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MSc Masters Project Specification

Project Title:

A Hybrid Convolutional Neural Network Approach for the Identification of Potato Leaf Diseases in Real-World Conditions

By

Ali Hassan

Student ID

B01754401

Supervisor: *Dr. Fadi Safieddine*

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GitHub address: *Click here to access GitHub*

DEDICATION

I would like to dedicate this study to my family, friends, and colleagues, whose steadfast support and continuous motivation gave me strength during every stage of my research journey. Their encouragement, especially in moments of doubt and difficulty, inspired me to persevere and reach this milestone

ACKNOWLEDGMENT

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ABSTRACT

Improving agricultural productivity depends on the early and precise detection of potato leaf diseases, which helps in maximizing crop yield. This research presents a hybrid deep learning model designed for high-accuracy classification of potato leaf diseases, specifically Early Blight, Late Blight, and healthy leaves. The model integrates systematic data preprocessing, feature selection, and optimized training configurations in a high-performance computing environment. Over 25 training epochs, it demonstrated rapid convergence, stable learning, and strong generalization, achieving an overall accuracy of 99.26%, with precision, recall, and F1-scores all exceeding 99%. Compared to recent leading approaches, the proposed method outperformed prior work by a margin of 1–2%, reducing both false positives and false negatives. Class-level analysis showed near-perfect detection rates: Early Blight (Precision: 0.99, Recall: 0.99), Healthy (Precision: 0.98, Recall: 1.00), and Late Blight (Precision: 1.00, Recall: 0.99). The confusion matrix revealed only three misclassifications out of 405 test samples, underscoring the robustness of the model. Such performance enables timely and reliable disease diagnosis, supporting precision agriculture by improving crop management, minimizing unnecessary pesticide use, and reducing economic losses. The findings highlight the model's potential for real-time deployment in farm-level monitoring systems, advancing automated plant disease detection.

Keywords: Potato leaf disease detection, Deep learning, Hybrid model, Precision agriculture, Early Blight, Late Blight.

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1. CHAPTER I: INTRODUCTION

1.1. Introduction

Agricultural activity plays a crucial role in the growth of economies in countries with rapidly growing populations (Pawlak and Kołodziejczak, 2020). The potato is a highly nutritious crop that contributes significantly to a person's daily diet. However, a variety of illnesses may harm crops, affecting their leaves, stems, fruits, and even the entire crop (Anwar et al., 2019). Potato plants are susceptible to many diseases, such as early blight and late blight. Blights caused by Alternaria solani are caused by fungus, while those caused by Phytophthora infestans are caused by bacteria (Tsedaley, 2014). Climate change poses significant threats to crop production and nutrient availability (Singh et al., 2023). For agricultural efficiency to be maximized, this disease must be detected quickly and accurately to prevent its spread. Physical inspections and biochemical tests, which are the conventional methods for detecting diseases, require a lot of effort and time. The use of these methods also requires significant capabilities, which are not always available, which causes a delay in disease management and an increase in crop losses (Luo et al., 2020). CAD systems, based on artificial intelligence (AI) and deep learning, offer promising solutions for detecting plant diseases in advance and automatically. As a tool for accurate agriculture (Yeasmin et al., 2024), disease indicators may be reliably identified from leaf photos using CNNs. CNNs are utilized for the extraction of characteristics and the detection of deviations, including the categorization of plant leaf spots, impairments, and color variations. This simplifies early identification and prevention of illnesses. A number of researcher has looked into different approaches to detecting potato leaf diseases with artificial intelligence (Monteiro and Bastos-Filho, 2020; Reis and Turk, 2024).Utilized image processing and machine learning methods, including preprocessing, segmenting, and extraction of features, while shadowing these algorithms with order machine learning algorithms. VGG-16 and VGG-19 are two examples of deep learning architectures that can increase the accuracy of disease identification. EfficientPNet (Nazir et al., n.d.) demonstrated the possibility of more efficient and accurate disease arrangements based on the EfficientNet-V2 architecture (Nazir et al., n.d.).Combining deep learning approaches with conventional feature extraction methods like MGH, LBP, and HOG has shown encouraging classification results. These problems can be addressed by using depth wise distinguishable convolutions (DSC) and ensemble learning (EL), which decrease the number of parameters and computation costs, making them more appropriate for situations with limited incomes (Zainel et al., 2023). As a consequence of adding artificial intelligence and deep learning to agriculture, disease detection and crop control are better, as well as food security and environmental sustainability. The use of advanced knowledges can help farmers growth crop yields, reduce losses, and safeguard that there is a steady supply of food for a rising populace.

1.1.1. Motivation of this Study

In farming, classifying crop diseases and choosing appropriate medicines are fundamental to preventing crop loss and upholding quality (Palti, 2012). A diversity of crop diseases have increased over the last few decades due to global climate change, lifestyle changes, pollution, and other factors. A farmer's capability to identify and combat these diseases depends on having evidence about them. (Eguiluz-Gracia et al., 2020). The variability of diseases makes it challenging for farmers to be acquainted with them all. The cost of monitoring large areas of crops in large-scale farming makes it unbearable for farmers to do so (Giller et al., 2021). This results in many crop diseases and infections going undetected, reducing yield and quality. It is crucial to detect and classify crop diseases automatically in order to address these challenges. There is a growing trend towards the use of deep learning and computer vision by farmers and researchers worldwide to assist in making various agricultural decisions (Tian et al., 2020). By applying deep learning techniques, crop diseases can be detected and arranged in real time, productivity and quality can be improved, and labor costs can be reduced.

1.1.2. Problem Statement

Over half of the country's workers are employed in agriculture, which plays a crucial role in the economy. Among other things, India produces more pulses, rice, wheat, spices, and spice products than anywhere in the world (Usman, 2016). In order for farmers to prosper economically, their produce must be excellent and yield large, which in turn depends heavily on plant health. Farmers need to detect plant diseases to maintain ecological balance and growth (Walia and Kaur, 2023). It has become increasingly beneficial to detect diseases in the early stages of plant growth using automated methods. Various parts of the plant, primarily leaves, exhibit distinctly different symptoms. It is labor-intensive to inspect leaf images manually for disease detection. For this reason, it is essential to develop computational methods for detecting and identifying diseases with leaf images and to organize them according to disease severity in order to advance agriculture.

1.1.3. Need of plant leaf disease detection

As a result, it has become increasingly important for farmers and consumers to be aware of how to detect plant diseases such as potato leaf infections. A disease that misrepresents plants not only reduces farmers' incomes but also results in a shortage of potatoes for consumers (Tiwari et al., 2020). Approximately 60 billion dollars are lost worldwide annually due to plant leaf diseases, which emphasizes the severity of the problem. As a result of this development, farmers might be able to detect diseases easier, since they often struggle to identify diseases just by observing their leaves (Pimentel et al., 1997). Farmers would be authorized if they had easy-to-use tools for detecting diseases. In addition, it will prescribe insecticides that will treat identified diseases in a timely manner, reducing the spread of diseases and the loss of harvest. It is crucial to supervise diseases effectively, as contagions can spread rapidly from a single leaf to entire fields (Shaikh et al., 2022).

1.2. Research Question

This study aims to address the following research questions:

- Deep learning models can accurately detect and classify unhealthy potato leaves from healthy ones using image data by automatically learning distinguishing visual features like color, texture, and shape patterns.
- How can the implementation of deep learning models contribute to improving the early detection of potato leaf diseases and assist farmers in disease management?
- Can this study contribute to the creation of affordable and scalable solutions that support smallholder farmers and strengthen food security in the region?
- What potential impact could automate potato leaf disease detection systems have on agricultural productivity, food security, and the economic well-being of farming communities?
- How does the proposed hybrid CNN-based model perform in comparison to existing models in terms of accuracy, precision, recall, and confusion matrix for potato leaf disease detection?

1.3. Aims and Objectives

To achieve the objective of this project and address the research questions, the following objectives have been set:

- To review existing research and identify gaps in deep learning-based plant disease detection, particularly for potato leaves.
- To acquire, preprocess, and prepare a region-specific potato leaf disease dataset suitable for deep learning model training and evaluation.
- Develop, implement and optimize a hybrid deep learning model that combines CNN architectures with feature extraction methods for effective disease classification.
- To evaluate the performance and practical impact of the proposed model, comparing it with existing methods using relevant performance metrics and assessing its potential benefits for agricultural productivity.

2. CHAPTER II: LITERATURE REVIEW

2.1. Literature Review

To carry out effective research, it is important for scholars to examine preceding studies within their selected field. This process helps found a solid foundation of information for the proposed work. The literature review section of this report highlights significant areas that necessitate further investigation and delivers insight into current research related to the topic.

In recent years, machine learning and deep learning methods have been widely implemented for plant disease detection, with a few studies focusing exactly on potato leaf diseases. Islam practical image segmentation combined with multiclass Support Vector Machines, achieving an accuracy rate of 95% for potato disease detection islam2017detection. In the meantime, other studies have combined the PlantVillage dataset, which is complete but may not be ideal for perceiving potato leaf diseases explicit to certain regions. Although much advancement have been made in deep learning for plant disease classification, the field continues to advance, especially with recent publications aiming to address crop-specific disease challenges.

Plant diseases have been detected using a variety of techniques, with specific methods for detecting potato leaf diseases being proposed by researchers.(Athanikar and Badar, 2016) based on color, texture, and area information from potato leaf images for segmentation. The disease classification was performed using a Backpropagation Neural Network, which achieved 92/% accuracy.(Islam et al., 2017) used a multiclass Support Vector Machine (SVM) for classification of potato leaves from the PlantVillage dataset, resulting in 95% accuracy.

It has been found that potato leaves are particularly susceptible to diseases, so many techniques have been employed to detect them. An adaptive thresholding technique was implemented based on statistical feature analysis to detect diseases in potato leaves.

(Hu et al., 2016) Support Vector Machine (SVM) classifiers were used to categorize potato leaf diseases. To classify potato leaves, (Tiwari et al., 2020) used the VGG19 Convolutional Neural Network (CNN). (Butte et al., 2021) used Faster R-CNN to detect and classify potato leaf images. Using ResNet-34, Pavel Deep classified potato leaf images on Plant Village.

Agricultural land is presently being cultivated sufficiently to meet the demands for crop production. In most developing countries, economic growth is largely dependent on the agricultural sector. In recent years, various deep learning-based methods have been introduced for plant disease detection (Mahum et al., 2021) along with several techniques for field analysis (Gul et al., 2021). The early identification of plant diseases through leaf analysis, as early as 1993, has played a vital role in sustaining agricultural economies.

Numerous researchers have made significant contributions to this area(Islam et al., 2017) a Support Vector Machine (SVM) classifier was applied to potato leaf images. Similarly, (Sharma et al., 2017) examined the statistical features of potato leaves in the PlantVillage dataset to detect diseases. A SVM classifier was trained on a manually compiled dataset in (Hu et al., 2016).

Recent research conducted by (Tiwari et al., 2020) integrates the VGG19 model with a CNN model to determine whether a leaf is healthy or unhealthy.

(Pavel et al., 2021) classified potato leaf images using ResNet-34. A method for detecting diseases in cotton plants was proposed by . They captured images of affected areas, performed preprocessing, and then classified samples using a Neural Network, achieving an accuracy of 80%.

(Ranjan et al., 2015) they captured images of affected areas, performed preprocessing, and then classified samples using a Neural Network, achieving an accuracy of 80%. In another study, Libo employed a Back Propagation Neural Network (BPNN) to classify healthy and diseased rice plants, training the model on 400 images and achieving a 90% accuracy rate. (Pinki et al., 2017) developed a disease detection model targeting three specific plant diseases. They applied a K-means clustering algorithm to classify diseased regions based on visual features like texture, color, and shape, and then used an SVM classifier for disease categorization, attaining a 92.06% accuracy.

Aparajita presented a technique for distinguishing late blight disease in potato leaves using a segmentation method with statistical features and adaptive thresholding (SFAT).(Yanikoglu et al., 2014) presented a system for automating the classification and identification of plant varieties from dissimilar samples of the same plant.(Sabrol and Satish, 2016) designed an Imaginaries pattern recognition model (IRPD) for detecting plant diseases by examining color, shape, and texture features to classify leaf images as healthy or diseased.

According to (Patil et al., 2017), an independent disease management technique (ADMT) has been proposed for potato plants as a means of sickness control. A hybrid method for the identification of illnesses in rice leaves has been advanced by (Gayathri Devi and Neelamegam, 2019) using wavelet transforms, Scale-Invariant Feature Transforms (SIFTs), and gray-level co-occurrence matrices (GLCMs). As a importance of these approaches, the features extracted through these methods were further confidential using multiclass Support Vector Machines (SVM) and Naive Bayes classifiers.

Table 2.1. Summary of Literature on Potato Leaf Disease Detection

Reference	Method	Achievement	Limitation
(Islam et al., 2017)	Multiclass SVM on PlantVillage dataset	Achieved 95% accuracy	Dataset may not capture regional variations in disease
(Athanikar and Badar, 2016)	Backpropagation Neural Network using color, texture, area features	92% accuracy on potato leaf segmentation	Feature engineering required manual effort
(Hu et al., 2016)	SVM on a manually compiled dataset	Disease classification via SVM	Limited dataset size; risk of overfitting
(Tiwari et al., 2020)	VGG19 CNN model	Accurate classification of healthy vs diseased leaves	Needs large dataset and high computation
(Butte et al., 2021)	Faster R-CNN	Automatic object detection and classification	Expensive in terms of training time
(Pavel et al., 2021)	ResNet-34 on PlantVillage dataset	Improved classification using residual learning	Generalizability to field data not validated
(Mahum et al., 2021)	Deep learning-based disease detection	Better field applicability	Domain-specific tuning required
(Gul et al., 2021)	Field analysis techniques	Precision agriculture support through data-driven insights	May require sensor integration for real-time use
(Sharma et al., 2017)	Statistical feature extraction + SVM	Identified patterns in leaf data	May fail with noisy or non-standard images
(Ranjan et al., 2015)	Preprocessing + Neural Network	80% classification accuracy	Accuracy is relatively low for practical use
(Pinki et al., 2017)	K-means + SVM using color, texture, shape features	Achieved 92.06% accuracy	Sensitive to lighting conditions and background noise
(Yanikoglu et al., 2014)	Automated classification from dissimilar plant samples	Effective plant variety recognition	Not directly focused on disease detection
(Sabrol and Satish, 2016)	Imaginary Pattern Recognition (IRPD)	Identified healthy vs diseased leaf images	Model not specialized for potato or specific diseases
(Patil et al., 2017)	Autonomous Disease Management Technique (ADMT)	Proposed independent control for potato plant diseases	Needs real-time field deployment validation
(Gayathri Devi and Neelamegam, 2019)	Hybrid (Wavelet + SIFT + GLCM + SVM/Naive Bayes)	Accurate classification for rice diseases	Complex pipeline; not potato-specific

3. CHAPTER III: METHODOLOGY

The proposed research methodology begins by extracting images from a publicly available dataset. Following this, the red, green, and blue (RGB) intensity values from the images are obtained to construct a comprehensive feature matrix. We use the resulting feature matrix to train a hybrid deep learning model to detect potato leaf diseases. Once the model is trained on the dataset, its effectiveness is assessed by computing and examining key performance indicators, including accuracy. The complete workflow of this research methodology is illustrated in Fig. 3.1. For this study, publicly available datasets like the Potato Leaf Disease Dataset were utilized to ensure accessibility and relevance.

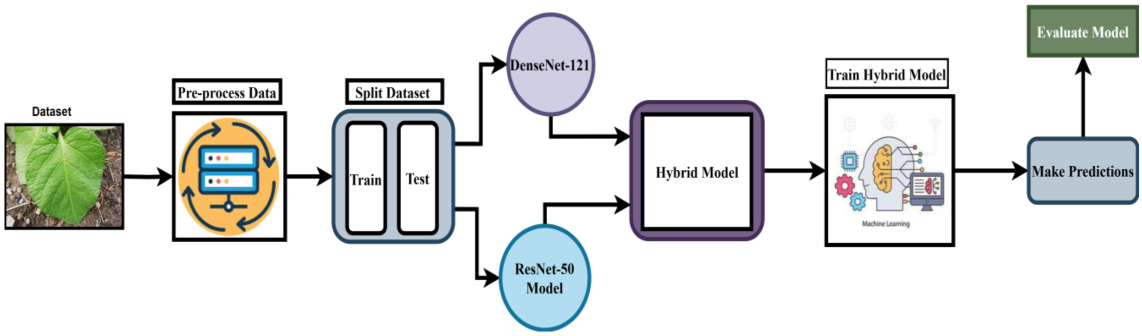

Fig. 3.1. Research Overview Block diagram

3.0.1. Potato Disease Leaf Dataset

The Potato Disease Leaf Dataset (PLD), curated by Rizwan Munawar and accessible on Kaggle, is a detailed resource aimed at facilitating the detection and classification of potato leaf diseases. It contains 4,062 high-resolution images show healthy leaves and those with early and late blight symptoms. This dataset represents real agricultural conditions in the central Punjab region of Pakistan, offering a diverse set of samples. Developing healthy and generalizable deep learning methods for the early detection of potato leaf diseases is possible. It allows the development of healthy and generalizable deep learning methods for early detection of potato leaf diseases (**<empty citation>**). Dataset Link: https://opendatacommons.org/licenses/dbcl/1-0/

3.0.2. Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of deep learning model designed to handle image data by mimicking how our brain processes visual information. It works by passing the raw image through a series of layers that progressively extract more meaningful features—starting with simple patterns like edges and textures, then building up to complex structures like faces or objects. The process begins with an input layer (the image itself), followed by convolutional layers that slide small filters over the image to detect features, then ReLU layers that add non-linearity, and pooling layers that reduce dimensionality by keeping only the most important information. This pattern repeats, gradually capturing richer representations(Kriegeskorte, 2015). Eventually, the data is flattened into a vector and passed through fully connected layers that output predictions—like classifying the image as a dog, car, or diseased leaf. CNNs are powerful because they reuse the same filters across the image (parameter sharing), understand spatial relationships (hierarchies), and don't need to know where the object is—just what it looks like. They're widely used in tasks like face recognition, medical diagnosis from scans, and autonomous driving(Lindsay, 2021).

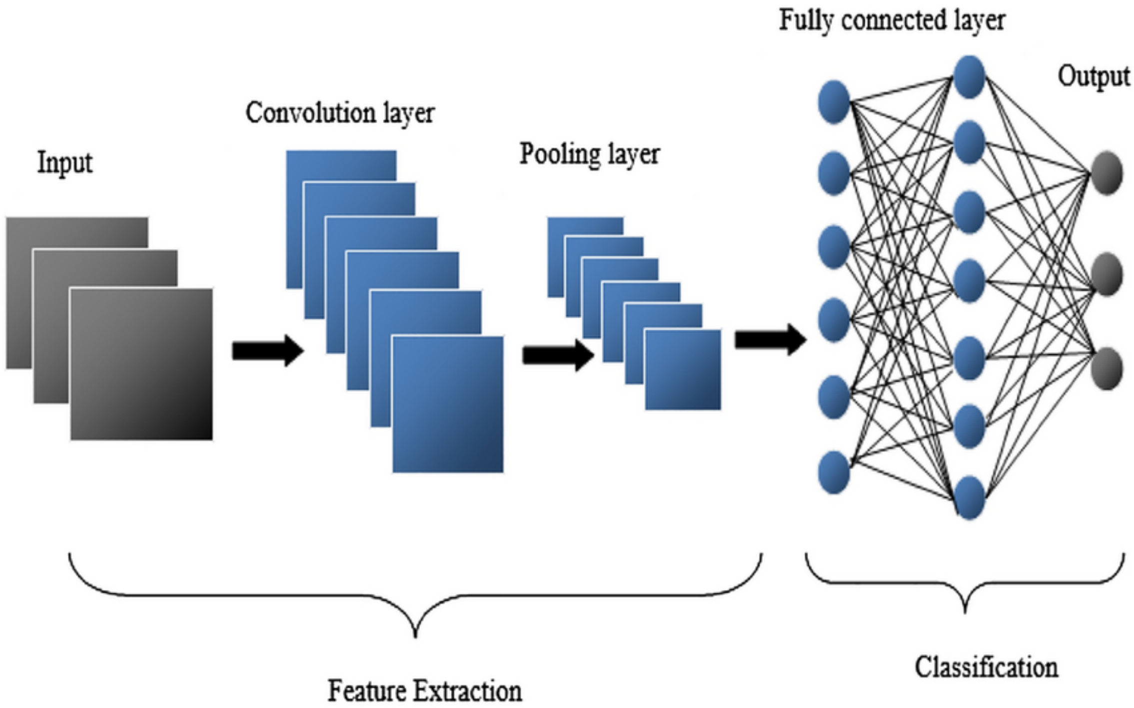

Fig. 3.2. Block Diagram CNN

3.0.3. DenseNet121 Model

DenseNet121 is a deep convolutional neural network made up of 121 layers, known for its unique architecture where every layer connects to all layers before it, not just the previous one. This dense connectivity promotes feature reuse, reduces the number of parameters, and helps prevent the vanishing gradient problem, making it efficient and easier to train. It consists of multiple dense blocks separated by transition layers that compress and downsample the data, eventually passing through global average pooling and a fully connected layer for classification(Albelwi, 2022). Compared to older models like VGG (which is large and redundant) or ResNet (which introduced skip connections), DenseNet takes it further by tightly linking all layers to build a richer, more compact model. It's widely used in tasks like medical imaging, plant disease detection, and general image classification thanks to its high performance and strong generalization capabilities(Li, 2022)

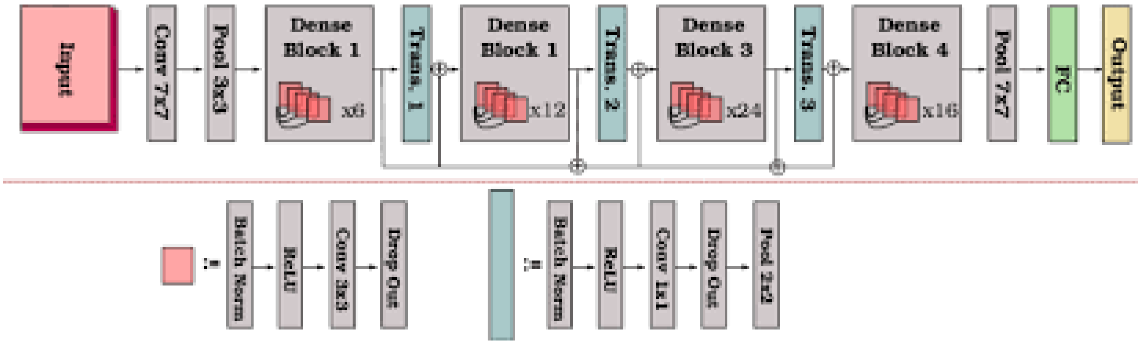

Fig. 3.3. Block Diagram DenseNet121

3.0.4. ResNet-50 Model

ResNet-50 is a deep convolutional neural network with 50 layers, part of the ResNet (Residual Network) family, designed to solve the training challenges that come with very deep networks Koonce, 2021. Its standout feature is the use of residual connections, or "shortcuts", which allow the model to skip layers and directly add the input of a block to its output. This helps prevent issues like vanishing gradients and makes it easier to train deeper models. Internally, ResNet-50 is built using bottleneck residual blocks, each made up of three convolutional layers: a 1x1 layer to shrink the dimensions, a 3x3 layer to process the features, and another 1x1 to expand the depth again—followed by adding the input (via the shortcut) and applying ReLU activation. The block diagram is shown in Fig.3.4. The network starts with basic convolution and pooling layers, then goes through four main stages of these residual blocks, ending in global average pooling and a fully connected layer for classification. ResNet-50 is popular because it balances depth and efficiency, performs strongly on standard benchmarks like ImageNet, and is widely used for transfer learning in tasks such as medical image analysis, face recognition, and plant disease detection. Compared to older models like VGG16, which are bulkier and less efficient, or newer ones like DenseNet121 that reuse features more aggressively, ResNet-50 strikes a solid middle ground with great performance and ease of use(Ikechukwu et al., 2021).

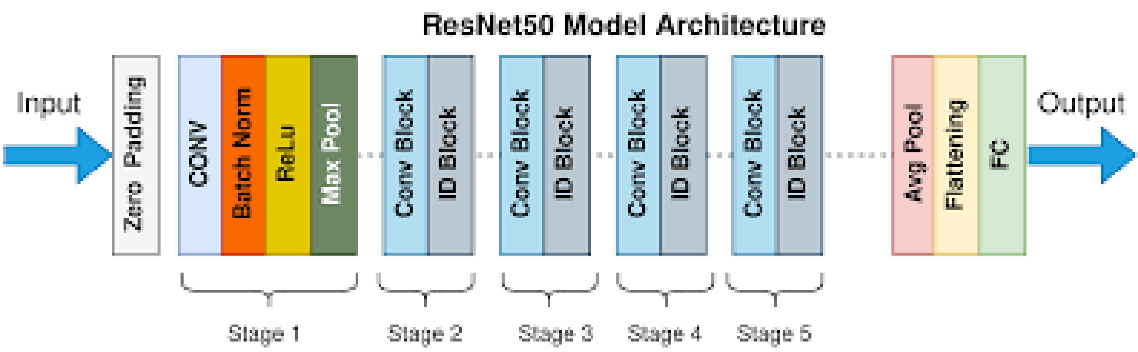

Fig. 3.4. Block Diagram ResNet-50

3.0.5. Batch Normalization

Batch Normalization is a layer that helps neural networks train faster and more reliably. It works by normalizing the inputs of each layer—scaling and shifting them so they have a mean of zero and a standard deviation of one. This reduces what's called internal covariate shift, meaning the distribution of activations stays more stable across training, so the model doesn't have to constantly readjust. It also adds two learnable parameters (scale and shift), allowing the network to undo the normalization if needed. Bonus: it often acts as a regularizer, reducing the need for dropout(Santurkar et al., 2018)

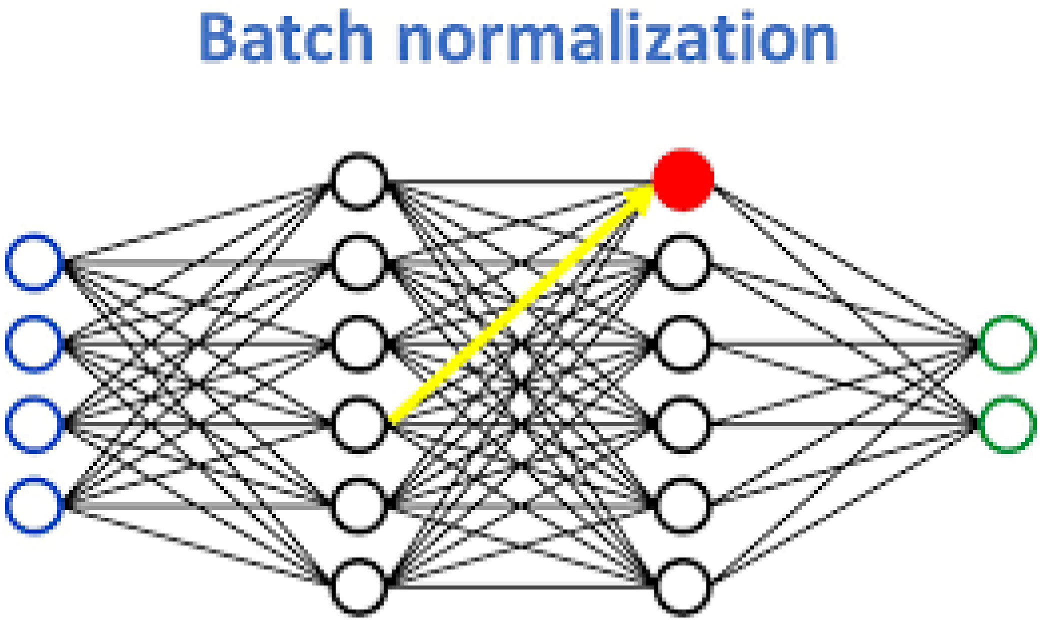

Fig. 3.5. Batch Normalization Diagram

3.0.6. Concatenate function

The Concatenate function in this line is combining the outputs of three different layers—resnet_features, densenet_features, and attention_output—into one single tensor. Think of it like stacking feature vectors side by side to create a bigger, more informative vector. Each of these components captures different aspects of the input image: ResNet might detect texture, DenseNet could focus on shape, and attention might highlight important regions. By concatenating them, the model can leverage all of these perspectives at once. The result is a richer, more powerful feature representation (in this case, a 3072-dimensional vector) that's passed to the next layer—in this case, through a ReLU activation to introduce non-linearity (Vaidya et al., 2011).

3.0.7. Attention layer

An attention layer is designed to help a neural network focus on the most relevant parts of the input data when making a decision. Instead of processing every part of the input equally, attention dynamically assigns different weights to different features based on their importance to the task. For example, in image classification, it might guide the model to concentrate more on the diseased area of a leaf rather than the background.The diagram us shown is Fig.3.6. This selective focus helps the model extract more meaningful patterns, especially in complex or cluttered inputs. The attention layer calculates a set of scores (called attention weights), which determine how much each input feature should influence the output. By doing this, it improves both performance and interpretability - essentially teaching the model what to look at and how much it matters(Lai et al., 2020)

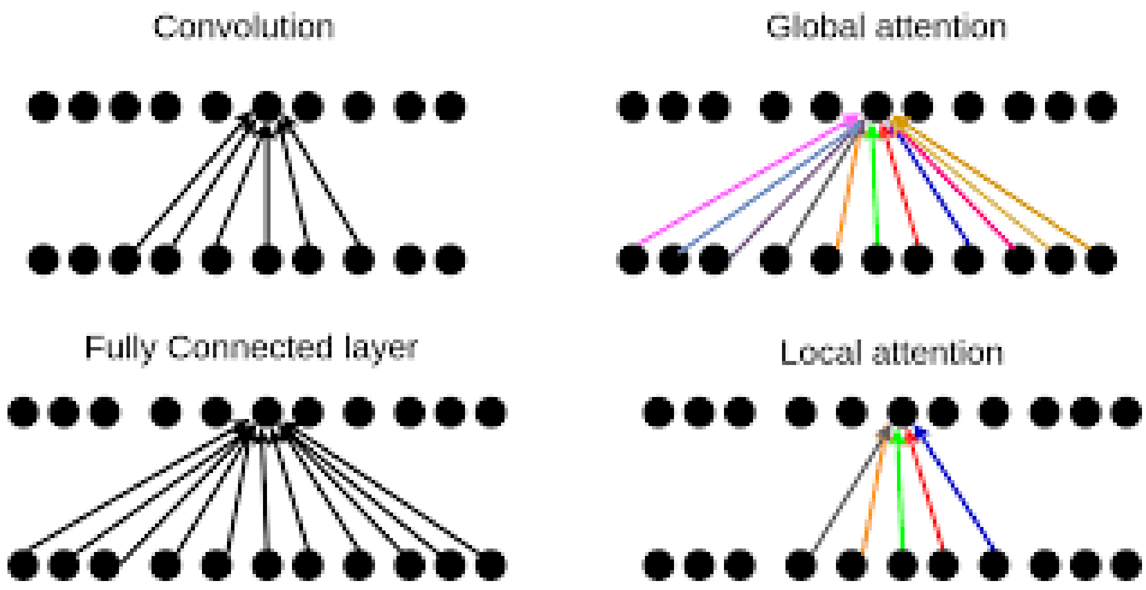

Fig. 3.6. Attention layer Diagram

3.0.8. Softmax Activation Function

Softmax turns raw model outputs (called logits) into probabilities. It takes a vector of numbers and squashes them into a range between 0 and 1, where the sum of all outputs is exactly 1. This makes it easy to interpret the output as probabilities for each class. The highest value is treated as the model's prediction(Liu et al., 2023).

3.0.9. Categorical Cross-Entropy

Categorical cross-entropy is the loss function used for multi-class classification problems where each example belongs to exactly one class. It compares the predicted probabilities (from softmax) to the actual class label (which is usually one-hot encoded). It penalizes the model more when it assigns low probability to the correct class. The lower the probability the model gives to the correct class, the higher the loss. The goal during training is to minimize this loss, so the model gets better at assigning high probabilities to the right classes(Rusiecki, 2019).

3.1. Performance Evaluation

Evaluating the performance of machine learning algorithms is a critical step in determining their effectiveness. Since these models are typically used for tasks like classification or prediction, their success depends on how accurately they assign correct labels to both positive and negative cases. To support this, a range of evaluation metrics—True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)—are used to provide a comprehensive picture of a model's performance. These metrics help measure how well the model distinguishes between relevant and irrelevant instances (Yacouby and Axman, 2020).

3.1.1. Precision

Precision measures the proportion of correctly predicted positive cases out of all cases predicted as positive. In other words, it reflects how accurate the model is when it predicts a positive outcome (Yacouby and Axman, 2020):

$$Precision = \frac{TP}{TP + FP} \tag{3.1}$$

3.1.2. Recall

Recall, also known as sensitivity, evaluates the model's ability to correctly identify all actual positive instances. It shows how many of the true positive cases were successfully detected by the model (Yacouby and Axman, 2020):

$$Recall = \frac{TP}{TP + FN} \tag{3.2}$$

3.1.3. Accuracy

Accuracy is a commonly used metric in binary classification that measures the proportion of total correct predictions—both positive and negative—out of all predictions made. It gives a general sense of how often the model is right (Yacouby and Axman, 2020):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.3}$$

3.1.4. F1 Score

The F1 Score combines precision and recall into a single metric by calculating their harmonic mean. It is particularly useful when the dataset is imbalanced, as it takes both false positives and false negatives into account, providing a balanced view of the model's performance (Yacouby and Axman, 2020):

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{3.4}$$

4. CHAPTER IV: EXPERIMENTAL RESULTS

Using the UNSW-NB15 dataset, six machine learning models were assessed for intrusion detection. Among the performance indicators are F1, recall, accuracy, and precision. Feature selection, data preparation, and model training lead to a thorough comparison analysis. The study follows established methodologies in cybersecurity research, employing suitable loss functions and optimized training configurations to enhance model performance. To guarantee reliable, consistent, and efficient outcomes, all models were trained and tested within a high-performance computing environment, enabling a comprehensive assessment of their capabilities in detecting network intrusions.

4.1. Training and Loss of Hybrid Model

The hybrid model demonstrated strong and consistent learning over 25 epochs. Training began with an accuracy of 75.8% and a validation accuracy of 81.9%, paired with a relatively high validation loss of 0.5185, hinting at early-stage underfitting. By the second epoch, show in Fig.4.1 validation accuracy rose sharply to 91.6%, with validation loss cut almost in half to 0.2882. While the third epoch saw a temporary drop in validation accuracy to 67.8% (and a spike in loss to 1.1546), the model quickly recovered. From the fifth epoch onward, validation accuracy consistently exceeded 95%, peaking at 99.76% by epoch 13, while validation loss dropped to as low as 0.0095 by epoch 23. Training accuracy also climbed steadily, reaching above 98% from epoch 10 onward. A scheduled reduction in learning rate after epoch 20 helped fine-tune performance, leading to stable convergence and minimal overfitting. Overall, the model showed excellent generalization to unseen data.

4.2. Hybrid Model Results

The hybrid model delivered exceptional performance in detecting potato leaf health status across all three categories—Early Blight, Healthy, and Late Blight. For Early Blight, a fungal disease that causes dark lesions and yield loss if not treated promptly, the model achieved a precision of 0.99, recall of 0.99, and F1-score of 0.99. This means it was highly accurate in identifying infected leaves while rarely misclassifying healthy ones as diseased. The Healthy category achieved a precision of 0.98 and a perfect recall of 1.00, indicating that all healthy potato leaves were correctly recognized, which is crucial for avoiding unnecessary pesticide application. For Late Blight, a more aggressive disease responsible for severe crop damage and even total crop loss in outbreaks, the model attained perfect precision (1.00) and a recall of 0.99, meaning nearly all infected leaves were detected with zero false positives. The overall accuracy was 99%, with macro and

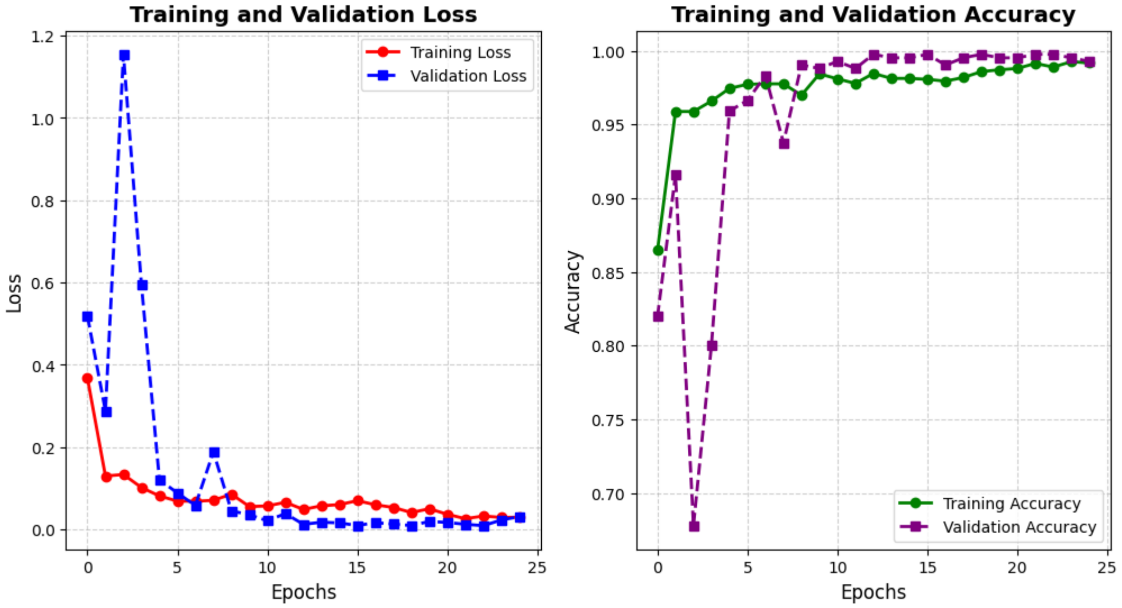

Fig. 4.1. Training and Loss of Hybrid model

weighted averages for precision, recall, and F1-score also at 0.99. The results shown in Table.4.1. These results suggest that the model can be a reliable tool for farmers and agricultural experts, enabling timely and precise disease diagnosis to improve crop management and reduce economic losses.

Table 4.1. Classification Report of the Hybrid Model for Potato Leaf Disease Detection

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Early Blight	0.99	0.99	0.99	162
Healthy	0.98	1.00	0.99	102
Late Blight	1.00	0.99	0.99	141
Accuracy			**0.99**	**405**
Macro Average	0.99	0.99	0.99	405
Weighted Average	0.99	0.99	0.99	405

4.2.1. Hybrid Model Average Accuracy

The hybrid model achieved an average accuracy of 99.26%, with precision at 99.15%, recall at 99.32%, and an F1-score of 99.23%. These metrics indicate that the model is highly reliable in correctly identifying both healthy and diseased potato leaves, with minimal false positives and false negatives, ensuring consistent and precise disease detection across all classes.

4.2.2. Results Comparison with other Models

The Table 4.2 compares the accuracy of different approaches used for potato leaf disease detection. Previous studies, such as those by Chen et al., 2022, Barman et al., 2020, Mahum et al., 2023, and Chakraborty et al., 2022, achieved accuracies ranging between 96.98 % and 97.89 %, while another unnamed technique reached 98.12 %. In contrast, the proposed hybrid model outperformed all these methods, achieving an accuracy of 99.26%. This improvement indicates that the hybrid model can identify potato leaf conditions—whether healthy, affected by Early Blight, or affected by Late Blight—with a higher level of precision. Such a high accuracy reduces the chances of misdiagnosis, enabling farmers and agricultural specialists to take timely and appropriate action for disease management, ultimately protecting crop yield and quality.

Table 4.2. Comparison of the proposed approach with recent methods

Sr. No	Reference / Method	Accuracy (%)
1	Chen et al., 2022	97.73
2	Barman et al., 2020	96.98
3	Mahum et al., 2023	97.20
4	Chakraborty et al., 2022	97.89
5	Nazir et al., n.d.	98.12
6	**Proposed Hybrid Model**	**99.26**

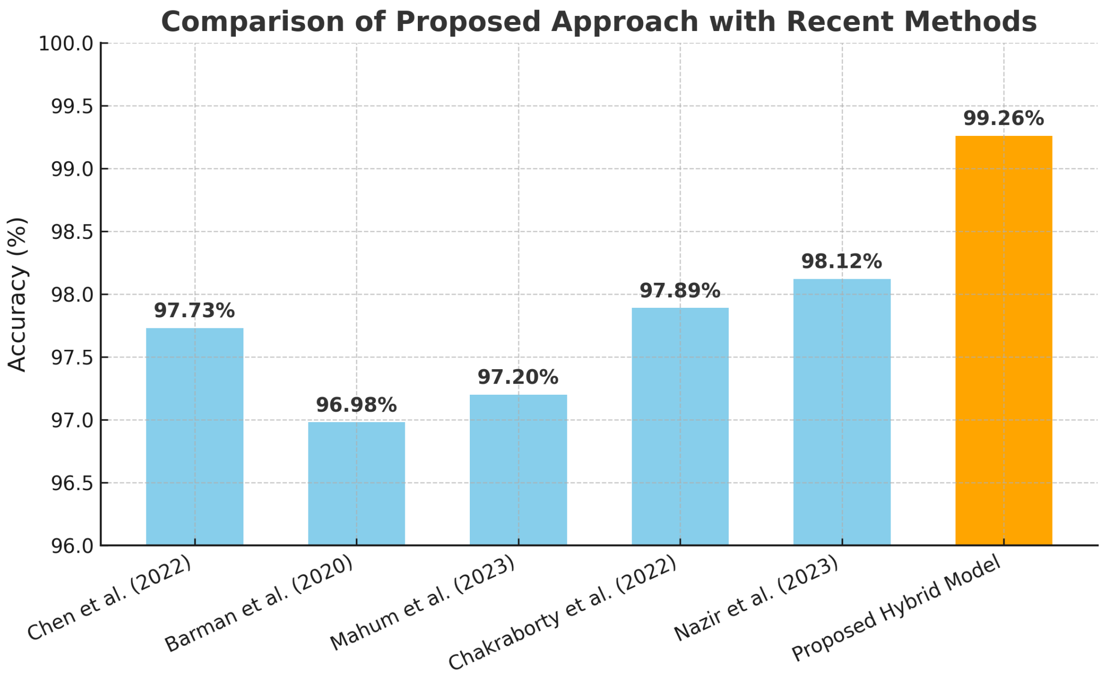

Fig. 4.2. Comparison of the proposed approach with recent methods in Bar Graph

4.3. Confusion Matrix of Hybrid Model

The confusion matrix demonstrates the high accuracy of the hybrid model in detecting potato leaf conditions across the three classes: Early Blight, Healthy, and Late Blight. Out of 405 test samples, the model made only three misclassifications. For Early Blight, it correctly identified 161 out of 162 cases, with one sample mislabeled as Healthy. All 102 Healthy leaf samples were classified perfectly, showing zero false positives or false negatives for this category. Showing in Fig.4.3 For Late Blight, the model accurately detected 139 out of 141 samples, with one case misclassified as Early Blight and another as Healthy. The strong diagonal pattern—where the highest counts are along the diagonal—shows the model's precision in matching predicted labels with actual classes. With just three minor errors, the model achieved an overall accuracy of about 99%, making it a reliable tool for real-world agricultural use in early detection and management of potato diseases. management.

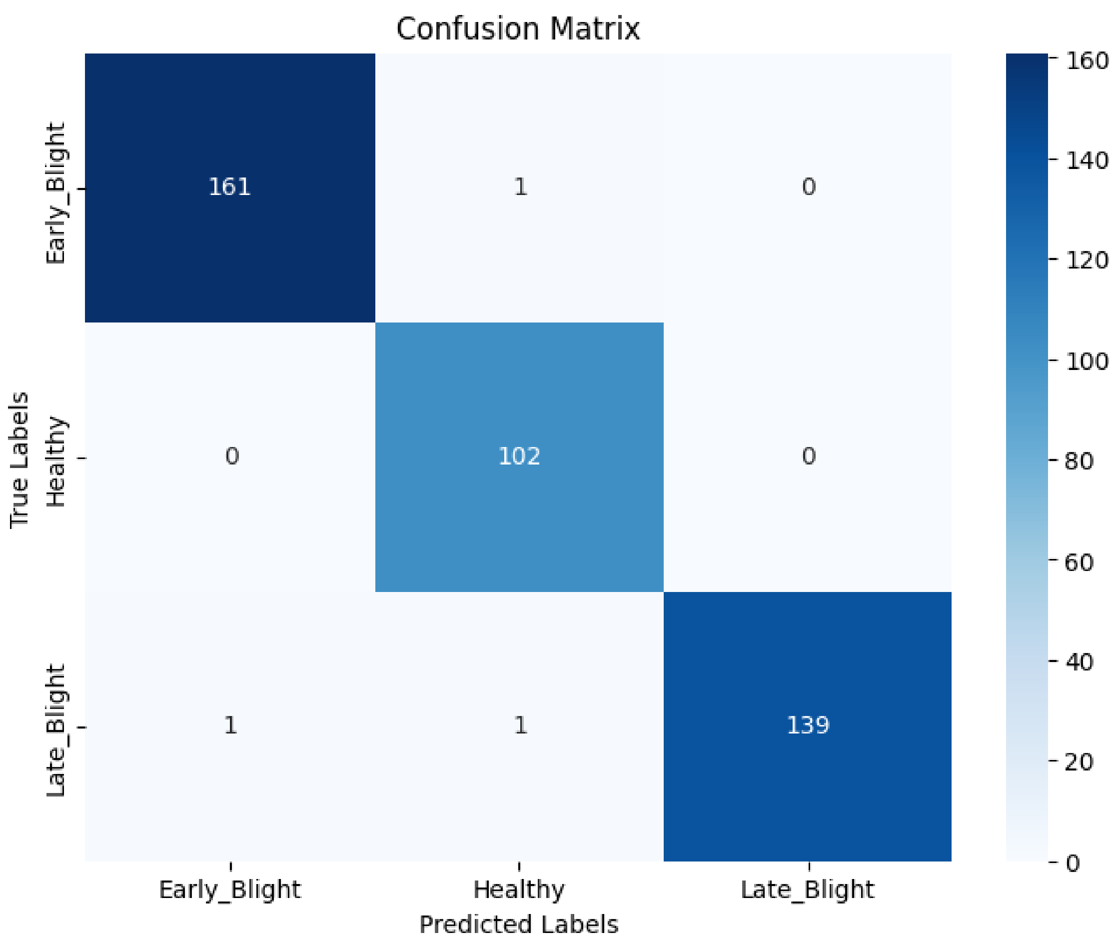

Fig. 4.3. Confusion Matrix of Hybrid Model

5. CONCLUSION

This study developed and evaluated a hybrid deep learning model capable of achieving state-of-the-art performance in potato leaf disease classification. Through systematic data preprocessing, feature selection, and optimized training configurations in a high-performance computing environment, the model achieved outstanding results, with an accuracy of 99.26% and consistently high performance across all metrics. Its performance exceeded that of recent leading methods, demonstrating superior precision in identifying both diseased and healthy classes, and robustness against false positives. The model proved highly effective in detecting Early Blight and Late Blight while maintaining perfect classification for healthy leaves—reducing the risk of misdiagnosis and enabling better crop management. The success of the model underlines its adaptability and effectiveness for complex agricultural image classification problems.

5.0.1. Future Work

While the hybrid model achieved impressive results, there are several opportunities for future research and improvement:

1. **Domain Expansion** – Apply and evaluate the model on additional agricultural datasets covering multiple crops and diseases to test its scalability in broader precision farming contexts.

2. **Real-Time Deployment** – Integrate the model into edge-computing or IoT-based systems for on-site disease detection with minimal latency.

3. **Model Optimization** – Explore model compression, pruning, and quantization to reduce computational costs and enable deployment on resource-constrained devices.

4. **Explainable AI (XAI)** – Incorporate interpretability frameworks such as Grad-CAM or SHAP to provide insights into the model's decision-making process, enhancing trust and adoption by non-technical users.

5. **Hybrid Data Sources** – Combine image-based analysis with environmental or sensor data (e.g., humidity, temperature) to further improve predictive accuracy.

6. **Continuous Learning** – Implement online learning mechanisms to adapt to new disease strains without full retraining.

By pursuing these directions, the hybrid model can evolve into a versatile, real-time decision-support system with wide-ranging applications in precision agriculture.

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