SDP END-TERM EVALUATION

AGRISENSE (INTELLIGENT PLANT DISEASE DETECTION SYSTEM FOR ENHANCED AGRICULTURAL PRODUCTIVITY)

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Introduction

❑ Overview

AgriSense is a cutting-edge plant disease detection system that utilizes image recognition algorithms to identify 28 types of plant diseases from uploaded images. This system is built on the Plant Village modified dataset and employs a sophisticated machine learning model trained on a large number of images to achieve exceptional precision.

The primary goal of AgriSense is to aid in the early detection of plant diseases, enabling farmers to take timely action and improve overall crop yields by accurately identifying diseases.

❑ Motivations

❖**Early Disease Detection:** To enable farmers to detect plant diseases early

❖**Improved Crop Yields**: To help farmers improve overall crop yields

❖**Enhanced Agricultural Productivity**: To enhance agricultural productivity

Introduction contd..

❑ Uniqueness of the work

- **AgriSense** simplifies access to agricultural solutions by providing an expert descision of plant disease detection, which eliminates the logistics involved in lab testing or hiring a professional.

- AgriSense's deployment on Google Cloud's high-performance & multi-region servers ensure consistent and precise results on all device types, enhancing scalability, performance, and accuracy.

- Instead of edge computing, deploying model on cloud ensures a consistent result regardless of the device specifications which often is a challenge for farmers.

Literature Survey

Existing System for Plant Disease Detection

- **Traditional Methods :** Traditional methods for plant disease detection involve visual inspection by experts, which can be time-consuming, subjective, and often inaccurate. These methods rely on manual observation of plant symptoms, such as discoloration, lesions, or other visual cues. This approach is limited by the expertise of the observer and the time required for inspection, which can lead to delayed detection and treatment of diseases.

How AgriSense Improves Upon Existing Technology

- **Exceptional Precision:** *AgriSense* employs a sophisticated machine learning model trained on a large number of images to achieve exceptional precision in identifying plant diseases.
- **Accessibility:** *AgriSense* is designed to be accessible to small-scale farmers, leveraging low-end IoT devices and a user-friendly interface.

Literature Survey

- **Past Researches on Plant Disease Detection**

Citation	Dataset	No. Of Classes	Result	Challenge
Li, L., Zhang, S., & Wang, B.	Custom PV dataset	2	96.7% accuracy	Noise in sensor data, environmental variations affecting sensor readings
Kumar, R., Chug, A., Singh, A. P., & Singh, D.	Various agricultural datasets	58	Varies across models	High variability in field conditions, need for large annotated datasets
Barbedo, J. G. A.	PlantVillage & real-field images	58	Up to 99% accuracy across classes	Imbalanced datasets, limited size of real-field image datasets, need for preprocessing and feature selection techniques

Table 1 [Past Researches and their results]

Literature Survey Contd..

❑ Problem Identification

There are challenges faced by farmers in detecting diseases correctly and timely, which leads to unhealthy yields. *AgriSense* addresses these challenges by providing farmers with a cutting-edge plant disease detection system that utilizes image recognition algorithms to identify 28 types of plant diseases from uploaded images.

- **Lack of Expertise:** Farmers often lack the necessary expertise to identify plant diseases accurately, leading to delayed or incorrect diagnosis.
- **Limited Access to Resources**: Small-scale farmers, in particular, may not have access to the necessary resources, such as equipment and training, to effectively detect and manage plant diseases.
- **Subjective Assessment:** Visual inspection of crops for disease symptoms can be subjective and prone to errors, as farmers may not have the necessary training or experience to accurately identify diseases.
- **Inadequate Adaptation to New Diseases:** Farmers may not have the necessary knowledge or resources to adapt to new diseases, which can lead to reduced crop yields and profitability.

Model Diagram

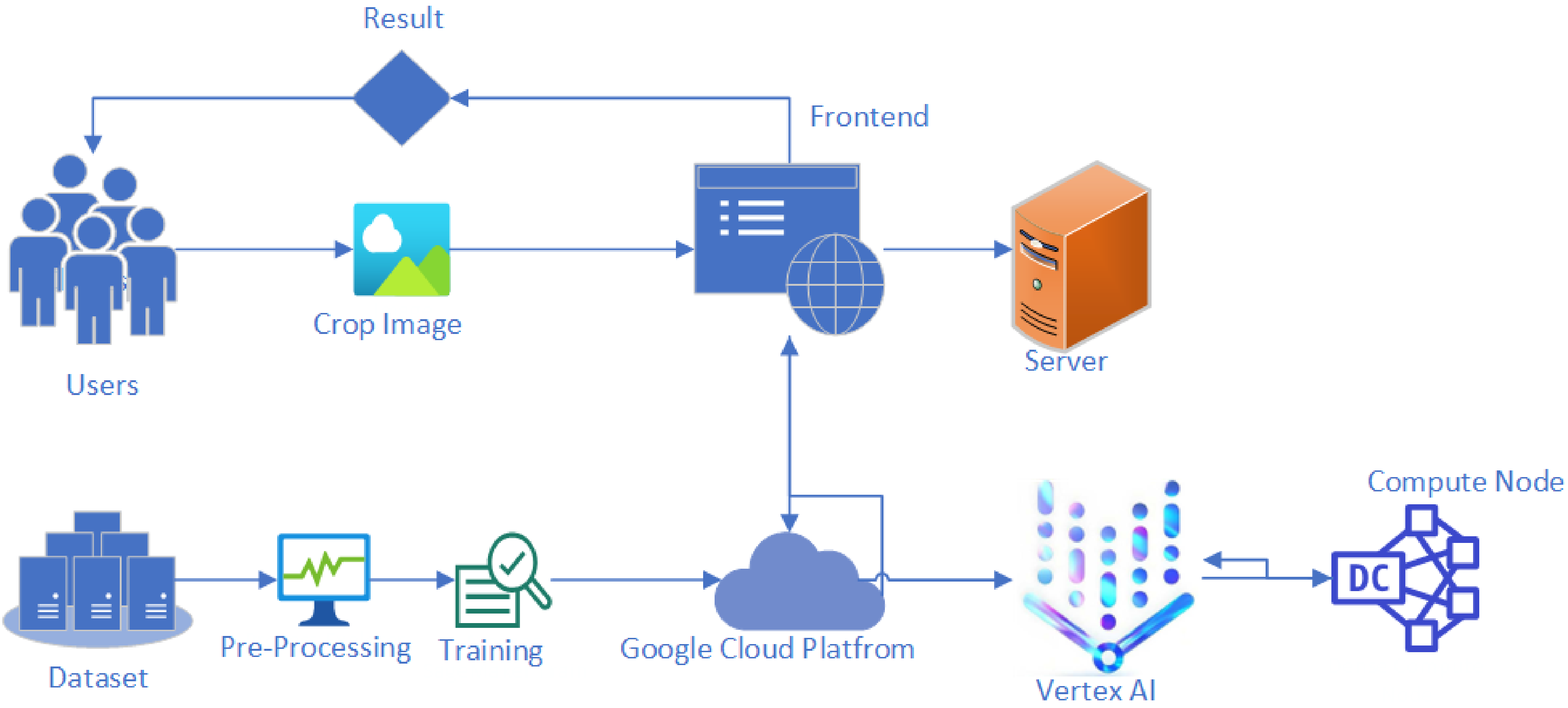

Figure 1 [AgriSense Model Diagram]

Methods & Tools Used

Methods:

- AgriSense employs transfer learning to create a sophisticated model for accurately identifying 28 plant diseases from uploaded images.
- The system utilizes advanced image recognition algorithms to analyze and classify plant leaf images for precise disease detection.
- AgriSense processes uploaded images using techniques to extract relevant features and patterns for accurate disease identification.

Tools:

- AgriSense is built on Google Cloud Platform, utilizing Vertex AI, a powerful machine learning platform for developing and deploying ML models.
- The system leverages Vertex AI to train the ML model, optimize performance, and ensure scalability.
- AgriSense uses an endpoint to receive images from the frontend, process them with the trained model, and send back the results.

Algorithms Used

- **Google Cloud Platform's Vertex AI:** *AgriSense* utilizes *Google Cloud Platform's Vertex AI*, an automated machine learning tool that automatically selects the best algorithm to suit the dataset for image classification tasks.

```python
import os
import csv
import concurrent.futures
from google.cloud import storage
from tqdm import tqdm

os.environ["GCLOUD_PROJECT"] = "nimble-factor-422112-t6"

# Function to upload a file to Google Cloud Storage
def upload_to_gcs(bucket_name, local_file_path, gcs_file_path):
    try:
        storage_client = storage.Client()
        bucket = storage_client.bucket(bucket_name)
        blob = bucket.blob(gcs_file_path)
        blob.upload_from_filename(local_file_path)
        return f"gs://{bucket_name}/{gcs_file_path}"
    except Exception as e:
        print(f"Error uploading {local_file_path} to {gcs_file_path}: {e}")
        return None

# Function to list files in directory and subdirectories
def list_files(directory):
    file_list = []
    for root, dirs, files in os.walk(directory):
        for file in files:
            file_list.append(os.path.join(root, file))
    return file_list

# Function to extract subfolder name from path
def get_subfolder_name(file_path):
    return os.path.basename(os.path.dirname(file_path))

# Function to upload files from subfolders to Google Cloud Storage and log details to CSV
def upload_files_and_log(directory, bucket_name, csv_file):
    file_list = list_files(directory)
    with open(csv_file, 'w', newline='') as csvfile:
        csv_writer = csv.writer(csvfile)
```

Figure 2 [Uploading to GC & generating a CSV]

Algorithms Used

- **Data Split:** The data was split into three parts for training, validation, and testing.
- **Automated Random Split:** The split was done randomly using an automated process.
- **Training Set:** The training set consisted of 129,942 images.
- **Validation Set:** The validation set consisted of 16,336 images.
- **Test Set:** The test set consisted of 16,564 images.
- **Split Ratio:** The split ratio was approximately 80/10/10, indicating that the training set was 80% of the total data, the validation set was 10%, and the test set was 10%.

Experimentation and Results

System Specifications

AgriSense utilizes Google Cloud Platform's Vertex AI, a powerful machine learning platform, to train and deploy the plant disease detection model.

Training:

- The machine learning model in *AgriSense* is trained on the modified Plant Village dataset using Vertex AI.
- The training process utilized 32 node hours which took 4 hr 26 min to finish.

Model Architecture:

- *AgriSense* employs a state-of-the-art transfer learning architecture, which is automatically selected and optimized by Vertex AI's capabilities.
- The model is designed to accurately classify plant leaves into 28 different disease categories.

Experimentation and Results

Dataset Description

- The ML model in *AgriSense* is trained on a modified Plant Village dataset, which contains a diverse range of images representing various plant diseases. Unlike other Plant Village datasets it comes with pre proccessed images in color, grayscale and segmented format. Including all the variations the dataset offers 162,000 images to train our model.
- The dataset covers 14 crop species including Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Bell Pepper, Potato, Raspberry, Soybean, Squash, Strawberry, and Tomato. The dataset is organized into 38 classes corresponding to plant-disease or healthy leaves.
- https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset

Experimentation and Results

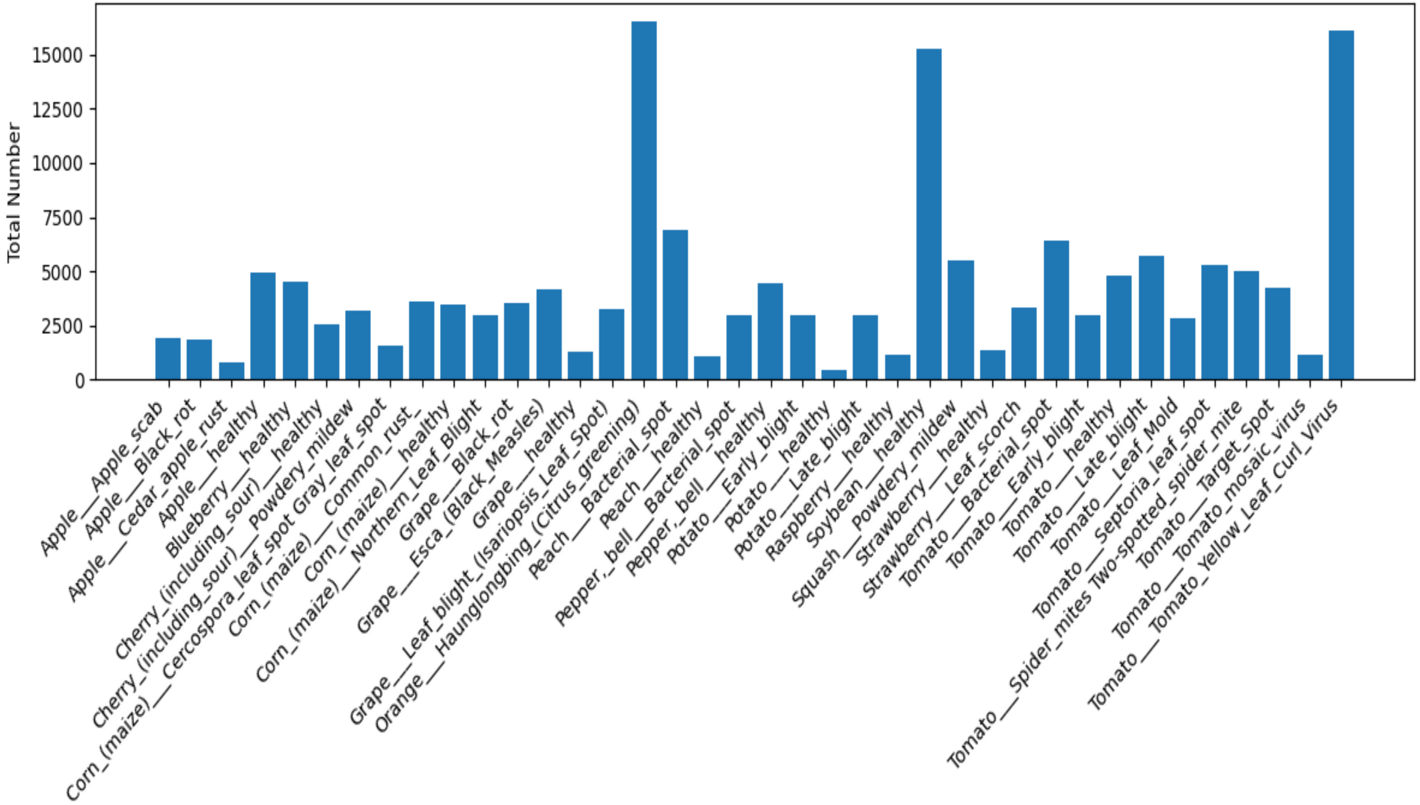

Figure 3 [Bar graph represnting no. of images to their corresponding classes]

Experimentation and Results Contd..

- Experimental outcomes

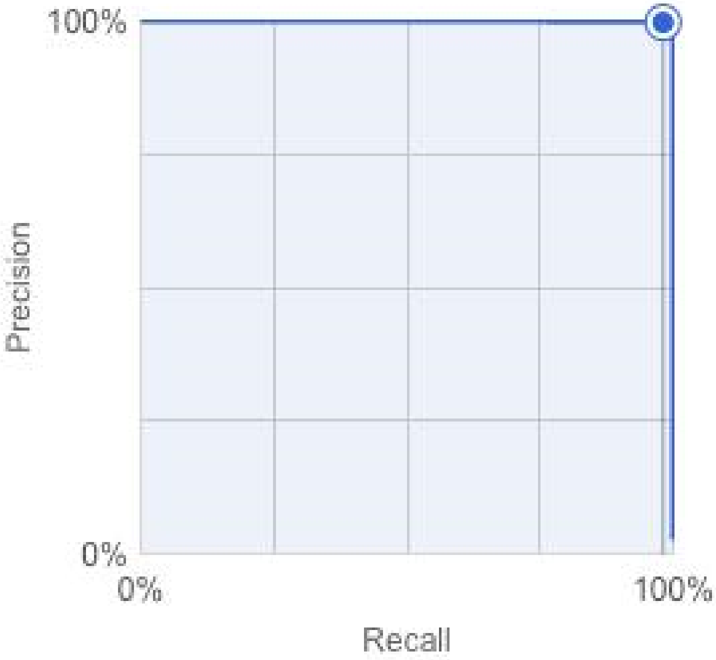

Figure 4 [Precision-Recall curve at 50% confidence Threshold]

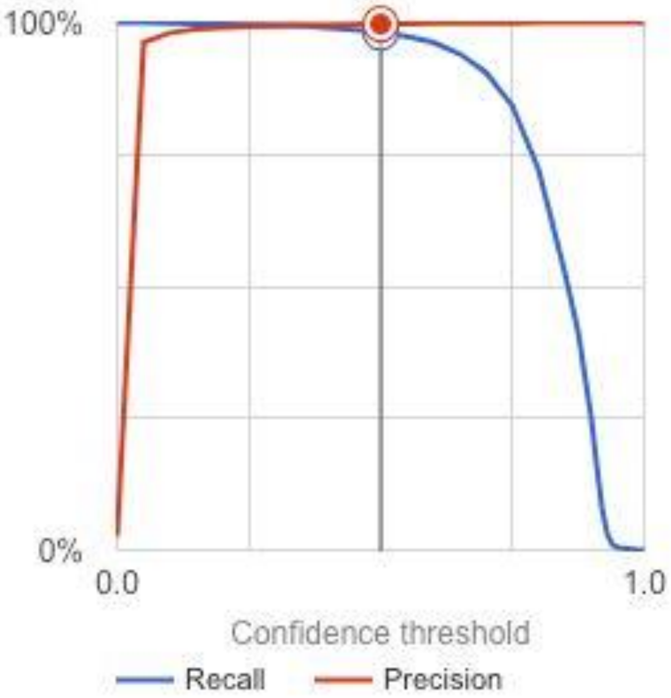

Figure 5 [Precision-Recall curve along full range of confidence threshold]

Experimentation and Results Contd..

- Experimental outcomes

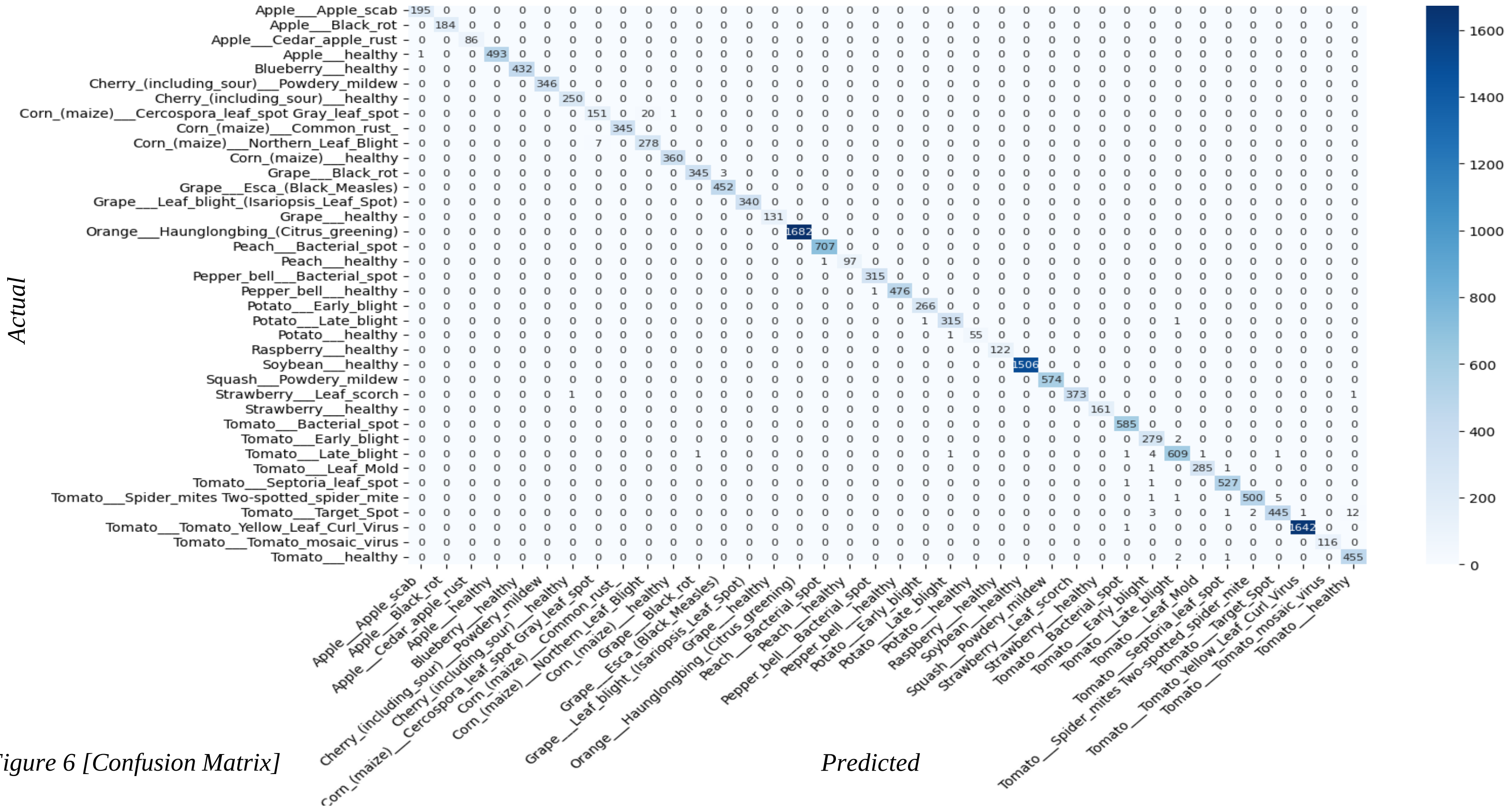

Figure 6 [Confusion Matrix]

Experimentation and Results Contd..

- Result Analysis and Validation

- **Validation:**
- **Cross-Validation:** Performed to ensure the model's robustness and generalizability across different subsets of data.
- **Real-World Testing:** Deployed on Google Cloud’s multi-region servers, ensuring consistent performance regardless of the device specifications used by farmers.
- **Accuracy and Performance Metrics:**
- **Confusion Matrix:** Shows model accuracy, with correct predictions along the diagonal.
- **Precision and Recall:** Precision is the accuracy of identified diseases, and recall is the proportion of actual diseases correctly identified.
- **Model Deployment and Use:**
- **Frontend Deployment:** Using Streamlit for real-time, interactive web applications.

Summary

AgriSense project demonstrates high accuracy in plant disease detection via modified dataset using multiple angle shots in grayscale and colour for enhanced precision.

- **Performance Metrics:** The model achieved an average precision of 0.999, precision of 99.7%, and recall of 98.1%.
- **Dataset Impact**: Training on Modified Dataset had best results and improved performance of the model.
- **Industrial Usability:** The model's performance on high-end hardware was subpar, indicating the need for advanced solutions like Vertex AI to achieve industrial-grade accuracy.
- **Web App :** URL - https://r2-2024-sdp.streamlit.app

Conclusion and Future Scope

AgriSense enhances early plant disease detection. Using algorithms and a robust dataset, it achieves high precision and recall in identifying 28 types of plant diseases. Deployment on Google Cloud's Vertex AI ensures scalability, reliability, and accessibility, especially for small-scale farmers without high-end computing resources. The system's accuracy and user-friendly interface make it a valuable tool for improving agricultural productivity and ensuring timely interventions to mitigate crop losses.

Future Scope

- Incorporating additional plant species and diseases to expand the system's applicability across more agricultural contexts.
- Implementing advanced security protocols to protect sensitive agricultural data and ensure the privacy and integrity of the information processed by the system.
- Expanding our portfolio with broader agricultural management platforms to provide comprehensive solutions for crop management, including pest control and nutrient management.

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V. Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Computers and electronics in agriculture, 153, 46-53.


Thank You