Sustainable Growth through Automation: Machine Learning and Computer Vision Advancements in Sri Lankan Floriculture

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***Abstract*— The production of floriculture in Sri Lanka is led by the country, with both small and large-scale businesses being established throughout the island. Various problems are experienced by many growers. An imperative requirement for a smart assistance system arises due to the current utilization of inefficient technology by producers. As a result, a solution that addresses significant barriers in the industry has been identified and implemented. The proposed system, titled 'Machine Learning and Computer Vision Advancements in Sri Lankan Floriculture', focuses on addressing these major aspects. To achieve this, a mobile application called 'PlantPal' has been developed and utilized. The implementation of the system primarily employs Machine Learning and Computer Vision techniques. With PlantPal, the monitoring and prediction of plant growth, calculation of the affected leaf's area from a mite attack or nutrient deficiency, demand forecasting, and selection of plants based on weather and resources are made accessible to anyone.**

Keywords— Floriculture, Sri Lanka, Mobile Application, Plant Growth, Affected Area, Plant Selection, Demand Forecasting, Machine Learning, Computer Vision, OpenCV

I. INTRODUCTION

Sri Lanka is one of the world's leading producers of floriculture, with growers establishing both small and large-scale businesses to meet the growing demand for high-quality plants and flowers [1]. Sri Lanka primarily targets the European market, accounting for 60% of its floriculture industry exports. However, there is growing interest from other regions, including the Middle East, Japan, USA, and Korea [2]. In a world rapidly adapting to new technology, the Sri Lankan floriculture sector seems to be lagging behind in adjusting to the changing environment. This hampers its ability to overcome obstacles and thrive. To improve the industry, it is essential to introduce smart assistance systems. Currently, critical tasks in the Sri Lankan sector heavily rely on manual methods and experience. Monitoring plant growth is done manually, making it challenging to estimate when plants will reach the desired level. Calculating the area of a leaf affected by deficiencies and mite attacks through visual inspection is also difficult, and recommending affected plants for export based solely on visual inspection proves to be a challenge. Beginners in the industry face difficulties in accessing reliable knowledge sources, making it hard to choose the right plants. Accurate demand forecasting is crucial, but currently relies solely on past experience, leading to potential losses and wasted resources due to incorrect decisions.

The initial study involved the utilization of CubeSat-based images and LAI maps by the research team [3] to monitor growth. In another study related to this field, a solution was proposed involving the capture of aerial images using drone cameras [4] to identify diseases in wheat crops. Furthermore, research was conducted on an agriculture system based on IoT and machine learning for predicting crop yield [5]. Within these studies, certain issues were identified, including the use of high-cost satellite technology, drone cameras, and IoT devices. The present research addresses these aforementioned concerns through the implementation of a cost-effective, straightforward mobile application designed to capture plant photos.

This research gap is bridging by PlantPal with four main sub functions. Ornamental plant growth prediction is the main function in PlanPal There can be mite attacks and deficiencies of plants. Monitoring and calculation of affected areas on a leaf is useful for the growers to make immediate caring of them. Therefore, it has been implemented as the second component of the system. The prediction of the optimal floriculture plant for cultivation was identified as another significant area to consider in PlantPal. Finally, the forecasting of demand for the floriculture included as another important function in the application.

A comprehensive exploration of the subject is presented in this research paper through a structured framework. Relevant studies are synthesized in the literature review, establishing the research foundation. The technical aspect of the study is outlined in the methodology. Lastly, findings are displayed, results are contextualized, and a contribution is made to the understanding of the field in the results and discussion section.

II. LITRETURE REVIEW

The first identified research is titled "Early season prediction of within-field crop yield variability by assimilating CubeSat data into a crop model." In that research, CubeSat-

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based images and LAI maps were utilized by the research party. The integration of images into APSIM was done using a particle filter. The desired growth level of plants and the time required to reach it can be forecasted by the final system, which overcomes the impacts of cloud cover on traditional satellite data. However, achieving such a system with a high-cost satellite-based image dataset in the Sri Lankan sector is challenging, and the study does not consider other factors like temperature, humidity, fertilizer level, etc [3]. The second research discusses an automated system for controlling and monitoring ornamental plants using the fuzzy logic method. In this case, the proposed system is an IoT-based solution with actuators employed to regulate the temperature, air humidity, and moisture level of the soil. Expensive sensors and a highly technologically controlled environment are required for this solution [6]. Expensive and highly technological smart greenhouse concepts [7], which consider essential growth monitoring factors such as temperature, humidity, and soil moisture for plants, have been proposed in several studies, including [8], [9], [10]. These studies explore the concept of smart greenhouses, not exclusively focused on the floriculture industry [11], [12] but also relevant to agriculture, though they may not be highly applicable to the Sri Lanka sector.

The affected area in a leaf was calculated in research [13]. This study was conducted in Sri Lanka for vegetable crops grown in Batticaloa to control pests after identifying the threat. The RGB images were first converted to HSV, followed by the necessary steps to detect the affected region. Based on this, the number of counts in that particular leaf was obtained. A CNN model was created for classification to identify the type of pest. Diseases in wheat crops were detected in research [4]. Identifying diseases individually becomes challenging in large-scale crops. Thus, this research proposed a solution by capturing aerial images using drone cameras. The BGR images were converted to the RGB format using OpenCV, and necessary steps were taken to detect the affected area. Location-wise results were obtained, enabling growers to take appropriate actions to halt or prevent disease spread.

An IoT and ML-based agriculture system for crop yield prediction [5] was researched. The goal was to predict efficient crops for specific field areas with high yield potential. Meteorological data, including temperature, humidity, soil moisture, etc., was used for predictions. An IoT-based sensor system collected the meteorological data, and ML algorithms were employed for crop prediction. Plant advice based on various factors such as humidity, pH, and rainfall were provided in research [14]. IoT was utilized to measure these factors. ML algorithms were trained on the dataset to make accurate forecasts and offer correct advice on which plants would thrive. The Crop scoring algorithm was used in Research [15] to help farmers choose the best crop based on Rainfall, soil type, cropping month, and location. Furthermore, in study [16], RNNs were employed to predict seasonal weather using soil factors, estimated weather characteristics, and random forest classification techniques.

The Smart Intelligent Floriculture Assistant Agent (SIFAA) system integrates expert knowledge with cutting-edge techniques, including deep learning, for plant disease diagnosis and treatment recommendations. It employs Reinforcement Learning to suggest the best products for customers and utilizes demand forecasting to motivate cultivators. Linear Regression, ensemble advanced LightGBM Regressors, and feature engineering techniques are applied. SIFAA provides solutions for plant development monitoring, pest identification, export standards maintenance, demand and supply prediction, plant selection, and proper care [17]. Sugar production in Sri Lanka, which currently meets only a small portion of the demand, was the subject of research [18]. ARIMA model and other ML methods were employed to forecast production, and the SVM model was used to assess accuracy. The ML models were utilized to predict production and more. Valuable insights into future requirements have been provided by employing various technologies to predict the growing demand for vegetables in Sri Lanka [19] and forecast the agricultural needs of the society [20].

III. METHODOLOGY

A. *Growth monitoring and prediction system*

The data collection phase involved the prediction of the current growth state of ornamental plants. Historical data, encompassing plant type, variety, height, leaf count, growing medium, planting date, growth categories, and current plant growth status, was gathered from a prominent floriculture company. Additionally, temperature and humidity data from past records were extracted through the open weather API. Users' provided plant details, including height and location, were also utilized to extract relevant temperature and humidity data. Fig. 1 represents the system architecture.

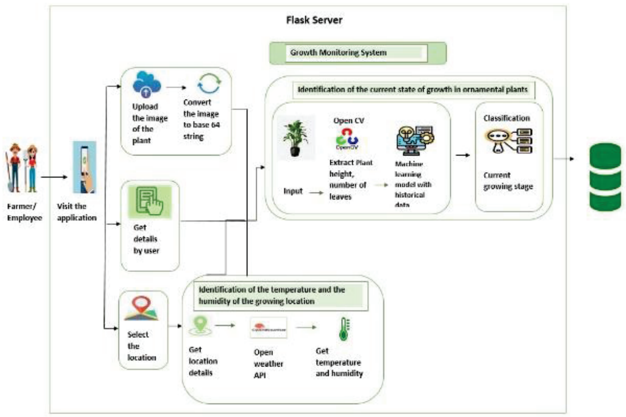

Fig. 1. Growth monitoring system architecture

The subsequent step encompassed data preprocessing and cleansing. Initially, data from diverse formats were consolidated into a unified CSV format. This dataset underwent preprocessing techniques, which encompassed addressing missing values, discarding irrelevant attributes, converting categorical data to numerical values, filtering out outliers, and visualizing the cleaned dataset. The resultant refined dataset formed the foundation for subsequent stages. Feature selection commenced with the evaluation of feature-class correlations and the application of Fisher's Score for feature ranking. Following this, the dataset was partitioned into training and testing subsets. The feature selection process aimed to ascertain the most relevant attributes for the model's efficacy. Subsequently, various machine learning algorithms, namely Decision Trees, Random Forest, and XG Boost, were considered for multi-label classification tasks. Model training followed, where the algorithms were applied to the training dataset. Hyperparameter tuning was then executed to enhance model accuracy. This involved adjustments to the number of trees in the Random Forest model and regularization techniques to mitigate overfitting. Cross-validation was employed to assess overfitting and pattern generalization. Subsequently, model evaluation involved scrutinizing accuracy, utilizing confusion matrices to measure precision and recall, and ultimately selecting the most accurate algorithm. The culmination of these efforts resulted in the prediction of current growth states for ornamental plants using the chosen model.

B. Calculate the affected leaf area due to afflictions

In Fig. 2, the system architecture is illustrated. To calculate the affected area, images of plant leaves with various types of affections were collected. These images were obtained from one of the leading floriculture companies in Sri Lanka and included different types of plants to ensure a diverse dataset.

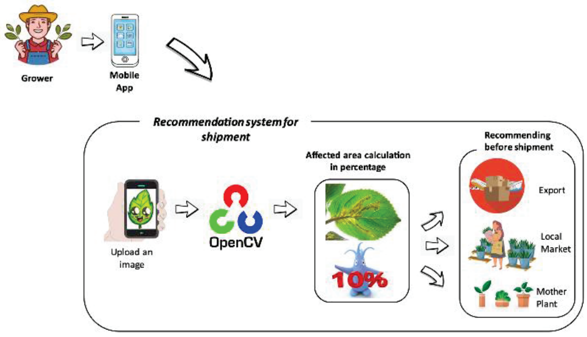

Fig. 2. Affected area calculation system architecture

Before providing images for the calculation, the images were preprocessed by resizing and cropping them to isolate the plant leaves. Additionally, a filter was applied to remove any noise, and thresholding was used to convert the images into a binary format. After the preprocessing stage, OpenCV was used to calculate the affected area of the plant. Techniques such as edge detection, color segmentation, and grayscale conversion were employed for this purpose. The best technique was selected based on its accuracy and used for further implementations. Once the affected area in percentage was determined, the system checked if it met the required export level. If the percentage met the requirement, the system recommended exporting the plant. If the percentage did not meet the export level, the system checked the local market percentage. If the percentage fell within the acceptable range, the system recommended selling the plant in the local market. If the plant was badly affected, the system recommended using it as a mother plant.

C. Plant recommendation system for industry beginners

The system architecture is detailed in Fig. 3. In the initial step, the grower's location is acquired. Once the geographic information has been secured, the open weather API is utilized to access relevant weather data, covering aspects such as temperature and relative humidity. Afterward, the grower's resource-related data is collected by the system, which is subsequently fed into the machine learning (ML) algorithm. Ultimately, the decision-making process to determine the most suitable flower crop for cultivation in the given context is undertaken by the ML algorithm.

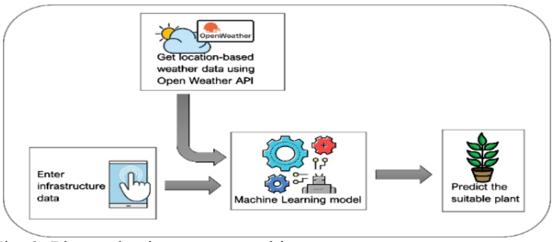

Fig. 3. Plant selection system architecture

The dataset of this study was compiled in collaboration with a prominent floriculture company in Sri Lanka. Furthermore, historical weather data relevant to the specific timeframe under consideration was extracted. Important roles are played by both the weather-related and resource-related data as features within this system. The ideal cut flower species for cultivation is designated by the label in the dataset. A careful cleaning process was executed, effectively addressing missing values. Additionally, data visualization techniques were employed. For the model training and evaluation, a partition was undertaken, with 33% of the dataset for testing and 67% for training. To perform the feature selection, the ANOVA f-test was implemented. Then, the dataset was distilled to contain 9 attributes. Temperature, relative humidity, space, plant count, water supply, costs linked with net house preparation, maintenance, planting, and the annual flower yield are all encompassed by these attributes. To select the best algorithm, a comparison was carried out among three prominent options for multiclass classification: the Decision Tree Classifier, Gaussian Naive Bayes, and Gradient Boosting Classifier. For each of these models, an evaluation setup was established using Stratified K-Fold cross-validation with 3 folds. The model performance was measured using accuracy as the primary scoring metric. Ultimately, the Gradient Boosting Classifier was selected as the best model. After the training process, hyperparameter tuning was set up using the GridSearchCV technique. Hyperparameters including the number of trees, maximum tree depth, and learning rate, were optimized during this tuning procedure. Then, the model was retrained using the identified optimal hyperparameters. Then, using test data, this improved model was evaluated. Predictions were produced using location-based weather data coming from the open weather API alongside resource-related data that had been entered into the system. Next, the most suitable cut flower plant for cultivation was determined by the developed ML model.

D. Predict seasonal and species-specific demand

The demand prediction system architecture is visually depicted in Fig. 4. Essential data sources, including historical sales data, order details, country information, order-specific seasonality, prevailing market trends, and customer behavior patterns, were identified and collected.

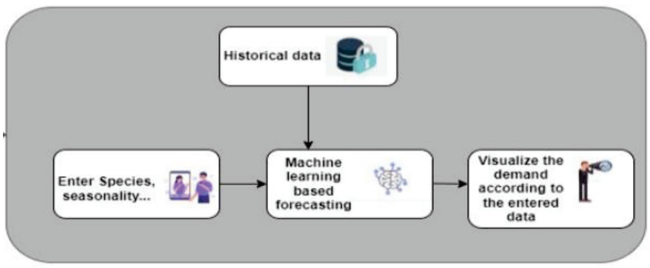

Fig. 4. Demand prediction system architecture

To ensure data integrity, a comprehensive check was conducted for missing data and outliers. Appropriate strategies, such as imputation or removal, were implemented to address these anomalies. Data quality concerns, such as duplicate entries and inconsistent formatting, were systematically identified and resolved. Data transformation played a critical role, involving the conversion of categorical variables into numerical representations aligned with the chosen predictive model. The identification of influential features affecting demand, such as weather data, holidays, and significant events, was given priority. Guided by exploratory data analysis and correlation assessments, pivotal features were selected. Additionally, innovative attributes like lagged variables, rolling averages, and seasonality indicators were engineered to capture nuanced patterns and trends present in the data. Stratified sampling was utilized to address the challenge of class imbalance in the target variable. This approach ensured equitable representation of each class in both training and testing datasets, thereby enhancing model robustness. The dataset was partitioned, with a portion allocated for validation purposes—facilitating model selection and the fine-tuning of hyperparameters. Feature scaling methodologies, including MinMaxScaler, StandardScaler, or RobustScaler, were judiciously applied to standardize the data and align feature scales. Diverse models amenable to demand prediction, including Linear Regression, Random Forest, and Gradient Boosting, were thoughtfully considered. Subsequently, these models underwent comprehensive training using the training dataset. Rigorous evaluation on the testing dataset facilitated the identification of the optimal-performing model, based on well-defined evaluation metrics. Ultimately, this intricate process culminated in the selection of the most adept model, empowering the demand prediction system to deliver accurate forecasts in response to dynamic market conditions.

IV. Results and Discussion

A. Growth monitoring and prediction system

In this research, a growth monitoring system was developed by utilizing historical data on the growth of five ornamental plants: Lemon Lime, Black Cardinal, Livistonia, Marble Queen, and Tropical Green Enjoy. The dataset consists of comprehensive and crucial features for each plant, including plant type, variety, growing media, applied fertilizers and their quantities, current growth categories, average minimum and maximum plant heights for the current stage, and the dates on which measurements were taken. Furthermore, temperature and humidity data were extracted from relevant sources. The dataset was then appropriately preprocessed. As a vital aspect of the research, the cleaned dataset was trained using four significant multiclass classifiers: the Random Forest classifier, XGBoost classifier, Decision tree classifier, and Naive Bayes classifier Fig. 5.

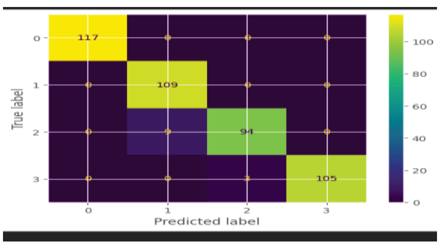

Fig. 5. Confusion matrix for Naïve Bayes classifier

Nevertheless, the Random Forest classifier exhibited the highest accuracy of 0.99 when evaluated with the test dataset. The classification report analyzed the performance of all four models, with the Random Forest classifier standing out impressively. Therefore, the Random Forest classifier was selected as the optimal model as shown in Table I.

TABLE I. Classification Report for Growth Monitoring Model

Index	Accuracy	Recall	Precision	F1_score
XGBoost	0.9	0.88	0.92	0.9
Randomforest	0.85	0.82	0.88	0.85
Decision Tree	0.82	0.8	0.85	0.82
GaussianNB	0.78	0.75	0.8	0.78

As the next step, utilizing the trained model, the research objective was tested. This involved collecting necessary details from the user, such as plant type, variety, and growing medium. The current temperature and humidity of the environment were also observed based on the user's inputted location, utilizing the open weather API. Finally, based on all the gathered information, the current growth state of the plant was predicted and successfully demonstrated to align with the expected results.

B. Calculate the affected leaf area due to afflictions

The test results were obtained based on the generated mask image, which provides detailed information about the affected areas of the leaf. The following Fig. 7 describes the original leaf image in left side and after removing the background in right side.

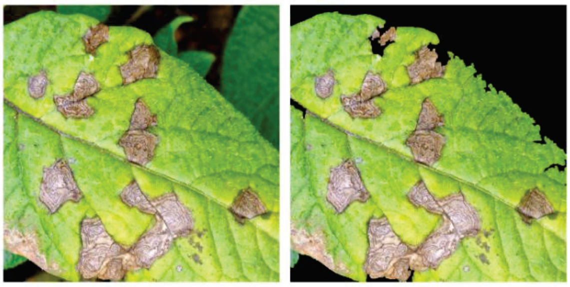

Fig. 7. Affected leaf and background-removed image for that

Through the utilization of color space transformations and thresholding techniques, the leaf was successfully segmented from the background, resulting in a binary mask where affected regions were represented by white pixels, while healthy regions remained black as in Fig. 8. This mask image serves as a visual representation of the leaf's condition, allowing for the identification and examination of damaged or diseased areas.

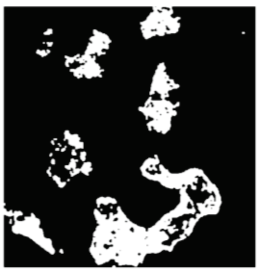

Fig. 8. Mask image for the leaf

By analyzing the mask image, the extent of the affected regions can be assessed. The percentage of affected area was calculated by determining the ratio of white pixels to the total number of pixels in the mask image. This quantitative measure enables a precise evaluation of the leaf's overall health, providing growers with valuable insights into the severity of the issue and facilitating the monitoring of changes over time. The mask image vividly portrays the spatial distribution of the affected areas, allowing for a comprehensive understanding of the leaf's condition.

*Percentage of affected area = (Number of white pixels / Total number of pixels) * 100*

(1)

Equation (1) represents the percentage of affected area. The number of white pixels represents the count of white pixels in the mask image, which corresponds to the affected regions. The total number of pixels refers to the overall number of pixels in the mask image. By dividing the number of white pixels by the total number of pixels and multiplying the result by 100, the percentage of affected area is obtained. This value represents the proportion of the leaf's surface that is affected by damage or disease.

C. Plant recommendation system for industry beginners

As a result of k-fold cross-validation to evaluate the performance of different machine learning algorithms, the highest level of mean accuracy, 0.999372, was demonstrated by the Gradient Boosting Classifier. Additionally, the lowest standard deviation, 0.000888 was exhibited by the Gradient Boosting model, indicating notable stability in performance across folds. The choice was made to utilize the Gradient Boosting Classifier due to its ability to combine multiple weak models through an ensemble approach, aiming to achieve improved accuracy with unseen data. Because of its ensemble nature and iterative training process, it possesses the capability to generalize more effectively and capture complex relationships within the data compared to a singular decision tree. The identification of the optimal choice, the Gradient Boosting Classifier, was the outcome of these considerations. Illustrated in Table II below is the chart displaying the mean accuracy and standard deviation for each evaluated model, utilizing k-fold cross-validation.

TABLE II. ACCURACY AND STANDARD DEVIATION SCORES

ML model	Mean Accuracy	Standard Deviation
Decision Tree Classifier	0.993720	0.004942
Gaussian Naive Bayes	0.902018	0.011549
Gradient Boosting Classifier	0.999372	0.000888

An accuracy of 84.71% was attained on the test dataset following the training of the Gradient Boosting model with number of trees set to 50 and learning rate to 0.01, while maintaining a maximum tree depth of 1. Subsequently, hyperparameter tuning was performed using GridSearchCV, resulting in the best combination of number of trees at 100, learning rate at 0.1, and maximum tree depth set to 1. Upon training the model with these optimized hyperparameters, an impressive accuracy of 99.87% was achieved on the test dataset, underscoring the robustness and reliability of the model. The performance of the developed model on a test dataset was evaluated in the research study to assess its effectiveness in predicting the most suitable cut flower crop. The model's ability to accurately classify data samples was clearly demonstrated by the notably high accuracy achieved. The learning curves for both training and testing data are visually depicted by Fig. 10. illustrating the evolution of the model's accuracy with an increasing number of boosting stages (estimators). The fact that the data is neither overfitted nor underfitted by the model is demonstrated by the graph.

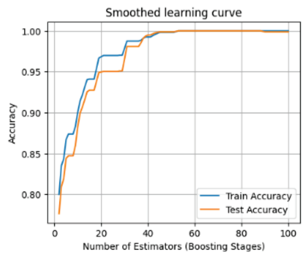

Fig. 10. Learning curve for plant selection model

D. Predict seasonal and species-specific demand

Demand prediction is vital for industries such as retail and supply chain management, as it assists in decision-making related to production planning and inventory management. While traditional regression analysis has been widely used for demand prediction, the XGBoost algorithm Fig. 11 offers the potential to capture complex patterns and interactions within the data, thus enhancing accuracy.

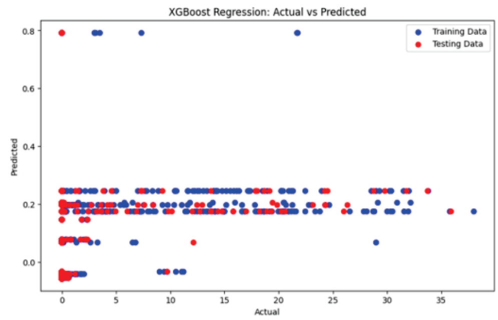

Fig. 11. Scatter plot for XGBoost actual and predicted values

The XGBoost algorithm is applied to the demand prediction problem. XGBoost is a powerful gradient boosting algorithm known for its ability to handle nonlinear relationships and optimize a differentiable loss function. The performance of both the regression analysis and XGBoost models is compared using the Mean Absolute Error (MAE) metric and other evaluation measures. Cross-validation techniques are employed to assess the models' generalizability. The results indicate that the XGBoost algorithm outperforms traditional regression analysis, achieving a significantly lower MAE and providing a better fit to the actual demand data as shown in Table III.

TABLE III. EVALUATION METRICS FOR DEMAND PREDICTION MODEL

Model	Train MSE	Test MSE	Train MAE	Test MAE	Train R-Sqrd	Test R-Sqrd
Linear Regression	0.954	1.136	0.112	0.120	0.009	0.089
XGBoost	0.953	1.133	0.112	0.113	0.011	0.012
Random Forest	0.953	1.132	0.112	0.113	0.011	0.012

The findings of this research demonstrate the potential of incorporating XGBoost into demand prediction tasks, leading to improved accuracy in forecasting.

V. Conclusion and Future Work

In conclusion, the Sri Lankan floriculture sector faces challenges in adapting to technological advancements. The implementation of smart assistance systems like PlantPal offers potential solutions. By utilizing Machine Learning and OpenCV, PlantPal enables accurate monitoring and prediction of plant growth, precise calculation of leaf damage, and effective plant recommendations. Integration of the open weather API facilitates optimal plant selection based on climate data. Additionally, employing multiclass classification techniques aids in recommending suitable plants, while Machine Learning approaches enhance demand forecasting. These advancements have the potential to improve efficiency and competitiveness in the floriculture industry. Crucially, embracing smart assistance systems is vital for industry growth and development in the digital era. The most exciting prospects lie in future work, including integrating a chatbot for real-time assistance, personalized recommendations, and community engagement. Utilizing NLP, machine learning, and a dynamic knowledge base will ensure continuous improvement and up-to-date information. Moreover, an unwavering commitment to cross-platform compatibility will extend these benefits, fostering a broader and more profound impact on the floriculture industry. The future holds immense potential for innovation and growth in this sector.

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