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Coconut Plant Disease Identified and Management for Agriculture Crops using Machine Learning

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ABSTRACT

This research paper introduces an innovative approach to improve the quality and sustainability of coconut farming and exports in Sri Lanka. It employs advanced image processing techniques to detect, classify, and grade pests and diseases early in coconut palms. This allows for swift interventions and reduces the need for harsh chemical treatments, promoting eco-friendly farming practices. Furthermore, the study goes beyond pest control to evaluate optimal conditions for coconut growth, considering factors like soil quality, water availability, and climate. It empowers farmers with insights to maximize coconut palm yield. Additionally, the system incorporates a growth prediction component using historical data and machine learning, enabling farmers to plan and allocate resources effectively. By combining early pest detection, pest management, growth classification, and predictive analysis, this research offers a comprehensive strategy to enhance Sri Lanka's coconut quality for export. This approach not only improves product quality but also safeguards the industry's sustainability by reducing economic losses and ecological impact. Leveraging cutting-edge tools like image processing and machine learning, this research aims to boost efficiency, economic viability, and international competitiveness in Sri Lanka's coconut farming sector.

Keywords-- Pest Detection, Machine Learning, Sustainable Cultivation, Grading, Image Processing, Coconut Industry

I. INTRODUCTION

Coconut farming holds a significant position in the agricultural landscape of Sri Lanka, contributing both to domestic sustenance and international trade. However, despite its economic importance, the industry grapples with numerous challenges, with pests, diseases, and suboptimal growth conditions being primary deterrents to achieving optimal coconut export quality. Addressing these challenges requires an innovative and integrated approach that harmonizes cutting-edge technologies with agricultural practices, aiming to enhance both the quality and sustainability of coconut cultivation.

Pest and disease management has been a longstanding concern for coconut farmers, as infestations and infections can severely impact crop yield and quality. Conventional pest control methods often rely on indiscriminate pesticide use, leading to ecological imbalances, health hazards, and diminishing product quality. Hence, a paradigm shift towards sustainable solutions that mitigate the impact of pests and diseases while preserving the environment is imperative. This paper proposes an integrated system that couples early pest detection, image processing-based classification, and grading techniques to provide an effective and eco-friendly pest and disease management strategy for coconut farming. The advent of image-processing technologies has opened doors to innovative agricultural practices. Leveraging these advancements, this research introduces a novel approach for pest detection and classification. By capturing and analyzing images of coconut palms and their associated foliage, the system can accurately identify a range of pests and diseases. Early detection empowers farmers with the opportunity for proactive intervention, thus minimizing the need for aggressive chemical interventions and reducing associated environmental and health risks.

Furthermore, the quality and yield of coconut exports are intricately linked with the growth conditions of coconut palms. Soil quality, water availability, and climatic factors significantly influence the health and productivity of coconut trees. Therefore, this research extends its focus to the classification of optimality in coconut growth conditions. Through the evaluation of various growth parameters, the system provides insights that enable farmers to make informed decisions in optimizing growth conditions and maximizing yield.

In addition to growth classification, the paper also presents a growth prediction component that harnesses historical data and machine learning algorithms. This predictive capability empowers farmers with the foresight to plan agricultural activities, allocate resources efficiently, and make adjustments in cultivation practices based on anticipated growth trajectories.

In sum, this research paper presents an integrated framework that encompasses early pest detection, pest and disease management, growth classification, and predictive growth analysis. By doing so, it strives to provide a comprehensive solution to elevate coconut export quality in Sri Lanka while promoting sustainable agricultural practices. Through the convergence of advanced image processing techniques, data-driven insights, and environmentally conscious strategies, this research endeavors to fortify the coconut farming sector's efficiency, competitiveness, and contribution to the nation's economic prosperity.

II. BACKGROUND AND LITERATURE REVIEW

Several studies have recently examined how image processing, machine learning, and deep learning approaches may be used to diagnose leaf diseases. The authors of [1] talk about the primary and small pests that cause illnesses in coconut leaf disease. According to P. Fernando, the main native pests are the red palm weevil, black beetle, coconut caterpillar, and coconut mite. Additionally, they noted that common illnesses like leaf light and stem bleeding are less significant than insect diseases, which results in significant economic losses in this industry. This research analyzed further information on these pests, including how similar they are, how they begin to target specific coconut tree parts, how they attack the leaves of the coconut tree, and how to use an integrated technique to tackle this.

According to T. Kumara et al., there are primarily three damaging pests that frequently damage coconut trees in Sri Lanka. They are the rhino beetle, black-headed caterpillar, and red palm weevil, and they often reside in locations where coconuts are widely cultivated. The control of these pests and their present state may be examined using the study approach of bioecology. The most important and crucial aspect of coconut production is early pest identification [2]. The use of image processing and computational intelligence for early pest identification from crops is covered by the authors in [3]. They discovered that although little, whiteflies inflict significant crop damage. To determine the number of insects on a leaf, they first counted the pests on the leaves. The RMI and the suggested method were the two separate algorithms used in their research, and when compared, both had success rates of over 98%[3].

One of Sri Lanka's industries that is expanding the quickest is one that is tied to coconuts. Therefore, it is essential to avoid resource and financial waste to manufacture high- quality goods. It will be more sustainable to introduce contemporary technology to the sector to raise product standards and quality while also gathering useful data.

A method for coconut size, color, and texture recognition based on image processing was created by Manali and Sumati [4]. The primary axis must be identified to identify the coconut size. The palette used for sorting changes orientation as the results of image processing are achieved. Decisions about size and color are made using fuzzy logic.

Although manually sorting and grading based on other exterior characteristics is not feasible, manually grading based on size is doable, but the results are not exact. Therefore, coconut quality checking needs to be automated. Mohammed and Kelvin [5] also created a method for quality assurance in the sectors involved in fruit processing.

An automatic vision-based device that might take the place of humans in the process of identifying coconut flaws was presented by Jayanthi et al. [6]. Coconut with defects were discovered utilizing an image processing method. The findings indicate that the measures that need to be taken are precise and effective. Thus, a significant number of coconuts in a location like a coconut plant may be modified in line with evolving technology. Numerous benefits are provided by this system, including low running costs, efficiency, and usability.

Previous studies in the field of coconut plant health assessment [7] utilized various techniques including backpropagation neural networks, feed-forward neural networks, and probabilistic neural networks to detect pests and diseases. Alongside these methods, image processing approaches such as morphological feature extraction, wavelet-based processing, zooming, and OSTU segmentation were employed for identification purposes. The research article [7] also incorporated advanced methodologies like Region Proposal Network (RPN) and Channel-Spatial Attention (CSA) to distinguish between areas of coconut plants affected by pests or diseases and those that were unaffected. The image processing was facilitated by a drone equipped with a System on Chip (SoC) featuring an ARM Cortex-based CPU and GPU, eliminating the need for extensive preprocessing. The integrated SoC and efficient interpretation algorithm enabled swift data processing.

The study presented in reference [8] concentrated on the application of Mobile Net and k-means clustering

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segmentation to adapt a 2D-CNN model for the automated identification of stem bleeding, leaf blight, and infestation by the red palm weevil pest in coconut plants. Natarajan et al. (2020) conducted research that involved utilizing Support Vector Machines (SVM) for diagnosing coconut plant illnesses based on color and shape. Although they employed the EfficientNetB0 CNN model for their work. Furthermore, the utilization of CNNs and customized features for the detection of human diseases, including tasks like identifying skin cancer and Covid-19, has been previously documented. It's worth noting that deep learning techniques find extensive application in various domains beyond disease detection, such as stereo matching and person recognition.

The first sub-section is soil classification of the proposed model pertains to soil classification, which plays a fundamental role in determining the success of coconut cultivation. Studies by Saranya. N and Mythili. A [9] have proposed a method for classifying the soil according to the macro nutrients and predicting the type of crop that can be cultivated in that soil type. It is difficult to quantify the amount of nutrients in the soil sample as needed for this prediction.

The next sub-section is the next sub-section is Classification of optimality for coconut growth of the model involves predicting coconut plant growth by considering multiple factors affecting their development. Studies by Dr. Ganesan V. et al. 's paper [10] uses Naive Bayes, Decision Tree, K-Means and Apriori algorithms to classify, cluster and associate based on their land area and their physical appearances identified each stage by its temporal data. These algorithms are applied on the coconut tree dataset using WEKA tool.

The integration of soil nutrient levels, pest infestation data, and weather conditions to accurately predict coconut growth patterns. Machine learning algorithms like Multivariate Polynomial Regressions exhibited high accuracy in forecasting coconut growth trajectories under varying environmental scenarios.

An engineering approach involves developing a novel architecture for a Hybrid Recommender System using Deep Learning techniques to support soil analysis, temperature control, and fertilizer recommendations. The Hybrid Intelligent Learning Method uses the ANFIS model with a Novel PSO optimization technique for growth predictions through simulation comparisons. The network topology depends on inputs, outputs, training samples, noise, activation functions, and problem complexity. This [11] framework combines Big Data and deep learning to provide accurate learning resources for learners in a Hybrid Recommendation System.

III. METHODOLOGY

The research methodology proposed in this study encompasses two intertwined aspects: integrated pest and disease management with early pest detection, and the classification of optimality for coconut growth along with growth prediction. Each aspect is designed to synergistically contribute to enhancing coconut export quality in Sri Lanka, leveraging advanced image processing techniques, classification algorithms, and historical data-driven approaches.

A. Coconut Plant Disease Identification using Machine Learning

I. Disease Identification of Coconut Leaves (Data Collection and Processing)

A deep learning (DL) model was trained using images of newly collected coconut leaves and coconut kernels. The upper surface was images A third of the middle portion of the coconut is added Mealybugs and frond yellowing. Similarly, below Images of the surface of the same area were captured for the Line Segment Detector, as well as the stripes and gravitations of the coconut for mites. Photographs were taken of the paper for mealybugs and mites.

These were picture Captured in various natural settings to avoid image sampling Similarities Leaf sampling was done with the help of Trained personnel of Coconut Research Institute Sri Lanka (CRISL). The images are divided into exercises (80 - 90) and validation (10 - 20). After training, An Added new image to test the model. Table Summarizes the data collection process. Preprocessing techniques were used to improve accuracy and to reduce the complexity of the dataset. From The generated images are of different sizes and different colors models, they were rescaled to the same dimensions (300 ×300) and changed from BGR to RGB for color conversion. to Normalize the data, dividing the pixel values by 255 Converted to numeric values between 0 and 1. Data Growth techniques like rotation, filling, cutting (horizontal and vertical), flip (horizontal and vertical), and Zoom were used to increase the number of data sets and Avoid overfitting models.

II. Training the Detection Models

To develop a deep learning detection model for identifying coconut mealybug and mites' infestation on the axial surface of coconut leaves (lower surface) and coconut fruit, a Convolutional Neural Network (CNN) approach was employed. The model's primary objective was to determine the presence of mealybugs and mites and assess the level of infestation progression. The training process involved using a large dataset of annotated images containing labeled instances of mealybug and mites on coconut leaves and fruits. The CNN model was trained to

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learn distinct features and patterns associated with these infestations, enabling it to make accurate classifications.

To identify the progression level of infestation, advanced deep learning techniques such as Mask R-CNN were utilized. This involved measuring the extent of blackening over the coconut leaves caused by mealybug and mites' infestation. By performing pixel-level instance segmentation, the model could precisely delineate the areas affected by the infestations, providing valuable information about the severity of damage. Moreover, the model was trained to count the number of mite-infested coconuts, enabling it to detect the level of damage progress on the coconut fruits. Additionally, it could identify leaves with mealybugs, aiding in the early detection and intervention of mealybug infestations.

By integrating the power of CNN and Mask R-CNN methodologies, the developed deep learning detection model provided a robust and effective solution for accurately identifying coconut mealybug and mites' infestation, assessing the severity of the infestations, and quantifying the extent of damage progression. The model's ability to automatically analyze images of coconut leaves and fruits would be immensely beneficial in monitoring and managing infestations, thus contributing to the preservation and protection of coconut crops.

B. Integrated Pest Management with an Early Pest Detection System for Coconut Farming

The suggested methodology combines an Early Pest Detection System and Integrated Pest Management (IPM) techniques, two essential elements for efficient pest management in coconut cultivation. Farmers may prevent insect infestations, lower crop losses, and advance sustainable agricultural practices by incorporating these factors.

The creation of an Early Pest Detection System using machine learning and image processing methods is the first step in the methodology. Entomologists with years of experience methodically annotate the photos to pinpoint the relevant pest species that are present. Then, using these annotated photos as training data, the machine learning model is taught to identify characteristic patterns linked to certain pests.

IPM is a thorough approach to pest control that includes biological, cultural, mechanical, and chemical methods. By harnessing natural enemies and increasing cultural practices like irrigation and sanitation, farmers make it impossible for pests to proliferate. Mechanical techniques like traps and hand removal are employed to minimize insect populations. Chemical safety measures are carefully put into place when necessary. The plant's resistance to specific pests is also increased by growing pest-resistant varieties of coconut.

The Early Pest Detection System improves IPM by immediately alerting farmers to potential pest infestations and offering them helpful advice. Armed with this knowledge, farmers can quickly put effective pest management strategies into place before infestations get worse, minimizing the harm to their coconut crop.

- Pest Identification and Baseline Survey: To record the common pests in the chosen research regions, conduct a thorough pest identification survey. In the coconut farms, compile a baseline database of pest species, their distribution, and the severity of infestations.
- Early Pest Detection System Development: To create an early pest detection system suited for coconut cultivation, work with entomologists, technology specialists, and farmers. Pheromone traps, sticky traps, or automated sensors are some ideal technologies to use for pest monitoring. Establish the best location for monitoring equipment within the coconut crops to ensure successful pest control.
- Integrated Pest Management (IPM): Find and promote coconut farming-friendly cultural, biological, and chemical management strategies. Promote the use of techniques like crop rotation, intercropping, and biodiversity preservation that lessen insect vulnerability. Include helpful organisms and natural enemies in your pest control plan.
- Farmer Training and Education: Create training programs to inform farmers about the value of IPM application and early pest identification. Give instructions on how to use the early pest detection system and evaluate monitoring results. The adoption of IPM methods has both economic and environmental advantages.

C. Classification of Optimality for Coconut Growth and Its Growth Prediction

The model consists of three sub-sections. That is soil classification, determining whether the environment is optimal for coconut cultivation or not, and predicting the growth of coconut plants. The sub-sections here are related to each other, Identifying the type of soil from soil classification, and determining the level of Nitrogen (N), Phosphorus (P), Potassium (K), and pH according to that type, Further (temperature, humidity, and rainfall) values are obtained with the support of Weather API, and based on them, it is decided whether coconut is optimal for the environment or not. Also, predicting the growth of coconut plants based on factors affecting their growth. Factors considered here are soil (Nitrogen, Phosphorus, and Potassium), pest infestation, and weather conditions.

I. Soil Classification

Five soil types are used for soil classification and CNN (Convolutional Neural Networks) algorithm is used to classify them. As shown in Table 1 below N, P, K, and pH values are obtained for each soil type.

Table 1: Classification of soil type

Soil type	N	P	K	pH	
Black Soil	184	27	229	5.5	[4]
Cinder Soil	50	100	30	5.8	[13]
Laterite Soil	103	13	126	5.3	[14]
Peat Soil	100	10	10	7.0	[15]
Yellow Soil	113	40	264	7.0	[16]

Data preprocessing improves model performance by performing procedures on the dataset before training. Redundant input data adds unnecessary complexity, and training on raw data may not yield satisfactory results. Images must be resized to meet CNN architecture requirements [17] After pre-processing, the model is compiled with essential elements like optimization function, loss function, and metrics. Nodes produce values in [0, 1]. Adam algorithm improves performance by modifying learning rate and loss. It requires less memory and is efficient and easy to implement[17].

Fine-tuning involves updating the CNN architecture by keeping earlier layers frozen and re-training only the top- most layer on new data. The models were trained for 40 epochs with early stopping implemented to monitor validation loss. Batch size was set to 32, and Keras' Callback API was used for early stopping using the ESC method [17].

II. Classification of Optimality for Coconut Growth

This subsection is about predicting whether the environment is optimal for coconut cultivation or not. The output, N, P, K and pH values obtained from the previous model are propagated to this one. The N, P, K, and pH values from that model are used as input for this model and temperature, rainfall, and humidity values are obtained using weather API and based on these details predict whether the environment is optimal for coconut cultivation.

It is a two-class clarification since the result of the prediction is whether the environment is ideal for coconuts or not. To forecast it, a logistic regression technique is applied. Logistic regression, in general, is helpful for articulating and assessing hypotheses regarding correlations between one or more categorical or continuous predictor variables and a categorical outcome variable [18]. This logistic regression binary categorization. And the optimization technique employed in this case was the gradient descent algorithm.

III. Predicting the Growth of Coconut Plants

The major goal of this component is to forecast coconut tree growth using multiple types of data. Datasets are first aggregated, then clustered, and then visualized. based on research that used multivariate polynomial regression and its outcomes. Seven characteristics and 100 data sets are used.

Figure 2 displays the Pearson correlation [19] between the independent variables. The chart shows that the majority of independent variables do not correlate, however this.

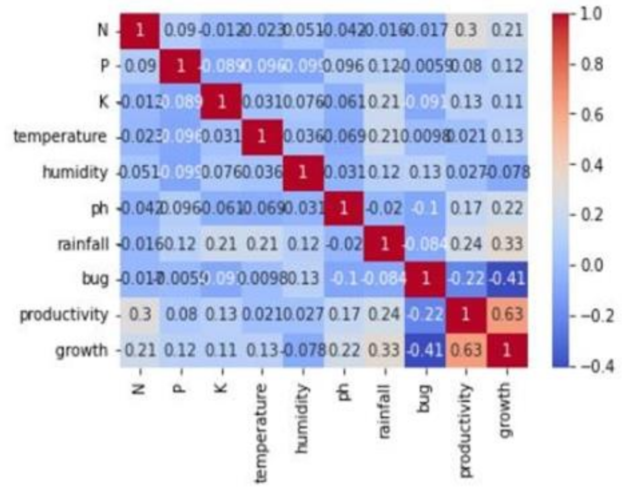

Figure 1: Growth Correlation Matrix

is apparently unimportant since MPR removes terms with excessive collinearity from the final model. The study's objective was to use multivariate polynomial regression (MPR), a nonlinear statistical technique [20]. Multivariable statistical approaches can be used as a helpful tool for understanding and analyzing difficult datasets [21]. In this study, the MPR model was used to forecast the development of coconut trees while accounting for soil quality, biological impacts, and meteorological factors. During the modelling phase, MPR was used to better understand and visualize the relationships between the predictors and the dependent variables, as well as to quantify the effect of each individual predictor on the dependent variables.

To utilize MPR for data modeling, the dataset is divided into three distinct parts: the fit dataset, the cross dataset, and the validation dataset. The fit dataset(n=140) is employed to compute the regression coefficients. The cross dataset(n=30) serves to assess the overall quality of fit through cross-validation. Once the models are developed or the best model is chosen based on the fit and cross datasets, the validation dataset (n=30) is utilized to provide consistent global goodness-of-fit metrics for final validation. This approach minimizes the risk of overfitting and enhances the assurance that the constructed model can be effectively applied to new data.

Before training the model, different fireprocessing operations must be carried out. initial processing the initial phase of the approach is presently under progress. Preprocessing is the process of transforming raw data into a format that will be easier to use and more effective during later processing stages.

The min-max method should be used first to normalize the data. Normalization helps speed up training by ensuring that all training data are of the same scale. The second goal of feature selection is to choose the top feature among the available features. The issue of minimizing unnecessary and excessive variables is solved using a variety of ways. The process of feature selection (variable removal) enhances performance while reducing processing requirements and dimensionality effects [22].

In this research, the Particle Swarm Optimization (PSO) is employed to enhance the performance of the Correlation- based Feature Selection (CFS) technique. CFS serves as a filter to select a subset of features using a multivariate approach. Its purpose is to identify features strongly linked to the target class. Notably, CFS might opt for a subset of features that are less optimal if the feature expression values are constrained within a narrower search range [23].

D. Enhancing Coconut Export Quality in Sri Lanka through Image Processing-Based Classification and Grading

I. Dentification of Coconut Image Process (Data Collection and Processing)

The first step in the methodology is Data Collection. This involves the comprehensive gathering of coconut samples representing different types and grades from various regions across Sri Lanka. The goal is to create a diverse and representative dataset that encompasses a wide range of coconut varieties and attributes. During this stage, researchers and experts involved in the project go to different locations in Sri Lanka known for their coconut production. They collect coconuts from different farms, plantations, and regions to ensure a broad sample. The collected coconuts may include various types, such as king coconuts, yellow coconuts, and green coconuts, as well as coconuts with different grades based on their size, ripeness, and quality. It's crucial to have a large and diverse dataset for accurate and robust classification and grading.

Therefore, the data collection process is meticulous and aims to cover as many variations in coconut characteristics as possible. Once the coconut samples are collected, they are labeled and documented with information about their respective types, grades, and origin locations. This labeled dataset will serve as the foundation for training and validating the machine learning algorithm responsible for the coconut classification and grading process. The success of the entire methodology heavily relies on the quality and representativeness of the data collected during this stage. A well-curated dataset ensures that the subsequent steps, such as feature extraction and model training, yield accurate results, leading to an effective coconut classification and export suitability assessment system.

II. Training the Detection Models

These images undergo preprocessing, including noise reduction, image enhancement, and normalization to standardize the data. Different characteristics such as size, color, shape, and texture are then extracted from the preprocessed images to serve as input data for the classification model. The chosen machine learning algorithm, such as a convolutional neural network (CNN), is then employed. This algorithm is trained with a labeled dataset of coconut images and their corresponding types or grades, enabling it to make accurate classifications based on the extracted features.

Through model training and validation, the algorithm learns to recognize patterns and relationships between coconut features and types, employing techniques like cross- validation to ensure accuracy and avoid overfitting. Once trained and validated, the model is used for coconut classification, assigning specific types or grades to unseen samples based on learned patterns and feature analysis. The algorithm then conducts an export suitability assessment, considering factors like freshness, ripeness, and physical condition to determine whether coconuts meet export criteria. This assessment ensures only premium-quality coconuts are eligible for export. As a result, exporters can optimize their selection process, supplying only the finest coconuts to the international market and enhancing Sri Lanka's reputation as a top-quality coconut product supplier.

IV. RESULT AND DISCUSION

For coconut farming, the combination of pest management and an Early Pest Detection System produced encouraging results in terms of spotting and reducing insect infestations. The Coconut Rhinoceros Beetle, Red Palm Weevil, Red Palm Weevil Larvae and Black Headed Caterpillars were among the important coconut pests that the Early Pest Detection System, based on Convolutional Neural Networks (CNN) and image processing techniques, successfully identified.

	precision	recall	f1-score	support
black_headed_caterpillars	1.00	1.00	1.00	992
red_palm_weevil	1.00	1.00	1.00	2006
red_palm_weevil_larvaes	1.00	1.00	1.00	1000
rhinoceros_beetle	1.00	1.00	1.00	976
accuracy			1.00	4974
macro avg	1.00	1.00	1.00	4974
weighted avg	1.00	1.00	1.00	4974

Figure 2: Classification report for pest detection

The system classified pests with great accuracy using CNN, making distinctions between various pest species and classifying the severity of infestations. Real-time pest warnings, informing farmers of the existence and severity of pest outbreaks, were made possible by the trained CNN model. Additionally, the image processing methods assisted in determining the insect population densities in various coconut crop zones. In order to visualize the spatial distribution of pests, the system created heatmaps showing pest density. These heatmaps were useful for locating high- risk regions and deciding where to focus pest control efforts. The efficiency of pest control measures was increased by the incorporation of a machine learning-based Early Pest Detection System into the overall Integrated Pest Management (IPM) strategy. When pest infestations were still in their early stages, farmers were provided with timely notifications that allowed them to implement targeted treatments such as cultural practices, biological control, or selective pesticide application. This lessened the need for broad-spectrum insecticides and lowered the negative effects on the environment.

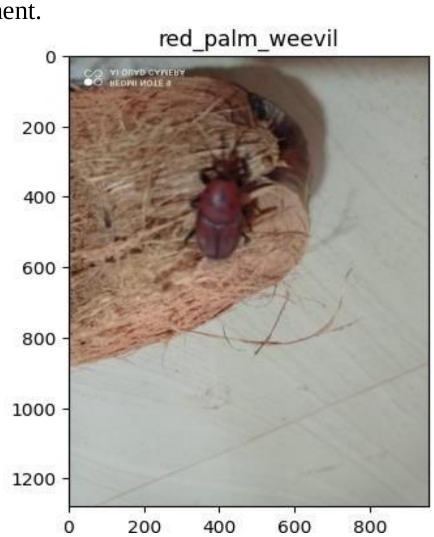

Figure 3: Detect pests.

The first subsection model focuses on optimizing coconut growth through a classification approach. Various machine learning algorithms were utilized for this purpose, including CNN for Soil Classification. The model was further fine-tuned using the logistic regression algorithm to determine the suitability of an environment for coconut cultivation. The experimental results demonstrate that the model achieved maximum accuracy, as depicted in Figure 4. This high accuracy indicates the effectiveness of the approach in identifying the optimal conditions for coconut growth, which can be valuable for farmers and agricultural experts in making informed decisions.

The next proposed model focuses on predicting the growth of coconut plants using an MPR approach in machine learning. The model was trained to make accurate growth predictions based on various input variables. The experimental results demonstrate that the model achieved maximum accuracy, as illustrated in Figure 5. This high prediction accuracy indicates the effectiveness of the multivariate polynomial regression method in estimating the growth of coconut plants. Such predictive capabilities can be highly beneficial for farmers and agricultural practitioners, aiding them in better planning and managing coconut cultivation to maximize yields and optimize resources.

	Actual	Predicted
1451	Other	Other
1334	Other	Other
1761	Other	Other
1735	Other	Other
1576	Other	Other
1110	Other	Other
1594	Other	Other
530	Other	Other
651	Other	Other
819	Other	Other
771	Other	Other
1878	coconut	coconut
915	Other	Other
2015	Other	Other
1876	coconut	coconut
937	Other	Other

Figure 4: Results of crops suggestion model

Actual Growth	Predicted Growth
[56.]	[58.46404144]
[20.]	[31.51510709]
[25.]	[27.01721007]
[56.]	[61.08789088]
[23.]	[35.56285422]
[24.]	[28.38825124]
[78.]	[57.10263975]
[89.]	[70.4216599]
[86.]	[59.24111155]
[54.]	[55.9496911]
[56.]	[58.05794903]

Figure 5: Predicted Growth

To evaluate the hypothesis regarding the link between the likelihood that the environment is optimal for coconut growth or not, a two-predictor logistic model was fitted to the data.

Here 0.00001 was used for the C value (Inverse of regularization strength). 10000 applied for maximum iterations, precision is displayed on those values. It is shown in Figure 6 below.

Values are given like this: it comes down to accuracy, a higher accuracy value indicates better performance, but it's important to consider other metrics as well. The confusion matrix then helps you understand how well the model performs in distinguishing between the two classes. Since there is much more data in the other category this is an imbalanced dataset so this classification report is useful when dealing with imbalanced datasets and can get a more comprehensive evaluation of the model's performance on individual classes.

```
Accuracy: 0.9954545454545455
Confusion Matrix:
 [[413   0]
 [  2  25]]
Classification Report:
              precision    recall  f1-score   support

       Other       1.00      1.00      1.00       413
     coconut       1.00      0.93      0.96        27

    accuracy                           1.00       440
   macro avg       1.00      0.96      0.98       440
weighted avg       1.00      1.00      1.00       440
```

Figure 6: Classification report

Research on using image processing to improve Sri Lankan coconut export quality shows how it may improve grading and classification. This strategy outperforms manual approaches in terms of accuracy, effectiveness, and objectivity, demonstrating how technology has the potential to increase the competitiveness and dependability of the coconut export industry. The method's extensive acceptance is encouraging since it addresses shortcomings and incorporates stakeholder feedback for the worldwide sustainable expansion of Sri Lanka's coconut industry.

The discussion section seeks to understand and context- Alize the preceding results while also discussing the rami- fictions of the findings, their importance, and prospective directions for additional study and real-world application.

Technological Advancements in Agriculture

The efficient application of classification and grading for coconut quality assessment based on image processing demon-stratus the growing influence of technology in modernizing conventional agricultural methods. This study shows how image processing methods, which have already been used in a variety of disciplines, can be used to speed up the grading of coconuts. Agriculture and image processing together have the potential to solve long-standing issues with manual grading systems.

Enhanced Objectivity and Consistency

This study emphasizes the objectivity and consistency that image processing-based grading offers as one of its main benefits. Due to things like weariness, human graders are prone to subjectivity, bias, and variances in judgment. On the other hand, the automated method consistently applies pride- ermined criteria, producing standardized and more dependable grading results. This neutrality is crucial for upholding the standard of exported coconuts and establishing confidence among foreign customers.

Coconut Diseases Identification

A team of researchers in coconut groves is working to protect these majestic trees from mealybugs, mites, and leaves yellowing. They used deep neural networks and a diverse dataset of coconut tree images to train their deep learning models. The DenseNet121 architecture was used for mealybug detection, with a 99.50% training accuracy. The InceptionResNetV2 architecture was used for mite detection, with a 99.68% training accuracy and 97% testing accuracy. The YOLOv5 object detection algorithm was used for leaves yellowing, with a mean average precision of 96.87%. Crowdsourcing was used to enhance the system's efficiency, allowing the community of coconut growers and enthusiasts to contribute valuable data and images. The researchers mapped the distribution of mealybugs, mites, and leaves yellowing on Google Maps, providing a deeper understanding of affected regions and strategizing targeted interventions. The team plans to extend their deep learning system's capabilities and use weather data and predictive modeling to forecast disease dispersions. This ambitious endeavor demonstrates the power of deep learning and innovation in protecting coconut trees and preserving their beauty for generations to come.

V. CONCLUSION AND FUTURE WORKS

In conclusion, an all-encompassing and cutting-edge solution for coconut farming is provided by the combination of an Early Pest Detection System and Integrated Pest Management. Farmers are given the tools they need to fight pest infestations effectively and sustainably thanks to the integration of cutting-edge machine learning technology and environmentally friendly pest management methods. The Early Pest Detection System offers a proactive, real-time method of spotting pests in the earliest stages, allowing for prompt action and reducing crop losses. Farmers may significantly enhance their pest control strategies by utilizing the power of machine learning, which results in higher yields and better financial consequences. Additionally, using integrated pest management techniques encourages a more peaceful and environmentally responsible approach to pest control. Reducing the use of chemical pesticides protects natural ecosystems while improving the environment and human health. A strong and tenacious defense against pest infestations is created by combining cultural methods, biological control agents, mechanical safeguards, and resistant coconut cultivars. The Early Pest Detection System is made available to farmers in rural areas by implementing the approach on mobile platforms or camera-equipped devices, facilitating wider adoption and distribution of best practices.

In this research paper, proposed and evaluated three models for different aspects of coconut cultivation: soil classification, optimal classification for coconut growth, and prediction of coconut plant growth. Each model employed machine learning algorithms such as CNN, logistic regression, and multivariate polynomial regression to achieve accurate results. Our experimental findings demonstrated that the models achieved maximum accuracy, making them effective tools for coconut farming.

In conclusion, the research has provided valuable insights into improving coconut cultivation through data-driven approaches and machine-learning techniques. By continually exploring these future research directions, this can advance the field of agricultural technology and contribute to the sustainable growth of the coconut industry.

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