

UAV Image Processing For Soybean Detection Using MATLAB

¹Sanika Chandgude, ²Tanvi Gund, ³Aishwarya Hanpude, ⁴Jagadish Hallur

¹UG Student, Department of ENTC, SVERI's College of Engineering, Pandharpur, PAHSUS, Maharashtra, India

²Assistant Professor, Department of E&TC, SVERI's College of Engineering, Pandharpur, PAHSUS, Maharashtra, India

Abstract. This paper presents an automated system for detecting and classifying soybean leaf diseases using UAV imagery and advanced image processing techniques. The system employs the SLIC algorithm for segmenting soybean leaf images into superpixels, followed by feature extraction and classification using deep learning models such as ResNet-50. MATLAB is used for image segmentation, dataset creation, and model training. The proposed system demonstrates high accuracy in identifying diseases such as Frogeye Leaf Spot, Septoria Brown Spot, and Soybean Mosaic Virus. This innovation offers a valuable tool for precision agriculture, improving disease detection and crop management practices.

Keywords: UAV, soybean leaf diseases, SLIC segmentation, deep learning, MATLAB, precision agriculture

1 Introduction

Precision agriculture plays a crucial role in optimizing crop management and disease detection. Unmanned Aerial Vehicles (UAVs), combined with advanced image processing techniques, have shown promise in detecting diseases in crops such as soybeans, enabling early interventions to improve crop health and yield. Previous studies have demonstrated the efficacy of UAVs in monitoring crop diseases (Yong et al., 2024), while deep learning models like CNNs have achieved remarkable accuracies in disease classification (Sadia et al., 2024).

Soybean diseases such as Soybean Rust, Frogeye Leaf Spot, and Mosaic Virus can severely impact crop yield and quality if not detected early. UAVs offer a solution by capturing high-resolution images allowing detailed plant health monitoring (Everton et al., 2020).

2 Methodology:-

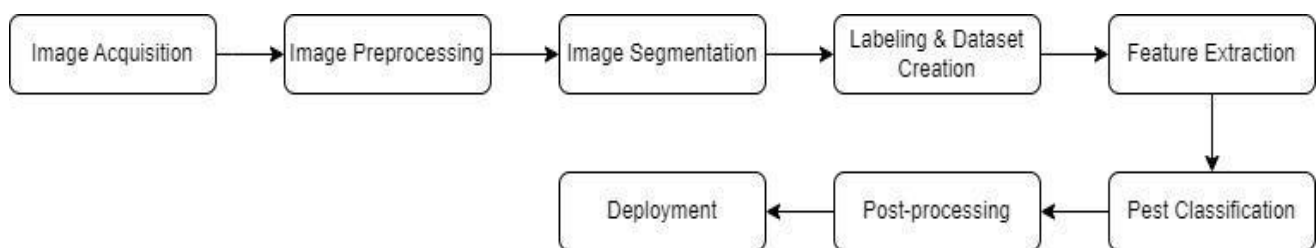


Fig.1 Methodology

2.1 UAV Imagery Collection

In this study, UAV imagery was collected using a DJI Phantom 4 UAV equipped with a 20 MP multispectral camera. The UAV was flown at heights of 2 meters and 3 meters over soybean fields to capture high-resolution images that could reveal details of both healthy and diseased leaves. The flights were conducted under optimal weather conditions to reduce noise, such as shadows or glare, which might interfere with the disease detection process. By capturing images from these altitudes, we ensured that the imagery provided sufficient detail for accurate disease classification, particularly for diseases such as Soybean Rust and Mosaic Virus (Yong et al., 2024; Sadia et al., 2024).

2.2 Image Segmentation Using SLIC

The collected UAV images were processed using MATLAB to apply Simple Linear Iterative Clustering (SLIC) for segmentation. This step divides the images into superpixels, allowing for a more detailed examination of individual soybean leaves. A superpixel count of 3000 to 5000 was used for each image, and a compactness value of 20 was selected

to balance color similarity and spatial proximity. This allowed the algorithm to effectively isolate diseased areas of the leaves, which were crucial for accurate classification (Everton et al., 2020). This approach is essential for identifying diseases with subtle visual symptoms, such as Soybean Rust and Frogeye Leaf Spot (Kadam, 2024).

2.3 Data Preprocessing

Before training the model, the segmented images were resized to 224x224 pixels to match the input size required by the ResNet-50 architecture. Additionally, data augmentation techniques were employed to improve the robustness of the model and avoid overfitting. These techniques included random rotation, reflection, and scaling to simulate real-world variations in leaf appearance, such as changes in angle or lighting conditions. By augmenting the dataset, we significantly increased its diversity and allowed the model to generalize better to unseen data during the testing phase (Sagar et al., 2024; Seralathan & Edward, 2024).

2.4 Classification Using ResNet-50

The core of the disease classification system relied on the ResNet-50 deep learning model, which was pre-trained on a large image dataset and fine-tuned for soybean

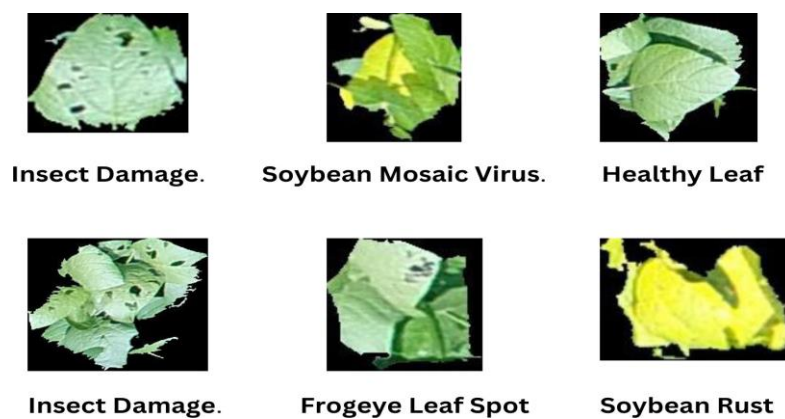


Fig.2 Classification images

disease detection. The model was modified to recognize five specific disease categories: Soybean Mosaic Virus, Insect Damage, Soybean Rust, Frogeye Leaf Spot, and Healthy Leaves. The final few layers of ResNet-50 were replaced with fully connected layers, which were tailored to this classification task. The model was trained over 30 epochs using Stochastic Gradient Descent with Momentum (SGDM), with a learning rate of 1e-4 and a drop factor of 0.1. The training achieved an accuracy of 76%, demonstrating the model's ability to differentiate between diseased and healthy soybean leaves (Sadia et al., 2024; Kadam, 2024).

2.5 Testing and Validation

The trained ResNet-50 model was tested using a separate dataset of unseen soybean leaf images. The testing images were preprocessed similarly to the training images, including resizing and augmentation. The model's predictions were evaluated against the true labels of the images, and a confusion matrix was generated to illustrate the classification performance across all five classes. The results indicated high accuracy for diseases like Soybean Rust and Insect Damage, while some confusion was observed between Soybean Mosaic Virus and Frogeye Leaf Spot, likely due to their visual similarities (Everton et al., 2020; Shuhei et al., 2023). The overall testing accuracy was 76%, validating the model's potential for real-world application in precision agriculture

3. Results and Discussion

3.1 Training Results:

The classification model for soybean leaf diseases was trained on UAV images divided into five categories: Frogeye Leaf Spot, Healthy Leaf, Insect Damage, Soybean Mosaic Virus, and Soybean Rust. After 30 epochs, the training accuracy reached nearly 90%, with a consistent decrease in loss. However, validation accuracy plateaued at 77%, suggesting potential

overfitting, where the model excelled on the training set but struggled with unseen validation data. This discrepancy indicates that the model may have memorized specific training patterns instead of learning generalizable features, a common issue in machine learning, particularly with small or imbalanced datasets.

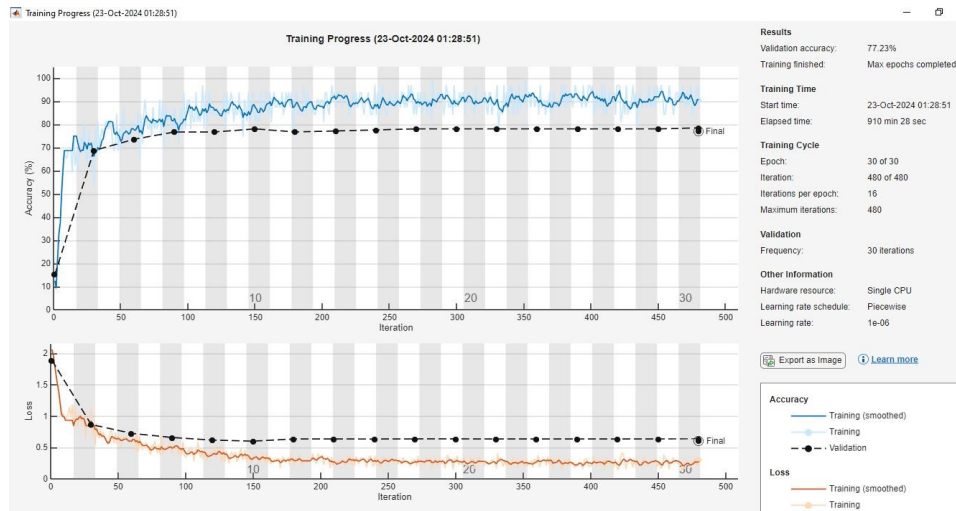


Fig.3 Training Result

3.2 Confusion Matrix and Predicted Output:

The confusion matrix provided insights into the model's performance across five disease categories. Soybean Rust and Insect Damage were the best-classified classes, with accuracies of 86% and 84%, respectively. However, the Soybean Mosaic Virus had lower accuracy, likely due to its visual similarity to Frogeye Leaf Spot (Everton et al., 2020). The matrix revealed that many Soybean Mosaic Virus instances were misclassified as Frogeye Leaf Spot or Insect Damage, indicating the model's difficulty in distinguishing between diseases with overlapping visual characteristics. This suggests that the model may need to learn more specific features or that additional training data is necessary for improved classification. (Sadia et al., 2024)

True Class \ Predicted Class	Frogeye_Leaf_Spot	Healthy_Leaf	Insect_Damage	Soybean_Mosaic_Virus	Soybean_Rust
Frogeye_Leaf_Spot	1	1	19	1	
Healthy_Leaf		33	11		
Insect_Damage	3	11	133		
Soybean_Mosaic_Virus			4	3	
Soybean_Rust				1	3

fig.4 Confusion Matrix

3.3 Testing and Prediction Results:

The trained model was tested on a separate set of UAV images, achieving an average prediction accuracy of 76%, indicating its robustness for real-world applications. The testing confirmed the model's strong generalization ability, particularly in identifying Insect Damage and Soybean Rust. In one case, it accurately predicted a Soybean Rust infection, consistent with its validation performance. However, the results also revealed difficulties in classifying the Mosaic Virus, highlighting areas for improvement. (Shuhe et al., 2023; Everton et al., 2017).

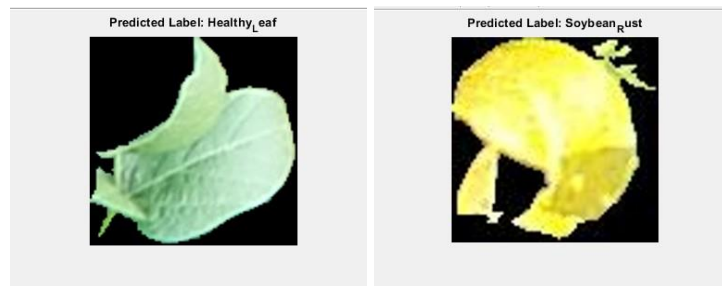


Fig.5 Testing And Prediction result

4. Conclusion

This study demonstrated the effectiveness of using UAV imagery and deep learning for automated soybean disease detection. By employing a ResNet-50 model trained on UAV-acquired images, we achieved a testing accuracy of 76% across five disease categories, with high performance in detecting Insect Damage and Soybean Rust. Challenges such as misclassification of visually similar diseases like Soybean Mosaic Virus and Frogeye Leaf Spot were identified, indicating the need for further model refinement and data augmentation. Overall, this approach offers significant potential for improving crop monitoring and disease management in precision agriculture.

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