A Literature Review of the Detection and Categorization of various Arecanut Diseases using Image Processing and Machine Learning Approaches

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ABSTRACT

Background/Purpose: *Every scholarly research project starts with a survey of the literature, which acts as a springboard for new ideas. The purpose of this literature review is to become familiar with the study domain and to assess the work's credibility. It also improves with the subject's integration and summary. This article briefly discusses the detection of disease and classification to achieve the objectives of the study.*

Objective: *The main objective of this literature survey is to explore the different techniques applied to identify and classify the various diseases on arecanut. This paper also recommends the methodology and techniques that can be used to achieve the objectives of the study.*

Design/Methodology/Approach: *Multiple data sources, such as journals, conference proceedings, books, and research papers published in reputable journals, were used to compile the essential literature on the chosen topic and collect information from the arecanuts research centre and many farmers in the south Canara and Udupi districts, before narrowing down the literature that is relevant to the research work. The shortlisted literature was carefully assessed by reading each paper and taking notes as appropriate. The information gathered is then examined to identify the potential gap in the study.*

Findings/Result: *Based on the analysis of the papers reviewed, discussion with farmers and research center officers, it is observed that, not much work is carried out in the field of disease identification and classification on arecanut using machine learning techniques. This survey paper recommends techniques and the methodology that can be applied to identify and classify the diseases in arecanut and to classify them in to healthy and unhealthy.*

Research limitations/implications: *The literature review mentioned in this paper are detection and classification of different diseases in arecanut.*

Originality/Value: *This paper focuses on various online research journals, conference papers, technical books, and web articles.*

Paper Type: *Literature review paper on techniques and methods used to achieve the objectives.*

Keywords: Arecanut diseases, Koleroga, Detection of arecanut diseases, Categorization of arecanut diseases, Segmentation of arecanut diseases, Machine learning, Image processing.

1. INTRODUCTION :

The seed of the areca palm is known as an arecanut, available in most throughout much of the tropical Pacific-ocean, South-East and South-Asian country, and Eastern Africa place. Betel nut is the common name for it. Areca is derived from the Malayalam word aaykka, it was used by Dutch and Portuguese sailors who imported the nut from India to Europe in the 16th century [1]. It is widely used in India by a vast number of people and is closely associated with religious traditions. In India, the arecanut is a commercial crop. India is the largest producer and eater of arecanut in the world. Karnataka (40 percent), Kerala (25 percent), Assam (20 percent), Tamilnadu, Meghalaya, and West-Bengal are among the states that grow this crop [2]. Karnataka is the larger producer of arecanut in India mainly in Dakshina Kannada and Uttara Kannada district and Malnad regions, now days Tumkur, Davangere, Hassan, Mysore districts cultivate arecanut. It thrives in the 14^0C to 36^0C temperature range but is harmed by temperatures below 10oC and above 40oC. Temperature extremes and large diurnal changes are not favorable to healthy palm growth. Arecanuts can be farmed in places with annual rainfall ranging from 750 mm in Maidan to 4,500 mm in Malnad in Karnataka. The palms are irrigated in locations where there is a lengthy dry period. A decent harvest of arecanut cannot be obtained at an altitude of more than 1000 m MSL due to its susceptibility to low temperatures [3]. Gravelly laterite soils of the red clay type have the most area under agriculture. It may also be grown on clay loam soils that are productive. Arecanuts cannot be grown in sticky clay, sandy, alluvial, brackish, or calcareous soils. The arecanut can be used to make diabetes formulations, Ayurveda medication, soaps, areca tea, teeth powder, and wines, in addition to chewing it [4][5]. Koleroga, Bud rot, Inflorescence die back, Yellow leaf disease, Anabe roga/foot rot, etc these all are common diseases on arecanut, these cause significant losses of arecanut tree, bunches, nuts. The Koleroga is the main disease of arecanut [6], Spraying the bunches with a 1 percent Bordeaux mixture before the monsoon, followed by another spray after 40 days, is successful in preventing the disease. Another option is to cover the bunches with plastic bags [7].

2. RESEARCH OBJECTIVES :

The objectives play a vital role in providing a detailed view of the goal of any research. The following are the objectives of this literature survey.

- To determine the different types of diseases on arecanut.
- To study the methodology and technology used to identify the diseases of arecanut.
- To know the present status of research on arecanut disease.
- To determine the research gaps and to propose the ideal solution to those research gaps.
- To list out the research agendas and limitations of the research.
- To analyze the proposed agenda using SWOC analysis.

3. METHODOLOGY :

Required data and information's are collected from different sources such as books, published research papers, journals, conference papers. The initial information related to arecanut and arecanut diseases was collected from farmers and arecanut research center vittala.

4. LITERATURE REVIEW :

Vinod Kanan L. et al., [8] proposed a disease prediction system by using temperature, rainfall, humidity, wind flow soil moisture around the agriculture area and developed a model to predict the diseases. He has summarized the study by concluding the occurrence of disease by analyzing different relationships among environmental factors.

The following papers are related to detecting and classification of arecanut using various machine learning techniques:

Mallikarjuna S. B. et al., [9] proposed a CNN based algorithm to classify the different diseases on arecanut images. He has classified different diseases like rot, split, and rot-split. Results from the four-class dataset show that the suggested strategy outperforms others in terms of classification rate, recall, precision, and F-measures.

Ajith Danthiz. [10], has developed a novel approach for arecanut classification based on the color of the arecanut, it was divided into two classes. The method was proposed in three different steps: segmentation, masking, and classification, according to the authors. For appropriate segmentation of arecanuts, three sigma control limits are applied to the image. He categorized the arecanut based on two different color like green and red color components of the segmented section. The proposed strategy is more efficient, according to an experimental outcome.

Santhos et al., [11] did the survey paper on different plants disease including arecanut leaf and various advanced techniques uses to detect diseases. In this paper the author has mentioned about different diseases on arecanut plant-like koleroga and yellow leaf. Further he added the cause and effect of the diseases.

Kuo-Yi Huang., [12] grade of arecanuts was discovered and classified. A detection line (DL) method was used to segment the illnesses of arecanuts. In the classification technique, six geometric features, three-color features, and the area of the fault were used. A back-propagation neural network classifier was used to sort the quality of arecanuts. This method was provided for classifying arecanuts with a 90.9 percent accuracy.

Rajendra B. et al. [13], has recognized and categorized arecanuts using neural networks and image processing techniques. A back-propagation cellular network classifier was employed to determine the relevance of the arecanut. Various pathogens, such as crops, bacteria, viruses, and insect damage, frequently attack the arecanut. The object color is depicted using the HSI technique, and the contrast curve enhances brightness changes equally over the image's dynamic range. Machine Vision Technology can be used to replace manual sorting in the arecanut advertising industry.

Akshay S. et al. [14], Used husk arecanut photos as input, categorizing healthy and harmful arecanuts. Background subtraction is used in the classification a method for removing shadow effects from pictures. They use the Otsu method to locate the diseased area of the arecanut. To identify the images, the author employs the GLCM texture feature extraction approach and a decision tree. This approach is developed in MATLAB and yields a 90% accuracy rate.

Anilkumar M. G. et al. [15], detected a system of diseases of arecanut, leaves, and its trunk using Convolutional Neural Networks and suggests remedies for it. A Convolutional Neural Network (CNN) is a Deep Learning algorithm used to detect the diseases of arecanut, that takes input as an image, assigns learnable weights and biases to various objects in the image, and then learns from the results to distinguish one from the other. To train and test the CNN model, created their dataset which has 620 images of arecanut both healthy and diseased. The train and test data are divided into an 80:20 ratio. For a compilation of the model categorical cross-entropy is used as loss function with adam as optimizer function and accuracy as metrics. A total of 50 Epochs are used to train the model to achieve high validation and test accuracy with minimum loss. The proposed approach was found to be effective and has 88.46 percent accuracy for detecting the arecanut disease.

Following papers are related to grading and quality of raw arecanut:

Siddesha S. et al. [16], have applied the KNN algorithm to find diseases using color histograms and color moments as features, and he focused on raw arecanut. An experiment is constructed on a dataset of 800 images of four classes using two-color features and four distance measurements with KNN. After 20 percent training, a classification accuracy of 98 percent is achieved with a K value of 3 and a Euclidean distance measure for color histogram features.

Suresh M. et al. [17]. proposed textural features of Local Binary Pattern (LBP), Haar Wavelets, GLCM, and Gabor used to identify diseases arecanut and undiseases arecanut. These procedures were carried out in two steps. (1) Each color component of the HSI and YCbCr color models has been treated with LBP. (2) A LBP histogram is created. The rate of success was 92.00 percent. The results were bad in the first stage, thus texture characteristics from Haar wavelets, GLCM, and Gabor were applied in the second stage. The RGB input arecanut image is converted to HSI and YCbCr color models in this stage, and texture details from each color component are extracted. The applied KNN classifier has a 100% success rate on a discriminative subset of texture.

Bharadwaj N K et al. [18], classified and graded the arecanut by using image processing and computer vision. The author uses color, size, and texture to classify the grading of arecanut. The major goal of this article is to give a comprehensive overview of arecanut, Computer Vision, and the needs and uses of vision-based technology in arecanut categorization and grading.

Dhanuja K. C. et al. [19], proposed a technique for detecting arecanut disease using image processing technology, and the author used texture-based grading of arecanut. To extract numerous textural features from arecanut, Wavelet, Gabor, Local binary (LBP), Gray Level Difference Matrix (GLDM), and Gray Level Co-Occurrence Matrix (GLCM) are employed. A total of 144 arecanut samples were utilized for training and testing the model, with 49 Good, 46 Poor, and 49 Negative samples, and the K N N algorithm was employed to detect illnesses in arecanut. The average accuracy was 90.9 percent.

Siddesh et al. [20], using K-Means and the Otsu approach, a disease detection model was presented to detect and identify afflicted raw arecanut. The arecanut image is segregated from the backdrop using color K-means clustering in preprocessing to remove shadow effects. The RGB image is transformed to monochrome using Otsu thresholding in illness detection. The connected components approach is then used to designate the afflicted arecanut regions. There were 50 disease-affected raw arecanut photos in the dataset. Counting the number of spots in the RGB image and then counting the number of spots spotted in the tagged images are used to evaluate the model's performance.

Bharadwaj N K [21] proposed to find the grade of the arecanut by using arecanut images. A proposed method for future extraction used the local binary pattern method. Support vector machine-classified used to find the grade of the arecanut. The accuracy, precision, recall, and F –measure generated from the confusion matrix are all used to evaluate the grading system's performance.

Siddesh et al. [22], proposed a texture grading method for arecanut. The textural features of arecanut are extracted using Wavelet, Gabor, Local Binary Pattern (LBP), Gray Level Difference Matrix (GLDM), and Gray Level Co-Occurrence Matrix (GLCM) features. The arecanuts were classified using the Nearest Neighbor (NN) classification technique. The suggested model's performance was demonstrated using 700 arecanut photos of seven distinct classes in an experiment, and the classification rate was 91.43 percent utilizing Gabor wavelet features.

Ajit Danti [23] proposed segmentation techniques and classification methods of raw arecanut. The author has developed a novel approach for categorizing arecanuts into two classes based on color. I Segmentation, (ii) Masking, and (iii) Classification. The classification is based on different two colors like red and green components of the arecanut segmented region. The categorization success rate in the experimental efficiency was around 97 to 98 percent.

Ajith Danti et al. [24], proposed the effective grading of arecanuts. The RGB image of the arecanut is transformed to YC B C R colour space. Three sigma control limits on colour characteristics were identified for successful segmentation of arecanuts. Arecants are graded using the support vector machine (SVM) method and colour features. Boiling and non-boiling nuts are efficiently graded, and experimental findings show that the suggested strategy is effective when using the k-fold cross-validation method.

Ajit Danti et al. [25], discussed techniques for grading arecanuts based on textural properties. Mean around features, Gray level co-occurrence matrix (GLCM) features, and combination (Mean around-GLCM) features are used for classification. Arecanuts are classified into six classes using a decision tree classifier. In Decision trees classifier used GLCM features and Mean Around-GLCM features. Testing is conducted by using the cross-validation method. The experimental outcome is a 97.65% success rate in GLCM features, a 98.28 percent success rate in Mean Around features, and a 99.05 percent success rate in Mean Around-GLCM features.

Sameer Patil et al. [26], proposed a technique for quality classification of arecanut using pre-processing techniques. A Raspberry-Pi board and a 5 Megapixel camera module are used to capture the images. Image filtering, contrast enhancement, and an image segmentation algorithm are all used in the pre-processing of the acquired image. Canny edge detection and the K-means segmentation method were used to detect the nut's boundary while cropping the arecanut photos. In this research, the author categorized eight distinct image pre-processing algorithms to produce the best results for arecanut segregation method.

Ajit Danti et al. [27], proposed a grading system of arecanut. The author combined two algorithms KNN and SUV to classify the nuts for better results.

The following papers are related to robot system arecanut farming:

Devang et al. [28], demonstrated the design and development of an arecanut farming-focused autonomous tree climbing and trimming robot. The robot has a non-linear self-regulatory system based on linear frictional force. The robot's chassis is designed to be both sturdy and light. The power source is an onboard battery. In a Digital Image Processing System, Artificial Intelligence is built on Object Recognition techniques. A guiding camera is installed over the Robotic Arm processor, which incorporates a Wavelet-based JPEG compression and noise reduction module for machine vision. When necessary, a display panel is used to view and control the robot.

S Kushal Gowda et al. [29], designed a smart arecanut plunking robot to climb the arecanut tree. The robot has a camera that gets the video stream through Raspberry pi. Android application is used so the user can watch the video stream. The arecanut bunch was successfully tested by the robot, and the operator was able to successfully lead the robot in cutting the ripened arecanut bunch.

The following paper is related to detecting bunches using various techniques:

Dhanesha R. et al. [30], Used the HSV color model, determine and identify the automated maturity level of arecanut bunches. Experiments were carried out on 200 photographs of arecanut bunches of varying ripeness degrees. The end findings of the investigation reveal that segments arecanut bunches photographs with an accuracy of 85 to 90%. The VOE and DSC segmentation performance matrices are used to assess the precision with which results are obtained.

Dhanesha R. et al. [31], identified the maturity level of arecanut bunches. The YCgCr color model automatically segments the arecanut bunch from a given image, using this segment image could determine the arecanut maturity level. The author has created a 1000 images database and captured them by mobile camera. The experimental result shows from this method for associate input image with an accuracy of 80%.

Dhanesha et al. [32], provided dynamic contouring segmentation, in which segments arecanut bunches in pictures. The author gathered 20 photographs of arecanut bunches at various stages of ripeness. VOE and DSC performance measures were used to assess the accuracy of the results. There are no published benchmark results to which the proposed method may be compared for efficiency. For low-quality photos, the proposed approach may not segment well. With the goal of determining the ripeness of arecanut bunches, the author presented a computer vision-based approach for segmentation utilizing active contouring.

Siddesha et al. [33], have segmented of oil palm crop bunch images using supervised and unsupervised approaches. The author used Hill climbing, Growcut, Random Walker, MSRM algorithms for supervised techniques, and K-Means, Fuzzy-C-Means algorithms for unsupervised techniques on a dataset of 100 bunch photos. If apply the same techniques to arecanut bunch would be getting a better result.

Hubert Cecotti et al. [34], have detected grape bunches using a convolution neural network. The different segmentation techniques use to segment the two types of grapes that are white and red grape bunches then apply the CNN algorithm it performed 99% accuracy.

Scarlett Liu et al., [35] proposed a grape bunch detection system from the image. The image processing and support-vector machine algorithm is used to count the grape bunches from images, and the overall success rate is 88% for red grape.

André Silva Aguiar et al. [36], proposed detection of the grape bunch in different growing stages using different image-processing and deep-learning models. The dataset has 1929 images with different growth stages of the bunch. The results showed difficulty to detect the bunches in the early and middle growing stage overall 66.96% detection accuracy.

Lucas Mohimon et al. [37], have been compared deep-learning and machine-learning techniques for grape bunches cluster segmentation. In dataset had 200 images of white color grape in normal light condition and reached 86% of accuracy. The results showed that deep-learning techniques are more robust to white color grape bunch detection compared with classic segmentation techniques.

Ashfaqur Rahman et al. [38], presented a sequence of image processing and intelligence process used to find the mature grape bunches. The entire process is divided into 2 steps, the grape bunches images are separated from the background image in the first step, wherein the second step the classify the grape bunch based on the mature group, and overall achieved 96% of accuracy.

Table 1: Related papers on disease detection, quality, and grading on different fruits and vegetables

S. No	Author	Year	Method	Plant	Finding	Results
1	Asmaa Ghazi Alharbi et al., [39]	2020	CNN	Apple	Detected and classified different diseases on apples	Good classification accuracy on 90% on testing images
2	Prasad et al., [40]	2012	SVM	crop	Detected various diseases on different crop	Around 89%
3	Arivazhagan et al., [41]	2013	S.V.M	Different fruits and vegetables like Lemon, Mango Jackfruits Banana Beans, Potato and Tomato	• Late-Scorch • Bacterial and Fungal-Spot diseases • Sun-Burn • Sooty-Mold • Early and Late-Blight • Scorch Ashen-Mold	94.74%

					• Leaf-Lesion	
4	Kiran Gavhale et al., [42]	2014	S.V.M-RBF and S.V.M-POLY	Citrus	Citrus-Canker, Anthracnose	96% and 95%
5	Singh and Mishra [43]	2016	Kmean and GA, SVM with GA	Banana Beans Lime Rose	• Bacterial and Frog-Eye Leaf-Spot • Sun-Burn • Early-Scorch	86.54, 93.63% and 95.71%
6	Jayamoorthy and Palanivel [44]	2017	Spatial Fuzzy C Mean (SFCM), SVM	Plants	Bacterial Blight, Foot Rot	Better accuracy
7	Mokhtar et al., [45]	2015	S.V.M with Cauchy kernel,	Tomato	Powdery-Mildew and Early-Blight	99.5 %.
8	Omrani et al., [46]	2014	SVR-RBF, SVR-POLY, ANN	Apple	Alternaria, Apple Black-Spot, Apple Leaf-Miner	SVR outperforms ANN.
9	Yadav and Verma [47]	2016	BPNN, GA	Tomato	Black-Mold	Improved precision
10	Bhog and Pawar [48]	2016	Neural-Network	Cotton	• Red, White and Yellow-Spot • Alternaria • Cercospora	89.55% accuracy
11	Suresha et al [49]	2017	K.N.N	Plant	Disease's detection	76.59%
12	Hossain et al [50]	2019	K.N.N	Plant	• Alternaria-Alternate, and Anthracnose • Bacterial-Blight • Leaf-Spot • Canker	96.76%
13	Abdhulridha et al., [51]	2019	KNN and MLP	Avacoda	• Laurel-Wilt, hytophthora Root Rot • Iron and Nitrogen-Nutrient Deficiencies	Inaccuracy MLP outperformed KNN
14	Ananthi N [52]	2019	DNN classification	Mango	fungus.	DNN classification is a good way to find out the diseases.
15	Nikhitha M et al., [53]	2019	Inception V3 Model	banana, apple, and cherry	Level of the disease and grades	More than 90% accuracy
16	HongJun Wang et al., [54]	2020	R-CNN	Apple Peach Orange, Pear	Detecting disease spots	Detection accuracy-95% detection speed-2.6. FastR-CNN and SSD algorithms are not superior

17	Mrunmayee Dhakate [55]	2015	ANN	Pomegranate	Detecting Bacterial-Blight, Fruit and Leaf spot.	More than 90% accuracy
18	Dhapitha Nesarajan et al., [56]	2020	SVM CNN	coconut	detection of insect infestation and nutrient shortage in coconut leaves, as well as disease analysis	SVM 93.54%, CNN 93.72% of accuracy
19	Abjirami S. et al., [57]	2019	Neural Network	Fruits	Separate the bacterial and fungal diseases into categories.	Bacterial-92% Fungal-86% of accuracy
20	Bhavini J et al., [58]	2016	Random forest classifier	Apple	Classify the diseases	The diseases are recognized using such a random forest classifier and Feature's level fusion gives better accurate
21	Eduardo Assunção et al., [59]	2020	CNN	Peach	Determine the three types of peach diseases and how to classify the healthy peach fruits.	The suggested model has a Macro-average F1-score of 0.96.
22	Santi Kumari Behera et al., [60]	2018	multi-class SVM with K-means clustering	orange	Classify the different 4 types of disease	90%
23	M. K. Monir Rabby et al., [61]	2018	CED MCED	Apple Orange	Color and shape to detect and classify the fruits	MCED is better than CED
24	B. Doh et al., [62]	2019	K-mean SVM CNN	citrus	Detected and classified diseases using their physical attributes.	CNN gives better accuracy
25	H. Al-Hiary et al., [63]	2012	K-means clustering Multi-class SVM	Apple	detect and classify the examined diseases	Accuracy 93%
26	Bargoti et al., [64]	2017	Faster R-CNN VGG and R-CNN ZF	mangoes, almonds, apples	Fruit detection	R-CNN VGG has given a best performance than R-CNN ZF
27	Ramesh Kestur et al., [65]	2019	Fully convolution al networks	Mango	In RGB photos, mangoes are detected and counted.	The better result with good accuracy
28	Ashwini Awate et al., [66]	2015	ANN	grape, apple, pomegranate	Classification of disease by using colour	Reduces Human efforts and 90% accurate classification.
29	P. Prathusha et al., [67]	2020	SVM, Naive Bayes, KNN	Tomato	Detected 15 various diseases	KNN is a best Machine learning algorithm
30	Harshal Waghmare et al., [68]	2016	multiclass SVM	grape	Major diseases of grapes downy mildew & black rot classified	96.6% of accuracy
31	Liton Jude Rozario et al., [69]	2016	Segmentation using K-mean and modified K-mean	Apple, banana, potato, tomato	Identify faulty areas in a variety of fruits and vegetables.	The Otsu technique performs better than K-means clustering.

			clustering, Otsu method		Examine various segmentation approaches to find the best one.	
32	Santi Kumari Behera et al., [70]	2021	KNN, SVM, Naïve Bayes	papaya	The maturity status using the classification of the machine (LBP, HOG, and GLCM features) and transfer learning approach.	KNN with HOG better perform with accuracy 100%
33	Dor Oppenheim et al., [71]	2019	Deep learning	Potato	Identify and classify the diseases	classification rates more than 90%.
34	Shiv Ram Dubey et al., [72]	2016	K-mean, SUV	Apple	• Apple blotch • rot and scab these diseases to detect and classified.	A combination of features CCV +CLBP + ZM got better accuracy
35	s. Usha [73]	2017	k-means clustering segmentation	Strawberry, brinjal	Present the maturity level	the threshold value for strawberry is 98 brinjal is 70
36	Guoxiang Zeng [74]	2017	CNN	All fruits and vegetables	Create a test database for a fruit and vegetable classification system based on visual saliency and the VGG model.	95.6% accuracy in classification
37	Gouri C. Khadabadi et al., [75]	2015	Probabilistic Neural Network	Carrot	Using various image processing techniques, identify and classify illnesses on carrots.	PNN had good results, with an 80.0 % recognition rate.
38	Santanu Phadikar et al., [76]	2013	extracted by developing novel algorithms	Rice	Classification diseases in rice	provides the best result compared to traditional classifiers.
39	Shiv Ram Dubey et al., [77]	2012	Multi-class Support Vector Machine.	Apple	Find and categorized of different diseases	93% classification accuracy
40	C. Santhosh Kumar et al., [78]	2021	K Means Clustering and SVM.	Tomato	A technique for detecting diseases in vegetables has been developed.	It has a high level of accuracy and takes less time to complete the entire operation.
41	Meenakshi Pawar et al., [79]	2012	SVM	Pomegranate	Pomegranate Fruit Sorting and Grading	Better accuracy
42	Ahmad Loti [80]	2021	SVM, RF, ANN	Chili	quick identification of chili disease	Best accuracy 92.10% with SVM classifier
43	Hafiz Tayyab Rauf et al., [81]	2019	Machine learning algorithms	Citrus	Detection and classification of different diseases	Maintain the database and classify diseases
44	Yao et al., [82]	2009	S.V.M	Rice	Three different diseases detected on rice leaf.	97.2% of accuracy

45	Benjamin Doh et al., [83]	2019	SVM ANN	Citrus	Fruit disease detection based on physical characteristics	SVM achieves a better classification accuracy over ANN
46	Pallavi U. Patil et al., [84]	2020	SVM ANN CNN	Dragon	To determine the grade, consider the shape, size, weight, colour, and diseases.	Both algorithms give a better result.
47	Fouzia Risdin et al., [85]	2020	Deep Convolutional Neural Network	Grape Green apple Lemon Lychee	CNN is utilized as a framework feature. Fruits are divided into categories based on their types, such as grapes, apples, lemons, and so on.	CNN 99.89% accuracy
48	1Sheril Angel. J et al., [86]	2021	CNN	Tomato	To detect and classify diseases on tomatoes, a deep learning algorithm is used.	achieved the accuracy of 97.12%
49	Mohanapriya S et al., [87]	2021	RNN CNN	Apple	RNN is used for the detection and segmentation of diseases. CNN used to identify the diseases	CNN algorithm shows better accuracy
50	Malathy S. et al., [88]	2021	CNN	Apple	Deep learning is used to identify and detect the diseased part in apple	97% overall result
51	Marani et al., [89]	2021	Deep Neural Network	Grape bunch	Segmentation accuracy and IoU method are used to segment images over four different deep Neural-Networks to find the bunches.	VGG19 accuracy 80% IoU 45% of accuracy

The following are the few major image processing and machine learning algorithms used by the authors in recent years.

Table 2: Image Processing and ML algorithms used in different task

Task	Techniques
Image Pre-processing	• Brightness correction • Gray scale transformation
Image Segmentation	• Thresholding methods • K-Means clustering
Feature Extraction	• Histogram thresholding • Edge detection approach • Fuzzy approach • Neural network approach
Disease Detection	• K-Means • Otsu method
Disease Classification	• CNN • Random Forest • Deep Neural Network • KNN • Decision Tree • SVM

5. PRESENT STATUS :

At present, there are not many research activities done on arecanut disease detection, disease classification, and early detection. The existing algorithms are used to identify the arecanut diseases but with less accuracy and much research has given the focus on checking the quality of the raw arecanut and classifying the arecanut based on the quality, size, color, etc.

If identified in the early stage, farmers can take preventive measures. Till date, no algorithms developed and no existing algorithms on the early detection of arecanut diseases. It's very useful for farmers to stop the spreading of other bunches and other arecanut trees and take precautionary measures. There are several illnesses that affect arecanuts, but the most common one appears during the rainy season and spreads rapidly across the crop. The following table gives the descriptions of different types of diseases in arecanut [90][91].

Table 3: Different types of diseases in arecanut [92].

Arecanut Image	Type of Diseases	Description
	Fruit-rot/ Koleroga/ Mahali	The disease is caused by Phytophthora meadii [93]. During the south-west monsoon, fruits rot and shed heavily (June-September). The disease is widespread in occurrence in all arecanut growing tracts. The crop losses due to this disease vary from 10-90 percent depending on the weather conditions [94]. Dark brown water-soaked lesions are formed near the perianth end and spread gradually covering the entire surface of the fruit and finally shed. Infected nuts had a discoloured kernel, a reduced weight, and a big vacuole. At the end of the monsoon, the fruits dry up, remain mummified without shedding [95][96].
	Nut splitting	The first indicator is an early yellow color of the nuts when its half to three quarters mature. This is followed by nut splitting on both sides. The splitting of arecanut was decreased drastically due to the application of boron as borax in the soil as well as through the fortified boronated KAB along with NPK fertilizers [97].
	Dot diseases	The arecanut has a black color dot which decreases the quality of the nut

	Kempu roga	The arecanut color becomes red but it's not perfectly matured which is decrease the quality of the nut.

Table 4: Healthy and unhealthy arecanut.

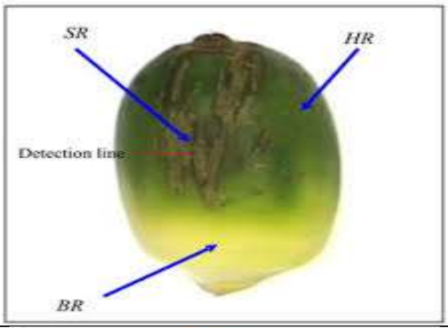
Image	Healthy/Unhealthy	Description
	Healthy	This is a healthy arecanut because nut becomes dark green color. There is no yellow color surface and black and white dots
	Unhealthy	It is an unhealthy arecanut because initial stage manifest as dark green or yellowish water-soaked lesions near the perianth on the nut surface. The nut turns a yellowish colour and has a black surface [98].
	Unhealthy	It is an unhealthy arecanut, on the whole surface of the nuts, a white, black, and brown mycelial mass envelope them.

Table 5: Healthy and unhealthy arecanut bunches

Image	Healthy/Unhealthy	Description
	Healthy bunch	This is a healthy arecanut bunch. There is no yellow, black, brown color dot or surfaces.
	Healthy bunch	This is a healthy arecanut bunch ready to cultivate. There is no black or brown color dot or surfaces

	Unhealthy Bunch	In the discoloured patches, the fungus' fruiting bodies (conidia) appear as concentric rings. The disease is more severe when the weather is dry.
	Unhealthy Bunch	The name of the disease is dry-mahali. When nuts become infected, they begin to rot and dry out without shedding. [99].

6. RESEARCH GAPS AND PROPOSAL :

After the literature survey, it is observed that the current methodology, models, and publications appear to be lagging in addressing the benefits and challenges of the agriculture area. There is a very insignificant amount of study on the application of technology in the arecanut field. This survey identifies the following research gaps and suggests the solution.

- **Research Gap 1:** To detect the arecanuts from the arecanut bunch.
- **Research Gap 2:** To detect and identify the diseases in arecanut.
- **Research Gap 3:** classify the different types of diseases on arecanut.
- **Research Gap 4:** Checking the quality of arecanut
- The proposed method can be implemented with SVM, random forests, boosting, fuzzy logic and results can be compared.
- The method has to be enhanced so that it can efficiently classify plants with different types of diseases.
- The percentage of destruction (diseases portion in the plants) can be displayed

7. RESEARCH AGENDAS :

1. Which image processing technology is used to pre-process image?
2. How do the segmentation methods to given images using image processing techniques?
3. How to use the feature extraction method to image set?
4. What object detection algorithms can be proposed to find the arecanut from the arecanut bunch?
5. Which machine learning technology platform or algorithms can be used to identify or detect the diseases on arecanut?
6. To find the best machine learning algorithm to detect or identify the diseases in arecanut with good accuracy.
7. What machine learning classification algorithms can be proposed to classify the different types of diseases in arecanut?

8. LIMITATIONS OF THE PROPOSAL :

This proposal is only limited to arecanut crop diseases. A similar kind of proposal can be developed for any other crop like coconut or any vegetables or fruits. This proposal only concentrates on arecanut diseases like Kole roga, kempu roga, dot diseases, nut split, etc. A similar kind of disease spreads in arecanut leaf, root, stem, etc. This proposal provides information like whether arecanuts are healthy or unhealthy but never give any solution for diseases and also never predict the diseases.

9. SWOC ANALYSIS :

SWOC analysis is primarily concerned with exploring strengths, limitations, opportunities, and challenges in a systematic manner. The SWOC analysis conducted on the research proposal yielded the following results [100][101][102][103].

Table 6: SWOC Analysis

Strengths	**Weaknesses**
• Quality product • Use of indigenous technology • Low cost • Controlled diseases spread • Data availability	• Low yield • Prediction of diseases. • Difficult to analyze unstructured data • Lack of quality contents
Opportunities	**Challenges**
• Technical Advancements • Increasing market demand • Growing purchase power of consumers • Growing environmental concern	• Control of pest and disease incidence • Climate change • Risk & uncertainty of marketing • Yield reduction

10. CONCLUSION :

In India, the arecanut is a commercial crop. Many of the farmers of the coastal district Dakshina Kannada, Udupi, Uttara Kannada, malenadu region Shivamoga, Chikmagalur, Davanagere cultivates arecanut, especially for the commercial purpose. Nowadays one of the highest demands and the highest rate of the crop is arecanut. Because of the high rate, almost all Uttara Karnataka and Mysore region farmers also showed interest in arecanut. The arecanut has many diseases because of chemical fertilizer, spraying chemical liquid, climate changes like heavy rain, variation of temperature. The farmers lose the product because of unpredictable diseases. The farmers Spray the arecanut bunches with Bordeaux mixture every year before the monsoon followed by every 40 days, this method follows all farmers for many years. If the farmers know which kind of the diseases and whether the bunch is infected or not before monsoon followed by another spray will be effective in preventing the disease, Covering the bunches with polythene bags is one more method of control. Our goal is to educate the farmers by giving technology touch to find and classify the diseases in arecanut. Our research work concentrates on implementing a system using machine learning and image processing to educate the farmers on different kinds of diseases on arecanut and detecting the diseases inorder to reduce the farmer's work and increase the revenue of the farmer. The proposed model also concentrates on early detection of diseases on arecanut so farmers could be avoided spray in monsoon time. There is a lot of scope for research to understand and find out an effective and reliable subset of technologies contributing to agriculture.

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