

## A Novel Approach to Interpret Plant Health Monitoring Using Star Transfer Learning with Explainable AI

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**Abstract:** There is a risk that plant leaf diseases will affect crop yields all over the world; it is necessary to make a diagnosis as quickly and accurately as possible. Even though human errors slow down the system and produce outcomes that are not systematic, the system is driven by expert insights. The advocated method uses Explainable Artificial Intelligence (XAI) to automatically identify potato leaf illnesses caused by bacteria, fungi, nematodes, viruses, pests, Phytophthora, and healthy potato leaves. The purpose of this investigation is to examine the similarities and differences between the accomplishments of ResNet50 and InceptionV3 and those of Star3-Net, which is an innovative architecture. The ResNet50 and VGG16 weights, in addition to the InceptionV3 weights, are included in Star3-6 via transfer learning. According to the studies, Star3-Net performs better than both ResNet50 (68.1%) and InceptionV3 (70.2%), achieving a maximum classification accuracy of 75.4%. The process of transfer learning helps enhance model categorisation by combining the attributes of several models. Using Local Interpretable Model-Agnostic Explanations (LIME) and Star3-Net, it is feasible to visually diagnose disease spots on plant leaves.

**Keywords:** Plant Disease Classification; Explainable AI; Deep Learning; Agricultural Disease Detection; Crop Production; Model Interpretability; Infections and Viruses.

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### 1. Introduction

The current agricultural system faces sustained challenges from rapid population growth and unpredictable climatic conditions. Plant leaf diseases constitute among the most serious threats to crop production among agricultural challenges [16]. Plant diseases have negative health consequences for plants, leading to significant yield reductions and poor agricultural output quality [8]. Plant leaf diseases cause substantial economic losses and endanger the stability of global food distribution systems. Leaf diseases in potato cultivation pose a serious problem because their widespread distribution disrupts food supply networks, increasing worldwide threats to food security. Agricultural professionals have, through traditional methods, performed manual inspections to detect and control plant diseases. Expert diagnosis provides accurate results but consumes significant resources, requires considerable time, and depends heavily on human observers. Such inspection methods often delay symptom detection,

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allowing diseases to spread without appropriate intervention. Early-stage plant diseases exhibit limited or identical visual indicators that are indistinguishable to most observers unless they use laboratory-based equipment. The development of new agricultural technology enabled the creation of improved diagnostic methods that are both efficient and scalable [17]; [18].

Machine learning uses image-based analysis as an effective tool for detecting diseases at early stages. By using convolutional neural networks (CNNs) in the field of machine learning known as deep learning, researchers have achieved unparalleled success in plant disease classification. The models excel at recognising advanced visual features in leaf images, enabling precise identification of different types of diseases [9]. ResNet50 and InceptionV3 are well-known architectural models that achieve high performance in plant disease identification. The complexity of these models makes it hard for users to properly understand the basis of their predictions, even though the models remain highly reliable [8]. This research integrates deep learning to develop a framework for identifying multiple potato leaf diseases, specifically bacterial infections, fungal diseases, viral pathogens, pest-related damage, nematode damage, and phytophthora infections, along with healthy plant leaves. The research presents Star3-Net as a new model for evaluation alongside ResNet50 and InceptionV3. Star3-Net incorporates pre-trained ResNet50, InceptionV3, and VGG16 components via transfer learning to improve classification accuracy [19]. User confidence improves with the addition of a model-agnostic explanation technique that displays diseased areas on leaf images, helping users better understand prediction results [26].

## 2. Related Work

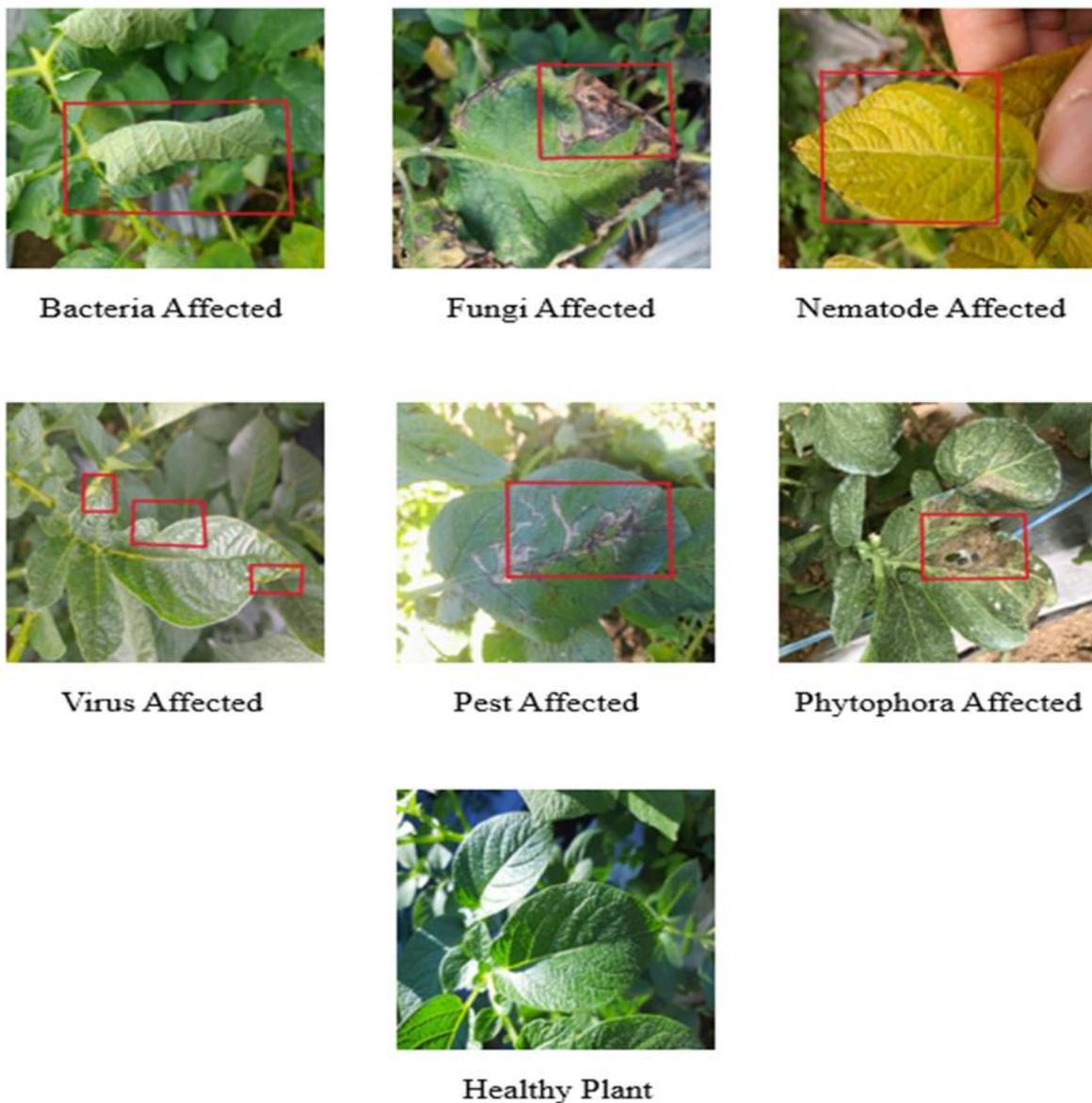
Habaragamuwa et al. [1] introduced disentangled variational autoencoders ( $\beta$ -VAEs) for plant disease classification to accomplish better model explainability. Through latent-variable decomposition, the model provides interpretable properties of disease-related features that emerge from the visual inputs. The system produced competing classification results until researchers encountered difficulties with large datasets and had to adjust multiple system parameters to achieve peak effectiveness. Girmay [2] developed an AI model that uses knowledge distillation to explain leaf-based classification of medicinal plants [20]. The methodology used a scaled-down student platform that replicated the operations of a larger teacher system, simplifying the model structure without sacrificing precision [14]. The approach improved both interpretation and computational speed. Research on medicinal plants limits its direct use for broader agricultural disease classification tasks, especially when the crops are outside the medicinal category, such as potatoes. Shams et al. [3] proposed explainable AI techniques for crop recommendation systems to enhance agricultural decision-making. Using machine learning models, they provided insights into their decision-making process, keeping it transparent to users. Although the method delivers clear explanations and useful support for farmers, it has certain limitations due to the specificity of its datasets and model-specific requirements. Akkem et al. [4] developed a Streamlit-based application that leverages advanced explainable AI methods to improve smart-farming crop recommendation platforms [13].

Users gained real-time, interactive agricultural insights through their system, which boosted transparency and user participation. The approach succeeded in enabling decision-making, but it encountered scalability and adoption challenges across various crops and farming environments. Jafar et al. [5] introduced plant disease detection techniques with artificial intelligence, yet they explored their agricultural applications and system constraints. AI demonstrates great promise for transforming plant disease management, though researchers identify data dependence, interpretability issues, and the need for abundant, diverse data to improve generalization. The research emphasises the need to eliminate such constraints so that agricultural practitioners can implement AI on a large scale. Srinivasu et al. [6] proposed an XAI-based model for precise crop recommendations in agriculture [12]. XAI techniques and machine learning formed the core of their system to enhance transparency and trust in agricultural decision-making processes [15]. The system faces a challenge in achieving wider agricultural applicability because its crop-specific database allows it to make recommendations only under specific conditions. Paul et al. [7] compared deep learning techniques for detecting potato leaf diseases through classification, using explainable AI methods. The study showed that making models explainable led to clear system transparency, high trust scores, and classification performance levels matching those of the best models. Model application across multiple environmental conditions remains a challenge, despite the need for substantial annotated datasets to maintain high classification accuracy across various disease types [27].

## 3. Methodology

### 3.1. Data Collection

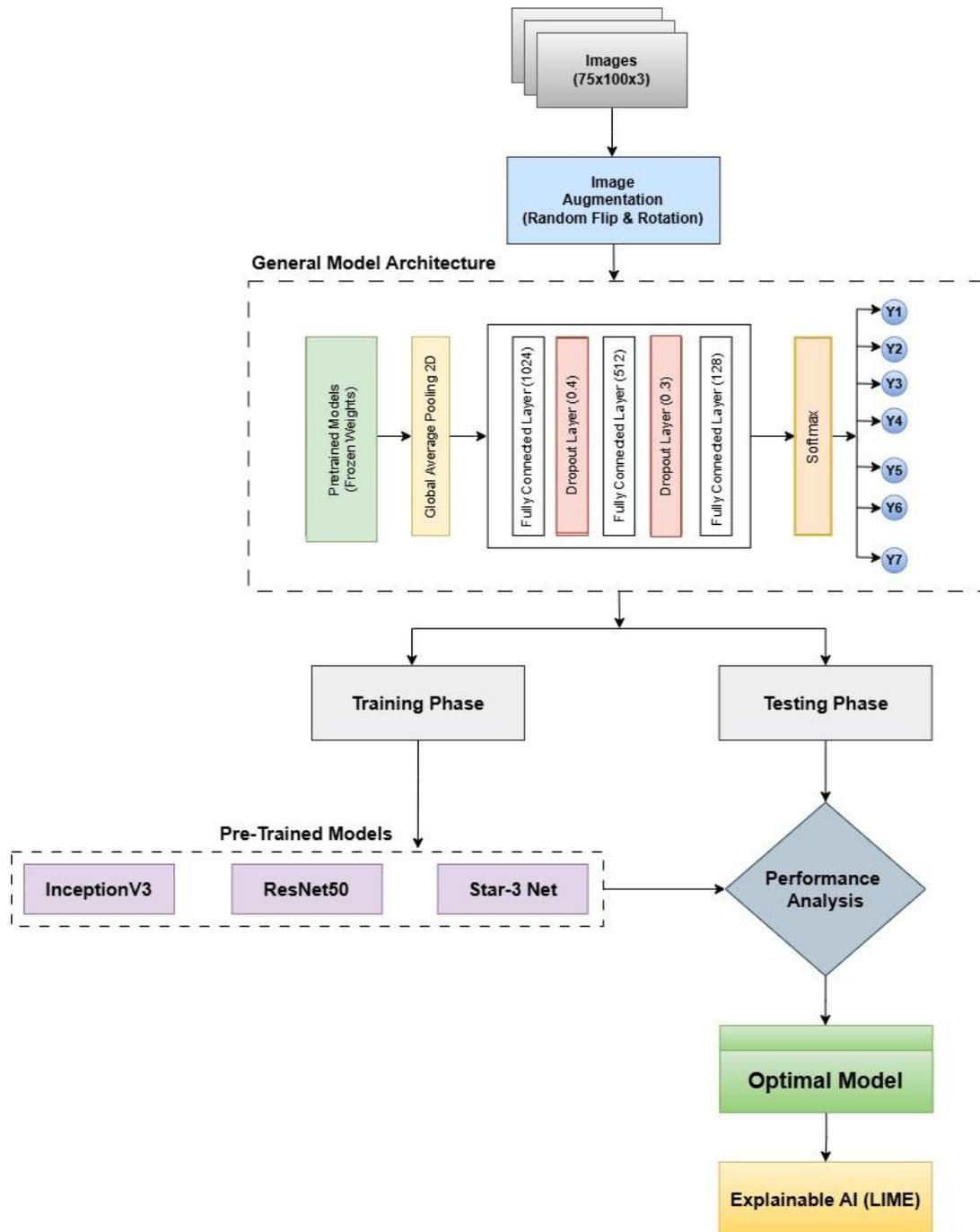
The dataset comprises high-quality images of seven classes of potato leaf diseases, totaling 3,076 elements. The 2,461 images from a total of 3,076 served as the training data for developing deep learning models, which served as the learning foundation. The testing set, which comprised 615 images (20% of the total data), was used to assess performance on unobserved inputs and to evaluate generalisation capabilities in realistic deployments (Figure 1).



**Figure 1:** Different classes of plant disease present in the plant disease dataset

The fundamental inputs for accurate classification of skin diseases include  $75 \times 100 \times 3$ , which form the essential elements of proper analysis [25]; [21]. The processing phase applies normalisation, then resizing functions, and includes data enhancement methods such as random rotations and flips. The step adds diversity to the data and enables the model to make better generalisations. The preprocessing step ends with a split that creates training and test sets [33]. The classification framework uses transfer learning with frozen weights, building on pre-trained convolutional neural networks (CNNs) as its base. The general architecture uses a 2D Global Average Pooling layer as the initial stage, followed by three fully connected layers with 1024, 512, and 128 neurons, respectively, and two dropout layers with rates of 0.4 and 0.3 to prevent overfitting.

A SoftMax layer serves as the final component, producing probability distributions over the seven potential skin disease categories (Y1-Y7). The research employs InceptionV3, ResNet50, and Star-3 Net pre-trained models with the designed architecture [10]. The training phase occurs independently for each model with its dedicated training data set, while the assessment stage uses standard performance metrics, including accuracy, precision, recall, and F1-score. Star-3 Net outperforms other models in performance assessments and is selected as the optimal classifier. Local Interpretable Model-agnostic Explanations (LIME) runs as an integration to boost predictive interpretation within the system [22]. The LIME algorithm creates local visual explanations through region highlighting that show which image parts drive the model's decision-making. Through its clearer display, the system enables healthcare staff to better understand and build trust in the predictions it generates.



**Figure 2:** Overview of proposed methodology

### 3.2. Data Pre-processing and Augmentation

Creating a quality input data set begins with the crucial image pre-processing step. Dermatoscopic image inspection removes images with excessive noise or poor resolution, as they can degrade model performance. The data selection process retains high-quality images from all 7 skin disease classes to maintain proper class representation and distribution [11]. After picking the desired images, they are submitted to multiple data augmentation protocols, which help boost the model's generalisation ability [30]. The dataset is augmented using random geometric transformations, including horizontal and vertical flips, rotations, and cropping and scaling, which represent normal variations observed during clinical image capture [28]. The model receives lighting adjustments, along with brightness and contrast modifications, as it tackles different illumination levels across dermatoscopic camera equipment [23]. The dataset's effectiveness is increased through augmentation techniques that

simultaneously help prevent overfitting by exposing models to diverse visual patterns. With a larger dataset, the model can discover stronger, more universal features, resulting in better performance when processing new test samples [24].

### 3.3. Model Description

The system design presented in Figure 2 depicts the architectural representation. An image augmentation process enhances standardised dermatoscopic images with dimensions  $75 \times 100 \times 3$  pixels to boost model robustness and improve input variability. The procedure combines random flipping with rotation, zooming, and brightness adjustments to boost generalisation and reduce overfitting. Transferring learning capability is achieved through the model architecture, which contains InceptionV3, ResNet50, and Star-3 Net as pre-trained deep convolutional neural networks. The pre-trained models are used in their frozen state, since they extract knowledge from large datasets at no additional training cost. The employed strategy leads to faster convergence and enhances stability during learning [32]. After applying 2D Global Average Pooling, the spatial dimensions are reduced while dominant features are extracted, resulting in a less resource-intensive, more efficient architecture. Secondly, the pooled features are fed into a three-layer sequence of fully connected neural networks with 1024 neurons, then 512, and finally 128. The layers include dropout layers with rates of 0.4 and 0.3 to enhance model regularisation. The SoftMax layer's output corresponds to seven specific categories of skin diseases. The model is compiled with the Adam optimiser at a learning rate of 0.001 because it demonstrates efficient deep learning performance and adaptive learning characteristics. The performance analysis shows that Star-3 Net achieves the best results, making it an optimal candidate for integration with LIME for explanation.

#### 3.3.1. InceptionV3

The deep convolutional neural network, InceptionV3, optimises image classification through an effective design. Multiple network layers with different-sized kernels operate simultaneously in Inception modules, enabling the algorithm to achieve efficient global and local feature recognition. The structure uses two efficient convolution techniques that combine factorised and asymmetric methods:  $7 \times 1$  followed by  $1 \times 7$  convolutions, rather than larger filters [31]. The network starts with conventional convolutional and pooling layers that lead to Inception blocks, which extract features at different scales. The Global Average Pooling layer reduces the spatial dimension of the output, followed by fully connected layers. A SoftMax activation function produces class-probability outputs as its final stage. The architectural design of InceptionV3 enables high-performance, efficient operation, making it appropriate for analysing complex image datasets, such as dermatoscopic images for skin disease diagnosis.

#### 3.3.2. ResNet50

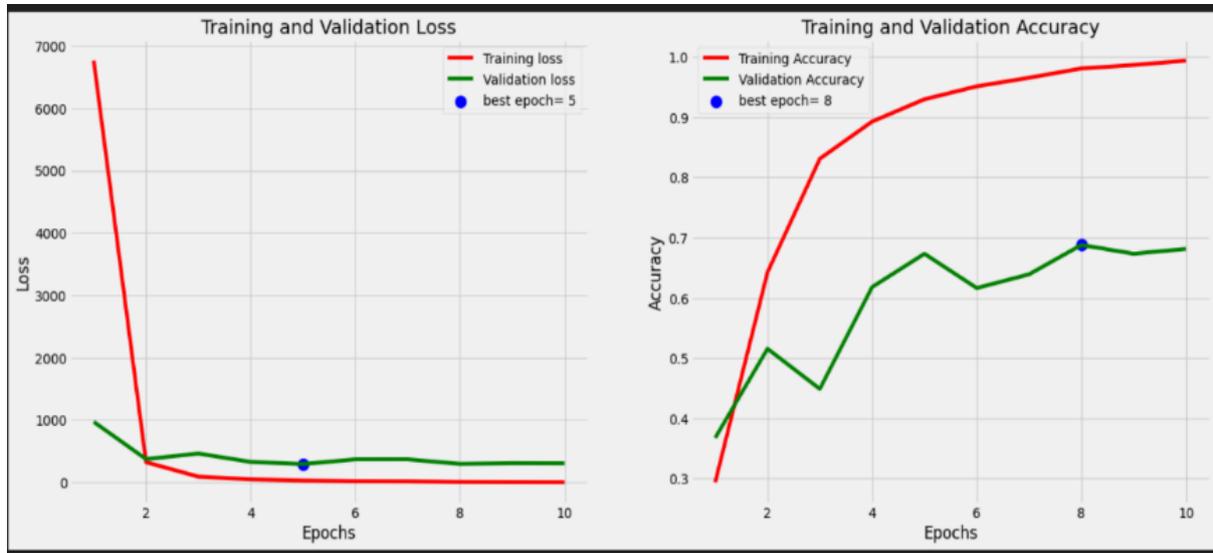
ResNet50 is a deep convolutional neural network that uses residual learning to address vanishing gradients in very deep models [30]. Its 50 layers enable the network to learn residual functions rather than direct mappings by introducing identity shortcuts or skip connections. Deeper networks can be trained without performance degradation thanks to these connections, which also help maintain gradient flow during backpropagation. Convolutional blocks and identity blocks, each with a sequence of convolutional layers followed by batch normalisation and ReLU activation, are used to construct the architecture. By avoiding one or more layers, the residual connections essentially enable the network to learn small adjustments rather than complete transformations [29].

#### 3.3.3. Star3-Net

A hybrid deep convolutional neural network architecture that uses transfer learning to combine the best features of several pre-trained models, including VGG16, ResNet50, and InceptionV3. By capturing a variety of feature representations, it is designed to increase classification accuracy on intricate plant disease datasets. Each of the three networks' feature maps is extracted separately by the architecture. These feature maps, which capture spatial, hierarchical, and semantic information, are produced from each base model's last convolutional layers. The final predictions are generated by concatenating the extracted features into a single feature vector, which is then fed to a SoftMax classifier and many fully connected layers. Star3-Net expands the variety of learned representations by fusing the advantages of shallow (VGG16), deep residual (ResNet50), and multi-scale (InceptionV3) feature extractors. This fusion enhances the model's generalisation to unseen data, enabling it to identify disease patterns at multiple levels of abstraction. The architecture optimises each model's pre-trained parameters for classifying potato leaf diseases. By reducing overfitting, enhancing feature robustness, and achieving excellent classification performance across multiple disease classes, Star3-Net's ensemble-like structure enables it to outperform individual base models.

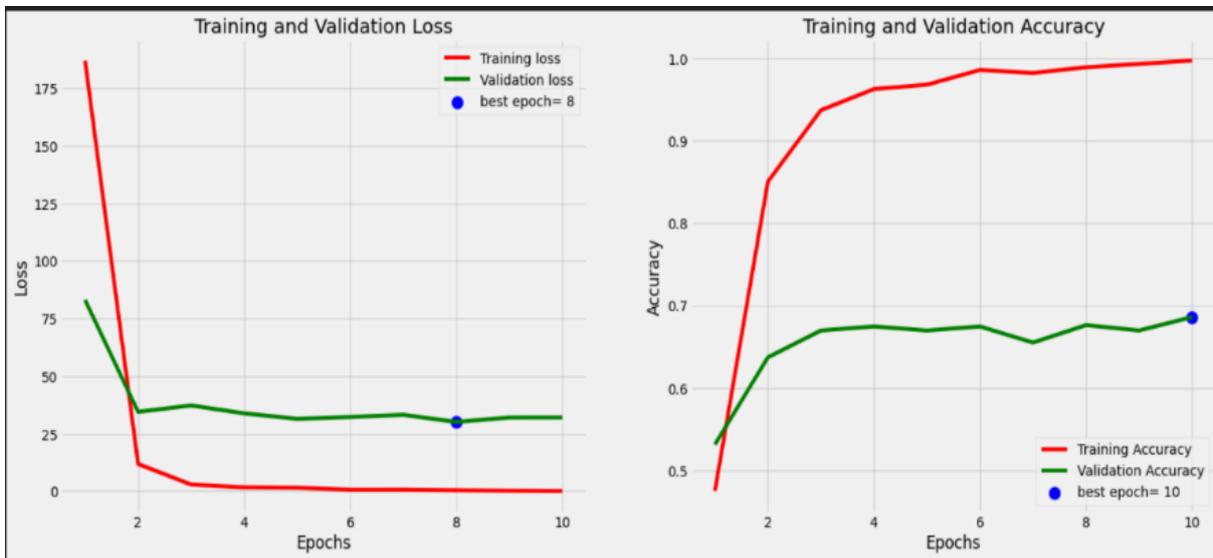
#### 4. Results

The InceptionV3 model was trained for 10 epochs. Figure 3 illustrates the training and validation accuracy achieved across epochs. The model attained a maximum training accuracy of 98.8% and a validation accuracy of 68.9%.



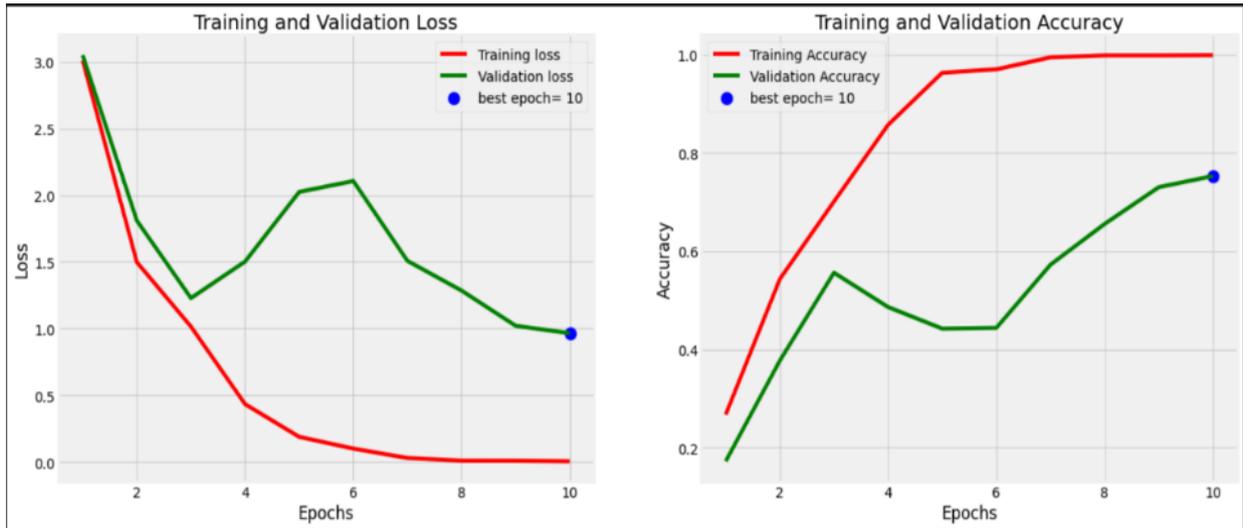
**Figure 3:** Training and validation accuracy of InceptionV3

Figure 4 also displays the corresponding training and validation loss trends. The training loss reduced steadily to below 0.1, while the validation loss stabilised around 350, indicating efficient learning with slight signs of overfitting after the 8th epoch.



**Figure 4:** Training and validation accuracy of ResNet50

The ResNet-50 model was trained for 10 epochs. As shown in Figure 4, the model achieved training accuracy of 99.3% and validation accuracy of 70.4%, indicating effective feature learning. Figure 5 also shows that the training loss rapidly dropped below 1, while the validation loss stabilised around 32, suggesting slight overfitting but strong convergence by the eighth epoch. The Star-3 Net model was trained for 10 epochs. As illustrated in Figure 5, the model achieved training accuracy of 99.9% and validation accuracy of 75.4%, indicating strong generalisation. The training loss steadily decreased and reached below 0.01, while the validation loss dropped to approximately 0.98 by the final epoch, demonstrating effective convergence with minimal overfitting.



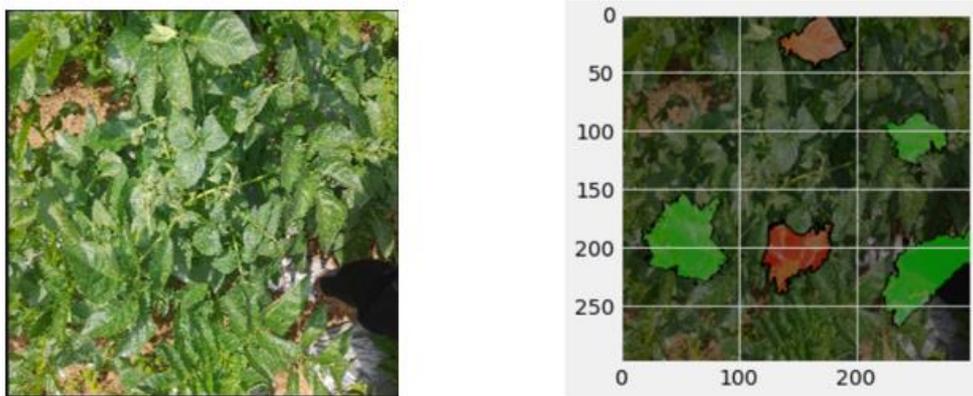
**Figure 5:** Training and validation accuracy of Star3-Net

Compared to the existing models, ResNet-50 and InceptionV3, the proposed Star-3 Net model outperformed both in terms of validation accuracy and lower validation loss, making it more reliable for recognition tasks in this domain (Table 1).

**Table 1:** Comparison of the performance metrics of various models

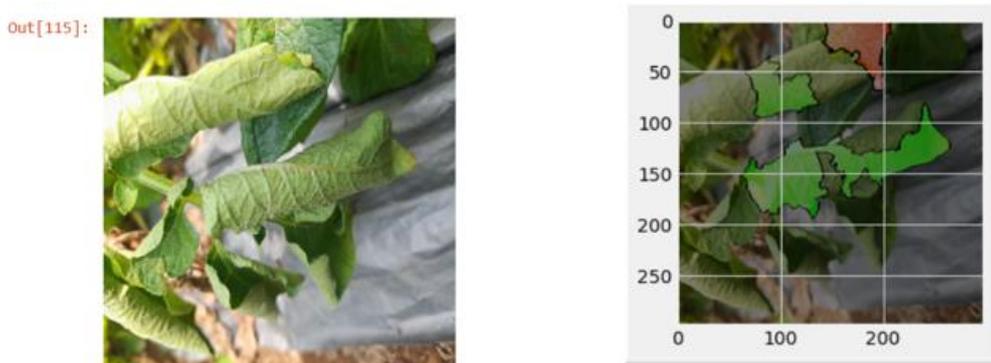
Model	Epochs	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
Star-3 Net (Proposed)	10	99.9	75.4	0.01	0.98
ResNet-50	10	99.8	70.4	0.01	0.99
InceptionV3	10	99.5	68.7	0.02	1.32

Among the three models, Star-3 Net, ResNet-50, and InceptionV3, the proposed Star-3 Net model demonstrates superior performance across key evaluation metrics, including higher training and validation accuracy as well as lower training and validation loss. Owing to its improved performance and robustness, the Star-3 Net model has been selected for further interpretation and analysis using the Explainable AI technique LIME (Local Interpretable Model-Agnostic Explanations). This integration aims to provide transparency and insights into the model's decision-making process.



**Figure 6:** Actual vs LIME interpretation of phytophthora

Figures 6 and 7 illustrate sample input images of diseased potato leaves along with their corresponding LIME-based interpretations. In the interpreted visualisations, the red-highlighted regions indicate the most influential and severely affected areas that strongly contribute to the model's prediction. In contrast, the green-highlighted regions represent the least affected areas with minimal impact on the classification decision. This visualisation aids understanding of the model's rationale and improves interpretability in disease diagnosis.



**Figure 7:** Actual vs LIME interpretation of fungi

## 5. Discussion

The comparative evaluation of deep learning architectures for potato leaf disease classification, as summarised in Table 1, reveals significant differences in performance across the selected models. Among the evaluated architectures, the proposed Star3-Net model demonstrated superior performance, achieving a classification accuracy of 75.4%, surpassing both InceptionV3 and ResNet50, which achieved accuracies of 70.2% and 68.1%, respectively. This improvement highlights the advantage of combining multiple pre-trained models via transfer learning, enabling Star3-Net to capture more diverse and discriminative features across various disease classes. The integration of LIME further enhances Star3-Net's interpretability by providing visual explanations that highlight disease-affected regions on plant leaves. These visual cues provide insights into the model's decision-making process and build trust in automated systems by addressing the black-box nature commonly associated with deep learning. Such interpretability is particularly vital in agricultural domains where actionable decisions are based on AI-generated predictions. The results affirm that a well-structured fusion of architectures through transfer learning can significantly enhance classification accuracy in plant disease detection tasks [12]. Moreover, the application of interpretability techniques ensures the practical relevance of these models in real-world scenarios, encouraging their adoption in precision agriculture and contributing to sustainable crop health management.

## 6. Conclusion

This study focused on evaluating the effectiveness of three deep learning models, ResNet50, InceptionV3, and the newly proposed Star3-Net, for accurate classification of potato leaf diseases across seven distinct categories. The dataset used in this study comprises 3,076 high-quality potato leaf images, with an 80:20 split between training and testing. The disease classes included bacterial, fungal, viral, pest-induced, nematode, Phytophthora, and healthy leaves, ensuring broad coverage of common potato leaf conditions. Among the three models, Star3-Net achieved the highest classification accuracy of 75.4%, outperforming InceptionV3 and ResNet50, which recorded 70.2% and 68.1%, respectively. This improvement is largely due to Star3-Net's hybrid design, which leverages the strengths of ResNet50, InceptionV3, and VGG16 via transfer learning, enabling deeper, more robust feature extraction. The model's performance was further supported by evaluation metrics such as precision, recall, and F1-score, all of which indicated consistent classification across all disease categories. To enhance interpretability, the LIME technique was applied to Star3-Net, generating visual explanations that highlight the regions of the leaf image contributing most to the model's prediction. These red and green overlays on the image help identify critical disease-affected regions and explain the rationale behind predictions, making the system more transparent and reliable for practical agricultural use. Future work may involve expanding the dataset with more diverse, real-time leaf images to improve model generalisation. Additionally, integrating segmentation techniques alongside classification could provide more precise detection of disease-affected areas. There is also potential to develop multi-leaf analysis models to evaluate plant health at the group level, supporting more advanced, scalable disease-monitoring systems.

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