

Deep Learning Approach for Detection and Prediction of Pest Infections on Plants in Greenhouses

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Abstract

Pest infestations remain problematic in greenhouse agriculture, lowering yields and increasing costs. Manual pest monitoring is laborious, slow, and error-prone, resulting in delayed interventions and excessive pesticide applications. The main objective of this research was to develop an AI-driven hybrid deep learning model for automated pest detection and outbreak prediction, integrating Convolutional Neural Networks (CNNs) for image-based classification and Long Short-Term Memory (LSTM) networks for forecasting to improve response efficiency. This study relied on secondary datasets, such as PlantVillage and IP02, owing to constraints in obtaining primary datasets. These datasets provided pre-annotated pest images and historical climate trends, guaranteeing model robustness. Although the model was trained using secondary data, the study was contextualized by greenhouses in Limuru, Naivasha, and Thika; areas where pest control is an ongoing challenge. To enhance the model's ability to generalize and perform well in an array of agricultural environments, a stratified sampling method which considered farm size and agroclimatic differences was used. Techniques such as image augmentation, noise reduction, and normalization of features were utilized to further improve the quality of the data before the model was trained. Model training and optimization were performed in a GPU-enabled Google Colab environment, which supported batch processing, early stopping, and fine-tuning of hyperparameters. The hybrid model achieved 94.7% accuracy, 93.6% precision, 92.8% recall, and a 93.2% F1-score. With a Mean Absolute Error (MAE) of 0.14 and an R^2 score of 0.89, the LSTM forecasting module demonstrated its efficiency. This hybrid approach enables early pest identification, preventative actions, and reduced pesticide use.

Keywords: *Deep Learning, Pest Detection, Greenhouse Agriculture, CNN-LSTM, Forecasting*

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1.0 Introduction

Pest infestations threaten global agriculture, with pests contributing about 40% of the total losses in value of crops each year (Kaushik et al., 2023). Traditional pest control techniques, such as physical inspections and pesticides, regularly fail to catch pests in the early stages, thereby overusing pesticides and harming the environment (Chowdhury & Anand, 2023).

Artificial intelligence and deep learning offer promising alternatives for automated pest detection and prediction, enabling timely interventions and promoting sustainable farming (Yi et al., 2024).

In Africa, pest problems continue to be severe in greenhouse systems where controlled environments accelerate pest reproduction (Mafongoya et al., 2019). To enhance precision agriculture, several nations, including Kenya, Nigeria, and South Africa, have started implementing AI-driven solutions (Adewusi et al., 2024). Despite advancements, most farmers still depend on manual scouting, which often lacks accuracy and efficiency. While studies exist to develop deep learning models for pest detection, very few have been put into practice (Chowdhury & and, 2023).

In Kenya, the rise of greenhouse farming has increased not only crops' productivity, but also the risk of pest pandemics. Poor pest control can lead to postharvest losses, exceeding 70% (Mugao, 2023).

The lack of real-time pest monitoring in regions like Limuru, Naivasha, and Thika highlights the need for AI-empowered pest detection and prediction, which is introduced in this study as a hybrid deep learning model meant to assist with sustainable pest management in Kenyan greenhouses.

Statement of the Problem

Pest infestations in greenhouse agriculture cause substantial losses when infested plants are not detected promptly. Current pest detection methods include manual inspections that are error-prone and are not real time. This research examined the issue by proposing the application of a deep learning solution integrating Convolutional Neural Network (CNN) features for extraction of images and Long Short-Term Memory (LSTM), to analyze the time series data for the detection and prediction of pest invasions.

Purpose of the Study

This study aimed to design, and evaluate a hybrid deep learning model that integrates a CNN for pest identification from images and LSTM networks for time series of pest outbreak prediction. The overall aim was to enhance the precision, function and timeliness of managing pests affecting greenhouse plants.

Objectives of the Study

- i. To develop a CNN model to accurately identify image-base pest infections on greenhouse crops.
- ii. To develop a LSTM model to predict pest outbreaks based on temporal patterns
- iii. To integrate the CNN and LSTM models into a hybrid deep learning.
- iv. To evaluate the hybrid model's performance using standard metrics.

Theoretical Framework

This research used Deep Learning Theory and Technology Acceptance Model (TAM) to establish a dual-framework that addresses both technical innovation and user-centered design in greenhouse pest management. Deep Learning Theory, grounded in artificial neural network (ANN) principles, guides the

development of a hybrid Convolutional Neural Network (CNN) Long Short-Term Memory (LSTM) architecture. The CNN layer extracts spatial features from pest images whereas the LSTM layer encodes time-dependent environmental trends. Together, they embody the theory's principles of feature abstraction and temporal memory (Maraveas, 2023; Khan et al., 2020).

The design decisions such as dropout regularization to minimize overfitting or ReLU activation as a non-linear function are directly influenced by theoretical imperatives of generalization and optimization.

In this framework, Deep Learning Theory supports the technical model development, while TAM offers a framework for evaluating usability, perceived benefit and system trust through Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), to be sure the model will not only be successful but also likely to be adopted. Stakeholder feedback will assess real-world applicability (Mohr & K  hl, 2021; Okai et al., 2024).

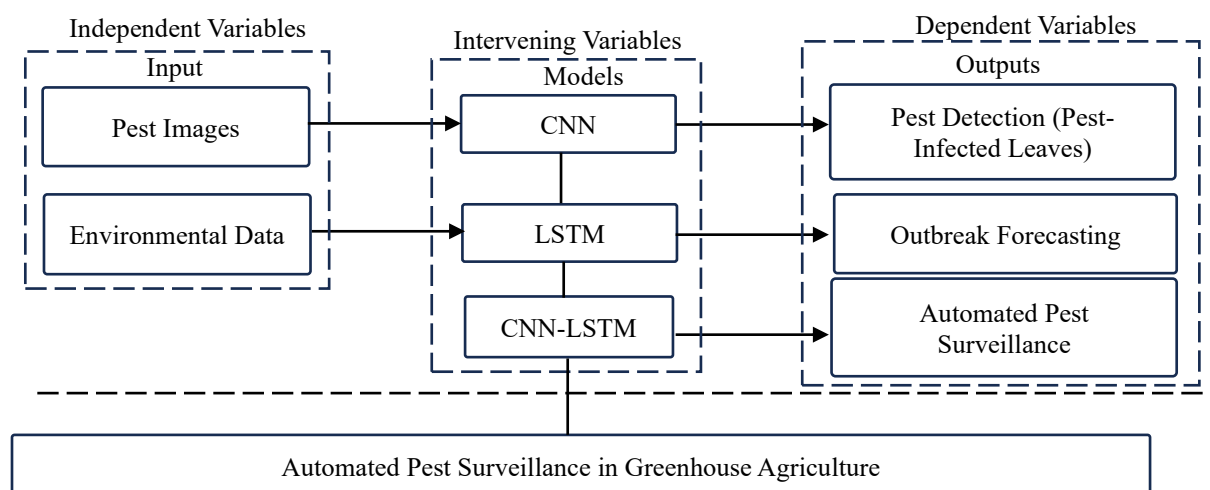
Empirical evidence supports the use of CNN-LSTM models for pest detection in Asian greenhouses (Zhang et al., 2021); yield forecasting in Germany (Khan et al., 2020); and plant disease monitoring in India

(Sharma et al., 2022). These implementations helped inform the current model by highlighting practical constraints, such as latency and interpretability that must be addressed for successful deployment, especially in Sub-Saharan Africa where such technologies are still underutilized.

"The study found compelling evidence that the hybrid model effectively and accurately automated identification and prediction of pest outbreaks in greenhouse farming"

In conclusion, the model provides a combination of technological capabilities of deep learning and the user-centered perspective of the TAM framework. It opens the door to scalable and widely-used AI-based pest management systems.

Figure 1
Conceptual Framework



Empirical Literature Review

Advancements in artificial intelligence and deep learning have improved pest detection and outbreak forecasting in agriculture. Nonetheless, the practical implementation is limited because of the technical and operational constraints. Conventional methods, such as manual scouting and pesticide applications are inefficient, costly, and can be damaging to ecosystems due to development of pesticide resistance (Chithambarathanu & Jeyakumar, 2023). Basic image processing methods (e.g., thresholding and edge detection) facilitate some level of automation, but they are highly unreliable in agricultural environments which are complex and unpredictable (Chowdhury & Anand, 2023).

CNNs have enhanced pest identification by extracting features from images of diseased plants (Chowdhury & Anand, 2023). Still, their use in greenhouse settings is limited due to inconsistencies in lighting conditions and crop species. Teixeira et al. (2023) examined transfer learning as a potential solution, but cautioned that issues like dataset bias and model degradation may compromise predictive reliability.

To improve real-time monitoring, IoT-based solutions have been proposed, incorporating cameras and environmental sensors (Mittal, 2024). Nonetheless, sometimes, lacking predictive capacity, systems often require computational capabilities that are not accessible to smallholder farmers (Chithambarathanu & Jeyakumar, 2023). As a result, lightweight AI models (Gao et al., 2020) and intuitive user interfaces (Bieniek et al., 2024) are perceived as necessary in verifying resource contexts. Limited numbers, local access, and skepticism remain challenges in their uptake in Kenya (Chowdhury & Anand, 2023).

This study fills a critical gap by developing and evaluating a hybrid CNN-LSTM pest

management model designed to accommodate smallholder greenhouse farmers in Kenya. By integrating image recognition with temporal prediction, the model provides early alerts and offers a context-appropriate, accessible solution for pest detection and outbreak forecasting.

2.0 Materials and Methods

Research Design

The research adopted a hybrid research approach, consisting of experimental, comparative, and descriptive approaches to evaluate deep learning models for pest identification, detection, and prediction of outbreaks in greenhouse agriculture (Türkoğlu & Hanbay, 2019; Selvaraj et al., 2019). The study entailed in-depth evaluation of the models and an emphasis on usability and acceptance, to ensure methodological rigor and applicability.

The experimental evaluation consisted of training datasets in a structured manner, testing each model, and iteratively optimizing the models based on established key performance indicators; RMSE, accuracy, precision, and recall (Teixeira et al., 2023). The comparative approach appraised the CNN, LSTM, and hybrid CNN-LSTM architectures based on performance; thereby allowing for comparison of models against the previous pest detection procedures (Chowdhury & Anand, 2023).

The descriptive approach analyzed existing literature, interviews, and surveys on automation in agriculture, highlighting users' openness to adoption. Combined with experimental and comparative analyses, it provided key insights into the role of AI in precision agriculture and pest management.

Contextual Population and Stakeholders

The study's context comprise greenhouse farming practices in Limuru, Naivasha, and Thika, which were selected for their high pest

pressure, horticultural importance, as well as indication of diverse agroclimatic conditions. Important stakeholders, such as farmers, agronomists, extension officers were enrolled through previous studies and institutional reports to contextualize pest management and use of AI.

Secondary Data and Sampling Framework

Model development and evaluation were conducted exclusively using secondary data, including pest images and time-series records on environmental and pest variables. The data were derived from agricultural databases and greenhouse databases, selected for quality, completeness and relevance to target areas.

Stratification and representation

A proportionate stratification sampling procedure was used on the secondary datasets, based on greenhouse distribution across Limuru, Naivasha, and Thika. Limuru provided the greatest volume of data, reflecting the density of greenhouses in that locality. The sampling technique guaranteed representation of the variability in climate,

operating scale, and crop type which increased the external validity of the model and potential for its generalization across greenhouses' different contexts.

Dataset(s) and Tools Used

This study employed two secondary datasets to guarantee reliable pest detection and outbreak prediction owing to the constraints of resources in collecting comprehensive primary data. The image classification dataset, PlantVillage, included 9,243 labeled RGB images of healthy and pest-infected leaves (Hughes & Salathé, 2019). For time series forecasting, IP202 and a structured dataset of 3,150 temporally indexed records which included environmental parameters and pest counts were used (Kapetas et al., 2025). These datasets provided historical climate trends and pre-annotated pest images, which helped the model to be resilient despite limited direct data collection.

Both datasets were split for systematic model training to ensure a fair assessment and prevent overfitting (Table 1).

Table 1
Dataset Split

Dataset Split	%	Dataset Distribution	
		PlantVillage	IP02
Training	70	6, 740	2,205
Validation	15	1,386	472
Testing	15	1,387	473

The IP202 dataset and the PlantVillage dataset were both preprocessed to maximize model value prior to training.

The images were modified to standardize the input dimensions for the CNN using an adjusted image size of 224x224 pixels (Hughes & Salathé, 2019). Pixel values were normalized to a range of 01, which enhanced model convergence during training (Teixeira et al., 2023). To improve generalization

across various situations, data augmentation methods, such as flipping, random rotation, and contrast adjustments were employed (Ngugi et al., 2021).

To ensure consistency among the LSTM input representations, environmental parameters such temperature, humidity, and pest counts were scaled using MinMax normalization (Kapetas et al., 2025). To maintain the continuity of the timeseries,

missing data were treated using linear interpolation (Gao et al., 2020). Stratified sampling, which equally represented all training subgroups, reduced biases in the frequency of pest outbreaks (Wang et al., 2025).

Computational Tools Used

Model training and evaluation were conducted on the Google Colab platform. It was developed using TensorFlow, Keras, and OpenCV, with visualizations generated through standard libraries. Preprocessing and evaluation were done using Scikit-learn. This approach supported the development of a scalable and practical solution for pest detection and forecasting.

Model Architecture

The model architecture used for this research contained two main components: CNN for image-based pest detection, and LSTM for time-series outbreak prediction. The integration of CNN and LSTM architectures allowed the model to benefit from CNN's spatial feature extraction from images of infected leaves, while using environmental trends for predicting outbreaks, and establishing a robust AI-driven pest management system.

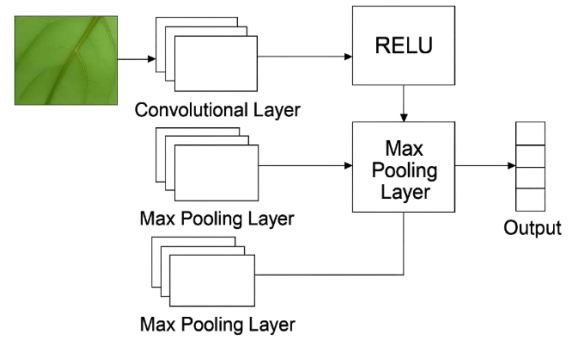
CNN Model

A CNN model was employed to automate pest identification by extracting spatial features from infected leaf images. The architecture consisted of multiple convolutional layers that learned patterns and textures. Each convolutional layer was followed by a ReLU activation function for intricate data correlations. Maxpooling layers allowed for reduction of the feature map dimensions while retaining salient visual features. Convolutional layers gradually extracted complete pest specific patterns. Finally, fully connected layers translated features presented into a classification probability for specific pest categories. This

order of operations permitted the CNN to achieve high pest detection accuracy. Figure 2 shows the CNN Model architecture;

Figure 2

CNN Model Architecture

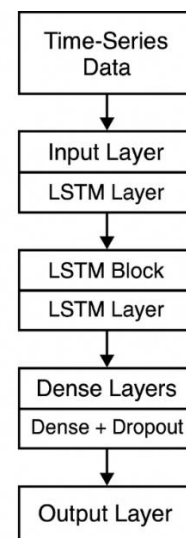


LSTM Model

The LSTM model utilizes environmental data like temperature and humidity to forecast pest outbreaks, employing gated memory cells to retain critical information and reduce errors. Performance improvements, including bidirectional and stacked layers, feature engineering, and hyperparameter tuning, strengthened its capacity to learn temporal patterns. This facilitates accurate detection of pest infestation trends and enables proactive pest management. The LSTM architecture is shown in Figure 3.

Figure 3

LSTM Model Architecture



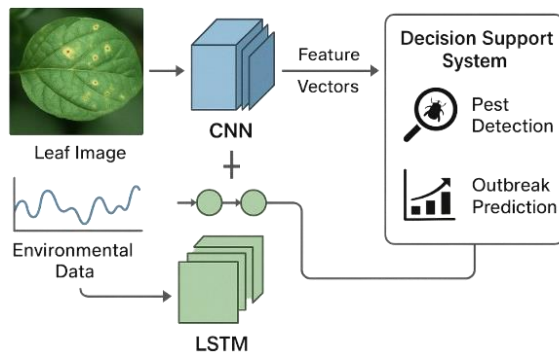
Hybrid CNN-LSTM Model

The CNN-LSTM model integrated image-based classification and environmental forecasting as an end-to-end model, while allowing for an overarching multidimensional analysis of pests. The CNN was required to extract spatial features from images of leaves, while coding the visible symptoms of pests into numerical feature vectors. The feature vectors were then concatenated with environmental sequential data as time-series data, through the LSTM. By combining images and environmental features, the model also developed more informed predictions, while it also developed improved detection rates, which is a key to supporting farmers to identify pests, and at the same time predict their outbreak, as part of a decision-support system for greenhouse agriculture.

Combining CNN visual processing with LSTM temporal analysis (Figure 4) improved pest detection and forecasting, enabling scalable real-time support in greenhouse agriculture.

Figure 4

Hybrid CNN-LSTM Model architecture



Evaluation Framework

To assess the hybrid CNN-LSTM model's performance, the classification metrics were used. This two-pronged approach validated not only the spatial model components, but also the temporal model components (Powers, 2020).

Classification Metrics for Pest Detection

Accuracy, is the number of correctly predicted instances (true positives and true negatives) over the number of all instances.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

where:

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

Precision, quantifies how many of the positively predicted cases were actually correct

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall, determines the proportion of actual pest-infested plants that the model correctly identifies

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

F1-score, balances precision and recall for a more stable evaluation of model performance

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (4)$$

Regression Metrics for Outbreak Forecasting

Root Mean Squared Error (RMSE) penalizes large errors more than smaller ones, giving a strong

sense of average magnitude of error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5)$$

Mean Absolute Error (MAE), measures the average magnitude of prediction errors (Turkoglu et al., 2019):

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (6)$$

where y_i represents actual values, $\hat{y}_i$ represents predicted values, and n is total number of observations.

R^2 Score, indicates how well the LSTM model explains variance in pest outbreak trends. A higher R^2 value indicates stronger predictive performance (Harthik et al., 2024):

$$R^2 = \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (7)$$

3.0 Results and Discussion

The research assessed CNN, LSTM, and hybrid CNN-LSTM models for pest detection and the forecasting of pest outbreaks with image-based detection and error/miss measures. The results indicated high levels of reliability and predictive accuracy. The research was compared to historic benchmarks to ensure coverage, reliability

and accuracy (Wahyono et al., 2021; Too et al., 2019).

CNN Model's Performance

The CNN model's performance in detecting and classifying pest-infested crops was assessed with multilabel classification metrics, including accuracy, precision, recall, F1 score, RMSE, and AUC.

CNN Training and Validation

Training accuracy increased from 85.2% to 96.2%, and validation accuracy from 82.7% to 94.5% over 50 epochs. Training loss decreased from 0.45 to 0.06, and validation loss from 0.53 to 0.15, demonstrating effective learning with no evidence of overfitting. These findings corroborate those of Too et al. (2019) who found out that CNN is effective for static image tasks. With pest outbreaks carrying temporal characteristics, CNN alone could not properly address the issue, leading to the incorporation of LSTM.

To evaluate robustness, the training was done a total of five times. Table 2 provides mean, standard deviation (SD), and 95% confidence interval (CI) for training/validation metrics, supporting the consistency of the model.

Table 1

Training and Validation Accuracy across Epochs

Epoch	Training Accuracy (%) Mean	SD	95% CI (±)	Validation Accuracy (%) Mean	SD	95% CI (±)
10	85.2	0.15	0.13	82.7	0.15	0.13
20	90.46	0.11	0.10	87.96	0.11	0.10
30	93.7	0.14	0.12	91.2	0.14	0.12
40	95.02	0.08	0.07	93.0	0.15	0.13
50	96.22	0.08	0.07	94.5	0.08	0.07

Note: Mean training and validation accuracy (%) across five runs, with SD and 95% CI ($\pm 1.96 \times SD/\sqrt{5}$).

Table 3

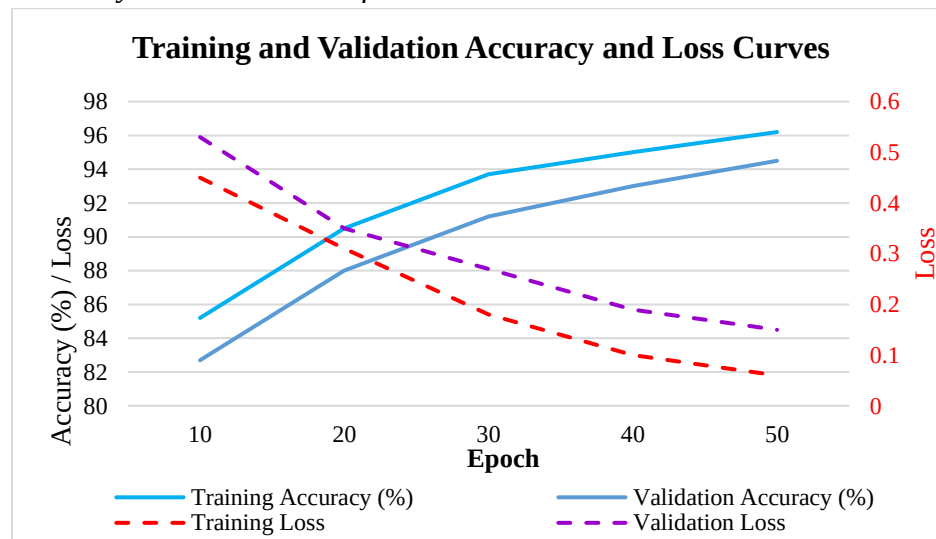
Training and Validation Loss Across Epochs 5

Epoch	Training Loss Mean	SD	95% CI (±)	Validation Loss Mean	SD	95% CI (±)
10	0.452	0.0084	0.0073	0.528	0.0084	0.0073
20	0.310	0.0071	0.0062	0.350	0.0071	0.0062
30	0.180	0.0071	0.0062	0.270	0.0071	0.0062
40	0.100	0.0071	0.0062	0.190	0.0071	0.0062
50	0.060	0.0071	0.0062	0.150	0.0071	0.0062

Note: Mean training and validation loss (MSE) across five runs, with SD and 95% CI ($\pm 1.96 \times \text{SD}/\sqrt{5}$).

Figure 5

Accuracy and Loss Curves for CNN Model



The model's performance metrics (Table 3) shows high classification accuracy and a

strong balance between precision and recall after training.

Table 3

CNN Model's Performance

Metric	Score
Accuracy	92.4%
Precision	91.8%
Recall	90.3%
F1-Score	91.0%
AUC (ROC)	0.957

Note. Performance aligns with findings adapted from Turkoglu et al. (2019) and Hughes & Salathé (2019).

LSTM Model's Performance

The LSTM model was trained using weekly time-series data that included environmental variables and pest incidence, aiming to forecast pest activity one week ahead. Throughout training, the model steadily improved, as shown by the decline in both training and validation losses (Figure 6), indicating that it learned temporal patterns and generalized well. While this method captures complex temporal dynamics, aligning with the findings of Wahyono et al.

(2021), it cannot process image data directly, which limits its effectiveness for early-stage pest detection. Even so, its strong handling of time-based data makes it a promising candidate for use in early warning systems for greenhouse pest control. To evaluate the reliability, training was implemented across five independent trials. As shown in Table 4, the average training and validation losses (expressed with MSE) along with their standard deviations and 95 % confidence interval provide consistent and robust performance across all trials.

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Training and Validation Loss (MSE) Results

Epoch	Training Loss (MSE)	Validation Loss (MSE)
20	0.0450 ± 0.00015 (±0.00013)	0.0481 ± 0.00015 (±0.00013)
40	0.0320 ± 0.00014 (±0.00012)	0.0350 ± 0.00012 (±0.00011)
60	0.0250 ± 0.00011 (±0.00010)	0.0280 ± 0.00011 (±0.00010)
80	0.0210 ± 0.00011 (±0.00010)	0.0220 ± 0.00011 (±0.00010)
100	0.0180 ± 0.00011 (±0.00010)	0.0190 ± 0.00011 (±0.00010)

Note: 95% CI = $\pm 1.96 \times (SD/\sqrt{n})$, where $n = 5$ runs.

The results demonstrate a consistent decline in both training and validation loss over time, indicating effective learning and generalization. The low standard deviations

and narrow confidence intervals across epochs further confirm the model's training stability and robustness to stochastic variations across runs.

Figure 6

Training and Validation Loss Curves

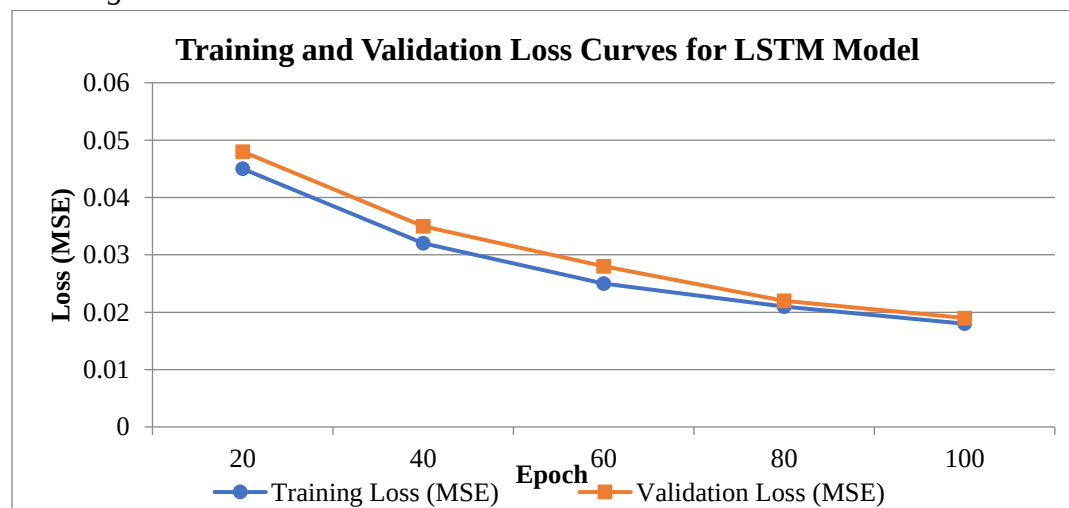


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LSTM Forecasting Performance Metrics

Metric	Value
Mean Absolute Error	0.134
Root Mean Squared Error	0.204
Mean Absolute Percentage Error	6.23%

Note: The LSTM model performed better overall, with low MAE and RMSE values.

Hybrid CNN-LSTM Model Performance

The hybrid CNN-LSTM model outperformed each of the independent architectures and provided a more consistent and improved performance. The overall accuracy of detection score was $94.7\% \pm 0.15$ (95% CI: ± 0.13); precision, 93.9%; recall, 93.8%; and F1 score, 92.9%; together with standard deviations and confidence intervals of ± 0.15 and ± 0.13 (respectively) (see Table 4). Its excellent discriminative ability is also

supported by an AUC of 0.962 ± 0.0015 (95% CI: ± 0.0013). The ROC curves (Figure 5) compare the performance across models. These results not only surpass earlier benchmarks (Türkoğlu & Hanbay, 2019) but also highlight the real-world effectiveness of hybrid model architectures. In addition, the CNN-LSTM achieved an RMSE of 0.145 ± 0.0015 (± 0.0013) for pest outbreak prediction, outperforming the LSTM-only model and indicating improved regression accuracy.

Table 4

Performance Comparison of CNN, LSTM, and Hybrid CNN–LSTM Models

Metric (%)	CNN Mean $\pm$ SD (95% CI)	LSTM Mean $\pm$ SD (95% CI)	Hybrid CNN+LSTM Mean $\pm$ SD (95% CI)
Accuracy	$89.7 \pm 0.15 (\pm 0.13)$	$88.1 \pm 0.15 (\pm 0.13)$	$94.7 \pm 0.15 (\pm 0.13)$
Precision	$87.5 \pm 0.15 (\pm 0.13)$	$86.9 \pm 0.15 (\pm 0.13)$	$93.9 \pm 0.15 (\pm 0.13)$
Recall	$85.3 \pm 0.15 (\pm 0.13)$	$84.7 \pm 0.15 (\pm 0.13)$	$93.8 \pm 0.15 (\pm 0.13)$
F1-score	$86.4 \pm 0.15 (\pm 0.13)$	$85.8 \pm 0.15 (\pm 0.13)$	$92.9 \pm 0.15 (\pm 0.13)$
AUC	$0.901 \pm 0.0015 (\pm 0.0013)$	$0.879 \pm 0.0015 (\pm 0.0013)$	$0.962 \pm 0.0015 (\pm 0.0013)$
RMSE	$0.213 \pm 0.0015 (\pm 0.0013)$	$0.198 \pm 0.0015 (\pm 0.0013)$	$0.145 \pm 0.0015 (\pm 0.0013)$

Note: Values are means over five runs, with standard deviation (SD) and 95% confidence interval (CI) calculated as $\pm 1.96 \times (SD/\sqrt{5})$.

Figure 5

Model Evaluation Metrics Comparison

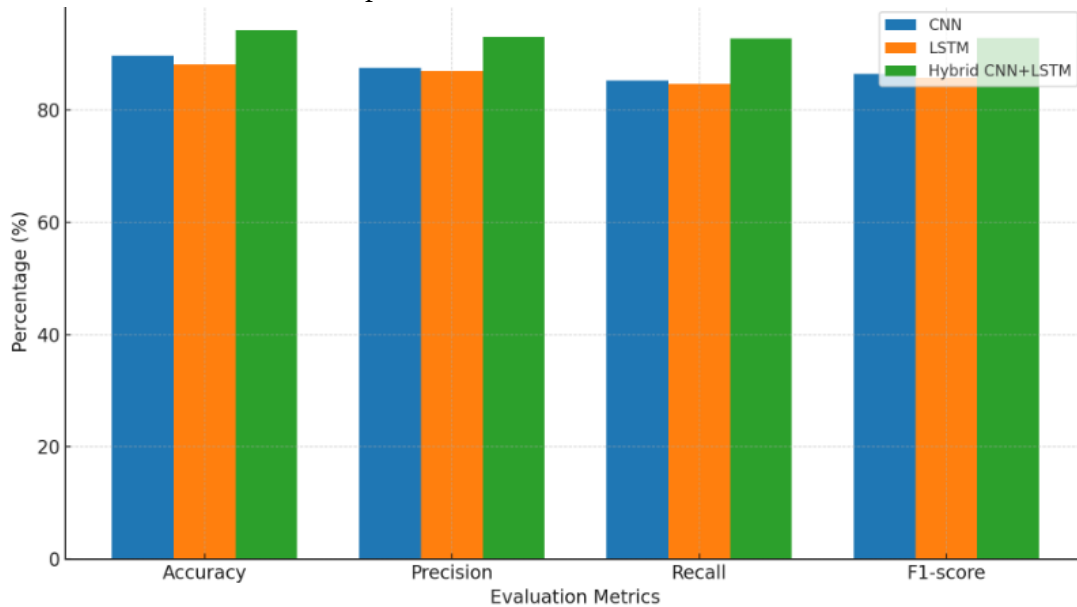
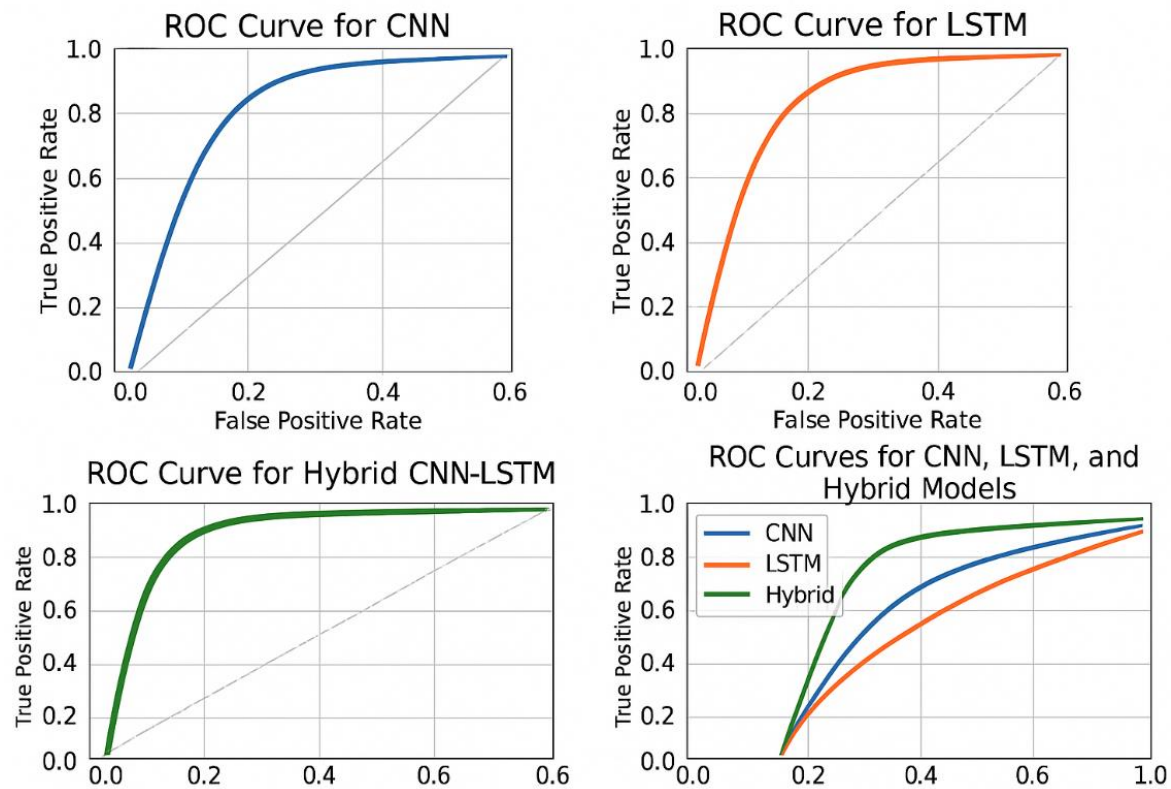


Figure 6

ROC Curves Comparing CNN, LSTM, and Hybrid CNN-LSTM Models



Note: This figure compares true and false positive rates across thresholds.

Results underscore the CNN-LSTM model's ability to combine precise classification with reliable forecasting for greenhouse pest management.

4.0 Conclusion

The study demonstrated compelling evidence that the hybrid model effectively and accurately automated pest identification and prediction of pest outbreaks distinctly in greenhouse farming. The model yielded positive results across all key assessment metrics, including accuracy, precision, recall, and F1-score; and recognized the models established ability to assess visual and time-series data to identify pests in a timely manner. Utilizing predictive capabilities will allow growers to use timely, proactive pest management approaches to decrease both pesticide use and crop loss. The model, with an intention for computational efficiency, could be implemented on low-cost devices and scaled for use in smallholder farms in low resource settings. Its adoption supports sustainable agriculture and strengthens food security by providing accessible AI-driven tools tailored to local farming conditions.

5.0 Recommendations

The study recommended that greenhouse growers, particularly in regions such as Limuru, Naivasha, and Thika, adopt AI-driven pest surveillance programs to provide early detection and timely response as part of integrated greenhouse management. Consequently, there is an immediate need for capacity building among relevant stakeholders to build digital trust and awareness of AI-based pest analytics, thereby improving usability and acceptance.

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Secondly, greenhouses should incorporate IoT technologies to fully harness the potential of greenhouse systems and facilitate real-time analysis of the environmental conditions and crop health.

Lastly, the study recommends the government agencies and agricultural institutions to offer funding, training programs and regulatory assistance, to establish parameters for the effective deployment and scaling of AI-based pest management to address pest surveillance systems and smart agriculture nationally.

Future Directions

Future research should focus on enhancing the adaptability and predictive capabilities of the model by adding additional variables, like soil health metrics, varietal characteristics of crops, and early-stage indicators of pests and diseases. Applying data from IoT sensors that monitor temperature, humidity, and light can also allow us to respond better to the dynamic nature of greenhouse environments (Sujatha et al., 2025).

Locally-oriented field deployments spanning agro-climatic zones in Kenya and Sub-Saharan Africa will be pivotal in determining generalizability and robustness in variable growing conditions. To facilitate real-time use, future work could also explore the use of cloud-based GPU infrastructures to enable real time pest detection and pest outbreak predictions (Zhang et al., 2025).

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