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Efficient Framework for Coconut Disease Prediction

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ABSTRACT
Since 1942, the Gold Coast Department of Agriculture has been studying the causes and advancement of Lethal Disease (LD) in coconut trees. Despite efforts from experts and financial institutions, the primary objective remains to identify resistant germplasm. Three species of Malayan coconuts were imported from Jamaica, Malaysia, and the Ivory Coast, but diseases led to their decline. A 1977 study at Cape Three Points revealed that while some trees sustained significant damage, others exhibited remarkable resilience. The France-Ghana-Côte d'Ivoire Coconut Project conducted seven studies investigating 27 coconut species from 1981 to 1983, finding the Sri Lanka Green Dwarf (SGD) as a potential LD-resistant variety. In 1995, two potential hybrids, SGD x VTT and Malayan Yellow Dwarf (MYD) x VTT, were found, despite some resistance constraints. The Coconut Sector Development Programme (CSDP) aims to restore 1,300 acres of coconut cultivation with optimal procedures for hybrid selection for transplantation. Data-driven methodologies, including deep learning algorithms and image analysis, may significantly improve disease detection in coconut farming practices.
KEYWORDS: *Coconut palm disease, CNN, machine learning, and Deep Learning.*

I. INTRODUCTION TO COCONUT DISEASE PREDICTION

Studies by Harrison et al. (1999) and Brown et al. (2008) suggest that the American LY phytoplasma may infect a number of grasses and palm plants. Potential routes of disease transmission in a coconut farm include external disease transmission via other hosts carrying phytoplasmas and internal disease transmission among coconut plants. Yankey et al. (2009) found no evidence of distinct plant species in their analysis of 57 species from 27 different plant groupings. Even though this research is a positive move for Ghana, time constraints limited the study to two locations and resulted in a tiny sample size, therefore other possible alternate hosts were not taken into consideration. Increasing the sample sizes of collections requires reevaluating previously researched plants, including additional LO infection locations, and researching new plant species.

The likelihood of phytoplasma infections spreading from one seed to another is very low since they reside in the phloem sieve components and are not linked to the embryo. Scientists have discovered evidence of phytoplasma DNA within plant embryos, which is corroborated by both recent and historical study. Botti and Bertaccini (2006) proposed the introduction of phytoplasmas into winter oilseed, tomato, and lime seedlings. Cordova et al. (2003) used nested PCR using LY-specific primers in addition to generic phytoplasma primers to find phytoplasma DNA in coconut embryos. Using in situ polymerase chain reaction (PCR) using oligonucleotide primers that target two specific genes, the presence of phytoplasma fragments was verified. Nipah et al. discovered phytoplasma DNA in coconut blossoms and embryos (2007).

Phytoplasmas may enter plants in a number of ways besides the components of the phloem sieve. In situ testing and traditional PCR methods were used in earlier research on coconut embryos, however neither method was able to distinguish between living and dead phytoplasma pieces. The outcome for the phytoplasma-infected embryos, which are categorised as compromised seedlings, is yet unknown. Both studies sought to assess the embryos' potential to develop into damaged plants, however the need to standardise the embryos and isolate DNA for polymerase chain reaction study precluded the use of tissue culture techniques. We need to be able to verify LY/LD seed transfer in order to better comprehend the epidemiological dynamics of the illness. Transferring seeds both domestically and internationally would have serious repercussions.

Because of the unique characteristics of each species, coconut reproduction is a laborious, intricate process that requires a lot of room. Due to its sluggish rate of reproduction, challenges with clonal multiplication, and the possibility of a seven-year fruiting cycle, this palm species has not been used by many people (Chan et al., 1998). To produce inbred lines that achieve homozygosity for hybrid production, it typically takes at least 60 years (Perera et al., 2008). Traditional breeding methods are seriously hampered by the issues raised by YflO in a number of fields.

Polyphenols and isozymes, which function as biochemical or protein indicators, have been used to characterise different types of coconut. Protein markers are not particularly helpful for identifying variety because of the low levels of polymorphism in coconuts and the fact that they can only identify a limited number of enzymes. Research on plant genetics relies heavily on the use of molecular markers. Numerous molecular markers are available, and novel combinations of previously used markers are constantly being developed. These markers' names differ depending on the detection techniques used; for example, you could come across markers based on restriction-hybridization, markers based on DNA sequence or polymerase chain reaction (PCR), and markers produced using both PCR and non-PCR techniques. Analysing genotypes that exhibit either homozygote or heterozygote traits allows one to distinguish between co-dominant and dominant markers. Utilising molecular markers in combination with the appropriate technology is crucial for trustworthy cultivar verification. Breeding techniques will thus be able to preserve their genetic integrity.

Our understanding of the genetic variety found in the parental lines utilised for the potential ecotype and hybrids of the Ghanaian breeding program would be improved by the application of genetic markers on these animals. This approach will make it simpler for future breeding initiatives to choose the genotype with the most improvement potential. It is crucial to investigate the spread of resistance in coconuts in order to enhance subsequent mapping efforts. This riddle may be solved by future ecotype and WAT escapees, who may exhibit traits linked to tolerance and resistance.

Fig:1 Ganoderma lucidum

Fig 2: Ganoderma applanatum

Fig :3Various symptoms of Basal stem rot : Ganoderma spp

Fig4Various symptoms of Basal stem rot : Ganoderma spp

Fig:5Intensity of Basal stem rot disease

Fig:6Intensity of Basal stem rot disease

Fig: 7 BUD ROT

Cocos nucifera, a member of the Arecaceae family, is a tropical plant that can grow up to 30 to 100 feet tall and produce 75 fruits annually. However, foliar diseases, which damage leaf structures, can significantly impact crop yields and agricultural output. Traditional methods, such as visual inspection, have limitations and can lead to lower output and quality. Recent developments in deep learning have led to the development of techniques for classifying plant diseases using image analysis of sick specimens.

Digital image processing methods can help farmers identify diseased plants early, preventing the spread of illness and boosting agricultural production. Accurately categorizing coconut trees can lead to increased harvest yields and more flexibility in growth methods. The advancement of image processing techniques has the potential to significantly assist various scientific fields, including biology, agriculture, and health sciences.

In Nigeria, where one-third of the population relies on agriculture, early detection of phytopathological diseases can help reduce issues with agricultural productivity. Integrated technology can improve precision agricultural techniques, potentially boosting agricultural production worldwide. Digitally categorizing plant leaf diseases using a mix of models and algorithms can help maintain crop integrity.

In conclusion, the use of computational image processing techniques in agriculture can significantly improve productivity and efficiency.

Coconut cultivation is crucial for Sri Lanka's agricultural landscape, impacting domestic consumption and global trade. However, challenges such as disease prevalence, insect infestations, and unsuitable growing conditions hinder coconut exports. To address these issues and enhance sustainability, a cost-effective and environmentally responsible method is proposed using advanced techniques such as sophisticated grading algorithms, image processing methods, and early pest identification.

The study aims to identify the ideal conditions for coconut growth and evaluate various growth indices to optimize output. It also incorporates machine learning techniques with historical data to forecast future growth patterns.

Recent studies have focused on using deep learning, machine learning, and image processing approaches to improve disease diagnosis in leaves. The most prevalent natural pests in the coconut industry are coconut mites, black beetles, red palm weevils, and coconut caterpillars. The economic impact of insect-borne illnesses in this industry is greater than less frequent problems like stem bleeding and leaf light concerns.

Manali and Sumati developed a method to evaluate the size, color, and surface properties of coconuts using image processing techniques. This method has shown benefits in improving consistency and efficiency. Quality assurance methods have been developed by Mohammed and Kelvin, and a vision-based automated method was introduced by Jayanthi et al.

Previous research on plant health evaluations has used techniques like back-propagation, feed forward, and probabilistic neural networks to accurately detect pests and diseases that affect coconut plants. Natarajan et al. (2020) used Support Vector Machines (SVMs) to identify illnesses in coconut trees using morphological and pigmentation research.

Soil classification is essential for cultivating coconut palms, which are composed of three layers: exocarp, mesocarp, and endocarp. By combining cutting-edge technological advancements with conventional agricultural practices, coconut production can be improved for both domestic consumption and global trade.

II. Major diseases affecting coconut tree

Ganoderma – Basal Stem Rot
But Rot
Leaf Blight
Stem Bleeding
Root(Wilt)Disease
Leaf Rot

Fig.8: Leaf Blight

Fig.:9 Stem Bleeding

Fig.:10 Red palm weevil

This research aims to improve the quality of Sri Lankan coconut exports by calculating the segmentation affected region of coconut tree illness from disease images. The study uses image processing methods, classification algorithms, and historical data to classify the best conditions for coconut development and early pest detection. The deep learning system was trained using images of well-preserved coconut fronds and seeds, and surface photos were used to examine for mealybugs and mites. The data set was processed using various methods, including normalization, augmentation, and data normalization, to enhance accuracy and optimize the model's performance. The research aims to improve the quality of coconut exports in Sri Lanka.

III. Training the Models Used for Detection

A method for detecting mites and coconut mealybug infestations on coconut leaves and fruit was developed using a conventional neural network (CNN) for deep learning analysis. The model was trained using an extensive dataset of annotated images of mealybugs and mites on coconut fruits and leaves. The model accurately identified the extent of viral proliferation and the damage caused by these pests. The system also assessed the incidence of coconuts impacted by mite infestations.

The first phase involved developing a system that could identify pests early using machine learning techniques and infrared technology. This system would warn farmers of potential infestations and provide timely information for efficient treatment plans. The system would also identify common pests and develop standards for pest identification.

A predictive system was created to identify pests impacting coconut production. Pheromone traps, sticky traps, and automated sensors were used to monitor insect populations. Integrated pest management (IPM) techniques, including intercropping and crop rotation, could help maximize coconut production. A degree in agriculture is required for training agricultural personnel in identifying pests and efficiently using IPM techniques.

The study focuses on forecasting the growth and development of coconuts using a methodical approach. The model involves three components: soil classification, meteorological API data, and machine learning algorithms. Soil classification involves sorting various types of soil, measuring pH, and determining the amount of potassium, phosphate, and nitrogen present. Meteorological API data is used to assess the viability of coconut cultivation.

The model incorporates measurements, optimization's function, and loss function, with the Adam algorithm enhancing performance metrics. The model is assessed at regular intervals during 40 training epochs and uses Keras's Callback API for early validation. The model now incorporates meteorological API data as inputs, allowing machine learning algorithms to evaluate the weather conditions for coconut cultivation.

The Coconut Tree Disease Data Set compiles a diverse collection of images to train machine learning algorithms for the automated identification and categorization of coconut tree diseases. The collection comprises high-resolution images of various diseases impacting coconut palms, each categorised into one of five established disease classifications.

The data was captured in Kendur, Maharashtra, using a high-definition rear camera of a Samsung F23 5G smartphone. The data collection is crucial for academics and practitioners aiming to enhance methodologies for illness diagnosis and classification due to the many characteristics and sources provided by mobile camera technology. The data collection is accurately classified and systematically arranged in separate folders to facilitate the identification of specific sickness samples.

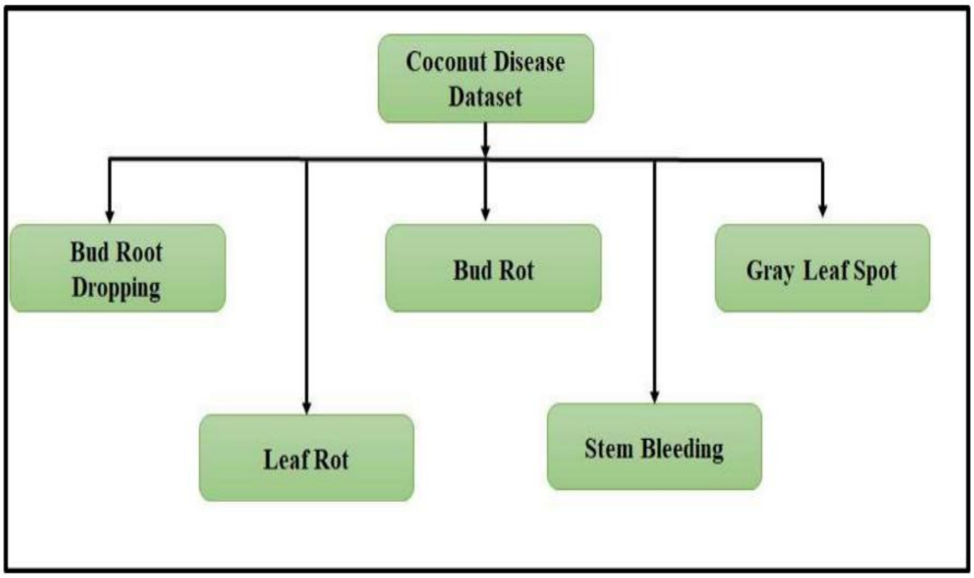

Fig.11 Directory structure coconut tree disease data set.

1. This research focuses on the forecasting of coconut tree development patterns using various data types, including photographs sourced from the TNAU database. The study uses multivariate polynomial regression (MPR) to analyze the growth of coconut trees by considering parameters such as soil quality, biological traits, and climatic circumstances. The data set is partitioned into training, cross-validation, and validation components, with 140 samples aiming to determine regression coefficients. The model's adaptability to new data is improved through preprocessing, feature selection, and Particle Swarm Optimisation (PSO).
2. Collecting pertinent data is crucial for accurate categorisation and grading, with a thorough sampling technique used to capture the extensive range of coconut characteristics. The coconut grading and classification system will undergo training and evaluation with this annotated dataset. The effectiveness of the whole method is significantly reliant on the precision and reliability of the collected data.
3. The categorisation model excels in identifying relationships and patterns in coconut features and classifications due to its stringent validation and training protocols. Techniques such as cross-validation can be used to mitigate the risk of overfitting and enhance accuracy. The algorithm considers many aspects while determining the export suitability of coconuts, including their physical condition, maturity, and freshness.
4. The adoption of a systematic classification framework using the K-means approach enhances the process of unsupervised area identification in photos with diverse backgrounds. The dataset is carefully arranged into K distinct clusters using K centroids, with the squared distances of each data point in relation to the cluster centroid being crucial for enhancing the efficacy of K-Means clustering.

IV. RESULTS AND DISCUSSION

Images captured with the Samsung F23 5G Mobile's high-resolution rear cameras were used to compile the Coconut Tree Disease data set. Table 2 summarizes the two primary phases data collecting procedure.

Data acquisition steps.

Data acquisition steps.

Sr. No.	Step	Duration	Activity
1.	Image Acquisition	April to July	During daytime field/farm visits to capture images.
2.	Image Pre-processing	July	The images appropriate for dataset were selected from gathered images and were pre-processed.

From April to July, field trips were conducted to photograph illnesses affecting coconut trees. The aim was to create an extensive repository of photos related to various disorders. The data was processed using Irfan View to ensure consistency and visual quality. The collection of 5,798 photos was categorized into five main diseases:

root drop, rot, leaf speckles, stem exudation, and leaf spots. Machine learning algorithms could improve the health of coconut farms by accurately detecting and categorizing diseases. The data collection's performance was evaluated using critical indicators like recall, accuracy, precision, and F1-score.

Accuracy values of disease detection models.

Model	Accuracy before training	Accuracy after training on our dataset
VGG16	0.26%	88%
ResNet50	0.4%	94%
MobileNetV2	0.25%	92%

Average 5-fold cross validation machine learning model performance.

Model	Precision	Recall	F1 Score
VGG16	86.94%	87.52%	87.69%
ResNet50	92.25%	93.42%	93.88%
MobileNetV2	89.68%	90.45%	91.54%

The study aimed to address class imbalance during model training by using a curated dataset and conducting 20 iterations to improve the validity and reliability of the findings. Overfitting was not a concern, as identification rates fluctuated by less than 10% across different classes. However, the models exhibited signs of overfitting at evaluation, indicating that they may be exhibiting suboptimal performance on novel datasets. To address this issue, researchers should explore transfer learning techniques, gather a broader array of datasets, and use regularization approaches. The data set demonstrated substantial performance improvements post-training, indicating that deep conventional neural networks are effective for diagnosing coconut leaf damage.

Advanced computational techniques can enhance methods for sickness identification and control, such as machine learning algorithms on an extensive dataset exhibiting plant illnesses. This knowledge can help automate systems to identify disease markers more swiftly and precisely, reducing the chance of disease spreading throughout plantations. This data collection also includes predictive abilities for disease outbreaks, resource distribution, and smart crop rotation.

The dataset has practical applications in agriculture and coconut plantation management, including real-time identification of plant diseases and tailored treatment recommendations. Collaborative efforts with agricultural extension organizations can lead to the development of platforms that enhance user accessibility and engagement.

Figure 5.18 Number of coconut tree disease data set photos per category

Disease Name	Total Images
Bud Root Dropping	514
Bud Rot	470
Gray Leaf spot	2135
Leaf Rot	1673
Stem Bleeding	1006
Total	**5798**

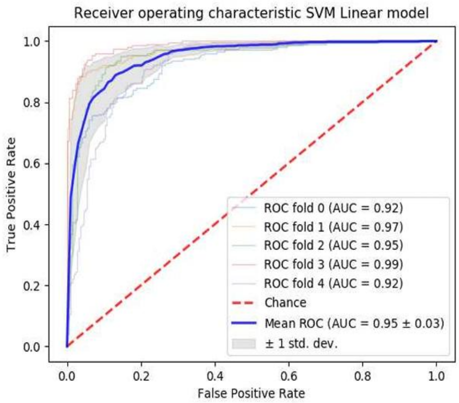

Figure SVM classifier ROC curve

Disease	Samples	Precision		Recall		Fscore		Specificity	
		DNN	GODNN	DNN	GODNN	DNN	GODNN	DNN	GODNN
Healthy Leaf	500	0.86	0.88	0.86	0.88	0.86	0.88	0.86	0.88
Root Wilt Disease	500	0.87	0.89	0.87	0.89	0.87	0.89	0.87	0.89
Leaf Blight	500	0.88	0.90	0.88	0.90	0.88	0.90	0.88	0.90
Stem Bleeding	500	0.89	0.91	0.89	0.91	0.89	0.91	0.89	0.91
But Rot	500	0.90	0.92	0.90	0.92	0.90	0.92	0.90	0.92

Figure Classification Accuracy

Disease	**Samples**	**DNN**	**GODNN**
Healthy Leaf	500	0.86	0.88
Root Wilt Disease	500	0.87	0.89
Leaf Blight	500	0.88	0.90
Stem Bleeding	500	0.89	0.91
But Rot	500	0.90	0.92

V. CONCLUSION

Automated evaluations of coconut groves are crucial for maintaining the quality of coconuts exported. Researchers use these groves to monitor disease spread and develop personalized treatments. Deep learning models, particularly Convolutional Neural Networks (CNNs), can autonomously derive image properties associated with illness symptoms. This approach can be integrated with conventional image processing techniques to enhance feature richness. In Thailand, the use of unmanned aerial vehicles (UAVs) in agriculture has led to the development of an Early Pest Detection System. This system integrates advanced computational techniques, such as neural networks, logistic regression, and multivariate polynomial regression, to achieve precise outcomes. The research aims to improve the efficiency and accuracy of detection and classification of coconut trees by improving the quality of segmented pictures and making feature extraction and selection easier. The researchers propose two approaches: adaptive thresholding using FCM and abnormality segmentation using AFKMRG. The proposed system is robust and salable, providing farmers, agronomists, and the agricultural industry with the data needed to make educated choices and administer targeted treatments. This could lead to more equitable resource allocation, less crop loss, and the encouragement of greener farming methods.

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