

Original Article

A Computer Vision Based System for Pesticides Overspray Detection Using ESP32-CAM

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Abstract:

Excessive pesticide spraying during agricultural operations leads to chemical wastage, crop surface damage, environmental contamination, and potential health risks. Spray coverage assessment is typically performed through manual visual inspection, which is subjective and inconsistent. This work presents a computer vision and AI-enabled system for pesticides overspray detection using a low-cost ESP32-CAM imaging module, wireless image acquisition and processing system. The proposed system captures sprayed leaf images and transfers them to a computer for processing. The received images are analyzed using color space transformation, leaf segmentation, and spray residue detection, followed by AI-based feature learning and quantitative feature extraction. Spray coverage metrics are computed and evaluated using a supervised machine learning model trained to classify spray conditions into under-spray, optimal spray, or overspray categories. An interactive graphical user interface displays intermediate processing stages and AI prediction outputs for transparency and validation. The developed prototype demonstrates fast, repeatable and objective overspray detection and provides a practical foundation for AI-assisted precision pesticide application and monitoring systems.

Keywords: Computer Vision, Machine Learning, Random Forest classifier and AI in agriculture.

Objective:

The main objective of this work is to develop a real-time pesticide overspray detection system using ESP32-CAM, image processing, and machine learning techniques for monitoring spray coverage on agricultural leaves. The proposed system aims to capture leaf images wirelessly, analyze spray deposition using computer vision methods such as color space transformation and segmentation, and classify the spraying condition into under-spray, optimal spray, or overspray categories using a Random Forest machine learning algorithm. The system is designed to provide fast, low-cost, and objective assessment of pesticide spraying in order to reduce chemical wastage, minimize environmental contamination, improve crop safety, and support precision agriculture practices.

Introduction:

Pesticides play a vital role in modern agriculture by controlling weeds, insects, and plant diseases, thereby significantly improving crop yield and food production. The rapid growth of the global population has been supported by increased agricultural productivity achieved through pesticide application. Studies indicate that without pesticides, agricultural losses could reach 78% in fruits, 54% in vegetables, and 32% in cereal crops. Despite their agricultural benefits, excessive and improper pesticide use leads to environmental contamination affecting soil, water, air, crops, and non-target organisms such as birds, fish, and beneficial insects. Pesticide residues can also enter the food chain and pose serious risks to human health. In addition, climate change and changing agricultural conditions have contributed to increased pesticide usage and associated pollution. Therefore, proper pesticide monitoring, controlled application, and sustainable management practices are essential to minimize environmental impact while maintaining agricultural productivity [1]. In conventional agricultural practices, spray coverage assessment is generally performed using manual visual inspection methods. Such approaches are highly subjective and depend on operator experience, lighting conditions, and human judgment. Manual inspection is also time-consuming and unsuitable for precision agriculture systems that require rapid, repeatable, and objective monitoring techniques.

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Advances in computer vision, image processing, wireless sensing, and artificial intelligence have enabled the development of intelligent agricultural monitoring systems for modern farming applications. Computer vision techniques make it possible to automatically analyze digital images for identifying spray patterns, pesticide residue distribution, and leaf coverage characteristics. In addition, machine learning models improve system reliability by learning relationships between extracted features and performing automated classification of spraying conditions. Therefore, the development of automated pesticide spray assessment systems has become increasingly important for improving precision agriculture and supporting sustainable farming practices [2].

This work proposes a computer vision-based pesticide overspray detection system using an ESP32-CAM imaging module and machine learning-assisted image analysis. The ESP32-CAM captures images of sprayed leaves and transfers them wirelessly to a computer for processing. The acquired images undergo preprocessing, leaf segmentation, spray residue detection, and feature extraction. A Random Forest classifier is used to classify spray conditions into under-spray, optimal spray, and overspray categories. The developed system provides an efficient and low-cost solution for intelligent pesticide spray monitoring in precision agriculture applications.

Data Collection:

The dataset used in this work consists of leaf images captured under different pesticide spraying conditions using an ESP32-CAM imaging module. Images were collected for three major spray categories namely under-spray, optimal spray, and overspray conditions. Different levels of pesticide deposition were intentionally created on leaf surfaces to observe variations in spray coverage, droplet density, and residue distribution. The captured images were wirelessly transferred to a computer system for further processing and analysis. The dataset contains images with variations in illumination, background, leaf texture, and spray intensity to improve the robustness of the proposed system. During preprocessing, all images were resized and standardized before feature extraction. Quantitative parameters such as spray coverage ratio, mean brightness, texture variation, and droplet distribution were extracted from the processed images and used as input features for machine learning-based classification.

Methodology

The proposed methodology consists of image acquisition, preprocessing, segmentation, feature extraction, machine learning-based classification, and graphical result visualization. Initially, the ESP32-CAM captures images of pesticide-sprayed leaves and transmits them wirelessly to the computer system. The received image is resized and converted into different color spaces for effective analysis. Leaf segmentation is performed using HSV color thresholding to isolate the leaf region from the background. Morphological filtering operations are applied to remove noise and improve segmentation accuracy. After leaf extraction, spray residue regions are detected using intensity and color-based thresholding techniques. The detected spray pixels are used to calculate spray coverage percentage and other statistical image features such as mean intensity and standard deviation. These extracted features are then provided to a Random Forest machine learning classifier trained to categorize the spray condition into under-spray, optimal spray, or overspray classes. Finally, the graphical user interface displays all intermediate processing stages including original image, segmented leaf, spray mask, highlighted overspray regions, and final prediction results for visual interpretation and system validation.

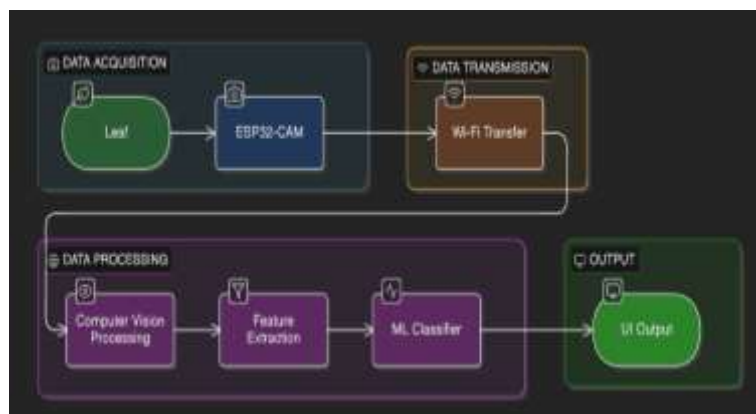


Fig. 1: Block Diagram of the Proposed Real-Time Pesticide Overspray Detection System

The block diagram represents the complete operational flow of the proposed real-time pesticide overspray detection system using ESP32-CAM, computer vision, machine learning, and Python-based implementation techniques. The entire system is divided into four major stages: data acquisition, data transmission, data processing, and output visualization. In the data acquisition stage, images of pesticide-sprayed leaves are captured using the ESP32-CAM module. The ESP32-CAM is a compact, low-cost microcontroller module developed using the Espressif ESP32 chipset with an integrated camera interface. It combines image capturing capability with built-in Wi-Fi and Bluetooth communication, making it highly suitable for IoT-based computer vision applications. The module commonly uses the OV2640 2MP camera sensor, which supports image capture in JPEG format and enables efficient wireless image transmission. Due to its small size, low power consumption, and wireless communication capability, the ESP32-CAM is widely used in surveillance systems, smart monitoring, robotics, industrial automation, and agricultural imaging applications [3].



Fig. 2: ESP32CAM Module

The data processing stage performs the major computational operations of the proposed system using Python programming language and associated libraries such as OpenCV, NumPy, Scikit-learn, PIL, and Tkinter [4]. Initially, the captured RGB leaf image is resized to a fixed dimension to reduce computational complexity and maintain uniform processing conditions. After resizing, color space conversion is performed by converting the RGB image into HSV (Hue, Saturation, Value) color space. HSV color representation is preferred in agricultural image analysis because it separates color information from brightness information, making green leaf regions easier to identify under varying illumination conditions [5]. The hue component represents the actual color, saturation indicates color intensity, and value represents brightness. Using predefined HSV threshold ranges, green leaf regions are isolated from the background through threshold-based masking techniques. Following color space conversion, noise filtering operations are applied to remove unwanted disturbances and improve segmentation quality. Morphological operations such as opening and closing are used to eliminate small unwanted particles, fill small holes, and smooth object boundaries [6]. Median filtering is also applied to reduce salt-and-pepper noise while preserving important edges and spray droplet structures. After noise removal, leaf segmentation is performed to separate the leaf area from the surrounding background. Segmentation is achieved using binary masking techniques where only pixels corresponding to the leaf region are retained for further analysis.

Once the leaf region is isolated, spray residue detection is carried out to identify pesticide deposition areas present on the leaf surface. Bright or reflective spray regions are extracted using intensity and color thresholding methods. From the detected spray regions, quantitative image features such as spray coverage percentage, mean brightness, texture variation, droplet distribution, and intensity deviation are computed. Spray coverage percentage represents the ratio of detected spray pixels to total leaf pixels and acts as an important parameter for overspray evaluation.

The extracted features are then provided to the Random Forest machine learning classifier for spray condition prediction. Random Forest is a supervised ensemble learning algorithm that operates by constructing multiple decision trees during training and combining their outputs for final classification. Each decision tree independently analyzes the input features and predicts a class label, while the final output is determined using majority voting among all trees. The algorithm improves prediction accuracy, reduces overfitting, and provides stable classification performance for complex image datasets. Based on the extracted image features, the classifier categorizes the spraying condition into under-spray, optimal spray, or overspray classes [7].

Finally, in the output stage, the processed results are displayed through a Python-designed graphical user interface. The interface presents intermediate image processing stages such as original image, segmented leaf, spray mask, highlighted overspray regions, spray coverage percentage, and final machine learning prediction. This visual output improves system transparency, enables easy interpretation of results, and supports real-time monitoring of pesticide spraying conditions in precision agriculture applications.

Results and Discussion:

The experimental results demonstrated that the proposed system successfully identified different pesticide spraying conditions in real time. The system was able to clearly distinguish between under-sprayed, optimally sprayed, and oversprayed leaf samples based on spray coverage characteristics. Oversprayed leaves showed significantly higher coverage values and larger highlighted spray regions compared to normal or lightly sprayed samples. The prediction results remained stable and consistent for multiple test images, indicating reliable classification performance. The graphical interface provided clear visual outputs of the detected spray regions along with the final classification result, making the analysis easy to interpret. The obtained results confirm that the proposed system provides fast, repeatable, and objective pesticide spray assessment suitable for precision agriculture and pesticide monitoring applications.

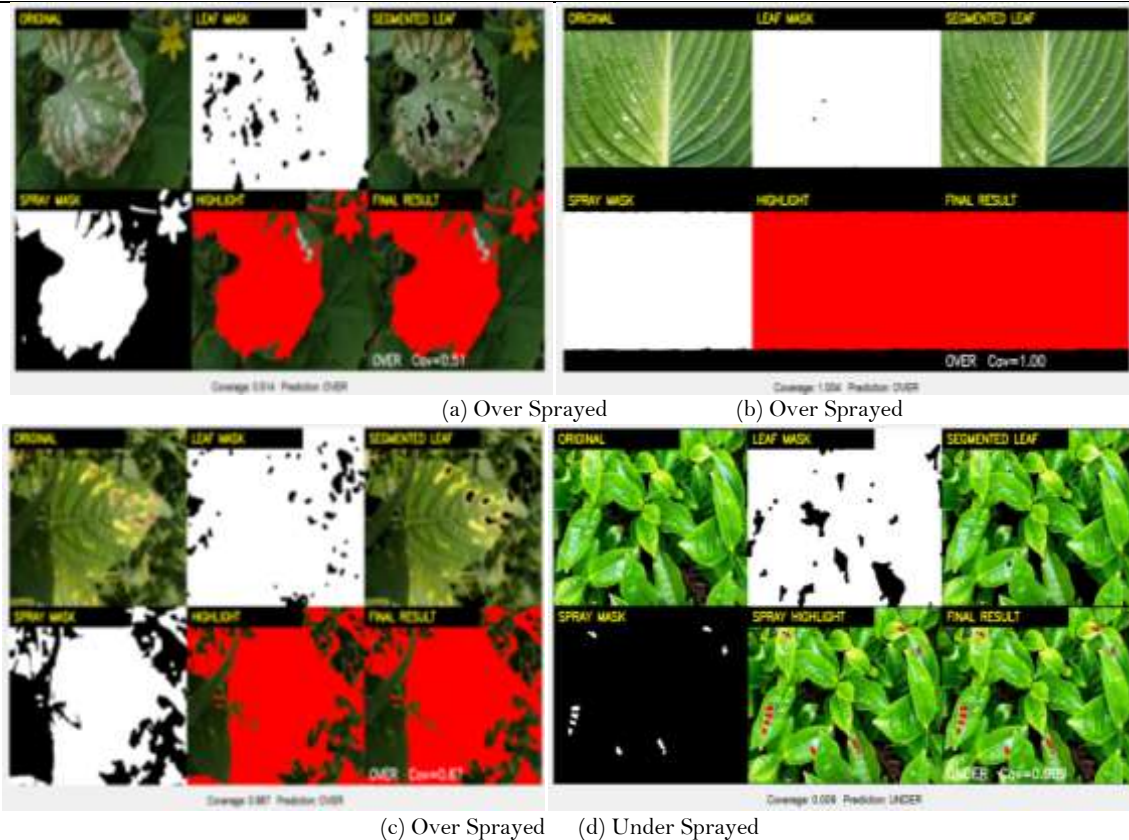


Fig. 3: Results showing different level of pesticides coverage on leaf surface

Conclusion:

The proposed system successfully detected pesticide overspray using ESP32-CAM, computer vision, and machine learning techniques. Experimental results showed reliable classification of under-spray, optimal spray, and overspray conditions with consistent prediction performance. The developed prototype provides fast, objective, and real-time spray assessment compared to manual inspection methods. The system can serve as a low-cost and practical solution for precision agriculture and pesticide monitoring applications.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper

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