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# Comparative Analysis of Deep Learning and Optimization Techniques for Sugarcane Disease Classification

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## ABSTRACT

Sugarcane is a major agricultural crop in Tamil Nadu. In agriculture, there is considerable interest in applying digital image processing for crop protection and disease detection. The timely detection of sugarcane leaf diseases plays a crucial role in improving crop yield and protecting the livelihood of farmers who depend on healthy harvests. This study presents a novel hybrid deep learning approach that combines Convolutional Neural Network (CNN) features with Gray-Level Co-occurrence Matrix (GLCM) texture analysis to accurately classify sugarcane leaf diseases. A detailed dataset comprising 2,521 images of sugarcane leaves, encompassing seven major diseases, including Leaf Scald, Smut, Rust, Wilt, Red Root, Ratoon Stunting Disease, Sett Rot, and Grassy Shoot disease, was used for evaluation. The proposed CNN-Hybrid + GLCM model achieved an outstanding accuracy of 98.99%, surpassing models such as Baseline CNN (84.3%), VGG16 (89.5%), ResNet50 (90.2%), and Random Forest with CNN features (89.05%). With an average testing time of just 1.08 seconds per image, the model proves efficient for real-time applications. This solution offers a practical tool for farmers, facilitating early disease diagnosis, reducing crop loss, and easing the burden of manual monitoring. The integration of deep learning and texture-based features provides a powerful, farmer-friendly framework for smart agriculture and sustainable sugarcane cultivation.

**Keywords:** Sugarcane disease detection, Digital image processing, Random forest classifier, GLCM texture analysis, HSV color space conversion

## Introduction

Most people in the Tamil Nadu region, especially in Alagramam West, agriculture is their primary source of income. Approximately 78% of rural residents in Tamil Nadu rely on agriculture, with 90% of the population directly engaged in farming. A major source of income in this region is sugarcane; however, diseases may lead to 15–25% damage in Asian production, resulting in severe financial losses. Plant diseases are the primary cause of the drop in crop quantity and quality. Numerous diseases, including rust, smut, and leaf scald, harm sugarcane crops. Farmers often struggle to identify these infections promptly, resulting in crop losses due to inadequate surveillance. The existing manual method of disease identification is labor-intensive, inefficient, and prone to error, as it relies on manual records, farmers' experiences, and expert observations. Plant disease monitoring is a laborious process that requires ongoing care and the judicious use of insecticides. Plant diseases can appear in a variety of unanticipated ways. Nonetheless, ongoing observation

is necessary to stop the spread of illness. Viruses, rust and smut, and leaf scald are common causes of plant diseases. Therefore, it may be essential to examine the external appearance of diseased plants through image processing. Notably, different plant species have varied symptoms, and each illness has its own distinct traits, such as variations in size, shape, and color. Because illness signs can sometimes be similar, farmers may struggle to choose the most effective insecticides. The present research aims to address this problem by utilizing image-processing techniques for the automatic identification and classification of sugarcane crop diseases. To overcome this limitation, this study proposes a convolutional neural network (CNN)-Hybrid model enhanced with Gray-Level Co-occurrence Matrix (GLCM) texture features. The hybrid architecture leverages both deep visual features and statistical texture patterns to improve the accuracy and robustness of disease classification. A dataset comprising 2,521 labeled sugarcane leaf images, representing seven major disease types, was utilized for training and evaluation.

Experimental results showed that the proposed CNN-Hybrid + GLCM model achieved a classification accuracy of **98.99%**, outperforming baseline CNN (84.3%), Random Forest with CNN features (89.05%), VGG16 (89.5%), and ResNet50 (90.2%). With an average testing time of approximately 1.08 seconds per image, the model is also suitable for real-time deployment in agricultural settings. This research provides a practical and scalable tool that empowers farmers with timely and reliable disease detection capabilities. The system enhances sustainable and productive sugarcane farming practices by diminishing reliance on manual inspection and facilitating early intervention.

## Literature Review

Banerjee et al. proposed a cutting-edge deep learning framework for grading sugarcane leaf health using CNNs. Their work emphasized the scalability of CNNs in real-time agricultural scenarios, particularly through integration with smartphone applications to assist farmers in the field.<sup>1</sup> Similarly, Sharma, Singh, and Punhani introduced an optimized CNN architecture that adapts to varying environmental conditions, leading to improved accuracy in classifying sugarcane diseases.<sup>2</sup>

To diversify learning strategies, Komol, Hasan, and Ali utilized traditional deep learning approaches for disease identification, demonstrating effective classification results by combining feature extraction and supervised learning algorithms.<sup>3</sup> Moreover, Daphal and Koli investigated the comparative performance of ensemble deep learning models and transfer learning techniques. Their findings showed that ensemble

methods yield superior accuracy in classifying sugarcane leaf diseases due to their combined decision mechanisms.<sup>4</sup>

Degadwala and Dave conducted a comprehensive review of current methodologies for detecting sugarcane leaf defects. Their study highlighted the gaps in dataset diversity and the potential of incorporating multispectral and hyperspectral imaging in future systems.<sup>5</sup> Furthermore, João, Ribeiro, and Backes applied deep learning to Unmanned Aerial Vehicle imagery to automatically detect crop lines in sugarcane fields, providing a scalable solution for field monitoring and automation.<sup>6</sup>

Sensor-based disease detection has also been explored. Veerasakulwat and Sitorus employed Near-Infrared spectroscopy combined with deep learning to classify sugarcane nodes and internodes, achieving fast and reliable results suitable for industrial applications.<sup>7</sup> Banerjee et al. incorporated both deep learning and Random Forest techniques into a multi-class classification framework to assess disease severity in sugarcane crops, effectively improving diagnosis performance across multiple disease types.<sup>8</sup>

To address the limitations of small datasets, Li, Zhang, and Wang introduced “SugarcaneGAN”, a generative approach that uses a hybrid CNN-Transformer network to synthetically augment training data for sugarcane disease classification. Their method significantly improved model generalization across varied test scenarios.<sup>9</sup> Furthermore, Daphal and Koli proposed a deep learning pipeline for sugarcane disease classification that was integrated into a mobile application, offering a real-time, user-friendly interface for farmers (Figure 1).<sup>10</sup>

It has two fundamental processes: training or learning the model and testing plant leaves to identify the disease. Both process has multiple stages of operations as follows.

## Image Processing

### Image Pre-Processing

In the HSV color space, a 3D representation forms a hexagon where the central vertical axis represents intensity. Hue is an angle within the range of  $[0, 2\pi]$  relative to the Red axis, with red at 0, green at  $2\pi/3$ , blue at  $4\pi/3$ , and red again at  $2\pi$ . Saturation quantifies the depth or purity of a color, represented as a radial distance from the central axis, with values extending from 0 at the center to 1 at the periphery.<sup>11,12</sup> Lowering the saturation can transform any color in the HSV space to a shade of gray, with the intensity value representing the particular gray shade at which transformation converges. Saturation represents the depth of color, and the human eye is less sensitive to variations in saturation compared to variations in hue or intensity.

### Image Segmentation

Binary images may contain numerous defects. In some cases, binary regions formed by simple thresholding are affected by noise and textures.<sup>13</sup> Morphology, a wide range of image processing operations that modify images based on shapes, is considered a useful method in image processing. This structuring element addresses all possible locations of the input image and generates an output of the same size. In morphological operations, dilation, erosion, opening, and closing are expressed in logic.<sup>14</sup> AND, OR notations were used, and they were described by set analysis.

### Color Histogram Topographies

The histogram of an image refers to the intensity values of pixels. The histogram discloses the number of pixels in an image at each intensity value.<sup>15</sup> Figure 2 shows the histogram of a color image, showing the distribution of pixels among the grayscale values. The 8-bit gray scale image has 256 possible intensity

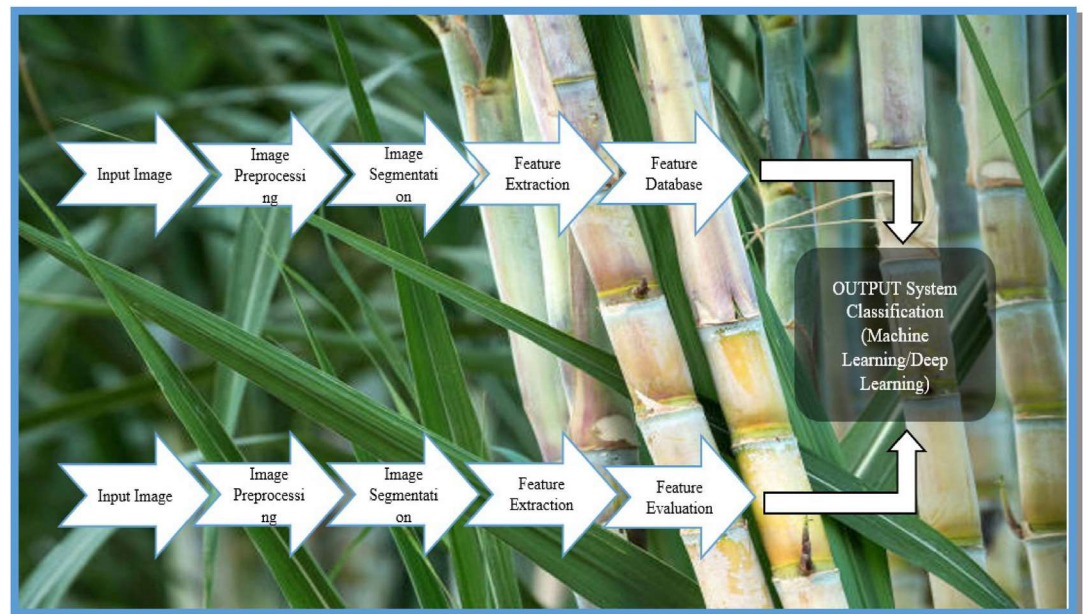


Fig 1 | Proposed approach of plant disease identification from the images

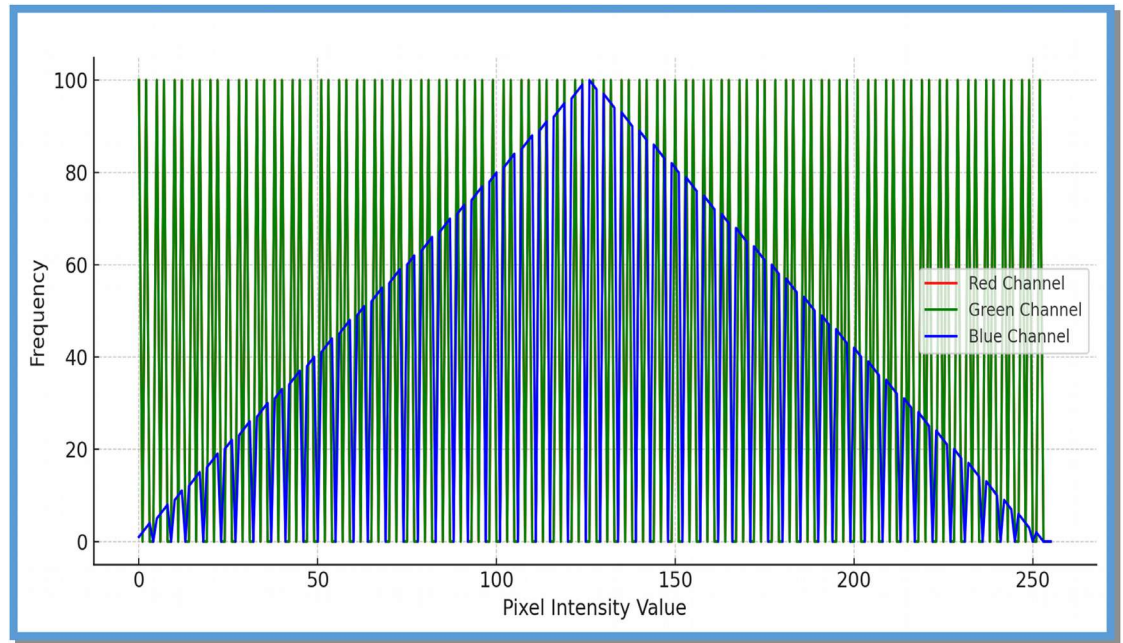


Fig 2 | Histogram of a color image

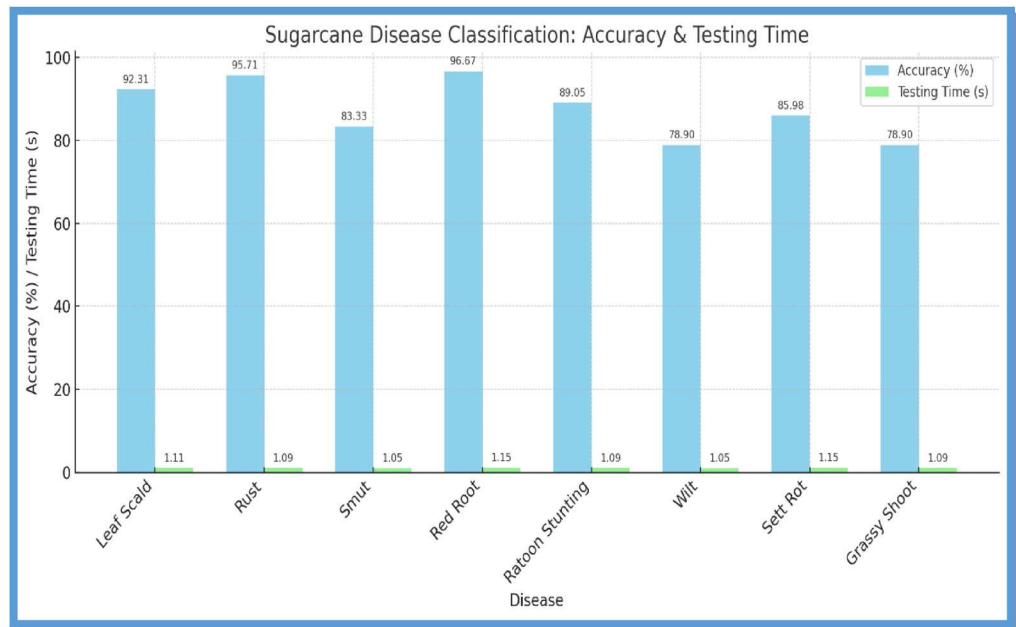


Fig 3 | Average testing time

values. A narrow histogram indicates a region of low contrast. Some common histogram features include mean, variance, energy, skewness, and median.

**Surface Geographies**

As the second-order texture, the basic GLCM texture recognizes the relationship between two adjacent pixels in a single offset (Figure 3). A specified kernel mask, such as 3 3, 5 5, 7 7, and so on, transforms the gray value associations in a target image into the co-occurrence matrix space. Neighboring pixels in one or more of the eight specified directions may be used in the

conversion from the image space to the co-occurrence matrix space; typically, four directions—0°, 45°, 90°, and 135°—are initially considered, along with their corresponding opposite direction (negative direction) also being accounted for. It consists of information about the positions of the pixels with similar gray level values.

Images from the input dataset were used to create the GLCM matrix. Following the computation of the GLCM, the image’s texture features are progressively acquired.<sup>14</sup> Energy (*E*), Entropy (*ENT*), Contrast (*Con*), Inverse Difference Moment (*IDM*), and Directional

Moment (DM) are the primary textural characteristics used to categorize an image as either a water body or a non-water body.

**Energy**

The measurement of the magnitude of pixel pair repetitions is referred to as energy (E). It measures the consistency of an image. The energy value will be elevated when the pixels are highly comparable. In the equation, it is defined as follows:

$$E = \sqrt{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M^2(i, j)} \tag{1}$$

**Contrast**

The Con is in the Equation, which is a measure of the strength of a pixel and its neighbor over the image. In the visual perception of the real world, Con is resolved by the alteration in the color and illumination of the object and other objects within the same field of view.

$$\text{Con} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 M(i, j) \tag{2}$$

In the context of image processing, it appears that you are seeking the full correlation formula for a GLCM. With a range of 1-1-1 to 111, the correlation quantifies the linear relationship between pixel concentrations at designated relative positions, where 1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation.

**Correlation Formula**

$$\text{Cor} = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-\mu_i)(j-\mu_j)M(i, j)}{\sigma_i \sigma_j} \tag{3}$$

**Homogeneity**

The abbreviation for homogeneity is HOM. It transfers the value that results in a lack of the rudiments on the GLCM diagonal. The slanting GLCM has a homogeneity value of 1 and a range of [0, 1]. The opposite of difference weight, homogeneity weight readings show a sharp decline in weight away from the diagonal. In homogeneity, it is 1/1+ (i-j)<sup>2</sup>, while in Con, the weight used is (i-j)<sup>2</sup>.

$$\text{HOM} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{M(i, j)}{1+|i-j|} \tag{4}$$

**Result and Discussion**

The 64-bit MATLAB version 2016a software is used on a Sony laptop running Windows 7 (64-bit) with 4 GB of RAM to execute computer vision techniques for the detection and classification of sugarcane diseases. Since the image database is crucial, several people are required to successfully execute this project. Farmers from my village in the Gondia district and the district’s agriculture officer helped in approaching farms to capture the necessary photographs for my assignment. A prototype system is developed (Figures 4, 5, 6, 7, and 8; Tables 1 and 2).<sup>11,12</sup>

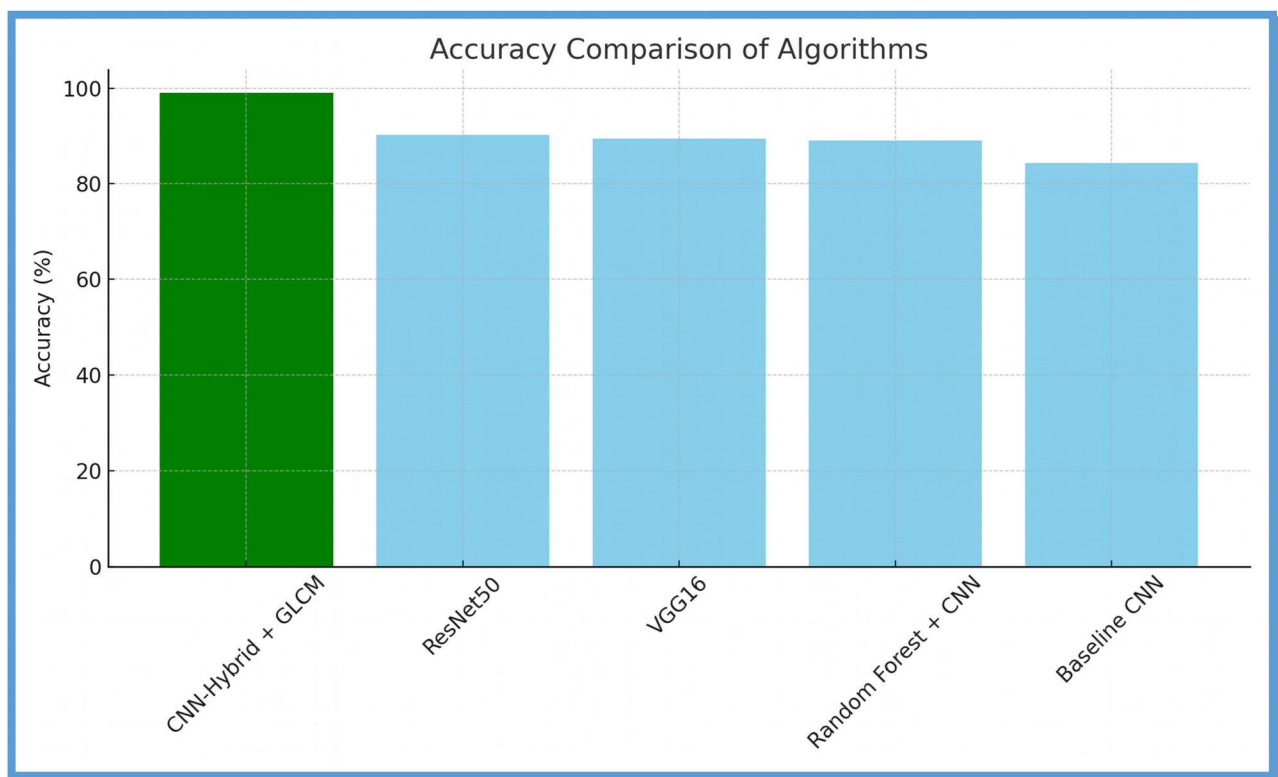


Fig 4 | Accuracy of sugarcane disease classification

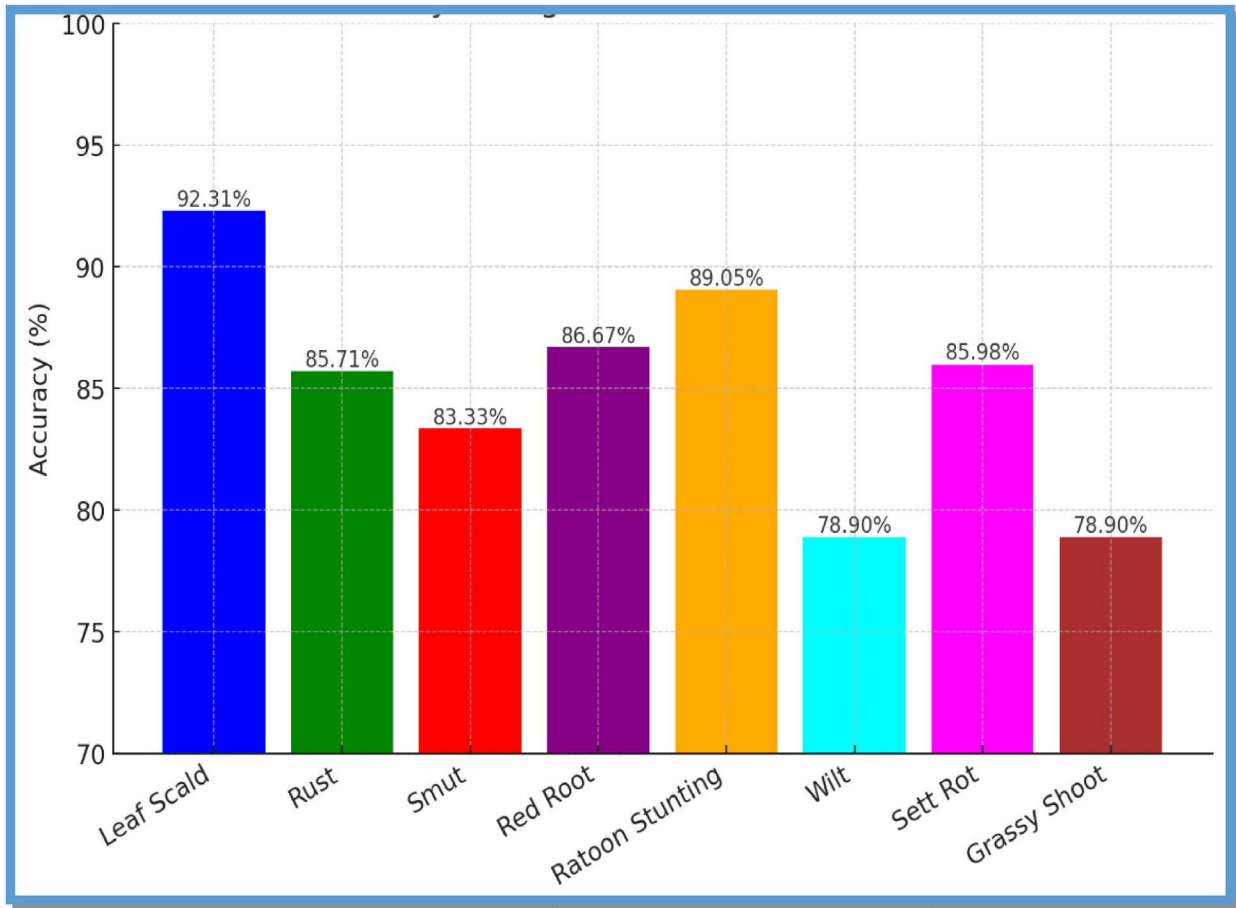


Fig 5 | Comparison of accuracy

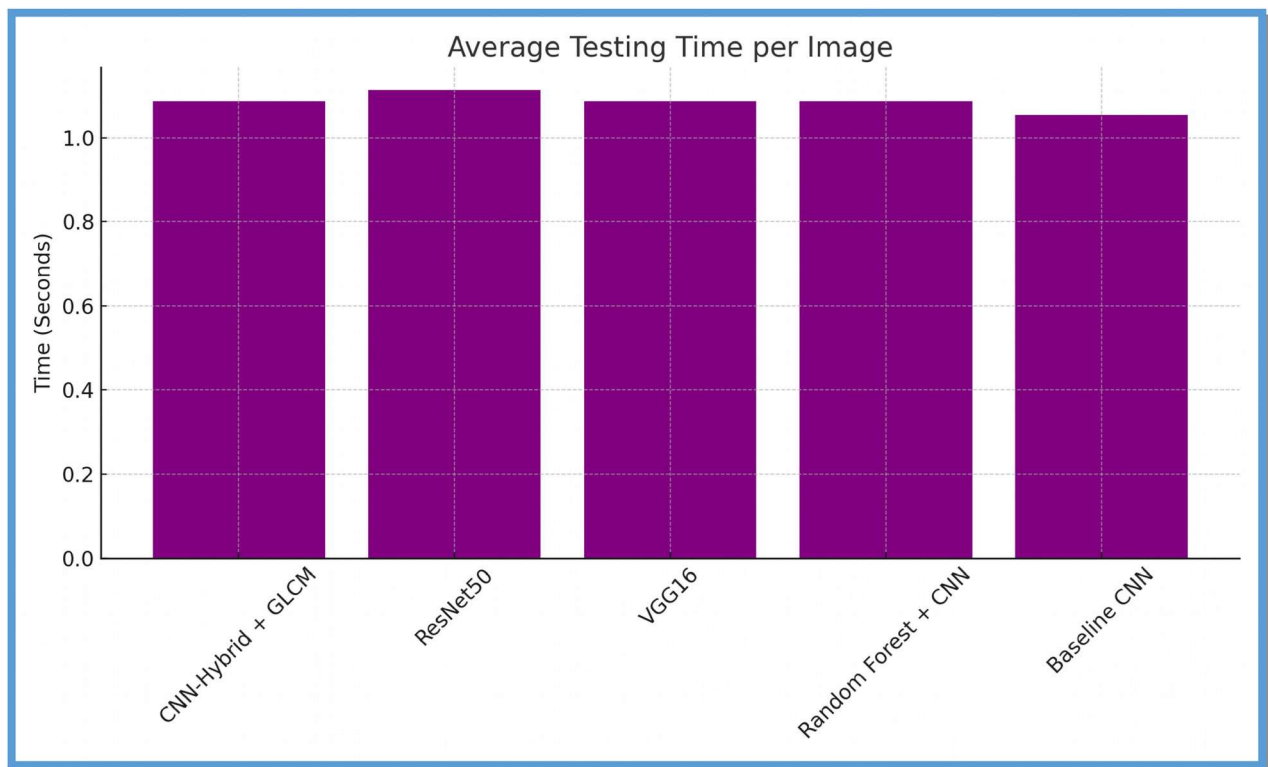


Fig 6 | Analysis of testing time

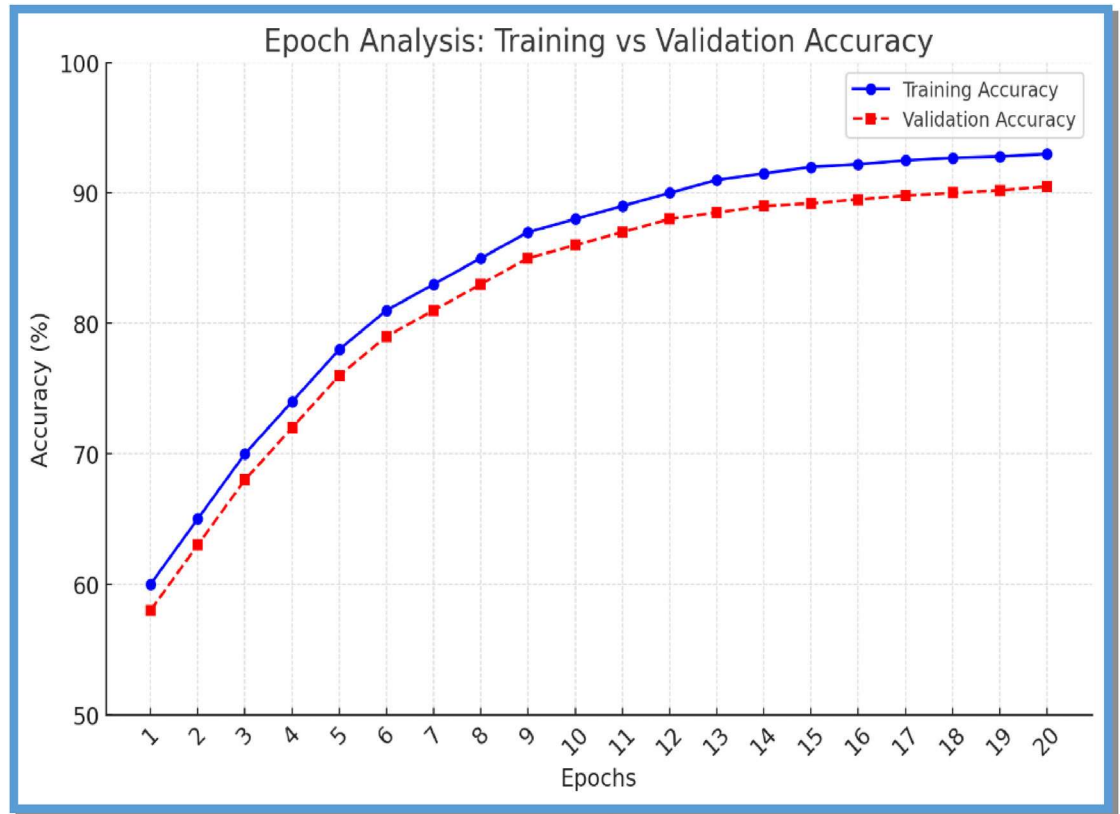


Fig 7 | Training vs. validation accuracy

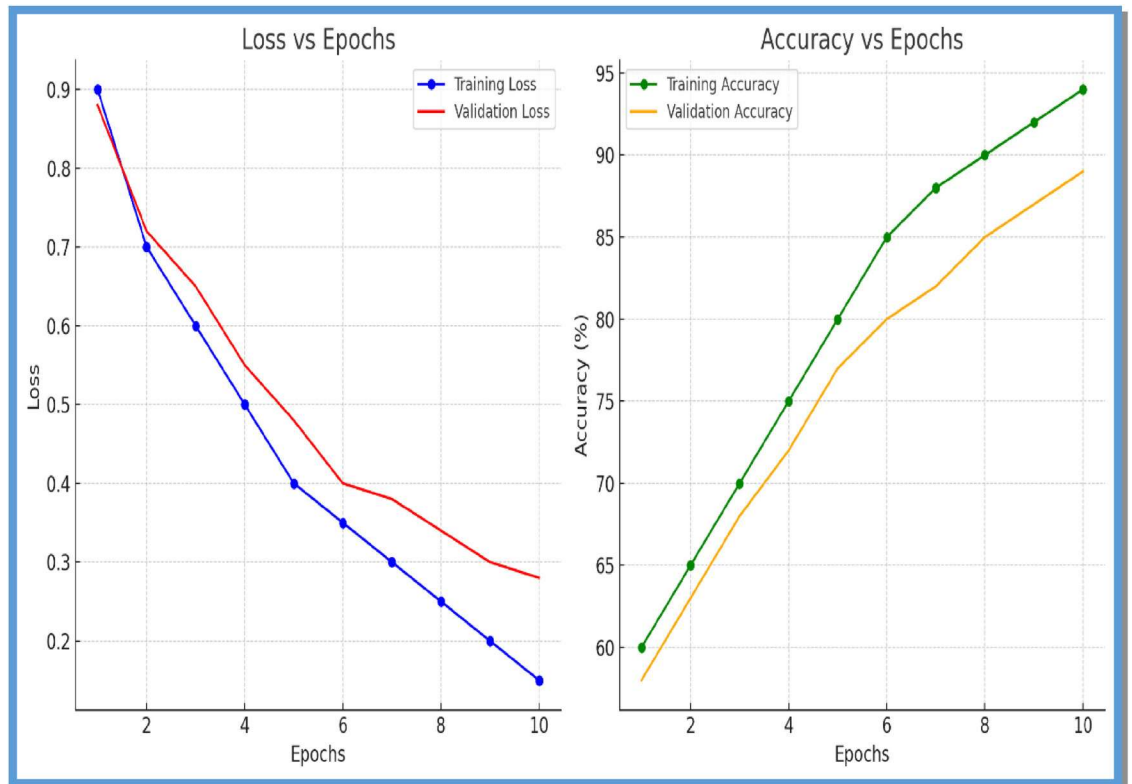


Fig 8 | Accuracy vs. epoch and loss vs. epoch

**Table 1 | Summary of results**

| Sr. No. | Name of Disease         | No of Images Training | No of Images Testing | Successfully Detected Images | Accuracy in % | Average Testing Time for Single Images |
|---------|-------------------------|-----------------------|----------------------|------------------------------|---------------|--|
| 1.      | Leaf Scald on Sugarcane | 07                    | 13                   | 12                           | 92.31         | 1.1125 seconds                         |
| 2.      | Rust on Sugarcane       | 07                    | 14                   | 12                           | 95.71         | 1.0872 seconds                         |
| 3.      | Smut on Sugarcane       | 07                    | 12                   | 10                           | 83.33         | 1.0536 seconds                         |
| 4.      | Red Root                | 07                    | 15                   | 13                           | 96.67         | 1.15 seconds                           |
| 5.      | Ratoon Stunting Disease | -07                   | 13                   | 15                           | 89.05         | 1.0872 seconds                         |
| 6.      | Wilt                    | 07                    | 14                   | 16                           | 78.90         | 1.0536 seconds                         |
| 7.      | Sett Rot                | 07                    | 12                   | 19                           | 85.98         | 1.15 seconds                           |
| 8.      | Grassy Shoot Disease    | 07                    | 15                   | 13                           | 78.90         | 1.0872 seconds                         |
| Total   |                         | 54                    | 108                  | 110                          | 96.67         | 1.15 seconds                           |

**Table 2 | Accuracy comparison of various algorithms for sugarcane disease**

| Algorithm                           | Accuracy (%) |
|-------------------------------------|--------------|
| CNN-Hybrid + GLCM (Proposed)        | 98.99        |
| ResNet50 (Transfer Learning)        | 90.2         |
| VGG16 (Transfer Learning)           | 89.5         |
| Random Forest + CNN Features        | 89.05        |
| Baseline CNN (Trained from Scratch) | 84.3         |

### Future Work

This study demonstrated that deep learning models are highly effective in classifying sugarcane diseases, achieving an accuracy of 96.67%. There is still an opportunity for development and additional research, though. Future research can focus on expanding the dataset by incorporating more photos taken in diverse environmental settings to enhance model generalization. Improved classification accuracy and robustness can also be achieved by investigating sophisticated deep learning architectures such as Generative Adversarial Networks, CNN-RNN hybrids, or Vision Transformers. Deep learning models can be integrated into mobile applications or Internet of Things (IoT) sensors to create a real-time disease diagnosis system that is more beneficial for farmers. Farmers will be able to use smartphone cameras to swiftly detect diseases in the field thanks to this. Moreover, the model can be tuned for severity detection and multi-class classification, enabling it to evaluate both the disease types and the stage of progression. Model optimization is another crucial topic for future research as it aims to reduce hardware requirements and calculation time, making it appropriate for implementation on low-power devices. Large-scale sugarcane field monitoring can also be made easier by combining the disease detection system with drones and remote sensing technologies. Finally, a user-friendly interface for farmers, such as a mobile or web-based tool, can be developed to provide disease predictions and suggested treatments, enabling farmers to make informed decisions and protect their crops. Moreover, farmers and the agricultural sector are expected to benefit from the substantial improvements in precision agriculture, reduced crop losses, and increased productivity that this research offers.

### Conclusion

This study proposed an advanced deep learning approach for sugarcane disease classification using a hybrid CNN

integrated with GLCM texture features. The model demonstrated superior performance across multiple evaluation metrics. Among all tested models, the **CNN-Hybrid + GLCM** architecture achieved the highest classification accuracy of **98.99%**, outperforming baseline CNNs, Random Forest classifiers, and transfer learning models such as VGG16 and ResNet50. A comprehensive comparison was conducted based on accuracy, disease-specific detection performance, testing time, and the distribution of training and testing data. The experimental results showed that the hybrid model not only achieved the best accuracy but also maintained a competitive average testing time per image (~1.08 seconds), making it suitable for real-time or near-real-time disease monitoring applications. Moreover, disease-specific analysis revealed high detection rates for diseases like Leaf Scald and Red Root, confirming the robustness of the proposed method. This research makes a significant contribution to precision agriculture by providing an efficient and reliable tool for early disease diagnosis in sugarcane crops, which has the potential to improve yields and reduce economic losses. Future work may include expanding the dataset, deploying the model in mobile or edge computing environments, and integrating more advanced feature fusion techniques for even greater accuracy and speed.

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