Crop Disease Detection Using Deep Learning Techniques

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Abstract—**The increasing threat of plant diseases severely impacts agricultural productivity and farmer livelihoods. With the advancement of artificial intelligence, deep learning offers a promising solution to detect crop diseases early and accurately. This paper investigates the classification of diseases in three essential crops—rice, wheat, and tomato—using a dataset of 3000 images collected from Indian farms. Three CNN architectures—ResNet50, DenseNet121, and Xception—were trained and evaluated. Among them, Xception achieved the highest accuracy of 94%, followed by DenseNet at 88% and ResNet at 87%. The models were assessed using precision, recall, F1-score, specificity, and confusion matrix. The results demonstrate the significant potential of CNNs in automating crop disease identification.**

Keywords— **[Crop Disease Detection, CNN, Xception, DenseNet, ResNet, Deep Learning, Tomato, Rice, Wheat, Indian Dataset, Precision, Accuracy].**

I. INTRODUCTION

India's agriculture sector contributes nearly 18% to the country's GDP and employs over 50% of the population [1]. However, crop diseases remain a major threat, responsible for up to 30-40% loss in yield annually [2]. Conventional disease detection relies on expert visual inspection, which is timeconsuming, subjective, and impractical on large farms.

With the advent of deep learning, specifically Convolutional Neural Networks (CNNs), it is now possible to automate plant disease detection using leaf images. This research focuses on three crops—rice, wheat, and tomato—critical to Indian agriculture. A custom Indian dataset with 3000 labeled images was used to train and compare ResNet50, DenseNet121, and Xception models. The study aims to identify the most accurate model and assess their comparative strengths.

II. LITERATURE REVIEW

The integration of deep learning in agriculture has gained traction in recent years. Mohanty et al. (2016) applied CNNs for plant disease detection and achieved promising results on the PlantVillage dataset [3]. Ferentinos (2018) emphasized the superiority of CNNs in learning complex leaf patterns, outperforming traditional classifiers [4].

He et al. proposed ResNet, which uses residual connections to solve vanishing gradient problems in deep networks [5]. DenseNet, introduced by Huang et al., improved feature reuse and gradient flow through dense connectivity [6]. Xception, based on depthwise separable convolutions, was shown by Chollet to outperform Inception V3 in multiple visual recognition tasks [7].

Recent research by Singh et al. and Bansal et al. highlighted the success of Xception in agriculture-related classification due to its efficient feature extraction [8][9]. Others, such as Zhang et al., explored the potential of CNNs for tomato disease detection in Indian environments [10].

III. METHODOLOGY

3.1 Dataset

The dataset comprises 3000 high-resolution images of diseased and healthy rice, wheat, and tomato leaves. The dataset includes:

- Tomato: Early blight, bacterial spot, late blight, yellow virus, etc.
- Rice: Brown spot, bacterial leaf blight, blast disease, etc.
- Wheat: Rust, scab, healthy, and leaf spot diseases.

The dataset was split into 80% training and 20% validation sets. Each image was resized to 180×180 pixels and normalized to [0, 1] pixel range.

3.2 Preprocessing Steps

- One-hot encoding for multiclass labels
- Standardization of input pixel values
- Label encoding for internal class representation
- Class balancing through equal sampling per class
- Confusion matrix construction postevaluation

IV. MODEL ARCHITECTURES AND METHODOLOGY

All three models were implemented using TensorFlow/Keras. Pre-trained weights from ImageNet were used, and the final classification layers were fine-tuned.

4.1 Xception Model

Xception achieved 94% accuracy. Key layers include:

- Pretrained base (frozen)
- Conv2D → BatchNormalization → ReLU → MaxPooling (3 blocks)
- GlobalAveragePooling → Dense(512, ReLU) → Dropout(0.5)
- Dense(softmax) for classification

4.2 ResNet50 Model

ResNet achieved 87% accuracy.
Key components:

- Pretrained ResNet50
- Additional convolutional layers
- Batch Normalization and Dropout
- Global Average Pooling + Dense Layers

4.3 DenseNet121 Model

DenseNet reached 88% accuracy, using:

- DenseNet121 base
- Multiple custom CNN layers
- Dropout and BatchNorm
- Dense softmax output

4.4 Compilation

- Optimizer: Adam (learning rate = 0.0001)
- Loss: Categorical Crossentropy
- Metrics: Accuracy, Precision, Recall

V. MATHEMATICAL FOUNDATION LET

- XXX = input image
- WWW = weight matrix
- bbb = bias
- fff = activation function (ReLU, Softmax)

$$Z = W \cdot X + b \quad ; \quad A = f(Z)$$

Categorical crossentropy loss function:

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

Backpropagation updates:

$$W := W - \eta \cdot \frac{\partial L}{\partial W}$$

Where η = learning rate.

VI. EVALUATION METRICS

We used standard classification metrics:

- Accuracy:

$$\frac{TP + TN}{TP + FP + TN + FN}$$

- Precision:

$$\frac{TP}{TP + FP}$$

- Recall:

$$\frac{TP}{TP + FN}$$

- F1-Score:

$$F1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

VII. CONCLUSION AND FUTURE WORK

This study demonstrated that deep learning models can accurately classify crop diseases using leaf images. Xception delivered stateof-the-art performance on a real-world Indian dataset, making it a strong candidate for deployment in smart farming systems. This can help farmers detect diseases early, reduce pesticide misuse, and increase yields.

7.1. Results and Discussion

Model	Accuracy
ResNet50	87%
DenseNet121	88%
Xception	94%

The Xception model consistently outperformed others across all crops. Its depthwise separable convolutions offered computational efficiency and better generalization. ResNet showed lower sensitivity due to potential overfitting. DenseNet's dense connections helped gradient flow, yielding stable results.

7.2 Future Enhancements

- Real-time app development for farmerfriendly deployment
- Use of LIME or Grad-CAM for model explainability
- Extend dataset to more crops like maize and sugarcane
- Include data augmentation for better generalization

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