Plant Disease Detection Using Convolutional Neural Network (CNN) and Transfer Learning

Abstract— **This work proposes an automatic plant disease detection and treatment recommendation system, based on computerized deep learning techniques, to diagnose bacterial infections in the crops through leaf image analysis. The system not only identifies the category of bacterial infection but also assesses the severity of the infection and generates customized recommendations of treatment. For constructing a Convolutional Neural Network (CNN) model, two publicly available datasets were used to train the approach of custom transfer learning so as to improve performance. The system produced overall accuracy of 86.40 percent over several disease classes. A web application using Next.js has been developed to provide easy user interfacing for end users. The amalgamation of treatment recommendations is an innovative contribution to usual plant disease detection systems and provides a holistic solution for disease management in agriculture. This paper describes the methodology and implementation details, associated performance metrics, as well as future potential applications for the proposed system in improving productivity and sustainability in agriculture.**

Keywords— plant disease detection, Convolutional Neural Networks, transfer learning, Image classification, treatment recommendation, Next.js, TensorFlow, AWS S3.

I. INTRODUCTION

Plant diseases are a serious threat to global food security and agricultural sustainability and contribute to an estimated 20-40% decline in yields worldwide [1]. Since an early and accurate diagnosis of plant diseases is paramount for timely intervention in minimizing crop losses and reducing pesticide consumption [2], traditional methods for disease detection mostly rely on visual inspection from agricultural experts, which are time-consuming, labor-intensive, and often subject to human error. These limitations indicate a clear need for the development of reliable and simple plant disease detection systems.

The development of computer vision and deep learning opened windows for automating systems for plant disease detection through image analysis [3]. Convolutional Neural Networks (CNNs) have achieved significant success in image classification tasks, including distinguishing between healthy and diseased plants based on leaf images [4]. Nevertheless, there are solutions that mainly focus on the classification task without providing supplementary actions or suggested treatment.

This paper describes an integrated system that encloses activities centered not just on the detection of the disease but further on the assessment of the severity and recommendations for treatment accordingly. The paper contributes to:

- Development of a CNN-based model with customized transfer learning for improving plant disease detection.
- Integration of disease severity assessment capability.
- Implementation of a treatment recommendation engine based on the types of disease detected along with the severity levels.
- Building an easy-to-use web application available to farmers and agricultural professionals.

This proposed system is a more general solution that generates a bridge uniting disease identification and management, promising change in farming response toward plant diseases at both smallholder and commercial scales.

II. RELATED WORK

An extensively cited work in this area is, of course, Mohanty et al. [5], where CNNs classified 38 different classes of plant diseases with an accuracy of more than 99% on the Plant Village dataset. Even though very effective, such models are typically dataset-specific and, thus, may not generalize well to real-world conditions or to novel plant species.

In the last couple of years, several machine learning and deep learning methods have been applied to plant disease detection. Traditional image processing methods were predominantly manual, which constrained the methods' scalability and accuracy. The advent of Convolutional Neural Networks (CNNs) led the researchers to achieve considerable breakthroughs in leaf-based disease classification. [6] evaluated several CNN architectures to detect diseases in plants and attained successful rates of over 99% on certain model configurations. In the same way, [7] compared the performances using various models such as VGG16, InceptionV4, and ResNet; according to their results, finetuned transfer-learning techniques always did better than training from scratch.

Transfer learning has, very recently, become an emerging solution to counter this limitation. [8] showed that models pre-trained on ImageNet can be effectively transferred for the detection of diseases in tomato plants. Hence, high accuracy could be attained with relatively small domain-specific datasets. The transfer learning method is now a common practice in any plant disease detection system where lack of data becomes an issue in generalizing the model. Nonetheless, most of these implementations have been solely concentrating on disease classifications, thus eliminating other features, such as severity estimation or treatment possibilities.

Only a few studies related to disease detection systems have covered treatment recommendations. [9] proposed an agricultural decision support framework that made simple treatment suggestions corresponding to disease, but not severity. This paper goes further than these approaches and offers coverage of comprehensive treatments according to disease types and severity in an entirely novel contribution to the field.

Moreover, only a few other studies have looked at the model's performance in real-world applications, using cloud-based data storage and on-demand processing. We fill this gap by implementing AWS S3 for dataset access and a FAST API backend for image processing and feedback rendering. Thus, we have created a true end-to-end pipeline from image acquisition to actionable output.

III. METHODOLOGY

A. *Problem Statement*

The goal of this project is to develop a deep learning based framework for detection of bacterial infections in plant leaves, classification of disease types, determination of the extent of disease and recommendation of treatment. The system should be acceptably deployable and have a web interface for easy access.

B. *Datasets*

Two publicly available datasets from Kaggle were incorporated in this study, namely:

- Plant Village Dataset: It has approximately 20000 images and organized into 38 classes given the plant species and disease types. There are healthy as well as diseased images of plant leaves and that of different crop species.
- New Plant Diseases Dataset: As an extended dataset, it consists of somewhere in the range of 87000 to 88000 healthy and diseased images of plant leaves, spread over 38 categories that provide a lot of combinations from crops to diseases.

These datasets were saved in AWS S3 for better access and easier access when training the models for evaluation. They were also split into 3 sets, training (70%), validation (15%), and test (15%) sets to ensure a robust evaluation for the models.

C. *Image Preprocessing Pipeline*

Before the model training, we carried out an extensive image preprocessing pipeline to guarantee uniformity in input quality and memory optimization. Some of the main *aspects* of our preprocessing approach include:

Fig. 1 Preprocessing

```python
import os
import numpy as np
from tensorflow.keras.preprocessing import image as keras_image

def is_valid_image_file(path):
    # Ensure it's a file and has a proper image extension
    return os.path.isfile(path) and path.lower().endswith(('.jpg', '.jpeg', '.png', '.bmp', '.gif'))

def preprocess_image(path, target_size=(128, 128)):
    """
    Loads an image from disk, resizes to target_size,
    scales pixels to [0,1], and returns a float32 array.
    """
    # normalize path separators
    path = os.path.normpath(path)
    img = keras_image.load_img(path, target_size=target_size)
    arr = keras_image.img_to_array(img).astype(np.float16) / 255.0  # use float16 to reduce memory usage
    return arr
```

The preprocessing pipeline entails the following:

a) *Image Validation:* Checks whether a file exists and whether it has valid image file extensions.
b) *Resizing:* Normalize all images to 128×128 pixels in size for a trade-off between some detail retention and computational efficiency.
c) *Normalization:* Normalizes pixel values within the [0,1] range to facilitate convergence of the model.
d) *Memory Optimization:* Uses float16 instead of float32 to cut memory even further by another 50%.

Implemented a controlled loading mechanism to handle large datasets efficiently:

Fig. 2 Loading Mechanism

```python
X = []
y = []

# Optional: limit number of images to avoid memory error
MAX_IMAGES = 5000  # Set to None to load all

count = 0
for path, label in zip(df['image_path'], df['label_encoded']):
    if MAX_IMAGES and count >= MAX_IMAGES:
        break
    if is_valid_image_file(path):
        try:
            img = preprocess_image(path)
            X.append(img)
            y.append(label)
            count += 1
        except Exception as e:
            print(f"❌ Error loading image: {path} -> {e}")
    else:
        print(f"⚠️ Skipping invalid or hidden file: {path}")

X = np.array(X)
y = np.array(y)
```

The approach includes the following:

a) *Batch Size Limiting:* This avoids memory overflow by capping the number of images processed.
b) *Error Handling:* Exception handling is robust; handling broken images and corrupt image files is included.
c) *Progress Monitoring:* Long data-loading operations are tracked for the progress of processing.

D. *Model Architecture*

The document proposes a CNN-based image classification system. CNNs are quite powerful for image interpreting because they learn and gain a hierarchical feature space from unprocessed pixel values [10]. Here is the architecture of our network:

a) *Input Layer:* 128*128*3
b) *Feature Extraction Layers:*
   - Convolutional layers with 3 *3 kernels
   - Batch normalizations after each convolutional layer
   - ReLU activation functions
   - Max pooling layers 2×2 pool size with a stride of 2
c) *Classification Layers:*
   - Global average pooling
   - Dense layers with dropout (rate = 0.5) for regularization
   - Softmax output layer for multi-class classification

E. *Custom Transfer Learning Approach*

The key innovation that underlies our methodology is a unique transfer learning technique, which has sequential

training on different datasets. The steps involved in this process are:

- Initial model training on Plant Disease Dataset.
- Converged model weights saved.
- Trained further using New Plant Diseases Dataset with the pre-saved model.

This approach facilitates the model to develop robust feature representations from the first dataset and further refines representations using second dataset. It outperformed training all together on the combined dataset or traditional transfer learning using general purpose models such as VGG16 or ResNet.

F. *Implementation Details*

We have used following tech stacks for implementation:

a) *Machine Learning Framework:* TensorFlow 2.6.0 and Keras model development and training.
b) *Data Processing:* Pandas 1.3.3 and Matplotlib for Data Analysis and Visualization, 3.4.3.
c) *Model Evaluation:* Scikit-learn 0.24.2 for assessing performance metrics.
d) *Frontend Development:* Next.js framework to build a responsive web application.
e) *Backend Integration:* Custom API to connect the front-end interface to the ML model trained.

G. *Data Augmentation and Generator Configuration*

Keras data generators have been implemented for successful data enhancement and memory-efficient batch processing while training the model. This approach creates a method of data augmentation on-the-fly during the training stage, such that the model generalizes the learning while keeping memory consumption manageable.
At first, we specified our augmentation parameters:

Fig. 3 Augmentation Parameters

```
new_datagen = ImageDataGenerator(
    rescale=1./255,
    validation_split=0.2
)
```

With these augmentation parameters, our model learns to identify the plant disease-exhibition under several different real-world conditions such as orientation, scale, and position in the frame.
At this point, we wrote a training data generator to load data efficiently in batches:

Fig. 4 Training data generator parameters

```
new_train_gen = new_datagen.flow_from_directory(
    directory=new_dataset_path,
    target_size=(128, 128),
    batch_size=32,
    class_mode='sparse',
    subset='training',
    shuffle=True,
    seed=42
)
```

Similarly, we configured a validation generator:

Fig. 5 Validation generator parameters

```
new_val_gen = new_datagen.flow_from_directory(
    directory=new_dataset_path,
    target_size=(128, 128),
    batch_size=32,
    class_mode='sparse',
    subset='validation',
    shuffle=False,
    seed=42
)
```

The advantages of this generator-based approach can be summarized as follows:

a) *Memory Efficient:* Loads only batch of images into memory; rest of the dataset is not loaded in memory.
b) *Real-Time Augmentation:* Creates variations of training images on-the-fly while training.
c) *Automated Labeling:* Class labels are inferred from the directory structure.
d) *Balanced Training:* Ensures equal representation of classes in each batch.

A batch size of 32 was chosen, which is a trade-off between memory efficiency and stability of training, while maintaining the target size of 128-by-128 pixels, as fits with our preprocessing pipeline specifications.

H. *Treatment Recommendation Engine*

The treatment recommendation component represents a novel addition to traditional plant disease detection systems. This module works by:

- The CNN model classifies the disease and will be received.
- Determines the severity depending on percentage area affected on the leaves.
- Retrieves effective remedies from a knowledge base against every disease-severity combination.
- If it generates a customized treatment, priority will be given to eco-friendly methods for low severity cases and much more intensive treatments for severe infections.

The knowledge base has been developed from various agricultural extension literature and resources in plant pathology, ensuring that recommendations provided do not deviate from known best practices in sustainable agriculture.

I. *System Integration and Web Interface*

To enable real-time disease predictions for users, a web application has been created using Next.js. Here, users upload pictures of plant leaves through the user interface, which sends the images to a back-end API that loads the trained model and returns predictions as follows:

- Disease Detected
- Confidence Level
- Severity
- Recommended Treatment

This end-to-end pipeline ensures a seamless user experience, from image upload to actionable insights.
.

IV. Results and Evaluation

A. *Model Performance*

The model was evaluated on a test set of 1000 images. The classification report is summarized as follows:

TABLE I. Confusion Matrix Summary

Class	Precision	Recall	F1-score	Support
0	1.00	0.94	0.97	199
1	0.98	1.00	0.99	296
3	1.00	0.99	0.99	200
4	1.00	0.82	0.90	200
5	0.90	0.60	0.72	30
6	0.00	0.00	0.00	75

Overall Accuracy: 86.4%
Macro Avg F1-Score: 0.57
Weighted Avg F1-score: 0.89

B. Interpretation

So here are some of the observations drawn from the comparative analysis of multiple classes.

- Classes 0, 1, and 3 have been shown to perform quite well, with near-perfect F1 scores.
- Classes 2 and 10 don't have any samples in the test, which affects the performance in macro average.
- Class 6 (75 samples) and Class 5 (30 samples) underperformed, suggesting class imbalance or overlapping features.

This points towards the fact that even though the model is very powerful for those classes that have a good representation, it needs either more data or a little more class balancing for very rare disease classes.

C. Severity Estimation and Treatment Recommendation

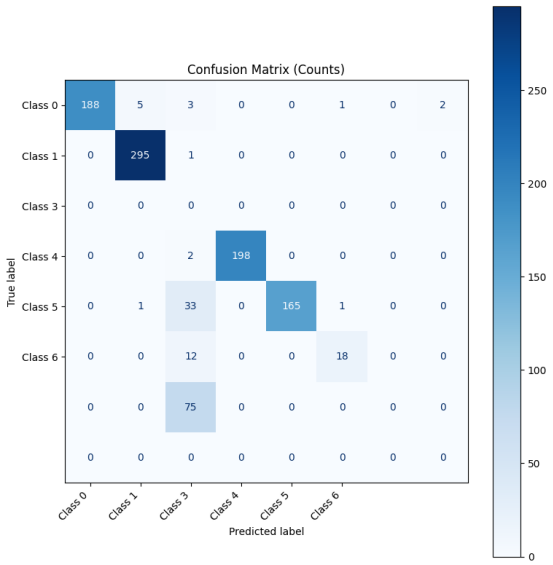
In addition to disease detection, we provided:

- A severity classification module (low, moderate, severe), segmented by probability thresholds.
- A treatment suggestion module, in which each disease label is correlated to a set of predetermined treatment steps (retrieved from a dictionary and served via the API).

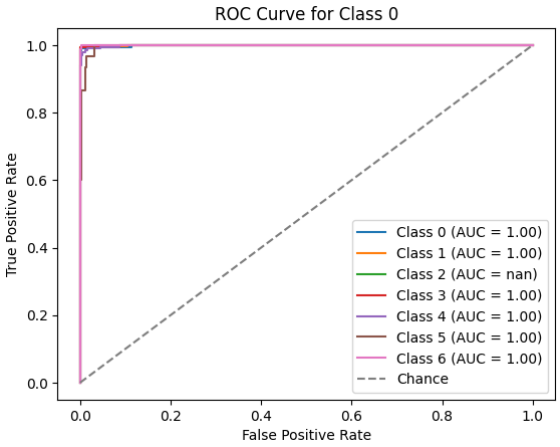
D. Figures

- **Confusion Matrix**

Fig. 1 Confusion Matrix

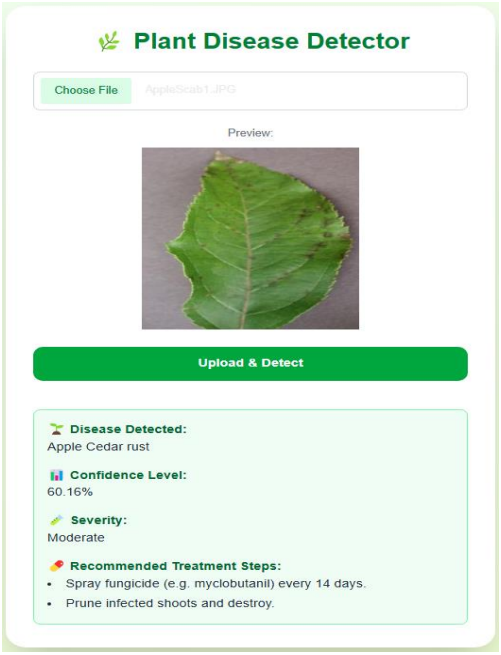


- **ROC Curve**



S

- **Web Interface**



E. Limitations

Despite promising results, several limitations and areas of improvement have been identified:

a) Class Imbalance: The poor performance on certain classes (particularly 2, 6, and 10) can indicate possible data imbalance problems that can be set right either by adding more data or by employing complex sampling methods.

b) Field Conditions: The model is found working nicely under the test dataset, but its performance under varying field conditions (different lighting, backgrounds, and orientations of the leaf) needs further testing and enhancement.

c) Disease Coverage: Currently, the model is restricted to diseases represented in the training datasets. For practical use, expanding to include other crops and diseases will enhance the utility of the system.

CONCLUSIONS AND FUTURE WORK

This paper presented a comprehensive plant disease detection and treatment recommendation system that comprised image classification through CNN with severity assessment and decision support elements for treatment. The system achieved overall accuracy of 86.40 percent with the different diseases, heightening the demand of their usage in agriculture practices.

Breakthroughs in this piece of work include designing a customized sequential transfer learning approach where the normal training process has failed, and also the development of a treatment recommendation engine that closes the disease detection-management gap. The online application provides a user-friendly interface to take advantage of these advanced capabilities.

Although there exist some limitations with respect to performance against certain classes of diseases and relatively adaptable field conditions, this system is, nevertheless, a significantly more informed step toward integrated agricultural disease management systems. The future work will overcome such limitations and add more features to further improve the practicality of the system in miscellaneous agricultural settings.

While this system really offers a proactive approach towards the digitalized agriculture model, along with effective disease detection, it obviously possesses potential therapy recommendations associated with its growing global food security threats.

Future Work

- *Data Addition and Augmentation:* It could be considered that enhancing the imbalanced classes and expanding the classes into the training dataset-mostly those diseases relatively lesser in numbers would help towards a better and robustness-laden model.
- *Multimodal Inputs:* Future versions could incorporate weather, soil, and geographical data to improve prediction and treatment precision.
- *Mobile Application:* A lightweight mobile version can be developed to improve access for rural users, using frameworks such as React Native or Flutter.
- *Real-Time Disease Monitoring:* With the integration of drones or IoT devices, automated real-time monitoring of plants and disease detection can be achieved.

This work shows how deep learning and practical deployment techniques can merge to attain real-world solutions in agriculture. By making plant disease detection faster, smarter, and more actionable, our system could have a serious impact on crop health management and food security.

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