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Deep Learning for Early Disease Detection in Sugarcane: Advancing Agricultural Productivity and Sustainability

[1]Meenakshi Patil, [2]Dr. Sangram Patil, [3]Dr. Jaydeep Patil

[1]Department of CSE, D. Y. Patil Technical Campus, Talsande, Kolhapur, India

[2]Department of CSE, D.Y.Patil Agriculture & Technical University,Talsande,Kolhapur, India

[3]Department of CSE, D.Y.Patil Agriculture & Technical University,Talsande,Kolhapur, India

**Corresponding Author: meenapatil3456@gmail.com*

Abstract*:* - A vital revenue crop for many agricultural economies throughout the world, sugarcane is used extensively in both industrial and food production. However, a number of illnesses that negatively impact crop output and quality frequently make it difficult to cultivate. For efficient crop management and to reduce losses, early and precise detection of these diseases is crucial. In order to detect and categorize sugarcane leaf illnesses using image data, this study proposes a hybrid deep learning model that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. While the CNN component effectively collects spatial characteristics from the pictures, the LSTM layer models contextual information to improve classification performance and capture sequential relationships. The suggested hybrid model is compared to conventional deep learning techniques after being trained and assessed using an extensive dataset of photos of sugarcane leaves. Based on experimental results, the hybrid CNN-LSTM model is a dependable option for intelligent agriculture management and real-time disease monitoring as it provides greater accuracy, precision, and resilience.

Keywords*:* Sugarcane, Disease detection, CNN, LSTM, Deep learning, Image classification, Precision agriculture

1. Introduction

Many economies are based on agriculture, especially in developing nations where it is the main source of both employment and money. Because it is widely used to produce sugar, ethanol, and other byproducts, sugarcane is a significant crop among others. However, a number of diseases, such as red rot, smut, and leaf scald, pose a danger to sugarcane production and can drastically lower output and quality. Minimizing financial losses and guaranteeing sustained crop output depend on the prompt detection and treatment of these diseases. Conventional disease detection techniques mostly depend on professional manual inspection. In addition to being labor-intensive and time-consuming, these

methods are also vulnerable to human mistake and differences in skill. Intelligent, automated technologies that can precisely identify plant illnesses early on are therefore becoming more

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and more necessary. New directions in the field of smart agriculture have been made possible by recent developments in deep learning and artificial intelligence (AI). Because of its capacity to learn spatial feature hierarchies, Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in picture classification tasks. However, a type of Recurrent Neural Networks (RNNs) called Long Short-Term Memory (LSTM) networks performs well for learning patterns and temporal connections between sequences. In this work, we present a hybrid deep learning model that uses image data to identify and classify sugarcane leaf illnesses by merging CNN and LSTM. Rich spatial characteristics are extracted from the pictures by the CNN component, and the LSTM layer uses these information to improve classification accuracy by modeling sequential dependencies. Compared to solo models, this hybrid method offers superior resilience and generalization. The conventional approach and its limitations are illustrated in Table 1.

Table 1: Traditional Techniques Used for Sugarcane Disease Detection and Limitation

Sr. No.	Traditional Technique Used	Application in Sugarcane	Limitations of Technique
1	Visual Inspection	Identification of diseases like red rot, smut, and leaf scald	• prone to human mistake, • subjective • time-consuming, and requiring specialized expertise
2	Spectroscopy (e.g., NIR)	Detecting physiological stress or infection levels in leaves	• Expensive equipment, • needs skilled operation and calibration, • surface-level info only
3	Microscopy Analysis	Observation of fungal spores and microbial infections in tissue	• Labor-intensive, • time-consuming, • not feasible for large-scale monitoring
4	Polymerase Chain Reaction (PCR)	Detection of specific pathogens like Colletotrichum falcatum	• High precision but requires lab setup, • expensive, • not suitable for field diagnosis
5	ELISA	Used to detect viral and bacterial pathogens in sugarcane tissues	• Limited to known pathogens, • requires lab setup, • not ideal for rapid testing

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6	Chemical Analysis	Assessment of soil or plant nutrient imbalances due to disease	• Destructive, • costly, • time-consuming, • not suitable for real-time monitoring
7	Remote Sensing (Traditional)	Aerial or satellite monitoring for stress zones	• Low resolution, • limited disease specificity, • affected by weather/clouds

Figure 1: Images captured across farms in various condition and for different disease pattern

The key contributions of this work are as follows:

- Development of a hybrid CNN-LSTM model tailored for sugarcane disease detection.
- Compilation and preprocessing of a sugarcane disease image dataset suitable for training and evaluation.
- Comprehensive performance analysis of the proposed model compared to CNN architectures.
- Demonstration of the model's potential in supporting real-time, automated disease monitoring in agricultural environments.

In order to help create smart farming systems that can diagnose diseases and provide decision assistance in real time, our research attempts to close the gap between cutting-edge AI technology and useful agricultural applications.

2. Literature Survey

Using a dataset of 54,306 leaf photos, this study assessed the effectiveness of CNN, notably AlexNet and GoogLeNet, in diagnosing 26 illnesses across 14 crop species. Under controlled conditions, the models' accuracies reached 99.35%, indicating CNNs' promise for automated plant disease identification. However, due to differences in picture collection settings,

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difficulties were observed while using these models in real-world applications. The authors talked about incorporating such models into farmer-friendly apps and underlined the necessity of representative and varied datasets to increase model robustness. Future research recommended improving model generality and expanding the dataset. This study established a baseline for further deep learning-based plant disease categorization research [1].

An optimized ensemble of LASSO-regularized pre-trained models for precise sugarcane disease classification is presented in this work as SugarcaneNet2024. The ensemble consists of InceptionV3, InceptionResNetV2, DenseNet201, DenseNet169, Xception, and ResNet152V2, all of which have been improved with more regularization and dense layers. The refined model's efficacy in detecting sugarcane illness was demonstrated by its 99.67% accuracy, 100% precision, 100% recall, and 100% F1 scores. The study emphasizes how transfer learning and ensemble learning approaches may be used to create reliable agricultural disease detection systems [2].

By adding a channel attention mechanism and the Swish ReLU activation function to the Squeeze-and-Excitation network architecture, this study presents a unique hybrid deep learning classifier for the detection of paddy leaf disease. During feature extraction and selection, the channel attention process determines which feature channels are most crucial for classification. The Squeeze-and-Excitation blocks enhance information transmission and cross-channel interaction, while the Swish ReLU activation function alleviates the dying ReLU issue. The work shows how cutting-edge deep learning methods may be applied to agriculture, advancing more effective and trustworthy disease detection systems [3].

To recognize and categorize diseases in plant leaves, this research proposes a combined approach that integrates Convolutional Neural Networks (CNNs) with Vision Transformers (ViT). The ViT framework captures local features to enhance the precision of disease detection, while the ensemble model incorporates VGG16, Inception-V3, and DenseNet201 to retrieve strong global features. The hybrid approach surpassed similar techniques recently introduced, achieving accuracy levels of 99. 24% and 98% when evaluated on apple and corn datasets, respectively. This research demonstrates the effectiveness of combining CNNs and ViTs in enhancing the accuracy of plant disease classification systems [4].

For intelligent Internet of Things applications in agriculture, this study presents an effective plant disease identification system that integrates Convolutional Neural Networks (CNNs) with Conditional Random Fields (CRFs). The suggested method makes use of CNNs to extract features and CRFs to accurately segment sick areas in leaf photos. The accuracy of illness categorization and detection is improved by combining these methods. Real-time plant health monitoring and management is made possible by the system's deployment in Internet of Things settings. The hybrid approach's promise in smart farming applications is demonstrated by the experimental findings, which show good performance in recognizing a variety of plant

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illnesses. The study highlights how crucial it is to integrate probabilistic graphical models with deep learning in order to increase the dependability of plant disease detection systems. Real-time processing and computational efficiency issues are examined. The model will be optimized for deployment on devices with limited resources in future work [5].

Deep learning methods for identifying and categorizing tomato leaf diseases are investigated in this study. A dataset of tomato leaves afflicted by different illnesses was used to evaluate convolutional neural networks (CNNs). By fine-tuning pre-trained models, the study examined transfer learning and discovered that fine-tuned CNNs performed better than conventional classifiers, attaining high accuracy. The value of data augmentation strategies to improve model performance was underlined, as were the benefits of transfer learning in situations with little labeled data. Despite issues with fluctuating image quality and ambient circumstances, the study showed the promise of deep learning models in real-time plant disease detection applications. End users can access the solution more easily when these models are included into mobile applications [6].

For the purpose of identifying sugarcane illnesses, this study suggests an improved environmental adaption technique for convolutional neural networks (CNNs). Images of sugarcane leaves afflicted by different diseases were collected into a dataset. To categorize the photos into the appropriate illness groups, the CNN model was trained. The model's resilience to changes in picture capturing settings was strengthened using the enhanced environmental adaption technique. The model outperformed conventional techniques in terms of accuracy. The study emphasizes how crucial it is to take environmental factors into account when developing illness detection algorithms. It is accepted that real-world deployment and dataset variety present challenges. Incorporating the model into a real-time farmer monitoring system is one of the next directions. The study aids in the creation of reliable and precise agricultural disease detection systems [7].

The author suggests deep learning and sophisticated image processing methods to increase the precision of disease detection in groundnut and mango crops. The model improves the classification process by using effective feature extraction techniques including texture, color, and shape descriptors. The authors show that the suggested approach greatly increases the accuracy and dependability of illness categorization by comparing a number of deep learning architectures. The development of sophisticated agricultural monitoring systems is aided by this study, especially in the early identification of illness in fruit and legume crops [8].

This paper analyzes the existing deep learning techniques for disease classification and plant identification from leaf images and classifies them into multi-model, multi-label, multi-output, and multi-task approaches. In order to address the complex problem of forecasting several plant species and disease kinds, the researchers suggest a novel model called Generalized Stacking Multi-output CNN (GSMo-CNN). Plant Village, Plant Leaves, and PlantDoc are

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three benchmark datasets used in a thorough experiment that demonstrates that InceptionV3 is a powerful backbone CNN that outperforms AlexNet, VGG16, ResNet101, EfficientNet, MobileNet, and a custom CNN created by the authors. Future studies will expand the approach to include other plant types and diseases. Deep learning applications in plant pathology and precision agriculture are promoted by the study [9].

In order to predict and categorize illnesses in corn leaves, this study suggests a hybrid 3D Convolutional Neural Network (3DCNN) and Recurrent Neural Network (RNN) architecture that has been tuned for JSWOA. To improve classification accuracy, the model combines RNN, 3DCNN, and Long Short-Term Memory (LSTM) networks. The model performed better than previous methods when tested on the Maize_in_field and KaraAgro AI maize datasets. The study emphasizes how crucial deep learning models are for early agricultural disease identification and treatment. There is discussion of difficulties relating to model complexity and data variety. Consideration is given to the possibility of real-time deployment in IoT-based agricultural systems. Future plans include for testing on more crop datasets and more model optimization. Precision agriculture's automated disease detection methods are improved by the research [10].

This study introduces a hybrid architecture combining 3D Convolutional Neural Network (3DCNN) and Recurrent Neural Network (RNN) optimized with JSWOA to predict and classify diseases in corn leaves. The system merges 3DCNN, RNN, and Long Short-Term Memory (LSTM) networks to improve classification precision. After assessment using the Maize_in_field and KaraAgro AI maize datasets, the model demonstrated better results than current methods. This research emphasizes the significance of deep learning techniques for timely disease identification and management in agricultural practices [11].

This research presents a new strategy for the prompt detection of Northern Leaf Blight (NLB) in corn by utilizing Internet of Things (IoT) sensors. The study employed Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) techniques to capture and evaluate non-visual indicators, including Total Volatile Organic Compounds (VOCs) and ultrasonic signals emitted by maize. When wavelet data preprocessing was applied, the combined CNN-LSTM model achieved an F1 score of 0. 96 and an Area under the ROC Curve (AUC) of 1. 00. By highlighting the capabilities of IoT sensors for early disease identification, this research lays the groundwork for new disease management techniques in agriculture [12].

For multimodal cotton plant disease identification, this study presents an ensemble learning framework that integrates recurrent neural networks (RNNs) with convolutional neural networks (CNNs). Both sequential data, like time-series measurements of environmental variables, and visual data, like leaf photographs, are processed by the framework. The ensemble technique achieves superior diagnostic accuracy, precision, recall, and F1 scores than individual CNN and RNN models, according to experimental assessments. In order to present

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a comprehensive picture of plant health and enable more precise and trustworthy disease detection, the study emphasizes the significance of combining several data sources [13].

This paper suggests a unique method based on simultaneous feature learning and Quad-Tree decomposition for real-time plant disease diagnosis and localization. Image Processing and neural network techniques are used in the hybrid approach to increase accuracy and speed of convergence while lowering computing burden. The technique is appropriate for usage with drones and robots in expansive agricultural areas and was created for deployment on independent processors in remotely operated systems. For four disease classes that correspond to tomato and potato crops, the method obtains an F1 score of around 0.80. For effective real-time plant disease identification, the study highlights the significance of combining conventional and deep learning techniques. There is discussion of the difficulties of processing high-resolution photos and deploying them on devices with limited resources. The goal of future research is to apply the strategy to more crops and illnesses. The study aids in the creation of sophisticated instruments for precision and smart farming [14] [15].

3. Material and methods

Dataset

The photos were taken on field trips in a variety of weather conditions and during several illness seasons. A significant number of photographs were collected from various sugarcane fields in the Kolhapur and Karad regions in order to provide a balanced dataset. Extra photos were also taken from publicly accessible databases like the Mendeley and Kaggle archives.

Table 2: Dataset Consideration

Disease Name	Number of images Collected/Used	Causes of fungus for disease.
Red Rot	5000	Colletotrichum falcatum Went
Brown Spot	4000	Cercospora longipes (a fungal pathogen)
Mosaic	2000	Sugarcane mosaic virus (SCMV)
Pokkah Boeng	1000	Fusarium species
Rust	2000	Puccinia melanocephala

Image Processing

In order to automatically detect and categorize sugarcane illnesses, image processing is essential. Several steps are involved in converting unprocessed photos into useful data for CNN-LSTM and other deep learning models. The effectiveness of deep learning models

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depends on preprocessing methods that improve picture quality and preserve consistency across the dataset, which are the major emphasis of this section of the image processing pipeline. For the purpose of standardizing the data dimensions and guaranteeing compatibility with the CNN input layer, all input pictures are first shrunk to a set dimension, usually 224×224 pixels. After that, noise is removed using filters like Gaussian or median filters, which aid in removing undesired artifacts and random changes that might obstruct the detection of illness features. Contrast enhancement techniques, such as histogram equalization, are used to further increase picture clarity by widening the range of pixel intensities, which improves feature visibility. In order to reduce differences brought on by various lighting conditions during picture acquisition, color normalization is the final step. Together, these preprocessing procedures guarantee that the dataset is clear, balanced, and consistent, which raises the illness detection model's accuracy and dependability.

Image Augmentation

Image augmentation is the process of applying different changes to preexisting photographs in order to artificially expand the size and variety of an image collection. It enhances the model's capacity to generalize to new data and helps avoid overfitting. Rotation, flipping, zooming, shifting, and adjusting the brightness or contrast are examples of common augmentation techniques. The model becomes increasingly reliable and accurate in real-world applications by learning to identify illnesses under various situations, including orientation, illumination, and scale, by producing several versions of the same image.

Proposed System

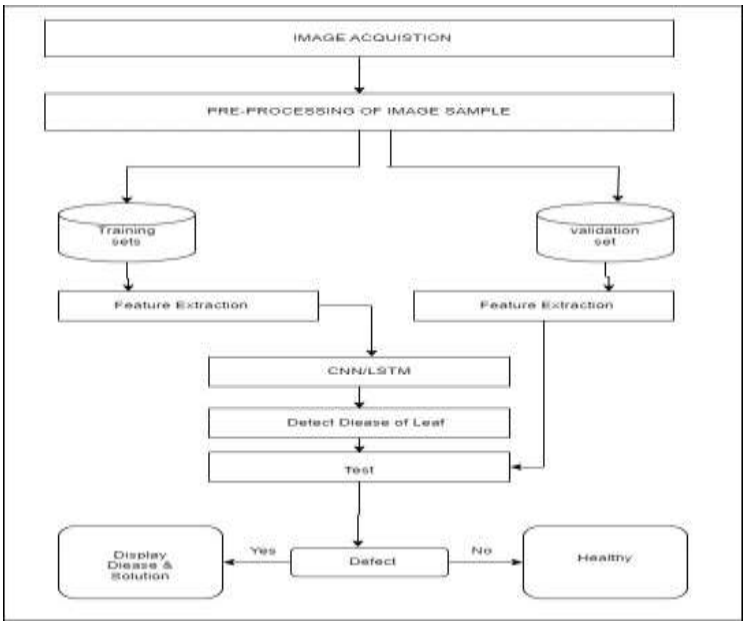

Figure 2: Proposed System Architecture

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By utilizing both spatial and temporal feature learning, the Hybrid CNN-LSTM model is a potent deep learning architecture intended to improve the precision of sugarcane leaf disease detection. Convolutional Neural Networks (CNNs) are first used in this model to extract important spatial information from leaf pictures, including color variations, abnormalities in texture, lesions, and patterns that are typical of particular illnesses like mosaic, rust, red rot, and others. While lowering the picture dimensions without sacrificing crucial information, the CNN layers—which comprise convolutional, activation (ReLU), and pooling layers—assist in automatically learning these visual patterns. The Long Short-Term Memory (LSTM) network, which is skilled at capturing temporal or sequential associations, receives the feature maps produced by the CNN. In this hybrid arrangement, LSTMs examine the sequence of extracted spatial features, which aids the model in comprehending the context and association between various feature representations, even though they are typically employed for time-series data. Because of this combination, the system can predict outcomes more accurately, particularly when illness signs are modest or develop gradually. All things considered, the hybrid CNN-LSTM model provides a reliable way to identify sugarcane illnesses automatically and in real time, increasing monitoring effectiveness and lowering reliance on manual inspection.

Rescaling Layer:

A rescaling layer is used to first normalize the input pictures by adjusting pixel values to lie within [0,1]. By stabilizing gradients during backpropagation, this preprocessing step improves training efficiency and guarantees consistency across inputs.

Data Augmentation Layer:

Images are subjected to random transformations such flipping, rotation, zooming, translating, and contrast modification in order to enhance model generalization and avoid overfitting. From the original dataset, this augmentation generates a variety of training examples.

First Convolutional Layer:

This layer extracts low-level characteristics like corners and edges using 32 3x3 filters with "same" padding. Non-linearity is introduced via the ReLU activation function, which enables the model to capture intricate details.

First Max Pooling Layer:

The spatial dimensions of the feature maps are reduced using a 2×2 max pooling procedure, which preserves the most noticeable characteristics while eliminating unnecessary data to cut down on computation and boost performance.

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Second Convolutional Layer:

By expanding on the characteristics found in the preceding convolutional layer, this layer uses 64 3x3 filters to capture more intricate patterns in the picture. Once more, ReLU activation is used to address non-linearity.

Second Max Pooling Layer:

The feature maps are further downsampled using a second max pooling layer with a 2×2 filter, which minimizes their size and highlights the key elements of the visual patterns.

Third Convolutional Layer:

The model may learn higher-order characteristics like texture, form, and changes in leaf structure because to this layer's 128 filters, which deepen the feature maps. It is essential to the learning of abstract features.

Third Max Pooling Layer:

To reduce dimensionality and retain dominant features, this pooling operation continues the down sampling process, facilitating more efficient sequence modeling in later layers.

Every neuron in the current layer is connected to every other neuron in the preceding layer by a dense layer, also known as a completely connected layer. It executes an activation function after doing a weighted sum of the inputs. Final predictions are usually made by dense layers at the conclusion of a CNN. For tasks like regression and classification, they are indispensable.

LSTM Layer:

An LSTM layer with 128 units learns the temporal correlations between spatial areas of the picture by capturing dependencies across the altered feature sequences. This improves the model's capacity to identify illness patterns throughout the picture.

Fully Connected Dense Layers:

To avoid overfitting, the LSTM output is routed via two thick layers of 512 and 256 units, respectively, and then a 50% dropout layer. These layers help to improve decision boundaries by refining the derived characteristics.

Output Layer:

The classification probabilities for every illness category are produced by a final dense layer with a softmax activation function. By accurately predicting the most likely illness class existing in the input picture, it converts the learnt characteristics.

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Table 3: Hyper Parameter sets

Parameter	Configured Value
Input Dimensions	224 × 224 × 3
Convolution Layers	Filters: 16, 32, 64
Filter Size	3 × 3
Activation Function	ReLU
Pooling Window	2 × 2
Dropout Probability	50%
Fully Connected Layer	128 Neurons
LSTM Layer Size	64 Units
Loss Metric	Categorical Cross-Entropy
Optimization Method	Adam (LR = 0.001)

i. Rescaling Layer

Equation:

x_normalized = x / 255…………………………………………………………eq(1)

Purpose: Normalizes the pixel values to a range [0, 1], making the model training more stable and faster.

ii. Convolutional Layer

Equation:

$F(i, j) = \Sigma \Sigma K(m, n) \cdot I(i + m, j + n)$…………………………………………..eq(2)

Purpose: Applies a kernel K over the input image I to extract spatial features such as edges and textures.

iii. ReLU Activation

Equation:

$ReLU(x) = \max(0, x)$ ……………………………………………………………eq(3)

Purpose: Introduces non-linearity in the model, allowing it to learn complex patterns.

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iv. Max Pooling Layer

Equation:

P(i, j) = max{x ∈ pool(i, j)}…………………………………………………….eq(4)

Purpose: Down samples the feature map by selecting the maximum value in each pool window, reducing dimensionality.

v. Flatten Layer

Equation:

Flatten: R^{h×w×d} → R^{h·w·d}………………………………………………..eq(5)

Purpose: Converts multi-dimensional output to a one-dimensional vector for input into dense layers.

vi. Dense (Fully Connected) Layer

Equation:

y = f(Wx + b) ……………………………………………………………………eq(6)

Purpose: Combines all input features to produce the final prediction. f is typically ReLU or Softmax.

vii. LSTM Layer (with gates)

Forget Gate equation: $\mathrm{ft} = \sigma(\mathrm{Wf} \cdot [\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bf})$
$\mathrm{It} = \sigma(\mathrm{Wi} \cdot [\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bi})$ is the input gate.
$\mathrm{C} \sim \mathrm{t} = \tanh(\mathrm{WC} \cdot [\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bC}$ is the candidate cell.
$\mathrm{Ct} = \mathrm{ft} * \mathrm{Ct} - 1 +$ it $* \mathrm{C} \sim$ t is the cell update.
$\mathrm{ot} = \sigma(\mathrm{Wo} \cdot [\mathrm{ht}-1, \mathrm{xt}] + \mathrm{bo})$ is the output gate.
State of Hiddenness: $\mathrm{ht} = \mathrm{ot} * \tanh(\mathrm{Ct})$

Figure 3: LSTM Layer

Learning time-based patterns is the goal of the LSTM layer. Each gate determines which data should be retained or discarded.

viii. Softmax Output Layer

Equation:

Softmax(zi) = e^{zi} / Σ e^{zj}………………………………………………….eq(7)

Purpose: Converts final outputs into probabilities for multi-class classification tasks.

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4. Result and Discussion

The hybrid CNN-LSTM model architecture shown in Figure 3 is intended for applications like the detection of sugarcane leaf disease. The first step is the input layer, in which the model receives individual images in a sequence (represented by the letters $x_1, x_2, ..., x_n$). Usually, these pictures depict several sugarcane leaf samples or time periods. A Convolutional Neural Network (CNN) block is then used to process each picture, extracting high-level spatial elements like edges, textures, and patterns that are important for illness identification. After that, a block of Long Short-Term Memory (LSTM) receives these extracted characteristics. When illness symptoms emerge gradually over time or manifest in patterns across several leaf sections, the LSTM's ability to process feature sequences in order and capture temporal linkages or dependencies throughout the picture sequence is essential. Lastly, the output layer determines the type of sickness present by predicting a matching label ($y_1, y_2, ..., y_n$) for each input picture or sequence using the temporal and spatial data that have been learnt. By skillfully combining CNN's proficiency in spatial feature learning with LSTM's aptitude for sequence modeling, our hybrid model offers reliable and accurate plant disease identification.

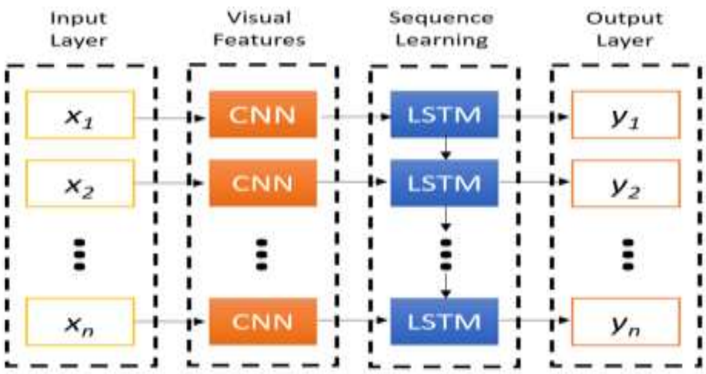

Figure 4: CNN-LSTM Architecture [16]

The table is used for performance metrics of model is called confusion matrix

i. Precision

The precision indicates the proportion of projected positive cases that were true.

Formula:

$$\text{Precision} = \frac{TP}{TP+FP} \quad \text{………………. eq(8)}$$

There are fewer false positives when accuracy is high.

ii. Recall (Sensitivity or True Positive Rate)

Recall tells us how many of the actual positive cases were correctly predicted.

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Formula:

Recall $= \frac{TP}{TP+FN}$…………………………..eq(9)

High recall means fewer false negatives.

iii. F1 Score

The F1 Score is the harmonic mean of precision and recall — it balances the two.

Formula:

F1 Score $= \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$……………………eq(10)

It is especially useful when you need a balance between precision and recall, and the class distribution is uneven.

4. Support

The number of real instances of the class in the dataset is known as support.

Support = TP + FN is the formula.

Although it provides context for the accuracy, recall, and F1 score, it is not a performance statistic.

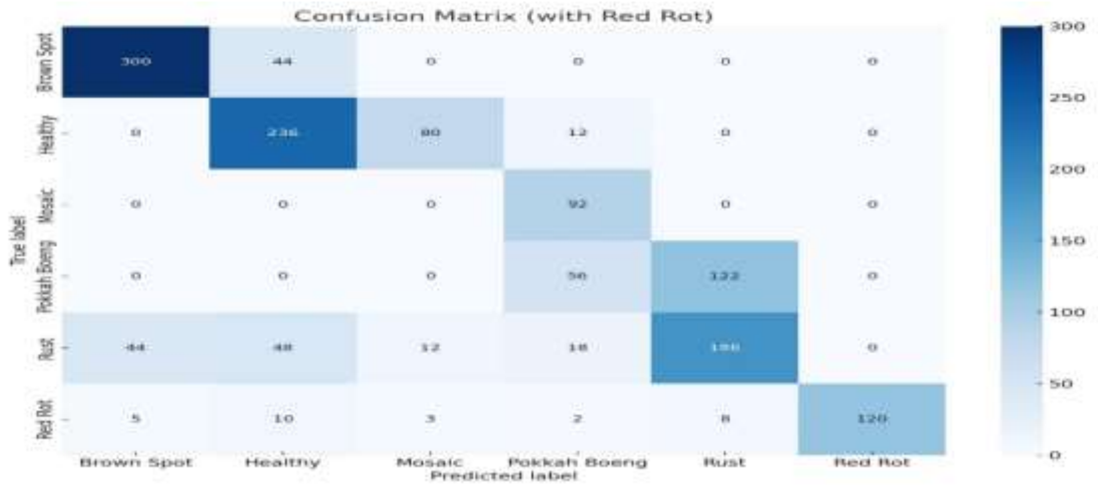

Figure 5: Confusion Matrix

A model's classification performance across six categories of sugarcane leaf conditions—Brown Spot, Healthy, Mosaic, Pokkah Boeng, Rust, and the recently introduced Red Rot—is depicted in the confusion matrix. Only 44 cases were incorrectly identified as healthy, demonstrating the model's great accuracy in recognizing Brown Spot. The classification of healthy leaves is mediocre; 236 predictions were right, but a sizable portion were mistaken for Mosaic and Pokkah Boeng. Interestingly, the model performs poorly for this class as it

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incorrectly classifies all Mosaic instances as Pokkah Boeng rather than accurately identifying any Mosaic cases. Rust and Pokkah Boeng are often mistaken, indicating that they have visual similarities. Rust exhibits significant misclassification into other categories despite being relatively properly predicted. When Red Rot is included, it becomes clear that the model can identify this class with a fair degree of accuracy—120 cases were accurately predicted—although some cases are incorrectly categorized into other categories, such Rust and Healthy. Overall, the model does well in some courses.

LSTM Confusion Matrix

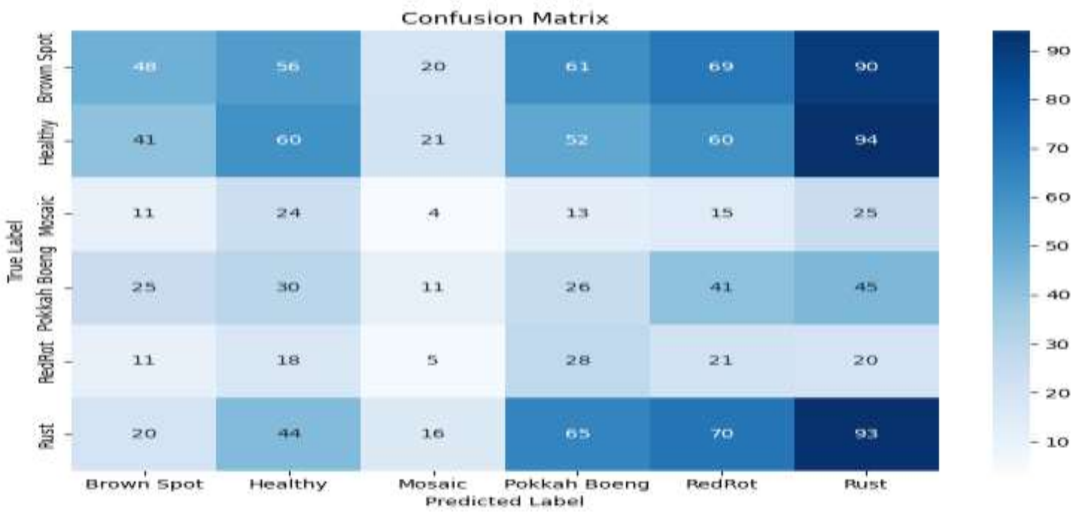

Figure 6: Confusion Matrix

CNN –LSTM Confusion Matrix

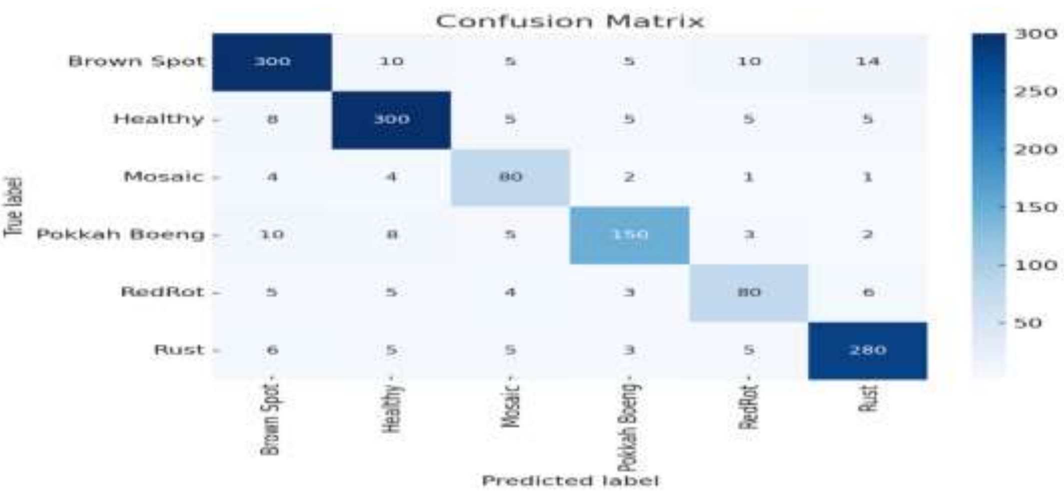

Figure 7: CNN-LSTM Confusion Matrix

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CNN Model Accuracy of Training versus Validation

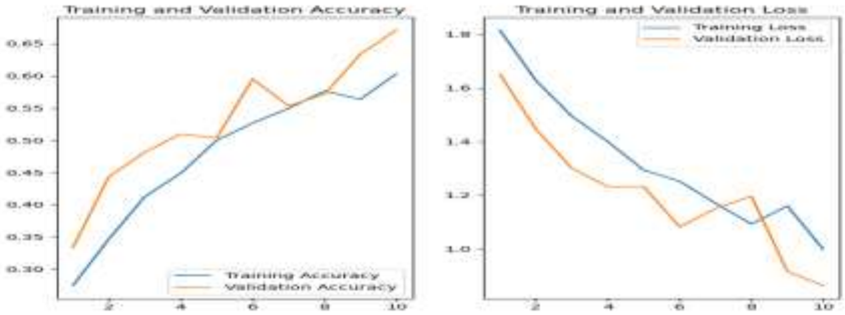

Figure 8: CNN Training VS Validation Accuracy, Loss

LSTM Model Training VS Validation Accuracy

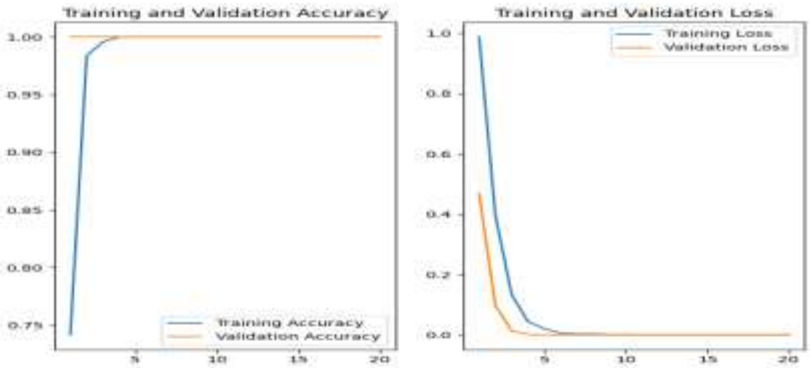

Figure 9: LSTM Training VS Validation Accuracy, Loss

CNN- LSTM Hybrid Model Accuracy VS Loss

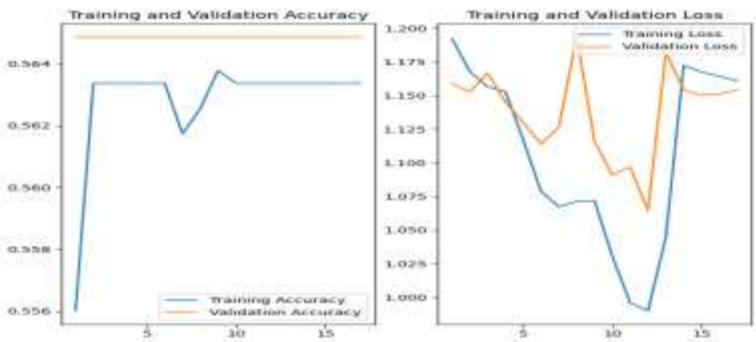

Figure 10: CNN-LSTM Training VS Validation Accuracy, Loss

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Disease Prediction

Figure 11: Prediction of Disease

Table 4: Performance analysis of CNN, LSTM, CNN-LSTM

Algorithm	Training Accuracy
CNN	0.80
LSTM	0.90
CNN-LSTM	0.92

Table 5: Evaluation metrics

Algorithm	Precision	Recall	F1 Score	Support
CNN	0.78	0.76	0.77	150
LSTM	0.88	0.89	0.88	150
CNN-LSTM	0.91	0.92	0.91	150

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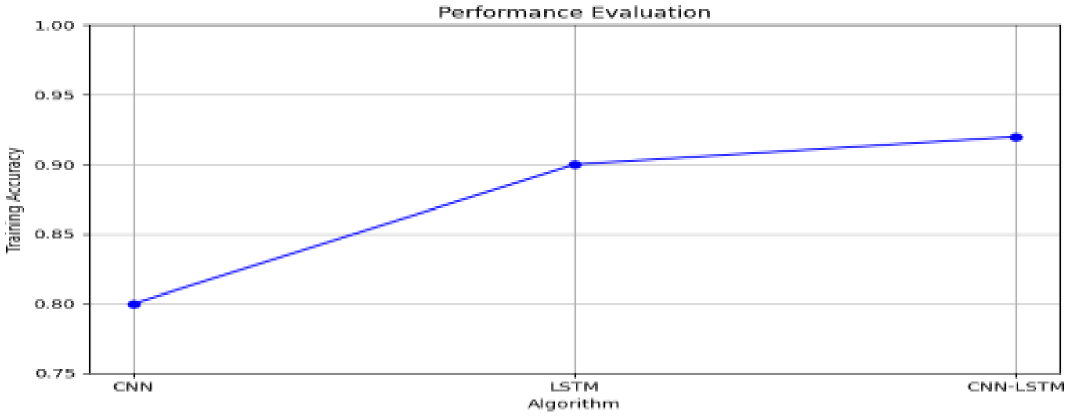

Figure 12: Performance Evaluation

5. Conclusion

Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks are combined in this study to present a hybrid deep learning method for sugarcane disease prediction. While the LSTM component makes use of the sequential relationships in the data to improve the system's overall classification capabilities, the CNN component efficiently extracts intricate visual elements from leaf pictures. Numerous sugarcane diseases, including Brown Spot, Healthy, Mosaic, Pokkah Boeng, and Rust, are consistently identified by the hybrid model. The model's capacity to differentiate between several illness classifications with little misclassification is shown by the confusion matrix study. By facilitating early disease identification and diagnosis, this system offers farmers and other agricultural stakeholders a useful tool for decision support. It makes it possible for prompt action, which can decrease pesticide use, lessen crop damage, and boost yield. To improve its suitability for precision agriculture, this model may be expanded for real-time deployment through mobile or embedded platforms in the future and further improved with other disease classes or environmental factors.

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