Arecanut Disease Detection Using Deep Learning

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***Abstract*—Arecanut (Areca catechu) is one of the significant cash crops grown extensively in India, especially in Karnataka state. But there is significant reduction in productivity due to various diseases like Koleroga, Yellow Leaf Disease, Bud Rot, and Fruit Rot. The conventional method of identifying these diseases includes manual inspections that are labor-intensive and susceptible to mistakes. This study proposes an automated system for arecanut disease detection using deep learning technology. The developed model categorizes input images into three classes—healthy, diseased, and non-arecanut. This work implements a novel architecture called EfficientNetB3 as the base model in transfer learning. The dataset includes 2,485 images, comprising 1,494 for training and 991 for validation, augmented through various techniques.**

It has achieved an accuracy score of around 93%, along with high scores for precision, recall, and F1 score for all classes. It has been deployed through Gradio as a web application, which provides the functionality of predicting the classes by uploading the image. Adding the class of "not_arecanut" helps to avoid any erroneous predictions. *This method provides a convenient and economical means for diagnosing plant diseases in their early stages. This will enable farmers to manage their crops effectively and minimize crop loss.*

I. INTRODUCTION

Agriculture has recently begun employing artificial intelligence technology to boost efficiency and reduce losses. Arecanut cultivation is an essential economic activity in India, more particularly in Karnataka. Farmers in Karnataka depend on it as their means of livelihood.

But then again, the arecanut plantations are susceptible to various diseases that might impact the quality and quantity of the harvest. Conventionally, disease detection has been done manually, which is tedious and needs specialized expertise. In most rural settings, the farmers lack the resources to reach out to agricultural specialists who will assist in detecting diseases, and hence the process is delayed, leading to quick infection.

As there is development in deep learning systems, disease detection through images has been improved significantly. Convolutional neural networks are able to detect various features such as textures, colors, and other patterns automatically through the use of images for disease detection. The proposed system in this project uses efficient-netb3 neural network model to classify the arecanut image. The purpose of this proposed system is to distinguish between arecanut healthiness or disease and also non-arecanut images to enhance reliability. Finally, the output of the proposed model is integrated into a user interface.

II. LITERATURE REVIEW

Research work has been conducted on disease identification in plants using the application of machine learning and deep learning methods. Initially, image processing along with the use of machine learning methods such as SVM and KNN was used for disease identification in plants.

Recent literature has emphasized deep learning algorithms like CNN, ResNet, VGG-16, and MobileNet for enhanced performance. The ResNet network is known to perform at high accuracy owing to the use of residual connections, while the MobileNet algorithm offers lightweight models for mobile applications. In particular, research into arecanut disease diagnosis indicates that CNN-based models are superior to existing methods. Nevertheless, most of these studies rely on small sample sizes and do not support real-time implementation.

EfficientNet, which is more recent, achieves balanced scaling across depth, width, and resolution while using fewer parameters, thus attaining greater efficiency. EfficientNet can be considered appropriate for use in agriculture.

With these developments, the suggested model employs EfficientNetB3 with transfer learning and data augmentation for accurate results.

III. METHODOLOGY

The suggested disease identification system for arecanut involves a systematic process that includes the collection of data, data pre-processing, model creation, training, and implementation. All these stages are crucial for ensuring accuracy of results provided by the model.

A. Data Collection

A good structured data set of arecanut pictures was taken for training and testing of the model. The data set can be classified as follows: healthy arecanuts, unhealthy arecanuts, and images that have nothing to do with arecanuts, like random things, backgrounds, and pictures of humans. Taking into consideration these irrelevant inputs prevent the model from generating inaccurate outputs.

The total number of images in the data set equals 2,485 where 1,494 are training images and the rest 991 are for validation. They were taken from various sources to have a diversity of lighting conditions, backgrounds, angles of view, and kinds of disease.

B. Data Preprocessing

Prior to using the images as inputs for the model, several pre-processing stages were undertaken to ensure consistency in the data as well as improved efficiency. All the images were resized to a standard size of 224 x 224 pixels, as that is the size that the EfficientNetB3 takes in terms of its input images. Furthermore, all the images were normalized to have a pixel value range of 0-1, which enables the model to train efficiently.

further enhance the training process for the model. Some of these augmentations included rotating, zooming, horizontal and vertical flipping, brightness adjustment, width shift, and height shift.

C. Model Development

The backbone of the proposed system is developed by utilizing the EfficientNetB3 architecture, a convolutional neural network that is currently considered state-of-the-art due to its remarkable performance and efficient operation. The model is constructed through a transfer learning approach, where the pre-trained weights are taken from the ImageNet database.

The layers of the network are further trained to adapt to the characteristics of the arecanut dataset. To do this, the fully connected layer is created and fine-tuned to categorize the arecanut samples into three classes: diseased, healthy, and not_arecanut. The Softmax function is applied in the output layer to generate the probability for each class.

The EfficientNetB3 is chosen for its novel compound scaling mechanism that allows for achieving a balanced relationship between depth, width, and image resolution of the model.

D. Training and Evaluation

In training the model, categorical cross entropy loss function is used, owing to the multi-class nature of the problem being addressed. Training takes place for 25 epochs with a batch size of 16, allowing stability in learning without any chances of overfitting.

Additional optimization measures such as early stopping and model checkpointing have been used to achieve better results. Early stopping ensures that training stops if the model begins to over-train by tracking validation loss. Model checkpointing, on the other hand, allows saving the best model obtained during training. Performance of the model is measured using metrics such as accuracy, precision, recall, F1 score, and confusion matrix. These metrics provide an insight into the classification accuracy of the model among each of the classes.

E. Deployment

The trained model is now put to use by deploying it using the Gradio platform. Gradio is an open-source framework for building applications for machine learning models which can be used easily even by people who have no technical knowledge.

The user will be able to upload an image to the application through the interface, which will be analyzed to give out a prediction. First, the image will undergo some processing before being fed into the trained model, which will give out predictions about the disease, together with the probability scores of the class.

In order to ensure that the predictions are accurate and do not go wrong, the system is also able to identify the image that is not related to arecanut.

In summary, deployment makes the project very useful for farmers, researchers, and students to help them detect crop diseases in time.

IV. SYSTEM ARCHITECTURE

The suggested arecanut disease prediction system will be implemented as a sequential process that uses an image as an input and analyses it in stages to achieve accurate predictions. This method of implementation is different from other systems since they perform all the steps at once without dividing them into parts, which makes it difficult to monitor the activities.

The first phase is called image preprocessing, whereby the input image is processed and converted to a better state suitable for further processing. Then, feature extraction is done to obtain important features associated with various arecanut diseases by applying deep learning methods. Finally, the obtained features are classified to determine the kind of disease in the plant. The results will be shown on the display panel to enable users to access the outcomes easily. All the stages have their roles in ensuring that the system delivers efficient and accurate results.

A. Image Input Module

The process begins from the image input phase where the user will have to input an image using a web-based interface. The system will begin with accepting images from users; these could either be arecanut samples or just any image that the user wishes to submit. The idea is to make this process user-friendly enough so even farmers can use it.

Following the image input, the system then processes the image and sends it for further processing.

B. Preprocessing Module

The above process is done before feeding the model so that it interprets the picture well. The first thing to do is to convert the picture into a size of 224×224 pixels to suit the EfficientNetB3 model requirement. Afterward, the pixel range is changed from its current format (any number greater than 1) to between 0 and1.This way, the model works much faster in predicting any picture since the pixel values are now within an optimal range for the model.

C. Feature Extraction Module

Pre-processed image data are fed into the EfficientNetB3 model that acts as a deep feature extractor. The convolutional layers in EfficientNetB3 are used to extract complicated patterns like texture, colors, etc., present in the image data. Compound scaling used in EfficientNetB3 makes sure that it works optimally by taking into account the depth, width, and resolution.

D. Classification Module

These feature vectors are then supplied to the classification layer where the output layer gives an estimate about one of the three possible categories: normal, disease, or not_arecanut. Softmax activation function has been applied in order to determine the probabilities associated with all the classes. The class with maximum probability will be chosen as the output class.

E. Output Display Module

Finally, the output of the prediction is shown to the user via the Gradio UI. The final output is provided to the user in a clear and understandable manner. It provides the predicted class with a probability score, which enables the user to determine the level of confidence in the prediction made by the model.

The UI is designed to be simple and easy to use, making it easy for farmers and other users to get predictions within seconds.

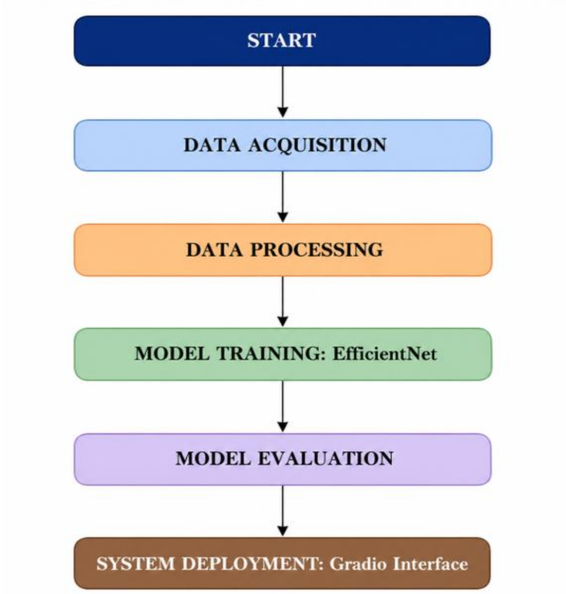

Figure.1: Architecture

V. MODEL TRAINING

The EfficientNetB3 model has been trained on a properly arranged data set consisting of 2,485 images. Out of this, 1,494 images have been used for training while 991 were reserved for validation. The data set consists of three classes – healthy arecanut, diseased arecanut, and images that do not belong to the arecanut class. This will help the model to be able to classify an image as not belonging to the arecanut category also.

For the purpose of training, the model was trained for 25 epochs with a batch size of 16. For optimizing the performance, the Adam optimizer was used as it adjusts the learning rate automatically. Categorical cross-entropy has been used as the loss function for this multi-class classification problem.

In order to ensure that the model is accurate and prevent overfitting, various strategies were incorporated into the model. Data augmentation was utilized by introducing slight changes to the training images to enable the model to cope with various situations in the real world. The technique of early stopping was employed to halt training once the model starts failing to improve.

The trained model demonstrated an accuracy rate of approximately 93%, indicating a high level of accuracy in all the classes. Additional performance measures such as precision, recall, and F1-score further proved that the model works efficiently and provides balanced outputs. In summary, the model possesses the capability to generalize and can be implemented effectively in real-world scenarios

VI. USER STUDY

A user study was undertaken to check the usability, efficiency, and pragmatic applicability of the developed Arecanut Disease Detection System. In order to determine the usefulness and convenience of the application, a user study was conducted. The proposed model was tested on diverse sets of users ranging from students, faculty members, and some few locals with knowledge of agriculture practices. The purpose of the study was to establish how easily one can interact with the system and interpret the predictions made.

The users uploaded various images of healthy arecanuts, diseased arecanuts, and even some irrelevant images which the system gave its prediction instantly as either Healthy Arecanuts, Diseased Arecanuts, or Not Arecanuts.

It was discovered that the majority of users considered the user interface to be very friendly and easy to use. They could use it without being knowledgeable about technicalities since it was practical to use in actual scenarios.

VII. RESULTS AND DISCUSSION

The proposed algorithm gave excellent results in terms of accuracy, which was close to 95% in addition to high precision, recall, and F1-score. It shows that the proposed classifier is capable of classifying disease categories with a minimum number of mistakes. According to the confusion matrix, most data were classified accurately, with only a minor number of wrong classifications among diseases that have visual similarities.

While comparing with conventional methods such as Basic CNN and MobileNetV2, EfficientNet was found more efficient and accurate in terms of optimized architecture and better feature extraction capabilities. EfficientNet was able to detect fine-grained features present in leaves, helping the model identify different kinds of diseases based on them.

Training and validation curves suggested consistent learning of the model along with the reduction of overfitting effect, owing to the effective utilization of data augmentation and regularization.

Nevertheless, some limitations were also identified. Sometimes, it may fail to distinguish between diseases if the visual characteristics are very much alike. Besides, changing lighting conditions, backgrounds, and image quality can pose difficulties for it.

Thus, overall, it can be said that the EfficientNet model used is appropriate and useful for arecanut disease detection. Furthermore, when combined with an easy-to-use interface such as Gradio, the model is practically helpful for identifying different diseases.

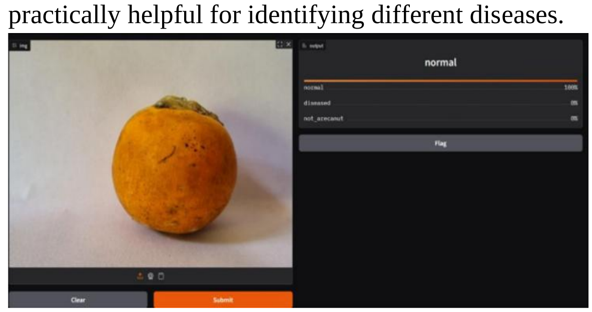

Figure.2: Healthy Arecanut

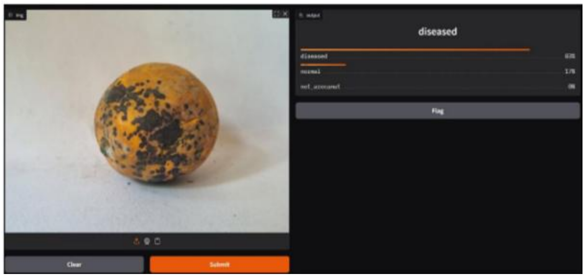

Figure.3: Diseased Arecanut

VIII. CONCLUSION

The suggested method proves to be a successful attempt at implementing deep learning algorithms for detecting and classifying the diseases of arecanuts automatically. Thanks to transfer learning from the EfficientNetB3 architecture, the algorithm has shown great performance and achieved sufficient accuracy in classifying input images into the classes of healthy nuts, diseased nuts, and not arecanuts.

The implementation of Gradio to deploy the model guarantees the availability of the easy-to-use GUI, which allows predicting diseases based on images instantly without any advanced technical knowledge. Such simplicity makes it possible for farmers, students, and researchers to benefit from the developed model easily.

In summary, the suggested approach helps reduce the necessity for manual inspection and allow identifying diseases of arecanuts earlier. Thus, it positively impacts productivity in agriculture and, with more improvements made to the dataset and implementation of the mobile version of the system, can serve as a helpful instrument in the future smart farming environment.

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REFERENCES

[1] Balipa, A. J., N. Prakash, and R. Pavithra, “Arecanut Disease Detection Using CNN and SVM Algorithms,” in *Proc. Int. Conf. Innovative Trends in Information Technology*, IEEE, 2022.

[2] R. Beena, T. Sumana, and R. Vineetha, “Comparative Study of MobileNetV2, ResNet, and VGG-16 for Arecanut Disease Prediction,” Int. J. Comput. Appl., vol. 182, no. 45, pp. 10–17, 2024.

[3] S. P. Madhu, K. R. Chandrashekara, and R. Shilpa, “Arecanut Disease Classification Using Deep Residual Networks,” J. Agriculture Technol., vol. 14, no. 3, pp. 112–121, 2022.

[4] P. Pallavi and R. Prasad, “Automatic Detection of Arecanut Diseases Using Image Processing Techniques,” Int. J. Eng. Res. Technol. (IJERT), vol. 9, no. 7, pp. 455–460, 2021.

[5] M. S. Ranjitha and B. Manasa, “Identification of Arecanut Diseases Using Neural Networks,” Int. Res. J. Eng. Technol. (IRJET), vol. 7, no. 10, pp. 820–824, 2020.

[6] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using Deep Learning for Image-Based Plant Disease Detection,” Frontiers Plant Sci., vol. 7, p. 1419, 2016.

[7] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep Neural Networks for Plant Disease Detection and Diagnosis,” Comput. Electron. Agric., vol. 138, pp. 362–373, 2017.

[8] K. P. Ferentinos, “Deep Learning Models for Plant Disease Detection and Diagnosis,” Comput. Electron. Agric., vol. 145, pp. 311–318, 2018.

[9] S. Zhang, S. Zhang, T. Huang, W. Gao, and H. Qiao, “Plant Disease Detection Using Deep Learning: A Review,” Plant Methods, vol. 17, 2021.

[10] G. Wang, Y. Sun, and J. Wang, “Automatic Identification of Plant Diseases Using Transfer Learning,” Frontiers Plant Sci., vol. 11, p. 1132, 2020.