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Classification of Costal Area Diseases of Arecanut using Dual Convolutional Neural Network

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Abstract - This study presents an automated approach for the detection and classification of coastal area arecanut diseases using Dual Convolutional Neural Networks (DCNNs). A custom dataset consisting of 1,000 images, captured under expert supervision from Navilgon village in Honnavara taluk, Karnataka. This was developed to represent four classes like Healthy, Rot, Split, and Rot+Split. All these images were preprocessed by resizing them to 128×128 pixels and converted into numerical arrays to facilitate model training. The proposed DCNN model incorporates double convolutional blocks, batch normalization, dropout, and max-pooling layers to efficiently extract and learn both lower-level and upper-level features. The architecture culminates in a softmax-activated dense layer to classify the input images into one of the four disease classes. The dataset was split in an 80:20 ratio for training and testing, and the model was trained using the ReLU activation function, Adam optimizer, and categorical cross-entropy as the loss function. Confusion matrix shows Healthy and Rot classes have the highest accuracy of 80%. Similarly Split and Rot + Split are slightly lower accuracy of 65%.

Key Words: arecanut, agriculture, healthy, diseases,entropy

1. INTRODUCTION

Arecanut cultivation in coastal areas, such as the Uttara Kannada, Dakshina Kannada, and Udupi districts of Karnataka, is vulnerable to a variety of diseases due to the humid, tropical monsoon climate. These conditions create an ideal environment for fungal and bacterial pathogens. India is the world's second-largest producer of agricultural crops. In emerging countries like India, the economy primarily depends on agriculture. Farmers in India cultivate a diverse range of crops. Crop expansion is predisposed by a variety of features such as climatic environments, soil conditions, illness, and so on. The present approach for identifying plant diseases is simply reflection with the bare eye and farmers have to carefully analyze each and every crop periodically to detect diseases, which is an extremely challenging and time-consuming task and which requires more manpower, adequately equipped laboratories and costly instruments and it's not possible for early detection of the diseases and avoid spreading of disease. Hence, there is a need for an automatic disease detection system.

Koleroga, also known as Fruit Rot of Arecanut, is one of the most serious and widespread fungal diseases affecting arecanut plantations, particularly in the coastal and Malnad regions of Karnataka. It is caused by the pathogen *Phytophthora arecae*, which thrives in the wet and humid conditions typical of the monsoon season. The disease primarily attacks the immature nuts, leading to significant yield losses if not detected and treated early. The initial symptoms of Koleroga appear as small, water-soaked brown spots on tender arecanut fruits. It is also called Rot disease. As the infection progresses, these lesions enlarge, eventually covering the entire surface of the nut. Infected nuts become blackened, soft, and are often shed prematurely. During prolonged periods of high humidity, a whitish fungal growth may also be observed on the affected surface, indicating advanced stages of the disease.

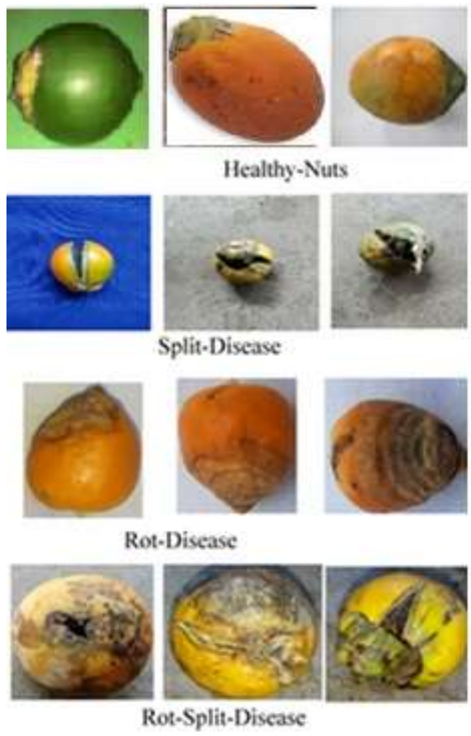

Fig -1: Arecanut image dataset samples

India is the highest producer of arecanut with a production of around 3.3lakh tones and a total acreage under cultivation of 2.64lakh hectares, with Karnataka and Kerala accounting for nearly 72 per cent of the total production. Commonly found diseases in areca tree are Split, Split Rot, Rot, (Koleroga), which occurs due to continuous rainfall and climatic changes, these diseases must be controlled in the primary stage of infection otherwise it may cause difficult to control in the final stage which may lead to loss to the farmer. To avoid this, we can use deep learning to detect disease and suggest remedies to it. Deep Learning specifically Convolution Neural Networks is the method we're using to detect the diseases. In this work we are going to identify healthy, Split, Split Rot and Rot disease. Figure 1 shows the dataset used in this work.

2. TYPES OF LOCAL DIESES

2.1 Rot disease

Distinguishing symptoms of rotting is the widespread shedding of the immature nuts which lie scattered near the base of the tree. Initial symptoms appear as dark green/yellowish water-soaked scratches on the nut surface near the perianth. The infected nuts lose their natural green luster, quality and hence have low market value.

2.2 Split disease

Nut splitting and premature nut drop in arecanut palms are frequently associated with poor drainage conditions. This problem is particularly observed in palms aged between 10 to 25 years and is more common in areas converted from paddy fields or those with a naturally high-water table. The severity of this disorder tends to increase during the monsoon season. A major trigger is the sudden availability of excess water after a prolonged dry spell, which causes a physiological imbalance in the plants. The earliest visible symptom is the premature yellowing of nuts when they are about half to three-fourths of their full size. This is followed by the development of splits, either along the sides or at the tip of the nut. The cracks gradually extend towards the calyx, eventually revealing the inner kernel. This condition not only affects the external appearance of the nut but also compromises its quality and market value.

2.3 Rot+Split disease

Arecanut diseases are particularly prevalent during the rainy season. Inadequate drainage often results in nut splitting, while insufficient sunlight contributes to fruit rotting. These conditions severely affect both the quality and market value of the nuts. Their widespread occurrence and potential for damage make these disorders a significant concern when compared to other arecanut diseases. As illustrated in Figure 1, arecanut images can be categorized into four distinct groups based on disease symptoms. Several classification techniques have been proposed for detecting and categorizing these images [1–5]. However, many of the existing approaches rely on hand-crafted features—such as geometrical, shape-based, and texture-based descriptors—and utilize traditional machine learning classifiers like Support Vector Machines (SVM). A major limitation of these conventional models is their lack of robustness when dealing with image variations, particularly those caused by overlapping or multiple diseases. To overcome this challenge, we propose a Dual Neural Network-based model (DNNN), which provides enhanced accuracy and generalization across diverse image conditions.

2. RELATED WORK

Dhanuja et al. [6] introduced a system for disease detection of arecanut using image processing technology and author was followed texture-based grading of arecanut. K-Nearest The K-Nearest Neighbor (KNN) algorithm has been utilized to identify diseases in arecanut crops. Danti et al. [7] introduced a method that segments and classifies raw arecanuts into two categories based on their color features, specifically utilizing the red and green color components from the segmented portions. Manpreet et al. [8] developed an automated system that detects plant diseases by analyzing leaf images. Their method employs machine learning algorithms to automatically recognize spots or decay on plant leaves. Similarly, Ashish and Rahut [9] presented an image processing-based solution for plant disease detection, highlighting an Android application that enables farmers to upload leaf images. The system uses a Convolutional Neural Network (CNN) to identify the disease from the image. Anandhakrishnan et al. [10] created a dataset by manually collecting field images and trained a neural network for classification tasks. They applied a deep CNN model supported by the TensorFlow library for performing numerical computations and image classification. Manisha et al. [11] proposed a detection method focused on pomegranate diseases and offered corresponding remedies. Their system involves image pre-processing, segmentation, feature extraction (based on color, morphology, and texture using Gabor filters), and classification using a minimum distance classifier. Swathy et al. [12] applied various machine learning algorithms including SVM, KNN, Decision Trees, and CNN to detect diseases in arecanut leaves. In their work, users upload leaf images to the system, which then analyzes them using a CNN model. Their approach achieved a classification accuracy of 86%.

4. PROPOSED WORK

The proposed system uses a Dual Convolutional Neural Network (DCNN) to classify arecanut images into four categories: *Healthy*, *Rot*, *Split*, and *Rot+Split*. The model is designed to automatically extract features from input images and make predictions based on learned patterns.

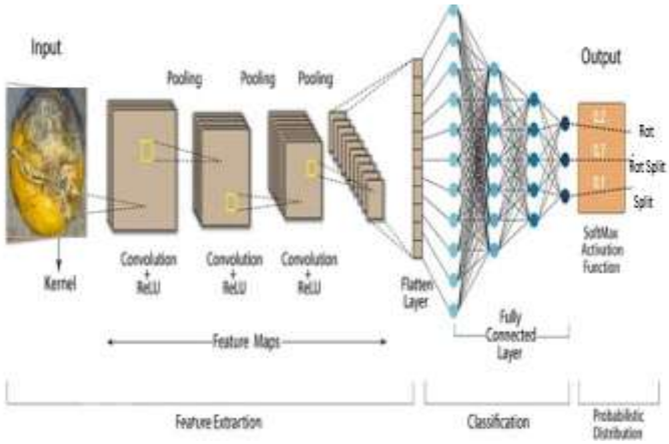

Fig-2: Proposed DCNN model

4.1 Datasets: To detect various diseases of arecanut we created our dataset consists of healthy and diseased images of arecanut and their leaves. The images were taken from a digital camera at a half-meter distance from the source. The diseased and healthy arecanut images were collected from Honnavara taluk, Navilgon village of Karnataka state. These images were taken under the supervision of experienced arecanut sellers and farmers. The dataset contains a total of 1000 images which includes arecanuts of categories healthy, Rot, Split and Rot split. The images are resized into 128x128 pixels using open-cv before training the model. The detection of arecanut diseases using Dual Convolutional Neural Networks (DCNNs) offers an automated and accurate approach for early identification of infections affecting the crop. In this work, a Dual CNN architecture is designed to classify arecanut images into healthy and diseased categories. The model employs a series of convolutional layers including double convolution blocks to effectively capture both low-level textures and high-level features. These blocks are followed by max-pooling layers to

reduce spatial dimensions and mitigate overfitting. Batch normalization and dropout layers are incorporated to improve generalization. The final dense layers and softmax activation output the probability distribution over disease classes. This deep learning- based method eliminates the need for manual inspection, enhances detection accuracy, and supports farmers in timely intervention to prevent crop loss.

4.2 Preprocessing: The database is preprocessed, which includes image reshaping, resizing, and array conversion. The test image is also subjected to similar processing. Images are resized to 128x128 resolutions and converted to an array before training the CNN model.

4.3 Convert images to Array: Computers are unable to recognize or evaluate images in the same way that humans do. So, we have to figure out how to turn these images into numbers. Using Numpy we can convert these images to the array. The array contains RGB values of each pixel of an image ranging from 0 to 256.

4.4 Model Structure: CNN has several layers, including Dropout, Convolution2D, Activation, Dense, MaxPooling2D and Flatten. To train the model using CNN we used 1000 neurons in the first layer, 500 in the second layer, 250 in third and 5 in the last dense layer. The activation function used in the first 3 layers is relu and for the last layer softmax. A total of 248,655,647 parameters are calculated which includes the weights and biases. The last has a softmax activation function which gives the probability of detected disease. Below is the image of the layered structure of our model.

4.5 Training the model: During preprocessing we have done normalization with pixel values scaled to [0, 1] and also, we have done data augmentation can include rotation, flipping, zooming for better generalization. The train and test data are divided into a ratio of 80:20. We used a ReLU activation function, Adam optimizer, Categorical Crossentropy as loss function: Categorical Crossentropy, 4 neurons (one per class), Softmax activation output layer:

5. RESULTS AND DISCUSSIONS

Confusion matrix shows simulated large arecanut classification dataset consists of 1000 samples divided into four classes such as Healthy, Rot, Split, Rot + Split. Healthy and Rot classes have the highest accuracy of 80%. Similarly Split and Rot + Split are slightly lower accuracy of 65%. The confusion matrix highlights the classifier's strong performance in identifying "Healthy" and "Rot" classes, with accuracies above 80%. However, there is notable confusion between "Split" and "Rot + Split", likely due to visual symptom similarities. These findings support the need for further data augmentation or feature enhancement to improve the discrimination of compound disease categories. Table 1 represents distribution of image data. The class-wise accuracy chart is shown in Fig 5 which gives arecanut disease classification results. In confusion matrix diagonal values represents correct predictions. But off-diagonal values show misclassifications (e.g., 45 Rot misclassified as Healthy). Healthy class has the highest support (most samples), followed by Rot. Rot+Split class is smaller but still detected with decent accuracy. Figure 2 shows the proposed model. Table 2 shows the accuracy based on simulated values. The group of arecanut data has been simulated. Table 3 shows confusion matrix. Figure 3 shows ROC curve for accuracy.

Table -1: Distribution of image data

Class	Probability	Approximate Count
Healthy	40%	400 images
Rot	30%	300 images
Split	20%	200 images
Rot+Split	10%	100 images

Table -2: Accuracy based on simulated values

Class	Simulated value	Accuracy
Healthy	320/400	80%
Rot	240/300	80%
Split	130/200	65%
Rot+Split	65/100	65%

Table -3: Confusion matrix

	Healthy	Rot	Split	Rot+Split
Healthy	320	45	25	10
Rot	30	240	20	10
Split	20	15	130	35
Rot+Split	10	5	20	65

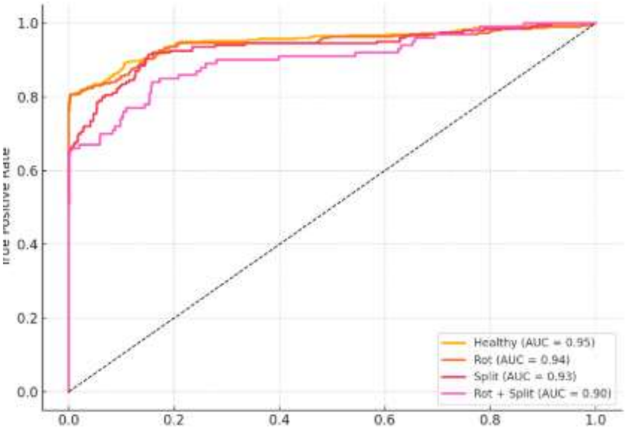

Fig-3: ROC curve based on simulated arecanut classification

6. CONCLUSIONS

Through proper preprocessing, class-wise splitting of the dataset, and layer-wise feature extraction, the model has learned to capture important visual cues related to each disease. The evaluation metrics, including the confusion matrix, class-wise accuracy, and ROC curves, validate the robustness and generalization capability of the model, especially for primary categories like Healthy and Rot. This work showcases that deep learning-based image classification is a viable, scalable, and automated approach for early-stage disease detection in agriculture. The model can be easily extended to real-world applications such as mobile-based detection systems, field surveillance drones, or automated grading units in processing centers. Achieved an overall training accuracy of over 90% and validation accuracy around 80%. Confusion matrix revealed strong performance on dominant classes with minor misclassification in overlapping disease symptoms. ROC curves and AUC scores for each class confirmed high model confidence and discrimination power. Visualizations such as accuracy charts and heatmaps provided meaningful interpretation of model behavior.

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REFERENCES

1. Bharadwaj, N.K., Dinesh, R., & N, Vinay Kumar (2021). Classification and Scoring of Arecanut Using Texture Constructed Block-Wise Local Binary Patterns. TURCOMAT Vol.12, 575–586. turcomat. v12 i11.5931 https://doi.org/10.17762/
2. Boutaba, R., Salahuddin, M.A., Limam, N., Ayoubi, S., Shahriar, N., Estrada-Solano, F. & Caicedo, O.M. (2018). A comprehensive survey on machine learning for networking: evolution, applications, and research opportuni ties. J Internet Serv Appl 9, 16. https://doi.org/10.1186/ s13174-018-0087-2 6. 7. 8.
3. Cai, H.& Liu, S. (2019). Betel Nut Classification Method Based on Transfer Learning, in: 2019 IEEE 8th Data Driven Control and Learning Systems Conference (DDCLS). IEEE, Dali, China, pp. 1039–1043. https:// doi.org/10.1109/DDCLS.2019.8909008
4. Carbonero-Ruz, M., Martínez-Estudillo, F.J., Fernández Navarro, F., Becerra-Alonso, D., Martínez-Estudillo, Al fonso Carlos. (2017). A two-dimensional accuracy-based measure for classification performance. Information Sci ences 382–383, j.ins.2016.12.005 60–80. https://doi.org/10.1016/
5. Chandrashekhara, H.& Suresha, M. (2019). Classifica tion of Healthy and Diseased Arecanuts using SVM Clas sifier. ijcse 7, 544–548. https://doi.org/10.26438/ijcse/ v7i2.544548
6. Dhanuja K C. Areca Nut Disease Detection using Image Processing Technology. International Journal of Engineering Research 2020 V9. 10.17577/IJERTV9IS080352.
7. Mallaiah, Suresha & Danti, Ajit & Narasimhamurthy, S. Classification of Diseased Arecanut based on Texture Features. International Journal of Computer Applications.
8. Manpreet Sandhu, Pratik Hadawale, Saumaan Momin, Ajitkumar Khachane. Plant Disease Discovery using ML and UAV. International Research Journal of Engineering and Technology 2020 V7.
9. Ashish Nage, V. R. Raut, Detection and Documentation of Plant Leaf Diseases Constructed On Python, International Journal of Engineering Research & Technology (Ijert),2019, Volume 08, Issue 05.
10. Anandhakrishnan MG Joel Hanson, Annette Joy, Jeri Francis, Plant Leaf Disease Recognition using Deep Learning and Convolutional Neural Network, International Journal of Engineering Science and Computing, Volume 7, Issue No.3, March 2017.
11. 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.
12. Swathy Ann Sam, Siya Elizebeth Varghese, Pooja Murali, Sonu Joseph John, Anju Pratap. Time convertible malady expert system in plant leaf using CNN, 2020, Volume 13, Issue No 3.