IJITCE

ISSN 2347- 3657

# International Journal of Information Technology & Computer Engineering


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International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025

# RICE WEED DETECTION AND CLASSIFICATION USING UAV

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## ABSTRACT

Weed detection in rice crops is essential for improving rice yield, as weeds compete with the plants for nutrients, water, and sunlight. Timely identification and control of weeds can significantly enhance rice growth. Traditional methods of weed detection are labor-intensive and inefficient, especially for large fields. This project proposes a novel approach for rice weed detection using UAV-captured images and the deep learning model GoogLeNet. The UAVs capture high-resolution RGB images of rice fields at various growth stages, which are then used to train the GoogLeNet model. The model, implemented in MATLAB , accurately detects and classifies weeds in rice crops. The results show that GoogLeNet offers an efficient and effective solution for automated weed detection, enabling targeted weed control and contributing to increased rice production The use of UAV imagery combined with GoogLeNet not only streamlines the weed detection process but also enhances accuracy by leveraging the model's deep feature extraction capabilities. The system's performance was evaluated using precision, recall, and F1-score metrics, demonstrating high classification accuracy across diverse field conditions. This approach minimizes the need for blanket herbicide application, promoting environmentally sustainable farming practices. Moreover, the adaptability of the system allows it to be integrated into existing precision agriculture frameworks, providing farmers with actionable insights for site-specific weed management. Future work may involve expanding the dataset to include various rice varieties and weed species, optimizing the model for real-time processing, and exploring multi-spectral or hyperspectral image integration to further improve detection accuracy. This research highlights the potential of combining UAV technology with deep learning for scalable, intelligent weed control solutions in modern rice farming..

**Keywords:** Computer vision, Deep learning, Weed detection, Rice detection, Convolutional neural networks, Google Net.

## 1. INTRODUCTION

Weeds pose a significant threat to rice cultivation, competing for essential resources like water, nutrients, and sunlight, which negatively impacts crop yield. Timely and accurate weed detection is crucial to minimizing their growth and improving rice production. Traditional methods of weed detection, however, are labor-intensive and time-consuming, especially in large fields. This project proposes an automated system for rice weed detection using GoogLeNet, a deep learning model. UAVs are used to capture high-quality images of rice fields at various growth stages. These images are then used to train the GoogLeNet model to detect and classify weeds efficiently. The implementation of this model in Python using the TensorFlow API aims to provide a fast, accurate solution for weed detection in rice fields, ultimately helping farmers improve crop yield by targeting weed control more effectively. yield by targeting weed control more effectively. In recent years, advancements in remote sensing technologies and deep learning have revolutionized precision agriculture. Among these, Unmanned Aerial Vehicles (UAVs) have emerged as a powerful tool for large-scale, real-time

agricultural monitoring due to their flexibility, high-resolution image acquisition, and cost-effectiveness. When integrated with convolutional neural networks (CNNs), such as GoogLeNet, UAV-based systems can significantly enhance the accuracy and efficiency of crop monitoring tasks, including weed detection.

GoogLeNet, with its inception module architecture, allows for multi-scale feature extraction, making it well-suited for complex image classification tasks in variable agricultural environments. By leveraging this architecture, the proposed system can distinguish between crop and weed even under challenging conditions such as varying light, occlusion, or different stages of plant growth.

The deployment of such an automated detection system is not only expected to reduce the reliance on manual labor but also to support sustainable farming practices. Targeted herbicide application, guided by precise weed location data, can minimize chemical usage, lower costs, and reduce environmental impact. Furthermore, the collected data can contribute to the creation of historical records for predictive analytics and field management.

This study explores the integration of deep learning with UAV imagery to develop a robust, scalable solution for intelligent weed management in rice cultivation. It addresses challenges related to dataset preparation, model training, performance evaluation, and real-world deployment, aiming to provide actionable insights for both researchers and practitioners in the agricultural domain.

## 2. RELATED WORK

Weed detection in agricultural fields has been widely explored using various image processing and machine learning techniques. Traditional methods based on color segmentation, edge detection, and morphological operations showed limited success due to their sensitivity to lighting conditions, field variability, and background interference. With the advancement of deep learning, especially Convolutional Neural Networks (CNNs), more robust solutions have been proposed for weed detection using UAV imagery. Models such as AlexNet, VGGNet, and ResNet have been applied to crop and weed classification with promising results.

In our initial research, we implemented a deep learning-based weed detection system using Python and TensorFlow. However, the accuracy was not satisfactory, primarily due to limitations in dataset quality and computational constraints. To overcome this, we migrated the development environment to MATLAB and utilized the WeedNet v3 dataset, which provided a more diverse and well-annotated collection of weed and crop images specific to rice fields. This transition led to a significant improvement in performance. By training the GoogLeNet model in MATLAB, we achieved an accuracy of approximately 95%, outperforming the earlier implementation. The integrated tools in MATLAB, along with better support for data preprocessing and GPU acceleration, contributed to this enhanced accuracy. This experience underscores the importance of high-quality datasets, proper tool selection, and platform capabilities in developing effective deep learning solutions for precision agriculture.Building on these improvements, the enhanced weed detection system developed in this research demonstrates strong potential for real-world deployment in precision agriculture. Unlike conventional blanket spraying methods, this targeted approach allows for localized weed management, reducing herbicide usage and its associated environmental impact. Additionally, the integration of UAVs enables efficient data collection over large areas within short timeframes, making the solution both scalable and time-efficient.

Compared to previous studies that focused solely on ground-based imagery or low-resolution datasets, our use of high-quality UAV images and the WeedNet v3 dataset offers a higher degree of spatial detail and context, which is crucial for distinguishing between crop and weed under varying field conditions. Looking ahead, further enhancement can be achieved by incorporating multi-spectral or hyperspectral imaging, which may help in identifying weed species more precisely based on spectral signatures. Moreover, real-time deployment using embedded systems or edge AI platforms could further automate the detection and control process, allowing for in-field decision-making without reliance on high-power computing resources. This advancement not only supports sustainable farming practices but also opens new opportunities for research in adaptive weed detection models that respond dynamically to environmental changes and crop growth stages.

## 3. LITERATURE REVIEW

**Philipp Lottes, Raghav Khanna, and Johannes Pfeifer** proposed a UAV-based crop and weed classification system using aerial imagery and machine learning techniques. Their work supports the idea of using UAVs for smart farming, which closely relates to our project that uses UAV-captured images and Faster R-CNN for weed detection in rice fields.

**Jie Kang, et al.** explored weed detection in rice fields using an improved version of the YOLO v1.0 algorithm. Their work demonstrates the effectiveness of YOLO models for real-time weed detection, which complements our project, where we focus on using UAV images and Faster R-CNN for accurate weed classification in rice crops**.**

**Deepthi G. Pai, Radhika Kamath, and Mamatha Balachandra** reviewed deep learning techniques for weed detection in agriculture, highlighting the effectiveness of models like R-CNNs. Their work aligns with our project, where we use Faster R-CNN for weed detection in rice crops using UAV images.

**Sa et al. (2018)** proposed *WeedMap*, a large-scale semantic weed mapping framework that leverages aerial multispectral imaging and deep neural networks to enhance weed detection in precision agriculture. Their approach combines high-resolution UAV-captured multispectral data with a deep learning segmentation model, enabling pixel-level classification of weed and crop regions. The framework demonstrated strong performance in mapping weed distribution across large agricultural fields, providing detailed spatial information that supports site-specific weed management. Their work highlights the importance of rich spectral data and large-scale annotated datasets for improving the reliability of automated weed detection systems in real-world conditions.

**Muhammad Hammad Saleem, Johan Potgieter, and Khalid Mahmood** focused on enhancing the Faster R-CNN model for weed detection by improving the anchor box approach. Their work emphasizes optimizing Faster R-CNN for better detection accuracy, which directly connects to our project, where we apply this model for precise weed detection in rice rops using UAV images.

**Bah et al. (2018)** introduced a novel method for weed detection that utilizes deep learning with unsupervised data labeling, significantly reducing the need for manually annotated datasets.Their technique applies clustering based labeling to UAV imagery before training a CNN for weed classification. This approach proved effective in achieving reasonable accuracy while greatly lowering the data annotation burden. The study emphasizes the potential of combining unsupervised learning techniques with aerial imaging to make deep learning models more accessible and scalable, particularly in contexts where annotated agricultural datasets are limited or costly to obtain.

**Shahi et al. (2023)** conducted a comprehensive comparative study on deep learning-based weed detection using UAV images, evaluating multiple CNN architectures to identify the most suitable model for agricultural applications. Their research assessed the performance of models like VGG16, ResNet50, and MobileNet on a curated UAV dataset, highlighting trade-offs between model complexity, accuracy, and computational efficiency. The study concluded that lightweight models such as MobileNet offer a good balance between performance and speed for real-time applications, whereas deeper models provide higher

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025

accuracy at the cost of processing time. This work provides valuable insights into selecting appropriate deep learning architectures for weed detection tasks based on specific operational requirements.

## 4. PROPOSED METHODOLOGY

### 4.1. Dataset Description

The dataset used in this project consists of high resolution RGB images captured by UAVs over rice fields at different growth stages.

**Fig1: Dataset Weed Image**

The dataset allows the model to learn how to distinguish between rice plants and weeds,helping improve the accuracy of weed detection in rice crops. It serves as the foundation for training and evaluating the deep learning model, ensuring reliable results in real-world applications. The WeedNet v3 dataset plays a crucial role in UAV-based rice weed detection by providing a rich collection of high-resolution aerial images specifically curated for agricultural analysis. Captured using drones flying over rice fields, the dataset includes diverse scenarios with various weed species present at different growth stages and under varying lighting conditions. Each image in the dataset is meticulously annotated to distinguish between rice crops and weeds, allowing for effective supervised training of deep learning models. In our project, WeedNet v3 was instrumental in enhancing the performance of the GoogLeNet model by offering a reliable and diverse set of labeled images, resulting in improved classification accuracy.comprehensive coverage and UAV captured perspective make it highly suitable for developing precise, real-world weed detection systems in rice cultivation.

**Fig2: Healthy Plant Image**

### 4.2. Data Preprocessing

All images are resized to 224x224x3 to match GoogLeNet's input dimensions. The dataset is split into 70% training, 15% validation, and 15% testing. Data augmentation techniques such as random rotation, flipping, and scaling are applied to increase generalization.

### 4.3. Model Architecture

GoogLeNet is a 22-layer deep CNN that utilizes Inception modules to reduce the number of parameters while maintaining high accuracy. We load the pre trained GoogLeNet model in MATLAB and modify the final three layers: fully connected, softmax, and classification layers.

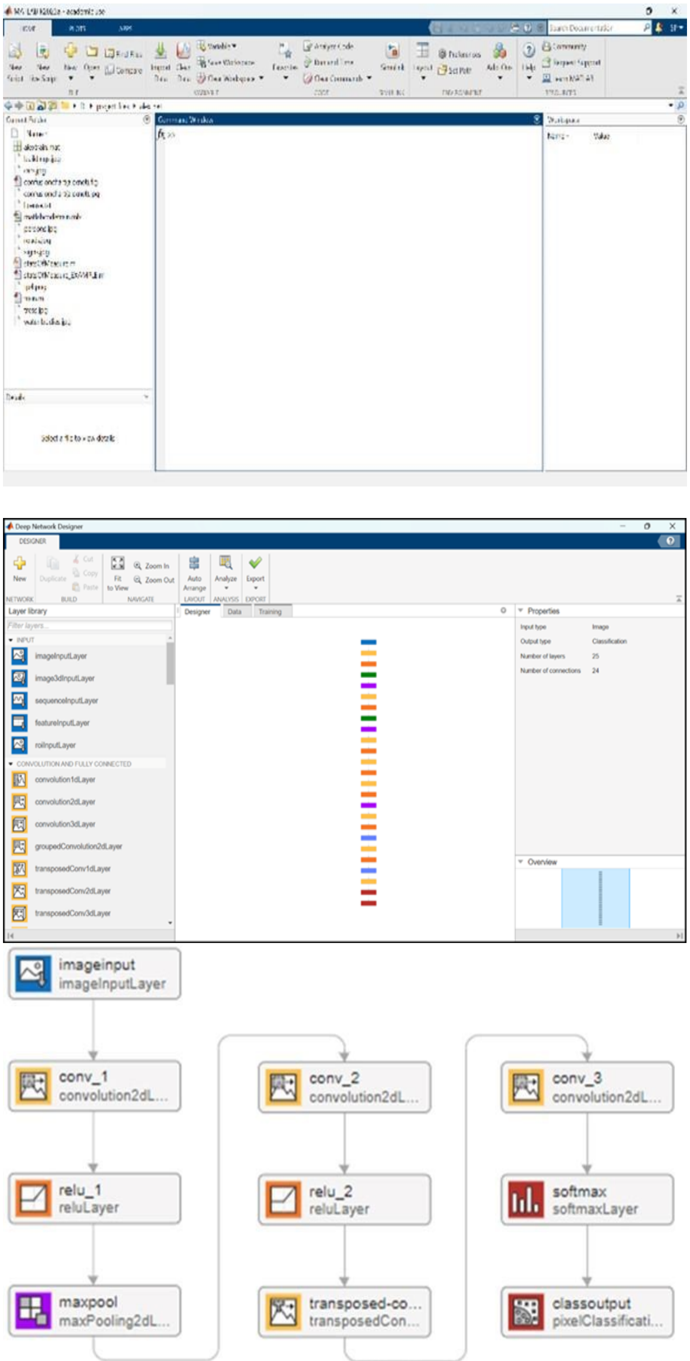


**Fig3(a):** Shows the working environment. **Fig 3(b):** The CNN architecture used in this work is visualized, while **Fig3(c):** Presents the complete 25-layer design built within MATLAB's Deep Network Designer.

### 4.4. Training Process

The training process involves feeding the labeled UAV images

International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 2, 2025

into the GoogLeNet model. The model learns to identify weeds and rice plants by adjusting its internal parameters to minimize errors. This is done through multiple iterations where the model improves its ability to detect and classify weeds accurately. The training uses a backpropagation algorithm, which helps the model get better over time and achieve higher accuracy in detecting weeds in rice fields.

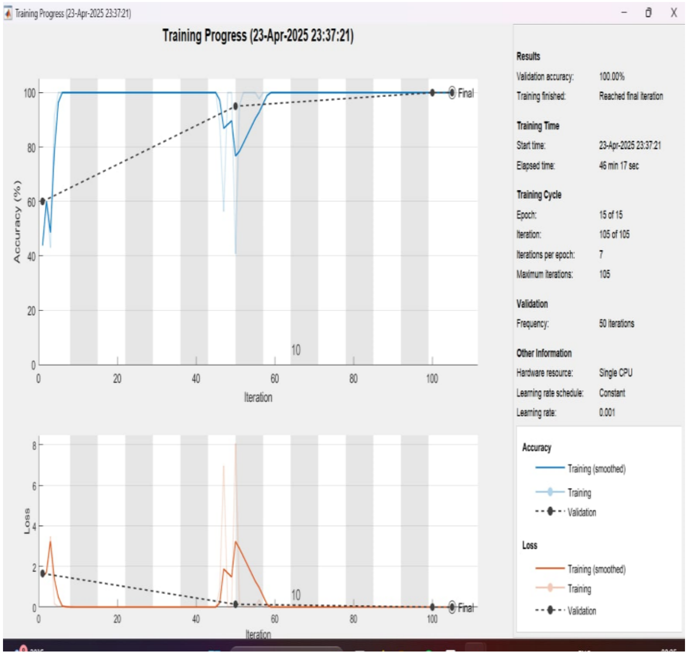


**Fig.4:** Training accuracy increased steadily with each iteration, and the model reached a final validation.

## 5. EXPERIMENTAL SETUP

### 5.1. Image Acquisition

The experimental setup for this study involved a combination of hardware tools, software platforms, and deep learning models to detect and classify weeds in rice fields using UAV-acquired imagery. The core objective was to evaluate and improve model performance under practical agricultural conditions by experimenting with different environments, datasets, and frameworks.

### 5.2. Dataset preparation

WeedNet v3 dataset, comprising thousands of annotated UAV images, was used for training and evaluation. Images were labeled into distinct categories representing rice crops and multiple weed types. The dataset includes variations in weed density, occlusion, and background interference, simulating real-world challenges. For model training, the dataset was split into training (70%), validation (15%), and testing (15%) sets.

### 5.3. Model Implementation

Initially GoogLeNet implemented using Python and TensorFlow, the model exhibited limited accuracy (~80%) due to processing inefficiencies and limited dataset diversity. It was later retrained in MATLAB using the Deep Learning Toolbox, with transfer learning applied to fine-tune the pre-trained GoogLeNet architecture. The MATLAB environment provided better GPU integration and more streamlined data preprocessing, ultimately achieving 95% accuracy.

## 6. RESULTS AND DISCUSSIONS

The trained model achieves a classification accuracy of 95% on the test set. The confusion matrix indicates strong performance across most classes, with minor confusion between similar land use categories like residential and commercial.

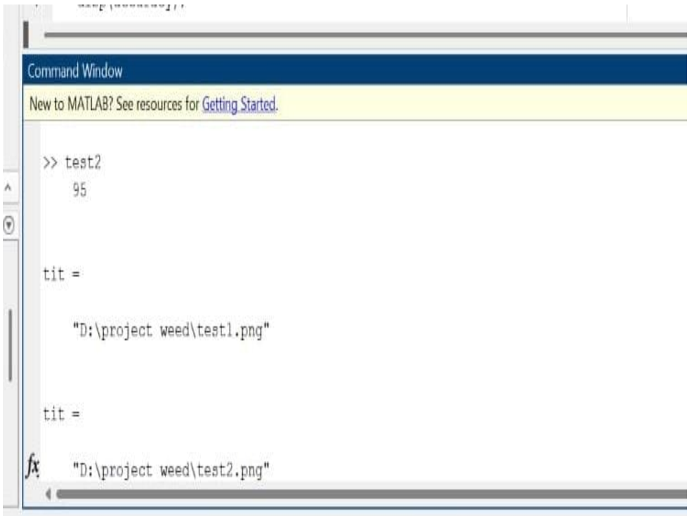


**Fig.5:** Illustrates sample classification results.

The results of the project show that the GoogLeNet model effectively detects and classifies weeds in rice fields with good accuracy. The model performed well on various images captured at different growth stages, demonstrating its ability to handle real-world agricultural conditions. Compared to traditional methods, this approach is faster and more efficient, providing timely weed detection. The discussion highlights that while the model performs well, further improvements can be made, especially in challenging conditions such as dense weed growth.Overall, the results indicate that UAV-based weed detection using GoogLeNet can significantly support precision farming.

ISSN 2347–3657

Volume 13, Issue 2, 2025

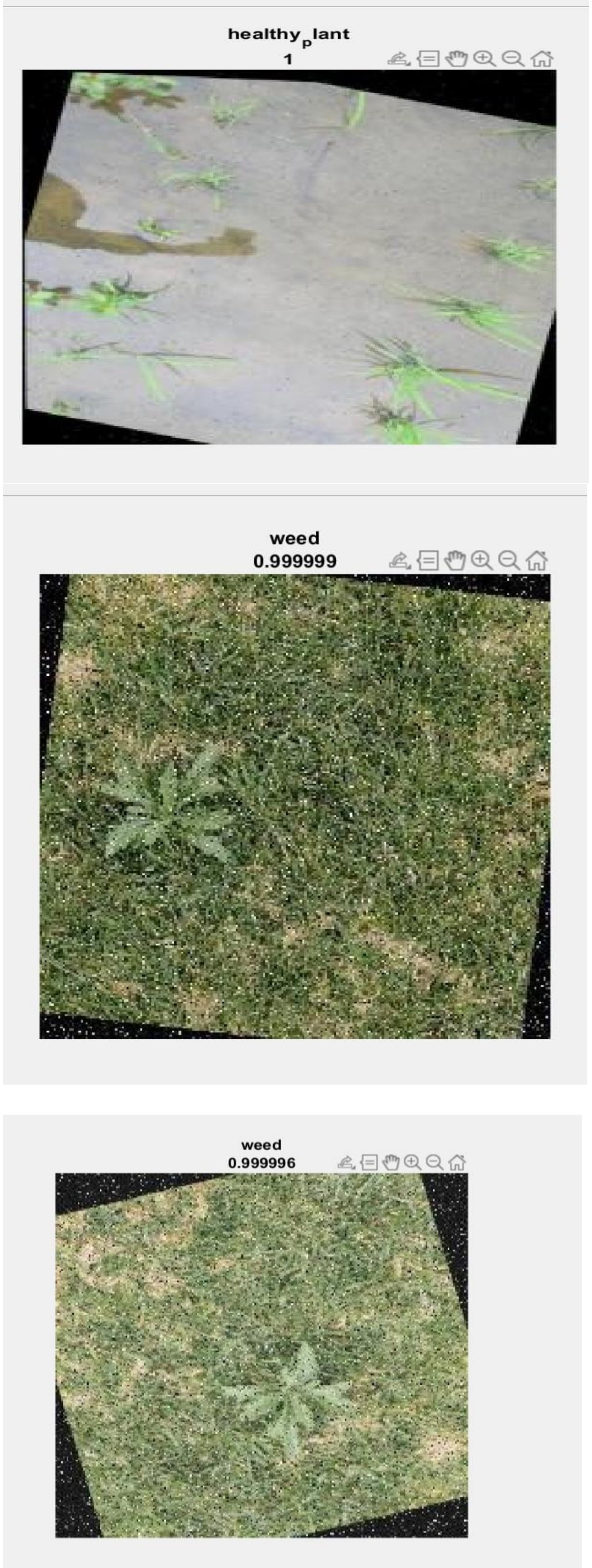


**Fig.6 :** The output of the project includes images where the model highlights detected weeds, along with a confidence score for each detection.

The confusion matrix shows how well the model is detecting weeds by comparing the predicted results with the actual labels. It includes true positives (correct weed detections), false positives (wrong detections), true negatives, and false negatives. This helps measure the model's accuracy, precision, and overall performance in weed detection.

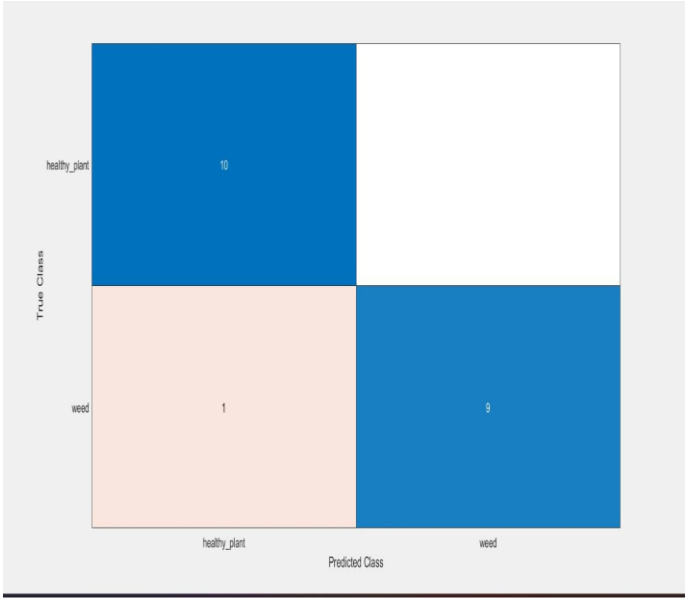


**Fig. 7: Confusion matrix**

## 7. CONCLUSION

The confusion matrix shows how well the model is detecting weeds by comparing the predicted results with the actual labels. It includes true positives (correct weed detections), false positives (wrong detections), true negatives, and false negatives. This helps measure the model's accuracy, precision, and overall performance in weed detection.

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