Arecanut Disease Detection

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ABSTRACT :

The tropical crop arecanut, sometimes referred to as betel nut, is primarily farmed in India. In terms of arecanut production and consumption, the nation ranks second in the world. The areca nut plant is vulnerable to numerous diseases that impact its roots, stem, leaves, and fruits throughout its life cycle. While some of these illnesses can be seen with the naked eye, others cannot. These illnesses are brought on by abrupt changes in temperature and other meteorological factors; early disease identification is crucial. In order to minimize losses for farmers, this work focuses on early and precise disease diagnosis. Using convolutional neural networks, we developed a system that assists in identifying arecanut, leaf, and trunk ailments and offers treatments. A Convolutional Neural Network (CNN) is a Deep Learning method that uses an image as input, gives different items in the image learnable weights and biases, and then uses the results to determine which objects are different. We took a dataset with 620 photos of arecanuts in both good and unhealthy conditions in order to train and evaluate the CNN model. An 80:20 ratio is used to separate the test and train data. Adam serves as the optimizer function, accuracy serves as a measure, and categorical cross-entropy serves as the loss function for the model compilation. To attain high validation and test accuracy with little loss, the model is trained over a total of 5 epochs. It was discovered that the suggested method was successful and 88.46 percent accurate in detecting arecanut illness. Diseases frequently seen in areca trees include Mahali Disease (Koleroga), Bud Rot Disorder, Stem Exudation, Yellow Leaf Blotch,Yellow Disease, which arises from persistent rainfall and climate alterations, these ailments need to be managed in the initial phase of infection; otherwise, it could lead to difficulties in oversight in the concluding phase that could result in detriment to the latter. To prevent this, we can utilize Machine Learning for disease detection. We will identify yellow leaf spot, stem bleeding, and Mahali disease (KoleRoga) in this project and provide treatments for the conditions we find.

Key words: Convolution Neural Networks, Arecanut, and Machine Learning

1.INTRODUCTION

The primary occupation in India is agriculture. India ranks second globally in terms of agricultural product production. India and other developing nations' economies primarily depends on farming. India's farmers cultivate a wide variety of crops. There are several variables that affect crop development, including disease, soil conditions, and climate. The current method of identifying plant diseases is merely visual observation, and farmers must carefully examine each crop on a regular basis to find diseases. This is a very difficult and time-consuming task that calls for more staff, well-equipped labs, and expensive equipment, and it is not feasible to identify diseases early on and prevent their spread. Therefore, an automatic illness detection system is required.

1.1.DISEASES:

1. MAHALI (KOLEROGA)

This condition is common and affects the majority of areca nut growing grooves. The most dreaded disease, Koleroga (rotting disease) or Mahali Disease (heavy destruction), is found in areas with high rainfall and results in the rotting of arecanut fruits. It is challenging to pinpoint the precise losses because this disease, although estimates of crop loss ranging from 10 to 75 percent have been documented in several states. Low temperatures, sporadic sunshine, excessive humidity, and intense rain can all contribute to the development of disease. The illness initially manifests as water-soaked sores on the fruit's surface close to the calyx. Because of their deteriorated quality, the infected nuts are not fit for chewing.

2. STEM BLEEDING

Grooves between the ages of 9 and 15 are more susceptible to stem bleeding. The symptoms manifest as tiny, discolored depressions on the basal, or bottom, part of the stem. The fibrous tissues inside the stem disintegrate as a result of the spots later coalescing and developing fissures on the stem. The signs of stem hemorrhage include seen on stems that turn dark red, the stem tissue releases a dark brown liquid, leaf blades have yellowish patches, the roots appear yellowish brown, and rot is prevalent. The fruit turns a deep shade of green. The fungus Thielaviopsis paradoxa is mostly responsible for this illness.

3. YELLOW LEAF SPOT

During the South-West monsoon season, this illness is most severe. Younger palms—those under ten years old—are particularly vulnerable. Usually, just three to four lower whorl leaves are infected. The symptoms start off as minor. Round dots that range from brown to dark brown or black. They come in different sizes, have a yellow halo surrounding them, and eventually develop into blighted areas.

2.LITERATURE SURVEY:

There are numerous publications in the literature that discuss plant disease detection, but very few focus on arecanuts. In his study, Dhanuja K C (2020) suggested a method for identifying arecanut illnesses by image processing and texture-based grading. Approximately 144 samples were used by the author for testing and training, including 46 samples are poor, 49 is negative, and 49 were good. The diseases were found using the K-nearest neighbor (KNN) technique. In 2020, Manpreet Sandhu and colleagues created a disease detection method that uses image classification of leaves. Using a machine learning algorithm, the technology automatically finds any spots or decaying areas in the leaf. The writers took pictures of the leaf using a drone camera.

Swathy Ann Sam et al. 2020 conducted similar research using other algorithms, including CNN, KNN, SVM, and Decision Trees, to identify plant diseases. The system uploads a picture of a sample leaf.

Proceedings of the Third International Conference on Operations Management and Industrial Engineering in India, India's New Delhi, November 2-4, 2023 © IEOM Society International. The algorithm will determine whether any diseases are present, and the system will publish the disease's diagnosis if it is. The accuracy of the CNN that the writers utilized was approximately 86%. According to the literature review, authors specifically focused on other general plant leaves in order to identify the disease using image processing software and other machine learning techniques, including K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Decision Tree by either building their own datasets or taking into account camera images.

3.OBJECTIVES:

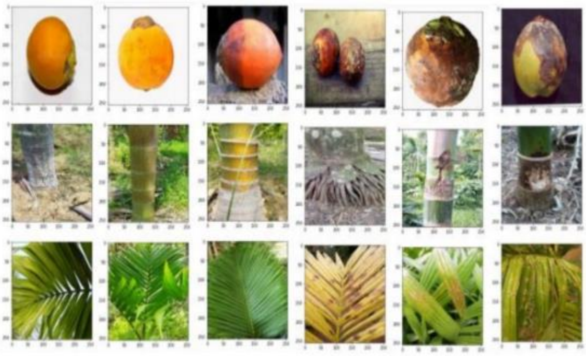
- Gather datasets with pictures of arecanuts and their leaves in both healthy and pathological conditions.
- Create and implement an algorithm for early arecanut disease detection that can prevent disease transmission.
- Create an algorithm that offers remedies for the illnesses that have been identified.

4.PROPOSED MODEL:

- Dataset Collection.
- Training a neural network model for the prediction of plant diseases.

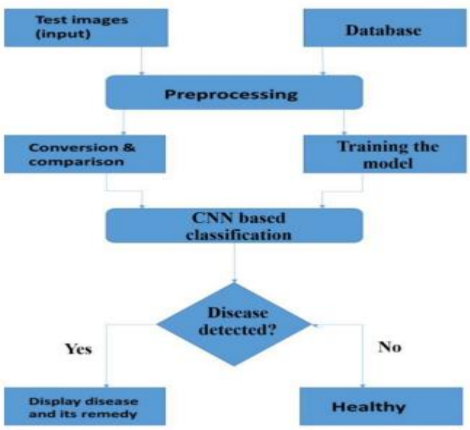
5.DATASET INFORMATION:

Prior to training the model, the images go through a number of stages, such as reshaping and resizing, to ensure that the images meet the requirements. The collected images are regarded as the fundamental dataset to provide accurate detection and also aid in demonstrating the project's efficiency. The dataset includes images of both healthy and diseased arecanuts, such as Mahali, stem bleeding, and yellow spot.



The Deep Learning Method After receiving an image as input, CNN learns from it and discerns between various features by assigning their significance (biases and learnable weights). Comparatively speaking to other classification techniques, ConvNet requires a lot less pre-processing. Convolutional networks. When properly trained, one can learn from the filters or traits with sufficient planning.

6.WORKING MODEL DESIGN:



7.PREPROCESSING:

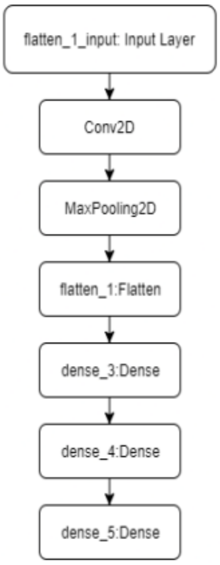
Preprocessing of the database include array conversion, image resizing, and reshaping. Similar processing is likewise applied to the test image. Pictures are scaled to 256*256 resolutions and transformed into an array prior to CNN model training.

CONVERT IMAGES TO ARRAY:

Images cannot be recognized or assessed by computers in the same way that people can. Therefore, we must determine how to convert these pictures into numerical values. With Numpy, we can transform these pictures into an array. The RGB values of each image pixel, which range from 0 to 256, are contained in the array.

MODEL STRUCTURE:

CNN has multiple layers, including Dropout, Convolution2D, Activation, Dense, MaxPooling2D, and Flatten. To train the CNN model, we used 1000 neurons in the first layer, 500 in the second layer, 250 in the third, and 5 in the last dense layer. A total of 248,655,647 parameters, including weights and biases, are calculated, with the final layer having a softmax activation function that provides the probability of detected disease. The image of our model's layered structure is shown below.



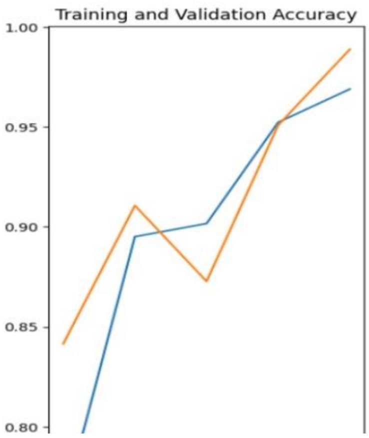
8.TRAINING THE MODEL:

The model is trained and tested using 620 photos in total, including both healthy and sick images. Due to the dataset's limitations, we employed the augmentation technique, which generates new training data by rotating, moving, zooming, and flipping the image. The ratio of the test data to the train data is 80:20. Adam serves as the optimizer function and accuracy, while categorical cross entropy is utilized as the loss function for model compilation as measurements. The model is trained for 5 epochs in order to attain excellent validation and test accuracy with the least amount of loss.

```python
#visualization of data
for image_batch, label_batch in dataset.take(1):
    plt.imshow(image_batch[0].numpy().astype("uint8"))
    # plt.imshow is used to visualize the image
    #convert the image_bacth from tensor to numpy for visualzation
    # and convert it into float to int
    #randomly selecting the images
    plt.axis("off") # hide x and y-axis
```

```
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(range(len(acc)), acc, label='Training Accuracy')
plt.plot(range(len(val_acc)), val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
```

MODEL ACCURACY:



LOSS VS EPOCH:

```
plt.subplot(1, 2, 2)
plt.plot(range(len(loss)), loss, label='Training Loss')
plt.plot(range(len(val_loss)), val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```


```
history = model.fit(
    train_ds,
    batch_size=BATCH_SIZE,
    validation_data=val_ds,
    verbose=1,
    epochs=5,
)
# here we get the validation accuracy and accuracy of the model at each train
# accuracy will be keep on increasing as we train

Epoch 1/5
115/115 [==============================] - 310s 2s/step - loss: 0.5910 - accuracy: 0.7598 - val_loss: 0.4806 - val_accuracy: 0.8415
Epoch 2/5
115/115 [==============================] - 221s 2s/step - loss: 0.2991 - accuracy: 0.8952 - val_loss: 0.2534 - val_accuracy: 0.9107
Epoch 3/5
115/115 [==============================] - 220s 2s/step - loss: 0.2751 - accuracy: 0.9017 - val_loss: 0.3393 - val_accuracy: 0.8728
Epoch 4/5
115/115 [==============================] - 221s 2s/step - loss: 0.1412 - accuracy: 0.9523 - val_loss: 0.1417 - val_accuracy: 0.9509
Epoch 5/5
115/115 [==============================] - 221s 2s/step - loss: 0.0942 - accuracy: 0.9690 - val_loss: 0.0530 - val_accuracy: 0.9888
```

9.RESULTS:

We observed test accuracy of 98% following model training. Training with CNN. The trained model identifies diseases in arecanuts and outputs the likelihood of the disease. For the user's reference, the treatment for the maximum probability disease is also displayed.

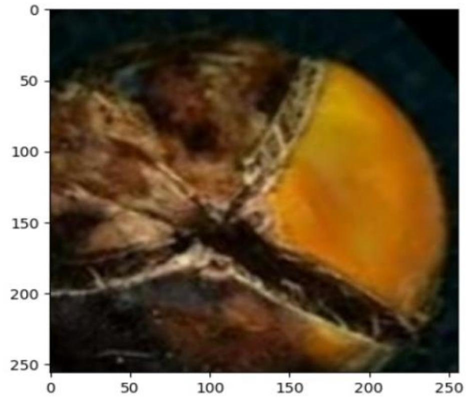
```
import numpy as np
for images_batch, labels_batch in test_ds.take(1):

    first_image = images_batch[0].numpy().astype('uint8')
    first_label = labels_batch[0].numpy()

    print("first image to predict")
    plt.imshow(first_image)
    print("actual label:",class_names[first_label])

    batch_prediction = model.predict(images_batch)
    print("predicted label:",class_names[np.argmax(batch_prediction[0])])
```

```
first image to predict
actual label: Mahali_Koleroga
predicted label: Mahali_Koleroga
```



10.CONCLUSION:

This study employs convolutional neural networks to detect illnesses in arecanuts, leaves, and trunks early. Experiments are carried out with sick and 620 photos in a healthy arecanut picture dataset. Pre-processing of the input image is done first, then feature extraction, training, and classification. Mahali, stem bleeding, and yellow leaf spot are among the arecanut diseases that the suggested system can identify and treat. The experimental results indicate different levels of disease identification accuracy depending on the disease stage and the quality of the input image. It is estimated that the system's total accuracy is 98% percent. This approach thus moves in the direction of motivating farmers to engage in smart farming and enabling them to produce higher yields. decisions by empowering them to implement the required corrective and preventive measures for their arecanut crop.

11.REFERENCES:

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