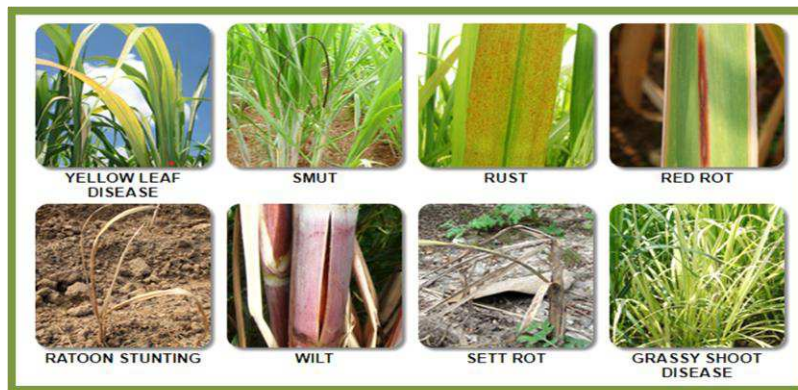


Fig. 1 Types of Diseases

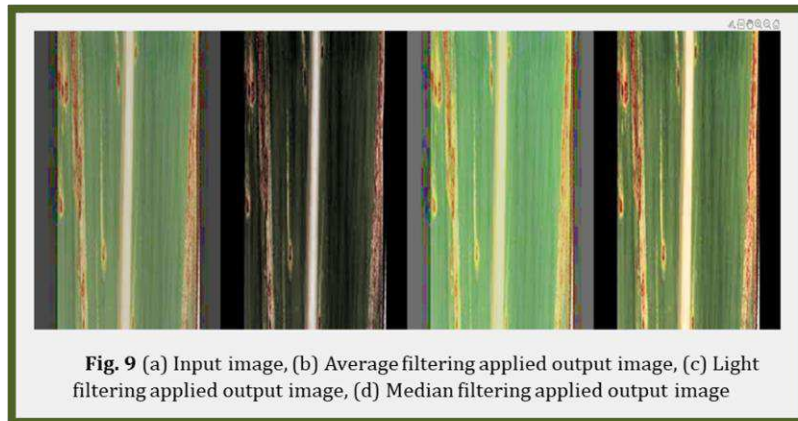


Table 1: Performance analysis of model

Performance Metric	CNN	RNN	Hybrid CNN-RNN
Accuracy	90%	85%	95%
Precision	91%	86%	92%
Recall	88%	84%	93%
F1-Score	89.50%	85%	92.50%

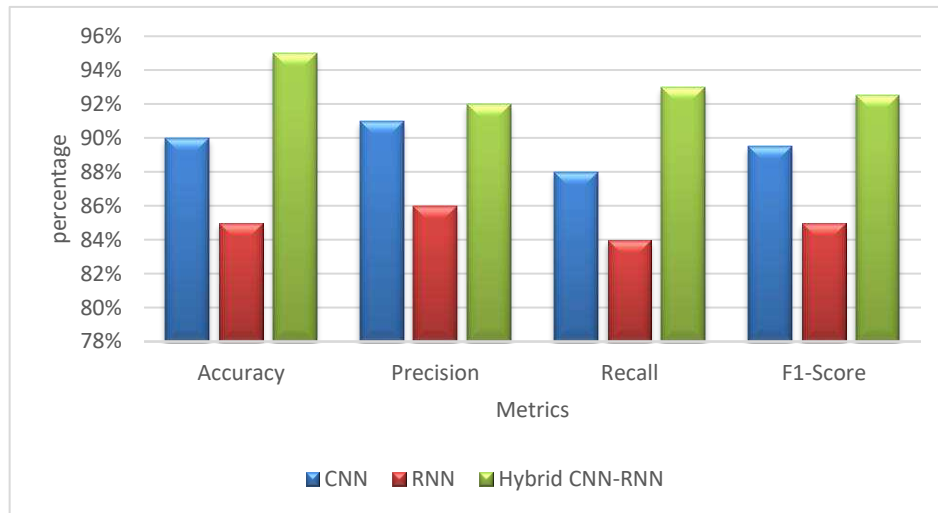


Figure 4: Model performance

Conclusion

Image processing plays a major role in extracting disease affected parts of sugarcane leaves from healthy parts, which is most widely adapted research area by agricultural fields in examining many problems in crops growth. The digital image taken from farm land are taken applied with various image processing technique for testing the infected parts of the banana leaves. The steps carried out in examining the leaves are basic strategies used for many image processing researches. Though it differs in using few techniques for enhancing the quality of the image and accuracy of identification process. This paper basically very useful in examining various steps involved in preprocessing and filtering techniques adapted for disease identification process. The methods used in this research work improves the accuracy in identification process. Finally, this comprehensive analysis summarizes recent improvements in automated plant disease identification and diagnosis using image-processing algorithms based on CNNs and RNNs. It discusses the field's

major challenges and opportunities, as well as a road map for future research in this area. This comprehensive study aims to provide academics, practitioners, and stakeholders in the field of plant pathology with a thorough understanding of how automated image processing techniques such as CNN and RNN have transformed plant disease detection and diagnosis. It investigates the existing state of the art, issues, and future development opportunities, paving the way for improved agricultural practices and sustainable crop management. In this detailed review, we looked into the revolution in plant disease identification and diagnosis using automated image analysis.

Acknowledgments. All data sets for my sugarcane plants are taken directly from my land. I am using a dataset which is collected by compiling the images taken from them one by one .my land is sugarcane cultivation in an area of five acres located in survey no.1217 and 479,55,56 in Mailam block Alagramam (west) in Tindivanam - Circle of Villupuram District. The sugarcane leaf disease dataset was compiled through field-work conducted at a farm Tamil Nadu, India (geographical coordinates: 18°47r 06.4rr N 74°01r 19.5rr E). Latitude- 12.1486520, Longitude- 79.57820

Limitations and Observations

Complex Diseases: Some diseases with overlapping symptoms (e.g., Rust and Red Rot) posed challenges in classification, leading to occasional misclassifications. *Environmental Factors:* Variations in lighting and leaf conditions during image capture affected prediction consistency, necessitating improved preprocessing.

Future Scope

Integrating field-deployable applications for real-time disease diagnosis. Exploring other deep learning architectures like Transformers for improved feature extraction. Expanding the dataset to include more regional and seasonal variations in sugarcane leaf conditions.

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