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Comparative Evaluation of Pre-Trained Deep Learning Models for Precision Diagnosis of Potato Leaf Diseases

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Abstract

Diagnosing plant diseases is a tedious and time-consuming process that requires the expertise of professionals whose success rate largely depends on their experience. Therefore, early and accurate diagnosis of plant diseases is important. Deep learning (DL) methods have been employed to tackle this challenge by developing automated detection systems capable of rapidly and accurately identifying plant diseases.Using the Potato Disease Leaf dataset and the fine-tuning concept, we compared five pre-trained models in this study: Resnet50, Xception,, Mobilenet, DenSeNet121, and EfficientNetB0. Among the pre-trained models, EfficientNetB0 performed the best, outperforming the others with equivalent accuracy values of 0.972, 0.971, 0.974, and 0.972 for precession, recall, and F1-Score.

Keywords: Machine Learning; Deep Neural Network; EfficientNetB0; Convolutional Neural Network; Potato Disease Leaf.

1 | Introduction

Plants offer essential life resources like food, fiber, shelter, medicine, and fuel. However, the precise identification of leaf diseases is crucial, as it can greatly impact both the quality and quantity of crop production [1, 2]. The US Food and Agriculture Organization predicts a 70% increase in food production by 2050 to meet human needs, considering a projected 9 billion-person population. Reliable crop appraisal is hampered by the old approach of identifying agricultural diseases. The conventional method of diagnosing crop illnesses starts with hiring a domain expert who comes to the farm and uses optical examination to evaluate the crop. It takes a lot of work and time to do this approach. Continuous crop monitoring is also required. Another significant problem is that farmers in some locations do not have access to professionals [3]. Plant diseases that are not discovered promptly cause a major decrease in food production. Artificial intelligence (AI) has the potential to minimize sustainability, cut costs, and maximize output yield. AI improves the working environment, social aspects, and profitability of farming businesses. It can enhance crop stress management, yields, and quality. Automated approaches are an efficient and effective way to detect plant illnesses. Deep learning (DL) and machine learning (ML) methods have been used to handle huge amounts of data with high computing performance. Convolutional neural networks (CNNs) have shown impressive performance in crop disease identification applications, negating the need for intricate image pre-

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processing. A review study is necessary to demonstrate the application of CNN-based designs for crop disease detection during crop growth [4]. Egypt stands to gain economically, environmentally, and technologically from developments in deep learning (DL) publications and research across various sectors, including food security and sustainability. These advancements align with Egypt's Vision 2030, which prioritizes the nation's long-term goals of improving agricultural productivity, reducing poverty, and preserving natural resources [18].

In this study, we compared five pre-trained models: Resnet50, Xception, EfficientNet, Mobilenet, DenSeNet121, and EfficientNetB0, using the principle of fine-tuning on the Potato Disease Leaf dataset. Python was used to implement each of these models on the Kaggle platform. To determine which of them might produce higher classification accuracy, it was put to the Potato Disease Detect problem. EfficientNetB0 achieved the best performance, outperforming all other pre-trained models with corresponding accuracy of 0.972, 0.971, 0.974, and 0.972 for precession, recall, and F1-Score.

The rest of the paper is organized as follows: Section 2 reviews recent related work. Section 3 provides a detailed explanation of the materials and methods used, including the proposed model. Section 4 presents and discusses the experimental results. In Section 5, the implications of this research are explored. Finally, Section 6 concludes the paper and outlines potential future work.

2 | Related Work

Studies on the usefulness of applying artificial intelligence methods, including machine learning and deep learning, in plant disease diagnosis, particularly for maize diseases, have been carried out more often in recent years. Ümit Atila et al. [5] present aproposed EfficientNet deep learning architecture for classifying plant leaf images in the PlantVillage dataset. Compared to existing deep learning models, the B4 and B5 models showed superior accuracy and precision, with the B5 model achieving 99.91% accuracy and 98.42% precision in the original dataset. Showmick Guha Paul et al. [1] Proposed acustom CNN model for classifying tomato leaf disease using pre-trained VGG-16 and VGG-19 models. The model's performance was compared with transfer-learning-based models and demonstrated significant robustness. The proposed model achieved a 95.00% accuracy rate and was deployed on a web- and Android-based application for tomato leaf disease prediction. The findings could serve as a state-of-the-art approach for real-time agriculture classification tasks and can be combined with other techniques for optimal results.

Arunangshu Pal et al. [6] present anAgriDet framework thatuses conventional INC-VGGN and Kohonen-based deep learning networks to detect plant diseases and classify their severity levels. The framework uses preprocessing to eliminate unequal images, segmentation to extract diseased leaf regions, and Kohonen-based deep learning to learn multi-scale features of leaf disease. Overfitting is avoided byusing a dropout layer in the network. The QDSC strategy extracts pre-learned features and classifies disease severity classes. The framework outperforms traditional image segmentation techniques like MBO, EWA, EHO, MS, SMA, HGS, RUN, CPA, and HHO. However, limitations include the lack of integrated and labeled images from practical scenarios and the inability to detect multiple diseases in a single image.

Ananda S. Paymode et al. [7] present a study on crop disease leaves and their classification using a convolutional neural network-based VGG16 model. The model improved accuracy for grapes by 98.40% and tomatoes by 95.71%, supporting agricultural development. Future research focuses on preparing datasets for deep learning models and using Inception V3 and ResNet-based CNN models for deeper crop image analysis. The study encourages farmers, to raise farm income and help build powerful countries.

[8] This Study proposes a MobileNet-based method for identifying apple leaf diseases, reducing experts' workload and offering stable results. It's low-cost and balances efficiency and precision through deep learning models. Plans include collecting 2,000,000 images for training and designing models to improve accuracy. The study also emphasizes the urgent need for quality apple leaf disease identification.

This study introduces a leaf disease detection model using ViT, outperforming previous studies [9]. Two optimization approaches, LeIAP and SPMM, are proposed to reduce model size and improve inference and training time while maintaining classification quality. Results show these algorithms reduce model size to 28% and increase training and inference speed by 10% and 15%, respectively.

This study uses deep learning to detect and classify plant diseases in cotton plants using images of leaves and plants collected in an uncontrolled environment [10]. The model, trained on 2293 images, achieved an accuracy of 97.98% in classifying leaves and plant diseases. The technique outperformed previous approaches and aims to reduce time spent identifying cotton leaf disease and human error, ultimately improving the efficiency of disease detection and classification in agriculture. This study introduces a chickpea disease identification model designed to detect fungal and foliar diseases, including Ascochyta Blight and Fusarium Wilt, prevalent in Ethiopia [11]. The model leverages a dataset of 8,391 images and employs a hybrid GF-MF filtering technique, combined with CNN and LSTM for feature extraction. Achieving a classification accuracy of 92.55%, the model shows strong potential for disease identification. Future research should focus on developing an alternative model using the Mask-RCNN efficient segmentation approach to enhance disease management and treatment.

3 | Methodology and Materials

3.1 | Dataset

In this study, the Potato Leaf Disease Dataset was utilized, comprising 3 distinct classes and consisting of around 4000 images [17]. The dataset consists of color images of varying sizes. Table 1 provides a statistical summary of the dataset.

Table 1. Statistics summary of the dataset.

	Classes	Images	Percentage	Total
Diseased	Early_Blight	1628	0.40%	3042
	Late_Blight	1896	0.35%	
Healthy	Healthy leaf (C2)	1871	0.25%	1020

3.2 | Dataset Preprocessing

The dataset is first input into the system for pre-processing to enhance model performance. In this study, the pre-processing involved resizing the images to a resolution of 224x224 pixels and normalizing the data to accelerate convergence. This normalization technique adjusts pixel values to a range between 0 and 1, as described by the equation below.

$$I' = I/255 \tag{1}$$

Here, I' represents the normalized image, I is the input image, and 255 denotes the maximum intensity value for each pixel in a grayscale image.

3.3 | Building the Studied DL Models

Deep learning (DL) models were created at this point with default parameters. The loss function was established by compiling each model, and the error rate was minimized by using the Adam optimizer. To evaluate the models' performance, a range of evaluation indicators were applied. To improve classification accuracy, the starting weights of particular DL models were optimized using the categorical cross-entropy (CCE) loss function. The following is a mathematical expression for the CCE loss function:

$$\textit{Minimize}: loss(CCE) = -\sum_{i=1}^{M} y_i \cdot log\check{y}_i \tag{2}$$

In Eq. (2), y_i represents the true value, and $\check{y}_i$ is a shorthand notation for a vector that includes all the predicted outputs based on the training samples.

3.4 | Compared Deep Learning Models

A comparison was done between Xception, Densenet121, MobileNet, ResNet50, and EfficientNetB0, five DL pre-trained models that were constructed in this work.

3.4.1 | Xception

The depth-wise separable convolutional neural network architecture Xception was proposed by Chollet [12]. Like traditional convolution, Xception does not require convolution across all channels. As a result, the model becomes lighter and has fewer connections.

3.4.2 | ResNet50

A subset of the ResNet family, the ResNet50 [13] model has 50 layers total of48 convolutional layers, 1 max pool layer, and 1 average pool layer. The residual blocks that makeup ResNet were developed to solve the vanishing/exploding gradient problem.

3.4.3 | DenSeNet121

A subset of the DenseNet family is called DenSeNet121. Gao Huang introduced DenseNet [14], a kind of convolutional neural network. It is built on two layers: Transition Block, which is used to reduce the amount of model parameters, and Dense Block, which connects each layer to the other.

3.4.4 | MobileNet

Google unveiled MobileNet [15], a CNN variant built on the depthwise separable convolution architecture with two primary stages. One convolution filter is applied to the input channels in the first stage of depthwise convolution, and a linear combination of all the outputs is made in the second step by using pointwise convolution.

3.4.5 | EfficientNet

Based on complex coefficient technology, EfficientNet [16] is a kind of convolutional neural network that measures the network's depth, width, and accuracy using a predetermined set of coefficients. Squeeze-and-excitation blocks and inverted bottleneck residual blocks from MobileNetV2 are essential to its creation.

3.5 |Training Deep Learning Models

For training all DL models, the Adam optimizer with a learning rate of 0.0001 is used. The error is calculated using the Categorical Cross-Entropy (CCE) loss function, and mini-batch gradient descent is applied to minimize it. by modifying the weights by a small portion of the training dataset's data. We use a batch size of 32 and the training Data Set comprises 4000 images. 125 times every epoch, the mean weights shift. The DL models were put through the evaluation stage, which evaluates the models' ability to generalize, following several training epochs using this methodology. Figure 1 shows the important phases of training and assessing the DL models that were analyzed for the Plant disease problem Classification challenge.

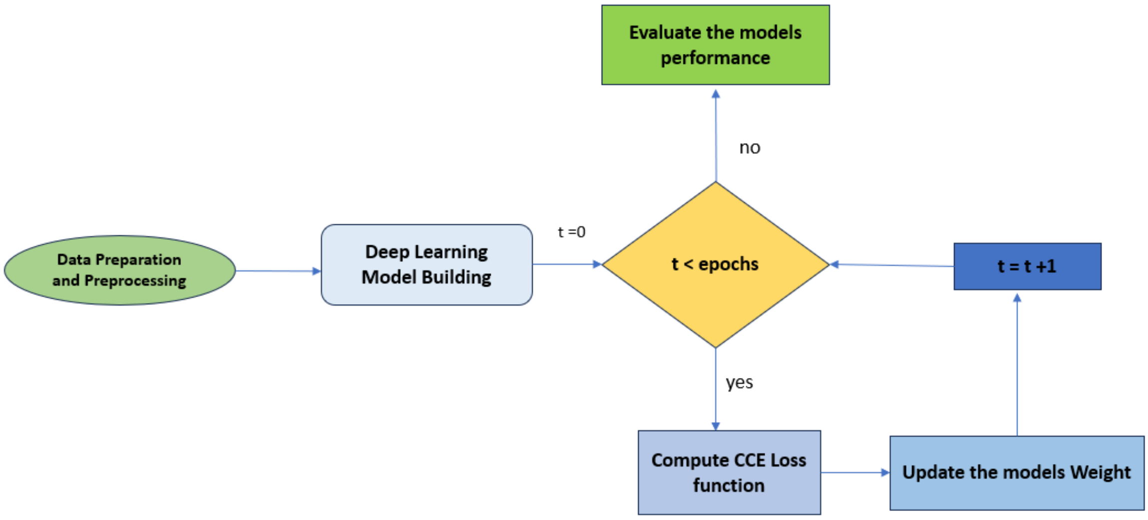

Figure 1. Flowchart outlining the primary steps for testing and training the DL models under study for the Potato disease problem.

4 | Result and Discussion

The performance of different DL models (Xception model, ResNet50 Model, DenSeNet121 Model and EfficientNetB0 model) used in training the Potato Disease Leaf Dataset dataset is extensively compared in the section that is presented.

4.1 | Evaluation Metrics

Metrics including accuracy, precision, recall, and F1-score are used to make the comparisons.

- Accuracy: This metric is calculated by comparing the number of correct predictions across all categories to the total number of predictions, as represented by the following formula:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}. \tag{2}$$

- Precision: This metric is calculated by dividing the number of correct predictions for a specific category by the total number of predictions made for that category. The equation is expressed as follows:

$$Precision = \frac{TP}{TP+FP}. \tag{3}$$

- Recall: This statistic measures the proportion of accurately predicted samples for a specific class relative to the total number of samples in that class within the dataset. This metric can be calculated using the following formula:

$$Recall = \frac{TP}{TP+FN}. \tag{4}$$

- F1 Score: This metric is calculated using the harmonic mean to balance precision and recall. The equation is expressed as follows:

$$F1 - score = \frac{2*Precision \cdot Recall}{Precision+Recal}. \tag{5}$$

4.2 | Experimental Environment Setup

The Nvidia Tesla P100 GPU, 16 GB of RAM, Python 3.9, and Keras 2.4 were used to implement all of the compared models in the Kaggle environment.For data processing, NumPy 1.19 and Pandas 1.2 are utilized.

Furthermore, the deep learning model training process employs the Adam optimizer, which has a learning rate of 0.0001 and a batch size of 32.

4.2 | Experimental Results

The experiments were conducted to evaluate the performance of deep-learning models for Potato disease detection. We compare results between mention models. Table 1 shows the performance of models with different metrics (accuracy, precision, recall, and F1-score), The EfficientNetB0 model achieved the best accuracy at 0.972 the Xception model achieved the lowest accuracy 0.770. Figure 2 shows the rank of each model with different matrices. The EfficientNetB0 model achieves the highest rank, followed by the Resnet50 model. Figure 3 shows the Confusion Matrix used to describe the performance of a EfficientNetB0 model from a Visualizes and summarize it. Figure 4 shows the Accuracy and Loss Curve of the EfficientNetB0 model during the training process by evaluating each epoch on the validation dataset.

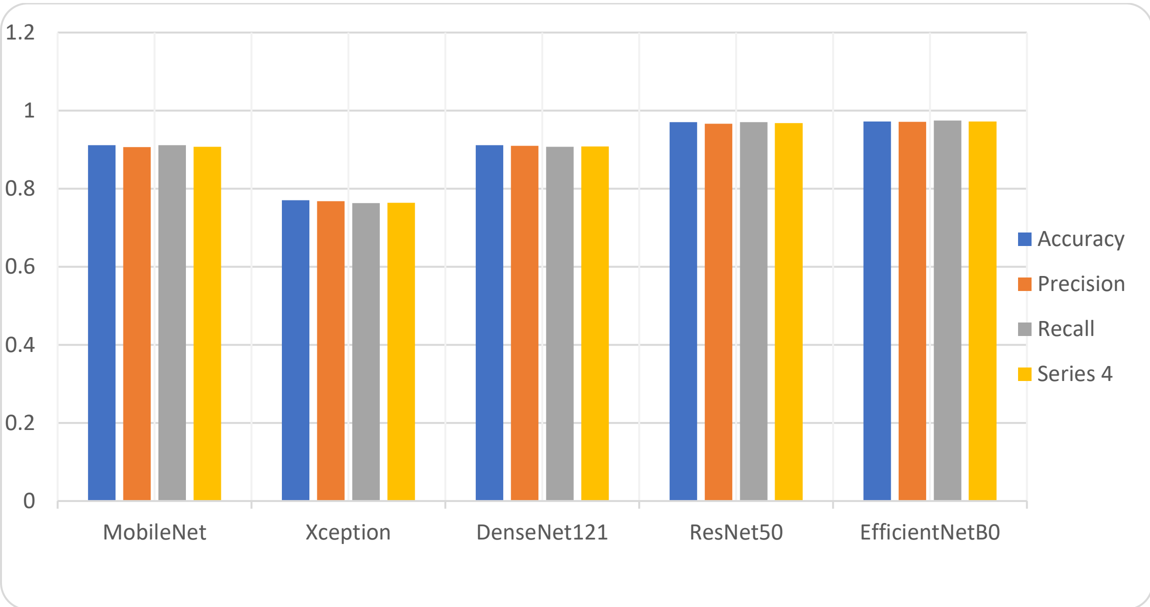

Figure 2. Illustrates the rank assigned to each model.

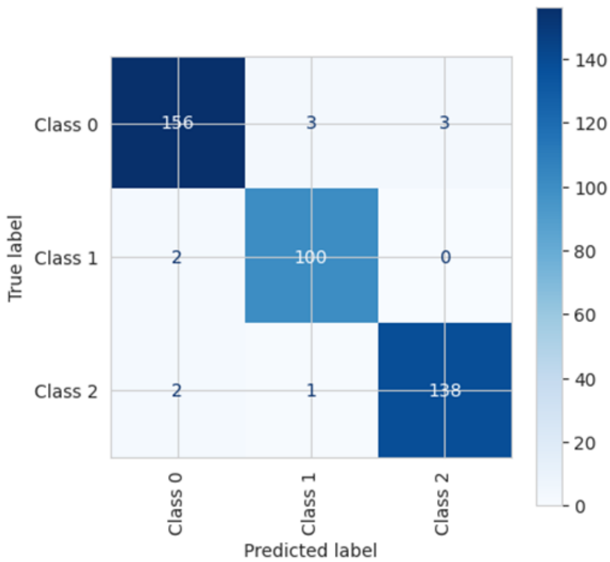

Figure 3. Confusion matrix of the EfficientNetB0 model.

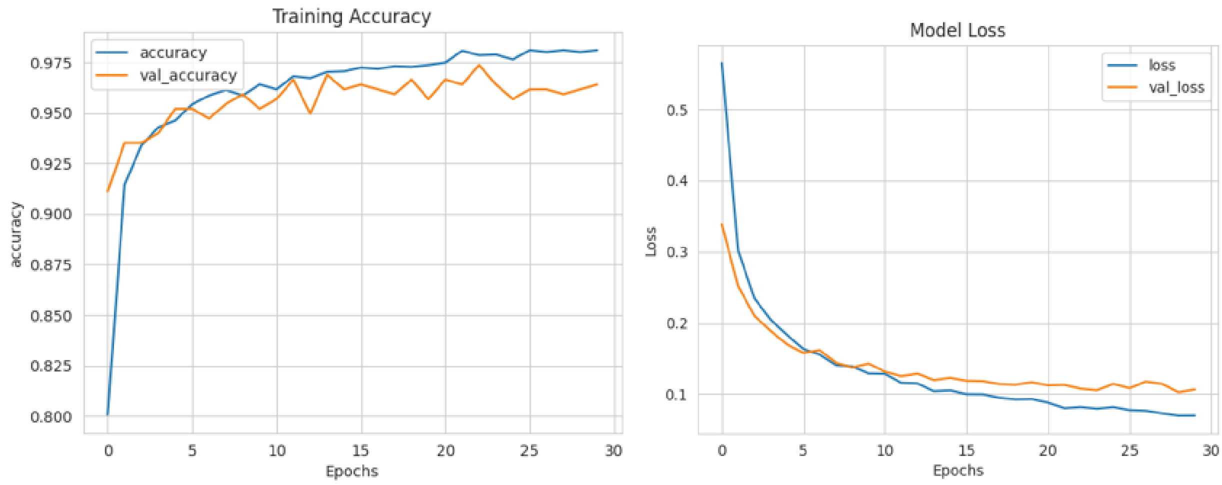

Figure 4. Loss and accuracy curves of the EfficientNetB0 model.

5 | Conclusion and Future Work

In this study, we compared five pre-trained models—ResNet50, Xception, EfficientNet, MobileNet, and DenseNet121—by applying the fine-tuning technique on the Potato Disease Leaf dataset. Experimental results demonstrated , EfficientNetB0 the best performance, accuracy the others with precision, recall, and F1-score values of 0.972, 0.971, 0.974, and 0.972, respectively. Our long-term goal is to create an interpretable deep learning model to improve the precision of plant disease diagnosis. We will also concentrate on analyzing the model's results to make sure they make sense and support sound decision-making.

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Data Availability

The dataset used in this article was in kaggle. For details, please refer to DataSet: https://www.kaggle.com/datasets/rizwan123456789/potato-disease-leaf-datasetpld

Conflicts of Interest

The author declares that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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