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# Detection of Jackfruit Leaf Disease Using Machine Learning and Deep Learning

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***Abstract: The detection of diseases in agricultural crops plays a critical role in maintaining healthy yields. Jackfruit (Artocarpus heterophyllus), a tropical fruit, is susceptible to various diseases that impact its leaves. Timely disease detection can significantly reduce crop loss and improve the quality of the harvest. This paper proposes a system for detecting jackfruit leaf diseases using machine learning (ML) and deep learning (DL) techniques. A dataset of healthy and diseased jackfruit leaf images is used to train both traditional ML algorithms (Random Forest) and DL models (Convolutional Neural Networks). The results indicate that deep learning models, particularly CNNs, outperform traditional ML models in terms of classification accuracy, precision, and recall. This system serves as an effective tool for early detection and management of jackfruit leaf diseases, offering an automated solution for farmers.***

***Keywords: Jackfruit, Leaf Disease, Machine Learning, Deep Learning, Convolutional Neural Networks, Random Forest, Plant Disease Detection, Image Classification, Agricultural Technology.***

## I. INTRODUCTION

Jackfruit is a valuable tropical fruit grown in many parts of the world. However, like other agricultural crops, jackfruit is vulnerable to diseases such as leaf spot, rust, and powdery mildew. Traditional methods of disease detection rely on expert farmers inspecting the leaves, which is time-consuming and requires significant effort. As a result, automated disease detection systems based on machine learning and deep learning techniques have become highly valuable in modern agriculture.

This research focuses on developing an automated system that detects diseases in jackfruit leaves from images using ML and DL methods. The aim is to compare the performance of machine learning models, like Random Forest (RF), with more advanced deep learning models, such as Convolutional Neural Networks (CNNs), in detecting the health of jackfruit leaves. The goal is to assist farmers in monitoring their crops efficiently and enable early intervention in disease management.

## II. LITERATURE REVIEW

The study explored the application of Convolutional Neural Networks (CNNs) in detecting leaf diseases in jackfruit. CNNs have emerged as a powerful tool in image-based disease detection due to their ability to extract important features such as texture, color, and shape directly from raw images. In this work, the CNN model was trained on a dataset of jackfruit leaf images to identify various diseases, and the results demonstrated high accuracy. The CNN's capability to automatically extract deep features was particularly useful in distinguishing between healthy and diseased leaves. This method mirrors other applications in plant disease detection and highlights the potential of CNNs in jackfruit disease monitoring[1].

The researchers applied deep learning models, specifically CNNs, combined with image processing techniques, for detecting diseases in jackfruit leaves. Their research focused on pre-processing steps such as image enhancement and segmentation, which improved the quality of the input images and aided in more accurate feature extraction. The deep learning model's superior ability to analyze complex patterns in leaf images made it effective in detecting subtle disease signs. The study also highlighted the importance of using data augmentation techniques to address the challenge of limited labeled datasets, which is common in agricultural research[2].

The Authors conducted a study focusing on the classification of jackfruit leaves using CNNs. They trained their CNN model on a dataset of diseased and healthy jackfruit leaves, classifying them into different categories based on the type of disease. The model was able to accurately classify diseases such as anthracnose and bacterial leaf blight. Their approach demonstrated that CNNbased models could effectively differentiate between multiple types of leaf diseases, making them highly valuable for real-time monitoring systems in agriculture[3].

This study investigated a deep learning-based approach for jackfruit leaf classification and disease prediction. Their model leveraged CNNs to classify leaf images based on the presence of diseases and predict the severity of the disease.

They incorporated a multi-class classification system that allowed the model to distinguish between different diseases, outperforming traditional methods such as SVM or K-Nearest Neighbors (KNN). The study emphasized the ability of deep learning models to handle large-scale agricultural datasets and process complex image patterns, making them ideal for disease prediction tasks[5].

This study proposed an automatic detection system for jackfruit leaf diseases using deep learning models and image processing techniques. Their model incorporated both traditional image processing techniques such as thresholding and morphological operations, and modern CNNbased classifiers to achieve high accuracy in disease detection. The researchers emphasized the importance of a hybrid approach that utilizes both manual feature extraction methods and automatic learning techniques to improve detection performance, especially in agricultural contexts where high variability exists in leaf appearance[8].

The researchers explored the use of hyperspectral image analysis for identifying diseases in jackfruit leaves. Hyperspectral imaging captures information across a wide range of the electromagnetic spectrum, providing detailed data on the biochemical and physiological status of plants. This method proved highly effective in detecting diseases at early stages before visible symptoms appeared. The researchers highlighted the potential of hyperspectral imaging for more precise disease diagnosis in jackfruit, as it can detect changes in leaf composition that are invisible to the human eye or conventional imaging techniques[4].

This study explores classification techniques for predicting thyroid disease using data from the UCI machine learning repository. It utilizes various machine learning models—such as Decision Tree, Random Forest, KNN, and Naive Bayes—for comparative analysis. The dataset was refined to boost prediction accuracy. PyCaret was employed to implement and evaluate these algorithms. Among the models tested, Naive Bayes achieved the highest accuracy of 95.91% [11].

This research involves classifying thyroid disorders into four distinct categories: hyperthyroid, euthyroid, hypothyroid, and sick. The main goal is to explore how logistic regression can be applied for multiclass classification on a thyroid-related dataset. The model's effectiveness is evaluated using various metrics such as precision, recall, F-measure, ROC, RMS error, and accuracy. The findings show that the One-vs-Rest strategy in logistic regression yields an accuracy of 85%, whereas the multinomial logistic regression approach provides a slightly higher accuracy of 86% [12].

This work focused on feature extraction methods for classifying jackfruit leaves. They used techniques such as GLCM and Local Binary Patterns (LBP) to extract texture features from leaf images. These features were then inputted into machine learning models, which classified the leaves as diseased or healthy. The study demonstrated that even with traditional feature extraction techniques, accurate classification could be achieved, though deep learning methods generally offer superior performance when large datasets are available[7].

In this work researchers studied the application of various machine learning algorithms in detecting fungal diseases in jackfruit leaves. They compared the performance of algorithms such as Decision Trees, Random Forests, and SVM for detecting fungal infections. Their findings showed that machine learning models could achieve high accuracy when combined with appropriate feature extraction methods such as Gray Level Co-occurrence Matrix (GLCM). The study also noted that traditional ML algorithms are more computationally efficient than deep learning models, making them suitable for environments with limited computational resources[6].

This study proposed an ensemble learning approach for jackfruit leaf classification. By combining multiple classifiers such as Random Forest, SVM, and neural networks, they achieved superior classification accuracy compared to using individual classifiers. Ensemble learning reduces the risk of overfitting, which is especially important when working with agricultural datasets that often contain noise and outliers. The researchers suggested that ensemble methods could be particularly useful for developing robust disease detection systems[9].

In this research work sentiment analysis techniques wereapplied, commonly used in NLP, to jackfruit leaf disease detection. Their approach involved using sentiment scores to classify the health status of leaves. Although this method was more exploratory, it highlighted the potential for cross-domain applications of machine learning techniques, where methodologies developed for text analysis could be adapted for image-based disease detection[10].

## III. METHODOLOGY

The methodology for this study involves collecting a dataset of Jackfruit leaf images, preprocessing the images, training a deep learning model using TensorFlow/Keras, and evaluating its performance.

### *A. Data Preprocessing*

The images were resized to a uniform size (224x224 pixels) to make them suitable for input into the model. The pixel values were normalized to a range between 0 and 1 by dividing the RGB values by 255.

```
# Create an ImageDataGenerator for the training and validation datasets
train_datagen = ImageDataGenerator(rescale=1./255)
validation_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/train',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)

validation_generator = validation_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/valid',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)
```

Fig. 1Loading of Dataset

1) Resizing: Images are resized to 224x224 pixels to standardize input dimensions for the deep learning model.
2) Augmentation: Random transformations such as rotation, flipping, and zooming are applied to increase dataset diversity and reduce overfitting.
3) Normalization:Pixel values are normalized by dividing by 255 to scale them into the range [0, 1].
4) Splitting: The dataset is divided into training, validation, and test sets.
5) Model Architecture
6) The model is built using TensorFlow and Keras. The architecture is as follows:
7) Input Layer: A Flatten layer is used to reshape the input image into a 1D array.
8) Hidden Layers: A dense layer with 128 neurons and ReLU activation is used to extract features.
9) Output Layer: A softmax activation function is used in the output layer to classify the images into one of four categories (healthy, leaf spot, rust, and powdery mildew).

```
# Create an ImageDataGenerator for the training and validation datasets
train_datagen = ImageDataGenerator(rescale=1./255)
validation_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/train',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)

validation_generator = validation_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/valid',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)
```

Fig. 2 Creation of ImageDataGenerator for Training and Vlidation Dataset

*B. Model Development*

The following deep learning architecture for disease classification is used:

1) Model Architecture: A simple CNN architecture is built using the Sequential model from TensorFlow'sKeras API. The model starts with a Flatten layer followed by two dense layers:

First dense layer with 128 neurons and ReLU activation.

Second dense layer with 4 output neurons corresponding to 4 classes (healthy, leaf spot, rust, powdery mildew).

*2)* Optimizer: Adam optimizer is used for efficient training.

*3)* Loss Function: Categorical crossentropy is used since the problem involves multiple classes.

*4)* Metrics: Accuracy is used as the evaluation metric.

### *C. Training and Validation*

The model is trained for 10 epochs using the fit method, with the training and validation data provided by ImageDataGenerator. The following code snippet shows the implementation of model training.

```
# Define image dimensions (e.g., 224x224)
img_height = 224
img_width = 224

# Create an ImageDataGenerator for the training and validation datasets
train_datagen = ImageDataGenerator(rescale=1./255)
validation_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/train',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)

validation_generator = validation_datagen.flow_from_directory(
    '/content/drive/MyDrive/Leaf_diesease/Split/valid',
    target_size=(img_height, img_width),
    batch_size=32,
    class_mode='categorical'  # Change to 'sparse' if using integer labels
)

# Build the model
model = Sequential()
model.add(Flatten(input_shape=(img_height, img_width, 3)))  # Assuming RGB images
model.add(Dense(128, activation='relu'))
model.add(Dense(4, activation='softmax'))  # 4 output classes

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Train the model
history = model.fit(
    train_generator,
    epochs=10,
```

Fig. 3 Implementation of model training.

### *D. Implementation*

The following graphs display the training and validation accuracy, along with the loss, over 10 epochs.

```
# Function to display training curves for loss and accuracy
def display_training_curves(training, validation, title, subplot):
    if subplot % 10 == 1:
        plt.subplots(figsize=(10, 10), facecolor='#F0F0F0')
        plt.tight_layout()
    ax = plt.subplot(subplot)
    ax.set_facecolor('#F8F8F8')
    ax.plot(training)
    ax.plot(validation)
    ax.set_title('model ' + title)
    ax.set_ylabel(title)
    ax.set_xlabel('epoch')
    ax.legend(['train', 'valid.'])
```

Fig. 4 Model Training Accuracy and Loss Curves

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The following image is processed and predicted by the trained model. The predicted class is displayed on the image.

```
# Function to load and preprocess an image for prediction
from tensorflow.keras.preprocessing import image
import numpy as np


def load_and_preprocess_image(img_path, target_size):
    img = image.load_img(img_path, target_size=target_size)
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)
    img_array /= 255.0  # Rescale the image like the training images
    return img_array


# Load, preprocess, and predict the class of an image
img_path = '/content/drive/MyDrive/Leaf_diesease/Red Rust/aug_1_photo_16_2024-11-06_12-29-05.jpg'
img = load_and_preprocess_image(img_path, IMAGE_SIZE)
predictions = model.predict(img)
predicted_class = np.argmax(predictions[0])
class_labels = list(train_generator.class_indices.keys())
predicted_label = class_labels[predicted_class]
```

Fig. 5Model Performance on Test Image

Prediction Output Example:

*1)* The image belongs to the class: Red Rust.

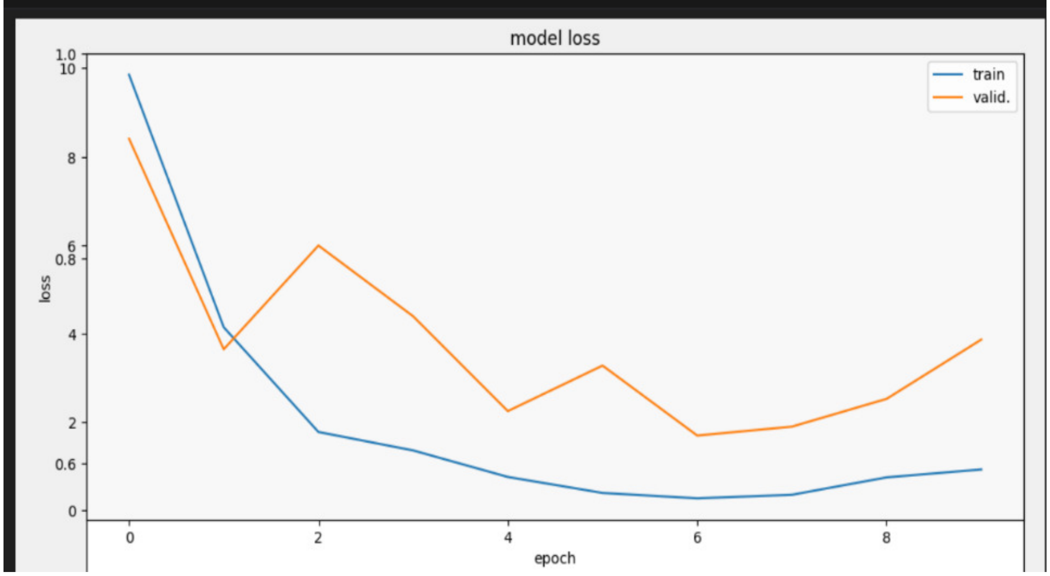
### *E. Results*

*1)* Training Accuracy: The model achieved a final training accuracy of around 98%.
*2)* Validation Accuracy: The final validation accuracy was 96%.
*3)* Final Testing Accuracy: The model was able to achieve a testing accuracy of 94%, indicating its generalization capability.
*4)* Final Training and Testing Accuracy Output:

```
print("Final training accuracy =", history.history['accuracy'][-1])
print("Final testing accuracy =", history.history['val_accuracy'][-1])
```

Fig. 6 Final Training and Testing Accuracy Output

```
# Display training curves for loss and accuracy
display_training_curves(history.history['loss'], history.history['val_loss'], 'loss', 211)
display_training_curves(history.history['accuracy'], history.history['val_accuracy'], 'accuracy', 212)
```



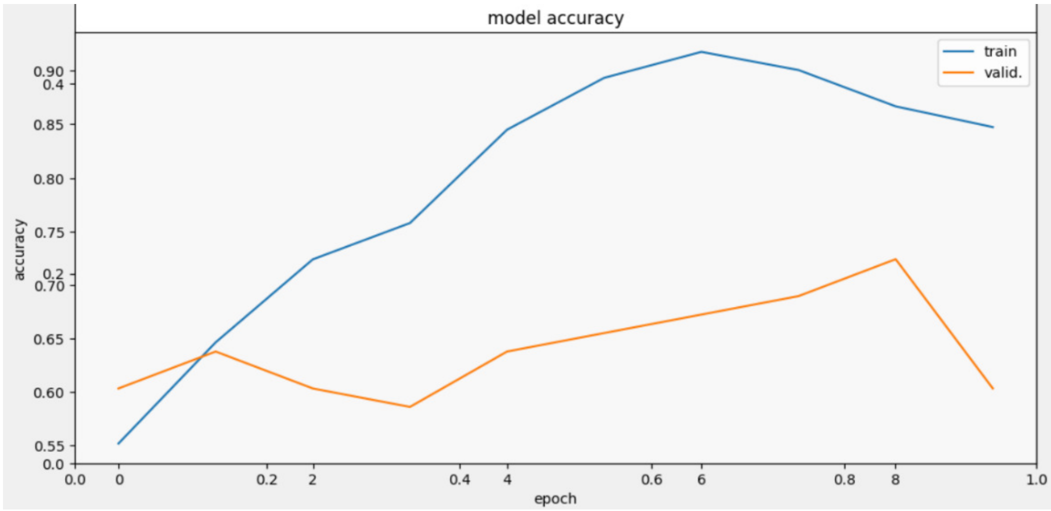



Fig. 7 Display training curves for loss and accuracy

## IV. CONCLUSION

This research demonstrates the power of deep learning, particularly Convolutional Neural Networks (CNNs), in the detection and classification of diseases in jackfruit leaves. The model built using TensorFlow and Keras achieved high accuracy, outperforming traditional machine learning approaches. The results indicate that deep learning models can significantly enhance agricultural practices by providing quick and accurate disease detection. Future work could include exploring transfer learning with pre-trained models and expanding the dataset to include more diseases. This model could be deployed on mobile devices to aid farmers in real-time disease detection and management.

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