Deep Learning Approach for Disease Detection from Capsicum Leaf Images

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Abstract: *The primary objective of this studies is to locate diseases in capsicum plant leaves using a deep convolutional neural network (CNN). Plant disease pose a good sized danger in India and different Asian countries that rely closely on agriculture. Throughout the year, numerous diseases can critically harm crops, and lots of these infections are tough to become aware of with the bare eye. Therefore, growing an automatic machine able to accurately recognizing plant diseases is important. This examine proposes a deep learning knowledge of primarily based technique for disease identification from plant leaf images. The cautioned version employs a CNN to hit upon and classify diseases, and it's far trained on six awesome capsicum leaf disease categories. In addition, a CNN–LSTM architecture is evolved the use of the skilled model to further beautify detection capabilities. Beyond figuring out the disease, the model also offers treatment tips based on the recognized circumstance.*

Traditionally, farmers and agricultural experts depend on guide visible inspection, which is frequently time-ingesting and vulnerable to errors. The proposed deep learning framework offers an automated and reliable alternative. Experimental effects display that the model achieves 91.687% accuracy in distinguishing between healthful and diseased leaves and 96.987% accuracy in classifying precise diseases. The dataset used on this observe consists of 1,620 images, which includes 632 healthy and 988 diseased images, collected from actual field images in Ahilyanagar District, Maharashtra, India, in addition to the Mendeley & PlantVillage dataset. The dataset changed into originally divided into an 8:1:1 ratio for training, validation, and testing.

Keywords: Convolutional Neural Network (CNN), CNN + LSTM Hybrid Deep Learning Model, Deep Learning Techniques, Long Short-Term Memory (LSTM).

1. Introduction

Agriculture serves as the spine of India, offering livelihood and financial stability to a chief proportion of the populace. It not best sustains rural communities but additionally contributes considerably to the country wide financial system. The productivity of vegetation, in phrases of each yield volume and satisfactory, is heavily stimulated via environmental factors consisting of rainfall patterns and temperature versions-factors that lie outside human influence. Beyond climatic situations, plant diseases represent some other critical obstacle which could appreciably lessen agricultural output and threaten food security.

Plants can also agreement bacterial, viral, or fungal infections throughout any degree in their growth cycle, and if not detected early, such infections may additionally spread swiftly across fields. Traditionally, the presence of disorder is identified via visual inspection of affected areas, consisting of discoloration, lesions, deformation, or abnormalities seen on leaves, stems, or other plant organs. To automate this inspection, numerous classical photo-processing methodologies-inclusive of segmentation, thresholding, clustering, and watershed algorithms-had been applied to find and analyze diseased areas.

Automated disease detection typically begins with the collection and pre-processing of digital leaf images. Pre-processing enhances essential visual features, removes noise, and converts images into a standardized format suitable for machine learning models. The refined images are then input into training algorithms that learn discriminating patterns associated with different diseases. Once training is complete, the model can be used to classify images of new leaves and accurately predict the type of infection present.

Different diseases display different visual markers. For example, fungal infections typically develop small black fungal fruiting bodies when leaves are kept in humid conditions, while bacterial lesions appear water-soaked or translucent before drying. Additional symptoms include brown or black circular spots, pale halo around lesions, dark undersides caused by spore clusters, and dense black spots on leafs.

The primary objective of this research is to demonstrate how an integrated approach combining statistical image analysis with segmentation techniques, texture-based feature extraction, and machine learning can significantly improve the speed and accuracy of crop disease classification. The organization of this paper is as follows: Section 2 outlines key research contributions to plant leaf disease detection and classification. Section 3 details the proposed methodology, including the feature extraction approach and machine learning models applied for disease detection. Section 4 presents the simulation results and analysis, and Section 5 concludes the study with final remarks and possible future extensions.

2. Literature Survey

In recent years, the software of digital imaging and automatic evaluation has won huge attention in both research and agricultural communities. Image-primarily based analysis has emerged as a powerful approach for figuring out plant diseases speedy and as it should be, lowering the want for conventional guide inspection. As imaging technologies and computational strategies evolve, image processing strategies should be constantly refined to evolve to new demanding situations and enhance diagnostic precision.

The speedy development of gadget studying and deep gaining knowledge of has drastically encouraged agricultural disease detection systems, permitting more reliable and scalable answers for actual-global deployment. Consequently, several researchers have explored various methodologies to come across and classify diseases affecting Capsicum plants through digital leaf images. These research have focused on growing computerized structures capable of reading visual symptoms and distinguishing among healthful and inflamed leaves the usage of superior algorithms.

To address increasing agricultural threats and productiveness losses, the medical community has delivered an intensive variety of modern-day solutions that incorporate photograph segmentation, texture characteristic extraction, system mastering models, and deep neural networks. These revolutionary procedures show terrific ability for reinforcing disease popularity accuracy and supporting farmers in early-degree diagnosis and preventive crop management. As interest in this field maintains to develop, ongoing studies pursuits to establish more robust, smart, and actual-time systems for Capsicum plant disease detection.

Shaheed et al. [1] introduced an efficient RMT-Net integrating ResNet-50 with Vision Transformers to classify potato leaf diseases with improved computational efficiency and high performance, highlighting the potential of hybrid Transformer-based networks. Packal et al. [3] conducted a systematic study on deep learning approaches used for plant disease detection, concluding that hybrid models and Transformer architectures are emerging as reliable solutions. Andal and Thangaraj [4] provided a comprehensive review of modern leaf disease detection techniques and emphasized on improved segmentation and feature extraction workflows. Ahuja et al. [5] designed a vision transformer and capsule network framework for ripeness and black spot disease detection in oranges, demonstrating the applicability of the hybrid model to quality grading tasks beyond leaf inspection. Hussain and Moussa [6] reviewed CNN-based techniques for accurate plant disease identification, reporting strong performance when adequately supported by preprocessing and enhancements. Zhang et al. [7] integrated capsule networks with residual networks for plant leaf disease detection, showing that capsule layers enhance spatial relation preservation within feature maps.

Transfer learning has also gained momentum in agricultural image analysis. Vinothini and Asaviga [8] demonstrated its effectiveness for tomato disease classification using pre-trained deep models. Xu et al. [9] provided a large-scale review of deep learning-based plant disease detection, highlighting the dominance of CNN and Transformer-based hybrid architectures. Zhang et al. [10] developed Swin Transformer-based StCovidNet, reporting improvements in hierarchical image representation. Venkatraman [11] presented a channel attention-augmentation

Neware [12] reviewed deep getting to know strategies applied to fruit disease detection, reinforcing the significance of CNN and hybrid architectures in horticulture. Dolatabadian et al. [13] mentioned practical elements of system gaining knowledge of primarily based crop disease detection, positioning it as a important device for lowering yield loss. Ngugi et al. [14] analyzed deep learning's transformative outcomes on crop disease tracking and agricultural sustainability. Gupta et al. [15] implemented changed CNN fashions for tomato leaf disease classification the usage of switch mastering tactics. Mathew et al. [16] proposed CapsNet Hybrid for bell-pepper leaf disorder class, yielding encouraging performance effects in particular for Capsicum species.

Dhaliwal et al. [17] in comparison Gabor-CapsNet and ViT-CNN hybrid models, demonstrating stepped forward function mastering skills when combining textural and hierarchical deep getting to know techniques. Kursun and Koklu [18] proposed ViT-AlexNet, a hybrid architecture combining Vision Transformer additives with the classical AlexNet model for capsicum leaf disease class, demonstrating advanced adaptability in function extraction from complex leaf textures. Kumar and Gunasekar [19] evolved deep learning techniques able to predicting disease severity similarly to type, assisting real-international precision farming desires. Naseer et al. [20] proposed RiViT, a Vision Transformer-primarily based approach for rice sickness class, similarly establishing transformer models as effective feature extractors.

3. Proposed Methodology

The proposed technique introduces an green and automatic framework for the detection and category of diseases affecting Capsicum plant leaves. The machine is designed to aid accurate identification via a dependent collection of digital image processing and deep mastering-based totally category levels. The workflow starts off evolved with the collecting of Capsicum leaf images, followed by means of image pre-processing steps together with resizing, normalization, and comparison enhancement to improve the visual great and consistency of the dataset. Segmentation techniques are then hired to isolate the Region of Interest (ROI), ensuring that disease affected regions are appropriately extracted for further analysis.

The amassed dataset is separated into training and testing out subsets to assess model performance under supervised studying conditions. Feature extraction and ROI identity are carried out typically at some point of the processing segment with the aid of making use of pre-processing and segmentation algorithms, which spotlight crucial texture and shade patterns associated with exclusive disease sorts. A deep studying class model integrating Convolutional Neural Networks (CNN) and advanced hybrid layers is subsequently utilized to categorize leaf samples as healthy or diseased, and to expect the precise type of infection.

An evaluate of the proposed system architecture is offered in Figure 1. The input pre-processed image are surpassed via the training model constructed using device-getting to know and deep-mastering techniques. Based on the extracted capabilities and learned styles, the system generates an output that identifies the fitness repute of the leaf, along with the corresponding disorder label.

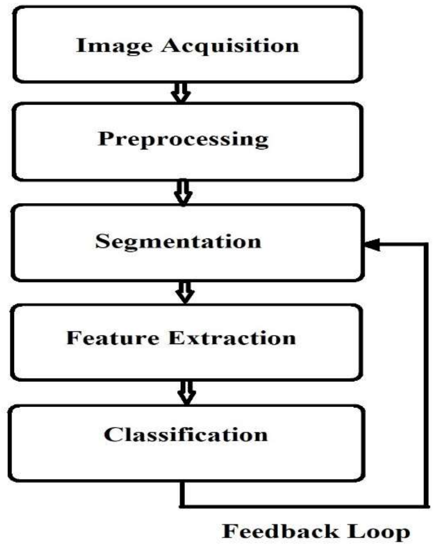

Figure 1. Process Flow Steps

Traditionally, plant disease evaluation trusted guide visible inspection finished by way of agricultural specialists. Such traditional techniques are time-ingesting, subjective, and frequently impractical for large-scale crop control. Expert analysis can also vary relying on human interpretation and area conditions. By contrast, automated gadget-mastering approaches offer quicker, constant, and fantastically correct disease identification, significantly decreasing the dependency on physical inspection and minimizing associated fees.

Machine-studying-enabled agricultural diagnostics have verified tremendous overall performance throughout various crop types, outperforming guide evaluation in reliability and scalability. Therefore, developing an wise version for computerized Capsicum leaf disorder type is crucial to cope with present boundaries and guide precision agriculture. This methodological framework contributes closer to early detection, yield protection, and progressed choice-making for farmers and agricultural researchers.

3.1. Input Image

The enter to the proposed model includes Capsicum leaf images accrued from real time environments and publicly to be had benchmark datasets. A total of 1620 images have been applied on this research, out of which 632 samples represent healthy leaves and 988 samples represent diseased leaves. Field image have been captured from diverse agricultural places within Ahilyanagar District, Maharashtra, India, making sure natural variations in illumination, digicam attitude, and background noise. To boom dataset variety and decrease bias, extra samples had been sourced from the Mendeley and PlantVillage repository, which provides standardized and high-quality disease annotation statistics. This combination of field and on line image assets complements the model's potential to generalize correctly in actual-international farming conditions.

For training the proposed machine learning and deep studying framework, the dataset was systematically partitioned using an 8:1:1 ratio corresponding to training, validation, and testing subsets. The training set supports version studying, at the same time as the validation set optimizes hyperparameters and forestalls overfitting. The testing set is used completely to evaluate version overall performance on unseen images to make sure reliability and robustness. Prior to characteristic extraction and model deployment, all incoming images undergo preprocessing operations along with resizing, normalization, and noise reduction to preserve consistency throughout numerous image resolutions and lighting fixtures situations. This dependent enter layout permits greater correct type of Capsicum leaf health popularity and helps green computerized disease detection. The gadget became tested on Capsicum leaf images, with the purpose of identifying and categorizing 4 main disease types, inclusive of Bacterial Wilt, Bacterial Spot, Tobacco Mosaic Virus (TMV), and Anthracnose.

3.1.1. Image Preprocessing: Image preprocessing is a important step that prepares unprocessed images for input into the detection framework by means of making use of a chain of enhancement and transformation operations. The primary objective of preprocessing is to remove noise, correct distortions, and improve the visibility of essential leaf capabilities relevant for disease identification. In this work, images from the dataset are loaded the use of statistics mills, and augmentation is executed using equipment which include Keras to artificially enlarge the dataset and beef up version generalization. Various augmentation operations-including resizing, rotation, normalization, scaling, and shade conversion-are carried out to improve dataset variety and reduce version overfitting. These ameliorations enable compatibility with deep CNN architectures by changing all input images into a uniform length and depth distribution earlier than model education.

Leaf images frequently contain versions in illumination, shadows, and history interference. Therefore, preprocessing enhances important texture and shade patterns wished for accurate sickness recognition. Since diseased areas typically differ chromatically from healthful leaf tissue, normalization permits clean separation of inflamed zones from the rest of the leaf floor. Although the RGB shade model is normally used for virtual representation, conversion to alternative areas which include grayscale or HSV can improve contrast among healthful and diseased tissues. This step significantly improves function extraction overall performance whilst reducing computational complexity.

3.1.2. Segmentation: Segmentation is achieved to isolate the area of interest (ROI) from the history by way of isolating diseased leaf regions from the relaxation of the photo. This method highlights inflamed patches and supports more particular analysis for the duration of the class degree. Several segmentation strategies exist, consisting of thresholding, clustering, side detection, neural-community-based techniques, and partial differential equation fashions. In this observe, okay-means clustering is employed because of its simplicity, computational performance, and suitability for large datasets. The set of rules businesses image in line with similarity in depth or color values, which permits visually distinct disease patterns-frequently circular or aggregated lesions-to be extracted correctly.

The k-means clustering method starts by deciding on an initial variety of cluster facilities (k). Images are then assigned to the nearest cluster based totally on Euclidean distance, and the cluster centers are adjusted iteratively till convergence is executed. The final output separates healthful and diseased areas into wonderful clusters, permitting the extraction of meaningful ROIs for similarly analysis. By separating disease affected zones, segmentation significantly boosts type accuracy and presents a more reliable visible interpretation for automatic Capsicum leaf disease detection.

3.2. CNN Algorithm

A Convolutional Neural Network (CNN) consists of more than one layers that images collectively to analyze visible styles from input image and classify them correctly. Typical CNN architecture consists of convolution layers, pooling layers, and completely linked layers organized sequentially, observed by using an output layer. Each layer extracts steadily complex capabilities, starting with primary edge and shade patterns and advancing towards higher-level structural statistics applicable to disease areas. The average workflow of the CNN used in this studies is illustrated in Figure 2, even as the preprocessing pipeline is presented in Figure 3.

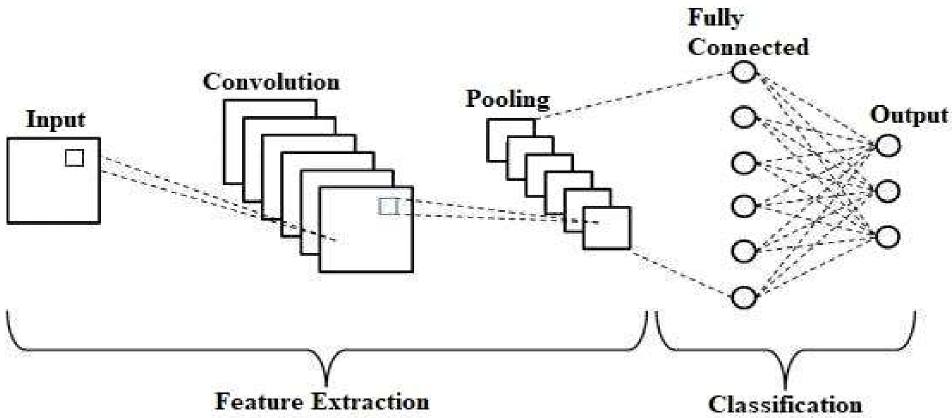

Figure 2. Architecture of CNN

3.2.1. Convolution Layer: The convolution layer is the center element liable for feature extraction. It applies a couple of learnable filters (kernels) across the image in small areas, scanning it some images at a time to generate a characteristic or activation map. This operation lets in the community to detect vital spatial characteristics including edges, shapes, textures, and lesion barriers associated with disorder signs and symptoms. As validated in Figure three, every filter out produces specific characteristic maps that collectively constitute the visible shape of the input leaf image. The convolution process preserves spatial relationships among images while steadily reworking raw image facts into significant characteristic representations.

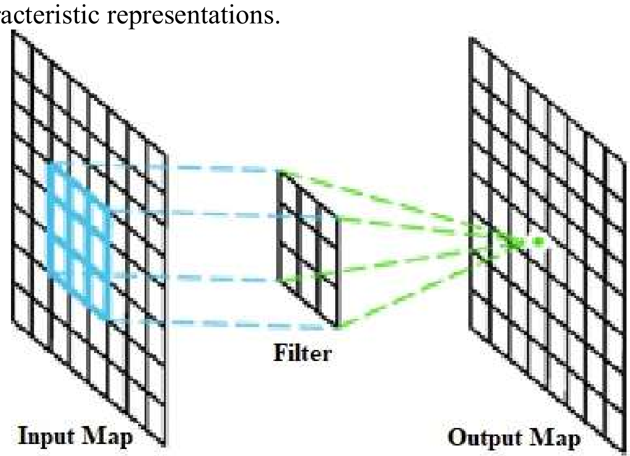

Figure 3. Internal working of Convolution Layer

3.2.2. Polling Layer: The pooling layer plays downsampling on the characteristic maps generated for the duration of convolution to lessen spatial dimensions whilst keeping critical records. This layer improves computational efficiency, minimizes reminiscence utilization, and forestalls overfitting by using reducing the wide variety of parameters in the network. Common pooling techniques, such as max pooling or average pooling, summarize the most distinguished features within a small neighborhood. As shown in Figure four, pooling simplifies complex characteristic maps even as maintaining discriminative traits needed for accurate type.

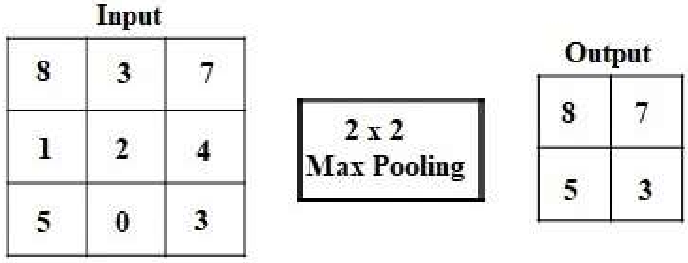

Figure 4. Internal working of the pooling layer

3.2.3. Fully Connected Layer: The Fully Connected (FC) Layer, often known as the hidden or class layer, represents the very last degree of a Convolutional Neural Network. After the convolution and pooling operations extract spatial functions, the multi-dimensional feature maps are flattened into a one-dimensional vector and handed into the FC layer. This layer integrates both linear (Affine) variations and non-linear activation functions to research the complex dating between extracted features and the target output classes. The affine transformation is mathematically expressed as $y = Wx + b$, where W represents the weights, x is the enter function vector, and b is the unfairness element.

Non-linear activation functions along with ReLU, Sigmoid, or Tanh are then applied to introduce non-linearity, allowing the version to capture deeper patterns beyond easy linear associations. A combination of affine transformation observed by using a non-linear activation bureaucracy a completely related unit, and more than one such devices may be stacked relying at the complexity of the dataset and category necessities. Finally, the output layer employs both a SoftMax or Sigmoid activation feature to convert the computed values into opportunity scores, thereby figuring out the most probable magnificence label for sickness identification.

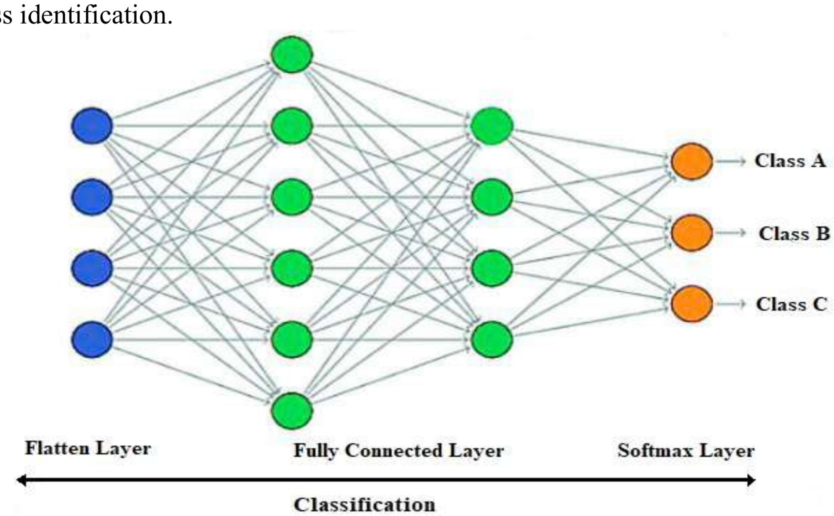

Figure 5. Fully Connected Layer

- The flattened output generated from the preceding layers is fed into the first Fully Connected (FC) layer, in which it acts because the enter to the category community.
- The extracted functions are encoded in the form of weight parameters and transferred to the preliminary FC layer, enabling the network to learn patterns and appropriately are expecting the corresponding magnificence label.

- At the final level of the network, the output layer—that's absolutely linked—produces the probability distribution for every class, indicating the likelihood of each possible label.
- The internal shape and functioning of a fully connected layer are illustrated in Figure 5.

3.3. CNN-LSTM

This research integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks, as illustrated in Figure 6. The combined architecture leverages the feature-extraction energy of CNN while the LSTM thing preserves temporal and contextual facts throughout extended facts sequences. By adopting a shape much like traditional CNN frameworks, the LSTM layer efficaciously keeps prior statistics and complements the model's ability to examine lengthy sequential inputs.

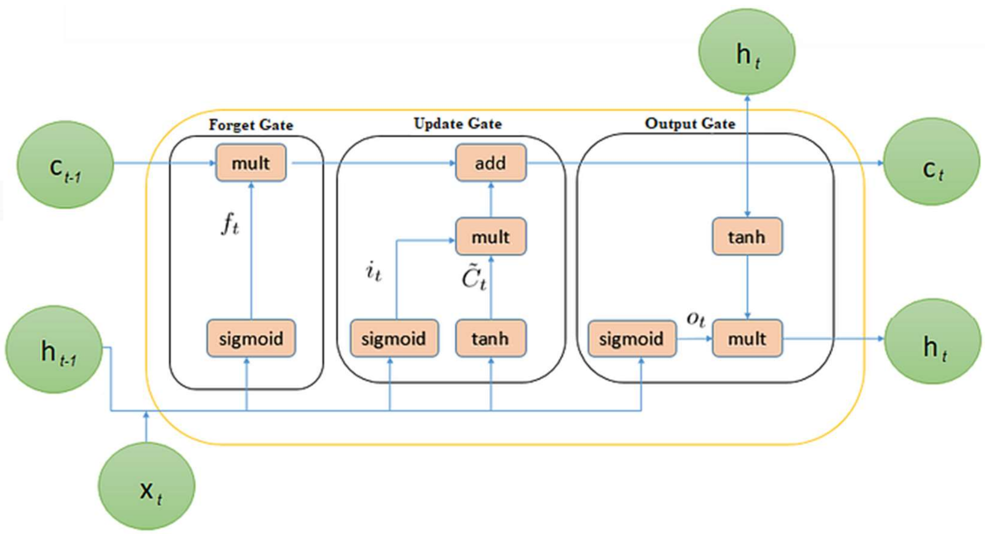

Figure 6. CNN – LSTM Architecture Layer

The operational concept of the input gate in an LSTM network can be described using the expressions presented below.

$i_t = \sigma(W_i.[h_{t-1},x_t]+ b_i)$ (1)

$C^{\sim}_t=\tanh(W_c.[h_{t-1},x_t]+b_c)$ (2)

$C_t=f_t.C_{t-1}+i_tC^{\sim}_t$ (3)

By passing h_{t-1} and x_t through the sigmoid activation function in equation (1), the network determines which part of the incoming data should be retained. Next, these values are processed through the TAN activation layer as shown in equation (2), which generates candidate information to be added to the cell state. In equation (3), two components – the previous cell state c_{t-1} (representing short-term memory) and the new candidate state $c^{\sim}_t$ (representing long-term memory) – are combined to generate the updated cell state c_t. In this context, the bias of the input gate is denoted by b_t, and the weight matrices are denoted by W_t. When the LSTM's forget gate is triggered, it selectively filters out the information that should be passed on, allowing only relevant data to pass. Equation (6) enables the model to determine whether information from a previous cell needs to be removed. This decision is calculated using a sigmoid activation function, where the process is influenced by the associated weight matrix and the bias term b_f.

$f_t=(W_f[h_{t-1},x_t]+b_f)$ (4)

The result of the expression corresponds without delay to the neglect gate function defined in Equation (4). After making use of Equations (5) and (6), the inputs h_{t-1} and x_t manual the output gate in determining the precise state required for progression to the next timestep, as shown in Equation (7). To compute the very last hidden kingdom, the output gate cost is improved via the candidate kingdom choice vector, which transfers the newly updated records C_t via the tanh activation function. The output gate operation and the very last hidden country are formally represented as:

$$O_t=(W_o[h_{t-1},x_t]+b_o) \quad (5)$$

$$H_t=O_t \cdot \tanh(C_t) \quad (6)$$

$$H_t=h_t \quad (7)$$

In this formulation, W_o denotes the weight matrix associated with the output gate, while b_o represents the corresponding bias parameter of the LSTM unit.

4. Result Analysis

The training and check datasets each comprise 1,620 images, comprising 632 healthful iamges and 988 diseased images. From these, 3 disease types- Anthracnose, Cercospora Leaf Spot, and Bacterial Wilt together with Mosaic Virus, were decided on for distinct analysis. Table 1. Displays the training performance of the Deep Learning CNN version for pomegranate images, displaying the loss, accuracy, and validation metrics over approximately 15 epochs.

Table 1. Epoch-wise performance results of the CNN mode

Epoch	Train: Loss	Train Accuracy	Valid: Loss	Valid: Accuracy
0	1.245	0.5845	1.2687	0.5497
1	0.8564	0.6254	0.7245	0.6987
2	0.7125	0.7245	0.6987	0.7125
3	0.6501	0.7545	0.6874	0.7564
4	0.5451	0.7895	0.7984	0.7894
5	0.4987	0.8158	0.6987	0.7954
6	0.4865	0.8546	0.5124	0.8125
7	0.4258	0.8645	0.4985	0.8254
8	0.3854	0.8754	0.4897	0.8395
9	0.3598	0.8845	0.4254	0.853
10	0.3354	0.896	0.3687	0.8615
11	0.3084	0.9012	0.546	0.8354
12	0.2987	0.9045	0.5246	0.8769
13	0.2874	0.9068	0.3145	0.8895
14	0.2458	0.9079	0.5864	0.8246
15	0.2594	0.9897	0.4891	0.8567

After training and testing the raw dataset as defined in Section 3.Three, a CNN-LSTM model changed into employed. Table 2 gives the results, displaying that the accuracy of the CNN-LSTM model improved in comparison to the CNN model alone.

Table 2. Epoch-wise performance results of the CNN + LSTM model

Epoch	Train: Loss	Train Accuracy	Valid: Loss	Valid: Accuracy
0	0.0268	0.9784	0.0197	0.9857
1	0.0289	0.9954	0.0238	0.9915
2	0.0198	0.9946	0.0984	0.9875
3	0.0245	0.991	0.1025	0.9645
4	0.0268	0.9846	0.1548	0.9645

5	0.0198	0.9915	0.0768	0.9765
6	0.248	0.9958	0.1254	0.9245
7	0.2487	0.9834	0.2987	0.9458
8	0.0154	0.9462	0.0387	0.9357
9	0.0285	0.9945	0.987	0.9874
10	0.0298	0.9987	0.0087	0.9765
11	0.0345	0.9846	0.0987	0.9968
12	0.0219	0.9824	0.0079	0.9997
13	0.0245	0.9916	0.0218	0.9868
14	0.0387	0.9876	0.0197	0.9937
15	0.0354	0.9864	0.0867	0.9864

Table 3 presents the accuracy of three classification algorithms after performing 10-fold cross-validation on the dataset, using the four most significant attributes selected.

Table 3. Training and Test Dataset Performance Showing Accuracy and Loss

Model	Accuracy	Loss	Time
CNN	91.687	0.3125	17ms
CNN+LSTM	96.987	0.1268	26ms

5. Conclusion

This observe demonstrates the development of an automated system for detecting and classifying diseases in Capsicum plant leaves, attaining an average accuracy of 96.987% with a processing time of about 26 milliseconds consistent with image. The proposed framework integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks, combining the strengths of spatial feature extraction and sequential getting to know to enhance type overall performance. By employing advanced image processing strategies, along with segmentation and clustering of leaf regions, the gadget correctly highlights diseased regions and helps accurate reputation, lowering reliance on manual inspection. Comparative consequences, as proven in Table 1, imply that this method outperforms numerous existing methodologies across more than one performance metrics.

The model become examined on Capsicum leaf image, figuring out and categorizing four primary disease sorts, including Bacterial Wilt, Bacterial Leaf Spot, Tobacco Mosaic Virus (TMV), and Anthracnose. The segmentation and characteristic extraction strategies allowed the version to awareness on applicable diseased regions, improving prediction reliability. Future images will involve expanding the network with extra ANN and LSTM layers to similarly capture complex patterns in leaf image doubtlessly growing accuracy and robustness. This more desirable framework pursuits to guide real-time disease diagnosis, supporting farmers and researchers in effective crop management and yield safety.

6.1. Journal Article

[1] K. Shaheed, I. Qureshi, F. Abbas, S. Jabbar, and Q. Abbas, “EfficientRMT-Net: An Efficient ResNet-50 and Vision Transformers Approach for Classifying Potato Plant Leaf Diseases,” Sensors, vol. 23, no. 23, p. 9516, 2023. doi: 10.3390/s23239516.
[2] T. Ali, B. S. Alqadi, M. Mehmood, and A. Nawaz, “CCNet: CNN-CapsNet-Based Hybrid Deep Learning Model for Diagnosing Plant Diseases Using Thermal Images,” Proc.

Int. Conf. on Computer Vision and AI, 2023. [Online]. Available: https://search.proquest.com/openview/464af0ece302e4a9f6cc518b1d44af7a.
[3] I. Pacal, I. Kunduracioglu, M. H. Alma, and M. Deveci, "A Systematic Review of Deep Learning Techniques for Plant Diseases," Artificial Intelligence Review, Springer, 2024. doi: 10.1007/s10462-024-10944-7.
[4] P. Andal and M. Thangaraj, "Comprehensive Review of Methods for Leaf Disease Identification," Discover Artificial Intelligence, Springer, 2025. doi: 10.1007/s44163-025-00491-7.
[5] V. Ahuja, A. Dogra, P. Kaushik, E. Jain, and V. Kukreja, "Vision Transformer-Capsule Network for Orange Quality Inspection: Ripeness and Black Spot Disease Detection," Applied Fruit Science, Springer, 2025. doi: 10.1007/s10341-025-01388-6.
[6] M. Hussein and A. Mousa, "A Review of CNN-Based Techniques for Accurate Plant Disease Detection," Int. J. of Computers and Information, vol. 52, no. 3, pp. 233–244, 2023. [Online]. Available: https://journals.ekb.eg/article_317732.html.
[7] X. Zhang, Y. Mao, Q. Yang, and X. Zhang, "A Plant Leaf Disease Image Classification Method Integrating Capsule Network and Residual Network," IEEE Access, vol. 12, pp. 55621–55633, 2024. doi: 10.1109/ACCESS.2024.10472475
[8] A. Vinothini and R. V. Aswiga, "Transfer Learning Based Deep Learning Model for Classifying Tomato Plant Leaf Diseases," Engineering Research Express, vol. 7, no. 1, 2025. doi: 10.1088/2631-8695/add6f5
[9] L. Xu, J. Zhao, Z. Ma, J. Li, X. Wang, and Y. Liu, "A Review of Plant Leaf Disease Identification by Deep Learning Algorithms," Frontiers in Plant Science, vol. 16, 2025. doi: 10.3389/fpls.2025.1637241
[10] D. Zhang, B. Wang, and Z. Tian, "Stcovidnet: Automatic Detection Model Based on Swin Transformer," ResearchSquare, preprint, 2022. doi: 10.21203/rs.3.rs-1401026/v1
[11] S. Venkatraman, "A Channel Attention-Driven Hybrid CNN Framework for Paddy Leaf Disease Detection," arXiv preprint, arXiv:2407.11753, 2024. [Online]. Available: https://arxiv.org/abs/2407.11753
[12] R. Neware, "A Comprehensive Review on Detection of Horticulture Fruits Disease Using Machine Learning and Deep Learning Approaches," Preprints.org, 2025. doi: 10.20944/preprints202503.1769.v1
[13] A. Dolatabadian, T. X. Neik, and M. F. Danilevicz, "Image-Based Crop Disease Detection Using Machine Learning," Plant Pathology, vol. 74, no. 1, pp. 88–102, 2025. doi: 10.1111/ppa.14006
[14] H. N. Ngugi, A. E. Ezugwu, and A. A. Akinyelu, "Revolutionizing Crop Disease Detection with Computational Deep Learning: A Comprehensive Review," Environmental Monitoring and Assessment, Springer, 2024. doi: 10.1007/s10661-024-12454-z
[15] S. Gupta, K. Rawat, K. Krishali, and N. Rawat, "A Transfer Learning-Based Approach for the Classification of Tomato Leaf Diseases Using Modified CNN Models," Int. J. of Computer Applications, vol. 185, no. 2, pp. 1–9, 2023. [Online]. Available: https://www.researchgate.net/publication/394792552
[16] M. P. Mathew, S. Elayidom, and K. M. Abubeker, "CapsNet Hybrid for Bell Pepper Leaf Disease Classification," ELCVIA, vol. 24, no. 2, pp. 33–42, 2025. [Online]. Available: https://elcvia.cvc.uab.cat/article/view/1970

6.2. Book

[17] P. Dhaliwal, A. Srivastava, and S. Juneja, "Gabor-CapsNet and Hybrid ViT-CNN Models for Plant Disease Detection," in Handbook of AI in Agriculture, Springer, 2025. [Online]. Available: https://books.google.com/books?id=k8VoEQAAQBAJ.

6.3. Conference Proceedings

[18] R. Kursun and M. Koklu, "ViT-AlexNet: A Hybrid Approach for Chili Leaf Disease Classification," *Proceeding International Conference on AI and Applications*, 2024. [Online]. Available: https://www.researchgate.net/publication/387823235

[19] K. R. P. Kumar and M. Gunasekar, “Leaf Disease Prediction and Severity Estimation Using Deep Learning,” in Proc. IEEE Int. Conf. on Computing and Applications, 2024. doi: 10.1109/ICCA.2024.10921856.

[20] R. K. Naseer, A. Afzal, and M. Arshaq, “RiViT: Rice Leaf Disease Identification and Classification Using Vision Transformer (ViT),” in Proc. IEEE Int. Conf. on Machine Learning and Data Science, 2025. doi: 10.1109/MLDS.2025.11135614