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Research Article

Potato Leaf Disease Classification Using Transfer Learning with VGG16 on an Expert-Annotated Field Dataset

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ABSTRACT

Potato is a staple crop cultivated widely across the globe, but its production is often threatened by diseases like early and late blight, which can lead to substantial economic losses. In recent times, deep learning has proven to be an effective approach for automating plant disease identification using image-based analysis. This research explores the application of the locally adapted VGG16 deep learning framework, which was pre-trained with the ImageNet dataset. Beginning layers were frozen to exploit the benefit of transfer learning. A custom field-captured expert-annotated dataset, referred to as the Potato Leaf Dataset (PLD), obtained from Okara, Pakistan, was used to train, validate, and test the developed system. The Synthetic Minority Oversampling Technique (SMOTE), followed by comprehensive preprocessing, was applied to avoid the class imbalance issue and improve learning stability across disease categories. The model's performance was assessed through various evaluation metrics, including accuracy, precision, recall, and F1-score. Findings suggest that the use of region-specific imagery combined with tailored preprocessing steps improves the model's dependability in classifying potato leaf diseases. This research highlights the importance of developing context-aware and scalable AI models for agricultural use, particularly in areas with limited technical resources and internet connectivity. By focusing on a practical and locally optimized approach, the study aims to support timely disease diagnosis and contribute to improved crop management practices in rural farming communities.

1. Introduction

Agriculture is one of the foundational pillars of food security, economic development, and rural livelihood [1]. With the steady increase in global population, the need for more effective and sustainable methods of crop cultivation is more critical than ever. Among major crops, potato (Solanum tuberosum L.) plays a particularly vital role [2]. Potato is considered the world's fourth most crucial food crop after rice, wheat, and maize, offering a substantial supply of carbohydrates, fiber, and vital nutrients such as vitamin C and potassium. Its adaptability, short growth cycle, and nutritional value make it a key component in ensuring dietary resilience and food security. Its short growth cycle, adaptability to different soil types, and high yield potential make it especially important for smallholder farmers in regions like Asia and Africa [3], [4]. In countries such as Pakistan, potatoes are widely cultivated in areas like Okara, Sahiwal, and Kasur, where they contribute both to household food needs and local market economies [5].

Despite its advantages, potato cultivation faces several challenges that threaten both yield and crop quality. Diseases, fluctuating weather conditions, and limited access to advanced farming techniques continue to affect farmers' ability to produce healthy crops. The rising impact of climate variability adds further pressure to manage plant health effectively. Researchers have increasingly turned to artificial intelligence and deep learning to help address these challenges. With recent advances in computer vision and image classification, deep learning models are now being trained to identify signs of disease in crop leaves, helping farmers detect problems early and reduce crop losses . However, most of these models are trained on globally available datasets, leaving a significant research gap in localized, region-specific datasets that better reflect actual farming environments. These technologies hold great promise for improving agricultural productivity in regions where traditional resources and expert support are limited.

Potato crops are prone to foliar diseases that reduce yield and quality, with early and late blight being the most widespread. Early blight, caused by Alternaria Solani, usually appears as dark spots with ring-like patterns on older leaves. Over time, it causes defoliation, weakens the plant, and limits tuber development. This disease often emerges during warm, humid conditions and can spread rapidly if left unmanaged [6]. On the other hand, late blight, caused by the water mold Phytophthora infestans, is far more aggressive. It thrives under cooler and wetter environmental conditions, leading to large, irregularly shaped brown spots on leaves and stems, eventually causing plant collapse. Late blight is infamous for its role in historical crop failures and remains a global threat to potato production [7].

Correctly distinguishing between early blight and late blight symptoms is essential for timely treatment and disease control, especially in regions where expert agricultural advice is scarce. However, disease symptoms often overlap or evolve similarly, making manual diagnosis unreliable. Adding to this complexity is the challenge of identifying healthy leaves that may have natural blemishes or nutrient-related discoloration not caused by pathogens. Therefore, the task of classifying leaves into healthy, early blight, and late blight categories demands precise image analysis tools. In recent years, researchers have employed convolutional neural networks (CNNs) and other deep learning methods to address this need with growing success [8], [9], [10]. Yet, limited emphasis has been placed on adapting these models for local environments using customized datasets, making this study distinct in its focus on regional adaptation and practical field applicability. The ability to automatically detect and categorize these leaf conditions through image classification has the potential to transform disease management practices, enabling early interventions and better crop protection.

This study aims to investigate how deep learning models perform when trained and tested on a locally sourced dataset rather than on large, standardized global datasets. To achieve this, we use the Potato Leaf Dataset (PLD), which was collected from the city of Pakistan called Okara and consists of images of potato leaves affected by early blight, late blight, as well as healthy samples. The dataset reflects real-world farming conditions such as varying lighting, leaf shapes, and disease progression stages, making it ideal for testing the robustness of CNN models in a local agricultural context.

This study sets out with three core objectives. The first is to design and implement a deep learning model for identifying potato leaf diseases, using VGG16 as the foundational architecture due to its proven effectiveness in image-based tasks. The second goal addresses the issue of class imbalance within the PLD by employing SMOTE, a technique that increases the presence of underrepresented disease categories. Lastly, the model's performance is rigorously assessed using key evaluation criteria, including accuracy, precision, recall, and F1-score.

2. Materials and Methods

This section details the procedural approach used to detect diseases in potato leaves with the help of deep learning techniques. The research specifically targets three types of leaf conditions: early blight, late blight, and healthy. The methodology includes several phases: acquiring the image dataset, performing preprocessing tasks, converting categorical labels, balancing the dataset using SMOTE, and training a deep learning model. A transfer learning strategy was employed, utilizing VGG16 as the base model to enhance learning efficiency. This structured pipeline was aimed at maximizing the model's accuracy and adaptability in real-world agricultural conditions.

2.1. Data Collection

The dataset used in this study was collected from potato farms located in the Okara district of Central Punjab, Pakistan. This region is known for cultivating three major potato varieties: Coroda, Mozika, and Sante. Images were captured directly from the field using smartphones, digital cameras, and drones to reflect various angles and lighting conditions. Close-up images were taken at a distance of 1 to 2 feet, while aerial imagery was acquired at a height of 5 to 10 feet to ensure clarity and avoid motion blur caused by wind or plant movement. This diversity in data collection helped mimic real-world conditions experienced by local farmers and ensured that the dataset would be robust for deep learning model training.

2.2. Dataset Description

The resulting Potato Leaf Dataset (PLD) contains a total of 4,062 annotated images. Images were manually annotated by plant pathology experts using the LabelMe tool, assigning them to one of three categories: early blight, late blight, or healthy. (Table 1)shows the class-wise distribution of the dataset prior to any preprocessing.

Table 1 Distribution of Potato Leaf Dataset (Raw Data)

Class Label	Image Count
Early Blight	1,628
Late Blight	1,414
Healthy	1,020
Total	**4,062**

The dataset was split into training, validation, and testing sets. (Figure 1)shows example images from each class in the training set.

Figure 1 A few samples from the Training Dataset

2.3. *Data Preprocessing and Encoding*

To ensure consistency in input dimensions, all images were resized to 224x224 pixels. Pixel values were normalized to fall between 0 and 1. Label encoding was applied using one-hot encoding to prepare the categorical disease labels for use in the neural network model. A significant challenge in the dataset was class imbalance, which was resolved using SMOTE. This technique generates samples in the minority classes synthetically to ensure equal representation across early blight, late blight, and healthy categories. (Table 2) summarizes the balanced distribution in both the training and validation sets after SMOTE.

The test dataset, consisting of 405 images, remained untouched to provide an unbiased evaluation.

Table 2 Balanced Class Distribution (After SMOTE)

Dataset Type	**Class**	**Image Count**
Training	Early Blight	1,303
	Late Blight	1,303
	Healthy	1,303
Validation	Early Blight	1,303
	Late Blight	1,303
	Healthy	1,303
Total		**7,818**

2.4. *Model Architecture and Learning Dynamics*

The model used in this experiment was built by integrating the pre-trained VGG16 architecture as the feature extractor.

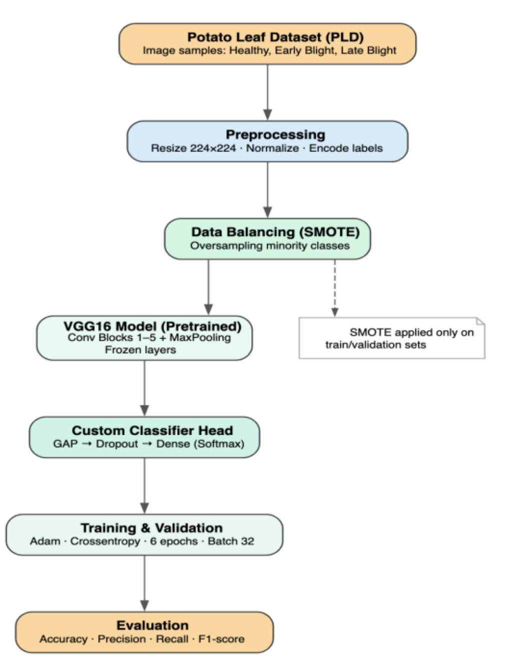

Figure 2 VGG-16 Algorithm Architecture

To preserve the features learned from ImageNet, the convolutional base was kept non-trainable, and additional fully connected layers were appended to perform the final classification task. These included a global average pooling layer, two dense layers (128 units and final 3-unit softmax), and two dropout layers to mitigate overfitting. (Table 3) provides the architecture summary of the proposed model.

Table 3 Model Architecture Summary

Layer Name	**Output Shape**	**Parameters**
VGG16 Base (frozen)	(None, 7, 7, 512)	14,714,688
Global Avg Pooling	(None, 512)	0
Dropout (0.3)	(None, 512)	0
Dense (128 units)	(None, 128)	65,664
Dropout (0.4)	(None, 128)	0
Output Dense (3 classes)	(None, 3)	387
Total Parameters	—	**14,780,739**
Trainable	—	**66,051**
Non-trainable	—	**14,714,688**

This proposed hybrid architecture allowed the model to utilize rich, already trained visual features while adapting to the nuances of the PLD dataset. Training a model from scratch would have required more data and computational resources, but by using transfer learning, the model reached acceptable accuracy levels more efficiently. Training parameters and architectural configuration to train the proposed system is tabulated in (Table 4).

Table 4 Training Parameters and Configuration

Parameter	Value
Size per Image	224 x 224
Size per batch	32
Number of Epochs	6
Model Architecture	VGG16 (with custom top layers)
Dropout	0.3 and 0.4
Optimizer	Adam
Loss Function	Categorical Cross-entropy
Pretrained Weights	ImageNet

2.5. *Model Training*

The model was developed using a transfer learning approach, where VGG16 served as the foundational backbone. Its convolutional layers, initialized with ImageNet-trained weights, were kept untrainable to preserve their ability to extract visual features. A custom classification head was added to the base model, including global average pooling, dropout layers to reduce overfitting, and dense layers for final class predictions. The model was compiled with the Adam optimizer and categorical cross-entropy loss, and trained over six epochs with a batch size of 32. The workflow followed throughout the training pipeline is shown in (Figure 2). Pseudocode for potato Leaf disease detection algorithm is shown in the (Table 5)

Table 5 Pseudocode for Potato Leaf Disease Detection Algorithm

Input: Potato Leaf Dataset (PLD)
Output: Classified potato leaf images (Healthy, Early Blight, Late Blight)
Begin
1. Initialize parameters: IMG_SIZE = 224×224, BATCH_SIZE = 32, EPOCHS = 6
2. Import required libraries (TensorFlow, Keras, NumPy, SMOTE, etc.)
3. Load the Potato Leaf Dataset (PLD)
4. Preprocess images: resize, normalize pixel values, and label data
5. Apply **SMOTE** on training and validation sets to balance classes
6. Encode categorical labels using one-hot encoding
7. Split dataset into training, validation, and testing sets
8. Load **VGG16** model with pretrained ImageNet weights
9. Freeze convolutional layers of VGG16
10. Add custom classifier head: GlobalAveragePooling → Dropout → Dense layers
11. Compile model with **Adam optimizer** and **categorical crossentropy loss**
12. Train model on training data and validate using validation set
13. Plot training and validation accuracy/loss curves
14. Evaluate final model on test data using accuracy, precision, recall, and F1-score
End

2.6. *Evaluation*

To evaluate the performance of the model, accuracy and loss were monitored across both training and validation sets over six epochs. The final test evaluation was carried out on a hold-out test set of 405 images. In addition to accuracy and loss metrics, the model's confusion matrix, recall, precision, and F1 Score were also considered for comprehensive performance analysis. These metrics offer insight into the model’s effectiveness at detecting healthy, early blight, and late blight leaves under varying conditions.

3. Result and Discussion

This section presents the experimental outcomes from implementing a VGG16-based deep learning model on the PLD (Potato Leaf Dataset) for the classification of early blight, late blight, and healthy leaves. The primary objective was to assess the model's performance after applying SMOTE for class balance and using dropout as a regularization technique. The model was trained for six epochs with a batch size of 32, using images resized to 224×224 pixels. The dataset was organized into separate directories containing 3,251 images for training, 416 for validation, and 405 for testing. Unlike many previous works that rely on standard global datasets, this experiment used locally captured and expert-verified imagery, making the results highly representative of real farming conditions in Punjab.

3.1. Model Performance Overview

In the first epoch, the training accuracy started at 38.8% with a corresponding training loss of 1.14, while the validation accuracy was already higher at 55.7%, and the validation loss stood at 1.01. These early results suggest the model began with some generalized understanding, likely inherited from the VGG16 base layers pre-trained on ImageNet. However, the performance gap between training and validation highlighted the need for further refinement.

As the training progressed, both accuracy and loss metrics showed steady improvements. By epoch 3, training accuracy reached 50.9%, and validation accuracy crossed the 56.9% mark. This trend continued in subsequent epochs, and by epoch 6, the training accuracy climbed to 65.5%, while validation accuracy peaked at 78.1%, indicating successful learning from the dataset. The training loss also declined consistently, reaching 0.81 by the final epoch, and validation loss dropped to 0.72, demonstrating a robust reduction in misclassification. This steady improvement reinforces that the proposed workflow — combining SMOTE with dropout regularization — was effective in stabilizing the learning curve, even with limited local data.

These results indicate the model was learning effectively without significant overfitting, even with limited epochs. The use of dropout in fully connected layers (Dropout rate: 0.3) helped reduce generalization error, and the global average pooling layer minimized the number of trainable parameters. (Figure 3) and (Figure 4) illustrate the training and validation accuracy over multiple epochs and training and validation loss graphs, respectively. These graphs highlight the model's consistent adaptation to local data characteristics, a key contribution of this study.

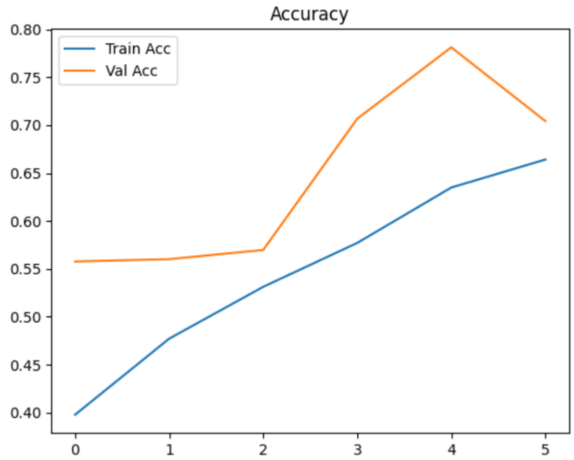

Figure 3 Graph of Training and validation accuracy over multiple epochs

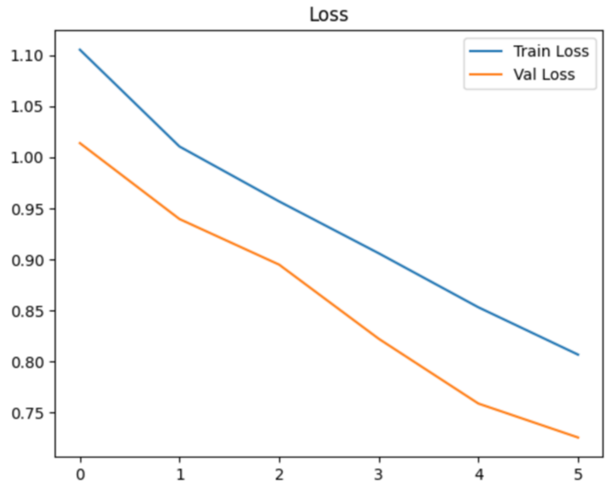

Figure 4 Graph of Training and Validation Loss

3.2. Test Set Evaluation

Once the model completed training, it was evaluated on a separate test set consisting of 405 images. The final test accuracy achieved was 76.7%, with a loss of 0.64. This result supports the conclusion that the model generalized well to unseen data, successfully learning the distinguishing features of late, early blight, and healthy leaves of potato. Given that the images were collected under varied lighting and environmental conditions, achieving this level of accuracy demonstrates the robustness of the model for real-world agricultural scenarios.

(Table 6) shows a progressive decline in loss and a rise in accuracy across all six epochs. This trend confirms that the model's learning process was on track, and no early signs of overfitting were observed. The alignment between training and validation metrics suggests that the model was able to generalize its predictions effectively across the three classes.

Table 6 Epoch-wise Accuracy and Loss Summary

Ep och	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.3882	0.5577	1.1426	1.0139
2	0.4587	0.5601	1.0298	0.9395
3	0.5090	0.5697	0.9750	0.8949
4	0.5663	0.7067	0.9137	0.8223
5	0.6330	0.7812	0.8599	0.7590
6	0.6550	0.7043	0.8141	0.7258

3.3. *Effect of SMOTE*

The Synthetic Minority Oversampling Technique (SMOTE) played an important role in the initial learning process. Before applying SMOTE, the class distribution was skewed, particularly with fewer instances of early blight. SMOTE generated synthetic samples for minority classes in both training and validation sets, ensuring the model had equal exposure to all classes. This step was essential in mitigating bias and improving classification fairness. The improved post-SMOTE validation accuracy reflects how balancing the dataset can lead to more equitable and accurate outcomes.

Without SMOTE, the model exhibited a clear bias toward the majority class, with higher prediction confidence for healthy leaves and misclassifications among disease classes. After SMOTE, however, the classification performance across all three classes became more uniform, indicating the model was no longer favoring specific labels.

3.4. *Discussion*

The steady performance increase over six epochs indicates that the model was able to learn from the data effectively despite the limited number of training iterations. Validation metrics mirrored the improvements seen in training, which suggests good generalization and limited overfitting, a common concern in deep learning models trained on relatively small datasets.

The use of SMOTE and dropout together created a balanced learning environment. SMOTE addressed class imbalance, giving the model equal opportunity to learn from each disease type, while dropout helped in regularization, ensuring the model did not memorize the training data. Together, these techniques contributed to a more stable and effective learning curve. This integration of simple yet adaptive strategies reflects the study's innovative focus on practicality rather than computational complexity — a crucial consideration for regions with limited technical infrastructure.

The test accuracy of 76.7% demonstrates a reasonable tradeoff between complexity and performance. Given the challenging conditions in which the images were captured (different devices, angles, lighting), the result reflects the model's resilience in handling real-world variation. This level of performance suggests practical applicability, especially for low-resource settings where early diagnosis can improve crop yield and reduce economic losses.

Although only VGG16 was used in this experiment, future comparisons with models like InceptionV3 or EfficientNetB0 may further validate the model's standing among other CNN architectures. Moreover, increasing training epochs and applying more extensive augmentation could help achieve even better performance. This adaptable framework sets a baseline for developing cost-effective, field-deployable AI tools that can empower small-scale farmers.

4. Conclusion and Future Work

This research highlights how deep learning, especially through transfer learning with the VGG16 model, can effectively classify healthy, early blight, and late blight potato leaves using images gathered from agricultural fields in Central Punjab, Pakistan. The model achieved strong classification performance after applying necessary preprocessing techniques, one-hot encoding, and data balancing through SMOTE. With a final test accuracy exceeding 76%, the model showed promising capability in real-world conditions despite the challenges of class imbalance and environmental variation in the dataset.

The results highlight how a well-structured model, even when trained on locally gathered data under diverse lighting and environmental conditions, can support precision agriculture. By automating disease detection, such models can aid non-technical farmers in identifying infections early, ultimately contributing to higher yields, lower pesticide use, and improved food security.

For future work, several directions can be pursued. First, additional architectures such as ResNet50, InceptionV3, and EfficientNet could be evaluated and compared on the same dataset to identify optimal models in terms of performance and training efficiency. Second, the integration of real-time mobile-based disease diagnosis applications could make the solution more accessible in remote farming communities. Lastly, expanding the dataset to include different growth stages and disease severities could further improve the model's robustness and practical utility in the field.

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Authors Introduction

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