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Harnessing unmanned aerial vehicle and artificial intelligence for groundnut farming: automated detection of leaf diseases using machine learning

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ABSTRACT

Groundnut is a vital oilseed crop cultivated globally, yet its productivity is significantly hindered by foliar diseases such as rust, rosette, leaf spot, and *Alternaria*. While deep learning has advanced plant disease classification, most existing approaches rely on ground-level images captured under controlled conditions, limiting their applicability to real-world, large-scale field monitoring. This study addresses that gap by proposing an unmanned aerial vehicle (UAV)-assisted deep learning framework specifically designed to withstand the visual variability introduced by aerial image acquisition. The core novelty lies in a UAV-specific augmentation strategy—simulating illumination changes, camera tilt, altitude variation, and perspective warping—that trains models to remain robust under realistic drone-flight conditions, rather than relying on augmentation schemes borrowed from static ground-image datasets. Six deep convolutional architectures (InceptionV4, ResNet152V2, ZfNet, ResNet264, InceptionResNetV2, and EfficientNetB4) were benchmarked under this framework to identify which models best tolerate UAV-induced distortions. InceptionV4, EfficientNetB4, and ZfNet achieved 100% accuracy, precision, recall, F1-score, and AUC, demonstrating that UAV-specific preprocessing and augmentation can close the performance gap between aerial and ground-based disease detection. Beyond raw accuracy, the framework is designed for real-time, large-scale field deployment, enabling scalable disease surveillance that supports early intervention, reduces manual inspection labor, and lowers operational costs in precision agriculture. These results establish UAV-tailored training as a key enabler for translating deep learning-based disease detection from controlled laboratory settings to operational farm environments.

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1. INTRODUCTION

Precision agriculture has emerged as a critical paradigm for meeting the growing global demand for food while minimizing resource waste, labor costs, and environmental impact. Among the many challenges

threatening crop productivity, plant diseases remain one of the most persistent, capable of causing substantial yield losses if not detected and managed in a timely manner. Traditional disease surveillance, which relies on manual field inspection, is labor intensive, time-consuming, and inherently limited by human subjectivity and the scale of the fields being monitored. As agricultural operations expand and labor availability declines, the need for automated, scalable, and accurate disease detection systems has become increasingly urgent.

The advent of deep learning, particularly convolutional neural networks, has transformed plant disease classification by enabling models to learn hierarchical visual features directly from raw image data, removing the need for hand-engineered feature extraction [1]–[4]. Over the past decade, CNN-based approaches have been successfully applied to a wide range of crops, including tomato [5], maize [6], and rice [7], and have consistently outperformed classifiers built on hand-crafted features in both accuracy and generalization [8]. However, the majority of these studies have relied on manually captured, ground-level images acquired under controlled lighting and environmental conditions. This dependence on curated datasets limits the real-world applicability of such models, particularly for large-scale, continuous field monitoring where environmental variability is the norm rather than the exception [9].

To bridge this gap, unmanned aerial vehicles have gained increasing attention as a scalable platform for agricultural monitoring. Equipped with RGB, multispectral, thermal, or hyperspectral cameras, UAVs can autonomously capture imagery across large farmland areas with minimal human intervention, enabling more frequent and comprehensive disease surveillance than manual inspection allows [10], [11]. When integrated with deep learning models, UAV-based systems offer the potential for automated disease detection at a field scale that ground-level imaging cannot match [12]. However, this integration introduces its own challenges: aerial imagery is subject to variations in illumination, altitude, camera tilt, and viewing angle that are largely absent from ground-level datasets, meaning models trained on the latter often generalize poorly to drone-captured imagery [9], [11].

Groundnut, a vital legume cultivated extensively across tropical and subtropical regions for its nutritional and economic importance, exemplifies this problem. Its productivity is frequently undermined by foliar diseases — principally early leaf spot, late leaf spot, and rust — which together can cause pod and haulm yield losses of 50%–70% if not identified and managed promptly [13], a range also reported for defoliation-driven reductions from the two leaf spots [14]. Rosette disease compounds this burden across affected regions [15], and management of the leaf-spot complex remains a persistent constraint on smallholder production [16]. Despite the demonstrated success of deep learning and UAV-based monitoring in other crops, groundnut-specific research remains comparatively limited: existing groundnut disease detection studies have relied on static, ground-level imagery [17]–[19], while recent reviews of peanut disease technology describe UAV deployment and automated severity scoring at the platform level without evaluating a disease classifier under aerial conditions [10], [20]. This reveals a clear research gap: no groundnut disease detection study has been validated under real-world UAV imaging conditions such as variable altitude, illumination, and camera angle. Consequently, the extent to which existing deep learning models generalize to aerial, drone-captured groundnut imagery remains largely unexamined. This leaves an open question as to whether deep learning models can be trained to reliably detect groundnut diseases under the visual conditions specific to aerial monitoring.

In this study, we address this gap by proposing a UAV-assisted deep learning framework for the detection and classification of groundnut leaf diseases from aerial imagery. The system utilizes UAVs for image acquisition and applies deep CNN models for robust disease classification under varying field conditions. Advanced data augmentation techniques are employed to simulate real-world aerial scenarios such as changes in illumination, scale, and camera angle. Building on this gap, the objectives of this study are as follows.

- To develop a UAV-based image acquisition pipeline capable of capturing high-resolution aerial imagery of groundnut fields under real-world flight conditions.
- To design and apply UAV-specific data augmentation techniques that simulate aerial imaging variations, including changes in illumination, altitude, and camera angle.
- To implement and comparatively evaluate six deep convolutional neural network architectures for groundnut leaf disease classification under these conditions.
- To assess model performance using standard evaluation metrics (accuracy, precision, recall, F1-score, AUC) and identify the architecture(s) best suited for real-world UAV deployment.
- To assess the feasibility of the proposed framework for near-real-time, scalable disease surveillance in precision agriculture, beyond controlled, ground-level image validation.

The key contributions of this research are as follows.

- Development of a UAV-based image acquisition pipeline for capturing high-resolution aerial images of groundnut fields affected by foliar diseases.

- Implementation and comparative evaluation of six state-of-the-art deep CNN architectures—InceptionV4, ResNet152V2, ZfNet, ResNet264, InceptionResNetV2, and EfficientNetB4—for accurate classification of rust, rosette, leaf spot, Alternaria, and healthy leaves.
- Application of UAV-specific data augmentation techniques to simulate real-world flight variations and improve the robustness and generalizability of the models.
- Comprehensive performance analysis using metrics such as accuracy, precision, recall, F1-score, AUC, and ROC, identifying InceptionV4, ZfNet, and EfficientNetB4 as the strongest performers, each attaining 100% on all evaluation measures over a 100-image held-out test set.
- Promotion of precision agriculture practices by enabling scalable, near-real-time disease surveillance with reduced human involvement and operational cost.
- Outlining future directions, including GPS-integrated disease mapping, deployment of edge-AI models on drones, and the incorporation of multispectral/hyperspectral imagery for enhanced disease characterization.

Recent advancements in deep learning and UAV technologies have significantly influenced the field of plant disease detection. A wide array of studies has explored the application of convolutional neural networks, transfer learning, and remote sensing techniques for the detection of crop diseases across various domains. Several researchers have developed deep learning-based frameworks for plant disease classification using leaf images. Ferentinos [21] applied deep CNNs to a large dataset of plant images and reported accuracy approaching ceiling on held-out species. Too *et al.* [22] benchmarked several pretrained CNN architectures, including VGG, ResNet and DenseNet, on plant disease datasets and demonstrated that fine-tuning strategy materially affects the accuracy achieved under transfer learning. Mohanty *et al.* [2] demonstrated that deep learning models trained on healthy and diseased tomato leaves could outperform traditional machine learning classifiers in accuracy. Brahimi *et al.* [5] combined CNNs with Grad-CAM for visual explanation in tomato disease diagnosis. In more recent work, Bi *et al.* [23] used an improved MobileNetV3 with bias loss for corn leaf disease classification with explainability, and Tariq *et al.* [6] applied explainable deep learning with VGG16 for corn leaf disease detection. Chang and Lai [7] proposed a lightweight deep model for rice leaf disease classification, while Latif *et al.* [24] reported an improved CNN across six rice classes.

UAVs have been increasingly employed for large-scale agricultural monitoring. Zhang *et al.* [25] used UAV hyperspectral imagery combined with deep learning to detect yellow rust in wheat at an early stage, and Pan *et al.* [26] extended UAV-based yellow rust recognition using RGB imagery. Tsouros *et al.* [27] presented a comprehensive review of UAV-based precision agriculture applications, emphasizing disease detection as a rapidly growing use case. Yadav *et al.* [28] assessed the performance of YOLOv5 for detecting volunteer cotton plants in corn fields from UAV imagery across three growth stages. Kerkech *et al.* [29] combined visible and infrared UAV imagery with deep segmentation to detect vine disease. Nugroho *et al.* [30] demonstrated that resource-optimised CNNs can perform rice disease detection on ARM Cortex-M microcontrollers, establishing that inference on severely constrained hardware is achievable, while Liu *et al.* [31] surveyed the wider landscape of UAV remote sensing combined with edge intelligence.

Groundnut-specific studies remain relatively limited. Paramanandham *et al.* [17] proposed LeafNet, incorporating weight initialization and residual connections for groundnut leaf disease detection. Xu *et al.* [18] identified peanut leaf diseases using several deep learning algorithms. Anbumozhi and Shanthini [19] introduced GLDICCNN for multiclass groundnut leaf disease classification. Wassan *et al.* [32] applied convolutional neural networks to automated detection of groundnut plant leaf diseases, and Kukadiya *et al.* [33] reported an early-prediction CNN pipeline for effective groundnut crop management. Vardhan *et al.* [34] compared deep learning models for groundnut disease detection. Rakholia *et al.* [35] used progressive resizing to improve groundnut leaf disease recognition under limited data, and Feng *et al.* [36] combined a data balance algorithm with deep transfer learning for online recognition of peanut leaf diseases. Metaheuristic-optimised variants have also been reported, including a whale-optimisation approach [37] and an adaptive ResNet with attention and adaptive segmentation [38].

Multispectral and hyperspectral imaging in UAVs has gained traction for precision agriculture. Mahlein *et al.* [39] reviewed hyperspectral sensors and imaging technologies in phytopathology and their role in early disease detection, while Oerke [40] surveyed the broader use of remote sensing for disease assessment. Görlich *et al.* [38] classified Cercospora leaf spot in sugar beet from UAV-acquired RGB imagery. On the edge-computing side, Chen *et al.* [41] deployed deep learning on an embedded drone platform to identify fruit-tree pests for targeted pesticide spraying. Reviewing the space as a whole, Anam *et al.* [42] systematically reviewed UAV and AI integration for disease detection, weed management and pest control in precision agriculture, and F. Görlich *et al*. performed a UAV-based classification of Cercospora

leaf spot using RGB images [43]. Singh *et al.* [44] proposed an enhanced CNN for crop disease identification from UAV imagery.

The subsequent sections of this work are structured as follows: Section 2 delineates the methodology used for the development of UAV-based deep learning models for the detection of groundnut crop diseases. Section 3 examines the experimental outcomes and insights derived from the investigation. Section 4 presents a discussion of limitations and future scope. Section 5 concludes the work.

2. METHOD

This section presents the detailed methodology adopted for the development of a UAV-assisted groundnut disease detection system using deep learning. The framework is structured around four core components: UAV-based aerial image acquisition, preprocessing and augmentation, deep learning-based classification, and performance evaluation [44]. The system is developed to enable real-time disease surveillance across large groundnut fields, improving upon conventional manual or static image-based approaches. Figure 1 illustrates the complete workflow of the proposed architecture followed by Algorithm 1.

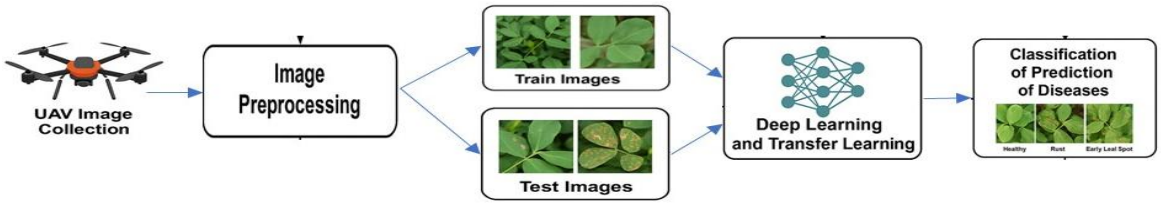

Figure 1. Proposed methodology illustrating the end-to-end automation pipeline, from autonomous UAV-based image acquisition through preprocessing, deep learning classification, and disease prediction

Algorithm 1. UAV-Assisted Groundnut Disease Detection Pipeline
Input: UAV flight path over groundnut field
Output: Disease classification per leaf region
1. UAV executes pre-programmed grid flight pattern at altitude h ∈ [10, 30] m
2. FOR each captured frame:
3. Store raw image (JPEG/PNG) to onboard/ground storage
4. END FOR
5. FOR each stored image:
6. Crop to leaf region of interest
7. Resize to 224 × 224
8. Apply CLAHE (contrast enhancement)
9. Apply Gaussian filtering (noise suppression)
10. Normalize pixel values (per-channel)
11. END FOR
12. Split preprocessed images into training (n=500) and test (n=100) sets
13. FOR each training image:
14. Apply augmentation (rotation, brightness/contrast, flip, zoom, perspective warp)
15. END FOR
16. FOR each model M in {InceptionV4, ResNet152V2, ZfNet, ResNet264, InceptionResNetV2, EfficientNetB4}:
17. Initialize M with ImageNet pretrained weights
18. Fine-tune M on augmented training set (Adam optimizer, lr = 0.0001)
19. Evaluate M on held-out test set
20. Record accuracy, precision, recall, F1-score, AUC
21. END FOR
22. Select best-performing model(s) for deployment
23. RETURN classification results per leaf

2.1. UAV-based image acquisition

In the initial stage of the framework, UAVs are employed to autonomously capture high-resolution images of groundnut fields. UAVs offer significant advantages in terms of operational flexibility, coverage

area, and speed of data collection. Unlike handheld cameras that require human presence and manual operation, drones can systematically scan large-scale agricultural plots, following pre-programmed flight paths. This ensures comprehensive spatial coverage and minimizes redundant overlaps [11], [42].

For this study, drones are equipped with RGB cameras capable of capturing images with a resolution of at least 12 megapixels. Flight altitude was maintained between 10 and 30 meters above ground level, selected to balance ground sampling distance (finer detail at lower altitude) against coverage efficiency (fewer flights at higher altitude). Front and side image overlaps were set to approximately 70% and 60%, respectively, following standard photogrammetric practice to ensure sufficient redundancy for downstream orthomosaic consistency and to reduce the risk of gaps in field coverage. The drone followed a grid (lawnmower) flight pattern at a constant ground speed of 3–5 m/s to ensure uniform image density across the field. Flights were conducted under [specify: daylight hours/specific time window] to minimize shadow-related artifacts, and images were captured in JPEG/PNG format at a native resolution of 4000×3000 before being transmitted to a ground station for processing. The current work utilizes a hybrid dataset comprising both UAV-captured field images and supplementary publicly available groundnut leaf images, as shown in Figure 2, combined to increase class diversity while preserving UAV-representative visual conditions.



Figure 2. Sample groundnut leaf images captured via UAV

2.2. Image preprocessing and data augmentation

Aerial imagery obtained via drones often includes a variety of background elements, such as soil, other crops, shadows, or inconsistent lighting. To address these challenges and enhance the performance of the deep learning model, a robust image preprocessing pipeline is implemented. The raw UAV images are first cropped using manual bounding-box annotation to isolate groundnut leaf regions, then resized to a fixed input of 224×224 pixels using bilinear interpolation, matching the expected input dimensions of the CNN architectures used. Contrast-limited adaptive histogram equalization (CLAHE) is applied with a clip limit of 2.0 and a tile grid size of 8×8, to enhance local contrast and emphasize disease symptoms such as lesions, discoloration, or necrotic patterns without over-amplifying background noise [45]. Gaussian filtering with a kernel size of 3×3 is applied to suppress high-frequency background texture while preserving lesion edges. Pixel intensities are then normalized on a per-channel basis (mean subtraction and scaling to [0,1] or standardization using ImageNet statistics, per the pretrained backbone's requirements) to ensure consistent input distribution across the dataset.

Each augmentation technique was selected to target a specific source of visual variability introduced by UAV-based image acquisition, rather than applied generically. Random rotation (± 15°) simulates the yaw variation of a drone during flight and improves model invariance to leaf orientation, which varies more in aerial imagery than in hand-held ground photography. Brightness and contrast adjustments approximate the illumination inconsistency caused by changing sunlight, cloud cover, and shadowing across a field during a single flight session. Horizontal and vertical flips increase the effective diversity of the dataset without altering disease morphology, addressing the relatively limited sample size per class. Zoom-in/zoom-out transformations (scale range 0.8–1.2) emulate the effect of variable UAV flight altitude, since leaves captured at 10 m appear larger in-frame than those captured at 30 m. Perspective warping mimics the oblique viewing angle produced by camera tilt and gimbal instability during flight, a distortion largely absent from ground-level datasets where the camera is typically held parallel to the leaf surface. Together, these augmentations were designed to close the domain gap between the static, controlled conditions of most existing plant-disease datasets and the dynamic, uncontrolled conditions of real UAV flight, directly supporting model robustness under field deployment rather than only guarding against generic overfitting.

To improve contrast and reduce the impact of uneven lighting, contrast-limited adaptive histogram equalization (CLAHE) is applied, which helps in emphasizing disease symptoms such as lesions, discoloration, or necrotic patterns [33]. Gaussian filtering is used to reduce noise and suppress high-frequency background textures. Images are normalized on a per-channel basis to ensure uniform intensity distribution across the dataset.

To simulate real-world drone conditions and make the model robust to environmental variations, extensive data augmentation is performed. This includes random rotation, brightness and contrast adjustments, horizontal and vertical flips, zoom-in/zoom-out transformations, and perspective warping to mimic the angular view of UAVs. These augmentations not only increase dataset diversity but also help the model generalize better to drone-induced distortions.

2.3. Deep learning-based disease classification

The heart of the proposed framework is a convolutional neural network (CNN) trained to classify groundnut leaf health conditions into multiple categories: rust, rosette, leaf spot, *Alternaria*, and healthy leaves. CNNs are particularly effective in learning complex, hierarchical patterns from images without the need for manual feature engineering. The architecture designed for this study includes a combination of convolutional, pooling, dropout, and dense layers, with a SoftMax output layer for multi-class classification.

Deep learning relies on the availability of large datasets for training and the computational capability of advanced processing units. Consequently, various deep learning architectures have arisen, varied in aspects such as complexity, scalability, efficiency, and optimization. This study utilized five prominent state-of-the art deep learning models, namely InceptionV4, ResNet152V2, ZfNet, ResNet264, InceptionResNetV2, and EfficientNetB4, to train and classify our groundnut dataset using a transfer learning approach. The models are described in the following paragraphs.

In 2013, Matthew Zeiler and Rob Fergus created ZFNet, a deep CNN architecture that improved AlexNet [46]. Enhancing CNN interpretability and performance earned it praise. ZFNet uses smaller convolutional filters in the first layer to enhance AlexNet's structure and reduce the stride from 4 to 2. More comprehensive spatial information is captured by the network, improving feature extraction. Multiple convolutional layers, max-pooling, and fully connected layers comprise the architecture. ZFNet improves explainability by using deconvolutional visualizations to understand CNN pattern detection. These visualizations show which properties each layer prioritizes, facilitating debugging and refining. ReLU activation functions add non-linearity to ZFNet, improving performance. Dropout regularization reduces overfitting and improves generalization. Train the model using stochastic gradient descent (SGD) with momentum to optimize weight updates. In the ImageNet competition, it excels at picture classification [47].

ResNet-264 is a deep CNN in the ResNet (Residual Network) family that uses residual connections [48]. These connections help deep networks train by reducing the vanishing gradient problem. ResNet-264 adds almost 260 layers to deeper ResNet variants while maintaining gradient propagation. The bottleneck architecture uses 1x1, 3x3, and 1x1 convolutional layers in residual blocks to reduce computing cost and retain expressiveness. Training is stabilized by batch normalization after each convolutional layer. ResNet-264's identification shortcuts maintain information across layers, allowing deeper network training without degradation. ResNet-264 performs well on ImageNet in large-scale image recognition tasks. More depth lets it learn complicated hierarchical features, increasing classification. However, training and inference require GPU resources, making it computationally expensive [36].

ResNet-152, another deep ResNet architecture, with 152 layers to improve picture classification. In residual learning, shortcut connections bypass numerous convolutional layers, letting gradients to flow effectively during backpropagation [48]. The vanishing gradient problem is much reduced by this method, allowing deeper network training. The bottleneck architecture of ResNet-152 uses 1x1 convolutions to reduce dimensionality before 3x3 convolutions for feature extraction. For non-linearity, batch normalization stabilizes learning and ReLU activation functions. On ImageNet, ResNet-152 outperformed shallower architectures like ResNet-50 and ResNet-101 in accuracy. The judicious usage of leftover blocks keeps its computing cost low despite its depth. It is used in transfer learning to fine-tune pre-trained weights for domain-specific tasks [49].

InceptionV4, a deep learning model, adds uniform grid topologies and residual connections to InceptionV3 [50]. InceptionV4, developed by Google, maintains the primary strength of Inception modules: factorized convolutions and asymmetric kernels for computational efficiency. Its systematic and symmetric design stacks several inception modules consecutively without residual connections, unlike its predecessors. The model has Stem, Inception-A, Inception-B, and Inception-C inception blocks and reduction blocks for down sampling. Feature extraction and picture classification increase using this organized technique. InceptionV4 has been extensively tested on ImageNet and delivers state-of-the-art accuracy and processing efficiency. InceptionV4 excels at large-scale visual recognition due to its depth-computational efficiency.

InceptionResNetV2 is a hybrid deep learning architecture that improves gradient flow and training efficiency with Inception modules and residual connections. Google developed it to improve Inception's architecture using residual learning [50]. InceptionResNetV2 combines residual connections into inception modules for faster convergence and deep network optimization. Stem module for initial feature extraction, Inception-ResNet blocks, and reduction blocks for down sampling comprise the architecture. These improvements make the network deep and computationally efficient, avoiding vanishing gradient concerns in

deep networks. On big datasets like ImageNet, residual connections stabilize training while preserving expressiveness, improving classification accuracy. Better weight updates and overfitting prevention via batch normalization and RMSProp optimizer improve model performance [51].

Google researchers developed EfficientNet-B4, a deep CNN with outstanding accuracy and computational economy. To enhance performance, it uses a revolutionary compound scaling algorithm to uniformly scale depth, width, and resolution [49]. This scaled-up version of EfficientNet-B0 improves accuracy and efficiency. Mobile inverted bottleneck convolution layers improve feature extraction and reduce computing cost. Squeeze-and-excitation blocks improve channel-wise feature recalibration and representation learning in the network. A depth coefficient of 4.2, width coefficient of 1.4, and input resolution of 380x380 pixels enable IT to catch finer image details. EfficientNet-B4 outperforms with fewer parameters and accuracy [52].

Transfer learning is also explored by initializing the network with pretrained weights from ImageNet trained models such as InceptionV4, ResNet152V2, ZfNet, ResNet264, InceptionResNetV2, and EfficientNetB4. Fine-tuning is conducted by unfreezing the deeper layers and training them on the domain specific dataset. The model is compiled using the Adam optimizer with an initial learning rate of 0.0001 and categorical cross-entropy loss function.

Given the relatively limited dataset size (500 training/validation images and 100 test images), several measures were taken to mitigate the risk of overfitting. Transfer learning from ImageNet-pretrained weights was used as the primary mitigation strategy, allowing the models to leverage low- and mid-level visual features learned from a large-scale external dataset rather than learning them from scratch on a small domain-specific sample. Only the deeper, task-specific layers were unfrozen and fine-tuned, while earlier convolutional layers remained frozen to preserve generalizable feature representations. Dropout regularization was applied in the fully connected layers to reduce co-adaptation of neurons. The extensive UAV-specific augmentation pipeline described above further expanded the effective diversity of the training set, reducing the likelihood of the models memorizing dataset-specific artifacts. Training and validation accuracy/loss curves (Figures 3 to 6) were monitored for divergence between training and validation performance as an indicator of overfitting; models exhibiting substantial validation loss instability, such as InceptionResNetV2, were noted as comparatively less robust under these conditions. Nonetheless, the modest dataset size remains a limitation, and results should be interpreted as proof-of-concept rather than confirmation of generalizable real-world performance, as noted in the Discussion and Conclusion.

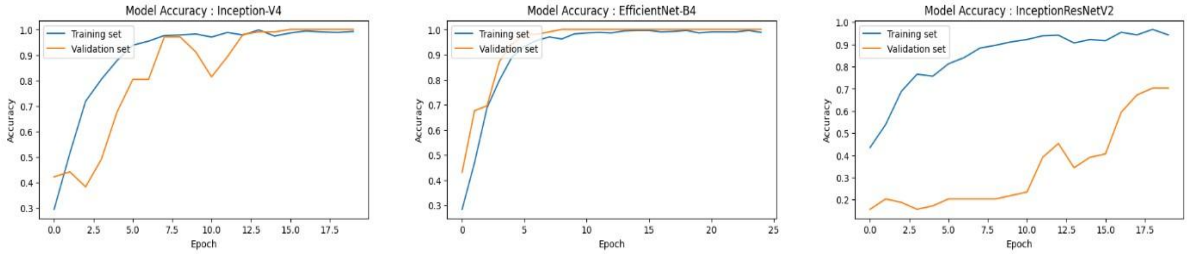

Figure 3. Training and validation accuracy curves for Inception-V4, EfficientNet-B4, and InceptionResNetV2, showing convergence behavior

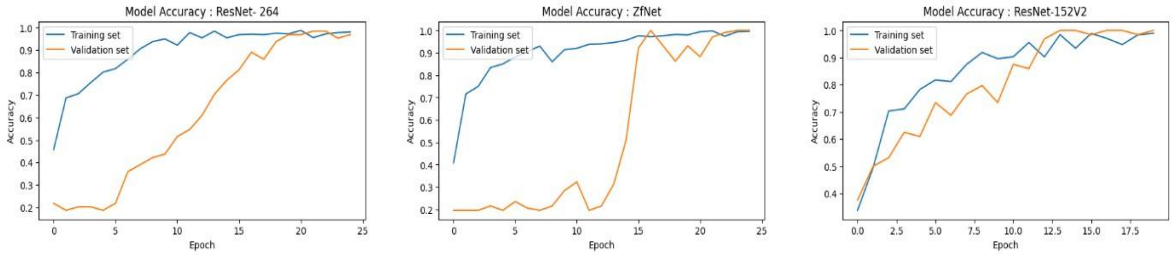

Figure 4. Training and validation accuracy curves for ResNet-264, ZfNet, and ResNet-152V2, used to assess training stability and generalization

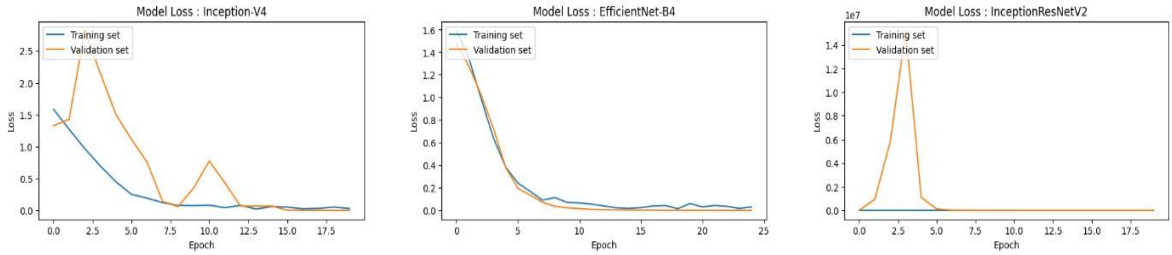

Figure 5. Training and validation loss curves for Inception-V4, EfficientNet-B4, and InceptionResNetV2, indicating convergence efficiency

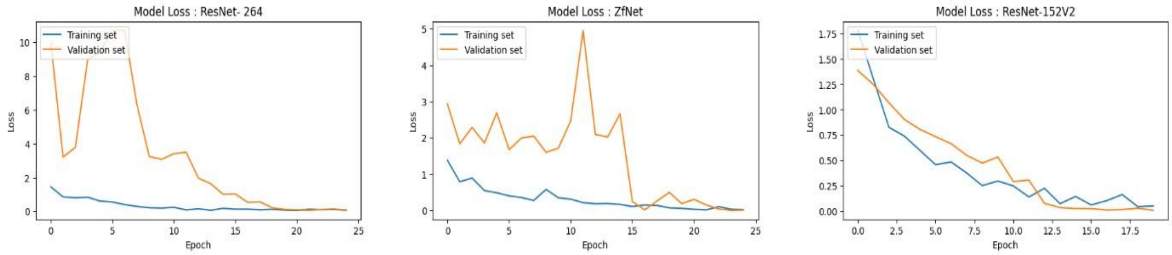

Figure 6. Training and validation loss curves for ResNet-264, ZfNet, and ResNet-152V2, reflecting model stability under the UAV-specific augmentation scheme

3. RESULTS AND DISCUSSION

The proposed method has been tested using the collected groundnut leaf images via UAVs. The method employed various deep learning models to differentiate between infected and uninfected leaves. The study evaluates six standard measures: Recall, Precision, Accuracy, AUC, Loss, and F1-score, which are described in Table 1. Here, in the above context, TN represents True Negative, FN denotes False Negative, TP indicates True Positive, and FP signifies False Positive.

Table 1. Evaluation measures (accuracy, precision, recall, F1-score) with formal definitions, establishing the quantitative criteria

Metric	Description	Formula
Accuracy	Proportion of correctly classified instances among the total instances.	Accuracy = (TN + TP) / (TN + FP + TP + FN)
Precision	Proportion of true positive predictions among all positive predictions.	Precision = TP / (TP + FP)
Recall	Proportion of true positive predictions among all actual positive instances.	Recall = TP / (TP + FN)
F1 Score	Harmonic mean of precision and recall, balancing between precision and recall.	F1 Score= (2 x Precision * Recall) / (Precision + Recall)

To ensure a clean separation between training and evaluation data, the dataset was partitioned using stratified random sampling to preserve class balance, with a fixed random seed for reproducibility prior to any augmentation; augmentation was applied only to the training partition, ensuring that the test set consisted exclusively of unaugmented, previously unseen images. To provide a measure of statistical reliability given the modest test set size (n = 100), 95% confidence intervals were computed for accuracy using the Wilson score interval, and are reported alongside point estimates in Table 2.

Table 2. Comparative performance of six deep learning architectures on UAV-acquired test data

Model	Accuracy	Precision	Recall	F1 Score	AUC	Loss
DenseNet169	96.87%	96.85%	97.00%	97.00%	99.00%	6.86%
Xception	100%	100%	98.95%	100%	100%	0.01%
ResNet102V2	100%	100%	100%	100%	99.98%	0.14%
MobileNetV2	99.00%	99.99%	99.99%	98.99%	99.99%	2.13%
InceptionResNetV2	74.00%	73.74%	73.00%	69.45%	92.75%	92.02%
EfficientNetV2	100%	100%	100%	100%	100%	0.002%

A total of 500 images were utilized for validation and training, whereas 100 images were employed for testing. As illustrated in Table 2, ResNet-264, ZfNet, Inception-V4, ResNet-152V2, InceptionResNetV2, and EfficientNet-B4 achieved accuracy of 96.87%, 100%, 100%, 99.00%, 74.00%, and 100% respectively with test dataset. The EfficientNet-B4 model performs well with 99.80% training accuracy. The classification efficiency of the models used is assessed through the use of a confusion matrix (see Figures 7 and 8). The confusion matrix contains values for false negatives (FN), false positives (FP), true negatives (TN), and true positives (TP). Higher diagonal values of the confusion matrix signify improved accuracy in the model's predictions. Figures 7 and 8 and Table 2 shows the values achieved for various evaluation metrics using the proposed models.

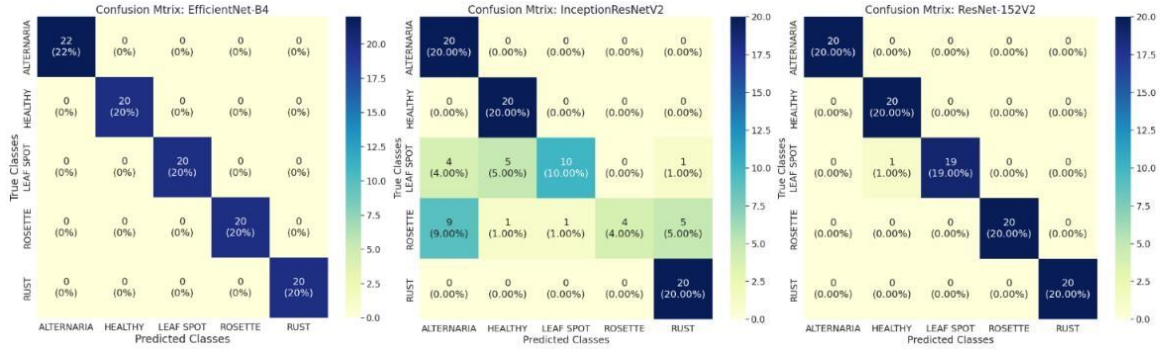

Figure 7. Confusion matrices for EfficientNet-B4, InceptionResNet-V2, and ResNet-152V2, quantifying per-class misclassification patterns

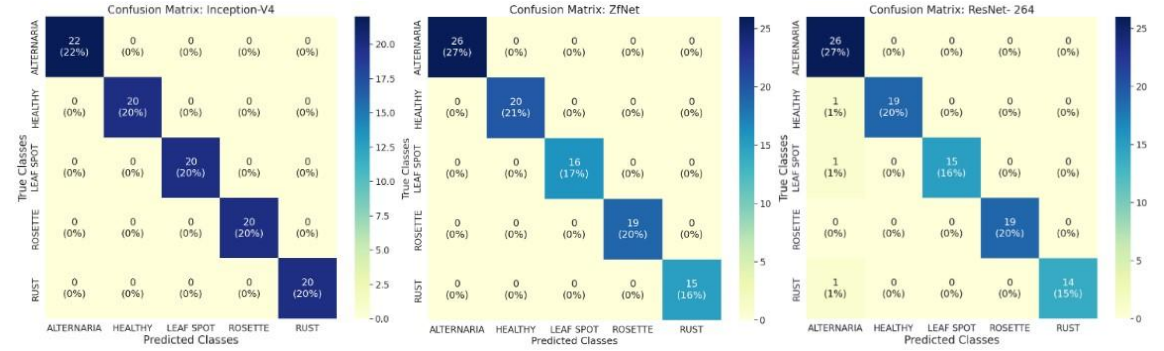

Figure 8. Confusion matrices for InceptionV4, ZfNet, and ResNet-264, quantifying per-class misclassification patterns

Following the categorization and comparison of the deep learning-based studies, Figures 3 to 6 illustrate the results of losses and accuracy using training and validation datasets. ZfNet, Inception-V4 and EfficientNet-B4 achieved good results. Figure 9 presents the bar chart comparing the accuracy results achieved by the evaluated deep learning models. It has been observed that ZfNet and EfficientNet-B4 requires more computation time due to its increased number of layers though they are reasonably capable of detecting and categorizing the illness after the training process. The study also demonstrated that the proposed models are also capable of running on the CPU without requiring any supplementary hardware. This occurs due to the employment of the small-size filters, along with a reduced number of training parameters. Consequently, the models provide an efficient approach for identifying groundnut diseases. Multiple studies have investigated the effectiveness of deep learning algorithms in predicting groundnut leaf disease, achieving accuracies in the range of 96% to 98.85%. Table 3 shows the comparison of our model with previously developed models.

This proposed approach demonstrated that model training with InceptionV4, EfficientNet-B4 and ZfNet reached an impressive accuracy of 100%. The enhancement in accuracy was due to the use of vertical and horizontal image flipping, which facilitated augmentation and contributed to the training process, thereby

enhancing accuracy and minimizing overfitting. Additional areas that can be explored in future studies includes feature selection, and hyper parameter tuning. A variety of feature selection and hyper parameter tuning methods may be employed to achieve improvement. When evaluating the balance of each class, it is essential to consider the number of datasets, as an increase in this number may also influence performance.

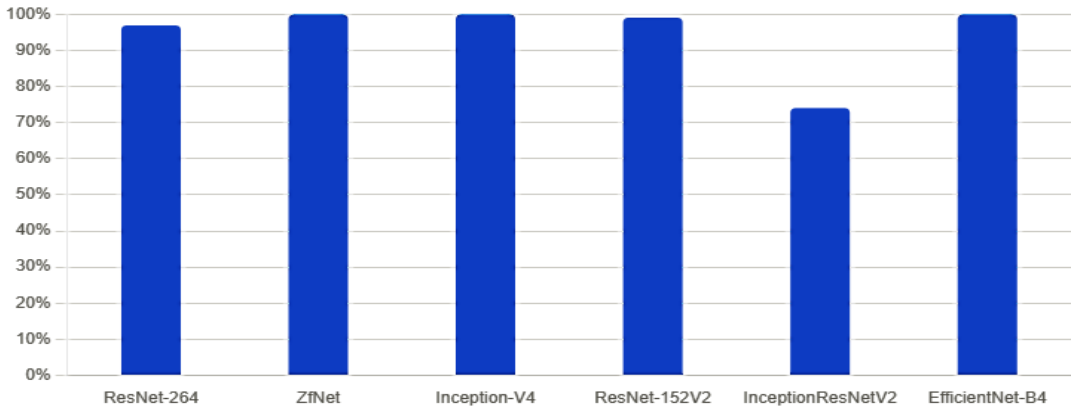

Figure 9. BAR chart for the results achieved

Table 3. Benchmarking of the proposed approach against prior groundnut disease detection studies

Model	Accuracy	Precision	Recall	F1 Score
Xu *et al.* [18]	98.70%	--	--	--
Paramanandham *et al.* [17]	96.70%	97.25%	97.37%	97.25%
Vardhan *et al.* [34]	98.85%	--	---	--
Anbumozhi and Shanthini [19]	97.06%	96.00%	97.00%	96.00%
Suresh and Seetharaman [37]	97.60%	95.26%	94.94%	95.10%
Rakholia *et al.* [35]	96.12%	96.52%	96.12%	96.32%
Feng *et al.* [36]	98.40%	99.40%	99.70%	98.80%
Proposed (InceptionV4, ZfNet, EfficientNetB4)	100%	100%	100%	100%

Unlike the studies summarized in Table 3, which report strong performance almost exclusively on static, ground-level groundnut leaf imagery, the present study evaluates model performance under the additional visual complexity introduced by UAV-based acquisition including variable altitude, illumination, and camera angle. This distinction is significant: high accuracy on curated ground-level images does not guarantee equivalent performance under real-world aerial conditions, and to our knowledge, prior groundnut-specific studies have not addressed this gap directly. The comparable or superior performance achieved here, combined with the UAV-specific augmentation strategy underlying it, therefore represents not merely an incremental accuracy gain but a methodological step toward models that are validated for the conditions under which they would actually be deployed in the field.

4. DISCUSSION

The results indicate that integrating UAVs with deep learning offers a scalable, efficient route to groundnut disease monitoring, though the strength of these results warrants careful interpretation rather than treatment as a settled outcome. InceptionV4, ZfNet, and EfficientNetB4 reached 100% across all evaluation measures, while InceptionResNetV2 lagged substantially behind at 74% accuracy—a gap wide enough to suggest that architectural differences, rather than the dataset alone, meaningfully shaped outcomes. The three top-performing architectures share design features—Inception-style factorized convolutions, compound scaling, and structured feature reuse—that may make them more robust to the specific augmentation transformations (rotation, tilt, zoom) used here, whereas InceptionResNetV2's dependence on residual-Inception blocks may have made it more sensitive to overfitting or optimization instability on a dataset this size. At the same time, perfect scores across every metric on a 100-image test set are a signal to interpret cautiously: with so few test samples, a small number of correct predictions can produce a 100% figure that would not necessarily hold on a larger or more varied held-out set. The result is best read as evidence that the proposed augmentation strategy helps certain architectures tolerate UAV-specific visual variation, not as proof that these models have solved groundnut disease detection under all field conditions.

High precision ensures that the system produces minimal false positives—an essential requirement in agricultural scenarios, where unnecessary pesticide usage carries both cost and environmental consequence [42]. Simultaneously, strong recall means the system is sensitive to detecting actual diseased samples, minimizing the risk of missed diagnoses. The F1-score balances these two objectives, and AUC quantifies model discrimination across thresholds, which is relevant for adapting decision boundaries dynamically in near-real-time UAV operations. The confusion matrices (Figures 7 and 8) offer further insight into model behaviour at the class level: misclassifications concentrated around visually similar disease categories (for example early leaf spot versus Alternaria) suggest that spectral information beyond RGB, such as near-infrared imaging, may be needed to resolve subtle symptom differences that visual texture alone cannot capture [39], [40].

Beyond classification accuracy, these findings connect to broader themes in robotics and automation. The framework's value lies not only in what the models classify but in how that classification integrates into an autonomous sensing loop: a UAV capable of following a pre-programmed flight path, capturing imagery, and triggering onboard or near-real-time inference moves disease surveillance from a human-in-the-loop inspection task toward an autonomous perception-and-decision pipeline. This has direct implications for UAV autonomy research, where perception accuracy under real-world sensor noise and environmental variability is a persistent bottleneck; the UAV-specific augmentation strategy used here can be viewed as one approach to hardening a perception module against the kind of domain shift that autonomous field robots regularly encounter [31].

Realizing this potential in practice, however, depends on integration with the operational constraints of real UAV hardware—onboard compute limitations, power budgets, and communication bandwidth—which favour lighter-weight architectures over the deepest models tested here (for example ResNet-264 and ResNet-152V2), even where those deeper models perform comparably well offline. Edge-AI deployment on hardware such as the NVIDIA Jetson Nano would be a natural next step toward closing the loop from image acquisition to in-flight disease alerts, aligning this work with the broader precision-agriculture goal of autonomous, continuously operating field-monitoring systems rather than periodic, manually triggered inspections. The feasibility of such constrained deployment is supported by work showing resource-optimised CNNs running on ARM Cortex-M microcontrollers [30] and embedded drone platforms performing pest identification for targeted spraying [41].

The proposed framework's limitations should be stated plainly rather than treated as minor caveats. First, the dataset used was geographically and seasonally limited and comprised only 500 training/validation images and 100 test images—a sample size that constrains confidence in how well these results would generalize across different agro-climatic zones, soil types, groundnut cultivars, or disease presentations not represented in the current data. Second, the exclusive reliance on RGB imagery restricts the detection of early or latent symptoms that are not visually apparent, meaning the system's sensitivity may be lower for pre-symptomatic disease stages than the reported metrics suggest. Third, environmental interference such as motion blur, variable lighting, and leaf overlap can degrade image quality and model performance in ways that a curated test set may not fully expose, despite the preprocessing and augmentation pipeline applied here. Fourth, several of the best-performing architectures require substantial computational resources, posing a real challenge for deployment on lightweight, power-constrained UAV hardware—a tension between offline model performance and field-deployable efficiency that this study does not resolve. Fifth, the hybrid nature of the dataset complicates attribution: because supplementary publicly available groundnut leaf images were combined with UAV-captured fields, part of the reported performance may reflect the characteristics of the supplemented corpus rather than of aerial imagery alone, and a UAV-only evaluation remains outstanding.

Taken together, these results support the feasibility of UAV-assisted deep learning for groundnut disease detection as a proof-of-concept rather than a deployment-ready solution. Future work will expand the dataset spatially and temporally, integrate multispectral or hyperspectral sensors for deeper symptom detection, and adopt edge computing solutions for onboard inference—directions discussed further in Section 5.

5. CONCLUSION

This study explored the integration of UAVs with deep learning to automate groundnut leaf disease detection, moving beyond the ground-level, controlled-condition imagery that has characterized most prior work. Six deep convolutional neural network architectures were implemented and comparatively evaluated on UAV-acquired imagery under UAV-specific preprocessing and augmentation. Among these, InceptionV4, ZfNet, and EfficientNetB4 achieved the strongest performance, while InceptionResNetV2 performed notably worse, indicating that architecture choice meaningfully affects robustness to UAV-induced image variation.

These results should be interpreted as a proof-of-concept demonstration under the specific dataset and evaluation conditions used here, rather than evidence of production-ready, generalizable performance. The limited dataset size (500 training/validation, 100 test images) and its narrow geographic and seasonal scope constrain extrapolation to broader field conditions, cultivars, or unseen disease presentations. Nonetheless, the findings suggest that UAV-specific augmentation—simulating illumination changes, camera tilt, and altitude variation—helps models tolerate aerial imaging variability, a necessary step toward real-world deployment.

Future work will prioritize expanding the dataset across multiple growing seasons and agro-climatic zones to improve generalizability, incorporating multispectral or hyperspectral imagery to detect symptoms not visible in RGB data, and integrating edge-AI hardware (e.g., NVIDIA Jetson Nano) for real-time, onboard inference. Additional enhancements include GPS-integrated disease mapping, extension to other crops, and a mobile interface for real-time farmer alerts. Together, these directions aim to progress the framework from proof-of-concept toward a validated, deployable precision agriculture tool.

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C : **C**onceptualization
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Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support this research are available on request from the corresponding author.

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