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Early Disease Detection and Optimizing Growth Conditions in Floral Plant Cultivation Using IOT

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Abstract **- This research paper explores a comprehensive approach to flower plant management, encompassing disease and pest identification with predictive solutions, the integration of IoT devices for soil analysis and environmental control, bud-based flower count estimation for income calculation, and the application of image processing for marketing insights. By combining advanced technology, this study aims to enhance the efficiency and sustainability of flower cultivation, from early disease detection to optimizing growth conditions, financial planning, and market research, ultimately revolutionizing the floral industry.**

Keywords: Flower plant management, Disease and pest identification, Predictive solutions, Soil analysis, Environmental control, Flower count estimation, Image processing.

I. INTRODUCTION

Flower cultivation is an integral part of the global horticultural industry, contributing significantly to both aesthetic and economic aspects. However, it is not immune to various challenges, including the identification and mitigation of diseases and pests, optimization of soil components, and the precise management of environmental factors. Moreover, flower production often involves predicting yields and market readiness, which in turn determines the profitability of this delicate endeavor. In a world driven by technology and innovation, it is essential to harness cutting-edge tools and methodologies to address these challenges and optimize flower plant management. This research paper explores a comprehensive approach to address the multifaceted issues in flower cultivation by leveraging the power of technology. Our objectives encompass four key areas:

1. Identifying Diseases and Pests of Flower Plants: We delve into the use of advanced techniques for the early detection and precise identification of diseases and pests that can affect flower plants. By doing so, we aim to develop predictive models for appropriate solutions that will mitigate potential damage, enhance plant health, and minimize chemical intervention.

2. IoT Device for Soil Component Identification and Environmental Control: We propose the integration of Internet of Things (IoT) devices to monitor and regulate the soil components and environmental conditions within the flower cultivation area. These smart systems will enable real-time data collection, analysis, and automated adjustments, ensuring the optimal growth conditions for flower plants.

3. Flower Counting and Yield Prediction: Utilizing innovative image processing techniques, we aim to accurately count the number of flowers on a plant from their bud stage, predict the overall yield in a selected area, and calculate the potential income. This information is critical for both growers and stakeholders in the flower industry, allowing for efficient resource allocation and better market planning.

4. Flower Information for Marketing Purposes: We will explore the utilization of image processing to extract detailed flower information that can be harnessed for marketing purposes. This involves creating a database of images and data that can be used to enhance marketing strategies, customer engagement, and overall industry visibility.

Through this research, we aim to provide a holistic solution that combines cutting-edge technology, data-driven insights, and best practices for flower plant management. The integration of IoT, image processing, and data analytics promises to revolutionize the flower cultivation industry, leading to more sustainable practices, increased yields, and improved profitability. In a rapidly evolving world, it is imperative to adapt and embrace innovation to ensure the continued success of flower cultivation.

II. LITERATURE REVIEW

Over the past few years, deep learning has made tremendous progress in the field of object identification and is steadily spreading throughout numerous fields, offering concepts for varied object recognition. Artificial intelligence is a major component of deep learning concept. When the research started, it was discovered that artificial intelligence can be used to a wide range of aspects. As one of them, attention was paid to the flower industry.

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The use of flowers as a marketing tool has been prevalent for centuries, and as consumers expect high-quality, visually appealing flowers that meet their expectations, the quality of flowers used in marketing campaigns is critical to their success. Using a convolutional neural network (CNN) for detecting plant diseases, images of healthy and sick leaves were identified using a dataset of 54,183 images of 38 different plant diseases [1]. It was found that CNN can provide great accuracy even in challenging circumstances and with small data sets. Using CNN, a cell phone camera was used to identify plant disease in images [2]. The accuracy of the study was 93.67%, which is lower than reported because only a small number of images were used in the study. This found that CNN can still perform well even with sparse data. Because they can learn to extract elements from images that are crucial for disease categorization, CNNs are especially well-suited for detecting plant diseases. RNNs can be used to detect diseases that develop over time since they can learn temporal patterns in data. A machine learning technique known as SVMs can be used to divide data into two or more categories. If the training data is not representative of the real-world data, the deep learning model may not be able to accurately diagnose diseases [3]. Overall, Kamilaris and Prenafeta-Bold's research provides a complete examination of the use of deep learning for the detection of plant diseases. Discusses the issues and limitations of using deep learning for plant diagnosis, along with the various deep learning models and data sets that have been used.[3]

In recent years, automated flower counting techniques have become more and more common, thanks to the application of computer vision and machine learning techniques. This overview of the literature's studies demonstrates the usefulness of several techniques, such as object recognition, deep learning, and color-based segmentation. These automated flower buds counting techniques have the potential to revolutionize the agriculture and horticulture industries by providing accurate and efficient estimates of crop yield and economic worth [4]. Over time, automated methods based on computer vision and machine learning algorithms have replaced manual counting approaches in the flower-counting industry. In this review of the literature, we focus on recent works that have developed and applied automated methods for flower counting. Forecasts of agricultural output and economic value [5].

An automated method for counting flowers is based on image segmentation methods. Divide an image into several segments. In automated flower counting, image segmentation is utilized to isolate the flowers from the background and to pinpoint individual blooms within the image, as seen in Figure 1.

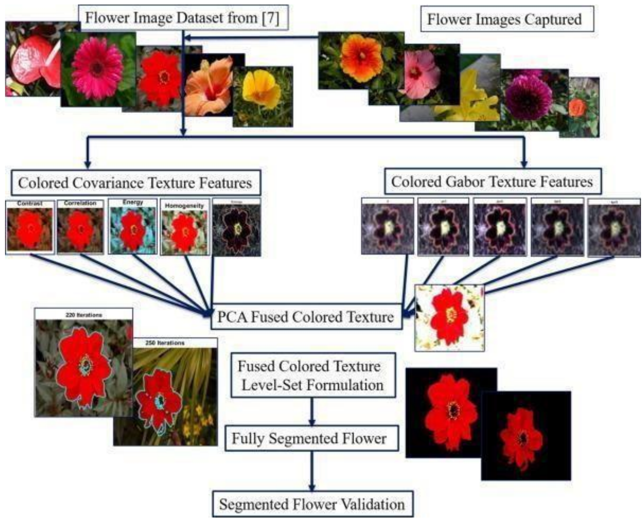

Figure 1: Image Segmentation

Based on deep learning algorithms, automatic flower counting is another widely used method. By studying massive datasets of annotated photos, these computers can learn to recognize and count flowers in plant photographs [6].

Recent developments in image processing and computer vision technology have created new chances to recognize valuable data in flowers, helping businesses to develop more successful marketing tactics. To determine floral quality information for marketing objectives, research has been done utilizing image processing.

Through early damage detection, it was hoped to increase the effectiveness of quality control in the flower industry [7]. Digital cameras were used to take pictures of flowers, which were then processed using image-processing software. The authors used several images processing algorithms, including color-based segmentation, morphological operations, and feature extraction, to identify damaged flowers. To recognize damaged flowers, researchers applied a variety of image processing algorithms, such as color-based segmentation, morphological procedures, and feature extraction. The collected features were then used to create a classification mode.

Using a four-dimensional (4D) deep learning strategy, a new method for ranking flower quality is described [8]. The framework was created to automatically rate the quality of flowers by combining color and depth data from flower images. To extract characteristics from the color and depth images, the framework employs a 4D convolutional neural network (CNN). Based on the recovered features, a regression model then predicts the quality score of the flowers. The authors experimented on a dataset of flowers with various quality grades to evaluate their methodology. The outcomes

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showed that their 4D deep learning system outperformed traditional 2D methods that just consider color information in flower quality evaluation. To determine the quality of the flowers, the authors created an image processing algorithm that examines the color and textural characteristics of floral images [9]. The technique uses a decision tree classifier to categorize the flowers into different quality categories after performing several image processing stages like image enhancement, segmentation, and feature extraction. The authors experimented on a dataset of yellow Fiji chrysanthemum cut flowers with various quality grades to validate their strategy. The findings demonstrated that their image processing technique has a high accuracy of over 93% when evaluating floral quality. To determine the freshness of the flower, all the characteristics related to the shape, color and texture for each image were calculated and critically evaluated and it became clear that high accuracy can be obtained to measure the freshness of the flower by the automatically developed model.

For the IoT device, the most recent advancements in Ag-IoT systems for reviewed in the study are all highlighted by the writers. They conclude that by giving farmers access to real-time data on crops and have the potential to completely transform agricultural production. The high cost of Ag-IoT systems, the absence of standards, and the security of data transfer are just a few of the issues that still need to be resolved [10].

M. Gomathy Nayagam et al.'s research suggests a parallel and distributed simulation framework (PDSF) for agricultural monitoring and pest control. The PDSF divides the workload among several GPUs to enhance the efficiency of Internet of Things-based pest management systems. A simulated dataset of agricultural and environmental data was used to assess the PDSF, and the findings indicated that the PDSF can enhance IoT-based pest management systems' performance by up to 98.65% [11].

The device can function in a range of weather situations and is made to be inexpensive and simple to use. The system was tested in a prototype greenhouse, and the findings shown that it could precisely assess the soil's temperature and moisture content as well as keep both variables within predetermined bounds. The IoT-based soil moisture and temperature monitoring system is a viable technique for increasing onion production, according to the authors' conclusion [12].

With the help of several sensors and an Arduino microcontroller, the system's architecture allows it to precisely measure the moisture content of the soil and regulate a water pump. The technology was put to the test in a prototype greenhouse, and the findings indicated that it might increase the watering efficiency of the native red onion, or Palu. To enhance the caliber of the data stored, the system must be modified [13].

III. METHODOLOGY

3.1 Identifying Diseases and Pests of Flower

Identifying the disease by uploading an image is another solution that we have implemented in the study. According to various studies conducted by us, the unavailability of mobile features to detect diseases using machine learning techniques has been observed and here in our study we have found a solution to this unavailability.

In the process of disease detection, the CNN (Convolutional Neural Network) xception approach is used. The disease identification model has been built using exception preprocessing technique, a highly efficient feature extraction algorithm for object detection and segmentation. The component output is the name of the identified disease and the corresponding solution for the disease. Here we have identified the most common diseases that affect popular flower plants. Popularity is based on the commercial aspects of flower plants. Powdery-mildew, Downey-mildew, Blackspot are common diseases which affect popular flower plants. Figure 2 extracts the flow of identification diseases process affecting major flower plants.

3.2 Identify the Buds Count in a Plant Predict the Number of Flowers Bloom

For the counting algorithm, the entire process is divided into smaller, more manageable components. Three different types of techniques can be employed for flower recognition in counting algorithms: shape, color, and texture. The HSV color space is used to extract the colors of flowers. These models are trained on a dataset of labeled images containing both buds and mature flowers, and CNN learns to recognize the relationship between bud characteristics and the ultimate flower count, which can help in the cultivation process. Several studies have used regression-based approaches with CNNs to predict the number of flowers on anthurium plants.

Data Collection: Using cell phone cameras, RGB photos of the plants were captured during the data gathering stage from various perspectives. Images of the flower buds were taken in clear clarity with meticulous attention to provide a diversified dataset. The gathering of photos was controlled during the data collection procedure to guarantee the inclusion of representative samples. Subject-matter experts, such as

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botanists or agricultural specialists, provided direction and monitoring to ensure that the dataset encompassed different phases and varieties of Buds. To capture crisp, accurate images of the flower buds, a variety of elements were considered. To get the highest possible image quality and resolution, the camera settings were modified to portrait mode. To avoid having features obscured by shadows or overexposure, the lighting was carefully controlled.

Pre-Processing: After being captured, the RGB photos were preprocessed to improve the flower buds and eliminate background noise. The RGB photos were first converted into the HSV color system (Hue, Saturation, Value). The flower buds could now be distinguished from their surroundings more clearly thanks to the HSV color space's ability to differentiate between color and brightness information. The flower buds' clarity and quality were improved by applying filters and image-enhancing techniques after entering the HSV color space. This included techniques for lowering noise and enhancing the overall appearance of the flower buds, such as the use of median or Gaussian smoothing filters. These filters helped to eliminate any little differences in pixel values that would have impeded further research.

Data Preprocessing: The preparation of the dataset for training and assessing a CNN regression model for predicting anthurium flower count involves two crucial phases in the data preprocessing stage. First, it's essential to resize all images to a standard size, like the frequently used 224x224 pixels, to ensure uniformity and compatibility with CNN input. This scaling standardization not only makes the data simpler and easier for the model to handle, but it also makes sure that the neural network can interpret the photos effectively without needing to resize them constantly while training.

Then, a training set, a validation set, and a test set should be deliberately created from the dataset. In a typical partitioning technique, the training set receives 70% of the data, the validation set receives 15%, and the test set receives the remaining 15%. In evaluating the model's performance and generalization abilities, this division is crucial. The model's parameters are trained using the training set so that it may learn from the data. To avoid overfitting and provide guidance for hyperparameter adjustment, the validation set is an essential tool for tracking the model's effectiveness during training. Finally, the test set is not touched during training and is only used to assess the model's efficacy and accuracy on unobserved data.

Model Architecture: Create a CNN architecture appropriate for workloads requiring regression. Multiple convolutional layers should be present in the CNN design, followed by fully linked layers for regression. Think about utilizing bespoke models or well-liked architectures like VGG or ResNet.

Model Training: The right loss function must be used to simplify the regression process of forecasting anthurium flower counts. In this situation, Mean Squared Error (MSE) is the preferred loss function. The squared discrepancy between the projected flower count and the actual blossom count in the labeled data is measured by MSE. With higher penalties for larger errors, this loss function efficiently quantifies the difference between expected and actual values. A key component of optimizing the model's parameter values during training is the use of MSE. The CNN regression model must be trained effectively using an optimizer, which adjusts the model's parameters to minimize the selected loss function (MSE). In this kind of machine learning assignment, two popular optimizers are typically used: Adam and Stochastic Gradient Descent (SGD). SGD adjusts the model's weights iteratively based on the gradient of the loss function relative to those weights. Adam, on the other hand, uses a combination of momentum and RMSprop to adapt learning rates for each parameter.

Feature Extraction: The segmented image is used to extract pertinent characteristics of the flower buds. To do this, features such as color, form, size, and texture must be eliminated. While color features can be discovered by examining the color distribution of the flower buds, form features can be discovered using contour analysis. Size aspects include measurements of dimensions like area or perimeter. Texture features can be extracted by examining the spatial distribution of pixel intensities.

Income Prediction: To provide farmers and growers with comprehensive help, the technology went beyond yield prediction and assessed the potential income gained from the plant's flower production. Both the present flower market price and the anticipated yield, which were computed using the flower bud counting and yield prediction techniques, were considered in this calculation.

3.3 Identifying the Flower Quality Information for Marketing

Data Capture and Collection: A diverse dataset of flower images was collected, representing different species and quality variations from different sources such as florists, nurseries, and markets to ensure a diverse range of specimens for the analysis. The dataset included images of flowers with varying levels of quality attributes such as color, size, shape, petal health, and overall appearance. Images were captured using high-resolution cameras under controlled lighting

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conditions to ensure consistency. Images were found showing different stages of high and low flower quality. The dataset can effectively represent the quality characteristics and assist in the identification of high-quality flowers by collecting images at different stages of flowers in searching for quality.

Pre-Processing: The collected flower images underwent preprocessing steps to enhance image quality and remove any noise or artifacts that could affect subsequent analysis. Common preprocessing techniques such as resizing, normalization, and noise reduction were applied to ensure standardized image inputs. The image is recorded in RGB color space, which will be resized for our research to reduce the computational complexity. Most computers and cameras use the industry standard RGB color space. Red, Green, and Blue make up its three channels. The intensity of a specific color in the image is represented by a channel in the image. By making it simpler for the machine learning model to differentiate between different colors, converting the photos to RGB color space can help to increase the accuracy of the model.

Feature Extraction: Relevant features were extracted from the flower images to quantify the quality attributes. Image processing algorithms were employed to capture various visual characteristics such as color intensity, texture, symmetry, and shape descriptors. These features provided measurable metrics to assess flower quality objectively.

Quality Attribute Modeling: Machine learning techniques were utilized to develop models that could predict and classify the quality attributes of flowers based on the extracted features. Deep learning architecture Inception_resnet_V2 like convolutional neural networks (CNNs), were trained on the labeled dataset to learn the relationships between the extracted features and the quality attributes.

Quality Attribute Prediction: Once the models were trained and validated, they were applied to new, unseen flower images to predict the quality attributes. The preprocessed flower images were fed into the trained models, which generated predictions for each quality attribute, such as color vibrancy, petal health, or overall visual appeal. These predictions provided valuable information for marketing purposes.

Marketing Insights and Decision Making: The predicted quality attributes were analyzed to derive meaningful insights for marketing strategies. The information obtained from the image processing and quality attribute modeling helped identify the strengths and weaknesses of different flower samples. This analysis facilitated informed decision-making regarding pricing, packaging, product placement, and targeted marketing campaigns to enhance sales and customer satisfaction.

System Integration: The developed models and image processing techniques were integrated into a software application or platform, providing an easy-to-use interface for marketers to input flower images and obtain quality attribute predictions. The system provided real-time results, enabling efficient decision-making and facilitating seamless integration into existing marketing workflows.

3.4 IoT Device for Identifying the Soil component & Controlling

Sensor Selection - Appropriate sensors were researched and selected for each parameter:

Water Level: HC-SR04 4Pin Ultrasonic sensor was chosen to measure and monitor the water level in the tank or reservoir. It provided accurate readings to ensure proper water management.

Water pH: pH Sensor with probe 0-14pH was used to measure pH level of water and by identifying its soil moisture pH will determine from those data.

Light Level: BH1750FVI Digital Light Intensity Sensor capable of measuring the intensity of light in the nursery was selected. It allowed for precise monitoring of light conditions to support optimal plant growth.

Temperature: DS18B20 Waterproof Digital Temperature Sensor was used to identify the temperature of water.

Soil Moisture: A soil moisture sensor was selected to gauge the soil's moisture content. It facilitated efficient irrigation management by monitoring soil moisture levels.

Hardware Setup: The hardware components, including microcontrollers (Channel relay), sensors, and ESP-32S Wi-Fi Bluetooth Dual Mode IoT Dev Board, were set up for data acquisition and control. The sensors were properly connected to the microcontroller to enable seamless data collection. Sensor Selection Hardware Setup Data Acquisition Data Transmission Assembly Testing and Evaluation Data Analysis Figure 2. 7 - IoT Device Flow. 36 Data Acquisition and Transmission: Code or firmware was developed to read data from the sensors connected to the microcontroller. A communication protocol, such as Wi-Fi, Bluetooth, was established to transmit the sensor data to a central system for further analysis. Actuator Integration: Appropriate actuators were connected to the microcontroller to control the environmental parameters. For water level control, Priming Diaphragm Water Pump 12V was integrated to adjust the

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water level in the tank based on sensor readings. BH1750FVI Digital Light Intensity Sensor was connected for light level control. Ventilation systems using cooling fan were integrated for temperature and for humidity control Ultrasonic mist maker fogger atomizer humidifier. Irrigation systems were connected for soil moisture control.

User Interface: A user-friendly interface, mobile application, was created to monitor and manage the nursery remotely. Real-time data visualization, control settings, and notifications were implemented to keep the user informed about the environmental conditions and enable remote control.

IV. RESULTS AND DISCUSSIONS

The disease identification model was created using CNN model approach xception.

Figure 2: results of model

Implemented mobile application shows as follows,

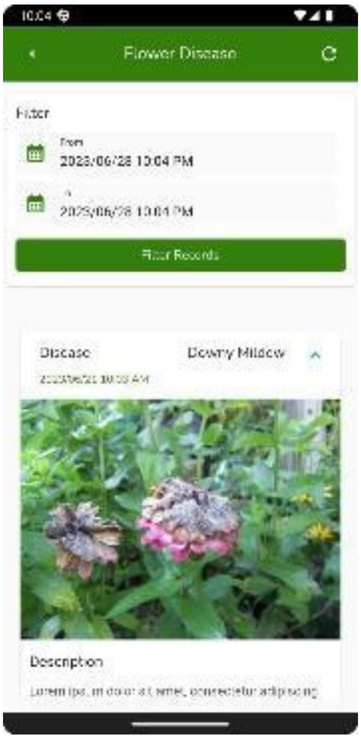

Figure 3: mobile user interfaces of Disease identification

A mobile application is developed to upload an image from the environment. Disease and the appropriate solution for the uploaded image is given as in figure 4.

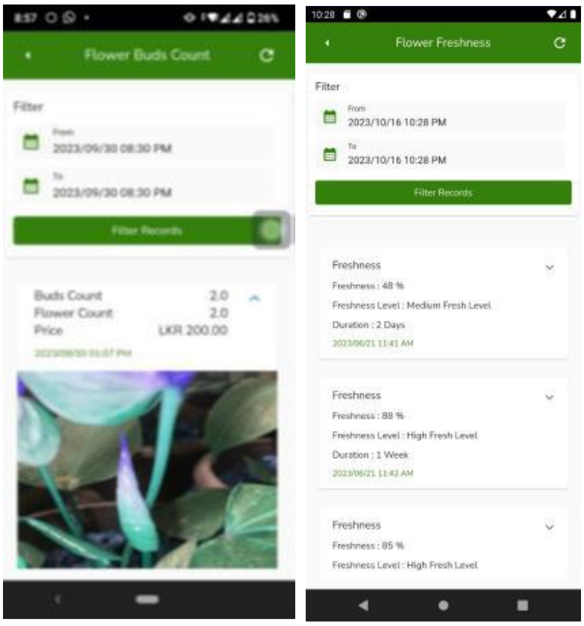

Figure 4: mobile user interfaces of buds count identification

The buds count identification and predict the flower from model was created using CNN regrassion based approch. Mobile application is developed to upoald a buds image and identify the buds count in the image then predict the flower from buds and calaculate the value of the buds in the image uploaded image is given as in figure 5.

A mobile application is developed to upload an image and retrieve data with freshness level and the duration time of flower for freshness detection using image processing with CNN model InceptionResnetV2. Firebase is used as the database to store data. The history of the data can be viewed as desired using the navigation bar.

In the IoT device after sensors identify the environmental factors sensor data was uploaded to firebase database with the help of ESP-32 board. Mobile applications have been developed to retrieve data from those uploaded live data results. The .apk file was installed on the Android smartphone and after logged into the application sensor data could be viewed on dashboard of the application. Using the navigation bar History of sensor data could view as expected. Below are the screenshots of the results.

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Figure 5: Presentation of the IoT Device's Results

V. CONCLUSION

To sum up, this research paper has investigated a variety of strategies to improve floral plant care and cultivation. We have made significant contributions to the world of horticulture by identifying pests and diseases that damage flower plants and providing forecasted remedies. Precision agriculture has advanced significantly with the integration of IoT devices to monitor soil components and control environmental elements, resulting in ideal circumstances for flower growth. Furthermore, our study has shown that it is feasible to estimate plant flower counts with accuracy, which makes it possible to forecast flower yields in particular regions. This forecasting capacity helps flower farmers make more educated decisions for increased profitability by assisting with income computation and facilitating optimal resource allocation. Additionally, our research into using image processing techniques to extract flower information for marketing purposes brings up new possibilities for the floral business. Flower businesses can obtain important insights about client preferences by utilizing computer vision and data analytics. This allows for customized marketing strategies that can increase sales and competitiveness. Finally, this dissertation offers a thorough investigation of novel strategies for managing flower plants, preventing illness, controlling the environment, predicting yield, and optimizing marketing. Promising opportunities for the flower industry's sustainable growth are presented by the integration of technology and data-driven solutions, which will ultimately benefit farmers, businesses, and consumers alike. By laying the foundation for future developments in flower marketing and cultivation, our research promotes a more successful and effective floral sector.

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