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# A Novel Lightweight AlexNet Convolutional Neural Network for Tomato Leaf Disease Classification

**Debabrat Bharal**
Department of Computer Science,
University of Science and Technology, Meghalaya, India
pindebu15@gmail.com
https://ror.org/0330j9a35
https://orcid.org/0009-0005-7075-8794
**Kanak Ch Bora**
Department of Computer Science,
University of Science and Technology, Meghalaya, India
boopborabora@yahoo.in
https://ror.org/0330j9a35
https://orcid.org/0009-0009-0491-1235
**Sailen Dutta Kalita**
School of Science and Technology,
MIT University of Meghalaya, India
Sailen.kalita@mitu.edu.in
https://ror.org/04702m080
https://orcid.org/0009-0004-7155-0138

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**Abstract:** Tomato leaf diseases must be identified early and accurately in order to reduce output loss and advance sustainable agriculture. Deep learning models have shown encouraging results in the identification of plant diseases, but their high processing requirements and inability to adjust to field-specific limitations sometimes make it difficult to implement them in real-world applications. For the purpose of accurately and efficiently classifying tomato leaf diseases, we present a convolutional neural network based on AlexNet that is lightweight and field-aware. Our proposed model is designed with less complexity than traditional architectures and is able to perform inference faster without sacrificing accuracy, making it suitable for real-time implementation in low resource agricultural environments. The algorithm was trained and tested on a dataset of 7704 augmented images of tomato leaves from 7 different disease categories. The Lightweight AlexNet achieved accuracy comparable to VGG variants and outperformed deeper models such as ResNet (96.81%) with lower parameter overhead. It was trained from scratch using TensorFlow & Keras on 100×100 pixel inputs, achieving a training accuracy of 99.15% and a validation accuracy of 99.74%. Moreover, an effective structure of the model enables the installation on edge devices, which offers a scalable precision farming solution. Our work helps to bridge the gap between deep learning research and real-world application in agriculture, allowing the development of real-field, resource-efficient disease detection systems.
**Keywords:** AlexNet; Tomato leaf diseases; Deep learning; Sustainable Agriculture; Precision Farming

## I. INTRODUCTION

Tomatoes are a major crop in both industrialized and developing countries and are critical to food security and the agri-economy. Their cultivation can be severely affected by foliar diseases such as early blight, late blight, bacterial spot and leaf mold that reduce productivity and quality. Therefore, the rapid and accurate diagnosis of these diseases is necessary to reduce economic losses, reduce the use of chemicals and ensure sustainable agricultural production. Traditional disease detection methods are laborious, unreliable and not suitable for large-scale surveillance especially in rural farming environments, and they are based on manual visual inspection by specialists. Deep learning, especially Convolutional Neural Networks (CNNs), has become a powerful automated tool that accurately identifies complex patterns in plant images (Anandhakrishnan and Jaisakthi, 2022). Recent works have obtained impressive results using deep CNN architectures. For example, Anandhakrishnan and Jaisakthi (2022) used a deep CNN to achieve a classification accuracy of 98.40% on the PlantVillage dataset.

The web-based DeepCrop system was developed by Islam et al. (2023) using ResNet-50 and VGG models with an accuracy of up to 98.98%. Similarly, Geetharamani and Pandian (2019) proposed a 9-layer CNN and achieved 96.46% accuracy. These models demonstrate the ability of CNNs in controlled environments, but they are not feasible for real-time deployment at the field level due to the high computational cost. We propose a Field-aware Lightweight AlexNet CNN that is aimed at balancing computational efficiency and good classification performance. Unlike many previous studies that used large, clean datasets, our study is based on a real-field dataset of 7,704 images of seven categories of tomato leaf disease. The training (6,160), validation (768), and testing (776) sets are composed of these augmented images. Based on a variety of performance criteria, such as accuracy, F1-score, loss values, parameter size, and model complexity, we assess and contrast six architectures: Lightweight AlexNet, ResNet, VGG11, VGG13, VGG16, and VGG19. With an F1-score of 99.28%, an overall accuracy of 99.48%, and a validation accuracy of 99.74%, Lightweight AlexNet performs better than the rest among them while keeping the model size small at 6.49 MB.

The novelty of this work is to develop a lightweight, tailored CNN model based on AlexNet suitable for real-world classification of tomato leaf diseases. The contributions of this paper are as follows:

- A detailed performance comparison of six CNNs using an improved dataset collected in the field.
- Demonstration of the deployability and efficiency of the proposed model without losing accuracy, unlike complex models such as ResNet and VGG19.

## II. METHODOLOGY

### A. Data Types and Description

Data was collected geographically from several agricultural locations in the Golaghat area of Assam, India. Authenticity is the main innovation here, as the dataset was only recorded in the outdoors and under natural lighting circumstances, as opposed to controlled lab setups or artificial datasets like PlantVillage. Such a dataset improves the model's usefulness in field settings by offering a more accurate depiction of disease manifestation. Representative samples of each class are shown in Fig. 1, emphasizing the range of symptoms and appearance they exhibit in authentic agricultural environments.

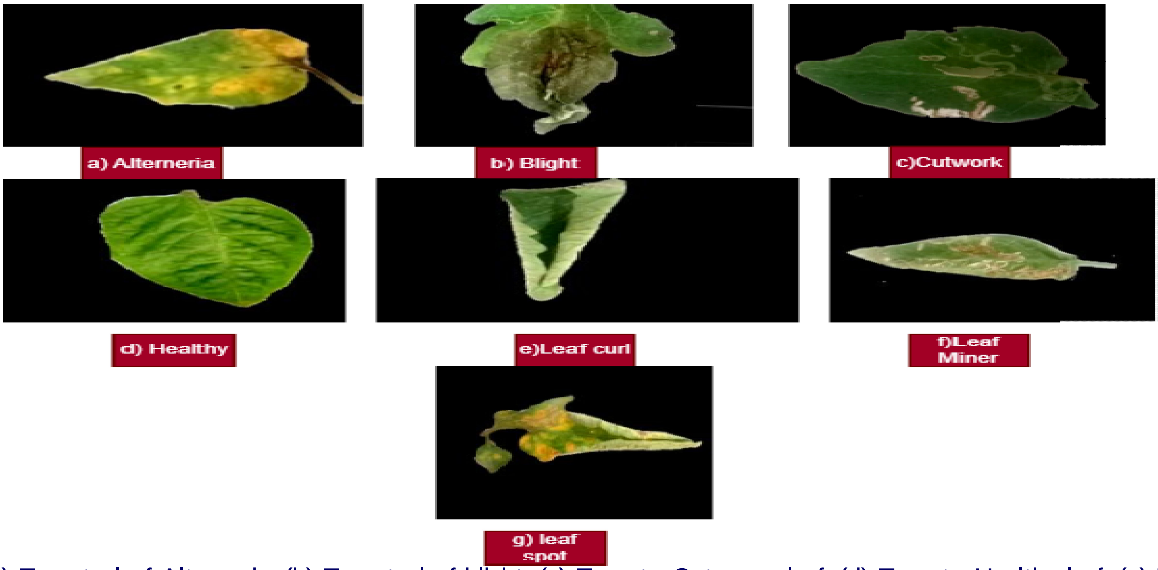


**Fig.1** (a) Tomato leaf Alternaria. (b) Tomato leaf blight. (c) Tomato Cutworm leaf. (d) Tomato Healthy leaf. (e) Tomato leaf curl. (f) Tomato leaf miner. (g) Tomato leaf spot.

**B. Quantity of Images of Diseased Tomato Leaf Images Table I** Enumerates the quantity of images in each type.

**Table I** Quantity of Diseased Tomato Leaf Images Gathered from the Golaghat District, Assam, India

| Labels for Classes | Number of Images |
|---|---|
| Tomato leaf Alternaria | 584 |
| Tomato leaf blight | 1541 |
| Tomato Cutworm leaf | 735 |
| Tomato Healthy leaf | 151 |
| Tomato leaf curl | 1676 |
| Tomato leaf miner | 2155 |
| Tomato leaf spot | 862 |

### C. Data Collection

All images were taken with an Oppo Reno 2F smartphone (16 MP cameras). With the help of an agricultural specialist who confirmed and classified the categories of infected and healthy leaves, images were taken directly from tomato fields in the Golaghat area of Assam, India.

### D. Data Format and Processing

To meet the standard input dimensions of CNN, all collected images were uniformly resized to 224×224 pixels and saved in the JPEG format. Our main methodological contribution is this targeted augmentation strategy which addresses both class imbalance and environmental unpredictability. The following augmentations were applied using Python-based image processing:

- Rotation (±25°)

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- Horizontal and vertical flipping
- Zoom in, zoom out, and brightness adjustment to normal level

All pictures were processed over a black background to reduce distractions and keep the focus on leaf features. These augmentations increased the dataset from a small initial set to 7,704 field photos, enabling more reliable model training and generalization in a variety of field scenarios.

### E. Lightweight AlexNet CNN

This part presents the end-to-end algorithm of tomato leaf disease classification by using a lightweight AlexNet convolutional neural network (CNN) adapted to the field. Its uniqueness lies in adapting the AlexNet architecture to field-collected data with a low input resolution of 100×100×3, utilizing real-time augmentation methods, and enabling successful training within limited CPU capabilities.

**1) Environment Setup and Library Import:** To facilitate reproducibility and efficiency: TensorFlow and Keras are used for deep learning model building and training; NumPy for fast array operations; OpenCV for image loading and pre-processing tasks. Input shape: (100, 100, 3). Batch size: size of data passed to the model per iteration. Epochs: number of full training cycles.

**2) Data Preprocessing and Augmentation:** To improve the model's generalization ability, the raw field images are augmented using ImageDataGenerator with the following transformations: rotation (random angles for varied orientations); shear and zoom (to simulate leaf distortion and scale variation); horizontal flipping (to prevent directional bias); and width/height shift. All images are rescaled to [0, 1] by dividing by 255. The dataset is divided as follows: 80% training, 10% validation, 10% testing. Images are resized to 100×100 and labels are in categorical mode to deal with 7 disease classes.

**3) Lightweight AlexNet CNN Construction:** A Field Data Specific Modified AlexNet CNN consists of:

- Convolutional Layers (5 total): Layer 1: 64 filters, 3×3; Layer 2: 128 filters, 3×3; Layer 3: 256 filters, 3×3. Each followed by ReLU activation.
- MaxPooling Layers: Used after some convolution to reduce the dimension.
- Fully Connected Layers: FC1: 4096 units, ReLU, Dropout (0.5); FC2: 4096 units, ReLU, Dropout (0.5).
- Output Layer: Dense layer of 7 units (softmax) for each class of tomato leaf.

**4) Model Compilation:** The model is compiled with: Optimizer: Adam with a learning rate of 0.0001; Loss Function: categorical cross-entropy; Metrics: accuracy monitored across epochs. Callbacks used: ReduceLROnPlateau and EarlyStopping.

**5) Model Training:** The model is trained using train_generator (training data with augmentations) and val_generator (validation data to observe interim performance). Epochs: 10 total (early stopping may terminate earlier). Accuracy and loss are stored per epoch for evaluation.

**6) Performance Evaluation:** After training, training and validation sets are evaluated for the model. Accuracy and loss metrics are saved to evaluate learning stability and convergence.

**7) Model and History Storage:** The trained model is stored in an .h5 file. Training history (accuracy, loss per epoch) is serialized to allow for reproducibility and visualization.

**8) Visualization of Training Results:** Training and validation accuracy and loss curves are plotted across epochs to visualize model convergence.

**9) Testing on Unseen Data:** The model is evaluated on the held-out test set to report final classification metrics on unseen data.

**10) Real-Time Validation:** To simulate real-world deployment: one image from the field is loaded and passed through the trained model; the output is the predicted disease class, indicating the ability for practical inference. Table II provides an overview of the architecture of the Lightweight AlexNet CNN.

**Table II** - Overview of the Lightweight AlexNet CNN Architecture

| Layer | Type | Details |
|---|---|---|
| Input Layer | Input | Image size: 100 × 100 × 3 (RGB) |
| Conv Layer 1 | Convolution + ReLU | 64 filters, 3×3 kernel, stride 1, padding "same" |
| | Max Pooling | 2×2 pooling |
| Conv Layer 2 | Convolution + ReLU | 128 filters, 3×3 kernel |
| | Max Pooling | 2×2 pooling |
| Conv Layer 3 | Convolution + ReLU | 256 filters, 3×3 kernel |
| | Max Pooling | 2×2 pooling |
| Fully Connected 1 | Dense + ReLU + Dropout | 512 neurons, Dropout rate = 0.5 |
| Fully Connected 2 | Dense + ReLU + Dropout | 256 neurons, Dropout rate = 0.5 |
| Output Layer | Dense + Softmax | 7 neurons (7 disease classes) |

### F. The Architecture's Innovative Contribution

- Lightweight processing due to reduced input dimension (100×100×3) compared to regular AlexNet.
- Reduced parameters: Provides a considerable reduction of processing load with a high degree of accuracy (~99.74%).
- Effective but shallow: A three-block convolutional architecture allows fast inference suitable for field conditions.
- Dropout regularization: Dense layers use 0.5 dropout to avoid overfitting.
- Real-world readiness: Built to classify seven different tomato leaf diseases from field conditions.

## III. RESULTS AND DISCUSSION

A dataset of 7,704 field-collected and enhanced photos from seven tomato leaf disease classes was used to assess the model. To show the efficiency of the suggested model, the outcomes were contrasted with benchmark CNN architectures such as ResNet, VGG11, VGG13, VGG16, and VGG19.

**1) Performance Evaluation:** To assess how well several CNN architectures specifically, the Lightweight AlexNet, ResNet, and VGG models—performed in classifying tomato leaf diseases, an experiment was conducted. The models were assessed using a dataset of field-collected diseased tomato leaf photos. Optimizer, loss function, batch size, epochs, training accuracy, validation accuracy, training loss, and validation loss were among the metrics utilized for assessment (Table III).

**Table III** - CNN Model Performance Comparison

| Model name | Optimizer | Loss function | Batch size | Epoch | Training acc. | Validation acc. | Train loss | Valid loss |
|---|---|---|---|---|---|---|---|---|
| Lightweight AlexNet | Adam | Categorical cross entropy | 32 | 10 | 99.15% | 99.74% | 0.0221 | 0.381 |
| ResNet | Adam | Categorical cross entropy | 32 | 10 | 99.85% | 98.17% | 0.00638 | 0.05301 |
| VGG11 | Adam | Categorical cross entropy | 32 | 10 | 99.83% | 97.65% | 0.99837 | 43.639 |
| VGG13 | Adam | Categorical cross entropy | 32 | 10 | 99.78% | 96.48% | 0.00609 | 37.830 |
| VGG16 | Adam | Categorical cross entropy | 32 | 10 | 99.87% | 95.83% | 0.00447 | 56.213 |
| VGG19 | Adam | Categorical cross entropy | 32 | 10 | 99.57% | 90.88% | 0.02108 | 20.201 |

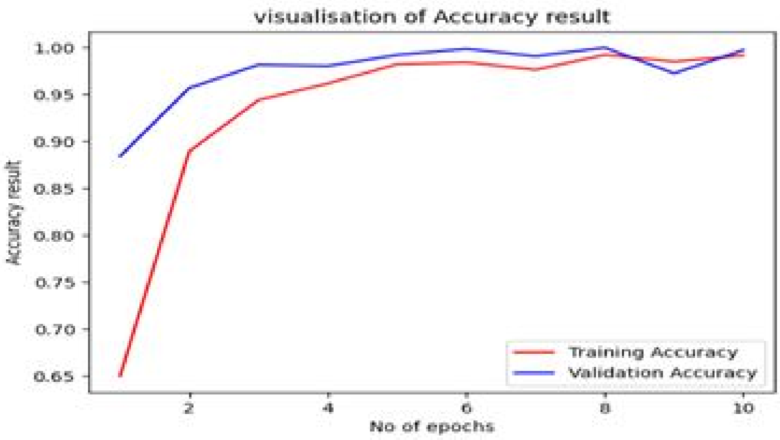


**Fig. 2** Training and Validation Accuracy of Lightweight AlexNet Model.

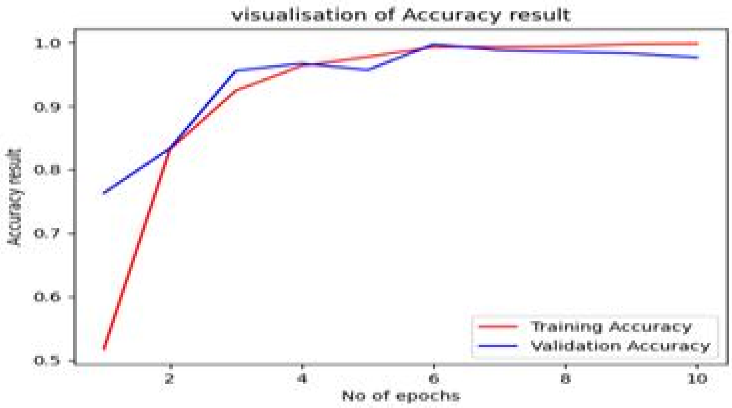


**Fig. 3** Training and Validation Accuracy of VGG11 Model.

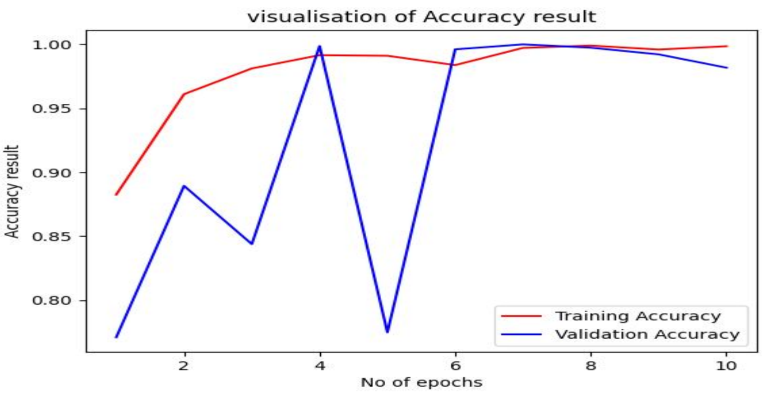


**Fig. 4** Training and Validation Accuracy of ResNet Model.

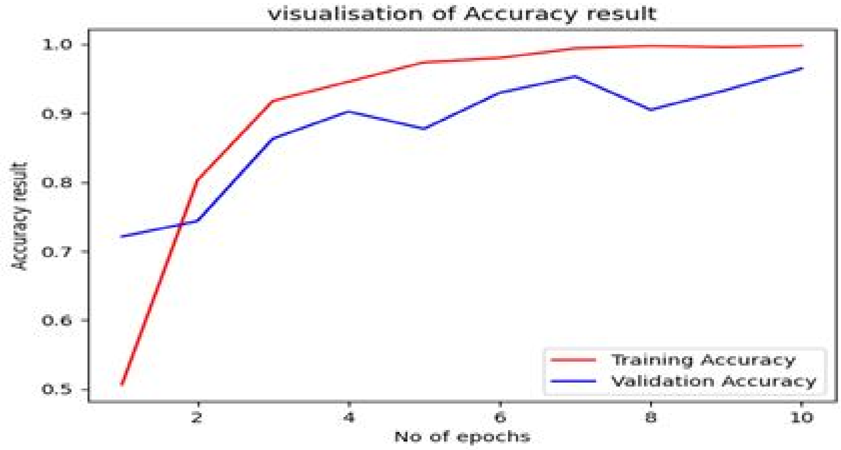


**Fig. 5** Training and Validation Accuracy of VGG13 Model.

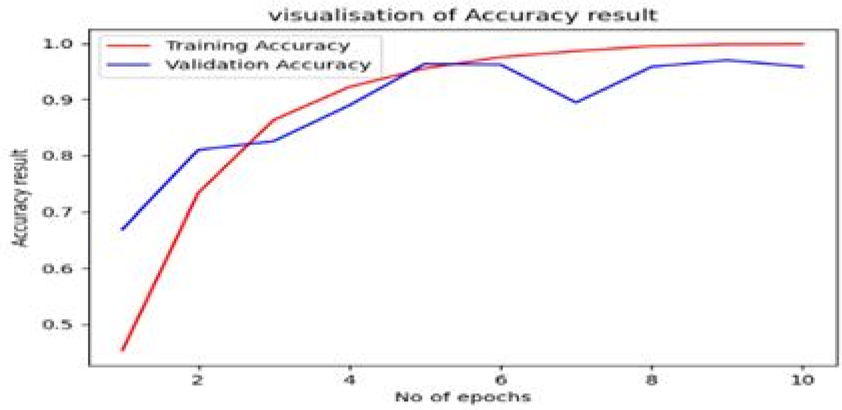


**Fig. 6** Training and Validation Accuracy of VGG16 Model.

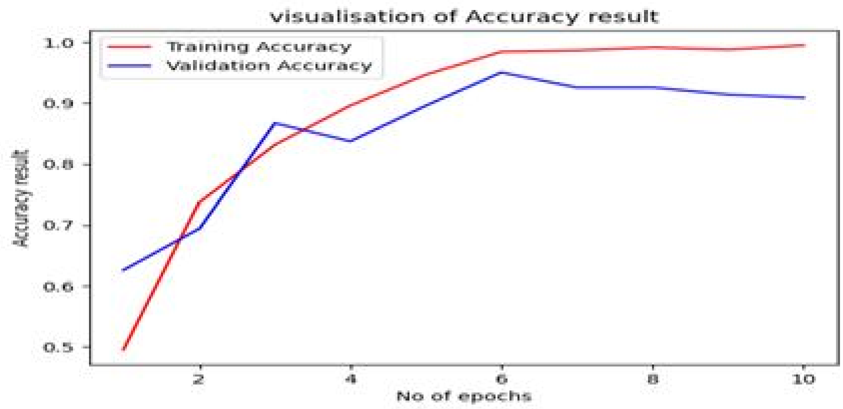


**Fig. 7** Training and Validation Accuracy of VGG19 Model.

The Lightweight AlexNet model outperformed VGG19 (90.88%) and VGG16 (95.83%) and marginally outperformed ResNet (96.81%) with a high validation accuracy of 99.74%. Despite having much higher model sizes, VGG11 and VGG13 also produced good results (97.65% and 96.48%, respectively). These findings show that even with less data and less complexity, the Lightweight AlexNet model may successfully learn discriminative features important to disease categorization.

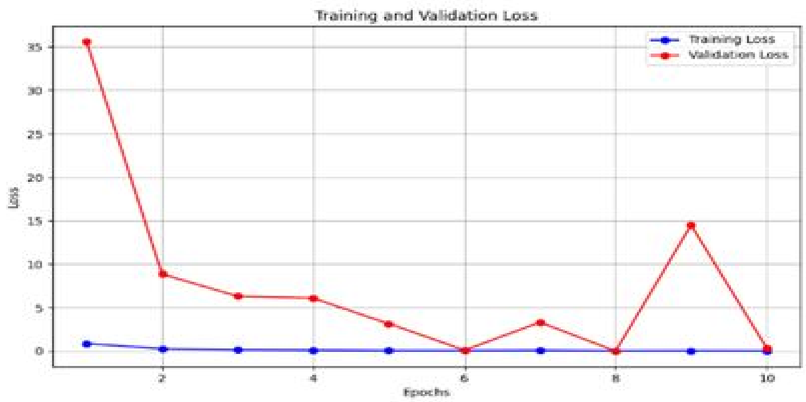


**Fig. 8** Training and Validation Loss of Lightweight AlexNet Model.

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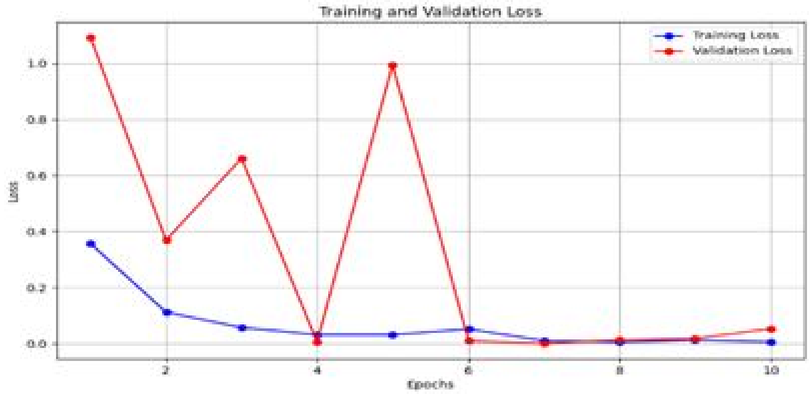


**Fig. 9** Training and Validation Loss of ResNet Model.

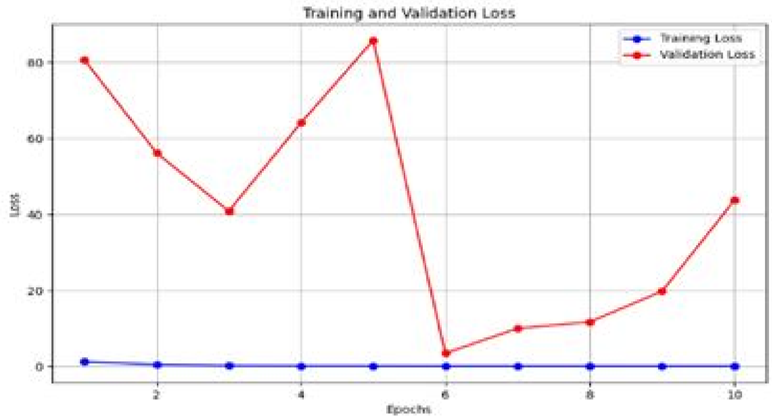


**Fig. 10** Training and Validation Loss of VGG11 Model.

The closely aligned training and validation loss curves showed that the Lightweight AlexNet model had a smooth convergence with little overfitting. Deeper networks like VGG19 and ResNet, on the other hand, displayed more variable and larger validation losses, underscoring their vulnerability to overfitting on the field-collected dataset. This demonstrates that the Lightweight AlexNet is a good fit for field deployments where data and processing limitations are common.


**Fig. 11** Training and Validation Loss of VGG13 Model.

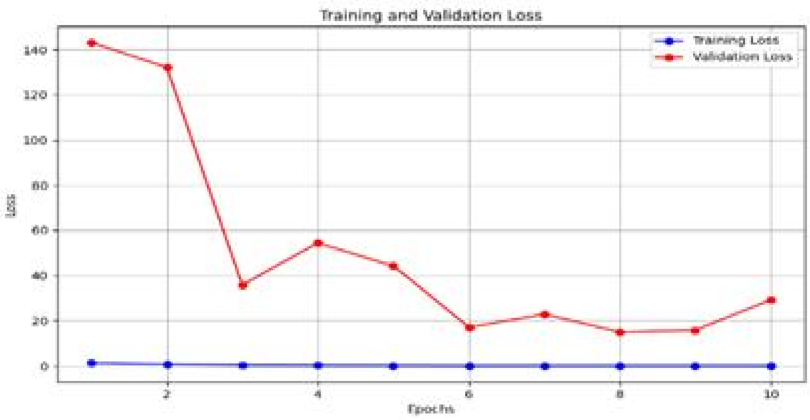


**Fig. 12** Training and Validation Loss of VGG16 Model.

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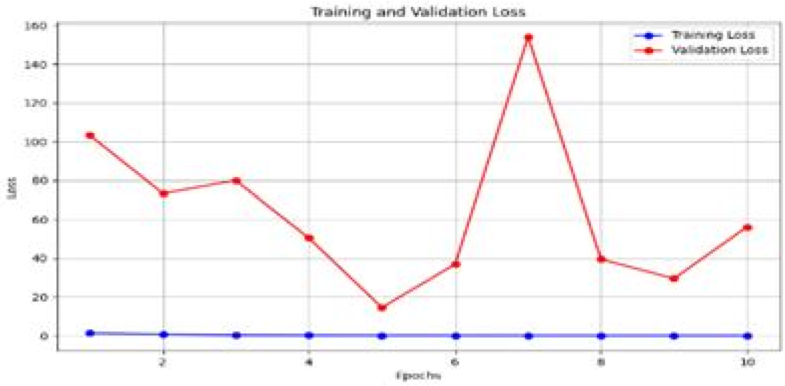


**Fig. 13** Training and Validation Loss of VGG19 Model.

**2) Memory Utilization and Parameter Count:** To gain insight into the storage and resource needs of each architecture, the models are compared according to their parameter counts and memory utilization (Table IV).

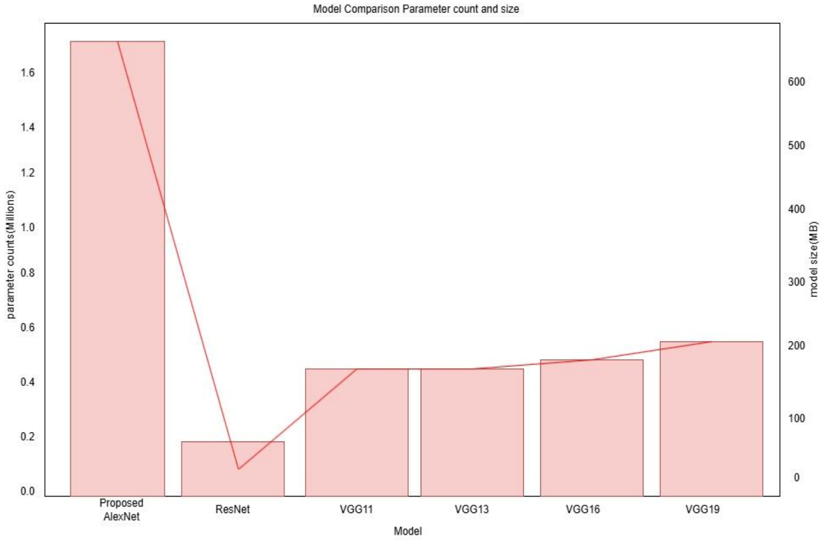


**Table IV** - Evaluation of Models According to Their Memory Utilization and Number of Parameters

| Model | Parameter count | Size of the Model |
|---|---|---|
| Lightweight AlexNet | 170,063,687 | 6.49 MB |
| ResNet | 4,344,071 | 15.57 MB |
| VGG11 | 44,908,935 | 171.31 MB |
| VGG13 | 45,093,447 | 172.02 MB |
| VGG16 | 50,403,143 | 192.27 MB |
| VGG19 | 55,712,839 | 212.53 MB |

**Fig. 14** The number of parameters and model size of the Lightweight AlexNet, ResNet, and VGG models.

As illustrated in Fig. 14, the suggested model is substantially smaller than the VGG series (each exceeding 170 MB) with only 1.7 million parameters and a compact size of roughly 6.49 MB. While Lightweight AlexNet is more resource-efficient and still achieves greater accuracy, ResNet contains the fewest parameters (4.34 million) of all the baselines. Because of its small size, the model can be deployed on low-power devices such as smartphones and embedded systems, making it ideal for edge computing applications in agriculture.

**3) Accuracy and F1-Score Comparison:** Using the dataset of diseased tomato leaf classification, the models' accuracy and F1-score are evaluated (Table V).

**Table V** - F1-Score and Accuracy of Different CNN Models

| Model | Accuracy | F1 score |
|---|---|---|
| Lightweight AlexNet | 99.48% | 99.28% |
| ResNet | 21.78% | 5.11% |
| VGG11 | 96.78% | 89.72% |
| VGG13 | 84% | 96.26% |
| VGG16 | 96.53% | 96% |
| VGG19 | 86% | 90% |

**4) Feature Extraction Using the Lightweight AlexNet Model:** Let us look at a tomato leaf disease called Miner. Tomato Leaf Miner Disease is depicted in Fig. 15. As seen in Fig. 16, based on the patterns that each filter is intended to identify, the colors in each feature map display activation values for various input image regions. The colors on each feature map correspond to the activation levels for various input image segments, based on the patterns that each filter is designed to identify:

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**Fig. 15** Tomato Leaf Miner Disease.

- Purple (dark areas): The filter was unable to identify the target feature because of low activation levels. There were no patterns or features (such as borders, textures, or signs of disease) in these areas.

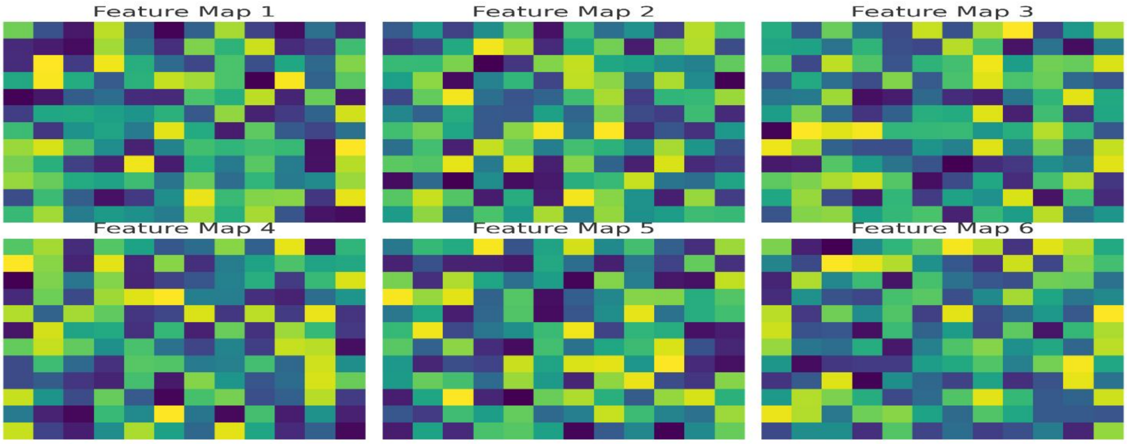


**Fig. 16** Feature maps showing activation values for various areas of the input image, corresponding to the patterns that each filter is designed to identify.

- Blue/Green (intermediate areas): Moderate activations showing that the filter partially recognized certain elements but not all matched the pattern the filter was trained to recognize.
- Yellow (bright patches): High activation levels showing that the filter responded significantly to these sections. The filter has identified traits that closely resemble the pattern it has learned, such as spots or lesions on leaves.

Edges, corners, and textural characteristics of tomato leaf miner disease are identified utilizing the Lightweight AlexNet Model through the following steps:

- Edge Detection (Canny Edge Detector): The Canny edge detector in OpenCV is used to find edges. The image is converted to grayscale and edges are highlighted using cv2.Canny.
- Corner Detection (Harris Corner Detector): OpenCV provides the Harris Corner Detection technique (cv2.cornerHarris) to find corner points marked in red on the original image.
- Texture Identification (Local Binary Patterns): Local Binary Patterns (LBP) is a valuable technique to identify texture patterns. The lbp_image function calculates LBP features for each pixel by examining its neighbors.
- Model Prediction **:**The trained Lightweight AlexNet model classifies the image for disease after edge, corner, and texture detection. The output displays the projected illness class as the title.

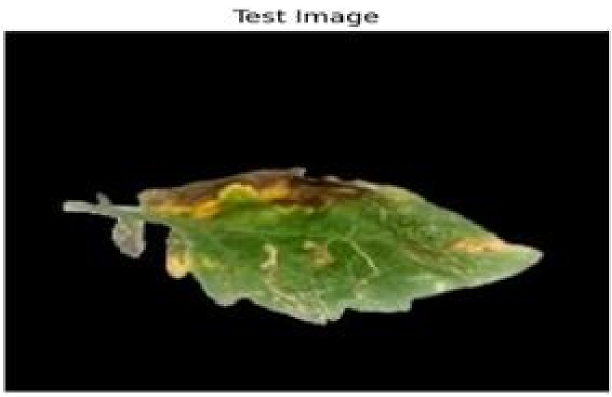


**Fig. 17** The test image is Tomato Leaf Miner Disease.

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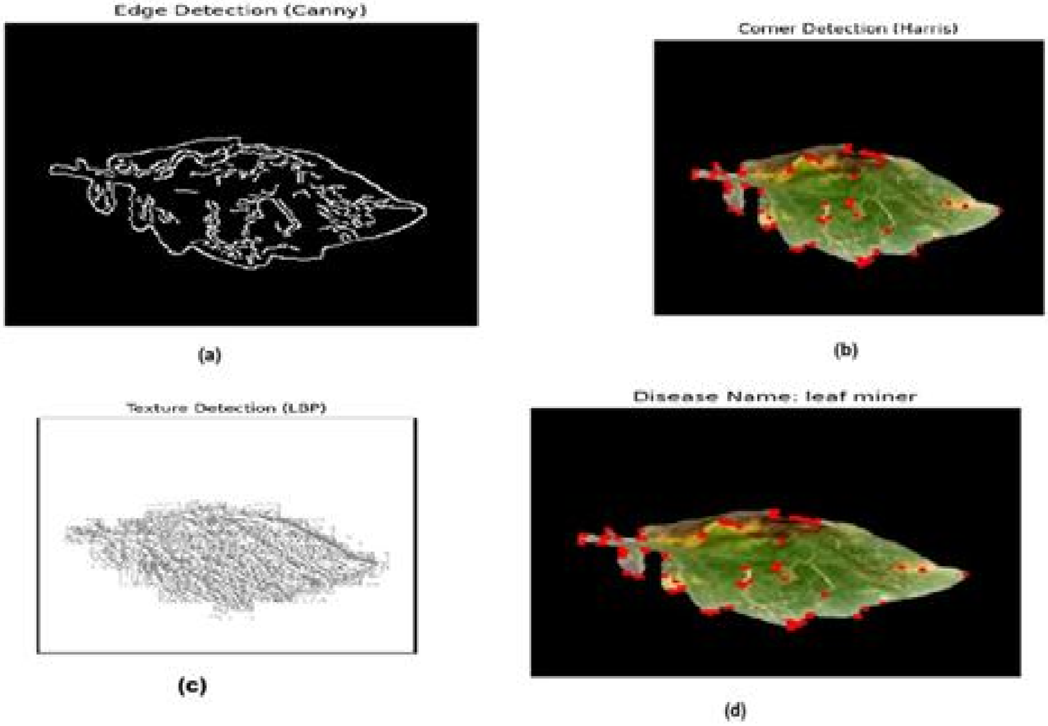


**Fig. 18** (a) Tomato leaf miner edge detection, (b) corner detection, (c) texture detection, and (d) predicted disease name: Tomato Leaf Miner.

## IV. CONCLUSION

In order to meet the urgent demand for resource-efficient yet highly effective models in agricultural contexts, this study presents a Lightweight AlexNet CNN designed for real-world tomato leaf disease classification. By achieving a validation accuracy of 99.74%, training accuracy of 99.15%, and an F1-score of 99.28% across seven field-derived disease classes, the suggested architecture, in contrast to traditional heavy models, strikes an impressive balance between accuracy and computational simplicity. In contrast to the majority of research that relies on lab-clean datasets, this performance highlights the model's strong generalization on noisy, field-collected data. Faster inference is made possible by the lightweight architecture, which makes it appropriate for deployment on mobile platforms and edge devices.

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### Author Contributions

Conceptualization: D.B. and S.D.K.; Methodology: D.B. and K.C.B.; Software: D.B.; Validation: D.B., K.C.B. and S.D.K.; Formal analysis: D.B. and K.C.B.; Investigation: D.B. and K.C.B.; Resources: K.C.B. and S.D.K.; Data Curation: D.B. and K.C.B.; Writing & original draft preparation: D.B.; Writing & review and editing: D.B., K.C.B. and S.D.K.; Visualization: D.B.; Supervision: S.D.K.; Project Administration: S.D.K. All authors have read and agreed to the published version of the manuscript.

### Conflict of Interest

The authors declare that there are no conflicts of interest.

### Data Availability Statement

The datasets generated and/or analyzed during the current study, comprising field-collected and augmented tomato leaf images from the Golaghat district of Assam, India, are available from the corresponding author upon reasonable request.



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