



A Study on Identification of Coconut Disease Using Deep Learning

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Abstract—Coconut is affected by a wide array of insects, mites, rodents, and lethal/debilitating diseases. For a perennial crop like coconut, cultural practices form an important component of integrated disease management (IDM). At the early stage the coconut leaf, flowers and tender coconut tends to be affected by pests. The coconut plantation industry depends heavily on expert advice to identify and treat infections. Computer vision in deep learning technology opened up a path in the agriculture domain to find a solution. One of the methods for prevention is providing adequate protection from the fierce sun when the plant is immature and giving the palm plenty of water, mainly during the growing season. In this paper, coconut diseases, coconut disease prediction using the deep learning techniques for coconut disease prevention had been reviewed. This paper also analyzes the comparison of deep learning model's validation accuracy before and after tuning in the coconut disease prediction and the severity of damage to coconut by pests.

Keywords— *Coconut disease, Coconut disease prediction, Machine learning, Deep learning, Coconut disease prevention, CNN, and Transfer learning*

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I. INTRODUCTION

Coconut plays a significant role in the agrarian economy of India. Coconut is a crop of small and marginal farmers since 98% of about five million coconut holdings in the country are less than two hectares [1]. Coconut palm (*Cocos nucifera*.) is considered one of the most important tropical species used by man, also known as the "tree of life", as it allows the elaboration of more than 100 products and byproducts being found in all tropical regions of the globe . The coconut industry plays a major role in sustaining the national economy and the food security of the people. Furthermore, 80 g of coconut meat provides 283 calories (14% of daily value) intake for an average person and coconut is the major source of 41% of edible oils and fats in the daily diet [2]. In India, the four south Indian states namely Kerala, Tamil Nadu, Karnataka, and Andhra Pradesh account for around 90% of the coconut production in the country. Botanically, the coconut fruit is a drupe. Like other fruits, it has three layers: exocarp, mesocarp, and endocarp [3]. The exocarp and mesocarp make up the "husk" of the coconut. Coconuts sold in the shops of non-tropical countries often have the exocarp (outermost layer)

removed. The mesocarp is composed of a fiber, called coir, which has many traditional and commercial uses. The shell has three germination pores that are clearly visible on its outside surface once the husk is removed [4]. The coconut inflorescence is monoecious with male and female flowers in each spadix. Each inflorescence is borne singly, emerging from the axil of successive leaves of a bearing palm. There are many common diseases of coconut such as bud rot, stem bleeding, leaf rot, Tanjore wilt, root (wilt), and Integrated Pest Management (*IPM*) for coconut [5]. Fig. 1 shows the disease *Aceria guerreronis* Keifer mite, fig. 2 shows the yellow leaflet disease, and fig. 3 shows stem bleeding in the coconut tree.



Fig. 1. Coconut disease due to *Aceria guerreronis* Keifer mite in the coconut



Fig. 2. Yellow leaflet disease in coconut leaves



Fig. 3. Stem bleeding disease in coconut plant

The structure of the paper is organized into different sections. Section 2 describes about methodology. Section 3 describes about literature review. Section 4 describes Prediction and prevention of coconut disease by common methods. Section 5 describes conclusion.

II. METHODS AND METHODOLOGY

A. Detection of Disease

Detection of diseases at the early stage helps farmers in the segregation of the disease crops from the healthy crops for the avoidance of the spreading of diseases. Manual disease detection when dealing with a large amount of coconut suffers from wrong decision making and this will have an impact on quality maintenance. Artificial intelligence (AI) tools like Deep Learning and Convolutional Neural Network (CNN) are gaining popularity in this field as they provide the optimum solution for coconut disease prediction and prevention [7]. There are some advantages to coconut disease prediction using deep learning techniques:

- Accuracy (%) will be high
- Low error rate
- Based on the deep learning features, the performance of the prediction will be high
- Datasets generated and used will seem to be more efficient when handling the deep learning

B. Diagnosis of coconut diseases is very complicated and the disease cannot be easily detected and predicted [8]. A deep learning framework is used in the field of automatic identification of disease through various models. Depending on the category of the application, different deep neural network architectures and local binary patterns are used for coconut disease prediction [9].

Coconut disease prediction using machine learning and deep learning has become more important and promising in the field of computer science and engineering. In the research field, fewer researchers explained them deeply. So, in this paper, coconut diseases, coconut disease prediction (specifically on leaves, stem, fruit and flower of coconut) using the deep learning techniques, and the prevention methods for coconut disease has been discussed.

III. LITERATURE REVIEW

A deep learning technique is applied to predict the occurrence of a button shedding diseases in a coconut tree

by observing the acidity level and moisture content of the soil. It will also reduce the wastage of time and energy for farmers. There are some methods for preventing coconut disease.

A. Types of Disease

Coconut is vulnerable to some diseases. Few of them are harmful and few are slowly affected by gradually reducing overall yield. Disease Management in Coconut is very crucial for high yield and obtaining quality and healthy produce for better rates and higher returns. Bacterial diseases, fungal diseases, virus and viroid diseases, and phytoplasmal diseases are some of the lists of diseases in the coconut palm (including fruit and flower). Table 1 explains the types of coconut diseases with their descriptions and results.

B. Types of Coconut disease with their description and results

- **M. A. H. Khan, et al. [20]** explained the leaf spot disease of coconut seedlings and its eco-friendly management. Incidence and severity of grey leaf spots at the seedling stage were determined and significant variations were observed depending on weather factors as well as locations. Results revealed that BAU-Biofungicide was effective for controlling leaf spots of coconut. Among the chemicals, Bavistin (0.2 %) as the foliar spray was also found good when incorporated with BAU-Biofungicide as a soil drench for controlling coconut disease.
- **Danilo B. Pinho, et al. [21]** described the notes on *Ceratocystis paradoxa* causing internal post-harvest rot disease on immature coconut in Brazil. Coconut fruits showing internal post-harvest rot symptoms were found in a market in Belo Horizonte and after incubation for 5 days in a humid chamber, fungal structures were observed. Data were compared with those of other *C. paradoxa* using phylogenetic analysis. Koch's postulates were confirmed by inoculation of 6-mm-diameter PDA plugs with the isolate on fruits of coconut. Evidence was not provided for the identification of cultures.
- **Nadia P. Morales, et al. [19]** explained the microbial diversity in leaves, trunk, and rhizosphere of coconut palms (*Cocos nucifera* L.) associated with the coconut lethal yellowing phytoplasma in Grand-Lahou. Results indicated that the CILY phytoplasma might be a factor determining the level of diversity of a microbial community in a given location. It was not clear about the role and the fact that Burkholderia was mostly isolated from symptomless and S1-like symptom bearing palms suggested it as a candidate for further assessment as a possible biocontrol against the CILY phytoplasma.
- **Asep Wawan Permana, et al. [20]** described the Influence of virgin coconut oil on the inhibitory effect of emulsion-based edible coatings containing cinnamaldehyde against the growth of *Colletotrichum gloeosporioides*. The slowest growth of fungi was observed from the emulsion containing beeswax, virgin coconut oil, and oleic acid. From these results,

coconut oil seems compatible with cinnamaldehyde in beeswax emulsion-based edible coatings as it did not negatively impact its antifungal properties.

- **Pramod Gairhe, et al. [21]** explained the evaluation of the effect of different essential oils in the management of post-harvest fruit rot of banana (*Musa Paradisiaca*) caused by *Colletotrichum* spp. At 1000 ppm concentration, cinnamon oil showed the lowest radial growth and the highest percent growth inhibition (1.67mm and 98.15%) followed by mustard oil (54.00mm and 40.00%), neem oil (55.17mm and 38.70%), castor oil (55.83mm and 37.96%), coconut oil (61.17mm and 32.04%) and control (90mm and 0.00%).
- **Tuhong Wang, et al. [22]** described the molecular diagnostics and detection of oomycetes on coconut. Specifically, oomycete clades infecting fiber crops correspond to clades 1, 2, 4, 7, 8, and 10 of the genus *Phytophthora* and to clades A, B, E, F, K, and I of the genus *Pythium*. These results indicated that oomycete pathogens of fiber crops were evolutionary diverse. The NGS technology could be used to directly identify the samples without culture, including those that could not be cultured and could not be identified by other technologies.
- **Rafael José, et al. [23]** explained that seasonality affected the community of endophytic fungi in coconut (*Cocos nucifera*) crop leaves. The influence of the season (rainy or dry) on the endophytic fungal community was also analyzed. Overall, 318 fungal isolates were obtained from 972 coconut leaf fragments. Nonmetric multidimensional scaling (NMDS) ordination and permutational analysis of variance (PERMANOVA) revealed significant seasonal effects on the composition of the endophyte community
- **Jean POHÉ, et al. [24]** described the components of coconut fruit susceptibility to *Phytophthora katusurae* (Pythiaceae) in Côte d'Ivoire. The infection rates of nuts under natural conditions and by inoculation techniques on wounds and deposition of inoculum on the pericarp were compared. As a result, a non-responsiveness of the distal zone of the young nuts was observed on nuts not wounded. Based on artificial inoculations on the fruit of different ages, the resistance mechanism in the fruit seems to be much more physically linked to nut anatomy than chemically.
- **Izzeddin A. Alshawwa, et al. [25]** explained the expert system for coconut disease diagnosis and prevention. The design of the applied Expert System was produced to help farmers in diagnosing most of the coconut diseases such as Bud Rot, Leaf Rot, Stem Bleeding, Tanjore wilt, and Root (wilt). The applied expert system about coconut diseases was given, the cause of diseases was outlined and the treatment of disease whenever possible was given out. Results of the applied system were evaluated and the performance of the system in predicting and treating was the best and most efficient. The limitation was the applied system specialized in fewer coconut diseases.

- **Ani Dath, et al. [26]** described the expert system for coconut disease management prediction, prevention, and variety selection. The expert system on Coconut disease management was developed to provide the management practices to be followed for getting maximum returns by detecting the disease at an early stage. The results showed that the expert system provided the management practices to be followed for the diseases affecting coconut by selecting the part affected and the symptoms. In the expert system of the knowledge base, there was a requirement for deep domain knowledge and manual work.
- **M. Balakrishnan, et al. [31]** explained the expert system for coconut diseases detection, prevention, and pest infection management. The system contains information on 21 pests of the coconut palm. Results indicated that the directions in the graph were links indicating dependencies that exist between nodes. Nodes represent propositions about events or events themselves. Conditional probabilities quantified the strength of dependencies. The expert system could also be used efficiently in places where there was a shortage of expert advice and timely detection of the pest and management was necessary for reducing the loss.
- **Husnain Saleem, et al. [32]** described the comprehensive review on the Application of diagnostic expert systems in the coconut disease prediction and prevention. Expert System was the most powerful approach that simulated human knowledge from an expert in a certain domain to assist humans during decision making at a level of or greater than a human expert. On analyzing the results, the rule-based method with the chaining technique showed good results in the detection. Disease diagnostic expert systems cannot be useable on mobile phones and almost all farmers use only mobile phone technology since they do not have the facility to use expert systems on laptops/desktop.

Table 1: Types of coconut diseases with their descriptions and results

Author Name	Disease	Description	Result
Pedro Henrique Dias, et al.[10]	Ceratocystis paradoxa (Fungal diseases)	Ceratocystis paradoxa or Black Rot of coconut was a plant pathogen that is a fungus part of the phylum Ascomycota	The applied scale showed good repeatability and high reproducibility, with absolute errors of around 8%, while the coefficient of determination presented and average of 91% with the aid of the scale and 59% without the scale.
Md Asad-Uz-Zaman, et al.[11]	Rhizoctonia solani (Fungal diseases)	R. solani was inhibited only by humus extract, while the growth was similar with biochar, peat, coconut fiber, cellulose,	The result suggested the superiority of the integrated approach to control the sclerotia forming pathogen R.

		glucose, and fish meal.	solani compared to the individual treatment either by an antagonist.				BLAST comparisons since the LY-PNG phytoplasma clustered as a single distinct branch related to group 16SrIV
G. A. Torres, et al.[12]	Phytophthora palmivora (Fungal diseases)	Phytophthora palmivora was an oomycete that causes bud-rot of palms, fruit-rot of coconut, and areca nut.	The result showed that the approach implemented on one of Cenipalma's research stations found a reduction from 20% incidence to 4% in a period of 4 months with a final incidence of 0.5% in 23 months after the treatments were initiated.	João Bila, et al.[16]	Phytoplasma disease	Phytoplasma palmae was the mid-stage foliar discoloration symptoms on the Atlantic tall coconut ecotype.	The results revealed that farm age, the presence of other palm species on the coconut farm, type of coconut variety grown, root cut practices, and intercropping all had a significant (P<0.05) effect on CLYD incidence.
Taburan, et al.[13]	Cephaleuros virescens (Fungal diseases)	Cephaleuros virescens was an algal plant pathogen that infects tea, coffee, and coconut plants, causing algal leaf spots or algal rust.	Results showed that 13 Cephaleuros species and one unidentifiable Cephaleuros species have been reported in Thailand. This accounted for almost 50 percent of worldwide Cephaleuros diversity as 29 Cephaleuros species have been reported in AlgaeBase.	Jameel M. Al-Khayri, et al.[17]	Bursaphelenchus cocophilus (Miscellaneous diseases)	Bursaphelenchus cocophilus causes red ring disease of palms. Symptoms of red ring disease were first described on Trinidad coconut palms.	In analysis, it has not been introgressed into those which were susceptible because of the difficulties in palm breeding. Current and emerging molecular techniques showed promise for overcoming many of the impediments.
Michael Jeger, et al.[14]	Cadang-Cadang (viroid diseases)	Cadang-cadang was a disease caused by Coconut cadang-cadang viroid (CCCVd), a lethal viroid of coconut (Cocos nucifera), African oil palm (Elaeis guineensis), anahaw (Saribus rotundifolius), and buri (Corypha utan) palms.	Detection results obtained using molecular hybridization assays should be considered with caution because of the presence in some palms that hybridize with probes representing part or all of the CCCVd genome but that have never been proven to be bona fide CCCVd.	Manuel Mota, et al.[18]	Bursaphelenchus cocophilus (Miscellaneous diseases)	Symptoms of red ring disease were first described on Trinidad coconut palms.	The results indicated that nearly 100 years after its original description B. cocophilus remains the only plant-parasitic nematode that cannot be cultivated for proper investigation
P.L. Kelly, et al.[15]	Phytoplasma palmae (Phytoplasma diseases)	Phytoplasma palmae (lethal yellowing LY); mid-stage foliar discoloration symptoms on the Atlantic tall coconut ecotype	BLAST comparisons showed that the partial 16S rDNA sequence of the LY-PNG phytoplasma matched most closely (96%) with members of group 16SrIV. Coconut lethal yellowing (CLY). Phylogenetic analysis supported				

IV. PREDICTION AND PREVENTION OF COCONUT DISEASE BY COMMON METHODS

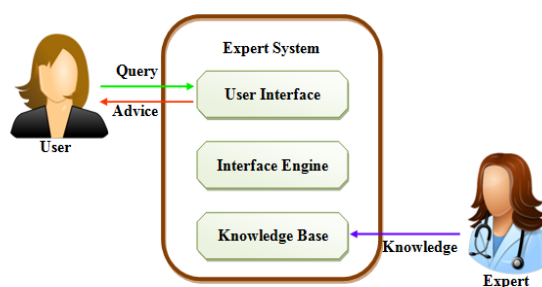


Fig. 2 Explains the main components of the expert system

As earlier mentioned it was difficult to detect the coconut diseases in the fruit and flower. But there is a general method named the expert system. It is a computer application for decision support and helps for reducing the costs, speeding the decision-making process, and make it available no matter what the time or place used, they substitute human experts [27]. Fig. 2 explains the main components of the expert system.

A. Coconut Disease Prediction and Prevention using The Machine Learning and Deep learning Techniques.

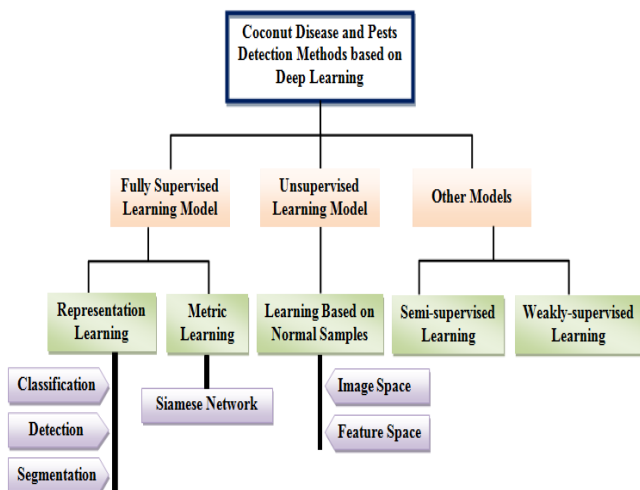


Fig. 3: Framework of plant diseases and pest detection methods based on deep learning

It is difficult for a farmer to monitor the coconut disease manually, which may consume a lot of time. The symptoms can be found on leaves, flower stems, fruits, and lesions of a tree. So when applying the machine learning (ML) techniques and deep learning (DL) techniques, the detection accuracy will be good. Table 2 explains the ML and DL techniques for the detection and prevention of the coconut disease with its results and limitations.

In the past methodologies, low-level features such as space, edges, lighting, rotation, spatial, and shapes were extracted to detect the pests effectively. In advanced technologies, machine learning and deep learning play an important role in the detection and protection of coconut disease in an effective way. Deep learning is a subfield of machine learning, and neural networks make up the backbone of deep learning algorithms. Algorithms were developed to detect the nutrient efficiency type and it was scaled up with better accuracy [28]. Figure 3 explains the framework of plant diseases and pest detection methods based on deep learning.

B. ML and DL techniques for the detection of the coconut disease with its results and limitations

Table 2: ML and DL techniques for the detection of the coconut disease with its results and limitations

Author Name	Technique Used	Results	Limitations
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S. Priyadharshini, et al. [29]	SVM Classifier (Support Vector Machine), KNN classifier (K-Nearest Neighbour) [ML]	The accuracy of SVM and KNN was 93% and 93%	SVM and KNN did not suitable for large datasets
Subramanian Parvathi, et al. [30]	Faster region-based convolutional neural network (R-CNN) [DL]	Test results showed that the detection performance of accuracy achieved using the improved R-CNN was greater than that for other object detectors such as the single-shot detector (SSD)	In R-CNN, each stage was an independent component
J Sujithra, et al. [31]	SVM and Neural network (NN) [ML]	NN showed a higher (55%) analysis of classification when compared to the other algorithms	The structure did not give any insights during the detection
Shrihari Kallapur, et al. [32]	Artificial Neural Network (ANN), Random Forest (RF), and SVM [ML]	The values of DBSCAN were below 5%. After actually detecting the coconut disease, the values obtained from the K-Means algorithm provide better performance.	Calculations could become complex when there are many class variables.
Dr. Abraham Chandy, et al. [33]	Deep neural network (DNN) [DL]	Images showing infested and infected areas were processed using artificial intelligence and a deep learning algorithm in the Nvidia Tegra SoC. Information such as pest infestation, yield prediction, precision fertilizer, precision irrigation, and so on was provided	It was extremely expensive to train due to complex data models

André S. Abade, et al. [34]	Convolutional Neural Networks(CNN)	The architecture achieved an overall accuracy of 97.62% and a significant reduction in the number of parameters compared to a standard AlexNet DL model	It did not receive the position and the orientation of the object
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- Muhammad Shakaib Iqbal, et al. [35]** explained the coconut disease detection, prevention, and segmentation in aerial imagery using mask R-CNN. The masked Region-based Convolution Neural Network (Mask R-CNN) approach was used for coconut disease identification and segmentation. For the segmentation, ResNet50 and ResNet101 were also used with the mask R-CNN. Results showed that the 96% classification accuracy was achieved with Resnet50 and 98% classification accuracy was achieved with Resnet51 for the identification and prevention. Generic shapes that have different objects were difficult to be differentiated in the aerial image.
- Dr. G Manjula, et al. [36]** described coconut disease identification using image processing and machine learning algorithms. The system provided the usage of mobile phones to capture the image of the affected parts. Results indicated that the methodology of the image processing, SVM classifier, and otsu's thresholding showed higher accuracy (95%) when compared with the other methodologies. If the number of features exceeded training data samples, the SVM would underperform.
- Dhapitha Nesarajan, et al. [37]** explained the coconut disease prediction and prevention system using image processing and deep learning techniques. Detection of pest attack and nutrient deficiency in the coconut leaves and analysis of the diseases had been applied. Results showed reasonably accurate performance with an overall detection accuracy of 93.7%, 83.2%, and 20.9% for EfficientNetB0, ResNet50, and VGG16 backbones on the fixed test set of healthy, nitrogen, potassium, and magnesium deficiency images for the nutrition deficiency class.
- Attapon Palananda, et al. [38]** described the classification of adulterated particle images in coconut disease prediction using deep learning approaches. CNN was applied to solve the problem of impurity identification and image analysis. The experimental results indicated that the MobileNetV2 architecture had the best performance, with the highest training accuracy rate of 94.05%, and a testing accuracy rate of 80.20%. Overfitting, exploding gradient, and class imbalance were the major challenges while training using CNN.

- André Abade, et al. [39]** explained the coconut diseases recognition on images using CNNs. The CNN aimed for the process of identification and classification of coconut diseases, delimiting trends, and indicating gaps. From the results, it was possible to understand the innovative trends regarding the use of CNNs in the identification of plant diseases and to identify the gaps that need the attention of the research community. It was not possible to find in the evaluated dataset that included images of crops using covered large areas of cultivation.
- Mariia Zakharova, et al. [40]** described the automated coconut disease detection in aerial imagery using deep learning. The model was tuned to classify each image obtained by the sliding window technique and predict a binary label for each sample. In the results, the combination of the aggregate channel features technique and the deep learning model has reached a precision of 71% at a recall of 93%. The whole classification process for the 10000 * 10000 px image took from 30 to 90 minutes depending on the score threshold.

V. RESULTS AND DISCUSSIONS

The methods discussed in the previous sections can be implemented using the below system and software requirements.

System requirements:

Operating System: Windows 7, 10 or 11 or Linux or Ubuntu, 64 bit.

Processor: 64-bit CPU (Intel / AMD architecture)

RAM: 4 GB.

Disk space: 5 GB free space.

Software requirements: Anaconda, Spyder, OpenCV, PyCharm, Tensorflow.

This section explains the comparison of deep learning models' validation accuracy before and after tuning in the coconut disease prediction and the severity of damage to coconut by pests. Deep learning models are effective in image classification, which depends on the number of layers and the amount of data with which the models are trained [41]. These models can be used for detection, feature extraction, classification, and fine-tuning [42]. The performance of DL models in the CD prediction is depicted in table 3. Here, in the CD prediction, *DL techniques like VGG16 [43], VGG19 [44], INCEPTIONV3 [45], DENSENET201 [46], MOBILE NET [47], XCEPTION [48], INCEPTIONRESNETV2 [49] and NASNETMOBILE [50]* were deployed. The comparison of DL models' validation accuracy before along with after tuning in the CD prediction is delineated in fig. 3

Table 3: Performance of DL models in the CD prediction

DEEP LEARNING MODELS	ACCURACY BEFORE TUNING (%)	ACCURACY AFTER TUNING (%)
VGG16 [43]	78.40%	80.86%

VGG19 [44]	72.84%	74.07%
INCEPTIONV3 [45]	74.69%	75.93%
DENSENET201 [46]	78.40%	79.01%
MOBILENET [47]	80.86%	82.10%
XCEPTION [48]	75.31%	74.07%
INCEPTIONRESNETV2 [49]	81.48%	81.48%
NASNETMOBILE [50]	71.60%	73.46%

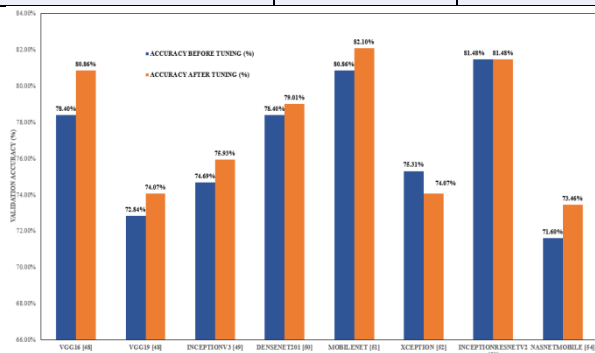


Fig. 3: Comparison of DL models validation accuracy before and after tuning in the CD prediction

The above models showed higher validation accuracy (80.86% and 81.48%) before tuning. A higher accuracy of 82.10% and 81.48% was exhibited by the MOBILE NET [49] and INCEPTIONRESNETV2 [50]. Thus, for predicting the CD prediction, the MOBILE NET and INCEPTIONRESNETV2 are suitable.

When weighed against other insects like SCALES, COREID BUG, ERIOPHYID MITE, TERMITES, MITES, and APHIDS, RHINOCEROUS BEETLE showed a higher prevalence of damage (88%). A lesser prevalence (15%) of damage to coconut was depicted by STINK BUG.

The severity of damage to the coconut by pests was also analyzed. Due to the problem in coconut owing to the insects like RHINOCEROUS BEETLE, SCALES, COREID BUG, ERIOPHYID MITE, TERMITES, MITES, and APHIDS, diseases occur in coconut. The severity of damage to the coconut by pests is depicted in fig. 4.

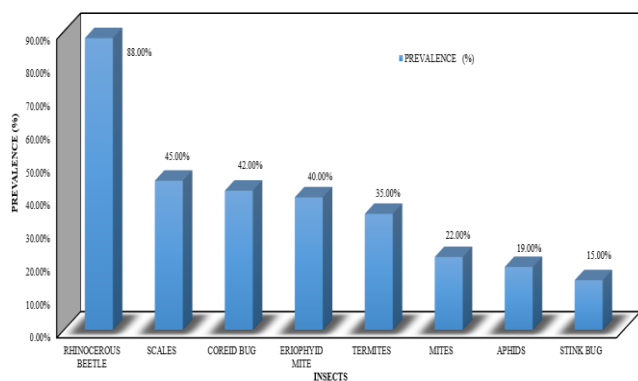


FIG. 4: SEVERITY OF DAMAGE TO COCONUT BY PESTS

VI CONCLUSION

Several diseases that are caused by various pathogens affect the coconut farming and it directly or indirectly minimizes the yield, either by killing or else by debilitating the palm and hindering production increase. In India, increased damage is caused to the coconut palms such as leaves roots, stems which leads to the yield loss of up to 80% in severe cases. Detecting the coconut disease is tedious. In the detection of coconut disease, the implemented ML techniques plays a key role. For presenting novel classification logic and improving the efficiency, ML techniques were wielded and optimized for processing speed and high accuracy of models. The process of feature extraction and classification process is clearly elucidated in the result section. Thus, coconut disease prediction and prevention by employing Machine Learning and Deep Learning methodologies are explained. An evaluation of Deep Learning model's validation, accuracy before and after tuning in the coconut disease prediction along with the severity of damage to coconut by pests is appraised.

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REFERENCES

- [1] Ana da Silva Ledo, Edson Eduardo MeloPassos, Humberto RolembergFontes, Joana Maria Santos Ferreira, Viviane Talamini and Wagner AVendrame, "Advances in coconut palm propagation", RevistaBrasileria de Fruticultura, vol. 41, no. 2, pp. 1-14, 2019.
- [2] Emojewwe Victor, "Cocos nuciferafruit a review of its medical properties advances in agriculture", Sciences and Engineering Research, vol. 3, no. 3, pp. 718-723, 2013.
- [3] Cesar Augusto Canciam and NehemiasCurvelo Pereira, "Assessment of the use of epicarp and mesocarp of green coconut for removal of fluoride ions in aqueous solution", International Journal of Chemical Engineering, vol. 2019, no. 2, pp. 1-8, 2019
- [4] "Coconut Diseases and Symptoms", <https://vikaspedia.in/agriculture/c-rop-production/integrated-pest-management/ipm-strategies-for-coconut/diseases-and-symptoms>.
- [5] Siddesha S and Niranjana S. K, "Detection of mite disease and computation of affected area in raw coconut", International Journal on Emerging Technologies, vol. 11, no. 2, pp. 8-12, 2020.
- [6] Monika Jhuria, Ashwani Kumar and Rushikesh Bose, "Image processing for smart farming etection of disease and fruit grading", 2nd International Conference on Image Information Processing, IEEE, 9-11 December 2013, Shimla, India, 2013.
- [7] Shiv Ram Dubey and Jalal A. S, "Detection and classification of apple fruit diseases using complete local binary patterns", 23-25 November 2012, Allahabad, India, 2012.
- [8] Pedro Henrique Dias dos Santos, Vicente Mussi-Dias, Maria das Graças Machado Freire, Beatriz MuriziniCarvalho and Silvaldo Felipe da Silveira, "Diagrammatic scale of severity for postharvest black rot in coconut palm fruits", Summa Phytopathol, vol. 43, no. 4, pp. 269-275, 2017.
- [9] Asad-Uz-Zaman, Mohammad RejwanBhuiyan, Mohammad Ashik Iqbal Khan, KhurshedAlamBhuiyan and Mohammad Abdul Latif, "Integrated options for the management of black root rot of strawberry caused by rhizoctoniasolanikuhn", ComptesRendusBiologies, vol. 338, no. 2, pp. 112-120, 2015.
- [10] Torres G. A, Sarria G. A, Martinez G, Varon F, Drenth A and Guest D. I, "Bud rot caused by phytophthorapalmivora a destructive emerging disease of oil palm", Phytopathology, vol. 106, no. 4, pp. 320-329, 2016.

- [11] WikromChanthapatchot and AnchitthaSatjarak, "Distribution, diversity and specificity of a parasitic algal genus cephalosporin Thailand", *SainsMalaysiana*, vol. 48, no. 8, pp. 1609-1618, 2019.
- [12] Michael Jeger et. al, "Pest categorisation of cadangcadang viroid", *EFSA Journal*, vol. 15, no. 7, pp. 1-23, 2017.
- [13] Kelly P. L, Reeder R, Kokoa P, Arocha Y, Nixon T and Fox A, "First report of a phytoplasma identified in coconut palms with lethal yellowing like symptoms in papua new guinea", *New Disease Reports*, vol. 25, no. 1, pp. 1-2, 2011.
- [14] Joao Bila, "Coconut lethal yellowing phytoplasma disease in mozambique diversity, host range and the impact of farming practices on disease incidence", Thesis, Swedish University of Agricultural Sciences, 2016.
- [15] Jameel M Al-Khayri and Charles L Niblett, "Envision of an international consortium for palm research", *Emirates Journal of Food and Agriculture*, vol. 24, no. 5, pp. 470-479, 2012.
- [16] Leticia Goncalves Ferreira, Manuel Motab and Ricardo Moreira Souza, "Culturing *Bursaphelenchus cocophilus* in vitro and in vivo", *Nematoda*, vol. 5, pp. 1-5, 2018.
- [17] Khan M. A. H and Hossain I, "Leaf spot disease of coconut seedling and its eco-friendly management", *Journal of the Bangladesh Agricultural University*, vol. 11, no. 2, pp. 199-208, 2013.
- [18] Danilo B. Pinho, Deiziane C Dutra and Olinto L Pereira, "Notes on ceratocystisparadoxacausing internal post harvest rot disease on immature coconut in Brazil", *Tropical Plant Pathology*, vol. 38, no. 2, pp. 152-157, 2013.
- [19] Nadia P Morales-Lizcano et. al, "Microbial diversity in leaves, trunk and rhizosphere of coconut palms associated with the coconut lethal yellowing phytoplasma in Grand-Lahou Cote d'Ivoire", *African Journal of Biotechnology*, vol. 16, no. 27, pp. 1534-1550, 2017.
- [20] Asep Wawan Permana, Imca Sampers and Paul Van der Meeren, "Influence of virgin coconut oil on the inhibitory effect of emulsion-based edible coatings containing cinnamaldehyde against the growth of *Colletotrichum gloeosporioides*", *Food Control*, vol. 121, pp. 1-7, 2021.
- [21] Pramod Gairhe, Sandesh Bhandari, Hom Prasad Sitaula, Beautina Karki and Hira Kaji Manandhar, "In vitro evaluation of effect of different essential oils in management of post-harvest fruit rot of banana caused by *colletotrichum* spp", *International Journal of Applied Sciences and Biotechnology*, vol. 9, no. 3, pp. 187-192, 2021.
- [22] Tuhong Wang, Chunsheng Gao, Yi Cheng, Zhimin Li, Jia Chen, Litao Guo and Jianping Xu, "Molecular diagnostics and detection of oomycetes on fiber crops", *Plants*, vol. 9, no. 6, pp. 1-22, 2020.
- [23] Rafael Jose Vilela de Oliveira, Natalia Mirelly Ferreira de Sousa, Walter de Paula Pinto Neto, Jose Luiz Bezerra, Gladstone Alves da Silva and Maria Auxiliadora de Queiroz Cavalcanti, "Seasonality affects the community of endophytic fungi in coconut crop leaves", *Acta Botanica Brasiliica*, vol. 34, no. 4, pp. 1-8, 2020.
- [24] Jean Pohe, Babaccauh Koffi Dongo and Therese Atham Agneroh, "Components of coconut fruit susceptibility to *Phytophthora katusurae* (Pythiaceae) in Cote d'Ivoire", *International Journal of Biological and Chemical Sciences*, vol. 5, no. 5, pp. 2004-2013, 2011.
- [25] Izzeddin A Alshawwa, Abeer A Elsharif and Samy S Abu-Naser, "An expert system for coconut diseases diagnosis", *International Journal of Academic Engineering Research*, vol. 3, no. 4, pp. 8-13, 2019.
- [26] Ani Dath and Balakrishnan M, "Expert system on coconut disease management and variety selection", *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 5, no. 4, pp. 242-246, 2016.
- [27] Husnain Saleem, Abdur Rashid Khan, Tehseen Ali Jilani, Javaria Sherani, Umar Khitab Saddozai, Muhammad Saleem Jilani, Muhammad Naveed Anjum, Kashif Waseem and Sami Ullah, "A comprehensive review on the application of diagnostic expert systems in the field of agriculture", *International Journal on Emerging Technologies*, vol. 12, no. 1, pp. 304-316, 2021.
- [28] Hdwehle, "Machine learning, deep learning and AI what's the difference" Data Scientist Innovation Day, 24 March 2017, Columbia, 2017.
- [29] Priyadarshini S, Rama Subramoniam S, Ganesha Raj K and Anandhi V, "Coconut inventory and mapping using object oriented classification", *International Journal of Current Microbiology and Applied Science*, vol. 8, no. 8, pp. 58-65, 2019.
- [30] Subramanian Parvathi and Sankar Tamil Selvi, "Detection of maturity stages of coconuts in complex background using faster R-CNN model", *Bio-systems Engineering*, vol. 202, pp. 119-132, 2021.
- [31] Sujithra J and Ferni Ukrit M, "A review on crop disease identification and classification through leaf images", *European Journal of Molecular and Clinical Medicine*, vol. 7, no. 9, pp. 1168-1183, 2020.
- [32] Shrihari Kallapur, Mahith Hegde, Adithya D Sanil, Raghavendra Pai, Sneha S. N, "Identification of aromatic coconuts using image processing and machine learning techniques", *Global Transitions Proceedings*, vol. 2, no. 2, pp. 441-447, 2021.
- [33] Abraham Chandy, "Pest infestation identification in coconut trees using deep learning", *Journal of Artificial Intelligence and Capsule Networks*, vol. 1, no. 1, pp. 10-18, 2019.
- [34] Andre S Abade, Paulo Afonso Ferreira and Flavio de Barros Vidal, "Plant diseases recognition on images using convolutional neural networks a systematic review", *Computers and Electronics in Agriculture, IET Computer Vision*, vol. 185, pp. 1-47, 2020.
- [35] Muhammad Shakaib Iqba, Hazrat Ali, Son N Trany and Talha Iqbal, "Coconut trees detection and segmentation in aerial imagery using mask R-CNN", vol. 15, no. 6, pp. 428-439, 2021.
- [36] Manjula, Shwetha, Spandana H. A and Mohammed Wasim Khan, "Coconut tree disease identification using image processing", *International Journal of Current Engineering and Scientific Research*, vol. 8, no. 1, pp. 6-10, 2021.
- [37] Dhaphitha Nesarajan, Lokini Kunalan, Mithun Logeswaran, Sanvitha Kasthuriarachchi and Dilani Lunugalage, "Coconut disease prediction system using image processing and deep learning techniques", 4th International Conference on Image Processing, Applications and Systems, 9-11 December 2020, Genova, Italy, 2020.
- [38] Attapon Palananda and Warang khana Kimpan, "Classification of adulterated particle images in coconut oil using deep learning approaches", *Applied Science*, vol. 12, no. 2, pp. 1-16, 2022.
- [39] Andre Abade, Paulo Afonso Ferreira and Flavio de Barros Vidal, "Plant diseases recognition on images using convolutional neural networks a systematic review", *Computers and Electronics in Agriculture*, vol. 185, pp. 1-31, 2021.
- [40] Mariia Zakharova, "Automated coconut tree detection in aerial imagery using deep learning", Thesis, KU Leuven Technology Campus De Nayer, 2016-2017.
- [41] Piyush Singh, Abhishek Verma and John Sahaya Rani Alex, "Disease and pest infection detection in coconut tree through deep learning techniques", *Computers and Electronics in Agriculture*, vol. 182, pp. 1-11, 2021.
- [42] Brady Kieffer, Morteza Babaie, Shivam Kalra and Tizhoosh H. R, "Convolutional neural networks for histopathology image classification training vs using pre-trained networks", 7th International Conference on Image Processing Theory, Tools and Applications, 28 November - 1 December, Montreal, QC, Canada, 2017.
- [43] Karen Simonyan and Andrew Zisserman, "Very deep convolutional networks for large scale image recognition", 2015.
- [44] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke and Andrew Rabinovich, "Going deeper with convolutions", Conference on Computer Vision and Pattern Recognition, IEEE, 7-12 June 2015, Boston, MA, 2015.
- [45] Gao Huang, Zhuang Liu and Laurens van der Maaten, "Densely connected convolutional networks", 2016.
- [46] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov and Liang-Chieh Chen, "MobileNetV2 inverted residuals and linear bottlenecks", 2019, <https://arxiv.org/abs/1801.04381v4>.

- [47] Francois Chollet, "Xception deep learning with depthwise separable convolutions", 2016, <https://arxiv.org/abs/1610.02357>.
- [48] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke and Alexander AAlemi, "Inception-v4, inception resnet and the impact of residual connections on learning", 31st AAAI Conference on Artificial Intelligence, 4-9 February, San Francisco, California USA, 2017.
- [49] Barret Zoph, Vijay Vasudevan, Jonathon Shlens and Quoc V Le, "Learning transferable architectures for scalable image recognition", 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 18-23 June 2018, Salt Lake City, UT, USA, 2018.
- [50] Pole F.N, Masha E, Muniu F.K, Nguma B and Mohammed N, "Status of coconut farming and the associated challenges in Kenya", Cord, vol. 30, no. 2, pp. 1-11, 2014.