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Precision Agriculture: Crop Segmentation and Loss Evaluation Through Drone Surveillance

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Abstract: Agriculture, as the backbone of livelihood for communities worldwide, has entered a new era with the advent of precision agriculture. The ability to make informed decisions about crop health, damage assessment, and yield prediction has become paramount in ensuring sustainable and efficient farming practices. Within this context, the integration of advanced technologies, such as drone surveillance, has emerged as a transformative tool for precise and timely data acquisition. Traditional methods of crop monitoring often fall short in providing the level of detail required for effective decision-making. This paper addresses the gap by focusing on the application of image segmentation techniques in the context of precision agriculture. Specifically, we develop into the categorization of crops into sparse and dense classes using multitemporal data obtained through drone surveillance.

Keywords: precision agriculture, image segmentation, drone surveillance, sparse and dense.

I. INTRODUCTION

Precision agriculture, also known as satellite agriculture, is an innovative farm management approach that leverages information technology to precisely provide crops and soil with what they need for optimal health and productivity. precision agriculture aims to maximize farm profits, promote sustainable practices, and protect the environment. Access real-time data about the conditions of crops, soil and ambient air,hyper-local weather predictions, labor costs and equipment availability. The data acts as a guide for crop rotation, optimal planting times, harvesting times and soil management decisions. The goal of precision agriculture is to increase the efficiency, sustainability, and productivity of agriculture practices by using data-driven insights and advanced technologies.

The use of NDVI cameras on drones for crop monitoring is gaining popularity in agriculture [16]. NDVI captures images in visible and near-infrared light to measure crop health and growth. These images provide valuable insights for identifying problems, tracking crop progress, and making informed decisions. Drone technology allows for efficient and cost-effective monitoring of large fields, providing farmers with a comprehensive view of their crops.

Convolutional neural network is a regularized type of feed-forward neural network that learns feature engineering by itself via filters optimization. Convolutional Neural Networks (CNNs) are commonly employed to segment crop images by dividing them into areas representing different crops. A CNN is trained to label each pixel in the image with a specific class. [3]. The network typically consists of multiple convolution and pooling layers, followed by up sampling layers to produce the final label map. The training process involves feeding the network with large amounts of annotated crop images, allowing it to learn the features and patterns associated with different crops. CNNs have proven to be highly effective for crop image segmentation, providing accurate and efficient results for various crops and field conditions.

Streamlit is an open-source Python library is utilized to

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streamline the development of web applications for machine learning and data science projects. It enables users to craft interactive web apps directly from Python scripts, eliminating the need to write HTML, CSS, or JavaScript code. streamlit is a robust instrument for constructing interactive web apps for data science and machine learning projects, enabling developers to concentrate on their analysis and insights rather than the intricacies of web development.

In contemporary agriculture, the fusion of technological innovations has revolutionized traditional farming practices, leading to the emergence of precision agriculture. Precision agriculture leverages advanced technologies such as drones, machine learning, and image processing to monitor crop health, optimize resource usage, and maximize yields. Among these technologies, drone-based crop image segmentation plays a critical role in providing farmers with detailed insights into the spatial distribution and condition of crops in their fields.

The paper aims to formulate and carry out a drone-based crop image segmentation system that enables precise monitoring and analysis of crop health and productivity. By leveraging aerial imagery captured by drones and sophisticated image processing algorithms, the system can segment crop images into distinct regions, allowing farmers to identify areas of interest, such as healthy vegetation, diseased plants, or nutrient-deficient areas. This granular information enables targeted interventions, such as precision spraying, irrigation management, and pest control, leading to improved crop yields, resource efficiency, and sustainability.

The drone-based crop image segmentation project represents a significant offering to farmers, advancing their capabilities and practices significantly in precision agriculture, offering farmers a powerful tool for monitoring, analyzing, and managing crop health and productivity. By harnessing the capabilities of drones, image processing algorithms, and data analytics, the project aims to revolutionize crop monitoring practices and pave the way for sustainable and efficient agriculture.

II. PROPOSED MODEL

Block diagram for proposed work

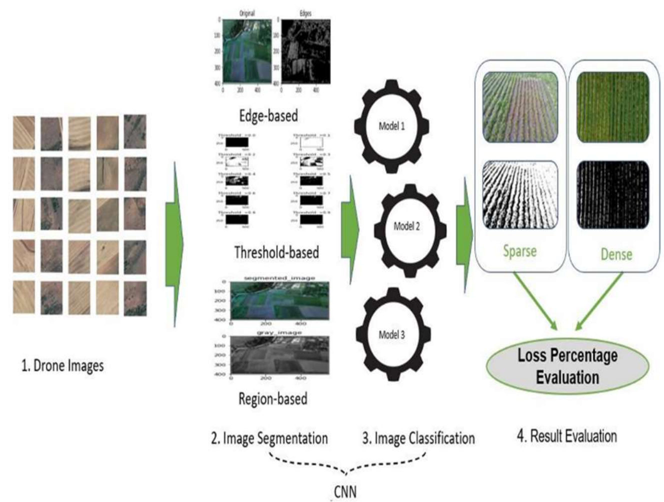

Fig 1 block diagram for the proposed model

The proposed research work focuses on crop image seg- mentation which is shown in Fig. 2. The main objectives are:

• To create an aerial crop dataset that can be used for experimentation and analysis.
• To perform image segmentation using different tech-niques such as threshold, region-based, and edge-based methods as shown in Fig. 2.
• To classify the segmented to produce images utilizing deep learning models such as R-CNN, U-Net, SegNet, and FCN [14].
• To assess models of the image classification process and determine its accuracy and effectiveness as shown in Fig. 2. Method to classify and segment the crop image is gone through this below points are:

• Drone images
• Image segmentation
• Crop classification

Drone images

Drone images, also known aerial images or drone captures, obtained from unmanned aerial vehicles. (UAVs), commonly referred to as drones. These images are obtained from an elevated perspective, providing a bird's-eye view of the landscape below. Drone images have become increasingly popular in

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various fields due to their ability to capture high-resolution, georeferenced data over large areas quickly and cost-effectively.

Image segmentation

Image segmentation is a fundamental computer vision task that divides an image into different parts or areas. on certain characteristics, such as color, intensity, texture, or semantic content. The goal of image segmentation is to make an image simpler and more useful by transforming it into a format that is easier to understand and analyze.

Thresholding is a simple and commonly used technique where pixels in an image are categorized as foreground or background based on their intensity values relative to a specified threshold. It is effective for separating objects from the background in images with well-defined intensity differences.

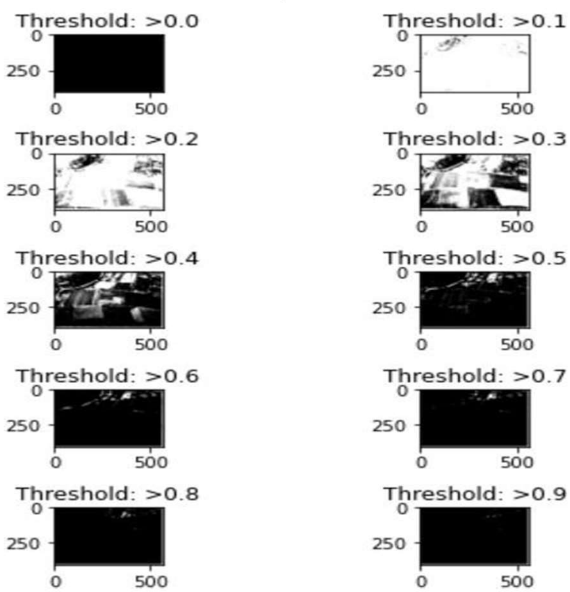

Fig 2 threshold based segmentation

Edge-based segmentation methods identify boundaries or edges between different objects in an image. Techniques like the Canny edge detector, Sobel operator, and Prewitt operator are used to detect edges by highlighting abrupt changes in pixel intensity. Edge-based segmentation methods identify boundaries or edges between different objects in an image. Techniques like the Canny edge detector, Sobel operator, and Prewitt operator are used to detect edges by highlighting abrupt changes in pixel intensity.

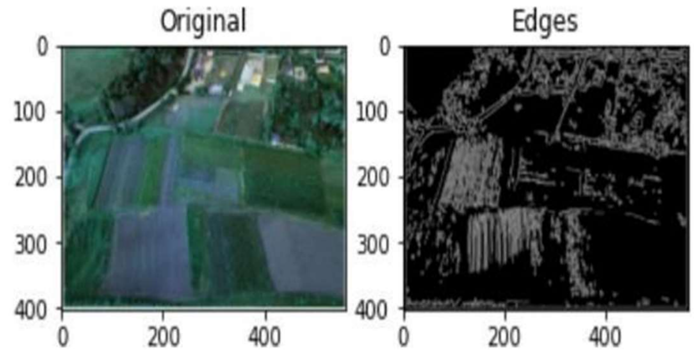

Fig 3 Edge based segmentation

Crop classification

Crop classification, also known as crop type mapping or land cover classification, is the process of categorizing agricultural land into different crop types or land cover classes based on remote sensing data such as satellite imagery or drone images. Crop classification plays a crucial role in various fields, including agriculture, environmental monitoring, and land management. The goal of crop classification is to accurately identify and delineate different crop types or land cover classes to support decision-making, resource management, and policy planning.

Crop classification into sparse and dense categories involves categorizing agricultural land based on the density or coverage of crops within a given area. This classification helps in understanding the spatial distribution of crops and can be valuable for various agricultural applications, including resource allocation, yield estimation, and precision farming. Common machine classifiers include Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNNs). The model learns to classify pixels or image patches into sparse and dense categories based on the extracted features and labeled training data.

III. RESULT AND ANALYSIS

Image Capture

Use a drone to capture high-resolution images of the crop field, using image which is shown in Fig. 4

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Fig 4 image capture from the drone

Streamlit provides widgets and input components that allow users to input parameters, select options, and control the behavior of the application. User can input the images captured from the drone in the console as shown in the fig 6. The captured image from the drone is uploaded in the streamlit were the image is taken for the pre processing.

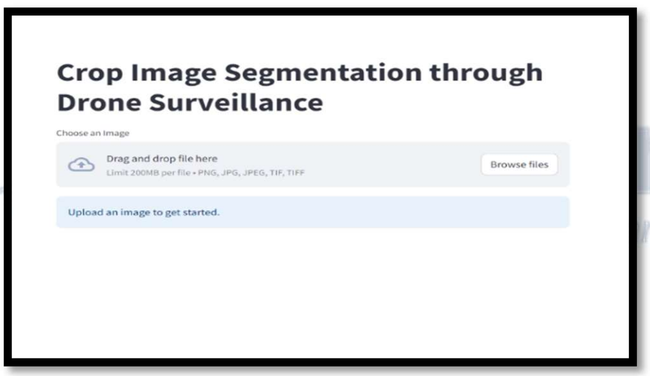

Fig 5 streamlit console

The uploaded image is resized to a smaller size (300x300 pixels) to reduce computational complexity and enhance processing speed. Resizing also helps in standardizing the input size for further processing. The resized image is converted from a PIL Image object to a NumPy array. Then, the image is converted from RGB format to BGR format, which is the standard format used by OpenCV for image processing. before performing segmentation, the application preprocesses the image by converting it to grayscale. This step simplifies subsequent processing and reduces

Fig 6 pre processed image

Image classification in precision agriculture involves using computer vision techniques to analyze images captured by drones, satellites, or other sensors to make informed decisions about crop health, soil conditions, pest infestations, and more.

Thresholding is a simple yet effective technique used to separate objects from the background in an image. It works by converting grayscale images into binary images, where pixels are classified as either foreground (object of interest) or background. In this application, a threshold value of 150 is applied to the grayscale image using OpenCV's cv2.threshold function. This converts the grayscale image into a binary image, where pixel values below the threshold are set to 0 (black) and pixel values above the threshold are set to 255 (white).

Edge detection is another important technique used in image processing to identify the boundaries of objects within an image. It works by detecting sudden changes in intensity or color between neighboring pixels.

. **Fig 7 threshold segmented image**

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In this application, the Canny edge detection algorithm is employed using OpenCV's cv2.Canny function. This algorithm identifies edges in the grayscale image by tracing the areas of high intensity gradient, which typically correspond to object boundaries. In this application, the Canny edge detection algorithm is employed using OpenCV's cv2.Canny function. This algorithm identifies edges in the grayscale image by tracing the areas of high intensity gradient, which typically correspond to object boundaries.

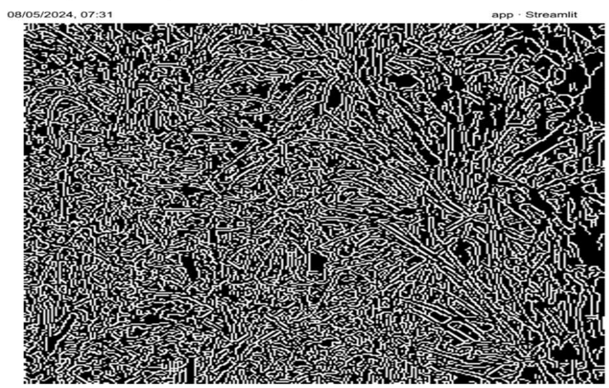

Fig 8 edge based segmentation

Loss percentage

Based on the characteristics of the thresholded image and the detected edges, your application assigns classes to the segmented regions using the following criteria:

1. If both the mean intensity of the thresholded image and the mean intensity of the edges are low (below 50), the region is classified as "Dense Healthy Crop".
2. If the mean intensity of the thresholded image is high (above 200), the region is classified as "diseased".
3. Otherwise, the region is classified as "Sparse Low Crop area".

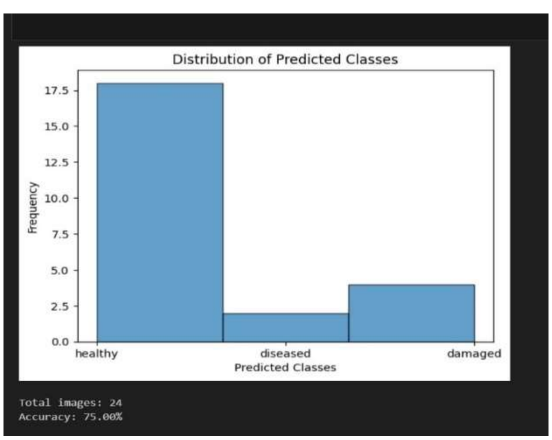

Fig 9 loss evaluation graph

This model has evaluated an unhealthy crop image determined that there is a 53% loss in image this calculation of loss percentage is based on the model analysis of the image and it helps in providing an accurate estimation of crop health .knowing the loss percentage of a crop can be crucial in making important decisions regarding crop management and reducing financial losses .the accuracy of this evaluation depends on the training and performance of the model ,as well as the quality of the input image.

IV. CONCLUSION

In conclusion, the project on crop image segmentation through drone surveillance presents a powerful solution for enhancing agricultural management practices and addressing challenges in modern farming systems. By leveraging the capabilities of drones and advanced image processing techniques, the project enables real-time monitoring, analysis, and decision-making in crop production. Through the segmentation of crop images captured by drones, farmers gain valuable insights into the health status of their crops, allowing for timely intervention in response to pests, diseases, nutrient deficiencies, and other stressors. The application of precision agriculture practices facilitated by the project promotes resource efficiency, reduces environmental impact, and improves crop yields and profitability. Furthermore, the project's potential extends beyond individual farm operations to broader applications in research, education, environmental monitoring, disaster response, and community engagement. By fostering collaboration between farmers, researchers, policymakers, and other stakeholders, the project contributes to building resilient and sustainable agricultural systems that can address global food security challenges.

the crop image segmentation project represents a promising advancement in agricultural technology, with significant potential to revolutionize crop monitoring and management practices. Through ongoing research, innovation, and adoption, the project can continue to make a positive impact on the livelihoods of farmers, the resilience of agricultural systems, and the sustainability of food production worldwide.

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