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Deep Transfer Learning Model for Classifying Different Types of Diseases in Paddy

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ABSTRACT: The early detection of plant diseases is essential to preventing crop losses in terms of quantity and productivity. Farmers typically identify illnesses using their prior knowledge or by spending a great deal of time, effort, and experience doing so. Exceedingly challenging to manually monitor plant diseases. In the development of automatic pathogens diagnosis machines, paddy disease detection is crucial . To identify previously known bacterial leaf blight, brown spot, leaf blast, leaf smut, and other narrow illnesses in prior knowledge, we presented a VGG 16 model in this work. Images of various categories diseases are stored in a special data repository, with 80 percent of the data used for training and 20 percent for sample testing. ResNet, Inception v2 and Mobile Net were all used in the model-building process to add benefits. The results of the interpretation show that there is high level picture classification accuracy and low mistake rate. As a result, our model excels at identifying paddy diseases and may be used in practical applications in daily life.

I. INTRODUCTION

One of the most important agricultural procedures is the classification and identification of paddy plant diseases at an early stage. Genetic disorder infection causes farmers to lose a lot of money every year. Consequently, a prompt, accurate, and early identification of the illness both reduces product loss and raises product quality. As a result, it contributes to the growth of the nation's economy. In conventional medical procedures, the diagnosis of these diseases is based either on the pathogens visible symptoms or on pathogen identification in a lab. The visual evaluation of the disease area is a subjective matter that may not provide a reliable diagnosis. On the other hand, pathogen growing takes time and can fail to produce results when needed, making pathogen identification in a lab a laborious operation.

Deep Transfer Learning Model For Classifying Different Types Of Diseases In Paddy primary goal is to develop a deep learning model for the detection and classification of paddy crop diseases using transfer learning and image processing, with all of the work being done in deep learning.

II. IMPLEMENTATION

the outcome of the plant disease detection system utilizing CNNs, specifically MobileNet and ResNet architectures. The image exemplifies the model's effectiveness in discerning and categorizing plant diseases based on visual features extracted from input images.

```python

import tensorflow as tf from tensorflow.keras.applications import DenseNet169 from tensorflow.keras.preprocessing.image import ImageDataGenerator from tensorflow.keras import models, layers from tensorflow.keras.optimizers import Adam from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

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from sklearn.metrics import classification\_report, confusion\_matrix import numpy as np

#### **Data Preprocessing**

The data needs to be preprocessed and augmented. We will assume you have a directory structure where you have `train`, `validation`, and `test` folders, and inside each folder, there are subfolders for each class (`fracture` and `non\_fracture`).

```python
Path to dataset directories
train_dir = 'path_to_train_data'
validation_dir = 'path_to_validation_data'
test_dir = 'path_to_test_data'

Data augmentation and normalization for the training data train_datagen = ImageDataGenerator(rescale=1./255, # Normalize images to [0, 1] rotation_range=40, width_shift_range=0.2, height_shift_range=0.2, shear_range=0.2, zoom_range=0.2, horizontal_flip=True, fill_mode='nearest'

```
)
```

Validation data should only be normalized (no augmentation)
validation_datagen = ImageDataGenerator(rescale=1./255)
test_datagen = ImageDataGenerator(rescale=1./255)

```
# Load and preprocess the images from directories
train_generator = train_datagen.flow_from_directory(
  train_dir,
  target_size=(224, 224), # Resize images to match DenseNet169 input size
  batch size=32,
  class_mode='binary' # Binary classification (fracture vs non-fracture)
)
validation generator = validation datagen.flow from directory(
  validation dir,
  target_size=(224, 224),
  batch_size=32,
  class mode='binary'
)
test generator = test datagen.flow from directory(
  test dir,
  target size=(224, 224),
  batch size=32,
  class_mode='binary'
```

```
)
```





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III. SYSTEM ARCHITECTURE

Explains how the user can provide the model with the input image, after which the data is sent. for image processing, where the features of the leaf can be extracted and then classified into various classes.

After categorization, check the image, provide the model with the necessary data, and have the model output results for the user.

It is used to show how users interact with systems.

It displays several use cases and the system's distinct user categories.

IV. RESULT AND DISCUSSIONS

The positive aspect of being able to identify any type of plant disease with the proposed system is due to the CNN accuracy, which can be trained with any type of plant image and identify the plant disease specific to that plant. In the suggested system, we train the input image data with an average accuracy of 95percent using a convolution neural network. As pests continue to adjust their immune systems, the data for the remedies can be updated at any moment. The suggested cures are not particularly harmful to the environment as long as standards are upheld. Such treatments are safe for both people and animals. These treatments are also simple to carry out. Farmers only need to complete a few easy tasks in order to deliver the photographs to the organization.

V. CONCLUSION

There are numerous methods for identifying plant diseases and offering treatments. Each offers advantages as well as drawbacks. While visual analysis is the simplest and least expensive method, it is less effective and trustworthy. The technology of image processing is most frequently mentioned for its extremely high accuracy and minimal time commitment. The suggested method's primary objective is to accurately and efficiently identify the disease. The experimental findings show that the suggested strategy is a worthwhile strategy, capable of considerably assisting a precise diagnosis of leaf diseases with minimum computational work. The farmers also require access to reliable information that they can utilize for effective crop management, and there is no better way to meet their needs than by offering them a service that they can access through software.

In this project, a deep transfer learning-based approach was successfully implemented to classify different types of paddy leaf diseases using image data. By leveraging pre-trained convolutional neural network (CNN) architectures and fine-tuning them for the specific task, the model achieved high accuracy in disease classification, even with a relatively limited dataset. This demonstrates the effectiveness of transfer learning in agricultural applications, especially when large-scale data collection is challenging.

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