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Development of An Optimized Deep Learning Technique for Tomato Leaf Diseases Recognition

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ABSTRACT

Tomatoes are among the most widely cultivated and consumed vegetables globally, valued for their rich nutritional content and versatility in culinary applications. However, tomatoes are bedevilled with diseases and pests that wipe out approximately half of farmers' harvests every year. Recent advancements in deep learning provide promising solutions for automating disease recognition; however, challenges still persist in achieving high accuracy and hyperparameter tuning. Hence, this research optimized Convolutional Neural Network (CNN) with Hippopotamus Optimizer (HO) for Tomato Leaf Diseases Recognition. Four thousand five hundred and thirty-six (4536) images of tomato leaf were downloaded from kaggle.com. The acquired images were grouped into four (4) classes: bacterial spot, early blight, leaf mould, and healthy leaves. The images were preprocessed by cropping to remove unwanted elements, converting to gray-scale for colour complexity reduction, normalizing and filtering to reduce noise. An optimized Convolutional Neural Network (CNN) using Hippopotamus Optimizer (HO), (HO-CNN) was developed. The HO-CNN was employed to select optimal values of number of neurons and dropout rates for CNN hyperparameters; The HO-CNN was implemented using MATLAB R(2023a). The evaluation metrics used were False Positive Rate (FPR), Specificity (Spec), Sensitivity (Sen), Precision (Pre), Accuracy (Acc), and Recognition Time (RT), and the HO-CNN was compared with the traditional CNN. The FPR, Spec, Sen, Pre, Acc, and RT for HO-CNN were 2.59%, 97.41%, 95.11%, 95.67%, 96.55% and 38.16 s respectively. The corresponding values for CNN were 5.29%, 94.71%, 90.61%, 91.14%, 93.17% and 81.66 s, respectively. A Hippopotamus optimized-Convolutional Neural Network (HO-CNN) improves tomato leaf disease recognition accuracy by about 3.6%, reduces false detections by approximately 51%, and decreases recognition time by nearly 53% compared to the traditional CNN. The HO-CNN developed can be applied for tomato leaf disease recognition in real world agricultural development.

INTRODUCTION

Tomatoes are among the most consumed crops worldwide, valued for their nutritional and economic importance, and beneficial in preventing diseases, gingival bleeding, hypertension, and hepatitis, due to their pharmacological and anti-cancer properties (Mohamed *et al*, 2022). Statistically, almost 80.00% of agricultural output in Asia and Sub-Saharan Africa is attributed to small farmers (Kaushik and Saini, 2019). However, diseases and pests wipe out approximately half of these farmers' harvests every year. It is essential to diagnose these diseases for effective management and control (Kumar *et al.,* 2019; Ola *et al.,* 2020). Research into field crop disease detection is essential because the diseases and insects that parasitize tomatoes have a significant effect on its growth. Deep learning models are necessary to achieve this. Notwithstanding its achievements, deep learning models frequently encounter difficulties that can restrict their performance and capacity for generalization, such as overfitting, high computational cost, and sensitivity to hyperparameter selection (Oguntoye *et al*., 2023; Olagunju et al., 2025). The large parameter space and the challenge of striking a balance between model complexity and performance are the causes of these problems (Adetunji *et al*, 2018; Belkin *et al*, 2019). This work addressed the problem by introducing a Hippopotamus Optimized CNN (HO-CNN) for enhanced tomato disease recognition. Hippopotamus Optimizer was preferred in this work because it is especially well-suited for fine-tuning since it is excellent at avoiding local minima, guaranteeing the global optimization of the model's parameters, and effectively managing high-dimensional search spaces.

RELATED WORKS

Plant disease detection using deep learning has advanced significantly. Nandhini and Ashokkumar (2021) presented an improved crossover-based Monarch Butterfly Optimization (ICMBO) algorithm for enhancing tomato leaf disease classification using Convolutional Neural Networks (CNNs). The dataset consists of tomato leaf images, sourced from PlantVillage dataset, covering multiple diseases (typically around 10 common infections, bacterial spot, early blight, and late blight). The ICMBO algorithm optimizes CNN parameters to improve classification accuracy. The model is evaluated using accuracy, precision, recall, and F1-score, achieving a high classification rate of 90%. However, areas for improvement include better generalization to real-field conditions, addressing class imbalance, and reducing computational overhead for efficient deployment in resource-constrained environments like mobile and IoT-based agricultural systems. Tarek *et al.,* (2022) explored the use of optimizing deep learning algorithms for tomato leaf disease detection in smart agriculture. The Plant Village, consisting of sixteen thousand (16,000) images categorized into 1 healthy class and 9 disease classes, including bacterial spot disease, early blight disease, late blight disease, yellow leaf curl virus, and others. Deep learning techniques, InceptionV3, ResNet50, and MobileNetV3 were employed to classify these diseases. The evaluation metrics included accuracy and loss values, with MobileNetV3 Large achieving the highest accuracy of 99.81% and a loss of 0.0088, demonstrating the effectiveness of the optimized deep learning models in disease detection. One aspect that could be improved upon is the dataset size, as the study mentioned, there is potential for overfitting. Chilakalapudi and Jayachandran (2024) focused on the automatic detection of plant leaf diseases using an optimized deep learning network. It utilizes dataset of leaf images to identify multiple diseases, although the exact number of diseases was not specified. The technique employed an optimized deep learning model for segmentation and recognition of disease symptoms. The evaluation metrics achieved include a maximum testing accuracy of 94.69%, sensitivity of 95.58%, and specificity of 92.90%. Improvement may involve expanding the dataset to encompass a wider variety of plant species and disease types, strengthening the model's consistency and generalization.

METHODOLOGY

The development of an Optimized Deep Learning Techniques (ODLT) for Tomato Leaf Diseases Recognition (TLDR) was achieved in the following stages: acquisition of tomato leaf images, as shown in Figure 1, The next stage was preprocessing, images were cropped to remove background regions and irrelevant objects from the tomato leaf images, conversion of the images to gray-scale for simplified image processing by reducing colour complexity; image normalization was carried out to improve data consistency and reduce redundancy in databases, and filtering to reduce noise. After preprocessing, the dataset was used to train and test the development of optimized Convolutional Neural Network (CNN) using Hippopotamus Optimizer (HO) to ensure accurate detection and classification of the diseases. The system was implemented using Matlab R(2023a), where the HO-CNN technique was integrated into a user-friendly platform that enabled automated detection and classification of tomato leaf diseases by analyzing images in real-time. The final system was evaluated based on false positive rate, specificity, sensitivity, precision, accuracy, and recognition time, ensuring its effectiveness and efficiency in tomato disease recognition.

Acquisition of Tomato Leaf Images

Tomato leaf images were downloaded from an online dataset, kaggle.com, which includes images of leaves captured under controlled or field conditions.. There are four thousand five hundred and thirty six (4536) images of tomato leaf in the dataset, the acquired images from kaggle.com were grouped into four (4) classes of tomato leaf, bacterial spot (1702 images as Bacterial), early blight (800 images as Fungi), leaf mold (761 images as Fungi) and healthy (1273 images) leaves, 70% of the dataset were allocated for training, while the remaining 30% for testing.

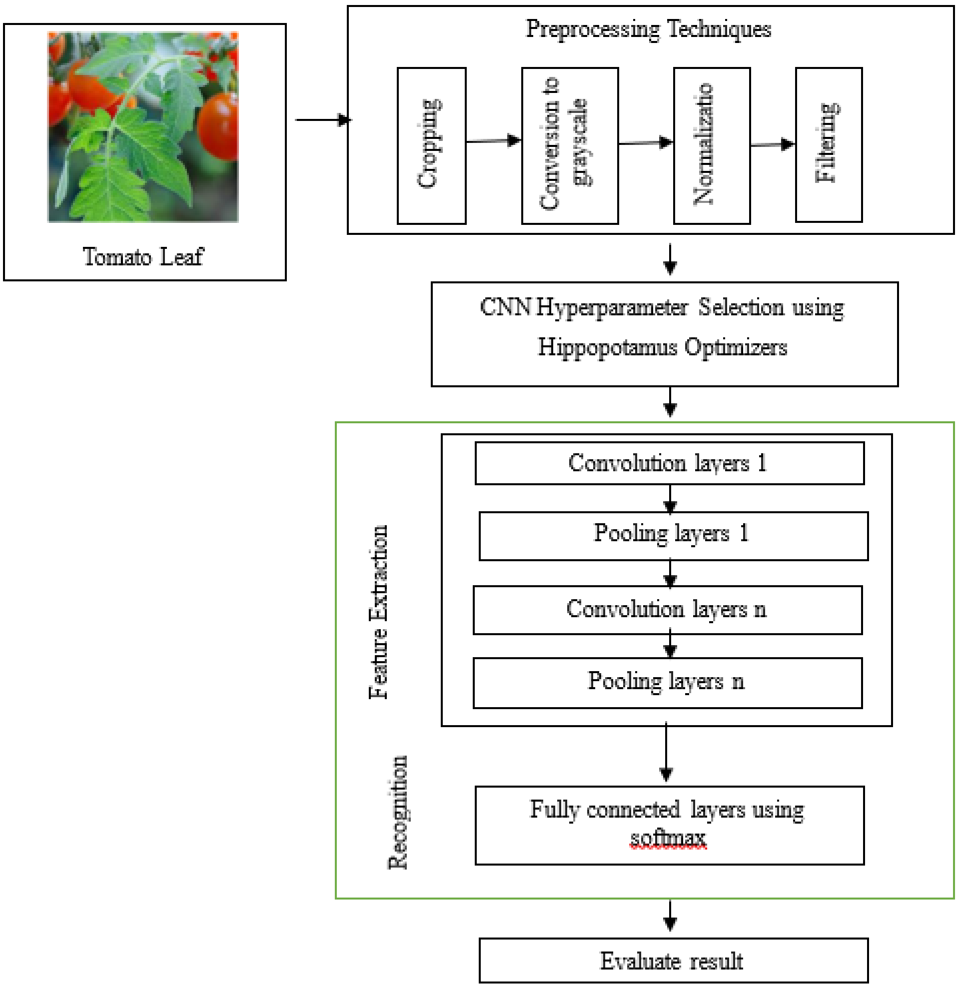

Figure 1: Tomatoes Disease Recognition System

Subsampling cross-validation was applied to ensure consistency in training and testing. This approach helps in reducing model overfitting and ensures consistent performance across different subsets of data. Figure 2 shows some sample acquired images of tomato leaves.

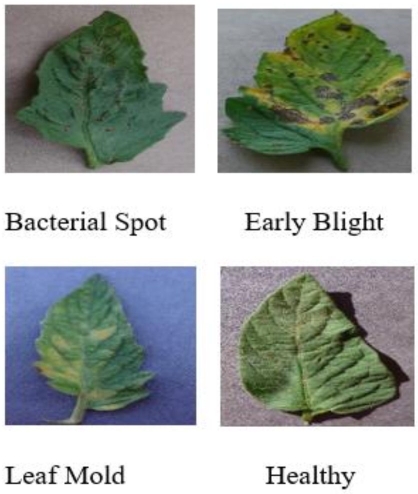

Figure 2: Sample Acquired Images of Tomato Leaves

Preprocessing of Tomato Leaf Images

Image preprocessing has to do with actions these are; image brightness, contrast alteration, image scaling, filtering, cropping and other operations that help in the enhancement of images. In this phase, preprocessing was carried out by cropping to remove unwanted elements from the tomato leaf images, conversion of the images to gray-scale for simplified image processing by reducing colour complexity, making it easier to identify key features within an image, normalization of images was carried out to improve data consistency and reduce redundancy in databases, and filtering to reduce noise.

Development of Hippopotamus Optimized Convolutional Neural Network Technique

This study developed the Hippopotamus Optimized Convolutional Neural Network (HO-CNN) technique for tomato disease recognition. The algorithm commenced by initializing key CNN hyperparameters, these are: the number of neurons and dropout rates in the fully connected layers, which form the initial population space (Atanda et al., 2023). The maximum number of iterations (T) and the number of HO-CNN hyperparameters were defined to ensure a structured optimization process. Using the position formula as described in Algorithm 1, the initial positions of the two (2) HO-CNN hyperparameters were generated, ensuring diverse candidate solutions. The objective function evaluates these initial positions to identify the dominant HO-CNN hyperparameters based on its performance in recognizing tomato diseases.

The optimization process comprises three phases, starting with the "Exploration Phase" (Oguntoye et al., 2025). During this phase, the position of the top half of the HO-CNN was updated as described in Algorithm 1 to incorporate the dominant hippopotamus influence, which ensures a balance between global exploration and fine-tuning of solutions. In the exploration phase, X_i^{Mhippo} represents the male hippopotamus position, Dhippo denotes the dominant hippopotamus position, the hippopotamus that has the best cost in the current iteration. I_1 and I_2 are integers between 1 and 2. MG_i refers to the mean values of some randomly selected hippopotamus with an equal probability of including the current considered hippopotamus (X_i) and $y1$ is a random number between 0 and 1. $X_i^{FBhippo}$ describes the female or immature hippopotamus position within the herd and Fi is the objective function value. Also, T denotes the current iteration. Position updates are selectively applied based on the comparison of fitness values, ensuring only better solutions are retained. The algorithm iteratively refines the positions of the HO-CNN to enhance their ability to identify disease patterns.

In the second phase, the defence against predators introduces a predator dynamism to simulate additional exploration and a random predator position was generated. The position challenges the HO-CNN, encouraging it to explore diverse regions of the solution space. The HO-CNN update their positions accordingly, using adaptive mechanisms to escape predators when its fitness value is superior to the predators. $\vec{r}$ represents a random vector ranging from zero to one. This phase ensures the avoidance of local optima by introducing randomness and dynamic threats, critical for robust model optimization.

Algorithm 1: Hippopotamus Optimised-Convolutional Neural Network Technique

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INPUT: Input CNN hyperparameters, these are the number of neurons and dropout rates (at Fully Connected Layer)
CNN hyperparameters form the population space
set the maximum number of iterations (*T*) and the number of HO-CNN (*N*)
Generate the initial position of all HO-CNNs based on

$$X_i : x_{ij} = lb_j + r.\left(ub_j - lb_j\right), \quad i = 1, 2, \dots, N, \quad j = 1, 2, \dots, m$$

and objective function evaluation for this initial population
For *i*:1:*T*.
Update the dominant HO-CNN position based on the objective function value criterion
Phase 1: The HO-CNNs position update in the river or pond (Exploration phase)
For *i* = 1: N/2.
Calculate the new position for HO-CNN using

$$X_i^{Mhippo}: x_i^{Mhippo} = x_{ij} + y1.\left(Dhippo - I_1 x_{ij}\right)$$

$$for\ i = 1, 2, \dots, \left[\frac{N}{2}\right]\ and\ j = 1, 2, \dots, m$$

$$X_i^{FBhippo} : x_{ij}^{FBhippo} = \{x_{ij} + h_1.(Dhippo -. I_2 MG_i)T > 0.6$$

Update position of ith HO-CNN using

$$x_i = \{x_i^{Mhippo} F_i^{Mhippo} < F\ x_i \qquad else$$

$$x_i = \{x_i^{FBhippo} F_i^{FBhippo} < F\ x_i \qquad else$$

End for
End for
Phase 2: HO-CNN defense against predators (Exploration phase)
For *i* = 1 + *N/2: N*
Generate random position for predator using

$$Predator : Predator_j = lb_j + \vec{r}\left(ub_j - lb_j\right), \quad j = 1, 2, \dots m$$

Calculate the new position for *i*th HO-CNN using

$$X_i^{HippoR}: X_{ij}^{HippoR} = \begin{cases} \overrightarrow{RL} \oplus Predator_j, + \left(\frac{f}{\left(\sigma - d \times cos(2\pi g)\right)}\right) . \left(\frac{1}{\vec{D}}\right) F_{Predator_j} < F_i \\ \overrightarrow{RL} \oplus Predator_j, + \left(\frac{f}{\left(\sigma - d \times cos(2\pi g)\right)}\right) . \left(\frac{1}{2 \times \vec{D} + \vec{r}}\right) F_{Predatorj} \geq F_i \end{cases}$$

$$for\ i = \left[\frac{N}{2}\right] + 1, \left[\frac{N}{2}\right] + 2, \dots, N\ and\ j = 1, 2, \dots, m$$

Update the position of ith HO-CNN using

$$x_i = \{x_i^{HippoR} F_i^{HippoR} < F_i\ x_i F_i^{HippoR} \geq F_i$$

End for
End for
Phase 3: HO-CNN escaping from the predator (exploitation phase)
Calculate new bounds of variables decision using

$$lb_j^{local} = \frac{lb_j}{t}, ub_j^{local} = \frac{ub_j}{t},\ t = 1, 2, \dots, T$$

For *i* = 1: *N*
Calculate the new position for ith HO-CNN using

$X_i^{Hippo\mathcal{E}}: X_{ij}^{Hippo\mathcal{E}} = x_{ij} + r \quad \left(lb_j^{local} + s1\left(ub_j^{local} - lb_j^{local}\right)\right)$

Update the position of ith HO-CNN using

$X_i = \{ \ X_i^{Hippo\mathcal{E}} F_i^{Hippo\mathcal{E}} < F_i \, X_i F_i^{Hippo\mathcal{E}} \geq F_i$

End for

Save the best candidate solution found so far

End for

OUTPUT: Output the best (number of neurons and dropout rate) of the objective function found by HO

Implementation of the Developed Technique for Tomatoes Disease Recognition using image datasets

The process started by loading the dataset of tomato leaf images for training, which was subjected to preprocessing to enhance the input quality. The tomato leaf images were converted into grayscale, and histogram equalization was applied to improve contrast and highlight essential features for disease recognition (Ogundepo *et al.,* 2022). The preprocessed images were saved and fed into the Hippopotamus Optimised-Convolutional Neural Network (HO-CNN) model. The Hippopotamus optimizer played a pivotal role here, dynamically selecting critical CNN hyperparameters, these are the number of neurons and dropout rate. These optimized parameters ensured an effective balance between the model's learning capacity and its resistance to overfitting during the training process. In the testing phase, tomato leaf images were loaded and preprocessed similarly to maintain consistency. These processed images passed through the trained HO-CNN model, which applied the selected hyperparameters to perform feature extraction and disease classification. The Hippopotamus optimization ensured that the CNN efficiently extracts features from the image dataset, accurately recognizing patterns corresponding to various tomato leaf diseases. The recognition results presented enabling the system to identify whether the input image shows a diseased or healthy for tomato leaf. The optimized approach significantly improved the model's performance in terms of precision, accuracy, and recognition time.

The overall system integrated training and testing to form a complete recognition pipeline for tomato leaf diseases. After obtaining the recognition results, the model allowed testing of another image or terminating the process. This iterative framework was implemented to allow continuous validation with new input. The Hippopotamus Optimization was used to adjust the CNN for the diverse image dataset, which contributed to improved recognition accuracy. This approach helped simplify the recognition and identification of tomato leaf diseases and also lower computational costs by guiding the selection of hyperparameters. An interactive Graphical User Interface (GUI) application was developed in MATLAB R2023a using the Image Processing, Deep Learning, and Optimization toolboxes.

Performance Evaluation of the Technique

The technique was evaluated using the following metrics: False Positive Rate, Specificity, Sensitivity, Precision, Accuracy, and Recognition Time. The technique was also compared with the conventional CNN using these metrics.

False Positive Rate (FPR): FPR measures the proportion of healthy (non-diseased) tomato images incorrectly classified as diseased. It is calculated as

$$FPR = \frac{False\ Positives}{False\ Positives + True\ Negatives} \times 100\% \quad (1)$$

Specificity: Specificity measures the model's ability to correctly identify healthy (non-diseased) tomatoes. It is calculated as:

$$Specificity = \frac{True\ Negatives}{True\ Negatives + False\ Positives} \times 100\% \quad (2)$$

Sensitivity (Recall): Sensitivity, or recall, represents the model's ability to correctly identify diseased tomato leaves. It is calculated as:

$$Sensitivity = \frac{True\ Positives}{True\ Positives + False\ Negatives} \times 100\% \quad (3)$$

Precision: Precision measures the proportion of correctly predicted positive cases out of all predicted positive cases. It is calculated as:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \times 100\% \quad (4)$$

Accuracy: Accuracy measures the overall correctness of the model in classifying both diseased and healthy images. It is calculated as:

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Samples} \times 100\% \quad (5)$$

Recognition Time: Recognition time measures the time taken to detect and classify a single tomato leaf image. In applications, the recognition time metric is essential for evaluating the model's speed and suitability for field deployment. $\boldsymbol{T_{recognition}}$ $(\boldsymbol{s})$: The time in seconds for end-to-end image processing.

$$T_{recognition}(s) = End\ time(s) - Start\ time(s) \quad (6)$$

Where True Positives (TP) represent correctly identified diseased regions.

True Negatives (TN) represent correctly identified healthy regions.

False Positives (FP) are regions incorrectly identified as diseased.

False Negatives (FN) are missed diseased regions.

RESULTS AND DISCUSSION

The preprocessing stage improved the quality of 4,536 tomato leaf images from the Kaggle dataset. Figure 3 shows a sample of preprocessed images which covers bacterial spot, early blight, leaf mould, and healthy classes. The process transformed raw images into segmented leaves, ensuring clearer features and reducing computational complexity for CNN analysis, as shown in Figure 4.

Result for design of HO-CNN

Figure 5 illustrates the developed tomato leaf disease classification system.

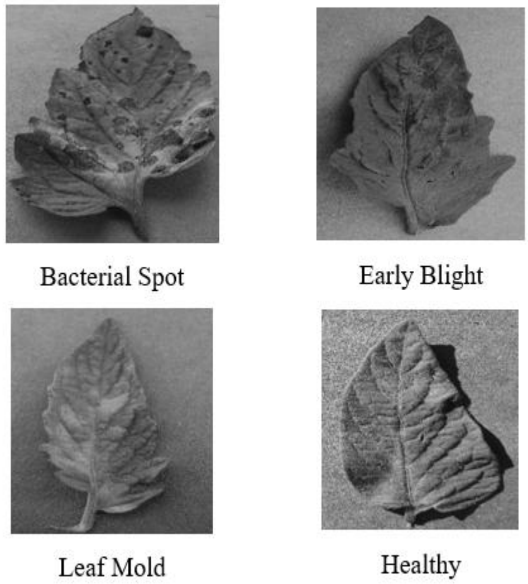

Figure 3: Grayscale Image for Tomatoes Leaves

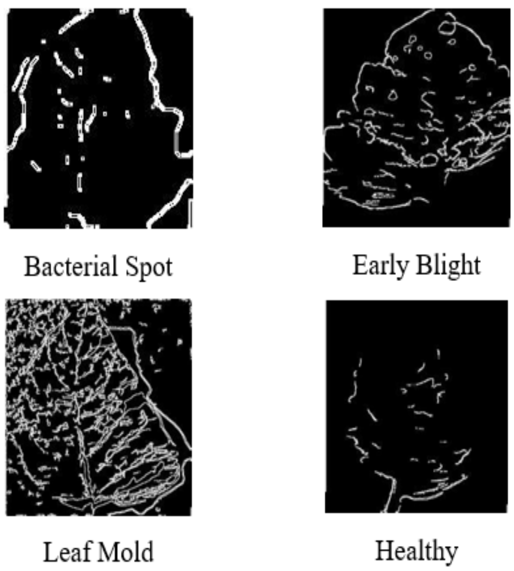

Figure 4. Segmented Image for Tomatoes Leaves

The design comprises dataset acquisition, image preprocessing, CNN feature extraction, HO Optimization, Classification, and Output Result. Image preprocessing enhances data quality, CNN extracts deep features, and HO optimization improves feature learning. The classification block assigns disease labels: Bacterial spot, Early blight, Leaf mold, and Healthy leaves, producing tomato leaf disease predictions with reduced recognition time and improved efficiency.

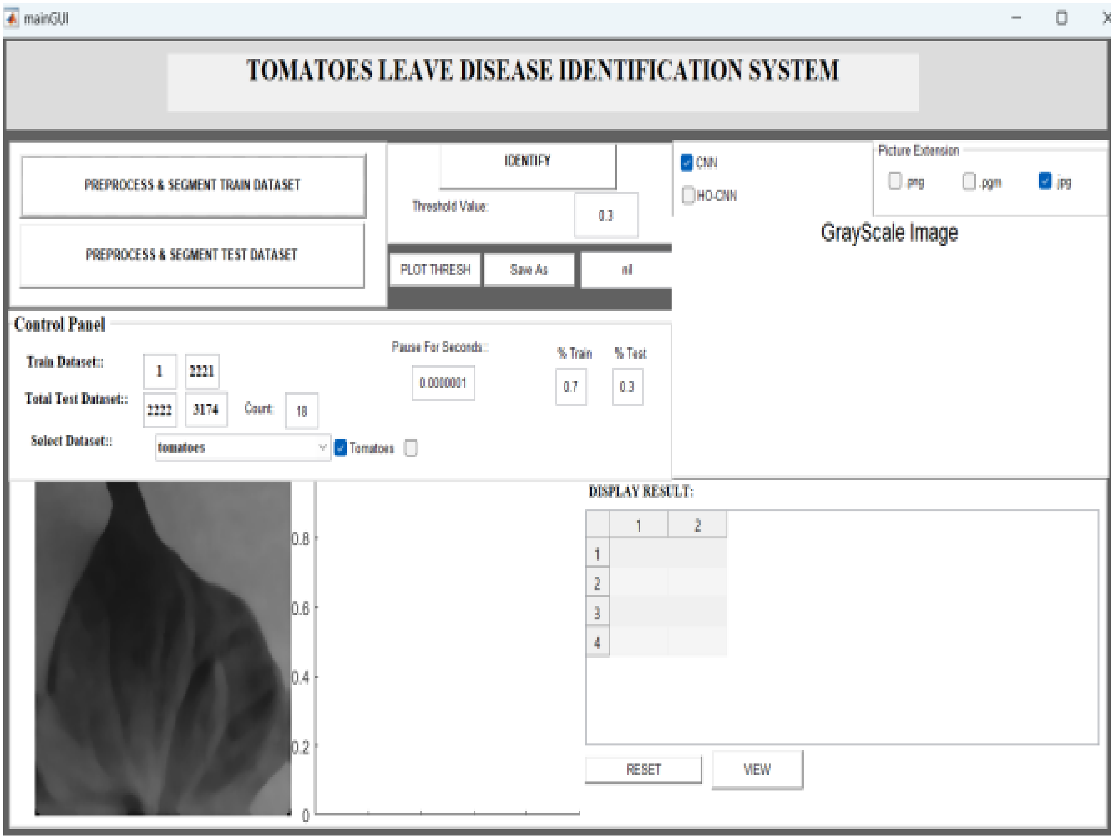

Figure 5: Training process with Tomatoes leaf diseases using CNN and HO-CNN

Evaluation of the Results

As summarized in Table 1, and Figure 6. Table 1 presents the four classes' performance of the developed technique for tomato leaf disease bacterial spot, Early blight, Leaf mold, and Healthy leaves evaluated using classification FPR, Spec, Sen, Pre, Acc, and RT under decision thresholds of 0.3, 0.4, 0.5, and 0.75. This threshold is chosen where high reliability is required to prevent incorrect disease identification. This four-class analysis confirms that lower thresholds of 0.3 and 0.4 improve disease detection sensitivity, while high thresholds of 0.5 and 0.75 enhance prediction reliability across all classes.

Comparison Results of Tomato Leaf Diseases at Optimum Threshold with HO-CNN and CNN

As summarized in Table 2, the comparative analysis of tomato leaf disease detection at the optimum threshold reveals that the Hippopotamus Optimization-based CNN (HO-CNN) consistently outperforms the standard CNN model across all disease classes. The HO-CNN outperformed the standard CNN across all evaluation metrics. It achieved higher classification accuracy and precision, lower FPR, and shorter recognition time. The optimization improved the CNN's convergence speed and prevented overfitting.

Table 1: Four Classes Performance Evaluation under Different Decision Threshold.

Class	Model	Threshold (%)	FPR (%)	SPEC (%)	SEN (%)	PRE (%)	ACC (%)	RT (sec)
Bacterial spot	HO-CNN vs CNN	0.3	3.53 vs 6.12	96.47 vs 93.88	95.69 vs 91.19	94.18 vs 92.87	38.23 vs 78.82	38.23 vs 78.82
		0.4	3.18 vs 5.88	96.82 vs 97.12	95.50 vs 91.00	96.33 vs 92.95	37.78 vs 81.24	37.78 vs 81.24
		0.5	2.82 vs 5.65	97.18 vs 94.35	95.30 vs 90.80	96.47 vs 93.02	38.36 vs 78.78	38.36 vs 78.78
		0.75	2.59 vs 5.29	97.41 vs 94.71	95.11 vs 90.61	96.55 vs 93.17	38.16 vs 81.66	38.16 vs 81.66
Early blight	HO-CNN vs CNN	0.3	2.77 vs 4.46	97.23 vs 95.54	90.42 vs 82.08	96.03 vs 93.17	32.34 vs 64.57	32.34 vs 64.57
		0.4	2.50 vs 4.28	97.50 vs 95.72	90.00 vs 81.67	96.18 vs 93.24	30.29 vs 65.45	30.29 vs 65.45
		0.5	2.23 vs 4.10	97.77 vs 95.90	89.58 vs 81.25	96.33 vs 93.31	30.74 vs 66.40	30.74 vs 66.40
		0.75	2.05 vs 3.87	97.95 vs 96.16	89.17 vs 80.83	96.40 vs 93.46	31.13 vs 64.34	31.13 vs 64.34
Leaf mold	HO-CNN vs CNN	0.3	2.38 vs 4.24	97.62 vs 95.76	88.13 vs 74.38	96.44 vs 93.12	39.88 vs 82.56	39.88 vs 82.56
		0.4	2.12 vs 4.06	97.88 vs 95.94	87.50 vs 73.75	96.60 vs 93.19	39.75 vs 83.01	39.75 vs 83.01
		0.5	1.85 vs 3.88	98.15 vs 96.12	86.88 vs 73.13	96.75 vs 93.27	40.13 vs 84.72	40.13 vs 84.72
		0.75	1.68 vs 3.62	98.32 vs 96.38	86.25 vs 72.50	96.83 vs 93.43	40.01 vs 82.50	40.01 vs 82.50
Healthy	HO-CNN vs CNN	0.3	2.54 vs 4.47	97.46 vs 95.53	94.17 vs 87.78	96.67 vs 93.67	43.83 vs 87.80	43.83 vs 87.80
		0.4	2.28 vs 4.30	97.72 vs 95.70	93.89 vs 87.50	96.80 vs 93.73	44.38 vs 88.57	44.38 vs 88.57
		0.5	2.02 vs 4.12	97.98 vs 95.88	93.61 vs 87.22	96.93 vs 93.80	44.24 vs 91.13	44.24 vs 91.13
		0.75	1.84 vs 3.86	98.16 vs 96.14	93.33 vs 83.94	97.00 vs 93. 93	44.27 vs 91.55	44.27 vs 91.55

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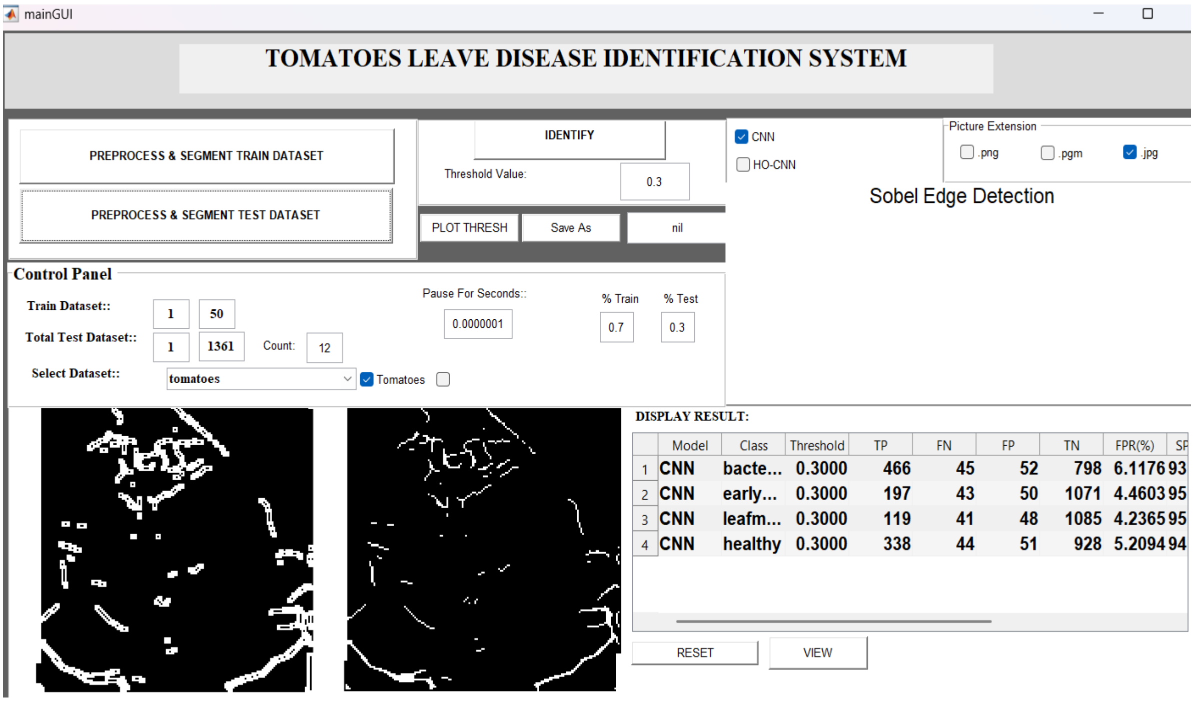
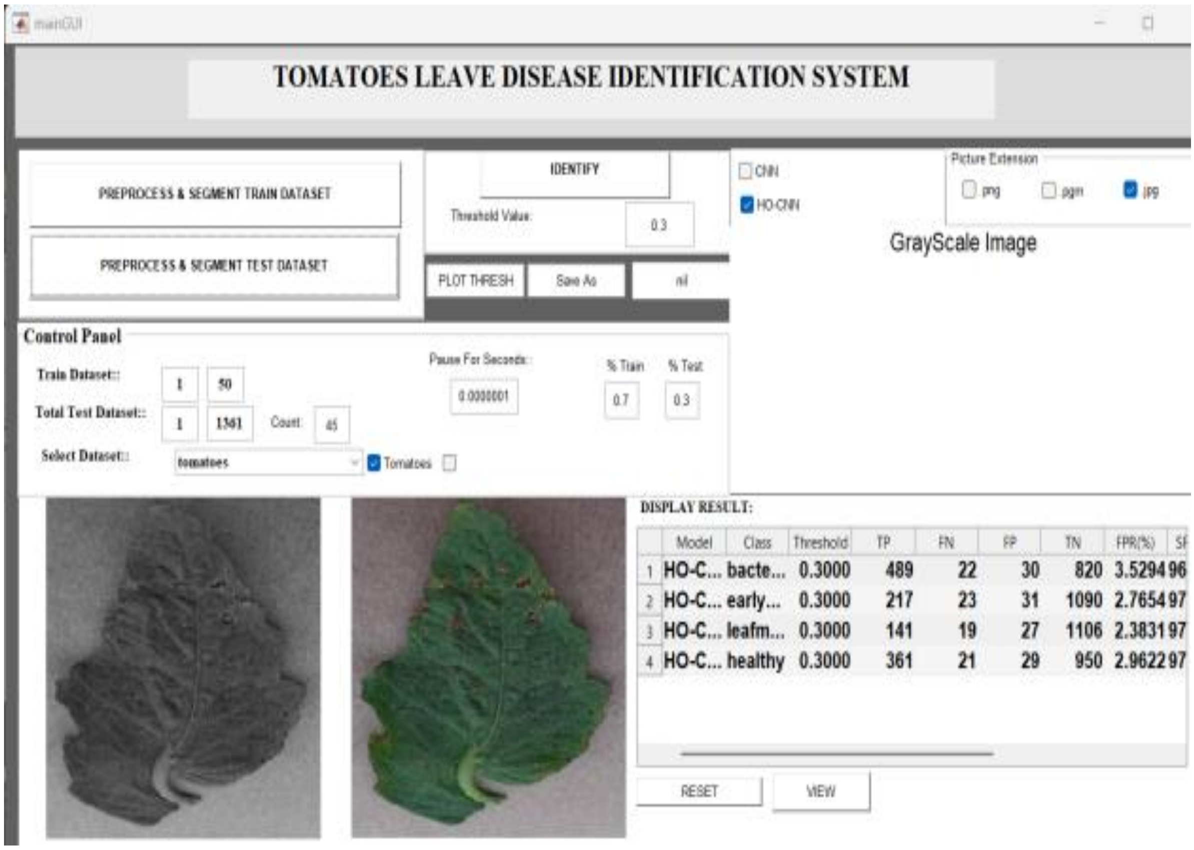


(a) Testing process with Tomatoes Diseases using CNN



(b) Testing process with Tomatoes Diseases using HO-CNN

Figure 6: Testing process with Tomatoes Disease using CNN and HO-CNN

Table 2: Performance Result between HO-CNN and CNN

Model	Class	FPR (%)	SPEC (%)	SEN (%)	PREC (%)	ACC (%)	Time (sec)
HO-CNN	Bacterial spot	2.59	97.41	95.11	95.67	96.55	38.16
CNN	Bacterial spot	5.29	94.71	90.61	91.14	93.17	81.66
HO-CNN	Early blight	2.05	97.95	89.17	90.30	96.40	31.13
CNN	Early blight	3.84	96.16	80.83	81.86	93.46	64.34
HO-CNN	Leaf mold	1.68	98.32	86.25	87.90	96.83	40.01
CNN	Leaf mold	3.62	96.38	72.50	73.89	93.43	82.50
HO-CNN	healthy	1.84	98.16	93.72	94.46	96.69	44.27
CNN	healthy	3.81	96.14	87.70	88.39	93.31	91.55
HO-CNN	Average	2.04	97.96	91.06	92.08	96.62	38.39
CNN	Average	4.14	95.85	82.91	83.82	93.34	80.01

The technique's performance indicates better adaptability to multiple tomato leaf disease classes and real-field conditions as shown in Figure 7.

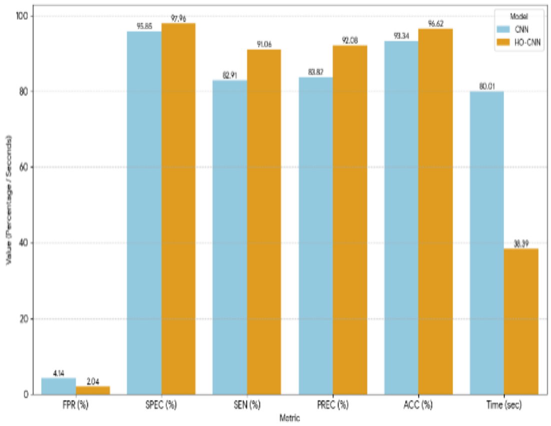


Figure 7: The Graph of Average Performance Result between HO-CNN and CNN

CONCLUSIONS AND RECOMMENDATION

The technique of Convolutional Neural Networks (CNN) and Hippopotamus Optimization CNN (HO-CNN) for tomato leaf disease recognition has demonstrated substantial improvements in classification performance. The conventional CNN showed moderate precision and accuracy. The HO-CNN not only provided better detection accuracy and precision but also achieved lower recognition time, indicating a more efficient and scalable technique. These improvements are particularly valuable in agricultural environments where timely and accurate disease detection can impact crop health and yield. It is recommended that the Agricultural technology developers and researchers should consider incorporating HO-CNN in intelligent crop monitoring systems to enhance early detection and disease management.

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