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Intelligent System for Crop Disease Identification and Solution Recommendation Using CNN and EfficientNetB0

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ABSTRACT

The global food supply chain depends heavily on agricultural productivity. Crop diseases, however, still result in significant yield losses, particularly in rural areas where farmers have little access to professional diagnosis. An intelligent web- based system that uses deep learning models to identify crop diseases from leaf photos and offer trustworthy treatment recommendations is presented in this study. A publicly accessible dataset (Samir Bhattarai, Kaggle) with roughly 54,000 photos of different crop types and disease categories was used to train and compare two architectures: Convolutional Neural Network (CNN) and EfficientNetB0. While the Efficient NetB0 showed better performance with higher 95% training accuracy and 96% validation accuracy and better generalization, the CNN achieved 98% training accuracy and 95% validation accuracy. Multilingual audio alerts are integrated into the system (Marathi and Hindi) and web accessibility, making it inclusive and practical for rural farmers. Results indicate that EfficientNetB0 is more reliable and efficient due to its depth-wise scaling and parameter optimization, making it a suitable choice for real-time agricultural advisory systems.

KEYWORDS: *Crop Disease Detection, CNN, EfficientNetB0, Deep Learning, Transfer Learning, Smart Agriculture, Web Application*

INTRODUCTION

India's economy is heavily dependent on agriculture, employing a large section of the population. However, crop diseases lead to substantial economic losses annually due to delayed diagnosis, inadequate knowledge, and limited access to agricultural experts. Traditional disease identification methods rely on visual inspection by specialists, which is impractical for remote areas.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have made it possible to automate disease detection with high precision. Convolutional Neural Networks (CNNs) have been particularly successful in plant leaf classification tasks. However, CNNs can suffer from overfitting and high computational demands when trained on large datasets.

This study addresses these challenges by integrating a Smart Crop Disease Detection Web Application powered by two deep learning architectures—CNN and EfficientNetB0. The research aims to identify the model that offers higher accuracy, efficiency, and reliability for real-world deployment. The proposed system not only detects diseases but also recommends preventive and curative measures, making it an end-to-end digital agricultural assistant.

LITERATURE REVIEW

Crop disease detection through computer vision and machine learning has been the subject of extensive research. Using conventional algorithms like SVM and k-NN, early research concentrated on manually created features like texture, color, and shape. These approaches, however, were not flexible enough to scale to large datasets.

CNN-based architectures like VGGNet, ResNet, and InceptionNet transformed the analysis of plant pathology images with the advent of deep learning. CNNs were shown to achieve accuracies above 90% for rice leaf diseases and tomato diseases in papers published in MDPI Sensors (2024) and Artificial Intelligence Review (2024).

However, CNNs' computational cost and static scaling represent a significant drawback. Tan and Le (Google Research, 2019) developed EfficientNet to address this issue by balancing network depth, width, and resolution through the use of compound scaling. With fewer parameters, EfficientNet variants (B0–B7) achieved state-of-the-art accuracy, which makes them perfect for environments with limited resources, like rural web servers.

By training and contrasting CNN and EfficientNetB0 models on a variety of datasets and evaluating their applicability for rural, multilingual, web-based agricultural systems, our study expands on these discoveries.

METHODOLOGY

A. Dataset Description

The Samir Bhattarai Plant Disease Dataset, which is available on Kaggle, contains roughly 54,000 high-resolution photos of both healthy and diseased leaves from a variety of crop types, including corn, tomato, and potato. The crop and related disease are labeled on each image. The following is how the dataset was divided:

- 70% goes toward training. 20% for verification
- 10% goes toward testing.

B. Preprocessing

To increase the robustness of the model, all images were resized to 128 x 128 pixels, normalized, and enhanced (rotation, zoom, and flip). During model evaluation, data augmentation improved generalization and reduced overfitting.

C. The Architecture of CNN

The CNN baseline model included:

- ReLU-activated three convolutional layers
- Using MaxPooling to reduce features
- Two thick layers and flattening
- Regularization dropout (0.5)
- Multi-class classification using the Softmax output layer.

TensorFlow/Keras 2.20 and Python 3.12 were used to train the CNN on a system with an NVIDIA RTX 2050 GPU. Adam, an optimizer with categorical cross-entropy loss and a learning rate of 0.001, was employed.

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D. Model EfficientNetB0

Transfer learning with pretrained ImageNet weights was used to implement EfficientNetB0. Compound scaling is used in the model to balance input resolution, network width, and depth. To prevent overfitting on the plant disease dataset, only the top layers were adjusted.

A softmax classifier that matched the number of disease classes was used in place of the network's last dense layer. Compared to CNN, EfficientNetB0 produced better generalization and convergence in fewer epochs.

RESULTS AND DISCUSSION

CNN Model Evaluation:

Model Evaluation

```
[22]: #Model Evaluation on Training set
      train_loss,train_acc = model.evaluate(training_set)

1732/1732 [==============================] - 175s 100ms/step - loss: 0.0480 - accuracy: 0.9845

[23]: print(train_loss,train_acc)

0.04800514876842499 0.9845176935195923

[24]: #Model on Validation set
      val_loss,val_acc = model.evaluate(validation_set)

433/433 [==============================] - 20s 45ms/step - loss: 0.1698 - accuracy: 0.9515

[25]: print(val_loss,val_acc)

0.1698242425918579 0.9514906406402588
```

Test Image

Suggestion: Avoid overhead watering, Plant disease-free seeds/transplants, Spray with copper-based bactericides in rotation with other products

EfficientNet B0 Model Evaluation:

```
[24]: # Assuming you have trained your model and have 'history' object
train_loss = history.history['loss'][-1]
train_acc = history.history['accuracy'][-1]
val_loss = history.history['val_loss'][-1]
val_acc = history.history['val_accuracy'][-1]

# Print the metrics as raw values
print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_acc:.4f}")
print(f"Training Loss: {train_loss:.4f}, Training Accuracy: {train_acc:.4f}")

Validation Loss: 0.1205, Validation Accuracy: 0.9630
Training Loss: 0.1545, Training Accuracy: 0.9508
```

Test Image

Suggestion: Remove and destroy affected lower leaves, Ensure good air circulation and avoid wet foliage, Consider using a copper-based or chlorothalonil fungicide.

Table 1: Compares the CNN and EfficientNetB0 models' performance

Metric/ Model	CNN	EfficientNetB0
Training Accuracy	0.9845	0.9508
Validation Accuracy	0.9515	0.9630
Training Loss	0.0480	0.1545

Validation Loss	0.1698	0.1205
Training Time per Epoch	30 to 45 minutes	3 hours
Model Complexity / Size	Moderate	Higher (EfficientNetB0)
Notes	Very low training loss, slightly lower val accuracy	Slightly lower training accuracy but better generalization

Table I demonstrates that the EfficientNetB0 architecture outperforms CNN in terms of training and validation accuracy, suggesting superior generalization. While EfficientNetB0 maintains a smoother convergence profile, CNN exhibits mild overfitting in its validation accuracy, despite achieving a slightly higher training accuracy.

Accuracy of Model Training (%) Accuracy of Validation (%) Millions of parameters Observations CNN 98, 95, ~8.5 High accuracy, slight overfitting EfficientNetB0 95,96, ~5.3 Improved generalization and portability

Analysis: EfficientNetB0 outperformed CNN in validation and traning, demonstrating superior generalization capability, even though CNN had a marginally higher training accuracy. EfficientNetB0 was better suited for low-resource deployment environments, like web or mobile servers, because of its smaller parameter size.

Furthermore, balanced accuracy and speed trade-offs are guaranteed by EfficientNet's use of compound scaling. Because of this, it is perfect for incorporating real-time inference into web-based systems in rural areas, especially when paired with multilingual audio support.

FUTURE SCOPE

The suggested system can be extended in the following ways in subsequent iterations:

- IoT Integration: Linking IoT-based leaf sensors to the web application to enable ongoing crop monitoring.
- Detection of Pests and Nutrients: Expanding model training to identify pests and

deficiencies in soil nutrients.

- Government API Integration: Using official agricultural advisory platforms to make recommendations tailored to a given location.
- Mobile App Deployment: Using cached models, the web system is transformed into a cross-platform mobile application for offline use.
- Explainable AI (XAI): Enhancing farmer confidence in AI forecasts through the visualization of model attention maps.

CONCLUSION

This study effectively illustrates how deep learning can offer a practical and affordable solution for automated crop disease detection. EfficientNetB0 is the best option for large-scale deployment because it provides higher validation accuracy, lower computational cost, and better reliability than CNN. The incorporation of audio alerts and a multilingual web interface guarantees inclusivity for farmers with low literacy levels. As a result, this project helps developing nations practice sustainable precision agriculture while bridging the technological divide.

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