Geohash-Based Maize Plant Monitoring System Ulitizing Drones

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ABSTRACT

Corn is one of the important food crops in the world. To ensure optimal results, farmers usually monitor crop conditions manually. Unfortunately, manual monitoring can take time and effort due to the large area of maize fields (approx.: 1 ha). In addition, corn plants are also susceptible to diseases and pests which often result in corn farmers experiencing losses due to crop failure. This can be supported by several cases of corn crop failure in Lampung caused by pests and water shortages, such as in Bumidaya Village, South Lampung. Therefore, this research will develop a corn crop monitoring system using geohash and drones. The primary objective of this research is to develop a comprehensive design for a corn crop monitoring system, leveraging the capabilities of machine learning for corn plant recognition. The application of geohash is expected to assist farmers in handling and early detection of plants that experience a decrease in health quality before it spreads to all other maize crops. The results of the model training carried out with the R-CNN are that the detection model is able to detect with an accuracy of 88.9% with a low distance of the drone in taking pictures or close to plants.

I. INTRODUCTION

Maize, commonly known as corn, holds a prominent position as one of the most extensively grown and significant staple crops worldwide. It is an exceptionally versatile plant, utilized in various ways across diverse cultures and industries. Its primary cultivation purpose revolves around the production of edible grains, which find extensive use in numerous culinary applications, serving as both a key ingredient and a raw material for diverse food products [1].

The kernels of maize exhibit a wide spectrum of colors, including yellow, white, red, blue, and even black, each boasting distinctive flavors and nutritional compositions. In the present day, maize is cultivated on a large scale in numerous regions globally, with major producers including the United States, China, Brazil, Mexico, and Indonesia. In Indonesia, particularly in the year 2020, the corn production is projected to reach a staggering 29.02 million tons, with the East Java Province emerging as the leading corn-producing province within the country [2]. This crop showcases remarkable adaptability, thriving in diverse climates and suitable for growth in tropical, subtropical, and temperate areas. The combination of its adaptability, high yields, and nutritional value has propelled maize to global recognition and widespread cultivation. Diseases play a significant role in reducing maize yield and productivity in Asia, as well as in other regions. Globally, it is estimated that diseases cause a yearly loss of 9.4% of the economic product, which is the grain. In the United States, this figure amounts to 12%, while in countries like India, an annual decrease in grain yield of at least 13.2% has been estimated. Considering a conservative estimate of 9.4%, the annual reduction in grain yield in Asia is approximately 9.1 million tons [3].

Maize in Southeast Asia, particularly in Indonesia, is vulnerable to various prevalent diseases that can have a significant impact on crop yield and overall productivity. One commonly encountered disease is maize rust, which is caused by the fungus Puccinia polysora. This disease primarily affects the leaves, stems, and husks of maize plants, leading to a decrease in photosynthesis and premature aging of the plants. Another notable disease is maize lethal necrosis (MLN), which is caused by a combination of viruses including maize chlorotic mottle virus (MCMV) and sugarcane mosaic virus (SCMV). MLN is characterized by severe stunting, leaf discoloration, and eventual plant death. Additionally, southern corn leaf blight, caused by the fungus

Bipolaris maydis, can lead to lesions on the leaves, reducing the plant's ability to efficiently capture sunlight for photosynthesis. Indonesian farmers consistently encounter the challenge of addressing these diseases through integrated pest management strategies, crop rotation, utilizing resistant maize varieties, and timely application of fungicides. These measures are essential to minimize the adverse impacts on maize production.

Many corn plant diseases can be readily recognized and observed visually. Leaf blight, rust, and wilt are common examples of diseases that affect corn plants and can be easily identified. Furthermore, the health condition of corn can also be assessed by examining the appearance of its tassels. Due to technological advancements, the identification of these diseases has become more accessible. In pursuit of this goal, the study aims to construct an integrated system that combines machine learning technology and agricultural practices. This system will facilitate real-time monitoring of corn crops, utilizing machine learning algorithms to accurately identify and assess the health and growth stages of the plants. By harnessing the power of machine learning, the research seeks to enhance the efficiency and precision of corn crop management, ultimately contributing to more sustainable and productive agricultural practices. Through this innovative approach, the study endeavours to advance our understanding of how technology can positively impact crop cultivation and food security.

A method to determine disease-infected plants involves the utilization of digital image recognition technology in conjunction with drones [4].

II. LITERATURE REVIEW

There are several studies that form the basis and reference of this research, the first is this journal discusses the development of a generalized deep learning-based system for detecting pine wilt disease using RGB-based UAV images [5]. They used a UAV equipped with an RGB camera to capture images of pine forests infected with pine wilt disease. The collected data was then used to train a deep learning model, which consisted of three main stages: data pre-processing, model development, and model testing using unseen data. The results of this study showed that the built deep learning model can be used to detect pine wilt disease with high accuracy, even in complex open field conditions. The model can also be used to detect other types of pine wilt disease with satisfactory accuracy. In conclusion, the use of deep learning to detect pine wilt disease from RGB-based UAV images can help forestry experts and farmers monitor and prevent the spread of the disease. This system can also be used to detect wilt disease in other crops, making its potential applications wide-ranging.

Another paper discusses the application of CNN to detect transmission centres of wheat stripe rust under complex field conditions using high spatial resolution RGB-based images from UAV [6]. CNNs semantic segmentation architecture (deeplabv3+) was applied to per-pixel classify the imagery for the detection of healthy wheat and stripe-rust-infected wheat (SRIW). The authors collected data using a UAV equipped with an RGB camera to capture images of wheat plants infected with stripe rust. The data collected included high spatial resolution RGB images of a large field area. With the end-to-end deep learning segmentation method greatly reducing the need for intensive preprocessing, the combination of CNNs and RGBbased ultra-high spatial resolution images from UAVs provides a simple and rapid method for accurate detection of crop disease on a large scale.

The extraction of maize seedling information from UAV images based on semi-automatic sample generation and the Mask R-CNN model discussed in this paper [7]. The authors used a UAV to capture images of maize seedlings in agricultural fields. They then used a semi-automatic method to generate data samples that included maize seedlings from different angles and varying lighting conditions. After collecting the data samples, the authors used the Mask R-CNN model to process and analyze the data. The model was trained using the generated data samples and used to extract important information about the maize seedlings, such as height, leaf area, and leaf size. n conclusion, the use of a semi-automatic method for sample generation and the Mask R-CNN model for extracting important information from UAV images can help farmers and agricultural experts monitor and develop agriculture more effectively and efficiently.

This journal discusses the detection and location of dead trees with pine wilt disease using deep learning and UAV remote sensing [8]. The authors used UAV technology to capture images of pine forests infected with pine wilt disease. These images were then processed using deep learning to detect and locate dead trees caused by the disease. In this study, the authors compared four different deep learning models, including Faster R-CNN, Mask R-CNN, YOLOv3, and SSD. The results showed that the Faster R-CNN model produced the highest accuracy in detecting and locating dead trees caused by pine wilt disease. The detection accuracy was improved and reached to about 90% after a series of optimizations to the network. Our new approach developed a corn crop monitoring system using geohash and drones. The application of geohash is expected to assist farmers in handling and early detection of plants that 3 experience a decrease in health quality before it spreads to all other maize crops.

III. METHODOLOGY

The experiment involves training the model using R-CNN on a publicly available dataset and a independently collected dataset. The independent dataset was collected using the DJI Mavic Air 2 drone and relied on geohash mapping. Geohash is a geocoding system that divides the Earth into small squares. By applying geohash to the cornfield, it is possible to obtain latitude and longitude coordinates that correspond to the specific location of the field. The sequence of processes performed in the system can be seen in Figure 1.

A. *Geohash mapping*

Mapping the cornfield area with geohash aims to facilitate the drone in automatically capturing images based on the known geohash and coordinates. Each geohash represents exactly one coordinate of a location, so these coordinates will be used as a reference for the drone's flight. The coordinates representing each geohash are in the center of the geohash area. Therefore, in the upcoming experiment, the drone's altitude for capturing images will be 5 meters above the ground, assuming that the entire represented geohash area can be clearly visible.

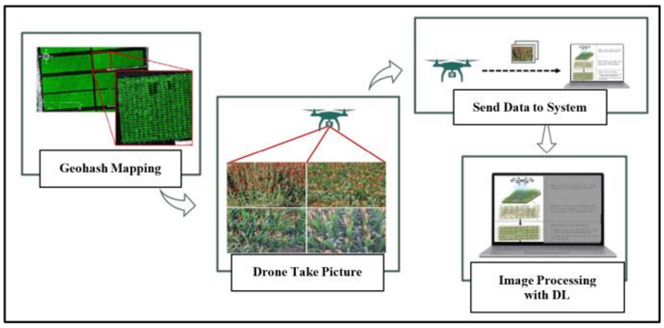

Figure 1. System Development Flowchart

The cornfield location to be used in this study is a cornfield situated in the Kedamaian District of Bandar Lampung City, with the coordinates of the cornfield being -5.412633, 105.28003. The total area of this cornfield is approximately 3.2 hectares, but for the experiments conducted in this study, a quarter of that area will be used, which is about 8 hectares.

Figure 2. Experimental Area Location in the Kedamaian Cornfield

The geohash characters used in this experiment are 9 characters long, covering an area of 5 x 5 meters. The geohash codes used for the experimental area can be seen in Table 1.

TABLE I
GEOHASH CODE

Area	1	2	3	4
1	qr4c5wwt4	qr4c5wwsf	qr4c5wwsd	qr4c5wws6
2	qr4c5wwt5	qr4c5wwsg	qr4c5wwse	qr4c5wws7
3	qr4c5wwth	qr4c5wwsu	qr4c5wwss	qr4c5wwsk
4	qr4c5wwtj	qr4c5wwsv	qr4c5wwst	qr4c5wwsm
5	qr4c5wwtn	qr4c5wwsy	qr4c5wwsw	qr4c5wwsq
6	qr4c5wwtp	qr4c5wwsz	qr4c5wwsx	qr4c5wwsx
7	qr4c5wwv0	qr4c5wwub	qr4c5wwu8	qr4c5wwu2
8	qr4c5wwv1	qr4c5wwuc	qr4c5wwu9	qr4c5wwu3

The information in the form of coordinates, geohash codes, and drone positions will be stored in the database with details as shown in Figure 3. The dataset includes attributes such as a name attribute that stores the location's name, a geohash code attribute storing the geohash code based on Table 1, latitude and longitude attributes that are automatically stored based on the geohash, and a status attribute to determine whether the location has been visited by the drone, with a Boolean data type.

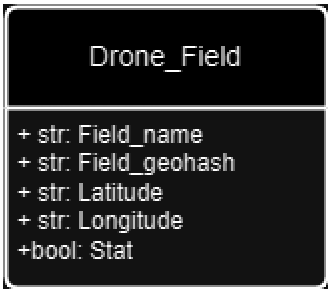

Figure 3. Drone Flight Path Database

Geohash plays a pivotal role in aiding the collection of crucial initial data essential for the development of models. Additionally, it is employed for capturing images during the monitoring process of corn crops. As depicted in Figure 4, illustrating the workflow of the monitoring system, the process unfolds in several stages. Initially, in the first phase, the system stores geohash data in a database while simultaneously preparing flight instructions for the drone. Subsequently, the constructed database, as seen in Figure 3, contains vital information including latitude, longitude, and geohash area codes. Once the system acquires location information and data capture directives, the drone embarks on its mission to capture images of the cornfields based on the predefined geohash sequence. The drone's flight duration for this task typically spans a period of approximately 30 minutes.

In the subsequent stage, after completing the image capture operation, the drone proceeds to upload the gathered data to the central system. This data is then subjected to processing using a corn recognition model, thus facilitating further analysis and insights into the corn crops.

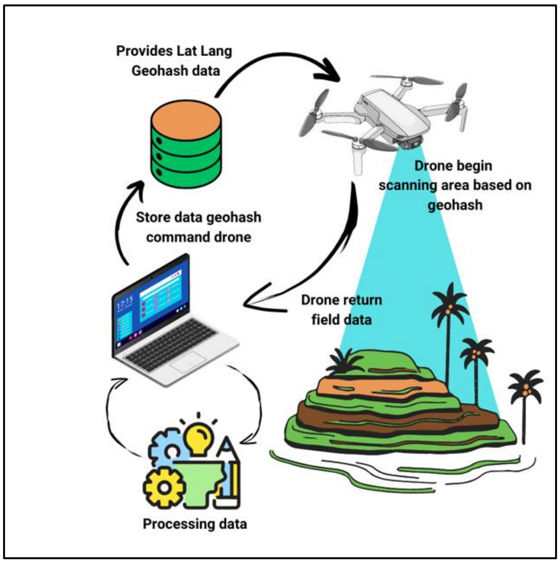

Figure 4. System Flow

B. Dataset Collection

The dataset used in this experiment consists of 969 images of corn plants available publicly, captured using a drone. These images were taken from a height of 5 meters. Apart from this dataset, there is an additional set of 50 images taken independently using the DJI Mavic Air 2 drone. This dataset is specifically annotated for corn tassels, as shown in Figure 5. The image capture is performed automatically based on the predetermined geohash on the drone.

Figure 5. Dataset

Collecting this dataset serves as the foundation for the development of a deep learning model for monitoring corn plants. In this experiment, the developed model focuses on detecting corn tassels to assess rice productivity conditions.

C. Model Development

The development of the corn tassel detection model is divided into 5 stages: data acquisition, data pre-processing, model training, evaluation, and implementation of the model into the system. In the data acquisition stage, data is collected based on publicly available corn plant datasets and a collection of corn plant photos taken independently with the DJI Mavic Air 2 drone. Subsequently, the corn plant images to be used are standardized in size, and the image saturation is adjusted to enhance the clarity of the images. In the model training stage, the deep learning method used in this research is Fast R-CNN. The final stage in model development is the evaluation of model performance using the COCO validation method. If the model shows good performance, it is then ready for use in the system. The model development flowchart can be seen in Figure 6.

Figure 6. Flowchart Model Development

D. Model Evaluation

The evaluation of the developed model's performance is conducted using average precision at 50, average precision at 75, small average precision, and medium average precision. Average Precision (AP) condenses the Precision-Recall (PR) Curve into a single scalar value. High average precision indicates that both precision and recall are high, while low average precision suggests that either precision or recall (or both) are low across various confidence threshold values [9]. The AP value ranges from 0 to 1.

IV. RESULTS AND ANALYSIS

The datasets obtained from public sources or independently collected are annotated using Roboflow annotations. The annotation results can be seen in Figure 7 below. The next annotated images are ready to undergo data pre-processing. The pre-processing technique applied to the data used in this experiment involves adjusting the brightness and contrast of the images. The subsequent step involves splitting the data into training, validation, and testing sets. The portions for each of these sets are 733 images for training, 205 for validation, and 30 for testing. The deep learning method used in model training is Fast R-CNN with a total of 1000 iterations. The prediction method utilized in this model development is Default Prediction, and the evaluation method employed is the COCO evaluator.

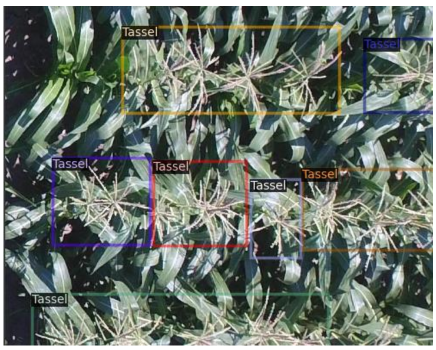

Figure 7. Corn Tassel Annotation

In this experiment, model training yielded satisfactory results in terms of detecting corn tassels. At 1000 iterations, the accuracy of corn tassel detection reached 88.9%. Figure 8 illustrates the accuracy graph of the model training, while Figure 8 shows the testing results. In the trained model, the average precision values were as follows: AP50 was 66.49%, AP75 was 16.83%, APs and APm did not yield satisfactory results, and Apl was 30.1%.

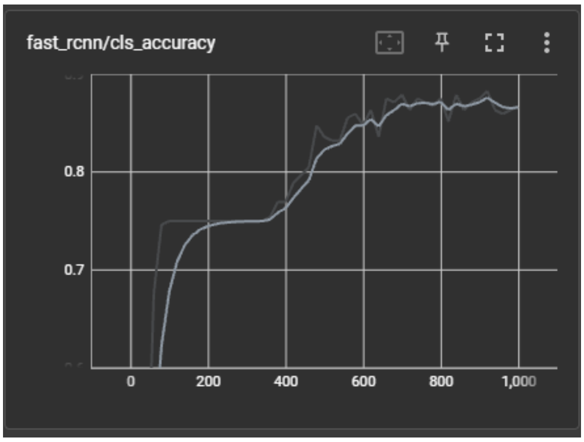

Figure 8. Model Accuracy

Based on these average precision results, it can be concluded that accurate detection of corn tassels can be achieved by using sufficiently large image sizes to visualize the corn plants. Furthermore, the average precision results also provide recommendations for the optimal flying height for drones. For more accurate detection, the drone should ideally fly at a height that is close to the corn plants.

V. CONCLUSION

Based on the results of the experiments conducted in this study, it can be concluded that the performance of R-CNN is quite good in detecting corn tubers with a detection accuracy of 88.9%. From the experimental results, it can also be concluded that capturing images and performing detection using a drone is better done at a relatively close distance to the plants, which would result in more accurate detection outcomes. The use of geohash in this experiment is considered highly beneficial for the research in gathering the required dataset.

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