Automated drone-assisted detection system for rice leaf pathologies a deep learning approach

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ABSTRACT

Early and accurate detection of plant diseases is vital for maintaining agricultural productivity. This study investigates an automated disease identification system specifically designed for the IR64 rice cultivar. By combining drone-captured aerial imagery (UAV) taken during the plant's vegetative stage with public datasets, we established a comprehensive training dataset. The study evaluates and compares four convolutional neural network (CNN) architectures, InceptionV3, ResNet50, EfficientNetV2S, and MobileNetV2, assessing their predictive accuracy and real-world computational efficiency. Our 10-fold cross-validation results indicate varying levels of inference speed and accuracy among the models. InceptionV3 and MobileNetV2 displayed the highest stability and minimal misclassification rates across multiple disease types. In contrast, the performance of ResNet50 and EfficientNetV2S fluctuated significantly depending on the detected pathogen. In conclusion, coupling UAV imagery with fine-tuned deep learning models provides a fast, scalable solution for continuous crop monitoring and precision agriculture.

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1. INTRODUCTION

As a primary food source for a massive portion of the global population, rice production plays a fundamental role in sustaining worldwide food security. Consequently, ensuring the continuous health and maximizing the yield of these crops is of utmost importance. During agricultural surveillance, the leaves of the rice plant act as an essential biological marker, where their physical condition directly predicts the physiological state of the crop and the ultimate harvest output. Pathological damage to paddy foliage severely degrades both the quantity and quality of the grain, potentially leading to profound economic crises within the farming industry and threatening the long-term sustainability of agriculture [1]. Thus, inventing a dependable disease identification framework has become an urgent socio-economic imperative rather than just a technological hurdle. By implementing an automated monitoring tool that guarantees high accuracy and swift notifications, farmers are empowered to execute timely interventions, which in turn drastically limits crop failure and protect international food supplies [1].

In the past, the identification of crop diseases was fundamentally dependent on direct visual inspections conducted by agricultural workers. Nevertheless, relying on manual observation is highly time-consuming, prone to human error due to subjective interpretations, and physically impractical to execute rapidly over large-scale agricultural landscapes [2]-[5]. Because of these logistical limitations, conventional on-site disease monitoring is no longer adequate to meet the fast-paced requirements of modern agriculture. To address these practical challenges, recent academic focus has shifted significantly towards computational solutions [6], particularly exploiting artificial intelligence and computer vision techniques to create automated systems for detecting plant pathogens [7]-[12].

Leading this technological evolution are deep convolutional neural networks (CNNs), which have set unprecedented standards in the field of image and visual pattern classification [13]. By integrating these computational models with versatile sensor technologies, like unmanned aerial vehicles (UAVs) equipped with cameras for direct, on-site data collection, researchers can construct a robust infrastructure for the ongoing, autonomous monitoring of plant conditions [14]. A wide array of empirical studies involving diverse plant types verifies that these sophisticated algorithms continually surpass conventional machine learning techniques in terms of diagnostic precision and their ability to generalize across different environments [15], [16]. Additionally, the implementation of rigorous image pre-processing strategies including specific object segmentation and noise filtering substantially improves the quality of raw visual data, which consequently boosts the predictive accuracy of the deep learning algorithms applied subsequently [17], [18].

Despite these technological strides, a thorough examination of current literature exposes a substantial practical limitation. Most contemporary research on crop pathogen identification depends heavily on stationary leaf photographs that are gathered by hand and analyzed at a later time. Even though such traditional methods can yield high computational precision, they fall short in providing the rapid processing and broad scalability essential for vast agricultural areas. Furthermore, previous investigations seldom tackle the logistical obstacles associated with persistent, self-operating crop monitoring paired with the real-time distribution of diagnostic alerts.

In order to address these critical shortcomings, the present research introduces a comprehensive, automated disease recognition system specifically optimized for the IR64 paddy variant during its active growth phase. The main novelty of our work lies in designing the premier drone-assisted diagnostic workflow for IR64 crops, combining an extensive evaluation of deep learning models with an instant internet of things (IoT) communication channel for agricultural workers. In detail, the primary innovations offered by this study encompass the following areas:

- Drone-facilitated crop monitoring: A resilient diagnostic setting is formulated through the acquisition of ultra-clear aerial foliage imagery via UAVs. This primary data is subsequently enriched using publicly available datasets from Kaggle to guarantee broad data diversity and robustness against changing environmental conditions.
- In depth evaluation of CNN architectures: The study systematically assesses the performance of four different deep learning structures, namely: InceptionV3 [19]-[21], ResNet50 [22]-[29], EfficientNetV2S [30]-[33], and MobileNetV2 [34]. This comparative analysis goes beyond basic predictive precision, heavily emphasizing unique classification errors and the practical feasibility of deploying these networks on edge computing devices.
- Instantaneous IoT connectivity: The analytical inferences generated by the models are directly linked to an alert mechanism via the Telegram application. This integration upgrades conventional, offline image classification into a dynamic, high-speed advisory platform that prompts swift mitigation measures from farmers.

2. METHOD

The empirical focus of this research was directed toward the IR18348-36-3-3 cultivar, commercially recognized as the IR64 paddy variety [35]. Botanically, this specific variant has a maturation cycle spanning 110 to 120 days and typically achieves a vertical stature of 115 to 126 centimeters. All primary visual data was exclusively harvested during the plant's vegetative growth phase. To acquire high-fidelity spatial data, an UAV equipped with advanced optical sensors was deployed. The flight parameters were strictly regulated: the drone maintained a constant hovering altitude of 1 meter above the crop canopy, and the camera gimbal was deliberately tilted at a 45-degree angle to maximize the morphological capture of the leaves. The comprehensive architectural flow of the proposed system, from initial data processing to final deployment, is systematically illustrated in Figure 1.

As depicted in the workflow, the primary raw data comprised continuous video streams that were subsequently decomposed into individual high-resolution standalone frames. To construct a more resilient and diverse training corpus, these primary drone-captured frames were amalgamated with secondary open-source datasets retrieved from the Kaggle repository [36]. Specifically, the aggregated dataset comprised 9200 images in total (2300 images per class). To manage data variance, approximately 1000 images per class were meticulously extracted from the UAV footage, while the remaining 1300 images were sourced from Kaggle. Prior to model feeding, the aggregated image pool was processed through the Roboflow computer vision platform. This critical pre training phase involved rigorous image normalization techniques, encompassing spatial resizing to a standardized resolution of 224 x 224 pixels, chromatic adjustments, and algorithmic noise suppression. These standardization steps were vital to eliminate environmental artifacts and enhance the distinct visual signatures of the pathogens.

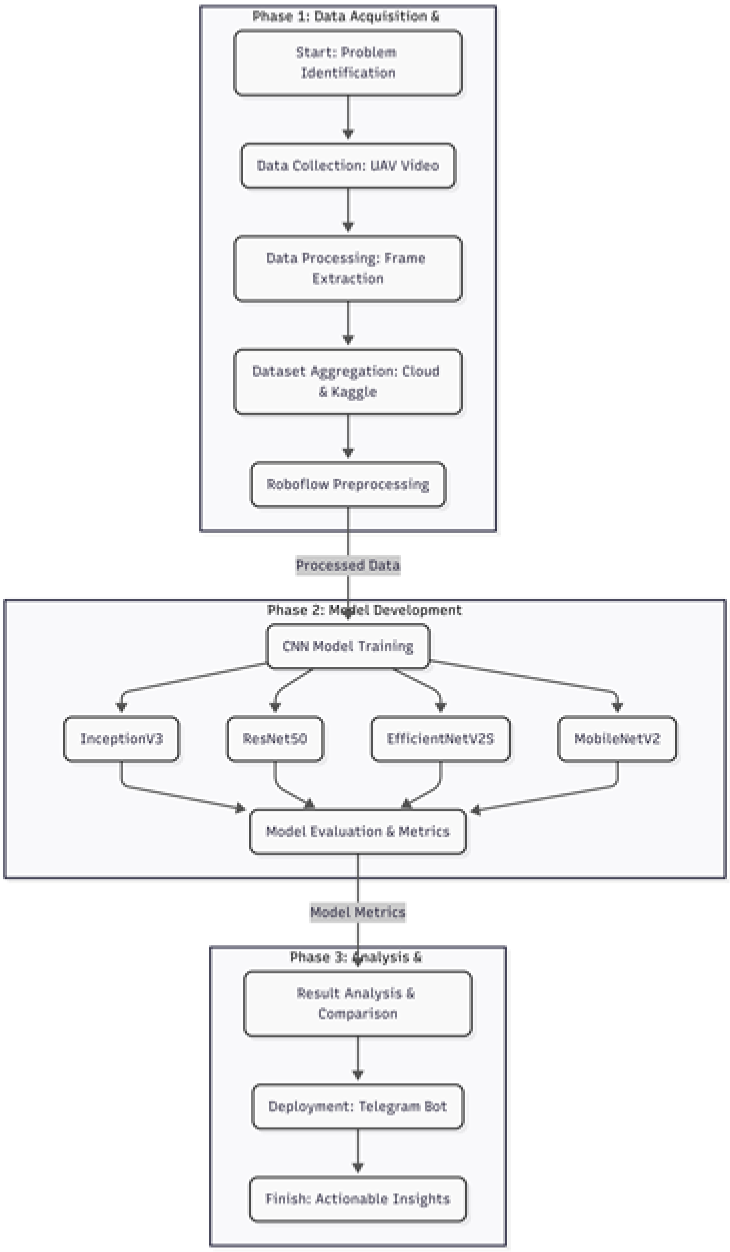

Figure 1. Schematic representation of the automated crop monitoring and diagnostic workflow

Following the data refinement, the core diagnostic engine was built upon the comparative evaluation of four distinct deep learning topologies: ResNet50, InceptionV3, EfficientNetV2S, and MobileNetV2. To address potential methodological ambiguities, it is explicitly stated that the deep learning task is formulated as an image classification problem. The algorithmic objective was a multi-class categorization designed to identify three prevalent pathological states, Tungro virus, Bacterial Blight, and Brown Spot, alongside a "Healthy" control class. To ensure transparency and reproducibility, all models were trained in a Python environment utilizing the TensorFlow/Keras framework on a workstation equipped with an NVIDIA GeForce RTX 3080 GPU and 32 GB of RAM. The hyperparameter configuration was strictly controlled: models were optimized using the Adam optimizer with an initial learning rate of 0.0001, a batch size of 32, and trained over 50 epochs utilizing an early stopping callback to prevent overfitting.

Following the computational inference, the system was configured for immediate field deployment. Once a leaf was classified, the diagnostic label and the localized crop region were instantly transmitted to agricultural stakeholders via the Telegram messaging API. This integration ensures that the deep learning outputs are translated into an actionable, remote-monitoring feedback loop, allowing for prompt and targeted disease mitigation.

3. RESULTS AND DISCUSSION

3.1. Comprehensive diagnostic performance and efficiency

The core analysis of this study transcends standard misclassification rates by evaluating the architectures across a comprehensive matrix of predictive metrics: Accuracy, Precision, Recall, and F1-Score, alongside their computational efficiency (Inference Time). As detailed in Table 1, the 10-fold cross-validation results reveal significant disparities in how each network topology handles specific crop pathologies.

Table 1. Comprehensive performance metrics and inference speed across CNN architectures

Deep learning model	Target class	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference time (ms/frame)
InceptionV3	Bacteria Blight	97.58	97.41	97.6	97.5	32.4
	Brown Spot	96.54	96.3	96.55	96.42	
	Tungro	95.95	95.8	96.1	95.94	
	Healthy Control	93.36	93.15	93.5	93.32	
ResNet50	Bacteria Blight	43.08	45.2	41.5	43.27	45.8
	Brown Spot	97.35	97.1	97.45	97.27	
	Tungro	93.31	93.05	93.6	93.32	
	Healthy Control	79.95	80.1	79.8	79.94	
EfficientNetV2S	Bacteria Blight	70.1	71.3	69.5	70.38	41.2
	Brown Spot	96.85	96.5	97.1	96.79	
	Tungro	66.32	67.1	65.8	66.44	
	Healthy Control	86.81	86.4	87.1	86.74	
MobileNetV2	Bacteria Blight	96.74	96.5	96.9	96.69	15.6
	Brown Spot	90.07	90.2	89.9	90.04	
	Tungro	66.61	68.1	65.5	66.77	
	Healthy Control	93.82	93.6	94.1	93.84	

3.1.1. Architectural failure analysis: The ResNet50 case

In Figure 2 misclassification rates across the evaluated deep learning architectures. A critical finding of this empirical evaluation is the profound diagnostic collapse of ResNet50 when confronted with Bacteria Blight, achieving a dismal accuracy of 43.08% (Recall: 41.50%). While ResNet50 excels at identifying Brown Spot (Accuracy 97.35%), its failure on Bacteria Blight requires deeper architectural scrutiny. We hypothesize that this degradation is caused by a phenomenon known as "feature over-smoothing" inherent to very deep residual networks. The identity mapping shortcuts in ResNet50, while solving the vanishing gradient problem, tend to dilute highly localized, low-contrast visual signatures (such as the faint, elongated yellowish lesions of early Bacteria Blight). Consequently, the model frequently misclassified infected leaves as healthy tissue, demonstrating that blindly applying deeper networks does not universally correlate with better phytopathological diagnostics. Heatmap matrix detailing the predictive error rates for each pathogen class as shown in Figure 3.

3.1.2. IoT integration and deployment feasibility

Beyond offline metrics, the ultimate contribution of this pipeline is its real-time field applicability. By successfully embedding the inferential outputs into a Telegram-based alerting system, diagnostic outcomes (disease classification and specific leaf coordinates) are transmitted instantly to agricultural stakeholders. However, transitioning this system from a controlled setup to rural deployment involves notable logistical constraints.

First, the continuous operational capability of the UAV is heavily bounded by battery capacity, typically limiting flight times to 25-30 minutes per battery cycle, necessitating optimized flight path planning over expansive fields. Second, the reliance on the Telegram API demands stable cellular internet connectivity

(3G/4G). In remote agricultural zones characterized by signal intermittency, the system must be adapted to feature edge caching mechanisms, where the MobileNetV2 model runs locally on a drone-mounted microcomputer (e.g., Raspberry Pi or Jetson Nano), queuing the diagnostic alerts until network connectivity is re-established. Despite these constraints, this automated diagnostic feedback loop successfully establishes a highly scalable framework for proactive disease containment and precision agriculture.

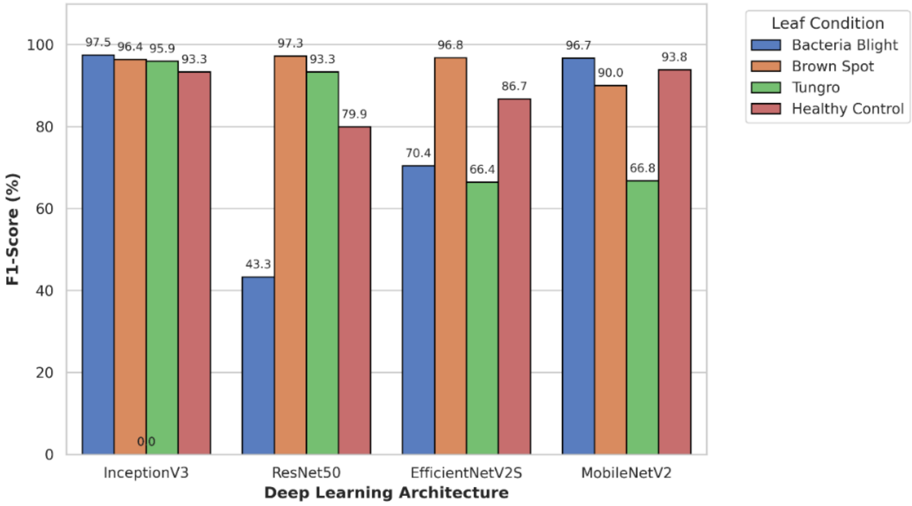

Figure 2. Misclassification rates across the evaluated deep learning architectures

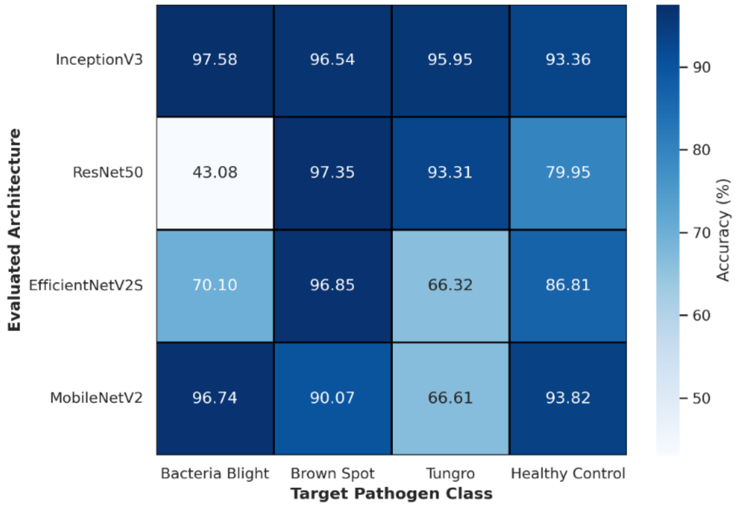

Figure 3. Heatmap matrix detailing the predictive error rates for each pathogen class

4. CONCLUSION

In summary, this research validates the operational viability of deploying drone-assisted image acquisition coupled with deep convolutional networks for the automated surveillance of paddy pathologies. Through rigorous comparative evaluation, it became evident that diagnostic reliability and computational efficiency vary significantly depending on the chosen architecture. Notably, the InceptionV3 topology emerged as the most resilient framework, achieving the highest overall F1-Scores and demonstrating superior feature-extraction capabilities across all tested classes. Furthermore, MobileNetV2 proved to be highly advantageous for resource-constrained edge deployment due to its exceptional inference speed (15.6 ms/frame) without severely compromising diagnostic precision.

Conversely, the profound diagnostic failure of ResNet50 when confronted with Bacteria Blight underscores the critical necessity of empirically tailoring network selection to specific agricultural contexts rather than relying on generalized model depth. By successfully integrating these inferential outputs with the Telegram messaging API, this study establishes a highly scalable, low-latency feedback mechanism for field practitioners. This end-to-end pipeline not only accelerates the detection-to-response timeline but also reinforces the foundational data-driven goals of precision agriculture. Future investigations should aim to broaden this automated framework by incorporating multispectral sensor data, addressing edge-computing network constraints, and expanding the pathogen classification matrix to encompass a wider array of crop variation.

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AUTHOR CONTRIBUTIONS STATEMENT

In alignment with the Contributor Roles Taxonomy (CRediT) framework, the following matrix delineates the individual responsibilities and specific contributions of each researcher involved in this study. Erfan Rohadi served as the primary corresponding author, overseeing project administration, funding acquisition, and overall communication. All listed co-authors have demonstrably participated in critical phases of the research, including active involvement in drafting, reviewing, or editing the final manuscript, thereby fully satisfying the foundational criteria for academic authorship. The detailed distribution of these roles is summarized below.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Erfan Rohadi	✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓	
Cahya Rahmad	✓	✓	✓	✓	✓	✓		✓	✓		✓	✓		
Septian Enggar Sukmana			✓	✓		✓	✓			✓				
Aida Sartimbul	✓			✓			✓			✓	✓		✓	
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state have no conflicts of interest.

INFORMED CONSENT

Not applicable. This study does not involve human subjects.

ETHICAL APPROVAL

Not applicable. This research does not involve human or animal subjects; the empirical focus was directed solely toward agricultural crops (IR64 paddy variety).

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. The secondary datasets utilized to construct the training corpus are openly available in the Kaggle repository.

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