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Comparative Analysis of Plant Disease Detection Using XceptionNet, MobileNet, and Custom CNN Model

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***Abstract*—The increasing need for efficient and automated plant crop disease detection has stimulated the investigation of advanced deep-learning models. This paper introduces a comparative study focusing on three prominent deep learning architectures—Custom CNN, MobileNet, and XceptionNet—specifically designed for plant disease detection. Through the evaluation of these architectures, this research aims to offer valuable insights into their suitability, contributing to the creation of robust and efficient automated detection systems essential for the progression of agricultural practices.**

***Index Terms*—crop disease detection, XceptionNet, MobileNet, CNN, Convolution Neural Network**

I. Introduction

The agricultural sector grapples with a critical challenge in preserving crop productivity attributed to prevalent plant diseases. These diseases significantly impact crop health, resulting in diminished yields, financial setbacks, and threats to global food security. Conventional methods for identifying plant diseases, relying on visual inspections by agricultural experts or farmers, suffer from subjectivity, labor intensity, and inefficacy. These constraints underscore the necessity for sophisticated, automated disease detection methodologies in agriculture.

Traditional approaches for identifying plant diseases are hindered by their reliance on subjective visual inspections, which limit accuracy and efficiency. In response, recent years have seen notable progress in deploying deep learning techniques, particularly Convolutional Neural Networks (CNNs). These CNNs have demonstrated remarkable capabilities in autonomously extracting intricate features from plant images, enabling precise disease identification. Nevertheless, despite their potential, there exists a crucial need to comprehensively assess and compare the efficacy of distinct architectures like XceptionNet, MobileNet, and Custom CNN models, within the domain of plant disease detection.

This study seeks to bridge this gap by conducting a comparative analysis of XceptionNet, MobileNet, and Custom CNN models specifically tailored for plant disease detection. Through a thorough evaluation encompassing performance metrics, accuracy, and suitability, this research aims to provide invaluable insights into the effectiveness and potential applications of these models in advancing agricultural practices.

The paper has 7 sections, with the introduction at the start of the paper. Following it, the summary of the related works regarding this paper is provided in section II. In section III, the dataset is discussed in a thorough discussion, followed by the Methodology. In section IV, the performance matrices used for the research are discussed. The results of the research and comparisons are discussed in section V. The paper's concluding remarks are discussed in section VI and followed by the References in section VII.

II. Related Works

The study discussed in [1] focuses on detecting and identifying plant diseases and pests using Convolutional Neural Network (CNN) models and image processing. It particularly emphasizes crops like Corn, Peach, Grape, Potato, and Strawberry, crucial to Bangladesh's agricultural economy. This research addresses the growing global food demand and the challenges farmers encounter in safeguarding their crops, which result in substantial financial losses. Highlighting the limitations of conventional manual disease identification methods, the paper proposes a machine learning-based solution to expedite disease detection, providing timely assistance in disease management for farmers.

Utilizing CNN, a deep learning algorithm, this research trains datasets containing images of both diseased and healthy leaves from various crops mentioned above. Achieving an accuracy rate of 94.29%, the model effectively discerns between healthy and diseased plant conditions. This advancement significantly benefits Bangladeshi farmers who predominantly rely on non-scientific methods for crop cultivation and disease detection.

In [3], a comprehensive study focusing on early disease and pest identification in crops using various deep-learning architectures is presented. The primary objective is to construct an accurate and efficient detection model to mitigate economic losses arising from plant diseases and pests. Leveraging Convolutional Neural Network (CNN), VGG16, InceptionV3, and Xception architectures, where the latter three are pre-trained models based on the CNN framework, this study employs transfer learning. The utilization of these models demonstrates Xception's superior performance, achieving 82.89% accuracy for disease detection and 77.9% for pest identification, highlighting its effectiveness in monitoring plant health.

This study underscores the critical challenges posed by plant diseases and pests to agriculture and food security. Conventional methods for insect identification prove inefficient for large-scale applications, and agricultural pests, such as mites or insects, cause considerable commercial damage. Rapid pest identification remains pivotal in maintaining yield productivity and reducing pesticide usage. The paper advocates for deep learning models due to their capacity to automatically extract features from large datasets, although it acknowledges the challenges in training large neural networks and the necessity for more extensive datasets to further integrate traditional and deep features.

III. Dataset

For this research, the goal was to find the most eloquent and simple method to detect plant disease and thus make the process easier and more robust. The start of this task was with a balanced dataset with distinguishable features from the publicly available domain Kaggle. The dataset consisted of images of apple plants in various conditions. The images were of plant leaves, as they show the most distinguishing effects of plant disease.

The dataset has 3 distinct classes, "Healthy"," Powdery" and "Rust". The first aforementioned class consisted of pictures of plants in healthy conditions and the subsequent two classes consisted of pictures of plants affected with unhealthy plants. The 3 classes were divided into train, test, and validation groups for training, testing the model, and validating the training.

A total of 1530 pictures of apple tree leaves in different state of healthy and diseased states were included in the dataset. The data was divided as, 86.4% for train data, 9.8% for test data, and 3.9% for validation data. The classes 'Healthy', 'Powdery', and 'Rust' in the training set consisted of 458 images, 430 images, and 434 images respectively, pointing towards the balanced nature of the dataset.

IV. Methodology

Utilizing neural networks for our model is the most convenient way of achieving the model's success. Neural networks are based on the transfer process of neuron information in the brain, and they learn a mapping for the prediction of data. Deep neural networks are used to classify various data to achieve deep learning capabilities. For this research, 3 distinct deep neural networks were chosen, a custom CNN model, a MobileNet model, and an XceptionNet model.

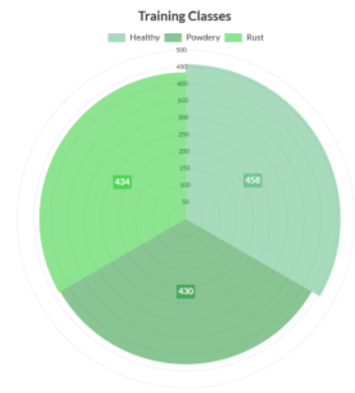

Fig. 1. Training Class Distribution

A. Data preprocessing

Data preprocessing plays a pivotal role in preparing our dataset to be effectively interpreted by our neural networks. Our specialized models, particularly MobileNet and Xception, have predetermined input parameters, necessitating the resizing of data to conform to the neural network's image specifications. This involved standardizing the images from 4000x2672 to 224x224 dimensions, ensuring uniformity for computational efficiency during model training. Additionally, data augmentation techniques were employed to mitigate overfitting during deep learning model training by generating multiple slightly modified copies of existing data.

B. classification

For classification purposes, we implemented three renowned neural networks extensively utilized in contemporary image detection studies. The selected models include CNN, Mobile Models MobileNet and Xception. To optimize the models for systems with lower memory capacities, we specifically incorporated mobile models like MobileNet and Xception.

- The Convolutional Neural Network (CNN) stands as a prevalent deep neural network design primarily used for image-related assignments. CNN is distinguished for its convolutional layers, which are adept at extracting essential features from images. Known for its versatility and effectiveness across a spectrum of image-based tasks, CNN is particularly valuable in tasks like identifying crop diseases. It presents a balanced and adaptable approach suitable for addressing diverse scenarios related to crop diseases.
- MobileNetV2 is a neural network architecture purposefully crafted for mobile and embedded vision applications, emphasizing efficiency without sacrificing accuracy. It is adept at overseeing and monitoring crop health within resource-constrained environments. Notably, it is well-suited for extensive, live monitoring in agricultural settings.

- XceptionNet is a deep convolutional neural network architecture recognized for its utilization of extreme depthwise separable convolutions, significantly enhancing efficiency and performance in tasks related to image recognition. Its proficiency lies in excelling at intricate pattern recognition, a pivotal aspect for precise and accurate identification of different crop diseases. This architecture is particularly well-suited for conducting fine-grained analyses of disease symptoms.

V. PERFORMANCE METRICS

To evaluate the model's effectiveness and overall accuracy, We examined the R2 Score, which measures accuracy, F1, recall, and precision, among the models of the employed classification algorithm:

A. Accuracy

One of the most predominant assessment techniques is computing the accuracy of the model that scales the overall correctness while predicting class designations for new data. This metric is calculated by dividing the total number of cases in the test set by the count of accurately predicted instances, determining the predictive accuracy. The Equation of Accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

B. Recall

The recall metric is employed in binary classification to assess a model's ability to detect all relevant instances within a dataset. As this measure holds significant importance in various applications it is particularly in scenarios where the consequences of overlooking relevant instances (false negatives) are substantial, like in Natural Language Processing (NLP), Customer Relationship Management (CRM), Risk Management etc .

Numerically, recall can be expressed as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

C. Precision

Precision gauges the number of accurately predicted positive instances thus indicating its focus on evaluating the accuracy of the minority class. A higher precision score signifies a model with fewer false positives, highlighting its ability to make minimal incorrect positive predictions.

$$\text{Precision} = \frac{TP}{TP + FP}$$

D. F1 Score

The F1 score is a statistical measure that combines both precision and recall into a single value thus offering a balanced assessment of a binary classification model's performance. It is calculated using the harmonic mean of precision and recall, providing an overall evaluation of how well the model identifies both true positive instances while minimizing false positives and false negatives. It is particularly useful when the dataset is imbalanced or when both precision and recall are equally important for decision-making in a given application or scenario.

Equations for Sensitivity and Specificity are:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Next, we determined the positive and negative predictive values.

$$\text{PPV} = \frac{TP}{TP + FP}$$

$$\text{NPV} = \frac{TN}{TN + FN}$$

We calculated the F1 Score using the matrices mentioned above,

$$F1 = \frac{2 \cdot \text{PPV} \cdot \text{Sensitivity}}{\text{PPV} + \text{Sensitivity}}$$

RESULT ANALYSIS

To find the best process, a comparative analysis of the neural networks was done using the Accuracy, Precision, Recall, and F1 scores of the models. The dataset was run for 10 epochs on all the models for an equal comparison.

TABLE I
ACCURACY RECALL, PRECISION AND F1 SCORE VALUES

Model Name	Accuracy	Recall	Precision	F1 Score
Convolution Neural Network	0.91	0.91	0.92	0.91
MobileNetV2	0.96	0.96	0.96	0.96
XceptionNet	0.88	0.33	0.32	0.32

Table 1 shows the comparison of From Table 1, Accuracy, Precision, Recall, and F1 scores of the models. From Table 1, we can see that all the models accomplish high levels of accuracy on the testing data, with MobileNetV2 achieving 96% accuracy. CNN and Xception were also close with 91 and 88% accuracy. For precision, recall, and F1 score, MobileNetV2 again comes up with the best scores with 96% accuracy on all the metrics of the R2 scores. This shows that MobileNetV2 is very precise in distinguishing between the classes and has a low chance of missing any data from any classes. CNN also shows similar levels of results in this matrix, with precision, recall, and f1 scores being 92%, 91%, and 91% subsequently. Xception here shows a different type of result, as it has only 3% precision, 33% recall, and 32% F1 score. Showing that it fails to precisely distinguish between the classes.

Figure 2 to 4 shows the confusion matrix between the True labels and Predicted Labels between the classes of the models. Here we see that MobileNetV2 and CNN have

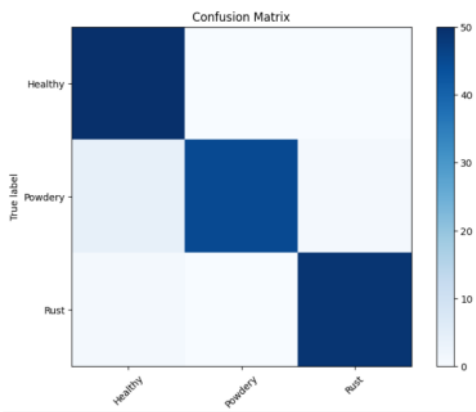

Fig. 2. Confusion Matrix of MobileNetV2

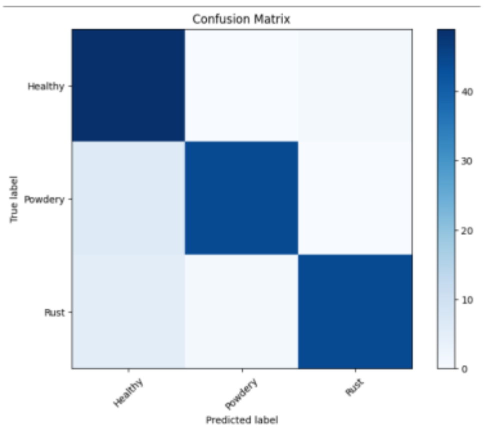

Fig. 3. Confusion Matrix of CNN

predicted the labels accurately thus boosting their precision and recall of these two Models. Xception on the other hand is very inaccurate while predicting the classes according to their true labels. We can see that between rust and powdery, also between powdery and healthy. Thus the recall and precision of the model stagnates.

Conclusion and Future Work

In this research, we saw the usability of Deep Learning models in categorizing and thus detecting plant diseases. Through extensive research, it has been established that deep learning models are well-versed in such tasks, and particularly MobileNetV2 model works very well in distinguishing diseased plants from healthy plants. Moreover, the 96% accuracy of MobilNetV2 and 91% accuracy of CNN suggest the dataset we used is of high quality. The high performance and success of MobileNetV2 suggest that this model can work for mobile architectures and thus can be utilized for underdeveloped areas.

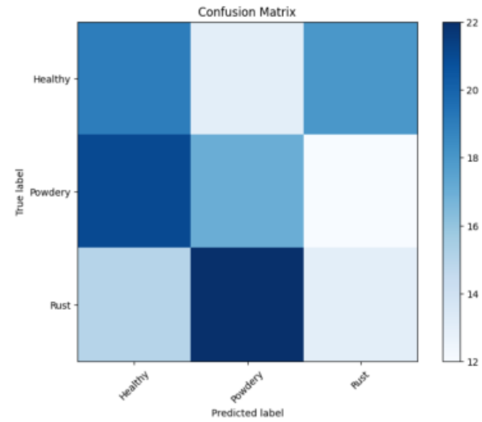

Fig. 4. Confusion Matrix of Xception

XceptionNet's underperformance presents a unique challenge to this work. The model analysis using Explainable AI(XAI) would be a target in future works to better utilize this model. Also, few more heavy architectures would be utilized to better understand the significance of heavier architecture in these situations.

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