

AUTONOMOUS DRONE APPLICATION IN INDOOR FARMING ENVIRONMENTS

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1. ABSTRACT:

This project explores the application of drone technology in indoor farming to improve the crop monitoring and support sustainable goods production. The study mainly focusses on the development of a semi-autonomous drone system which can navigate within an indoor farm and collecting visual data for the plant health analysis. The system integrates two main component autonomous drone navigation for the data acquisition and an artificial intelligence model for plant health classification. The Tello drone which is equipped with a camera will capture the required images while navigating through the indoor farm using the QR code for positioning. The captured images are then processed by CNN developed with tensor flow and keras to segregated whether that plant is healthy or unhealthy.

2. KEYWORDS:

Drone technology, Indoor Farming, UAV, Plant health Monitoring, Computer Vision, Convolution Neural Network (CNN), Autonomous Navigation, Precision Agriculture, Indoor Farming, Artificial Intelligence.

3. INTRODUCTION:

Indoor farming is a modern agricultural way of approaching the derived from the urban agriculture, where crops are cultivated in vertically stacked layers using the minimal water and without soil. This method is typically implemented in controlled environments such as buildings, containers or warehouse to maximize crop production within limited space. Even though the concept was there for more than decade the practical implementation was only feasible with the advancement of controlled environment agriculture (CEA) which also helps to enable precise regulation of environmental features such as temperature, humidity, lighting and gas concentration. These controlled features help the crop to grow efficiently and consistently, making Indoor farming a proper solution for food production.

The increasing growth of the population has led to a rapid rise in food demand, by creating signification challenges for the traditional agricultural systems. It is calculated in the way that food production must increase the substantially in the coming years to meet the population needs. However, the conventional farming methods are affected by the climate change, land degradation and resource limitations. Various environmental issues such as global warming

and deforestation further reduce the availability of fertile land, making the sustainable agricultural alternatives essential. Indoor farming helps in providing a proper solution by enabling efficient crop production in urban environments while helping to reduce the land and water usage.

Regardless of the advantages, Indoor farming also faces several challenges, which includes high cost for operation and dependence on advanced technologies. The need for continuous monitoring and maintenance of the crop can increase the labour requirements and the complexity of the operation. To address these limitations, the automation technologies such as the unmanned aerial vehicles can be integrated into Indoor farming systems. Drones can help in monitoring the health of the plant, collecting data and reducing manual labour, thereby improving efficiency and scalability.

The study mainly focuses on the development of the drone-based system for monitoring plant health in a Indoor farming environment. the system aims to automate the data collection and analysis using the AI techniques, by enabling the efficient and accurate assessment of the crop conditions. By integrating the technology of drone with Indoor farming, the system can enhance the productivity and support sustainable agricultural practices.

3.1 LITERATURE REVIEW

According to Attigui (2021) an autonomous drone system was developed to detect and track specific features while collecting and storing data from the environment. the drone could operate with an area defined by avoiding the obstacles and switching between the manual control and autonomous modes when it is required. The system used a commercial drone to test in a controlled environment with the obstacle placed around in the surroundings.

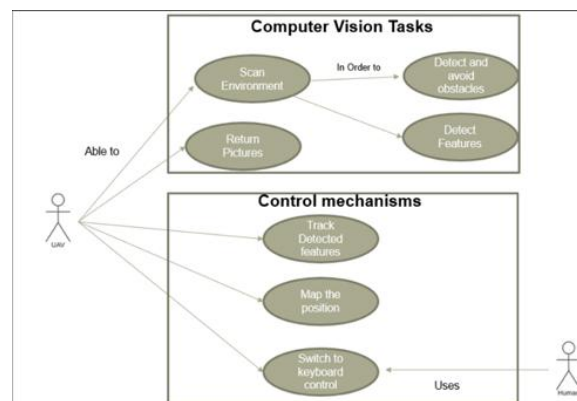


Figure 1: flowchart

The Tello drone was programmed using the python libraries, which includes the drone control library and image processing libraries. To identify object the marker detection techniques were used to avoid the obstacle which are placed around the area. These markers also helped the drone to let know its position and movement. The drone movement was controlled along the multiple axes to make it has smooth navigation and the system also used the feature detection algorithms to identify the nearby objects (Szeliski, 2010).

To detect specific feature the system used an image processing technique. The VioLo-Jones algorithm was used for feature detection, which will include techniques such as Haar-like features, integral images and cascade classifier (Viola & Jones, 2001). The captured images are detected using these techniques as well. These images are captured by the drone's camera.

Obstacles detection was achieved using the QR code placed around the environment. the drone camera detected these QR code and used them to determine obstacle positions. By calculating the coordinates and orientation of the drone over time the position tracking was implemented (Kato & Billinghurst, 1999).

The system was tested under different lighting conditions and the results showed that the lighting does have an important effect on the accuracy. When there are higher lighting conditions then the results are much better than compared to low lighting performance. The placement of the QR code also affected the accuracy of the detection and navigation (Gonzalez & Woods, 2018).

However, several limitations were identified in the system. The drone movement was not always stable and sudden landing occurred due to battery issues. Additionally, when multiple objects were detected, the system was unable to determine the specific one to take the required action. These limitations showcase the challenges involved in developing an autonomous drone system (Corke, 2017).

Another study proposed the use of CNN for processing the mages which were captured by the drones. CNN models can extract features such as the edges and contrast from images and use tthem for the object detection (LeCun et al., 1998). These models are then widely used because they can automatically learn features from the images and provide accurate classification results.

Deep learning techniques are particularly useful for plant monitoring system because they allow automatic classification of the plant health conditions. These models require training data and computational resources to achieve good performance. Despite these requirements, deep learning provides an effective method for automated plant health detection (Krizhevsky et al., 2012).

3.2 Summary

Based on the literature review the drone technology combined with the image processing and deep learning provides a proper solution for the automated plant monitoring system. The drone system allows to do efficient data collection, meanwhile image processing and deep learning techniques allow accurate classification of the plants health.

The system performance can be affecting various factors such as lighting conditions, drone stability and hardware limitations. These factors must be considered before designing a drone-based monitoring system.

The information which was gathered from the literature review was used as the base for the developing drone-based plant health monitoring system for the Indoor farming.

4. Proposed Methodology

A. System Overview

The proposed system is used to monitor the plant health in the Indoor farming environment using a drone-based imaging system and artificial intelligence. The system consists of two major components: image acquisition using a drone and the classification of the plant health using a deep learning model. The drone is used to navigate through the vertical farm structure and capture the images of the plants, which are then used to analyse whether they are healthy or not.

The system operates using a live video feed transmitted from the drone to computing unit. The image which is captured by the drone is then processed and trained into a convolutional neural network model that classifies plants as healthy or unhealthy.

The overall system consists of four main modules:

1. Drone movement and image acquisition
2. Image processing
3. AI model training
4. Plant health prediction

These modules work together to provide a real time monitoring of the plant conditions.

B. Drone movement and Navigation



Figure 1: DJI Tello drone



Figure 2: Navigation of the Tello drone



Figure 3: QR code used for navigation for the Tello drone

The drone is used as the basic component to get the data to capture images of plants in the vertical, farming system. The drone connects to a computing unit and transmit the live video feed from its onboard camera. This video feed serves to be the main input for the plant monitoring system.

The navigation is achieved using the QR code which is placed around the vertical towers. Each of the QR code has its unique ID which will respond to a specific drone movement. The drone movement commands are as such moving up, down and landing. The drone will detect these QR code using its camera and move accordingly.

If no QR code is detected, then the drone can be manually controlled using the keyboard inputs. This type of approach provides the flexibility in navigation and ensures that the drone can still operate even when there is no QR code detected.

The drone fly through the predefined path and captures images of the plant at different levels of vertical farms. Once the flight is completed the drone returns to its starting position.

After the established connection the battery status of the drone is checked, and the onboard camera begins streaming the live video to the computing unit. This video which is recorded is used for both the navigation and plant monitoring purposes. During the flight the drone usually follows a predefined path around the Indoor farming structure and capture images of plants at different levels.

C. Image Acquisition

The image acquisition is performed using the build in camera of the drone. The drone captures the images of the plants as it navigates through the Indoor farming structure. The images which are captured are then transmitted using the computing unit through the live video stream.

The system will continuously monitor the video feed and capture images whenever the plants are detected. These images are then stored in the computing system and is used further analysis. The process can be repeated multiple time to monitor the health of the crop over the time.

The drone enables data collection from areas that are difficult to reach manually making it suitable for monitoring Indoor farming structure.

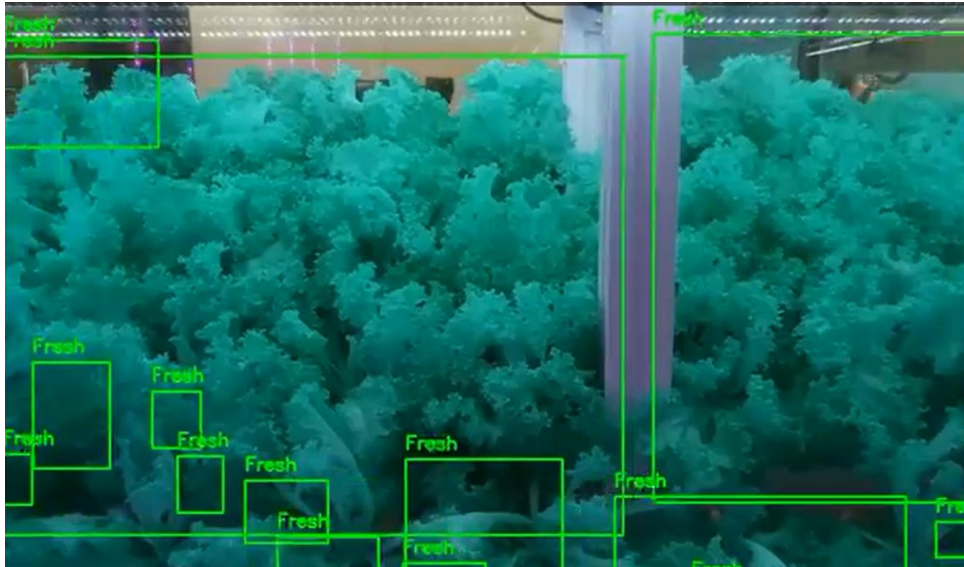


Figure 4: Annotation image from the Tello drone

D. Image Processing

After image acquisition done, the captured images undergo preprocessing before being analysed by the AI model. Image preprocessing improves the quality of the images and prepares them for classification.

- Converting images into RGB format
- Resizing images
- Normalizing image data
- Converting images into arrays

These steps make sure that the images are properly compatible with the convolutional neural network model and improve prediction accuracy.

Image processing also includes filtering and adjustments to make the image clearer and more suitable for analysis.

E. AI model Training

The health of plant classification model is developed using a CNN model. The CNN model is trained using a dataset of the plant images which are categorized into healthy and unhealthy classes.

The training process includes:

1. Preparing the dataset
2. Building the neural network model
3. Training model
4. Saving the trained model

The model is trained using multiple epochs to improve the accuracy. After the training model is done the model is saved and used later for the plant health predication.

The CNN is selected because it provide high accuracy in image classification tasks and requires minimal manual features extraction.

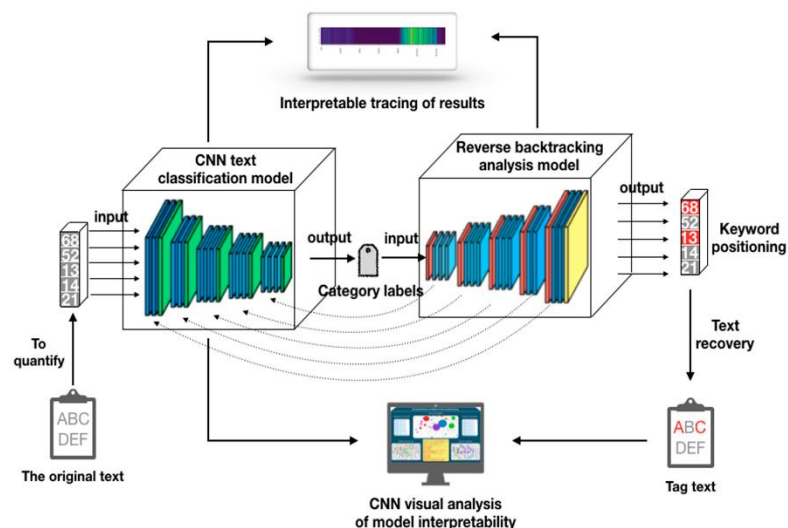


Figure 4: CNN model process

F. Plant health prediction

Plant health prediction is performed using the trained CNN model. The processed images from the drone's camera are then passed into the model, which classifies the plants into healthy or unhealthy categories:

The prediction process involves:

1. Loading the trained model
2. Processing the input images
3. Running the predictions
4. Displaying the results

The system can perform predictions on both images and live video feeds. Diseased plants can be highlighted and there are then saved for furthermore analysis.

G. System Workflow

The overall workflow of the system is:

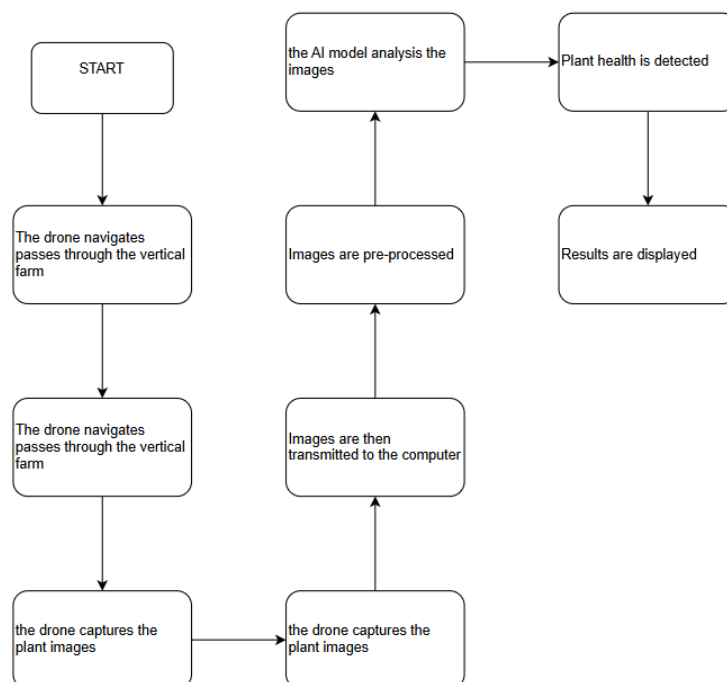


Figure 5: Flowchart for the overall workflow of the system

The flowchart describes the working process of a Indoor farming monitoring system using an autonomous drone and AI Based image analysis. It showcases how the Tello drone helps to collect the plant data and how is the AI model trained to determine the plant health.

The process starts with a start stage. After the initialization process the drone will then navigates through the vertical farm, moving between the rows and columns of the plants to monitor it. While navigating through the plant environment the drone will capture the images of the plant using the onboard camera system. These collected images will provide the necessary information which is required to analysis using the AI model. These provides the info about the crops leaf colour, growth condition, or the possible diseases symptoms.

Once the images are captured, they then transmitted to the computer system for further analysis. Before the analysis began the images will go through a pre-processing stage, where various task such as resizing, noise reduction and image normalization were performed to improve the quality of the data captured. The steps ensures that the images are suitable for accurate analysis by the AI model.

After the preprocessing done, then the AI model will analyse the image to detect the pattern related to the plant health. The model will be used to identify the signs of the plant stress, diseases, nutrient deficiencies or the normal healthy growth. Based on this analysis the system determines the health status of the plant.

Finally, the results are displayed to the user allowing the system operators to monitor the conditions of the plant and take the required actions. This automated workflow helps to improve the efficiency in the Indoor farming by continuously monitoring and early detection of the plant health problem.

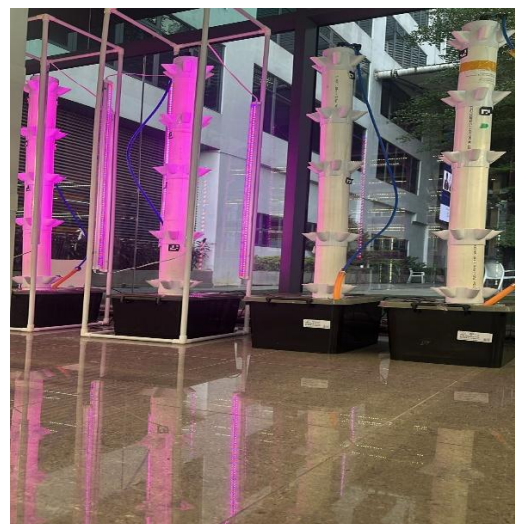
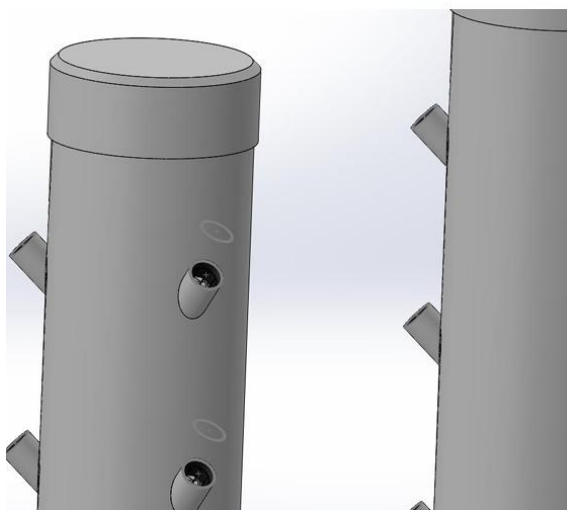
H. Indoor tower Design

Vertical tower hydroponic system is the base of the Indoor farming structure which is designed to maximize the growth of the plant also ensuring the accessibility for the drone navigation. As the system mainly relies on drone to monitor the plant health, the layout of the vertical farm was designed to allow the drone to move freely between the towers and capture clear images of the plant.

The farms have four vertical towers where plants are arranged at different level along the structure. Each tower has a specific place to grow plant while also maintaining adequate distance between them to ensure that it receives proper lighting and airflow. The spacing between the towers is also maintained so that the drone can easily and safely navigate through the farm and collect the images which are required.

The estimated dimension of the vertical tower system was defined during the design stage. The approximate height of each tower is 193.04cm with the plants spaced approximately around 30.5cm apart along the tower. The distance between all the four towers were maintained at 100cm to allow sufficient navigation space for the drone. The base of the system measure 150cm × 200cm which provides stability for the structure while supporting multiple plant levels.

This configuration of the tower enables efficient use of the vertical space while supporting automated monitoring through the drone technology. by combing the Indoor farming structure with drone-based surveillance, the system can efficiently capture the plant images for the further processing and health analysis.



I. Simulated results



Figure 7: Health detection

The developed system was tested using a Tello drone video feed in a indoor farming environment. the YOLO-based deep learning model was used to detect and classify the plant health in real time.

From the output various regions were successfully detected as Healthy and unhealthy based on the trained model each enclosed within a bounding box along with the confidence score.

The Yolo based model showcase an effective detection and classification of the plant health with various region identified. The system was able to achieve the highest confidence prediction of reaching 81.7% confidence which indicates a strong model in identifying healthy vegetation.

Various other detection was observed within the range of 58% to 75% confidence range, which still represent the acceptable classification performance under the real time conditions. These variations are expected mainly because of:

- Dynamic drone movements
- Variations in lighting conditions
- Differences in leaf orientation and density

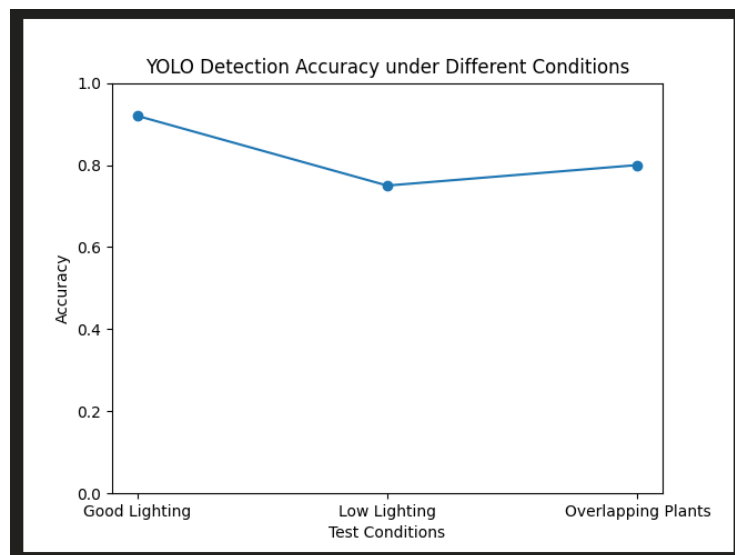
The model was able to:

- Accurately detect the plant regions in dense crop environments.
- Maintain real time processing capability.
- Provide the consistent classification output across multiple frames.

The presence of the multiple bounding boxes indicates that the system performs localized feature detection which allows it to analyse different sections of the plant canopy independently. This enhances the robustness, as the model does not rely on a single global prediction.

Overall, this system showcases a strong potential precision agriculture application, specifically in:

- Automated crop monitoring.
- Early-stage health assessment.
- Integration with the autonomous drone navigation systems.



The performance of the YOLO based plant health detection model was evaluated under three main different conditions: good lighting, low lighting and overlapping plant structures.

From the results

- Under the good lighting conditions, the model can achieve the highest accuracy of approx 85% which indicates that sufficient illumination significantly improves the feature extraction and detection performance.
- In the low lighting conditions the accuracy might dropped up to 51% this reduction is mainly due to decreased visibility of the plant features, which affect the model's ability to differentiate the important pattern such as the leaf texture and colour.
- For overlapping plants, the model achieved an accuracy of about 80%. Despite the complexity caused by the occlusion and dense plant arrangements, the model was still able to maintain relatively stable performance by detecting the localised features.

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