Application of Drone systems in Crop Monitoring

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I. Introduction

Modern agriculture faces the challenge of making precision agriculture accessible to all, especially smallholders and farmers in developing countries. This abstract explores an innovative solution utilizing drones equipped with RGB cameras for crop monitoring. The drones will perform area segmentation, soil composition detection, and irrigation problem identification, aiding in decision-making. Additionally, the drones will monitor crop health, detect pest and fungal infections. This research serves as a proof-of-concept for small-scale autonomous geographical region mapping, offering a promising path towards democratizing precision agriculture for wider adoption.

II. Literature Review

Despite the undeniable progress made by industry leaders like Agribotix, Parrot, DJI Agras Series, Sentera, PrecisionHawk, senseFly, and Delair in revolutionizing agricultural practices through drone-based crop monitoring systems, affordability and accessibility remain significant hurdles, particularly for resource-constrained smallholder farmers. These systems, equipped with advanced technologies like NDVI multispectral sensors, sophisticated data analytics, and high-resolution imaging capabilities, empower farmers to closely monitor crop health, promptly identify problematic areas, and make informed decisions regarding irrigation, fertilization, and pest management. However, the high cost of these systems often limits their adoption by smallholder farmers, hindering the widespread adoption of precision agriculture. Furthermore, traditional satellite imaging techniques face inherent limitations in accurately delineating land compositions and distinguishing between various crops, such as rice, wheat, and cotton. This necessitates a reevaluation of our approach to land segmentation and crop type differentiation. This proposed crop monitoring system tackles these challenges with a simplified yet powerful approach. Leveraging an affordable RGB camera, robust index algorithms, advanced computer vision techniques, and the cost-effective infrastructure of cloud computing services, this solution prioritizes affordability and directly addresses these persistent limitations.

III. Materials and Methods

A low-cost drone was equipped with a Raspberry Pi 4 and a camera module (Raspberry Pi Camera Module V2) to capture images of agricultural fields. A luminosity module (Adafruit TSL2561 Light Sensor Breakout Board) was also attached to the drone to measure the ambient light conditions. The drone was programmed to fly autonomously over a designated field, taking images at regular intervals. The images were then processed using Python scripts to extract information about the field and its crops.

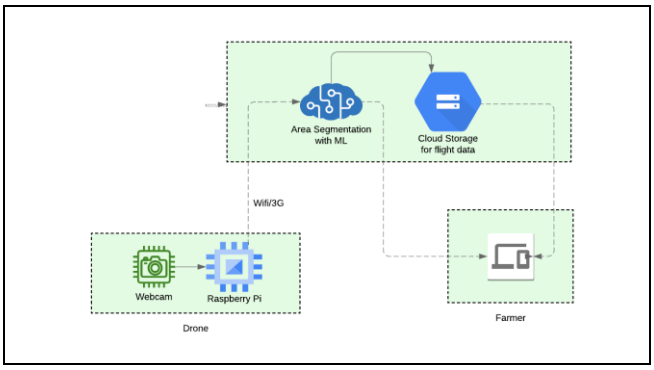

Fig. 2. System architecture

The proposed drone-based crop monitoring system employs a cost-effective and efficient communication architecture to seamlessly transfer captured images to cloud storage and process them using cloud-based computer vision algorithms. This architecture leverages the ubiquitous availability of 3G/4G cellular networks to ensure uninterrupted data transmission, even in remote areas. By utilizing cloud services for image processing and analysis, the system eliminates the need for expensive and power-hungry hardware on the drone itself. A low-power computing module, Raspberry Pi 4 is employed, significantly reducing costs and extending battery life instead of powerful modules like NVIDIA Jetson series computers. Further, the cloud-based architecture is highly scalable and can accommodate a growing number of drones and fields, enabling widespread adoption. Upon reaching the cloud storage service, the images are retrieved by a cloud-based server hosting the computer vision algorithms. These algorithms perform image analysis tasks, such as vegetation segmentation, crop health assessment, and pest detection, extracting valuable insights from the captured data. The processed image data and extracted insights are then stored in the cloud, accessible to farmers through web and mobile applications. Farmers can remotely access these applications to view detailed crop health maps, identify potential problems, and make informed decisions regarding irrigation, fertilization, and pest control.

A. Firebase Storage and Database

The system employs Firebase Storage and Firestore, cloud-based services that offer scalability, durability, and ease of integration with Google Cloud hosted computer vision algorithms. Firebase also simplifies image uploading from the Raspberry Pi 4, minimizing computational requirements, and enabling minor preprocessing tasks.

B. U-net for segmentation

U-Net, a convolutional neural network (CNN) architecture specifically designed for biomedical and satellite image segmentation.

U-Net's unique architecture, characterized by its encoder-decoder structure and skip connections, allows for precise and accurate segmentation of complex images, such as those captured by drones. The encoder extracts features from the input image, gradually reducing its size while increasing the number of feature channels. Conversely, the decoder gradually upsamples the feature maps, combining them with corresponding high-resolution feature maps from the encoder, enabling precise localization of features. This architecture enables U-Net to effectively segment agricultural fields into distinct areas based on vegetation levels, land composition and soil variation.

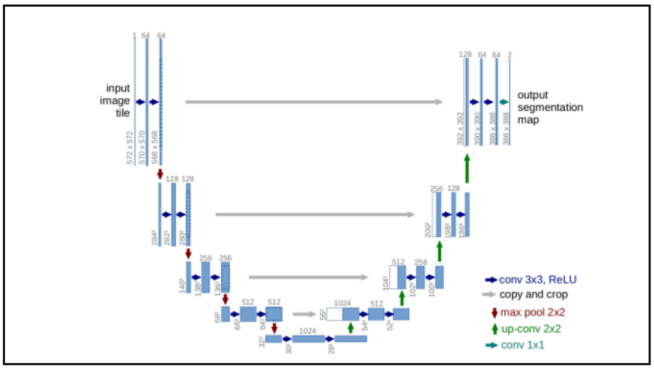

Fig. 2. U-net architecture

C. Disease Detection

The detection of deformed leaves is a critical task for plant infection identification and treatment. To address this challenge, a two-fold approach has proven effective, employing image classification with the VGG model and object detection with Faster R-CNN. The VGG model is employed for image classification, enabling the identification of deformed leaves at the image level. This initial categorization provides a broad assessment of the presence of leaf deformities. Simultaneously, the Faster R-CNN model takes the analysis further, performing object detection to delineate the precise location and extent of individual deformed leaves within the image. The combination of image classification and object detection delivers a comprehensive understanding of leaf health, facilitating the targeted management of deformed leaves, disease identification, and informed decision-making in precision agriculture.

IV. Results and Discussion

The U-Net model's performance in segmenting vegetation areas was evaluated using a comprehensive dataset of agricultural field images captured under varying lighting conditions and crop stages. The model demonstrated exceptional segmentation accuracy, effectively differentiating between vegetation and non-vegetation regions. The model's precision in identifying vegetation boundaries was particularly noteworthy, enabling accurate area classification and resource management. Remarkably, the model effectively segmented vegetation areas regardless of crop type or soil conditions, highlighting its robustness and generalizability. These results strongly support the effectiveness of U-Net as a powerful tool for vegetation segmentation in drone-based crop monitoring systems.

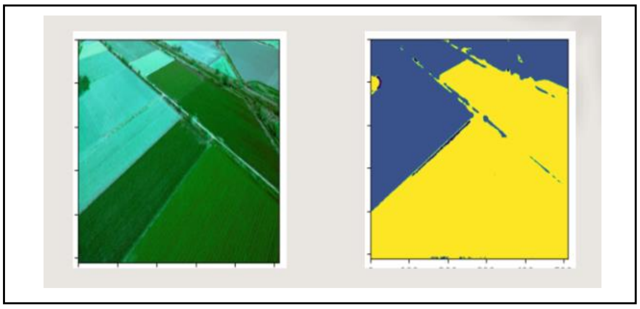

Fig. 3. Area segmentation results

V. Conclusion

In summary, utilizing drones for evaluating plant diseases presents an effective means of monitoring and detecting issues in the field of smart agriculture. Drones offer enhanced accessibility, extended coverage, and swift data collection. The research has effectively met its objective of creating a novel and budget-friendly drone-driven crop monitoring system, showcasing the viability of precision agriculture for small-scale farmers in developing nations. By effectively utilizing low-cost drone technology and advanced computer vision algorithms for vegetation segmentation and disease detection, the study has paved the way for accessible and efficient crop management. However, certain limitations, such as data availability, computational resources, and the need for further scalability, must be addressed. Future research opportunities lie in expanding datasets, exploring edge computing solutions, transitioning from proof-of-concept to real-world implementation, and conducting economic assessments, all of which can contribute to the practicality and economic viability of this transformative agricultural technology.

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