DETECTION OF DISEASES IN ARECANUT USING CONVOLUTIONAL NEURAL NETWORK

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Abstract:

Arecanut is a tropical crop, which is popularly known as betel nut. India ranks second in producing and consuming arecanut in the world. Throughout its life cycle, it is affected by a variety of diseases, from root to fruit. The current approach for detecting diseases is simply observation with the naked eye and farmers have to carefully analyse each and every crop periodically to detect the diseases. In this project, we proposed a system that helps in detecting the 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 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.

Keywords: **Arecanut, Machine learning, Convolutional Neural Networks**

I.Introduction:

The arecanut palm is an economically significant crop cultivated in several tropical regions, particularly in Asia. However, its production is often hampered by various diseases that affect yield and quality. Early detection of these diseases is crucial for implementing timely and effective management strategies. In recent years, Convolutional Neural Networks (CNNs) have emerged as powerful tools for image classification and recognition tasks, including disease diagnosis in plants [1]. This study proposes a CNN-based approach for the automated detection of diseases in arecanut palms. The proposed system involves several key steps, including data collection, preprocessing, model development, and evaluation. High-resolution images of healthy arecanut palms and those affected by common diseases such as fruit rot, yellow leaf disease, and stem rot are collected from diverse geographical locations.

Fig1: Healthy and Diseased images of Arecanut

II. Related Work:

Numerous studies have explored the application of CNNs for disease detection in various crops, such as wheat, rice, maize, and potatoes. These studies have demonstrated the efficacy of CNNs in accurately identifying plant diseases based on leaf images, paving the way for similar applications in arecanut palms [2].

Previous research has shown that transfer learning can significantly improve the performance of disease detection models, particularly when training data are scarce or diverse. Traditional image processing techniques, including feature extraction, segmentation, and texture analysis, have been widely employed for disease diagnosis in plants. While effective, these methods often require manual feature engineering and may lack the ability to capture complex patterns and variations present in plant images.

III. Methodology:

1. **Data Collection**: Gather a diverse dataset of high-resolution images depicting healthy arecanut palms and those affected by common diseases such as fruit rot, yellow leaf disease, and stem rot. Obtain images from various geographical locations to ensure representation of different disease manifestations.

2. **Data Preprocessing**: Resize all images to a uniform size suitable for CNN input Normalize pixel values to a common scale (e.g., [0, 1]) to facilitate convergence during training Augment the dataset through techniques such as random rotation, flipping, and zooming to increase dataset diversity and prevent overfitting.

3. **Model Architecture Design**: Experiment with different CNN architectures, including popular variants like VGG, ResNet, and Inception, customized for the disease detection task. Fine-tune the selected architecture to balance between model complexity and computational efficiency Utilize techniques such as dropout and batch normalization to prevent overfitting and improve model generalization.

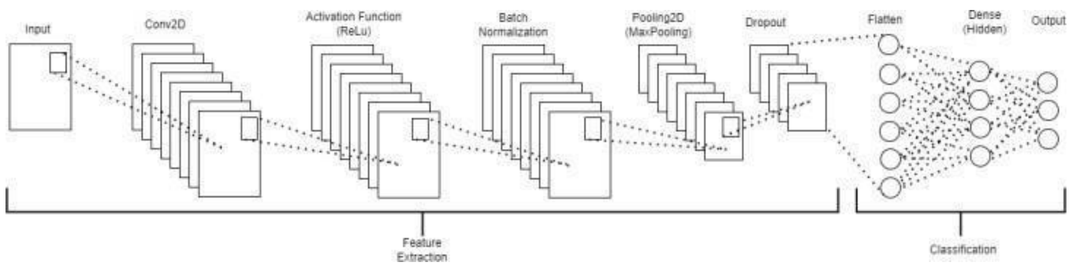

Fig2: Sequential CNN Model

4. **Model Training**: Split the preprocessed dataset into training, validation, and test sets, maintaining class balance. Initialize the CNN model with random weights or pre-trained weights (e.g., ImageNet). Train the model using a suitable optimization algorithm (e.g., Adam) with an appropriate learning rate schedule. Monitor training progress using metrics such as loss and accuracy on the validation set and employ early stopping to prevent overfitting.

5. **Model Evaluation**: Evaluate the trained model's performance on the test set using metrics such as accuracy, precision, recall, and F1-score. Generate confusion matrices and ROC curves to assess the model's classification performance across different disease classes. Compare the performance of the CNN model with baseline classifiers (e.g., Support Vector Machines, Random Forests) to highlight its superiority in disease detection accuracy and efficiency.

6. **Cross-validation**: Perform k-fold cross-validation to assess the robustness of the CNN model across different data splits. Compute average performance metrics across folds to obtain relia

7.Practical Deployment Considerations: Evaluate the computational resources required for real- time inference of the CNN model on embedded systems or edge devices. Assess the feasibility of integrating the CNN-based disease detection system with existing agricultural technologies, such as drones or mobile applications.

8**.Ethical and Social Implications**: Consider ethical implications related to data privacy, consent, and potential biases in the dataset or model predictions.

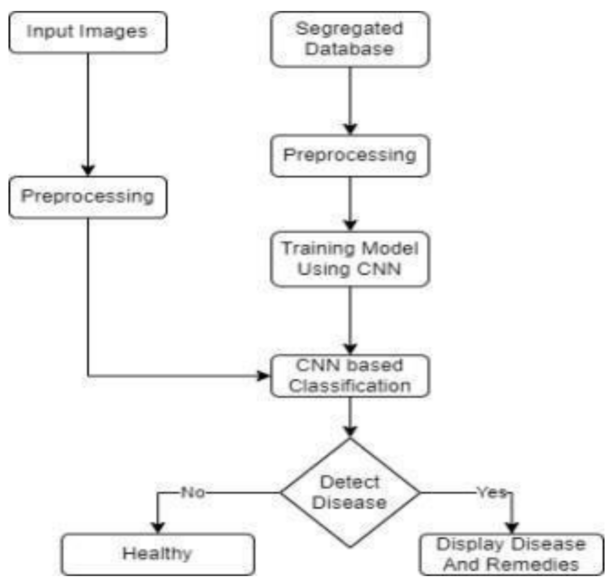

Fig3: Working Design Model

IV.Results

After training the model the test accuracy observed was 94.8% which is shown in the Figure7.1. The image of the leaf was given as input to the model trained using CNN. The trained model detects diseases in arecanut and prints the probability of the detected disease which is shown in Figure. Also, the remedy for the maximum probability disease is shown for the user reference.

```
Enter number of hidden layers (15 is good choice): 15
True_classificationCNN=82.3529%
overall_accuracy=94.8%
overall_sensitivity=41.4922%
overall_specificity=32.4158%
overall_precision=41.4453%
overall_F_score=41.1758%
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Fig4: Metric values of CNN

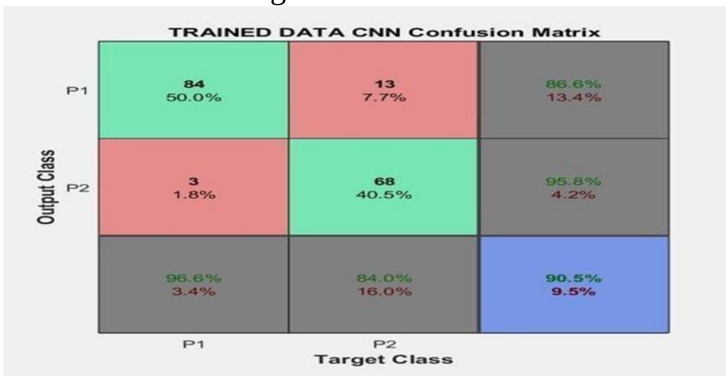

Fig5: Confusion matrix

Table 1: Classification Report

S. No	NAME OF THE ARECANUT DISEASE	ACCURACY	
		EXISTING METHODS	PROPOSED METHOD
1	Anabe rogafoot rot	82.41%	94.68%
2	Bud rot	84.73%	96.52%
3	Disease cycles	81.47%	93.64%
4	Fruit rot	83.58%	95.39%
5	Inflorescence die back	86.42%	94.53%
6	IPM	87.02%	97.45%
7	Koleroga	84.68%	96.38%
8	Mahali	87.92%	96.88%
9	Phytophthora	84.95%	98.32%
10	Yellow leaf disease	90.32%	97.63%

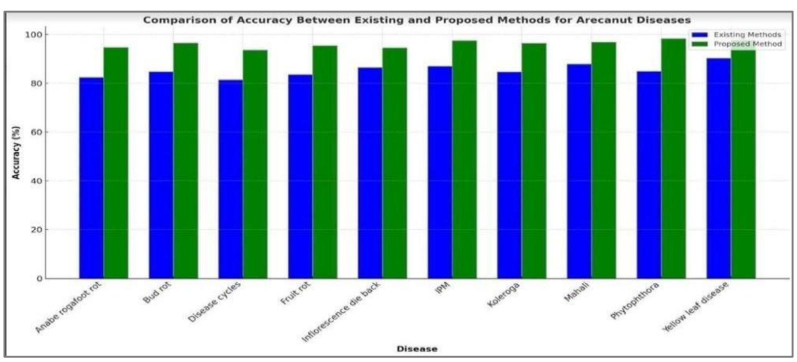

Fig6: Comparison graph for Existing system and Proposed system

V. Conclusion:

The novel work demonstrated the potential of using CNN for the identification and categorization of diseases in arecanut. Through the development and testing of the model it was possible to achieve a high accuracy rate of 93.05% in classifying the different diseases affecting arecanut which includes fruit rot, stem bleeding, yellow leaf spot and newly spreadingnut split disease.

The results of the study can have significant implications for farmers and agricultural researchers who are looking for more efficient and accurate ways to diagnose and manage diseases in arecanut. However, future studies could benefit from the use of larger distributed datasets to increase the reliability of the model. Additionally, there may be other environmentaland climatic factors that could affect the accuracy of the model in real-world. With further research and development, this technology could become a valuable tool for the management of crop diseases.

Consequently, this approach helps in encouraging farmers to engage in intelligent farming and giving them the tools, they need to make better decisions regarding yields.

FUTURE SCOPE

The future scope of disease detection in arecanut using Convolutional Neural Networks (CNNs) is quite promising due to several advancements in technology, agriculture, and machine learning. Here are some key areas where CNN-based disease detection in arecanut is likely to progress:

- **Improved Accuracy and Efficiency**:

  a. **Enhanced Algorithms**: Development of more sophisticated CNN architectures and algorithms will improve the accuracy and efficiency of disease detection. This includes the integration of advanced techniques like transfer learning and data augmentation.
  b. **Large Datasets**: Availability of larger, annotated datasets will train models better, increasing the precision of disease identification.

- **Integration with IoT and Remote Sensing**:

  c. **Smart Farming**: Combining CNNs with Internet of Things (IoT) devices and remote sensing technologies can lead to real-time disease monitoring. Drones and sensors can capture images and data from arecanut plantations, which can then be analyzed by CNN models.
  d. **Automated Systems**: Automated disease detection systems can be developed, which notify farmers about the presence of diseases promptly, enabling quicker intervention and reducing crop losses.

VI. References:

1.B. R. Puneeth and P. S. Nethravathi, “A literature review of the detection and categorizati0n of various arecanut diseases using image processing and machine learning approaches,” International Journal of Applied Engineering and Management Letters, pp. 183–204, Dec. 2021, doi: 10.47992/ijaeml.2581.7000.0112.

2.K. C. Dhanuja and H. P. M. Kumar, “Areca nut disease detection using image processing technology,” International Journal of Engineering Research and, vol. V9, no. 08, Sep. 2020, doi: 10.17577/ijertv9is080352.