JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

CLASSIFICATION AND DECTECTION OF DISEASES OF ARECA NUT AND LEAF USING MACHINE LEARNING

Prajwal Annasab Chougale
UG Student, Dept.of IS Engg.
Sir M. Visvesvaraya Institute ofTechnology, Visvesvaraya Technological University, Bengaluru, India

Ashok Ammanagi
UG Student, Dept. of IS Engg., Sir M. Visvesvaraya Institute of Technology, Visvesvaraya Technological University, Bengaluru, India

Mohammed Tayyab Hussain
UG Student, Dept. of ISEngg., Sir M. Visvesvaraya Institute ofTechnology, Visvesvaraya TechnologicalUniversity, Bengaluru, India

Avinash K
UG Student, Dept. of IS Engg.Sir M. Visvesvaraya Institute ofTechnology, Visvesvaraya TechnologicalUniversity, Bengaluru, India

Byregowda B K
Associate Professor, Dept. of IS Engg. Sir M. Visvesvaraya Institute ofTechnology, Visvesvaraya TechnologicalUniversity, Bengaluru, India

***Abstract* - Arecanut, sometimes referred to as betel nut, is a tropical crop. India is the world's second-largest producer and consumer of arecanuts. It is afflicted by a number of illnesses from root to fruit throughout its life cycle. The only method used to identify illnesses at the moment is visual inspection, and farmers must periodically examine each crop carefully to look for infections. In this study, we suggested a system that, with the use of convolutional neural networks, aids in identifying arecanut disorders and offers possible treatments. An image is used as the input for a convolutional neural network (CNN), which then gives different objects in the image learnable weights and biases. 888 photos of healthy and ill arecanuts were used to generate our own dataset. The ratio between the train and test data is 80:20. Categorical cross-entropy is employed as the loss function for model construction, with Adam serving as the optimizer function and accuracy serving as the metrics. The model is trained over the course of 50 epochs in order to maximize validation and test accuracy while minimizing loss. The proposed method identified the arecanut illness with an accuracy rate of 88.46% and was shown to be effective.**

***Keywords* – Arecanut, artificial intelligence, and convolutional neural networks.**

I. INTRODUCTION

Precision Agriculture is typically defined as a homestead administration framework based on information and innovation that manages spatial and frequent change inner fields for ideal effectiveness and efficiency, supportability, and confirmation of the land resource by limiting the introduction costs. We must govern horticulture administration to ensure the best, most fiscally feasible upkeep of feature property, such as water, air, and soil, as a result of the general population's growing ecological awareness. The key problem with the use of machine learning algorithms is that the most crucial tasks in this job are picture segmentation, feature extraction, and classification.

In India's economy, arecanuts play a key part in precision agriculture. One of India's most important industrial plants is the arecanut. India is the global leader in arecanut production, accounting for at least half of global output. The importance of arecanuts to human survival cannot be overstated. Arecanut is a traditional ayurvedic medicine that is used to treat various skin conditions as well as leukoderma, leprosy, cough, fits, worm's anaemia, and obesity. Dry nuts are produced from freshly-picked fruit. It is utilized by people all around the world. The primary industry in India is agriculture. The second-largest producer of agricultural goods in the world is India. Agriculture is the mainstay of the economy in emerging nations like India. In India, a wide variety of crops are raised by farmers. Numerous elements, including the climate, the soil, disease, and others, have an impact on crop development. Currently, plant diseases are only discovered through observation with the naked eye, and farmers must periodically examine each crop carefully in order to find any diseases. This is a very difficult task that takes a lot of time and manpower, and it also necessitates expensive equipment, well-equipped labs, and more manpower. Early disease detection and disease prevention are not currently possible. Consequently, a system for automatically detecting diseases is required. The production of arecanuts in India, which is the largest producer with a total area under cultivation of around 3.3 lakh tones. Karnataka and Kerala contribute for roughly 72% of the entire production on 2.64 lakh hectares.

Mahali Disease (Koleroga), Bud Rot Disease, Stem Bleeding, Yellow Leaf spot, and Yellow Disease, which affect areca trees frequently and are brought on by constant rainfall and climatic changes, must be controlled in the early stages of infection in order to avoid difficult control in the later stages and potential loss to the We can prevent this by using machine learning to identify illness and offer treatments. Look for a spot on the infected nut, leaves, or trunk to identify the arecanut disease. We employ machine learning, more especially convolution neural networks, to identify illnesses. We will identify the ailments Stem Bleeding, Yellow Leaf Spot, and Mahali Disease (Koleroga) in this study and offer remedies for the diseases found.

Fig 1.1 Stem Bleeding

Fig 1.2 Koleroga

Fig 1.3 Healthy Leaf

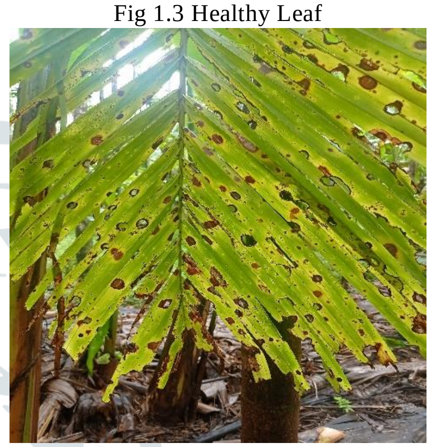

Fig 1.4 YellowLeaf Spot

Areca Nut: A kind of palm tree called an areca catechu (areca nut) tree is planted in several Asian countries, including Taiwan, Malaysia, and India. (Preeti Jaiswal, 2011) Countries are valued for their economically significant seed crop. Early Christian medicinal texts in India extensively discussed the use of arecanuts, and later Hindu and Buddhist writings followed suit. Areca nut has been mentioned as a medicinal treatment for leukoderma, leprosy, anaemia, and de-worming characteristics in Indian writings such as Vaghbhata (4th century) and Bhavamista (13th century). In India, areca nuts are used for religious, social, and cultural purposes. Its inclusion in the ceremonial plate is essential since it is said to bring about greater prosperity (Senthil Amudhan et al., 2012).

Mahali Disease (Koleroga): Phytophthora meadii is the disease's culprit. All arecanut growing regions experience a high prevalence of the disease. Depending on the season, this disease causes crop losses that range from 10 to 90 percent. On the nut surface, close to the penanth end, water-soaked sores are the first visible signs. In Fruit and the axis of the inflorescence are also impacted in extreme situations. Usually, compared to other arecanuts, the sick nuts will weigh less.

Stem Bleeding: Palms between the ages of 10-15 are more vulnerable to stem bleeding. On the base of the stem, symptoms take the form of small, discolored depressions. Later, these spots combine and fissures form on the stem, which causes the fibrous tissues inside to disintegrate. An oozy brown exudate emerges from these fissures as the illness worsens. A high-water table makes the palm more susceptible to this illness. Thielaviopsis paradoxa is a fungus linked to this illness.

Yellow Leafspot: The South West monsoon season is when yellow leaf spot is at its worst. Young palms that are under ten years old are more vulnerable. Typically, only 3–4 lower whorl leaves are infected. Small brown to dark brown or black round spots are the first signs to appear. They come in different sizes, have a yellow halo surrounding them, and, as they progress, form blighted regions. In extreme cases, the infection results in leaf loss, drying, and drooping. The pathogens causing this illness include Colletotrichum gloeosporioides and Phyllosticta are the pathogens involved in this disease.

with the used of practical requisitions, due to the images are apprehended at once directly from the farmland without plenty efforts wanted through the farmers. The system approach will give advice to the farmer with minimum efforts. The farmer most effective require to seize the image of the plant leaf the usage of mobile camera and forward it to the DSS, without any additional inputs.

II. RELATED WORK

Srdjan Sladojevic et al,2016 [4], There are many methods in automated or computer vision plant disease detection and classification process, but still, this research field is lacking. In addition, there are still no commercial solutions on the market, except those dealing with plant species recognition based on the leaves images. In this paper, a new approach of using deep learning method was explored in order to automatically classify and detect plant diseases from leaf images. The developed model was able to detect leaf presence and distinguish between healthy leaves and 13 different diseases, which can be visually in this proposed work classification of Healthy and Diseases arecanut is carried out. In this method, segmentation of arecanut using existing method such as structured matrix decomposition (SMD) method. LBP features are extracted features from both training and testing samples. Using SVM classifier for the classification and obtained success rate 98%
of accuracy.

Muhammad Dedi Irawan et al, 2020 [3], The study has been implemented a forward chain-based expert system. The result showed the inference engine has been successfully predict a disease, starting from the fact symptoms of areca nut collection and the areca nut disease prediction. Therefore, a solution for handling the disease can be taken which can become beneficial information to farmers for which the farmers can take good care of areca plants. This system is also useful for the Asahan Regency Agriculture Office in socializing how to properly care for areca plants by showing symptoms of the disease. So that not only the data of areca planters is high, but the areca nut production can also be balanced.

Narendra Nath Singh et al,2016 [2], each individual/ phenomenon has two aspects – Good & Bad. In this paper they have dedicated ample amount of time in explaining the deleterious effects of Areca nut. Time has come to explore the other aspects of Areca nut. Areca nut seed biochemical compounds have been recently recognized as functionally active molecules, possessing antioxidant, antidiabetic, antiallergic and other useful properties, as well as exert protective effects against cardiovascular and other diseases. Further studies are required to know the underlying mechanisms and type of biochemical compounds involved in this beneficial effect and to ensure these studies, it would enable for utilization in modern world.

K. A. Garrett et al,2006 [8], Since climate change effects are challenging to study but of potentially great importance, the topic has been reviewed and recommendations put forward almost as frequently as climate change effects have been studied empirically. Thus, a number of authors have supplied recommendations for needed research and syntheses. One broad recommendation would be an increased focus on how a changing environment affects evolution. What pathogen characteristics, such as frequency of generations and proportion of sexual reproduction, affect the rate of adaptation? What host characteristics, such as life span, affect rates of adaptation in both host populations and pathogen populations? Are invasive plant species better able to adapt to climate change and move to new areas rapidly, leaving pathogens behind or at least limiting their evolutionary options through bottlenecks.

Chaitali G. Dhaware et al, 2017 [6], A method focus on image processing is applied for automatic leaf unhealthiness classification which establish on leaf image processing. The project system can apply

Raman Ramesh et al, 2013 [9], The severity, persistence and spread of fruit rot are related to the pattern of rain. The disease appears usually 15 to 20 days after the onset of regular monsoon rains and may continue up to the end of the rainy season. Continuous heavy rainfall coupled with low temperature (20 to 23 °C), high relative humidity (>90%) and intermittent rain and sunshine hours favor the occurrence of fruit rot. Disease spread is through heavy wind and rain splashes. The fruit bunches infected towards the end of rainy season may remain mummified on the palm and such nuts provide inoculums for bud rot or crown rot or the recurrence of fruit rot in the next season.

Sanket Jayesh Muchhala et al,2021 [10], The methodology section lays out the study's strategy and methods. The research's universe, sample, data and sources of data, study variables, and analytical approach are all included. Following are the specifics. They researched on models using other research papers and other projects on GitHub and other websites for selection of algorithms and concluded to decide 3 algorithms for model. Decision tree classifier, Naïve Bayes algorithm and Random Forest algorithm. Comparing the accuracy between random forest, naïve bayes and decision tree algorithm. They conclude that random forest has the highest accuracy as compared to the other 2 algorithms. But for project all 3 models are combined to give the best accuracy output.

Shuhan Lei et al,2021 [7], UAV multispectral remote sensing has been widely applied in agriculture, forestry, resources, ecology, environmental protection, and various other fields. This study used the UAV multisource remote sensing data to achieve a novel quantitative expression of the severity of the yellow leaf disease of arecanut, and analyzed the correlation between the LVV of areca and the severity of the yellow leaf disease of arecanut. Despite the precise, refined, and intelligent monitoring of the yellow leaf disease of arecanut achieved by this study, the accuracy of the areca crown edge extraction, the LVV measurement accuracy of areca, and the measurement of the areca crown yellowing area accuracy must still be improved. Therefore, in terms of hardware, the hyperspectral sensors must be combined with 3D laser radar in future research applications, and more deep learning algorithms must be integrated. Additionally, this study further proves that UAV multispectral remote sensing presents considerable application potential in vegetation growth monitoring, identification of the existing problems, fine classification and ground object identification, pest and disease monitoring, biomass and yield estimation, and so on. This study can be considered as the basis for the development of relevant research.

Martina Machová et al,2021 [12], The areca nut is the fourth most used drug in the world, so it is very beneficial to know what compounds are found inside. The compounds of the areca nut were extracted in two different ways, concretely using HS-SPME and SHDE. A total of three samples (distillation residue, hydrolat, and SHDE extract) were obtained by SHDE. These extracts were separated and identified by GC-MS. The obtained spectra were compared with a library of reference MS spectra, and to confirm the correctness of the identification, the obtained retention indices were compared with the reference retention indices. During all our experiments, we identified in total 98 volatile compounds. The main groups of identified substances were alkanes, alcohols, aldehydes, esters, fatty acids, ketones, and terpenes. Furthermore, arecoline, the main alkaloid of areca nuts, was found. The extracts obtained using SHDE were tested for their antibacterial activity.

III. METHODOLOGY

The System design mainly consists of:

A. Image Collection

B. Image Preprocessing

C.CNN Model

D. Training

E. Classification

A. Image Collection

The dataset that we have used in this project is collected by ourselves. The data is divided into 2 datasets, that is, training and test. The training set is used to train the model and the test set is used to evaluate the final performance of the trained model on unseen data.

The dataset consists of images like healthy leaf, healthy trunk, and the images of infected arecanut (disease like Koleroga, nut split, steam bleeding and yellow leaf spot). DSLR camera photos were captured at a distance of half a meter from the source. These images were shot with the assistance of knowledgeable arecanut growers and researchers. The total datasets are consisting of 888 images in which 200 are healthy trunk, 92 are Koleroga, 101 nut shell, 247 steam bleeding and 278 yellowleaf spot.

B. Image Preprocessing

The goal of pre-processing is an improvement of image data that reduces unwanted distortions and enhances some image features important for further image processing. Preprocessing of the database entails resizing, reshaping, and array conversion. Similar processing is likewise applied to the test image. Before training the CNN model, images are reduced to 256*256 resolution and converted to an array. Image pre-processing involves three main things:

1. Grayscale conversion: Only brightness information is contained in a grayscale image. In a grayscale picture, each pixel value represents a certain amount or quantity of light. In grayscale images, the brightness graduation can be distinguished. Only light intensity is measured in a grayscale image. The brightness of the 8-bit picture will range from 0 to 255, where 0 denotes black and 255 denotes white. A colour image is turned into a grayscale image during the grayscale conversion process. Compared to coloured photographs, grayscale images are simpler and quicker to process. Grayscale pictures are used to apply all image processing algorithms.

2. Image to Array Conversion: for image processing, machine learning, computer vision, and real-time operation, all of which are crucial in the systems of today. Using it, one can analyses pictures and videos to find faces, objects. Python is able to handle the OpenCV array structure for analysis when it is combined with other libraries, such as NumPy. We can transform these photos to an array using NumPy. Each pixel's RGB value, which ranges from 0 to 256, is contained in the array.

Image Enhancement: The objective Image processing is done with the intention of making elements of interest more visible. Here, colour enhancement is used to produce results of higher quality. Colour enhancement is the process of changing an image's colours to make them more vivid, harmonious, or realistic. It may be used to fix any colour issues or issues with an image. Enhancing colour is crucial since it might It can be helpful for fixing colour issues in an image and can make it simpler to view the image's details and characteristics.

C. CNN Model

A CNN is a type of Deep neural network (DNN) consisting of multiple hidden layers such as convolutional layer. A deep learning neural network called a convolutional neural network, or CNN, is made for processing organized arrays of input, like photographs. Widespread in computer vision, convolutional neural networks are the cutting edge for many visual applications like image classification. A feed-forward neural network with up to 20 or 30 layers is known as a convolutional neural network. The convolutional layer is a unique type of layer that gives convolutional neural networks its strength.

Convolutional layers, pooling layers, and fully linked layers are the fundamental components of a CNN. Each of these parts is as follows:

1. **Convolutional Layers**: The core of CNNs are convolutional operations. An input image is subjected to a convolutional layer, which employs a number of filters or kernels to perform element-wise multiplication and summing in order to create a feature map. Each filter recognizes particular motifs or characteristics in the input. The filters in the network develop their ability to recognize various visual patterns as it trains, starting with basic edges and textures and progressing to more intricate forms and structures.
2. **Pooling Layers**: By using pooling layers, the spatial dimensions of the feature maps that the convolutional layers output are reduced. They support the management of overfitting and the reduction of computational complexity. Max pooling is a popular pooling technique that, by effectively sampling the input, chooses the maximum value from a limited neighborhood in each feature map.
3. **Fully Connected Layers**: In a fully connected layer, which is a standard neural network layer, every neuron is linked to every neuron in the layer above it and every layer below it. These layers are often included in the CNN after the final classification or regression task has been completed. They translate the high-level characteristics discovered by the convolutional and pooling layers to the intended output.

Convolutional and pooling levels are often followed by one or more fully linked layers in the design of a CNN. From the input images, the convolutional layers extract hierarchical characteristics, which the fully connected layers then process for the final prediction.

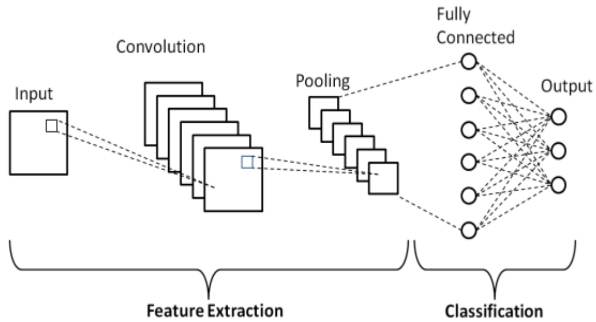

Fig.3.1: Simple Convolution NN model

D. Training

The preprocessed and feature-extracted dataset must be used to train the deep learning model, and a separate testing dataset must be used to evaluate its performance. The model needs to be taught to recognize the various patterns and features related to Areca Nut disease.

The Model is trained and tested with 888 photos, including both healthy and sick images. Due to the little dataset, we employed the augmentation technique, which rotates, shifts, zooms, and flips the image to produce new data for training.

In our proposed system consists of several layers, including Dropout, Convolution2D, Activation, Dense, MaxPooling2D, and Flatten. These layers play crucial roles in capturing features, reducing dimensions, and making predictions. The Conv2D layers in the model's architecture perform convolutional operations on the input image to extract features using a predetermined number of filters (neurons). There are 1000 filters in the first Conv2D layer, 500 filters in the second Conv2D layer, and 250 filters in the third Conv2D layer. The complexity and richness of the features that are recorded are determined by the quantity of filters.

The ReLU (Rectified Linear Unit) activation function, which promotes non-linearity and aids the model in learning complex correlations between the collected features, is applied by the Activation layer after each Conv2D layer. Down sampling is used by MaxPooling2D layers to shrink the feature maps' spatial dimensions while preserving crucial data. The pool size for the MaxPooling2D layers is 2x2, which cuts the width and height in half. a dense layer connects every neuron in one layer to every neuron in the one above it. An adjustable hyperparameter that can be changed during model training is the number of neurons in each layer.

A CNN layer called MaxPooling2D decreases the spatial dimensionality of the feature maps by choosing the highest value contained within a specific window size. By doing so, the model's parameter count is decreased and overfitting is avoided. Feature maps are flattened into a 1D vector by the CNN layer called "Flatten," which is then input into a fully connected layer for classification.

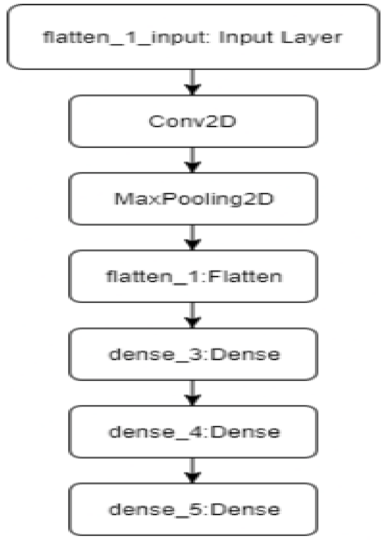

Fig 3.2: Basic Structure of Train Model

Finally, the softmax activation function is utilized in the last dense layer. Each class is given a probability by Softmax, reflecting the chance that the input belongs to that class. In multi-class classification jobs, it is frequently employed.

We employed 1000 neurons in the first layer, 500 in the second, 250 in the third, and 5 in the final dense layer when training the model using CNN. ReLU and softmax are the activation functions utilized in the first three levels and the final layer, respectively. The weights and biases are calculated together with a total of 248,655,647 parameters. The final has a softmax activation function that indicates the likelihood that an illness will be discovered.

Layer (type)	Output Shape	Param #
Conv2D_1 (Conv2D)	(None, width, height, 1000)	10000
Activation_1 (Activation)	(None, width, height, 1000)	0
MaxPooling2D_1 (MaxPooling2D)	(None, width/2, height/2, 1000)	0
Conv2D_2 (Conv2D)	(None, width/2, height/2, 500)	4500500
Activation_2 (Activation)	(None, width/2, height/2, 500)	0
MaxPooling2D_2 (MaxPooling2D)	(None, width/4, height/4, 500)	0
Conv2D_3 (Conv2D)	(None, width/4, height/4, 250)	1125250
Activation_3 (Activation)	(None, width/4, height/4, 250)	0
MaxPooling2D_3 (MaxPooling2D)	(None, width/8, height/8, 250)	0
Flatten_1 (Flatten)	(None, width/8 * height/8 * 250)	0
Dense_1 (Dense)	(None, 1000)	2505000
Activation_4 (Activation)	(None, 1000)	0
Dense_2 (Dense)	(None, 500)	500500
Activation_5 (Activation)	(None, 500)	0
Dense_3 (Dense)	(None, 250)	125250
Activation_6 (Activation)	(None, 250)	0
Dense_4 (Dense)	(None, 5)	1255
Activation_7 (Activation)	(None, 5)	0

Total params: 6,834,755
Trainable params: 6,834,755
Non-trainable params: 0

Fig 3.3 Detailed Layered Structure

E. Classification

Classify the health state of new arecanut plant photos using the learned model. The input image is first processed, then it is run through the trained model to determine the predicted class (healthy or diseased). Obtain the corresponding remedy information from the dataset and output it if the plant is identified as being unhealthy. You can offer the appropriate remedy or treatment information once the model has accurately identified a diseased arecanut plant. During preprocessing, this data should be kept in the same location as the labelled dataset. Each disease class can be linked to a specific treatment, which can then be shown or output when the model detects a sick plant.

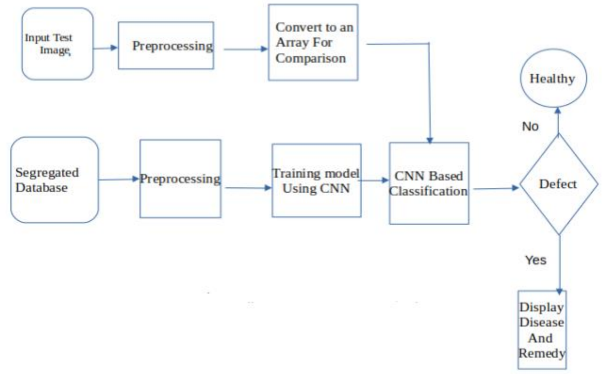

Fig 3.4. Flowchart for classification of healthy Arecanut

IV. RESULTS

Figure 4.1 illustrates the test accuracy that was observed following model training, which was 89.65%. The model trained using CNN received the leaf picture as input, as seen in Figure 4.2. The trained model recognizes illnesses in arecanuts leaf and prints the likelihood of the detected illness, as seen in Figure 4.3 with the accuracy of 95.94%. Additionally, the treatment for the condition with the highest probability is displayed for user reference.

```
print("[INFO] Calculating model accuracy")
scores = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {scores[1]*100}")

[INFO] Calculating model accuracy
8/8 [==============================] - 0s 38ms/step - loss: 0.1190 - accuracy: 0.8966
Test Accuracy: 89.65517282485962
```

Fig 4.1

Fig 4.2

Areca	Probability Score
Healthy Leaf	
Healthy Nut	0.14
Healthy Trunk	0.2
Mahali/Koleroga	0.1
Stem bleeding	1.21
Yellow disease	95.94

Fig 4.3

V. CONCLUSION

This study employs convolutional neural networks to identify disease in the stem, leaves, and arecanut early. 888 photos of healthy and sick arecanuts are used in the experimentation. Preprocessing the input picture comes first, then feature extraction, training, and classification. The suggested System gives treatments for arecanut ailments such Mahali, Stem Bleeding, and Yellow Leaf Spot. The experimental findings demonstrate a range of illness detection accuracy depending on the input image quality and disease stage. The system's total accuracy is predicted to be 88.46%. By enabling farmers to take the required preventative and corrective action on their arecanut crop, this technology moves in the direction of encouraging farmers to practice smart farming and helping them to make better yield decisions.

VI. REFERENCES

[1] Martina Machová, Tomáš Bajer, David Šilha, Karel Ventura and Petra Bajerová, "Volatiles Composition and Antimicrobial Activities of Areca Nut Extracts Obtained by Simultaneous Distillation–Extraction and Headspace Solid-Phase Microextraction," Published: 7 December

2021 at Molecules.

[2] Narendra Nath Singh, Naheela Rasheed and Abdul Rasheed Ansari, "ETIOPATHOGENESIS OF OSMF VERSUS BENEFICIAL EFFECTS OF ARECA NUT: A REVIEW," International Journal of Current Research Published online 30th October, 2016.

[3] Muhammad Dedi Irawan, Helmi Fauzi Siregar, Muhammad Yasin Simargolang, Tika Liana, "Expert System for Areca Plant Disease Detection Using Forward Chaining Method," Published: 25 September 2020, Journal Penelitian Ilmu computer, System Embedded & Logic.

[4] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, and Darko Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," Published 29 May 2016 at Hindawi Publishing Corporation Computational Intelligence and Neuroscience.

[5] Edurado Assuncao, Pedro Dinis gaspar, Hugo Proenca," Decision-making support system for fruit diseases classification using Deep Learning", Published on November 2020 International Conference on Decision Aid Sciences and Application (DASA).

[6] Chaitali G. Dhaware, Mrs. K.H. Wanjale, "A Modern Approach for Plant Leaf Disease Classification Which Depends on Leaf Image Processing", 2017 International Conference on Computer Communication and Informatics (ICCCI -2017), Jan. 05 – 07, 2017, Coimbatore, INDIA.

[7] Shuhan Lei, Jianbiao Luo, Xiaojun Tao and Zixuan Qiu, "Remote Sensing Detecting of Yellow Leaf Disease of Arecanut Based on UAV Multisource Sensors", Published: 13 November 2021 at Remote Sens.

[8] K. A. Garrett, S. P. Dendy, E. E. Frank, M. N. Rouse, and S. E. Travers, "Climate Change Effects on Plant Disease: Genomes to Ecosystems", Published by Boston University on 09/08/13.

[9] Raman Ramesh, Maruthadurai Ramasamy, N. P. Singh, "Management of fruit rot (Koleroga/ Mahali) disease of arecanut", Technical Report Published by Research gate on January 2013.

[10] Sanket Jayesh Muchhala, Hardik Sodhani, "Disease Prediction using ML", Conference Paper Published by research gate on November 2021.

[11] Anandhakrishnan MG Joel Hanson, Annette Joy, Jeri Francis, Plant Leaf Disease Detection using Deep Learning and Convolutional Neural Network, International Journal of Engineering Science and Computing, Volume 7, Issue No.3, March 2017.

[12] Manisha Bhange, H.A. Hingoliwala, Smart Farming: Pomegranate Disease Detection Using Image Processing, Procedia Computer Science, Volume 58,2015, Pages 280-288, ISSN 1877-0509.

[13] Swathy Ann Sam, Siya Elizebeth Varghese, Pooja Murali, Sonu Joseph John, Dr. Anju Pratap. Time saving malady expert system in plant leaf using CNN, 2020, Volume 13, Issue No 3.

[14] A. Gavhane, G. Kokkula, I. Pandya, and K. Devadkar, "Prediction of heart disease using machine learning," in 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA), 2018, pp. 1275–1278.

[15] Y. Hasija, N. Garg, and S. Sourav, "Automated detection of dermatological disorders through image-processing and machine learning," in 2017 International Conference on Intelligent Sustainable Systems (ICISS),2017, pp. 1047–1051.

[16] S. Uddin, A. Khan, M. E. Hossain, and M. A. Moni, "Comparing different supervised machine learning algorithms for disease prediction" BMC Medical Informatics and Decision Making, vol. 19, no. 1, pp. 1–16, 2019.

[17] R. Katarya and P. Srinivas, "Predicting heart disease at early stages using machine learning: A survey," in 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 302–305.

[18] F. Q. Yuan, "Critical issues of applying machine learning to condition monitoring for failure diagnosis," in 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM),2016, pp. 1903–19