UAV-Aided Crop Disease Detection: A Comprehensive Dataset Analysis and Algorithmic Framework

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***Abstract*—Automated plant diagnosis has a lot of promise to increase agricultural productivity, but the adoption of drone-based solutions is hampered by issues including the trade-off between processing speed and image resolution and the scarcity of labeled training data. To address these challenges, this research presents a novel two-step machine learning approach that uses Convolutional Neural Networks (CNN). Our approach guarantees the production of representative data from UAV photos while efficiently addressing class imbalance in datasets. Our method, which focuses on a dataset of apple trees with class imbalance, entails preprocessing the images, building a CNN architecture with dropout layers strewn in between convolutional and pooling layers to mitigate overfitting, and then training the model to distinguish between images that are diseased and those that are not. Our model then performs a two-step approach to identify possibly unhealthy plants and offer actual diagnosis. The experimental results provide a remarkable 80.90% accuracy rate on training data and 74.79% on test data, demonstrating the efficacy of our CNN-based drone technology for automated crop disease diagnosis and providing a viable substitute for labor-intensive diagnostic techniques.**

***Index Terms*—Automated Plant Disease Detection, Machine Learning, Convolutional Neural Network, Data Augmentation, Unmanned Aerial Vehicles**

I. Introduction

Food security is a crucial aspect of human survival, and agriculture is the main way to provide this basic need. Cultivation involves the growing of necessary plants and the rearing of domesticated animals, which are sources of nourishment, fiber, and other important commodities. The notion of crop yield is essential for agricultural productivity as it refers to the amount of crops produced per unit area of farmed land and their ability to produce seeds. Throughout the years, this measurement has been impacted by several factors, such as the significant increase in the world's population from 3.71 billion in 1950 to 8 billion in 2024. The rapid increase in the global population highlights the crucial importance of agriculture in addressing the growing need for food.

We are going to examine the difficulties these diseases present to apple tree productivity and health, delving into the specifics of each one. Many diseases pose serious threats to apple trees (Malus domestica), but two particularly well-known offenders are Apple Scab and Cedar Apple Rust. Apple Scab, which is caused by the fungus Venturia inadequacies, is a serious hazard to apple trees, hawthorn, and crab-apples. The fungus grows black pseudothecia structures in dead apple leaves or fruit left on the ground over the winter. As spring moisture and a variety of temperatures arrive, pseudothecia produce ascospores that cause diseases on emerging fruit and leaves. Visible indications of infection develop quickly, followed by the development of asexual spores, or conidia, which continue the disease cycle. Apple Scab is most common in the Pacific Northwest, East Asia, and some parts of South

(°F)	(°C)	Basidiospore Formation	Light Infection	Severe Infection
36	2	NB	24	NSI
39	4	NB	12	24
43	6	NB	8	10
46	8	7	6	7
50	10	5	5	6
54	12	4	4	5
57	14	4	3	5
61	16	4	3	4
64	18	4	3	4
68	20	4	2	4
72	22	4	2	4
75	24	4	2	4
>79	>26	NB	NI	NI

Fig. 1. Temperature and moisture requirements for apple rust disease

America. It causes severe damage to fruit, including malformations and early fruit and leaf drop, drastically lowering productivity, and quality.

Cedar Apple Rust, a member of the Pucciniaceae family, typically requires two hosts for its life cycle. On the upper leaf surfaces, it first appears as little yellow dots that progressively grow into brilliant yellow-orange lesions with a reddish border. Mostly widespread in rural areas that alternate between agriculture and forest in eastern North America, Cedar Apple Rust also affects apple orchards in temperate locations like Europe and East Asia. In severe cases, the disease results in tree stunting, greater vulnerability to winter injury, and eventual mortality. It also weakens the trees and reduces the amount and quality of their fruit. In Fig.1, the temperature and moisture requirements for apple rust infection are given.

NB denotes no basidiospores formed at this temperature. NSI denotes no severe infection observed at this temperature, and NI denotes no infection observed at this temperature.

In order to overcome these obstacles and facilitate the wider integration of UAVs in the identification of apple tree diseases, this study offers a thorough examination of a specifically designed dataset. By utilizing convolutional neural networks (CNNs) and unmanned aerial vehicle (UAV) technology, we provide an algorithmic framework for detecting crop diseases. This framework has the potential to significantly transform agricultural diagnostics. Our system utilizes sophisticated image processing techniques and machine learning algorithms to address the inherent difficulties presented by UAV footage. The goal is to provide a scalable and effective solution for precise and rapid disease detection in agriculture.

This study not only presents our proposed framework but also examines the wider consequences of our research and its potential influence on agricultural practices. Our goal is to connect advanced technology with practical agricultural issues to advance sustainable farming methods that can meet the demands of a fast-growing global population.

II. Literature Review

Unmanned Aerial Vehicle (UAV)-assisted crop disease detection has become a viable method for efficiently monitoring and controlling agricultural health. Manual inspection is a common component of traditional methods, but it can be laborious and subjective. On the other hand, crop disease detection can be accomplished quickly and objectively with unmanned aerial vehicles (UAVs) equipped with cutting-edge imaging technology [1, 2].

UAVs are crucial for monitoring agricultural diseases, according to several studies. UAV-captured high-resolution imagery allows for the detailed observation of crop health indicators, such as morphology, color, and texture changes in the leaves. This abundant data source offers insightful information about the temporal and spatial distribution of diseases in agricultural fields [3, 4]. The availability of annotated datasets for algorithm training and evaluation is critical to the success of UAV-aided crop disease detection. Datasets like the Plant Pathology Challenge Dataset, which offer sizable collections of labeled photos showing a variety of crop diseases, have facilitated research in this field. These datasets allow researchers to efficiently and accurately develop and validate machine learning algorithms for disease detection [5, 6].

Algorithmic frameworks are essential components of UAV-based systems for disease detection. Because convolutional neural networks (CNNs) can extract intricate patterns from image data, they have become a popular option. Transfer learning methods, which involve fine-tuning CNN models that have already been trained on datasets about crop diseases, have shown promise in improving the ability to detect problems. To improve the scalability and resilience of UAV-based disease detection systems, researchers have also looked into object detection algorithms and ensemble learning techniques [7, 8, 9].

There are still a few obstacles in the way of UAV-assisted crop disease detection, despite recent progress. One of the main obstacles facing researchers in this field is the limited availability of annotated datasets. Other challenges include model generalization to diverse environmental conditions and issues with domain adaptation. To develop reliable and scalable solutions for practical applications, interdisciplinary teams comprising researchers, data annotators, and domain experts must work together to address these challenges [10, 11].

In conclusion, by enabling early and accurate identification of crop diseases, UAV-aided crop disease detection holds great potential to revolutionize agricultural practices. Researchers can continue to enhance the efficacy and practicality of UAV-based systems for agricultural disease monitoring and management by analyzing current datasets and algorithmic frameworks.

III. Data preparation and Techniques

We obtained a varied range of landscapes and environmental conditions; therefore, remote sensing and drone imagery were collected from multiple vendors. The dataset ensured representation across several relevant elements by including photos of landscapes, vegetation, and infrastructure. To improve and standardize the dataset, extensive preprocessing was performed before augmentation and fusion. The photos were resized to a standard size of 224 by 224 pixels to maintain uniform representation and enhance computational efficiency. Additionally, dimensionality was reduced and key characteristics were highlighted by dividing each pixel value by 255 to perform grayscale conversion.

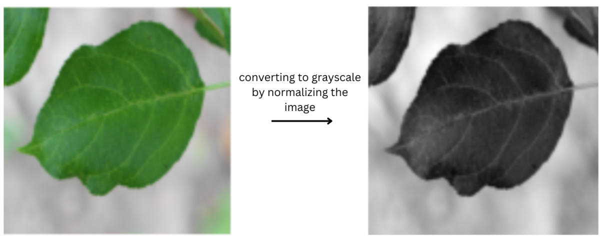

Fig. 2. Converting image to grayscale after preprocessing and dimensionality reduction

Techniques for data augmentation were used to add variety and improve the dataset. This comprised brightness and contrast adjustments as well as rotation. Grayscale photos were specifically targeted using augmentation techniques to maintain important characteristics and increase diversity, as shown in Fig.2.

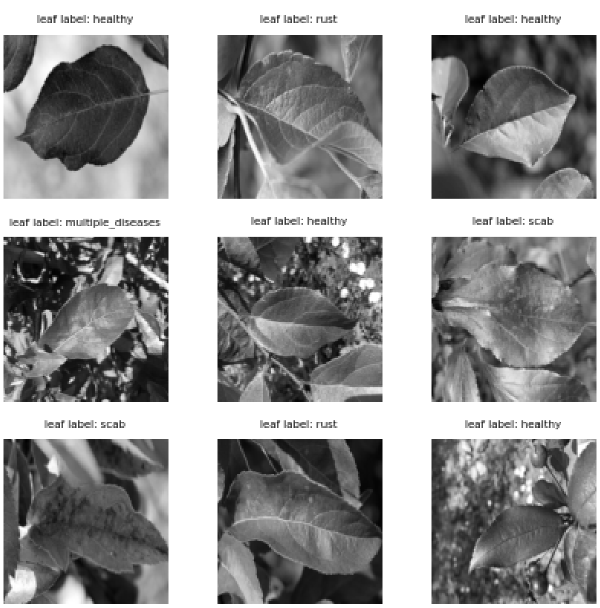

Fig. 3. Downscaled and grayscaled images as outputs of image processing pipeline

Drone and remote sensing imagery were combined using a data fusion technique after grayscale conversion and augmentation. This integration facilitated the creation of mixed data samples that consistently represented grayscale information while gathering complementary information from both modalities. The final processed input images for the model are shown in Fig. 3 in a formatted grid.

IV. Methodology

Data augmentation techniques were employed during the data preparation phase of this investigation to enhance the quality and consistency of the dataset. By applying image resizing and rescaling techniques, these solutions achieved uniformity in the dataset by converting all images to a consistent size. Data augmentation was also used to improve the dataset and facilitate the identification of mirrored images.

The foundation of our approach relied on the Convolutional Neural Network (CNN) architecture, originally introduced by Fukushima in 1988. Due to its renowned efficacy in image identification and classification tasks, Convolutional Neural Networks (CNNs) are a suitable option for detecting bacterial spots on apple leaves. Medical image recognition tasks considerably benefit from their capacity to discern objects and detect patterns within images. The fundamental advantage of CNNs is their ability to increase network depth while minimizing the total number of parameters. This enables the construction of deeper neural networks that require fewer parameters. This streamlined architecture enhances computational efficiency and simplifies feature extraction.

Convolutional layers for feature extraction, spatial pooling for dimensionality reduction, and fully connected layers for classification are some of the crucial elements in the CNN process. When all of these stages are combined, the network is able to recognize complex patterns and features in images, which makes it easier to detect diseases in apple leaves, as shown in Fig. 5.

A. *Convolution Layer*

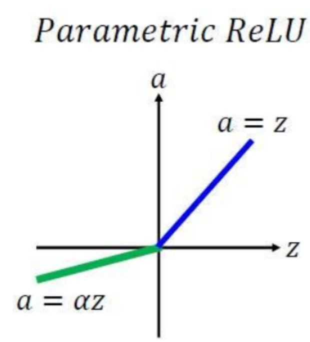

Fig. 4. PReLU

The convolutional layer, a core component of CNN architecture, serves a critical function as the uppermost layer in the network design. The primary objective is to discover and extract features from input data matrices, often achieved by utilizing word embedding techniques to process sentences. The convolutional layer applies a sliding filter approach to the embedding matrix to generate distinct feature maps. Various filters are employed to extract different features from the input data.

Instead of utilizing LeNet's activation functions in this convolutional layer, we opt for the utilization of Parametric Rectified Linear Unit (PReLU) activation functions. PReLU activation functions introduce non-linearities to the network, enhancing the extraction and representation of features and

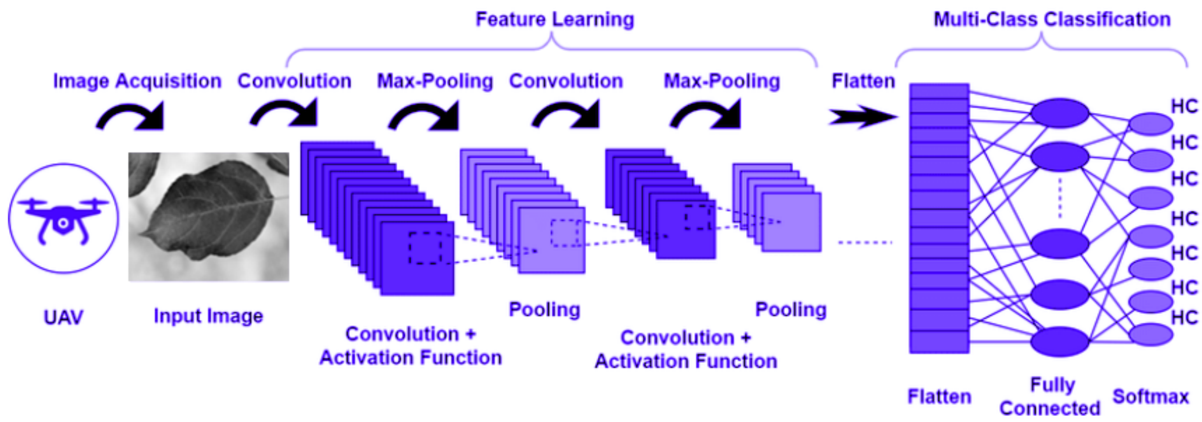

Fig. 5. Methodology

augmenting the model's capability to detect intricate patterns in the input.

B. Pooling Layer

After convolving the embedding matrix with multiple filters in the first stage (convolution layer), the second phase is the application of the pooling layer to reduce the dimensionality of the obtained feature maps. This step reduces the total number of CNN parameters, helping to decrease computational complexity, control overfitting, and extract invariant features, as shown in Fig. 6. In this model, we are using Max Pooling.

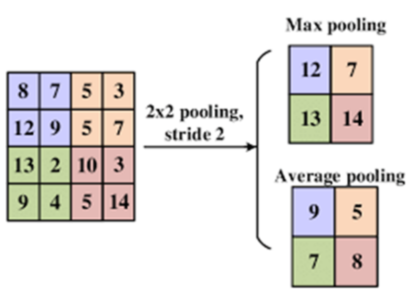

Fig. 6. Pooling

C. Fully Connected Layer

The fully connected layer, also known as the dense layer, is crucial as it computes the sentiment scores (PSS and NSS) for each input text. Each input in a linear process is connected to each output with an individual weight. The fully connected layer is roughly analogous to a standard neural network layer commonly found in traditional systems. The system aggregates information from the preceding pooling layer to compute sentiment ratings. The Softmax function is frequently employed in this layer as an activation function to facilitate non-linear transformations of the input data. The process in the CNN architecture entails transforming the matrix into a vector and inputting it into the fully connected layer, which is similar to a neural network. The CNN architecture is well-suited for this research as it provides strong capabilities for extracting features and computing sentiment scores.
Equations used are as follows:

1) Convolution:

$$Y[i,j] = \sum_{m=0}^{K-1} \sum_{n=0}^{K-1} X[i+m, j+n] \cdot W[m,n] + b \quad (1)$$

2) Max Pooling:

$$Y[i,j] = \max_{m=0}^{K-1} \max_{n=0}^{K-1} X[i \cdot s + m, j \cdot s + n] \quad (2)$$

3) Fully Connected Layer:

$$Y = W \cdot X + b \quad (3)$$

4) Parametric ReLU:

$$Y = \max(0, x) + \alpha \cdot \min(0, x) \quad (4)$$

5) Softmax Function:

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}} \quad (5)$$

V. RESULTS

The TensorFlow Sequential Model was utilized to train the model, which consists of a total of 3,108,868 parameters, requiring approximately 11.86 MB of memory. All of these parameters are trainable. The architecture is displayed in Table 1, labeled as "Model Architecture."

The model's classification accuracy on the training dataset is 80.90%, demonstrating its efficacy in learning from the given training data. The model achieves an accuracy of 74.79% on the validation dataset, indicating its capacity to generalize to unfamiliar data. These results were obtained after training the model for 30 epochs. Figure 7 showcases the training and validation accuracy obtained after each epoch, illustrating how the model was trained.

TABLE I
Model Architecture

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
sequential (Sequential)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 222, 222, 8)	224
p_re_lu (PReLU)	(None, 222, 222, 8)	394,272
max_pooling2d (MaxPooling2D)	(None, 111, 111, 8)	0
dropout (Dropout)	(None, 111, 111, 8)	0
conv2d_1 (Conv2D)	(None, 109, 109, 16)	1,168
p_re_lu_1 (PReLU)	(None, 109, 109, 16)	190,096
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 16)	0
dropout_1 (Dropout)	(None, 54, 54, 16)	0
conv2d_2 (Conv2D)	(None, 52, 52, 32)	4,640
p_re_lu_2 (PReLU)	(None, 52, 52, 32)	86,528
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 32)	0
dropout_2 (Dropout)	(None, 26, 26, 32)	0
conv2d_3 (Conv2D)	(None, 24, 24, 64)	18,496
p_re_lu_3 (PReLU)	(None, 24, 24, 64)	36,864
max_pooling2d_3 (MaxPooling2D)	(None, 12, 12, 64)	0
dropout_3 (Dropout)	(None, 12, 12, 64)	0
flatten (Flatten)	(None, 9216)	0
dense (Dense)	(None, 256)	2,359,552
p_re_lu_4 (PReLU)	(None, 256)	256
dense_1 (Dense)	(None, 64)	16,448
p_re_lu_5 (PReLU)	(None, 64)	64
dense_2 (Dense)	(None, 4)	260

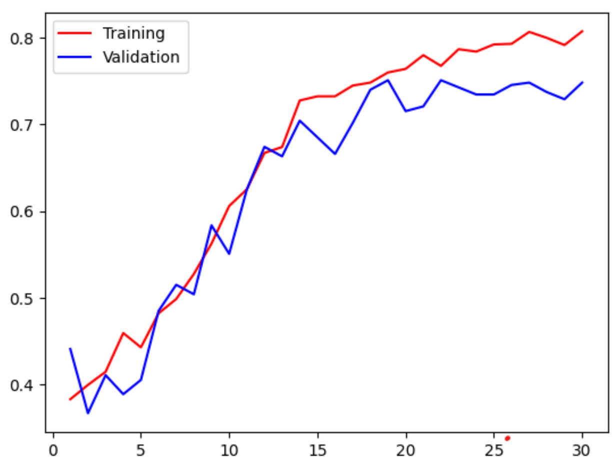

Fig. 7. Validation Accuracy v/s Training Accuracy per epoch

This highlights the potential impact of UAV technology and machine learning on improving agricultural productivity and sustainability. Our model's ability to predict on unseen data is shown in Figure 8. We have taken an image from the test dataset, and our model has perfectly predicted the leaf to be healthy, matching the actual label of the data.

VI. Discussion

This study investigates the utilization of datasets obtained from unmanned aerial vehicles (UAVs) for detecting crop diseases. The detection process involves the application of a convolutional neural network (CNN) architecture, implemented using the TensorFlow Sequential Model. The model performed favorably, achieving a classification accuracy of 80.90% on the training set and 74.79% on the validation set.

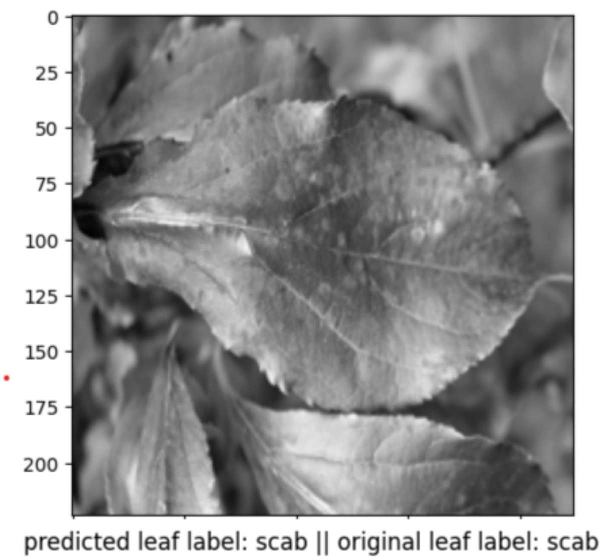

Fig. 8. Result Comparison of actual data and predicted data using our CNN model

The model's high accuracy on the training set indicates that it has successfully learned from the provided UAV imagery data to detect crop diseases. However, the somewhat reduced accuracy on the validation set suggests the presence of overfitting, highlighting the need for additional regularization methods or data augmentation to enhance overall generalization performance.

An important benefit of utilizing UAV-derived datasets for crop disease identification is the capability to obtain high-resolution imagery of agricultural areas at a low cost and with minimal effort. Conventional techniques for monitoring fields typically rely on ground surveys or satellite images. However, these approaches may not offer the same level of precision and timeliness as data collection using UAVs. Through UAV technology, farmers and agronomists can acquire prompt and comprehensive data regarding crop health, facilitating early identification and targeted intervention to minimize disease spread.

Additionally, using UAVs for identifying crop diseases has significant implications for aeronautical applications. UAVs provide a flexible and efficient means of remote sensing and data collection, capable of independently covering extensive agricultural areas. By incorporating advanced sensor technologies like multispectral and hyperspectral cameras onto UAVs, it becomes possible to gather comprehensive, multispectral images. These images can then be used to spot minor fluctuations in crop health and promptly detect instances of disease outbreaks.

Moreover, UAVs' lightweight and agile characteristics make them highly suitable for deployment in remote or inaccessible regions, where conventional monitoring techniques may be unfeasible or expensive. By utilizing UAV technology to identify crop diseases, aeronautical applications can help enhance agricultural output, ensure food security, and promote sustainability by facilitating more effective and focused management techniques.

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