

Deep Learning-Driven Sustainable Strategies for Potato Leaf Disease Detection to Enhance Crop Yield and Soil Fertility

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Abstract: Potato plants are very important in world food security but also have a high susceptibility to diseases like early blight and late blight, which increase crop loss and hamper stable production practices. In this study, an early potato leaf disease detection method using deep learning is proposed, apply transfer-learning methods to improve model accuracy and efficiency. The network was trained with Potato Disease Leaf Dataset from Kaggle, with leaves classified as healthy, early blight, and late blight. Three pre-trained Convolutional neural networks VGG16, GoogLeNet, and ResNet-50 were employed and compared. ResNet-50 performed best among them, with superior 100% training accuracy, 99.75% validation accuracy, and 99.26% testing accuracy, then GoogLeNet and VGG16. All the models were excellent on Precision, Recall, F1-score, and Misclassification Rate. The system enables farmers to make timely and precise interventions, reducing their use of agrochemicals, improving the resistance of their crops, and contributing to sustainable agriculture practices in line with the United Nations' Sustainable Development Goals. By combining modern Artificial Intelligence (AI) technologies with green approaches, this work emphasizes the potential to increase crop production, save soil fertility, and achieve long-term agricultural productivity.

Keywords: Sustainable Agriculture; Potato Leaf Disease Detection; Deep Learning in Agriculture; Transfer Learning (VGG16, GoogLeNet, ResNet-50); Sustainable Crop Management; Precision Agriculture

1. Introduction

Agriculture is one of the critical sectors in ensuring food security and economic development globally. The crop disease, especially those that affect staple crops such as potatoes threatens this productivity. Timely and precise identification of plant diseases is very important for their effective management, which reduces crop loss and improves food supply [1]. Recently, due to the advancement of technology, machine learning (ML) and deep learning (DL) have become the most powerful tools for the automation of plant disease detection. Recent advances in artificial intelligence have significantly improved the automated detection and classification of plant leaf diseases, contributing to enhanced agricultural productivity and precision farming. Alzoubi et al. proposed an image processing framework integrated with an enhanced Support Vector Machine (SVM) for accurate fig leaf disease classification [2]. Sasmal et al. introduced a comprehensive groundnut leaf disease dataset to facilitate the development and benchmarking of

intelligent disease detection models [3]. Gatla et al. optimized Edge AI techniques for efficient and real-time tomato leaf disease identification, enabling deployment on resource-constrained devices [4]. More recently, Tanveer et al. developed a novel transfer learning approach for classifying healthy and infected maize leaves, demonstrating the effectiveness of deep learning in improving disease detection accuracy and supporting sustainable crop management [5]. This research employed an in-depth dataset obtained from Kaggle as Potato Disease Leaf Dataset (PLD), comprising both infected and non-infected images of potato leaves [6]. With the availability of TL, even modest datasets can also have decent model performance with a very good pre-trained network. This paper focuses on our approach, results, and discussion for potato leaf diseases with the main diseases under observation: early blight and late blight, using DL techniques.

Plant diseases have a very great impact on the quality and quantity of agricultural produce, which reduces the total yield and economic stability of crops [7]. The challenge is that the plants are not monitored continuously. Inexperienced farmers may fail to recognize symptoms or be aware of when diseases generally occur, leading to unexpected strikes. Continuous monitoring would thus help in prevention or reduction of outbreaks, hence making plant disease detection an important research area in agriculture [8].

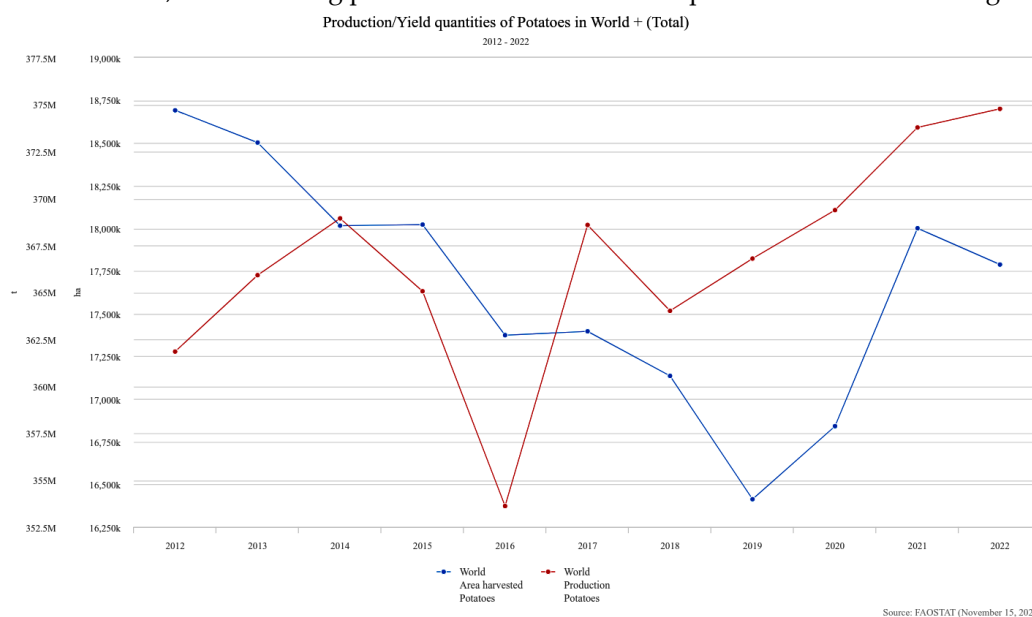


Figure 1. Production/Yield quantities of Potatoes in World + (Total) 2012 – 2022 [9]

Potatoes are one of the staple foods and nutritious sources in every part of the world. They stand out among the most important food crops and are of leading agricultural importance. Belonging to the family of Solanaceae, potatoes are widely cultivated into diverse climates of Asia, Europe, and the Americas. According to Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) [9], global potato production and harvested areas have fluctuated notably from 2012 to 2022. Production saw a decline around 2016 but has steadily recovered to higher levels recently, while the harvested area has gradually decreased as shown in Fig. 1, indicating improvements in yield and efficiency. This trend indicates the dire need for advanced agricultural methodologies that include early disease diagnosis and optimized cultivation techniques for ensuring maximum output. Due to growing demand for potatoes, a technology TL-based methodology for the detection of disease in potato leaves becomes mandatory to keep production high to meet the demands, despite crop diseases and other environmental pressures.

FAOSTAT, in its prediction from 2012 to 2022, notes that the Asia-Pacific area is the largest potato-producing continent, accounting for 49.9% of world production [9]. The large demand created by the huge population in Asia and heavy dependence on agriculture in the region has brought this about. Europe is the second-largest producer of potatoes in the world and accounts for 29.9% of total production. Another 12.4% is produced by the Americas, where the US and Canada are among the top producers. The share of Africa in world production is 7.4%, while Oceania contributes hardly 0.5%. Such a pattern of production depicts well the importance of potatoes for food security and regional economies in general, particularly for the Asian and European parts of the world. These trends prove that the solutions like TL-based disease

detection and management systems are significant in ensuring healthy crop yields in all regions, as shown in Fig. 2.

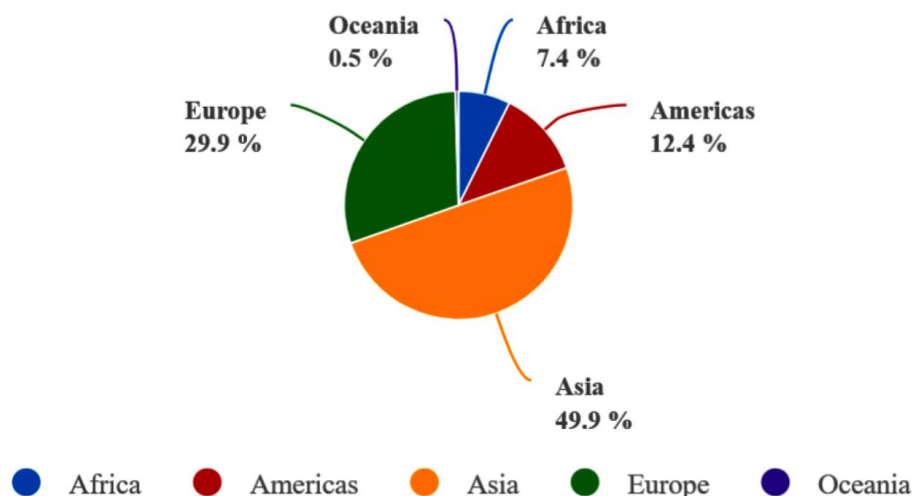


Figure 2. Production share of Potatoes by region Average 2012 – 2022 [9]

The chart shown in Fig. 3 is based on data obtained from the U.S. Environmental Protection Agency, United Nations Economic Commission for Europe (UNECE), and the Government of Alberta website, illustrating the annual loss of vegetables caused by diseases. Specifically, it shows that 32% of potatoes are wasted each year due to various factors [10].

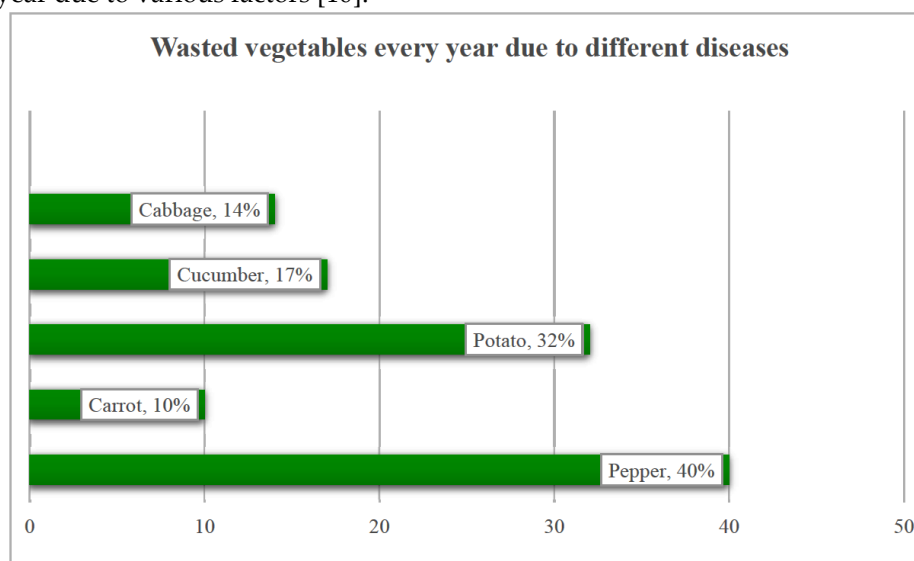


Figure 3. Percentage of wasted vegetables every year due to disease attacks (from 2009-2020) [10]

Sustainable agriculture provides the answer to solving food security issues for the world and is particularly supported by the United Nations' Sustainable Development Goals (SDGs). In particular, SDG 2 (Zero Hunger) discusses the need to enhance agricultural production and attain access to food that is safe, nutritious, and sufficient for everyone. Improved early disease identification and precision agriculture are just some of the breakthroughs that enable this. In addition, SDG 12 (Responsible Consumption and Production) stresses limiting food losses and adopting resource-smart use of resources. In embracing AI-enabled disease identification, this work furthers sustainable agricultural practices to prevent crop losses, maximize the efficient use of pesticides, and promote agricultural production for a more durable and ecologically friendly food system [11].

Potatoes are the fourth most valued food crop worldwide, being the staple for the majority of two billion people [1, 9]. Still, they are extremely vulnerable to foliar infections such as early blight and late blight, which tremendously lower yield and quality. For FAO [1], yield losses caused by pests and diseases can be up to 40% per annum, which strongly threatens global food security.

As shown in Fig. 4, early blight and late blight are two of the most common diseases of potatoes. Crop yield may be significantly reduced by these diseases. Early blight is caused by the fungus *Alternaria solani* and typically appears as black spots on older leaves with concentric rings. This disease may result in leaf yellowing, defoliation, and a smaller, inferior quality of the tubers. Late Blight is more severe due to infection by the oomycete *Phytophthora infestans* and, prefers the wet, humid environments [12]. It does appear initially as water-soaked lesions, quickly followed by darkening, growth and decay of leaves, hence infecting the tubers. These visual symptoms tend to overlap in the initial stages, hence manual detection becomes difficult even to specialists. Both the diseases have a tendency to spread quickly over fields if not promptly diagnosed and treated, resulting in extensive yield loss. In order to prevent these diseases from seriously affecting potato production, effective management strategies, including early detection and timely application of fungicides, are important.



Figure 4. Sample Image Common Potato Leaf Disease types [Early Blight, Healthy, Late Blight]

Traditional disease identification in potato plants is performed through manual inspection by an expert, which is naturally error-prone, laborious, and costly.

Traditional control of such diseases includes chemical fungicides, resistant cultivars, crop rotation, and field sanitation. Yet, the use of fungicides poses environmental and health issues and can be economically unfeasible for small-scale farmers. Climate variability has also changed disease patterns, rendering surveillance by humans less efficient. This highlights the importance of AI-based detection systems, which provide rapid, precise, and affordable disease diagnosis from leaf images [2–5, 10].

There has been limited research into potato leaf disease detection through comparative analysis of multiple deep learning architectures. Bridging this, the current study compares three strong CNN architectures VGG16, GoogLeNet, and ResNet-50 on a potato disease dataset [6], in an effort to present a high-accuracy and scalable diagnostic platform to support precision agriculture and increase food security.

DL models, particularly VGG16, GoogLeNet and ResNet-50 do offer a much more viable alternative for detecting diseases but sometimes fail to distinguish very similar diseases visually, possibly leading to misdiagnoses that hurt crop yields and quality. Agricultural research is now more focused on increasing the productivity and quality of crops, while reducing costs, to achieve maximum profitability. Hence, fast and accurate identification of diseases is very important for good crop management, as this aid in the rapid correction of field problems and supports sustainable agricultural practices.

2. Related Work

In 2017, Patil et al. conducted a study in which they investigated the efficiency of three ML techniques: Random Forest, Support Vector Machine, and Artificial Neural Networks, in identifying blight disease in potato leaf images. They used a dataset from PlantVillage and the University of Agricultural Sciences, India, comprising 892 images representing healthy leaves, along with early and late blight. They used a fuzzy c-mean clustering technique for distinguishing healthy leaves from diseased ones in each image. ANN was the most accurate technique, with an accuracy of 92%, followed by SVM at 84% and RF at 79% [13].

Recently, Suttapakti and Bunpeng, in their 2019 work, proposed a method for classification using a Euclidean distance-based classifier with the PlantVillage dataset. They performed color and texture feature selections to differentiate healthy leaves and early and late blight diseased leaves. Their algorithm had an accuracy of 89%. It was characterized to be very simple and highly computational. However, it also indicated a number of challenges when treating complex variations in symptoms of diseases, lighting, and

background noise. The study indicated that more advanced techniques using CNNs could provide more robust and accurate classification for practical agricultural settings [14].

In 2020, Chugh et al. proposed a model that classifies potato leaf diseases, using the InceptionV3 CNN Architecture. The study targeted diseases caused by fungal infections, such as early and late blight conditions, which significantly reduce tuber yields. This is because the model can classify the leaves by disease with an accuracy of 90%. The study laid the bedrock for developing automated tools to aid farmers in carrying out better management of crop health and showed how well InceptionV3 detects potato illnesses [15].

In the year 2020, to overcome the difficulties of early and precise disease identification, Sholihati et al. presented a DL-based technique for potato leaf disease classification. Four types of potato leaf diseases, with outward appearances different from one another, were classified using VGG16 and VGG19 CNN architectures. A mean accuracy of 91% is an example of how well the deep neural networks performed for recognizing potato diseases. This, however, is quite encouraging, with the huge and rising demand for potatoes in the world, as models can be used to increase output and improve quality [16].

Afzaal et al in 2021 looked at how DL can be used through machine vision for the live tracking of potato plants early blight. They employed the dataset of 5,199 images collected in different shadow and light aspects across four fields to create a DL based model. The work was concerned with training and testing three CNN GoogleNet, VGGNet and EfficientNet in the farm of disease detection in three sets of classification (2-class, 4-class and 6-class). EfficientNet was the most accurate, with the lowest F-scores of 0.79 and 0.98 for all the schemes considered. This research proved the efficiency of using DL frameworks for site-specific application of fungicides reducing environmental pollution bringing about more profits [17].

Verma and Singh in the year 2021 focused on the detection of diseases on leaves of tomato and potato plants using DL technologies and stressed the importance of such technologies in ensuring food security across the world. So, Using the DenseNet architecture their study recovered an impressive figure of 96.24% accuracy on detecting and classifying different plant diseases. The study highlighted the strength posed by DL in detecting plant diseases and its capability of reducing spoilage in agriculture and conserving resources in food production [18].

In the same year 2019, Akther et al. employed TL on VGG16 architecture to isolate blight affected potato leaves. The model was great at feature extraction from a custom dataset which enabled it make strong classifications even where data was scarce due to the fact that it employed pretrained weights from ImageNet. This approach achieved an accuracy as high as 96.88% which was higher than other models developed to detect potato blight in the past. The research proved the effectiveness of TL technology in disease diagnosis which enhances crop management and increases food security capacity [19].

Chen et al. (2022) propose MobOca_Net, another lightweight DL model that addresses the issues of potato leaves diseases. This model is based on MobileNet V2 and integrates an attention module with octave convolution block for improved detection of fine lesion features. And through TL with the PlantVillage dataset, the model obtained a great accuracy of 97.73% in disease detection with the model. The Research pointed to the fact that MobOca_Net can be used for rapid detection of diseases which is a good way of limiting crop loss and increasing potato production and consequently contributes to global food security [20].

Kothari et al. (2022) designed a deep-learning framework for potato leaf disease classification, keeping in view both early and late blight. Further, they constructed an exact classificatory model using different architectures such as GoogleNet, ResNet-50, and VGG16. This paper achieved an accuracy rate of 97% on the first 40 epochs in their training process, which underlined the effectiveness of a deep neural network in the determination of potato leaf diseases. With this system, one can be able to escape the challenges faced with manual detection and comes well as a suitable way to meet growing crop quality and yield requirements [21].

Mahum et al. (2023) worked on a new DL architecture for the identification and classification of potato leaves diseases into five categories, which are Potato Late Blight, Potato Early Blight, Potato Leaf Roll, Potato Verticillium Wilt, and Healthy Potato. The model was based on augmented DenseNet-201 with one additional transition layer and new loss function in the form of reweighted cross-entropy to solve the problem of data imbalance. It integrated the images from PlantVillage with some other experimentally

gathered data for the undercovered classes. The model obtained a good classification accuracy of 97.2% making it better than the previous techniques. This method worked well and showed great results to pallet data with imbalance issues and classified potato crops disease better [22].

Bajpai et al. (2023) put out a machine that detects the diseases that affect potatoes. Potatoes suffer from diseases such as Late Blight, Early Blight, Septoria Leaf Spots, Curly Leaves, and Bacterial Wilt which are detrimental to not only the economy, but the environment as well. The aim of their study was to classify leaf samples into four classes, three leaves for diseased leaves, and one for healthy leaves. Out of the three models, VGGNet16, ResNet101 and a variation of AlexNet, the second one or Modified AlexNet had the most favorable results as it achieved a 99.97 percent training accuracy along with a 61 percent testing accuracy rate. In particular, this type of study proves that early detection systems are efficient in reducing wastage in agriculture [23].

Sharma and Sharma (2024) developed a system for the recognition of potato leaves, using the PlantVillage dataset, based on RNN. By applying the time-aware features of RNNs and adding LSTM units, they created a system that learned patterns contained within sequential data, an important aspect in understanding the growth of plants and the eventual diseases they may have. The RNN model also showed a better performance than CNN's and feedforward neural networks, attaining an accuracy of 92.7%. This case shows how in the future RNN's could help in precision farming where early detection of diseases would help in bettering the management of crops, which promotes sustainability [24].

In 2024 Sharma and Sharma proposed PotatoLeafGuard, a novel hybrid CNN architecture for the improved potato leaf diseases detection. Considering the potato as one of the major food crops around the world, its protection against pathogens is crucial for effective crop management. This model couples DL with TL to predict disease risks with great accuracy. This work presents a model using 3,076 images across seven categories of viral, bacterial, fungal, and other diseases, with the use of CNNs, VGG16, and Xception models, which enhance the classification performance. Data augmentation increases the ability of the model to overcome the limitations in the dataset. It achieved a high overall classification accuracy of 94.70%, and precision, recall, and F1-score were 93.75%, 93.6%, and 92.75%, respectively. Thus, this work improved potato leaf disease detection accordingly [25].

Lanjewar et al. (2024) discussed different modified TL-based frameworks for potato leaf disease identification, which was stated to be a critical issue concerning Indian agriculture. Potatoes play a very important role in the economy of the nation; hence, early identification of the disease is an absolute necessity to reduce losses to the crops. The various DL algorithms used for this study were the Sequential Model, ResNet-50, VGG-16, and Inception V3, representing different CNN architectures. These models were evaluated on the basis of their performance metrics, where the sparse categorical cross-entropy loss function was used because the nature of the training data is balanced. The models yield the following accuracies: ResNet-50-96.00%, VGG-16-92.67%, Inception V3-85.00%, and Sequential Model-94.33%. This research puts weight on how such techniques can go a long way in the detection and categorization of potato leaf diseases, thus improving agricultural productivity due to early detection of the disease [26].

2.1. Comparative Analysis of Related Works

The comparative study in Table 1 below summarizes the different ML and DL techniques applied towards the detection of diseases from potato leaves. The critical reviewed study portrays works developed by RF, SVM, ANN, and most recent ones using CNN-based approaches along with hybrid deep models. Several such studies are based on datasets from PlantVillage and others compiled from various agricultural fields. As observed, while most ML models give quite modest accuracy, DL approaches have always reported high values of accuracy, especially the architectures related to CNN. The example models are EfficientNet, VGG16, DenseNet, GoogLeNet and ResNet-50 among others, which show very high accuracy: EfficientNet-0.79 to 0.98 F-score and VGG16 as high as 97%. However, dataset imbalance and differences in image quality pose challenges to model performance; therefore, refinement is needed. The results also point out that hybrid CNN models, among them the one proposed by Sharma & Sharma (2024), perform remarkably high accuracy rates, which further highlights promising potential for DL in detecting potato diseases automatically.

Table 1. Comparative Analysis of state-of-the-art literature

Study (Year)[Ref.]	Methods/Models Used	Dataset Used	Key Findings	Limitations	Accuracy
Patil et al. (2017) [13]	Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN)	PlantVillage, University of Agricultural Sciences, India	ANN outperformed other methods for detecting blight diseases in potato leaves.	Limited dataset size (892 images), and not generalize well for complex, real-world conditions.	92% (ANN), 84% (SVM), 79% (RF)
Suttapakti & Bunpeng (2019) [14]	Euclidean distance-based classifier	PlantVillage	Achieved 89% accuracy in classifying potato leaves with early and late blight using color and texture features.	Challenges with complex disease variations and background noise	89%
Chugh et al. (2020) [15]	InceptionV3 CNN	Custom Dataset	InceptionV3 achieved 90% accuracy in detecting fungal infections (early and late blight) in potato leaves.	Custom dataset, not cover all disease variations; performance might drop with more complex datasets	90%
Sholihati et al. (2020) [16]	VGG16, VGG19 CNN	Custom Dataset	Achieved 91% accuracy in classifying four types of potato leaf diseases using DL techniques.	Limited dataset and not generalize across different potato varieties or environmental conditions.	91%
Afzaal et al. (2021) [17]	GoogLeNet, VGGNet, EfficientNet CNN	5199 images from four fields	EfficientNet outperformed other models, with F-scores ranging from 0.79 to 0.98 for disease detection.	Environmental factors (lighting, shadow) affect performance	Avg. 90% (EfficientNet)
Verma & Singh (2021) [18]	DenseNet CNN	Custom Dataset	DenseNet achieved 96.24% accuracy in detecting	Custom dataset limits generalization to other	96.24%

			potato and tomato leaf diseases.	regions or disease types.	
Akther et al. (2021) [19]	TL with VGG16	Self-prepared dataset	Achieved high accuracy (96.88%) in classifying potato leaves affected by blight diseases.	Limited dataset for potato blight	96.88%
Chen et al. (2022) [20]	MobOca_Net (MobileNet V2-based architecture with attention mechanism)	PlantVillage	MobOca_Net achieved 97.73% accuracy, showing robustness for early potato disease detection.	Performance degrades with low-quality images or complex disease symptoms.	97.73%
Kothari et al. (2022) [21]	GoogLeNet, ResNet-50, VGG16 CNN	Custom Dataset	Achieved 97% accuracy with DL-based system for early blight and late blight classification.	Not generalize well to datasets with more diverse disease variations or environmental factors.	97%
Mahum et al. (2023) [22]	DenseNet-201 with transition layer and reweighted cross-entropy loss	PlantVillage + additional data	Achieved 97.2% accuracy in detecting and classifying potato leaf diseases, addressing dataset imbalance.	Dataset limitations for less represented classes.	97.2%
Bajpai et al. (2023) [23]	VGGNet16, ResNet101, modified AlexNet	Custom Dataset	Modified AlexNet achieved 99.97% training accuracy but lower testing accuracy (61%) for disease detection.	Overfitting on training data, poor generalization to unseen data.	61%
Sharma & Sharma (2024) [24]	Recurrent Neural Networks (RNNs), Long	PlantVillage	RNN with LSTM units achieved 92.7%	Struggles with large-scale datasets and noise	92.7%

Short-Term Memory (LSTM)			accuracy, outperforming CNNs for disease detection in potato leaves.		
Sharma & Sharma (2024) [25]	Hybrid CNN architecture (VGG16, Xception)	3,076 images, seven disease categories	Hybrid CNN model achieved 94.7% accuracy, with high precision, recall, and F1-scores.	Complexity of hybrid models might lead to overfitting and require extensive fine-tuning.	94.7%
Lanjewar et al. (2024) [26]	ResNet-50, VGG-16, Inception V3 CNN	Custom Dataset	ResNet-50 achieved 96% accuracy, followed by VGG-16 and Inception V3 with varying performances in detecting diseases.	Inconsistent performance across models, potentially leading to difficulty in choosing the right model.	96% (ResNet-50), 92.67% (VGG-16), 85% (Inception V3)

2.1. Limitations of Related Works

Table 1 highlights the key limitations identified in previously published works on potato leaf disease detection, as outlined below:

- The Diversity of the dataset: There is a very less diversity of conditions for illumination, type of crops in various publicly available datasets such as PlantVillage, Patil et al. [13], Chugh et al. [15], and Akther et al. [19].
- Overfitting Issues: Most models overfit, as seen by Bajpai et al. [23], who reported 99.97% training accuracy but only 61% testing, to Sharma & Sharma [25], and hence their reliability in diverse sets is limited.
- Dataset Imbalance: Class imbalance, which Mahum et al. [22], Suttapakti & Bunpeng [14] and Sharma & Sharma [24] identified, results in poor performance concerning under-represented diseases or their stages.
- High Computational Requirements: These big models like DenseNet proposed by Verma & Singh [18] and EfficientNet by Afzaal et al. [17], if used, will have high computational requirements for training and inference also, which might be problematic for farmers or researchers with low access to high-performance hardware.

2.2. Contributions of Proposed Model

The key contributions of this study on potato leaf disease detection, emphasizing advancements in accuracy, evaluation metrics, and practical applicability, as detailed below:

- **Multi-Model DL Framework:** This study presents a DL based system utilizing TL with **VGG16, GoogLeNet, and ResNet-50** for the accurate detection of potato leaf diseases, specifically early blight and late blight. Among these, **ResNet-50 achieved the highest performance.**
- **Innovative Approach for Disease Detection:** This study introduces a DL based system employing TL for detecting potato leaf diseases, including early blight and late blight, with significantly higher accuracy compared to existing methods.

- **Comprehensive Model Evaluation:** The model's performance is rigorously assessed using key metrics such as Precision, Recall, F1-score, and Misclassification Rate, providing a detailed understanding of its effectiveness in real-world scenarios.
- **High Accuracy and Real-World Readiness:** The **ResNet-50 model achieved 100% training accuracy, 99.75% validation accuracy, and 99.26% testing accuracy**, demonstrating superior accuracy and reliability for field-level deployment.
- **Alignment with Sustainable Agriculture Goals:** By reducing reliance on chemical treatments and improving disease management efficiency, this research supports sustainable agricultural practices, enhancing crop yield while preserving soil health and fertility.
- **Contribution to Food Security:** This work highlights the role of advanced AI technologies in reducing the impact of plant diseases, thereby securing food supplies and promoting sustainable farming practices.

3. Materials and Methods

Advanced DL techniques will be employed in the proposed system to detect diseases on potato leaves automatically. It classifies leaf images into three main categories: healthy, early blight, and late blight. The proposed system automatically detects diseases and helps farmers and agriculture experts by finding out the disease at an early stage. Early detection of disease can save crops from potential losses and enhance the overall productivity.

The proposed system architecture consists of the following components, as illustrated in Fig. 5: each component interlinked together to ensure that there is accurate detection of diseases found on potato leaves. Major steps in the system flow are as follows:

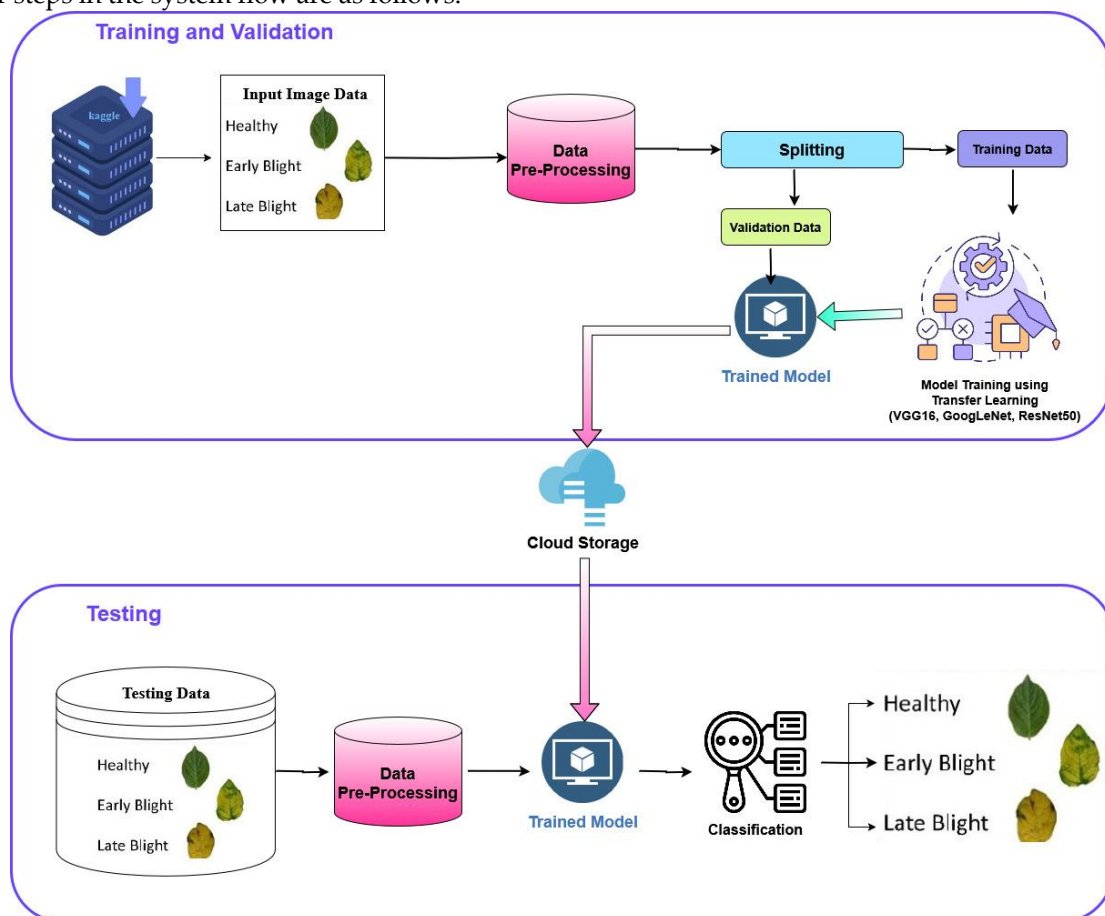


Figure 5. Proposed Model Research Methodology

The system processes potato leaf images that undergo pre-processing steps, including resizing, normalization, and data augmentation, to standardize and enhance the dataset. The data is then divided into training, validation and testing subsets for model development and assessment. TL is employed to

train the model, utilizing pre-trained models VGG16, GoogLeNet and ResNet-50 that is fine-tuned on the potato leaf dataset to boost classification accuracy.

3.1. Dataset

The Potato Leaf Disease (PLD) dataset includes three categories of images representing different potato leaf conditions: early blight, late blight, and healthy leaves. To maximize model performance, the dataset was preprocessed with the following steps:

- All images were resized to 224×224 pixels, converted into tensors, and normalized using the mean [0.485, 0.456, 0.406] and standard deviation [0.229, 0.224, 0.225]. These preprocessing parameters align with the ImageNet standard, ensuring compatibility and optimal performance for VGG16, GoogLeNet, and ResNet-50 architectures.
- The dataset was split into 80% for training, 10% for validation and 10% for testing ensuring a balanced evaluation across all stages.

Three DL models VGG16, GoogLeNet, and ResNet-50 were employed to classify the leaf images based on disease presence. The class distribution within the dataset is illustrated in Fig. 6.

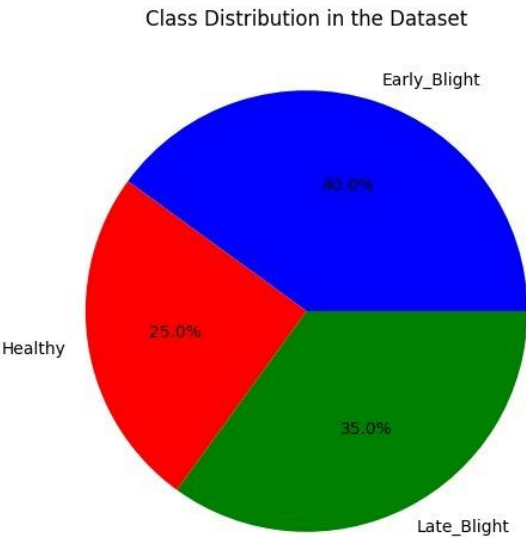


Figure 6. Class distribution in the Dataset

The dataset comprises three primary classes:

- 1. Early Blight (40%):** The blue section of the dataset shows Early Blight, which is 40% of the total. This is a common fungal disease in potatoes characterized by dark lesions that destroy the leaf tissue. Its detection is very crucial and has to be done in time, since it can spread so fast when the environment is favorable.
- 2. Late Blight (35%):** The green section represents the Late Blight, which comprises 35% of the dataset. Notorious for severity on potato crops, its detection is quite timely and has to be accurate, for it affects leaves and tubers much, especially in wet weather conditions.
- 3. Healthy (25%):** It is the red section with the healthy potato leaves amounting to 25%. It will help in drawing a reference when deciding upon a diseased leaf.

In this study, three DL models VGG16, GoogLeNet, and ResNet-50 were applied to classify potato leaf conditions based on these categories. Each model's deep Convolutional layers enabled effective feature extraction for accurate classification. The dataset's class distribution provides valuable insights into balance, with a slight predominance of Early Blight. This minor bias was carefully considered during training and evaluation to ensure consistent model performance across all classes.

Table2 shows the workflow for Potato Leaf Disease detection using TL with VGG16, GoogLeNet, and ResNet-50.

Table 2. Potato Leaf Disease Detection WorkFlow	
Start	
Step 1:	Acquire Dataset
Used PLD [12] having 3 classes (Early_Blight, Healthy, and Late_Blight)	

Step 2: Data Pre-Processing

Resizes, Normalize, and Data Augmentation to prepare for training

Step 3: Data Splitting

Split the data into Training and Testing

Step 4: Model Training and Validation

Pre-trained VGG16, GoogLeNet, and ResNet-50 are fine-tuned and further trained it on potato leaf dataset

Step 5: Model Testing

Testing the trained model on Testing dataset

Step 6: Model Evaluation

Model evaluated on key metrics (Accuracy, Misclassification Rate, Precision, Specificity, Sensitivity, and F1-Score)

Step 7: Deploy Model

Model Storage and Cloud Integration

End

VGG16

In 2014, researchers Simonyan and Zisserman developed VGG16, a CNN model that use TL and has a straightforward, sequential structure [27]. VGG16 is a DL architecture comprising 16 layers, which include 13 layers dedicated to convolution and 3 fully connected layers as shown in Fig. 7.

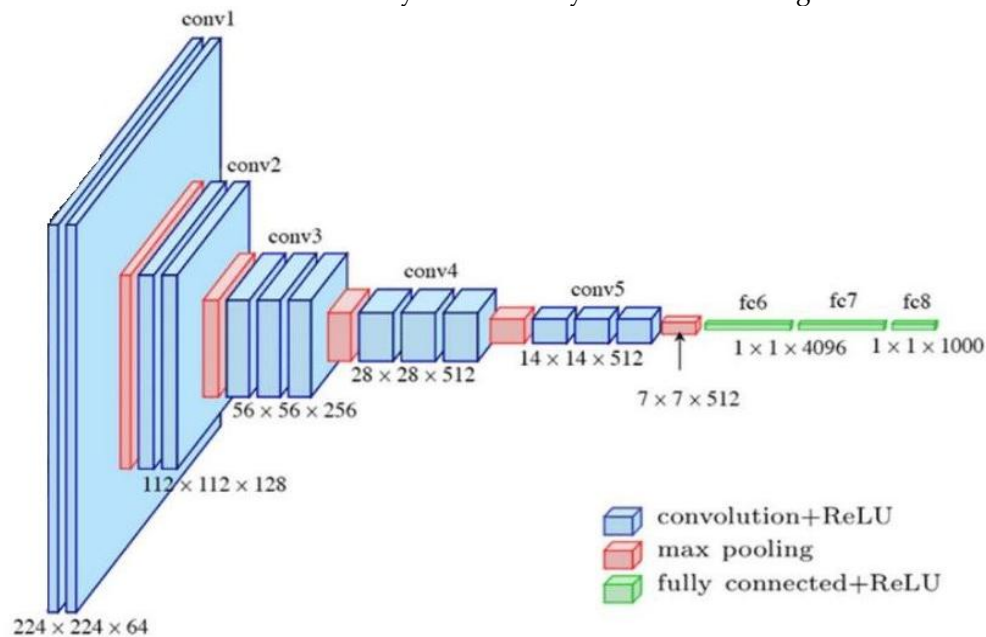


Figure 7. VGG16 architecture [27]

GoogLeNet

Introduced by Szegedy et al. in 2014, GoogLeNet is a deep Convolutional neural network that marked a significant advancement in computer vision tasks [28]. It introduced the Inception architecture, which allows the model to perform multiple types of convolutions in parallel, improving computational efficiency and accuracy. GoogLeNet consists of 22 layers, including Inception modules that capture spatial features at different scales. Its design significantly reduces the number of parameters compared to earlier networks, making it both powerful and resource-efficient. The overall structure of GoogLeNet is illustrated in Fig. 8.

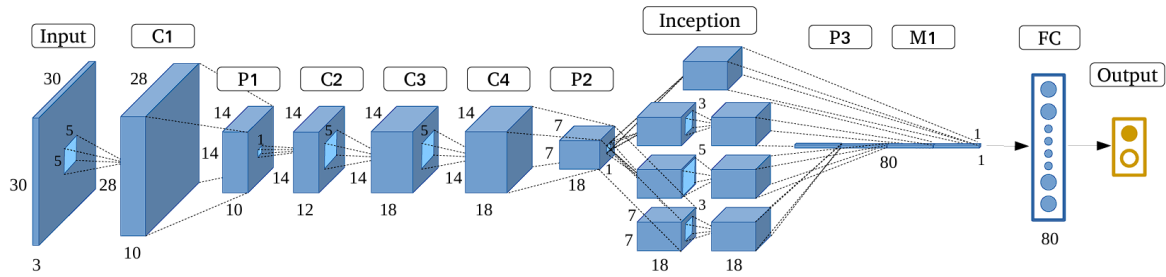


Figure 8. GoogLeNet architecture [28]

ResNet-50

ResNet-50 was developed by Microsoft Research and introduced in 2015 by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, researchers at Microsoft Research Asia [29]. It is a highly influential DL architecture that introduced the concept of residual learning to overcome the vanishing gradient problem in very deep neural networks. Comprising 50 layers, ResNet-50 uses skip connections—also known as residual connections—to allow gradients to flow more easily during backpropagation. This enables the model to train deeper networks effectively without performance degradation. ResNet-50 has become one of the most robust and widely adopted architectures for image classification tasks. The detailed structure of ResNet-50 is illustrated in Fig. 9.

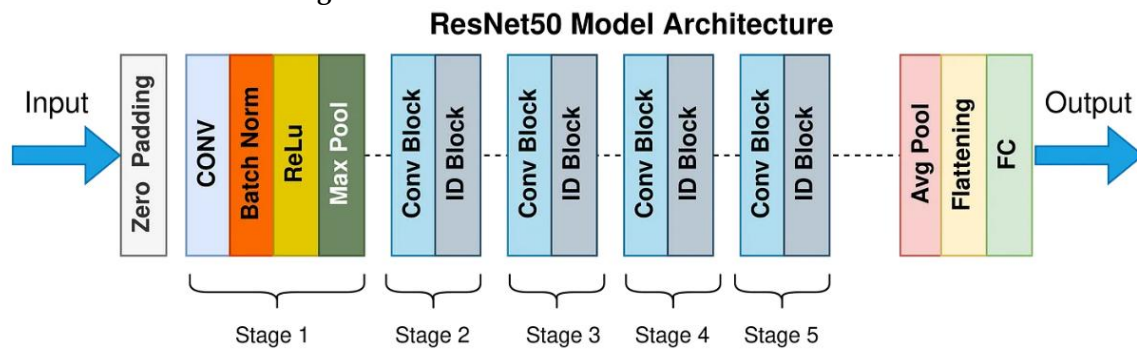


Figure 9. ResNet-50 architecture [29]

Once the model is trained, it is saved in a secure cloud environment, making it easily accessible for deployment. This cloud storage option allows users to access the model remotely, facilitating real-time disease detection via mobile devices or web applications.

After training, the performance of the trained model is evaluated by following performance metrics:

- Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$
- Misclassification Rate = $\frac{FP+FN}{TP+TN+FP+FN}$
- Precision = $\frac{TP}{TP+FP}$
- Sensitivity = $\frac{TP}{TP+FN}$
- Specificity = $\frac{TN}{TN+FP}$
- F1 – Score = $2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}}$

These metrics help evaluate how effectively the model can identify potato leaf diseases. By utilizing pre-trained models and cloud storage, the system provides farmers with the ability to detect diseases in real time. This automated approach not only helps minimize crop damage but also enhances overall plant health. The whole dataset and trained models are stored on cloud servers for convenient access, reliable backup, and easy sharing in future research efforts.

4. Simulation and Results

For simulation, Google Colab and PyTorch were used. Google Colab provided the necessary computational resources, including access to GPUs, which significantly accelerated the training and testing of DL models. PyTorch was chosen as the primary framework due to its flexibility and user-friendly

interface, which facilitated the construction and training of the VGG16, GoogLeNet, and ResNet-50 models. The simulations were conducted with a batch size of 32, learning rate of 0.0001, Adam optimizer, and 10 training epochs. These hyperparameters were carefully selected to ensure efficient training, stable convergence, and optimal model performance. This configuration resulted in accurate classification of potato leaf diseases across all three models, with ResNet-50 yielding the highest accuracy.

Fig. 10 shows the Training Confusion Matrices of the proposed models VGG16, GoogLeNet, and ResNet-50 illustrating their performance in classifying potato leaves into three categories: Early Blight, Healthy, and Late Blight. The matrices highlight the accuracy of predictions during training for each model, with ResNet-50 demonstrating superior classification performance.

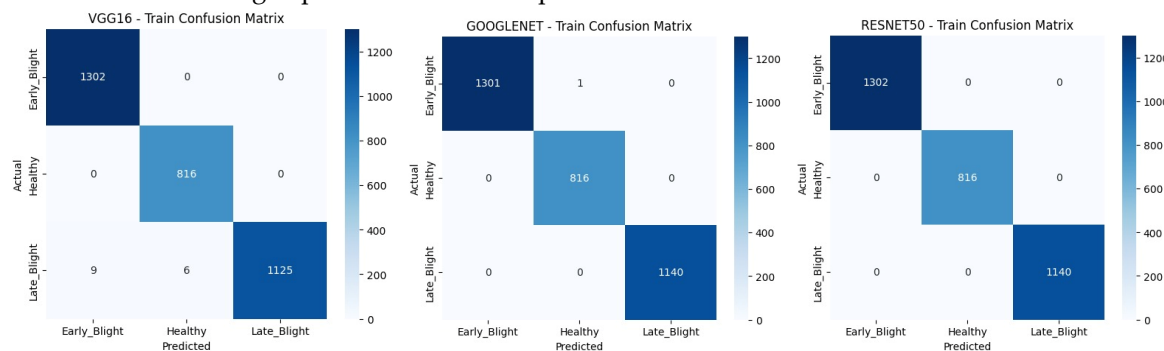


Figure 10. Proposed Models Training Confusion Matrices

The confusion matrices of the training results show outstanding performances across all models, with minimal misclassifications. VGG16 demonstrated strong performance but showed a slight drop in precision compared to the others, misclassifying 9 samples of Late Blight as Early Blight and 6 samples as Healthy. GoogLeNet achieved near-perfect classification, with only a single Early Blight sample misclassified as Healthy. ResNet-50 performed flawlessly, correctly classifying every sample without a single error across all categories.

When comparing the three models, ResNet-50 demonstrated the highest training accuracy with zero misclassifications, indicating a very strong fit to the training data. GoogLeNet followed closely, with only one minor misclassification. All three models show great promise for practical applications in precision agriculture, with ResNet-50 emerging as the top performer during the training phase.

Fig. 11 shows the validation Confusion Matrices of the VGG16, GoogLeNet, and ResNet-50 illustrating their performance.

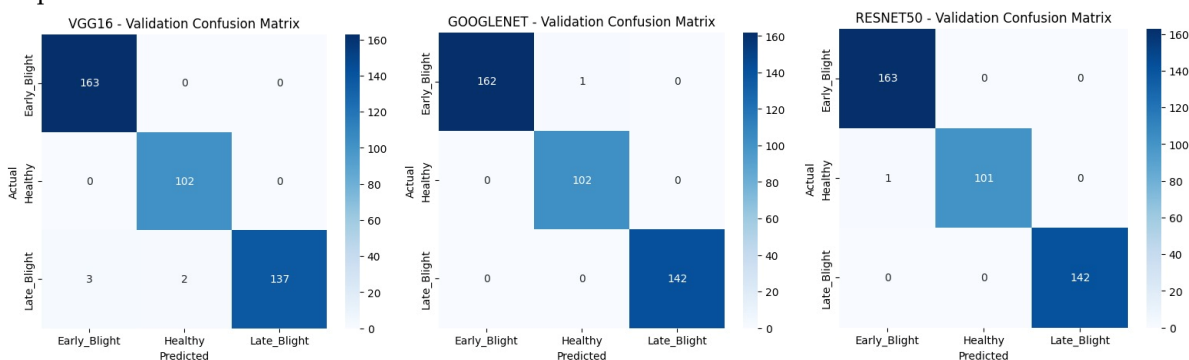


Figure 11. Proposed Models Validation Confusion Matrices

VGG16 showed slightly lower performance compared to the other two models by misclassifying three Late Blight samples as Early Blight and two as Healthy. GoogLeNet achieved excellent results with only one misclassification where an Early Blight sample was wrongly predicted as Healthy. ResNet-50 also performed strongly, misclassifying just one Healthy sample as Early Blight, maintaining high precision in distinguishing disease types. Despite these small inaccuracies, all models correctly classified Healthy samples with very high accuracy, which is vital for minimizing unnecessary treatments and promoting sustainable farming practices [30-33].

Fig. 12 shows the Testing Confusion Matrices of the proposed models VGG16, GoogLeNet, and ResNet-50 illustrating their performance in classifying potato leaves into three categories: Early Blight, Healthy, and Late Blight. The matrices highlight the accuracy of predictions during testing.

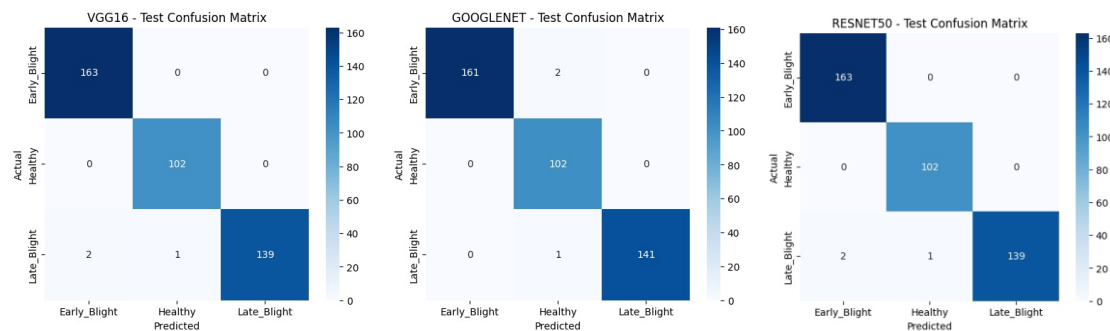


Figure 12. Proposed Models Testing Confusion Matrices

VGG16 presented an identical confusion pattern to ResNet-50, suggesting a consistent but slightly less robust performance on Late Blight class predictions. The GoogLeNet model exhibited strong generalization, correctly classifying most samples with only minor errors: 2 Early Blight samples were misclassified as Healthy and 1 Late Blight sample was also confused as Healthy. ResNet-50 demonstrated excellent results, perfectly classifying Early Blight and Healthy samples, while slightly misclassifying 2 Late Blight samples as Early Blight and 1 as Healthy. Notably, all three models performed flawlessly in recognizing Healthy leaves, which is critical for practical applications in agricultural monitoring.

The models based on test results, ResNet-50 and VGG16 performed slightly better than GoogLeNet in terms of Early Blight classification, as GoogLeNet showed a minor confusion. However, the overall differences among the models were marginal, confirming their suitability for real-world deployment. ResNet-50, maintaining consistency across both training and testing phases, can be regarded as the most reliable model among the three, followed closely by VGG16 and GoogLeNet.

Fig. 13 shows the Training ROC curves of the VGG16, GoogLeNet, and ResNet-50.

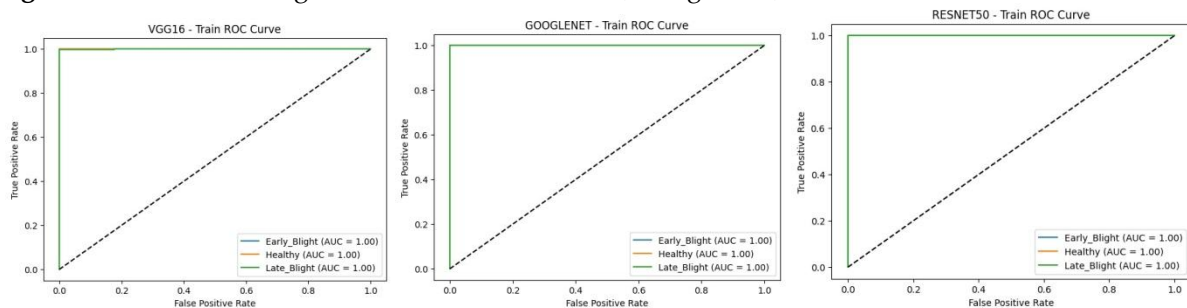


Figure 13. Proposed Models Training ROC Curves

The ROC curves for the VGG16, GoogLeNet, and ResNet-50 models on the training dataset illustrate outstanding classification performance. Each model achieved a perfect Area Under the Curve (AUC) of 1.00 across all three classes: Early Blight, Healthy, and Late Blight. The sharp rise and flat curve towards the top left corner indicate excellent sensitivity and specificity during training. VGG16, GoogLeNet, and ResNet-50 all successfully learned the intricate patterns within the training data, resulting in flawless separability between the classes, as reflected by their ideal ROC curves.

Fig. 14 shows the Validation ROC curves of the VGG16, GoogLeNet, and ResNet-50.

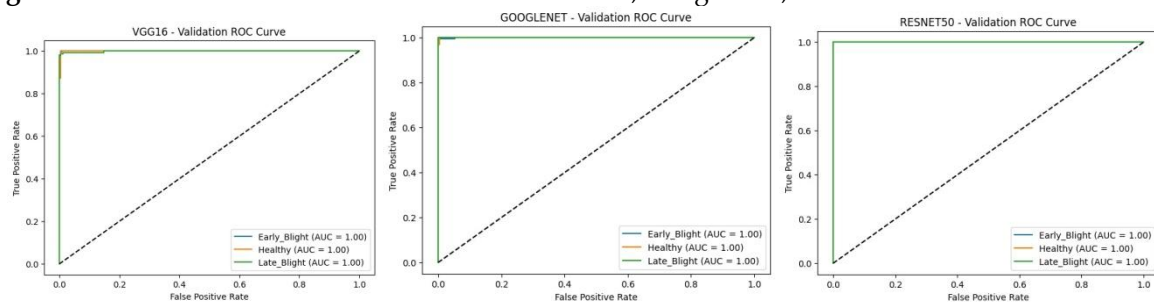


Figure 14. Proposed Models Validation ROC Curves

The ROC validation curves confirm that all three models retain excellent classification ability beyond training and testing, reinforcing their effectiveness for real-world potato leaf disease detection applications.

Fig. 15 shows the Testing ROC curves of the VGG16, GoogLeNet, and ResNet-50.

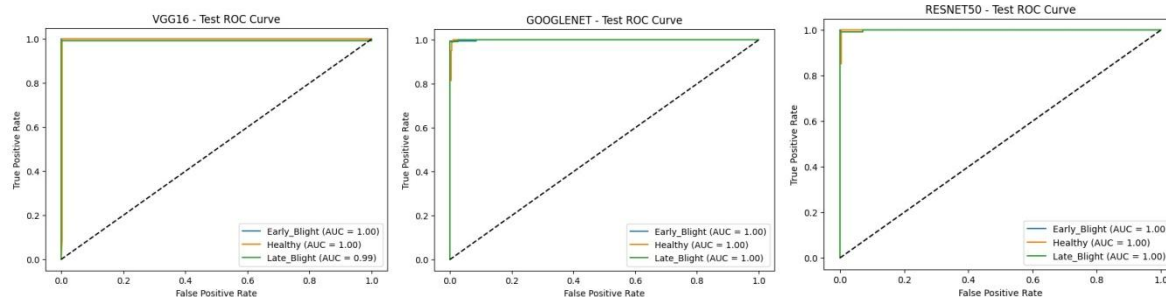


Figure 15. Proposed Models Testing ROC Curves

The ROC testing curves confirm that all three models possess superior discriminative power, making them highly effective for potato leaf disease detection during testing.

Fig. 16 shows the Loss and Accuracy of the VGG16, GoogLeNet, and ResNet-50.

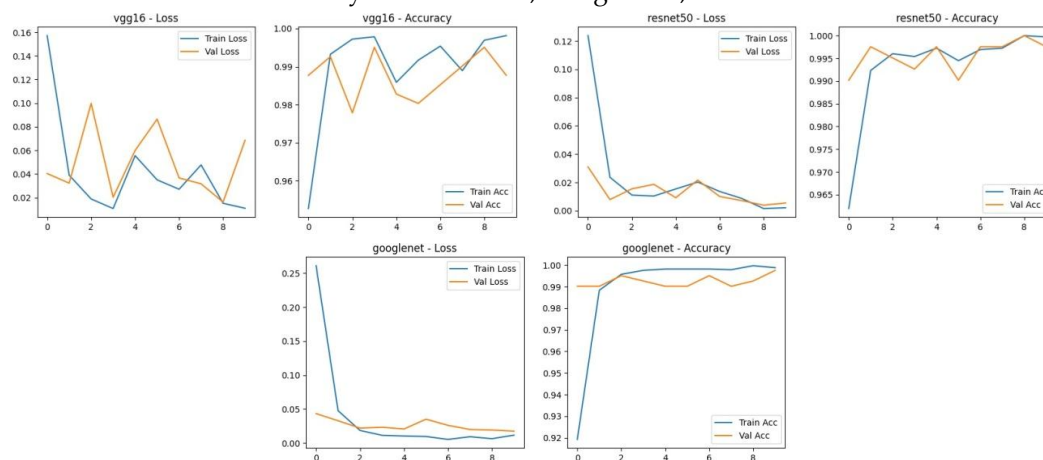


Figure 16. Proposed Models Loss and Accuracy

The validation and training curves for VGG16 indicate a fluctuating pattern in accuracy and loss across epochs. Although the training accuracy improves with time, the validation loss is highly unstable, which could reflect over fitting or sensitivity to the data. GoogLeNet indicates a consistent and steep decline for training as well as validation loss, reaching very low values for loss and high, consistent accuracy across epochs, which reflects the ability of GoogLeNet to learn generalized features. ResNet-50 shows the most stable performance among all models with closely follow-through training and validation losses and almost flawless accuracy after some epochs, which is an indicator of superior generalization and little over fitting.

Misclassification rates of every class of leaf disease on the three models deployed VGG16, GoogLeNet, and ResNet-50 exhibit interesting patterns that enhance model behavior and disease classification problem comprehension as shown in **Table 3**.

Table 3. Misclassification Rates (%) for Each Potato Leaf Disease Class Across VGG16, GoogLeNet, and ResNet-50 Models During Training, Validation, and Testing Phases

Type	VGG16			GoogLeNet			ResNet-50		
	Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
Early Blight	0.28	0.74	0.49	0.03	0.25	0.49	0.00	0.25	0.49
Healthy	0.18	0.49	0.25	0.03	0.25	0.74	0.00	0.25	0.25
Late Blight	0.46	1.23	0.74	0.00	0.00	0.25	0.00	0.00	0.74

For the Early Blight class, the three models all demonstrated a uniform testing misclassification rate of 0.49%, suggesting that the class perhaps shares redundant features with Late Blight or Healthy leaves, possibly because of similar visual symptoms at some points. VGG16 posted slightly higher validation error (0.74%) than GoogLeNet and ResNet-50 (both 0.25%), which indicate lower generalization during training. In Healthy class, the lowest misclassification rate during testing (0.25%) was achieved by ResNet-50,

indicating its excellent capacity to differentiate between healthy and sick leaves, whereas GoogLeNet achieved the highest error (0.74%), which could be due to its deeper inception structure not being as discriminative of fine changes in texture within healthy leaves. With de de Late Blight class, GoogLeNet and ResNet-50 worked with minimal misclassification during testing (0.25% and 0.74% respectively), while VGG16 made a comparably higher error in de testing, which was 0.74%. This may be due to the fact that the complex and multitudinous visual appearance of Late Blight like water-soaked lesions and patterns of decay has the possibility of causing confusion, especially where initial symptoms can be confused with those of Early Blight. Such misclassification patterns suggest that while all three models were generally good, slight errors are mostly due to overlapping symptom features and intra-class variation in disease progress stages.

Table 4. Statistical significance of proposed models for the training, validation and testing using VGG16, GoogLeNet and ResNet-50

Parameters	VGG16			GoogLeNet			ResNet-50		
	Trainin g	Validati on	Testing	Trainin g	Validati on	Testin g	Trainin g	Validati on	Testing
Accuracy	99.54	98.77	99.26	99.97	99.75	99.26	100.00	99.75	99.26
Misclassification Rate	0.46	1.23	0.74	0.03	0.25	0.74	0.00	0.25	0.74
Precision	99.53	98.76	99.27	99.96	99.68	99.05	100.00	99.80	99.27
Sensitivity (Recall)	99.56	98.83	99.30	99.97	99.80	99.36	100.00	99.67	99.30
Specificity	99.53	98.76	99.27	99.96	99.68	99.05	100.00	99.80	99.30
FNR	0.44	1.17	0.70	0.03	0.20	0.64	0.00	0.33	0.70
FPR	0.47	1.24	0.73	0.04	0.32	0.95	0.00	0.20	0.73
F1 Score	99.54	98.78	99.28	99.97	99.73	99.19	100.00	99.73	99.28

Table 4 illustrates statistical significance of VGG16, GoogLeNet, and ResNet-50 performance measurement using training, validation, and testing confusion matrices, which show clear differences in their efficacy. VGG16 recorded high accuracies across all phases, achieving 99.54% on training, 98.77% on validation, and 99.26% on testing, although it recorded a slightly higher misclassification rate on validation (1.23%) compared to the other models. GoogLeNet also came in close behind, with tremendous performance at 99.97% accuracy on training, 99.75% on validation, and 99.26% on testing, with excellent generalization. ResNet-50 had the best overall performance with a flawless 100% accuracy on training, 99.75% on validation, and 99.26% on testing, with excellent robustness with minimal overfitting. Precision, sensitivity, specificity, and F1 score were all high in all three models, but the ResNet-50 had perfect precision, recall, and F1 score during training. Overall, although all the models performed well, ResNet-50 performed slightly better than some of them, and GoogLeNet produced competitive results with slightly lower misclassification rates than VGG16.

The accuracy of the models proposed in this work was compared to various other studies in this field. From **Table 5**, it is observed that the model performs better compared to all other research publications regarding accuracy. That proves that the approach is much more effective in recognizing potato leaf diseases with high accuracy, hence marking a milestone in the field of plant disease detection by DL techniques.

Table 5. Comparison of the proposed model with state-of-the-art literature.

Study (Year)[Ref.]	Methods/Mode ls Used	Dataset Used	Key Findings	Limitations	Accuracy
Patil et al. (2017) [13]	Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Networks (ANN)	PlantVillage, University of Agricultural Sciences, India	ANN outperformed other methods for detecting blight	Limited dataset size (892 images), and not generalize well for complex, real- world conditions.	92% (ANN), 84% (SVM), 79% (RF)

Suttapakti & Bupeng (2019) [14]	Euclidean distance-based classifier	PlantVillage	diseases in potato leaves. Achieved 89% accuracy in classifying potato leaves with early and late blight using color and texture features.	Challenges with complex disease variations and background noise	89%
Chugh et al. (2020) [15]	InceptionV3 CNN	Custom Dataset	InceptionV3 achieved 90% accuracy in detecting fungal infections (early and late blight) in potato leaves. Achieved 91% accuracy in classifying four types of potato leaf diseases using DL techniques.	Custom dataset, not cover all disease variations; performance might drop with more complex datasets	90%
Sholihati et al. (2020) [16]	VGG16, VGG19 CNN	Custom Dataset	EfficientNet outperformed other models, with F-scores ranging from 0.79 to 0.98 for disease detection. DenseNet achieved 96.24% accuracy in detecting potato and tomato leaf diseases.	Limited dataset and not generalize across different potato varieties or environmental conditions.	91%
Afzaal et al. (2021) [17]	GoogleNet, VGGNet, EfficientNet CNN	5199 images from four fields	Achieved high accuracy (96.88%) in classifying potato leaves affected by blight diseases.	Environmental factors (lighting, shadow) affect performance	Avg. 90% (Efficient-Net)
Verma & Singh (2021) [18]	DenseNet CNN	Custom Dataset		Custom dataset limits generalization to other regions or disease types.	96.24%
Akther et al. (2021) [19]	TL with VGG16	Self-prepared dataset		Limited dataset for potato blight	96.88%

Chen et al. (2022) [20]	MobOca_Net (MobileNet V2- based architecture with attention mechanism)	PlantVillage	MobOca_Net achieved 97.73% accuracy, showing robustness for early potato disease detection.	Performance degrades with low-quality images or complex disease symptoms.	97.73%
Kothari et al. (2022) [21]	GoogleNet, ResNet-50, VGG16 CNN	Custom Dataset	Achieved 97% accuracy with DL-based system for early blight and late blight classification.	Not generalize well to datasets with more diverse disease variations or environmental factors.	97%
Mahum et al. (2023) [22]	DenseNet-201 with transition layer and reweighted cross-entropy loss	PlantVillage + additional data	Achieved 97.2% accuracy in detecting and classifying potato leaf diseases, addressing dataset imbalance.	Dataset limitations for less represented classes.	97.2%
Bajpai et al. (2023) [23]	VGGNet16, ResNet101, modified AlexNet	Custom Dataset	Modified AlexNet achieved 99.97% training accuracy but lower testing accuracy (61%) for disease detection.	Overfitting on training data, poor generalization to unseen data.	61%
Sharma & Sharma (2024) [24]	Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM)	PlantVillage	RNN with LSTM units achieved 92.7% accuracy, outperformin g CNNs for disease detection in potato leaves.	Struggles with large-scale datasets and noise	92.7%
Sharma & Sharma (2024) [25]	Hybrid CNN architecture (VGG16, Xception)	3,076 images, seven disease categories	Hybrid CNN model achieved 94.7% accuracy,	Complexity of hybrid models might lead to overfitting and	94.7%

			with high precision, recall, and F1-scores.	require extensive fine-tuning.	
Lanjewar et al. (2024) [26]	ResNet-50, VGG-16, Inception V3 CNN	Custom Dataset	ResNet-50 achieved 96% accuracy, followed by VGG-16 and Inception V3 with varying performances in detecting diseases.	Inconsistent performance across models, potentially leading to difficulty in choosing the right model.	96% (ResNet-50), 92.67% (VGG-16), 85% (Inception V3)
Proposed Model (2024)	VGG16, GoogLeNet, ResNet-50 (TL)	Kaggle Potato Leaf Dataset [6]	Achieved high classification accuracy using TL; demonstrated excellent performance across training, testing, and validation	Minor misclassifications, especially in late blight class; limited dataset diversity; further improvement needed through XAI integration.	VGG16: 98.77% GoogLeNet: 99.75% ResNet-50: 99.75%

5. Conclusion and Future Work

This paper proposes a DL based approach for automatic potato leaf disease detection using TL methods on three strong models: VGG16, GoogLeNet, and ResNet-50. The VGG16 model demonstrated a training accuracy of 99.54%, validation accuracy of 98.77%, and testing accuracy of 99.26%. GoogLeNet was slightly superior with the training accuracy at 99.97%, validation accuracy at 99.75%, and the testing accuracy at 99.26%. ResNet-50 performed exceptionally well with 100% training accuracy, 99.75% validation accuracy, and 99.26% test accuracy. All the models could classify potato leaves into three classes: healthy, early blight, and late blight. While the overall performance was highly accurate, small misclassifications, especially in late blight identification, leave room for improvement. Not only did the use of TL speed up training but also enhance generalization across a variety of datasets, demonstrating the approach's viability for agricultural applications. The research highlights the potential of AI to revolutionize disease management in agriculture through rapid and accurate identification, eventually contributing to improved yields and a smaller ecological footprint. To further investigate, increasing diversity in the dataset would improve robustness and flexibility in the model.

Future work includes conducting a detailed ablation study with varying batch sizes, learning rates, optimizers, and numbers of epochs, along with presenting the results in a comparative table to better understand their impact on the performance of different DL models. Additionally, including Explainable AI (XAI) techniques is highly recommended to further increase transparency in the decision-making process of the model. That would also enhance the credibility, trustworthiness, and acceptance of the system by farmers and agricultural workers, offering a realistic and practical implementation in reality.

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Data availability: The dataset & Simulation files used during the current study are available from the corresponding author upon reasonable request.

Declarations:

Institutional review board: Not applicable.

Clinical trial number: Not applicable.

Consent to Publish declaration: Not applicable.

Informed consent: Not applicable.

Competing interests: The authors declare no competing interests.

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