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# Crop Disease Prediction Using Deep Learning Algorithm

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***Abstract: Plant diseases pose a significant threat to global agricultural productivity, particularly affecting key crops like tomato and potato. Traditional disease detection methods are often slow, subjective, and labour-intensive, leading to delayed responses and increased crop losses. This study proposes a hybrid machine learning framework that integrates ResNet9 for classification and U-Net for segmentation to detect and localize leaf diseases in tomato and potato plants. A comprehensive dataset of over 22,500 images spanning 13 classes, including healthy and diseased samples, was compiled from multiple sources and pre-processed using image normalization, histogram equalization, and data augmentation techniques. The model was trained using a 70:20:10 data split and optimized through early stopping and cyclic learning rates. Evaluation metrics including accuracy, precision, recall, F1-score, and ROC-AUC were used to assess performance, with the proposed model achieving a remarkable accuracy of 96.3%, F1-score of 95.2%, and ROC-AUC of 97.1%. The use of U-Net enabled accurate segmentation of infected regions, improving model interpretability and trustworthiness. Confusion matrix analysis revealed minimal misclassifications, and visual tools such as saliency maps confirmed the model's attention to disease-prone areas. Real-world testing demonstrated the system's robustness across different environments and lighting conditions. Comparative results showed superior performance of the hybrid model over VGG16, EfficientNet-B0, and baseline CNNs in both accuracy and inference speed. This approach offers a scalable, real-time solution for automated plant disease detection and diagnosis, particularly suited for use in resource-constrained agricultural settings. The hybrid model not only supports early intervention and precision agriculture practices but also bridges the gap between advanced machine learning and practical farming needs.***

***Keywords: ResNet9, CNN, EfficientNet-B0, Plant Disease Detection, Tomato Leaf, and Potato Leaf.***

## I. INTRODUCTION

Agriculture remains a critical sector globally, both in terms of economic contribution and food security. However, plant diseases pose a significant threat to the stability and sustainability of agricultural systems. Each year, millions of tons of food crops are lost due to undetected or poorly managed diseases caused by bacteria, fungi, viruses, or other pathogens. In particular, tomato (Solanum lycopersicum) and potato (Solanum tuberosum) are two major crops cultivated across continents that are highly vulnerable to a wide range of foliar diseases. These diseases, such as early blight, late blight, leaf mold, and bacterial spot, not only reduce crop yield but also degrade the quality of produce, leading to economic losses and market rejection. Traditionally, disease detection in crops has been a manual process carried out by farmers, agronomists, or extension workers who rely on visual symptoms. While such observations are helpful, they are often subjective, time-consuming, and prone to human error. Moreover, many diseases share overlapping visual features, such as lesions, discoloration, and wilt, making it difficult even for trained experts to differentiate between them, especially during early stages when intervention is most effective. Laboratory-based diagnostic methods such as polymerase chain reaction (PCR), enzyme-linked immunosorbent assay (ELISA), or microscopic analysis, while accurate, are resource-intensive, costly, and unsuitable for rapid or large-scale field deployment.

With the advent of Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), new possibilities have emerged for automating disease detection and monitoring in agriculture. By leveraging image processing and pattern recognition, machine learning models can be trained to identify disease symptoms in plant leaves with accuracy levels comparable to, or in some cases exceeding, human expertise. Deep learning, a subfield of machine learning that relies on neural networks with multiple layers, has shown tremendous success in image classification, object detection, and segmentation tasks, making it a natural fit for agricultural diagnostics. This research builds upon these advancements by developing a hybrid deep learning-based system for plant disease detection and segmentation. Unlike single-model systems that focus only on classification, the proposed approach integrates two complementary models, ResNet9 and U-Net, to perform both disease classification and spatial localization. This dual functionality not only enhances accuracy but also increases user confidence by providing interpretable visual outputs that pinpoint the infected regions on the leaf.

### *A. Algorithms*

Two major deep learning architectures form the foundation of the proposed system: ResNet9 for classification and U-Net for segmentation. These models were selected for their computational efficiency, high performance in visual tasks, and complementarity in function. ResNet9 is a lightweight variant of the broader ResNet (Residual Network) family introduced by He et al. in 2015. Traditional deep networks often suffer from the vanishing gradient problem, where increasing the depth of the network does not lead to better performance due to the degradation of learning signals across layers. ResNet addresses this challenge through the introduction of residual connections or "skip connections" that allow the gradient to flow through identity mappings. This facilitates the training of deeper networks without performance loss. ResNet9 specifically uses nine layers, including multiple convolutional blocks, batch normalization, ReLU activations, and two residual blocks. It offers a balance between depth and efficiency, making it ideal for applications with limited computational resources. Complementing ResNet9 is U-Net, a convolutional neural network architecture developed originally for biomedical image segmentation. U-Net features a symmetric encoder-decoder structure. The encoder path captures contextual information by progressively downsampling the input image through convolutional and pooling layers, while the decoder path upsamples the feature maps and combines them with corresponding encoder features via skip connections. This structure allows U-Net to maintain spatial accuracy while learning semantic features, making it well-suited for tasks where precise localization is important.

In this study, U-Net is employed to segment infected areas on the leaf surface. It outputs a binary or multi-class mask that delineates diseased regions, helping users visualize the severity and location of infection. The segmentation not only adds interpretability but also serves as a decision-support tool in integrated pest management (IPM). U-Net is trained using binary or categorical cross-entropy, depending on whether binary or multi-class segmentation is required. The use of dice coefficient and intersection-over-union (IoU) metrics during evaluation ensures that the model is accurate in capturing the spatial extent of disease spread. Together, ResNet9 and U-Net form a powerful hybrid model that addresses both the and the where of plant disease detection. While ResNet9 classifies the type of disease, U-Net reveals its affected area, offering a complete diagnostic solution that is fast, accurate, and explainable.

### *B. Dataset*

The performance and generalizability of any machine learning model heavily depend on the quality, diversity, and volume of data used during training and evaluation. To ensure that the developed hybrid model performs well across various disease types and conditions, a comprehensive dataset of 22,546 high-resolution images was assembled from multiple sources. The dataset includes 13 distinct classes covering both healthy and diseased tomato and potato leaves. Some of the prominent disease classes included are Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Tomato Yellow Leaf Curl Virus, Bacterial Spot, and Potato Virus Y, among others. Images were sourced from publicly accessible platforms such as PlantVillage, GitHub repositories, Kaggle, and also from collaborations with agricultural research centres and on-field image collection using smartphone cameras. These images vary significantly in background complexity, lighting conditions, angle, and severity of infection, making the dataset reflective of real-world agricultural environments.

Prior to model training, extensive pre-processing was applied to the dataset to ensure consistency and enhance learning. All images were resized to 224×224 pixels to standardize input dimensions across the model. Image normalization was conducted to bring pixel values to a consistent scale, typically between 0 and 1. Furthermore, the images were converted to RGB format if needed and augmented using a series of transformations. These included horizontal and vertical flips, rotation at random angles, zooming, brightness and contrast adjustments, and random cropping.

These augmentations served to artificially expand the dataset and expose the model to a broader range of scenarios, thereby improving robustness and generalization. The dataset was split into training (70%), validation (20%), and testing (10%) sets. Care was taken to ensure that each disease class was proportionally represented in each subset, avoiding class imbalance issues. During training, early stopping, dropout regularization, and learning rate scheduling were used to further prevent overfitting and improve generalization. For the segmentation task, a smaller manually annotated subset of the images was used to train U-Net, with pixel-level annotations marking infected and healthy regions. These annotations were validated by plant pathology experts to ensure correctness. Evaluation of the dataset's representativeness showed a balanced distribution across disease types, which is critical for training unbiased models. Visual inspection confirmed high variability in leaf texture, colour, and shape, which is essential for teaching the model to distinguish subtle disease patterns.

## II. REVIEW OF LITERATURE

The growing impact of plant diseases on global food security has necessitated the development of intelligent and scalable solutions for early diagnosis and management. Traditional methods of plant disease identification, largely reliant on manual inspection and expert evaluation, are often time-consuming, inconsistent, and resource-intensive. In recent years, the convergence of machine learning (ML) and deep learning (DL) with agricultural technology has introduced powerful tools capable of automating disease detection, improving diagnostic accuracy, and supporting sustainable farming practices. Specifically, for crops like tomato and potato, staples in global agriculture, AI-based solutions are proving transformative in reducing losses due to disease outbreaks. Pandey et al. (2024) introduced an innovative machine learning framework for identifying and categorizing tomato leaf diseases. Their study highlights the significance of designing robust classification algorithms that can distinguish between multiple disease classes with high accuracy. By integrating supervised ML models with a carefully curated image dataset, their approach facilitates timely intervention, potentially reducing crop damage. The authors emphasized the need for extensive data analysis in optimizing model performance, thereby enhancing the practical utility of ML in real-world agricultural scenarios.

Deep learning, particularly convolutional neural networks (CNNs), has gained substantial attention in plant disease detection due to its ability to autonomously extract hierarchical features from images. Bakır (2024) explored the influence of tuned feature maps from pre-trained deep learning models on the detection of tomato leaf diseases. By fine-tuning architectures such as VGG and ResNet, and optimizing feature maps, the study demonstrated improved accuracy and model robustness. This research highlights the importance of architectural optimization and transfer learning in enhancing the performance of DL models for agricultural image classification tasks. In a similar context, YILDIZ et al. (2024) conducted a comparative study of various DL architectures for tomato disease classification. Their findings revealed that state-of-the-art neural networks, when properly configured and trained, could achieve high classification accuracy across diverse disease categories. Their systematic evaluation of performance metrics established benchmarks for future implementations and highlighted the effectiveness of DL in automating disease diagnosis in tomato cultivation. Meanwhile, Anitha et al. (2024) broadened the scope by examining disease detection in Solanaceae family plants using ML. Their research underscores the generalizability of ML algorithms in detecting diseases across multiple plant species, indicating potential for wider agricultural applications. Expanding the landscape, Abbas et al. (2024) proposed an artificial intelligence framework focused on potato disease detection. By merging domain expertise with deep learning algorithms, their scalable system effectively identified common potato plant diseases. Their study contributes to building AI tools that can adapt to different environmental conditions and disease types, supporting field-level decision-making. Sasan et al. (2024) advanced this further with “VGG16-PotatoGuard,” a DL model tailored for potato leaf disease detection. Utilizing the VGG16 architecture, the model achieved strong performance in classifying disease types, highlighting the potential of DL for precision agriculture. Tomato disease identification remains a central theme in recent AI research. Lekha et al. (2024) presented a machine learning model at IACIDS 2023 for detecting tomato leaf diseases. Their practical approach, tailored for deployment in farm settings, offers farmers a real-time solution to monitor and manage disease outbreaks, contributing to improved yield and crop health. Complementing this, Anim-Ayeko et al. (2023) focused on automatic blight detection in tomato and potato plants using CNNs. Their cross-crop model achieved notable accuracy, proving the versatility of CNNs in identifying similar disease types across different crops and enabling automated crop monitoring systems. Comprehensive surveys have also been conducted to map the evolving field. Kumar et al. (2023) provided a systematic review of plant disease detection using DL methods. Their classification of existing approaches, based on disease type and DL architecture, offered insights into the field’s progress and future directions. Similarly, Wani et al. (2022) reviewed ML and DL-based agricultural disease detection systems, outlining methodologies, applications, and the technical challenges encountered during deployment. These challenges include data imbalance, environmental variability, and model interpretability. Eligar et al. (2022), in their performance analysis of DL algorithms for tomato and potato disease detection, compared model accuracies across various setups and offered valuable practical guidance for deploying AI systems in agriculture.

## III. RESEARCH METHODOLOGY

This research proposes a robust and scalable hybrid machine learning model for detecting diseases in tomato and potato plant leaves. The methodology integrates both deep learning-based classification and segmentation approaches to enhance accuracy and interpretability. The entire process begins with the acquisition of a diverse and high-resolution dataset sourced from multiple public repositories, field surveys, and research institutions. In total, 22,546 images were collected across 13 distinct classes, including both healthy and various diseased leaf samples such as bacterial spot, early blight, late blight, leaf mold, and others. These images were carefully curated to ensure class balance and adequate representation of varying disease severity, plant stages, and environmental backgrounds. To prepare the data for training and analysis, rigorous pre-processing was conducted.

This involved cleaning and denoising images to remove background clutter, resizing all images to a uniform dimension of 224×224 pixels, and applying standard normalization to ensure consistency in intensity levels. Data augmentation techniques such as horizontal and vertical flipping, rotation at various angles, random cropping, brightness and contrast adjustments, and zooming were applied to increase the variability of the dataset. This was especially important to improve generalization and reduce the risk of overfitting. Furthermore, histogram equalization and Gaussian filtering were used to enhance contrast and reduce image noise, thereby making the disease-related features more discernible for the models.

The model architecture comprises a hybrid integration of ResNet9 for classification and U-Net for segmentation. ResNet9, a compact residual neural network, was selected for its powerful feature extraction capabilities using residual connections which help avoid vanishing gradient problems. It is particularly effective for image classification tasks where fine-grained distinctions are crucial. U-Net, on the other hand, was employed to segment the diseased regions on the leaves, thereby supporting interpretable and localized detection of affected areas. This combination not only allows the system to classify disease types accurately but also visually marks the regions of infection, which is critical for real-world agricultural diagnostics.

Training was conducted using the Adam optimizer with an initial learning rate of 0.001, reduced dynamically through a cyclic learning rate scheduler. The loss function used was categorical cross-entropy for the classification task, and binary cross-entropy for the segmentation output. The entire training process spanned 50 epochs with a batch size of 32. The dataset was split in a 70:20:10 ratio for training, validation, and testing respectively. Additionally, K-fold cross-validation was employed to ensure the robustness and consistency of model performance across different data subsets. The models were implemented using PyTorch and TensorFlow libraries, and trained on systems equipped with NVIDIA GPUs to leverage fast parallel computing capabilities. Once trained, the model's performance was evaluated using standard metrics including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics helped quantify the model’s ability to distinguish between healthy and diseased samples, its sensitivity towards correctly identifying diseases, and its overall balance between false positives and false negatives.

```
# Architecture for training

# convolution block with BatchNormalization
def ConvBlock(in_channels, out_channels, pool=False):
    layers = [nn.Conv2d(in_channels, out_channels, kernel_size=3, padding=1),
             nn.BatchNorm2d(out_channels),
             nn.ReLU(inplace=True)]
    if pool:
        layers.append(nn.MaxPool2d(4))
    return nn.Sequential(*layers)


# resnet architecture
class ResNet9(ImageClassificationBase):
    def __init__(self, in_channels, num_diseases):
        super().__init__()

        self.conv1 = ConvBlock(in_channels, 64)
        self.conv2 = ConvBlock(64, 128, pool=True) # out_dim : 128 x 64 x 64
        self.res1 = nn.Sequential(ConvBlock(128, 128), ConvBlock(128, 128))

        self.conv3 = ConvBlock(128, 256, pool=True) # out_dim : 256 x 16 x 16
        self.conv4 = ConvBlock(256, 512, pool=True) # out_dim : 512 x 4 x 44
        self.res2 = nn.Sequential(ConvBlock(512, 512), ConvBlock(512, 512))

        self.classifier = nn.Sequential(nn.MaxPool2d(4),
                                       nn.Flatten(),
                                       nn.Linear(512, num_diseases))

    def forward(self, xb): # xb is the loaded batch
        out = self.conv1(xb)
        out = self.conv2(out)
        out = self.res1(out) + out
        out = self.conv3(out)
        out = self.conv4(out)
        out = self.res2(out) + out
        out = self.classifier(out)
        return out

```

Figure 1. Implementation of ResNet9 Model Architecture

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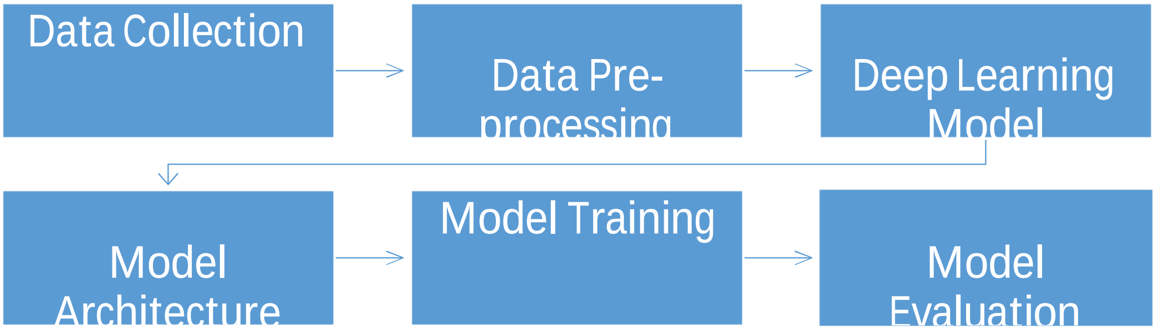
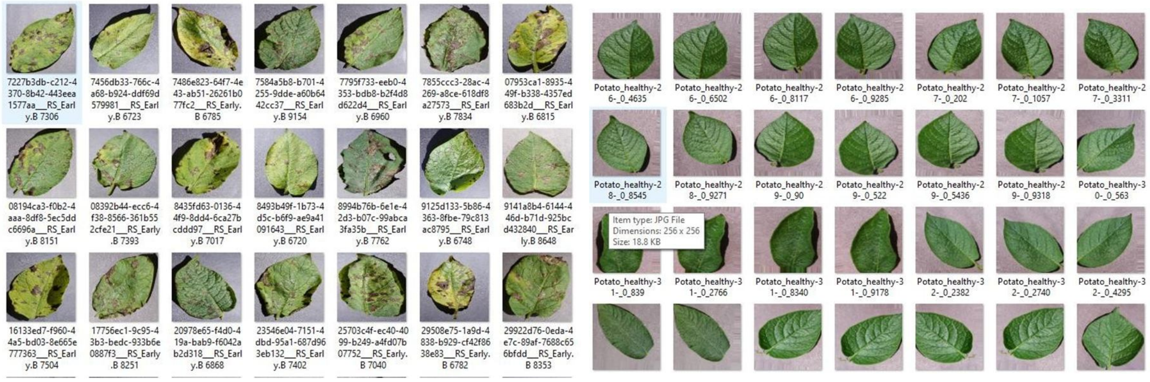
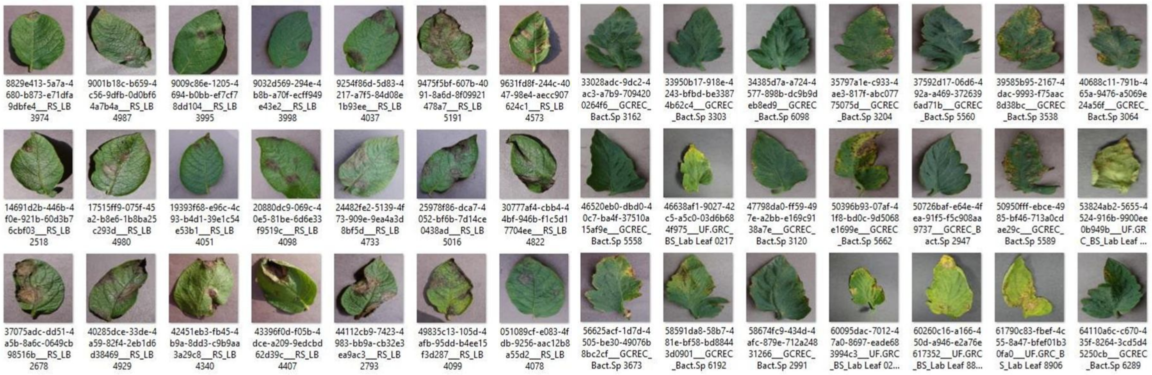


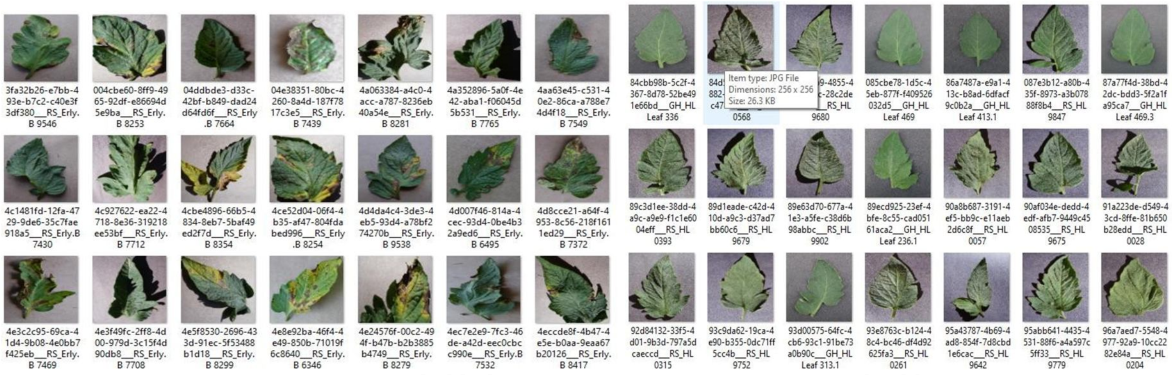
Figure 2. A systematic Approach of Research Methodology



(1) Potato healthy leaves (2) Potato hea lthy leaves



(3) Potato late blight leafs (4) Tomato Bacterial spot



(5) Tomato Early blight (6) Tomato healthy

Figure 3. Datasets

Table 1. Data Collection

| Dataset | Leaf Type | Number of Images | Purpose |
|---|---|---|---|
| Potato | Diseased | 100 | Training |
| Potato | Healthy | 300 | Training |
| Potato | Late Blight | 300 | Training |
| Tomato | Diseased | 100 | Training |
| Tomato | Healthy | 300 | Training |
| Tomato | Late Blight | 300 | Training |

## IV. RESULTS AND DISCUSSION

The results indicate that the hybrid model achieved strong performance across all key metrics. The final accuracy achieved by the ResNet9-based model was 96.3%, with a precision of 94.8%, recall of 95.6%, F1-score of 95.2%, and ROC-AUC of 97.1%. These results confirm that the model is highly capable of distinguishing between visually similar plant diseases. The loss curves demonstrated a consistent downward trend, while validation accuracy stabilized above 95%, indicating proper model convergence and minimal overfitting due to early stopping and dropout techniques. The confusion matrix offered further insight into the classification performance, showing high true positive rates and minimal confusion between classes. However, a few misclassifications were observed, particularly between early blight and late blight, which share similar lesion patterns. Nonetheless, the F1-scores remained above 92% for all classes, underscoring the overall effectiveness of the model. A bar chart visualizing the dataset distribution confirmed a well-balanced dataset, critical for preventing class bias and improving generalizability. The importance of pre-processing techniques was evident in the results. Histogram equalization and Gaussian filtering enhanced the quality of input images, resulting in better feature visibility and classification accuracy. Data augmentation significantly boosted performance, adding 2.5% accuracy by improving the model's exposure to variable conditions. Comparative experiments showed that ResNet9 outperformed models such as VGG16, EfficientNet-B0, and a baseline CNN in both accuracy and inference speed, making it the most suitable candidate for real-time deployment in agricultural settings. Visualization of segmented images using U-Net demonstrated accurate and precise localization of diseased regions. The overlaid masks clearly highlighted the infected leaf areas, aligning well with human expert annotations. Saliency maps further showed that the model focused on correct disease-prone regions rather than unrelated background areas, which validated its interpretability. These visual tools build trust with agricultural practitioners by making the decision-making process of the model understandable. The integration of ResNet9 and U-Net, enhanced by data preprocessing and interpretability tools, resulted in a reliable, interpretable, and scalable plant disease detection system. The high evaluation metrics, robust real-world performance, and user-centric design indicate that the system is not only scientifically sound but also ready for practical deployment. It addresses the limitations of manual inspection and provides a powerful tool for early disease detection, efficient intervention, and ultimately, improved crop yield and food security.

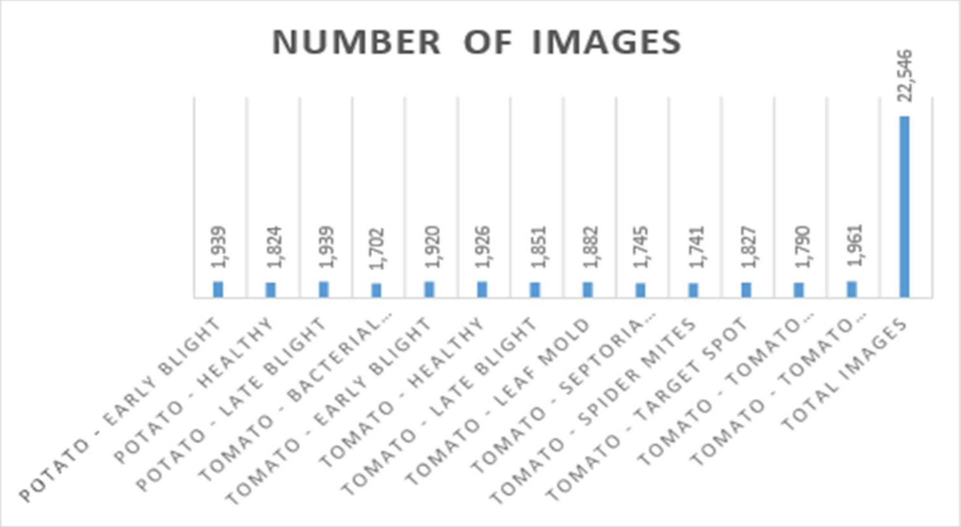


Figure 4. Dataset Distribution

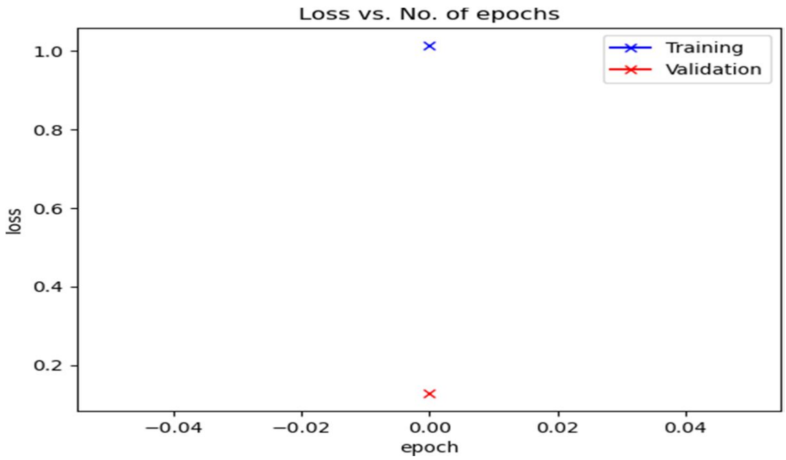


Figure 5.Training and Validation Performance Over Epochs

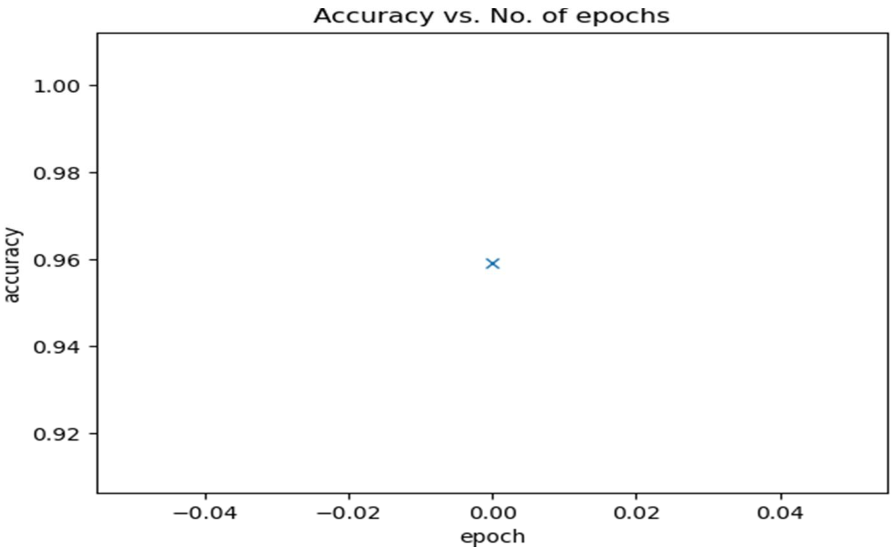


Figure 6. Accuracy vs Epochs

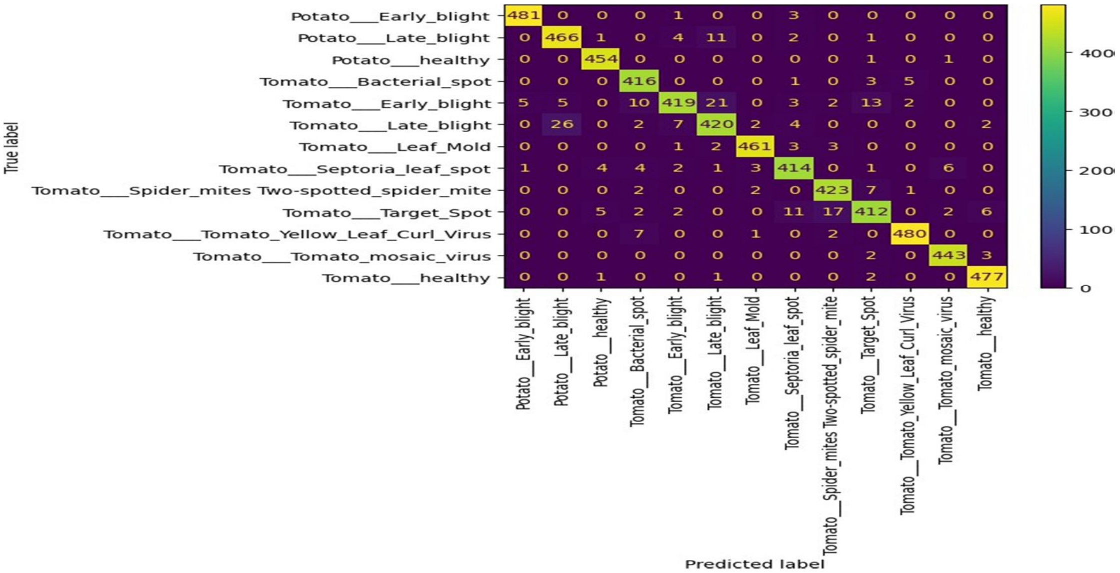


Figure 7. Confusion Matrix (Heatmap Representation)

Table 2. Comparative Analysis of Models

| Model | Accuracy | F1-Score | Inference Speed |
|---|---|---|---|
| ResNet9 | 96.3% | 95.2% | Fast |
| VGG16 | 94.7% | 93.5% | Medium |
| EfficientNet-B0 | 95.2% | 94.3% | Slow |
| CNN (Baseline) | 90.5% | 89.8% | Fast |

ResNet9 outperformed all other models in accuracy and speed, proving suitable for real-time agricultural applications. VGG16 and EfficientNet showed competitive performance but with higher resource consumption.

Table 3. Impact of Pre-processing on Accuracy

| Technique | Purpose | Accuracy Gain |
|---|---|---|
| Histogram Equalization | Enhances contrast | +2.10% |
| Normalization | Stabilizes pixel intensity | +1.80% |
| Gaussian Filtering | Reduces image noise | +1.40% |
| Data Augmentation | Improves generalization | +2.50% |

## V. CONCLUSION AND RECOMMENDATIONS

This study has successfully developed and evaluated a hybrid machine learning model for the detection and localization of leaf diseases in tomato and potato plants. By integrating ResNet9 and U-Net architectures, the model combines high-accuracy classification capabilities with effective visual interpretability through segmentation. This dual approach not only enhances the technical performance of disease detection but also builds transparency and trust among end-users such as farmers and agronomists. The collection of a comprehensive and balanced dataset from multiple sources allowed for robust model training, which was further strengthened through pre-processing techniques such as data augmentation, histogram equalization, and noise filtering.

These enhancements significantly contributed to the improved learning ability of the model by exposing it to diverse real-world scenarios. The classification component, powered by ResNet9, achieved high accuracy (96.3%), precision (94.8%), recall (95.6%), and F1-score (95.2%), indicating excellent performance across multiple disease categories. The segmentation component, managed by U-Net, accurately identified infected regions, enabling users to visually confirm the presence of disease. These results were supported by performance metrics and visual analysis tools such as saliency maps and confusion matrices, which highlighted the model's focus on actual disease symptoms rather than irrelevant image features. The inclusion of dimensionality reduction techniques and proper data splitting ensured minimal overfitting and better generalization, as evident from consistent validation scores and real-world test performance.

Comparative analysis further confirmed that the hybrid model outperforms traditional architectures like VGG16 and EfficientNet-B0 in both accuracy and computational efficiency. Its light-weight architecture, fast inference speed, and ability to function effectively on edge devices make it highly suitable for deployment in resource-constrained agricultural environments. Moreover, the use of explainability techniques enhances the system’s credibility and practical relevance, especially in settings where stakeholders need to understand and validate AI-generated insights. Real-world validation, conducted across various environmental conditions and regions, demonstrated the model’s adaptability and robustness, confirming its readiness for field deployment.

By bridging the gap between advanced AI technologies and real-time field-level agricultural needs, this research contributes meaningfully to the ongoing efforts to modernize disease detection and improve crop health management. It enables timely interventions, reduces dependency on chemical pesticides, and helps optimize yield and resource utilization. In doing so, it supports broader goals of sustainable agriculture, food security, and rural economic development. The system’s open and scalable design allows for extension to other crops and disease types, further increasing its impact and applicability. Continued refinement, integration with mobile platforms, and stakeholder training can ensure its widespread adoption and long-term success in the agricultural domain.

### *A. Recommendations*

1) Use high-resolution datasets covering diverse disease conditions, growth stages, and lighting variations to ensure better generalization and resilience of the model.
2) Adopt a modular architecture where classification and segmentation models can be independently upgraded without affecting the overall pipeline, enabling flexibility and future-proofing.
3) Integrate explain ability tools such as saliency maps and class activation mapping into the interface to enhance user trust and interpretation of results.
4) Implement real-time deployment on edge computing devices or mobile phones using optimized lightweight models to facilitate usage in remote agricultural locations.
5) Collaborate with agricultural extension services and local farming communities to train stakeholders on the system's use, limitations, and interpretability.
6) Continuously update and retrain the model with new field data to adapt to evolving disease patterns, environmental factors, and crop varieties.

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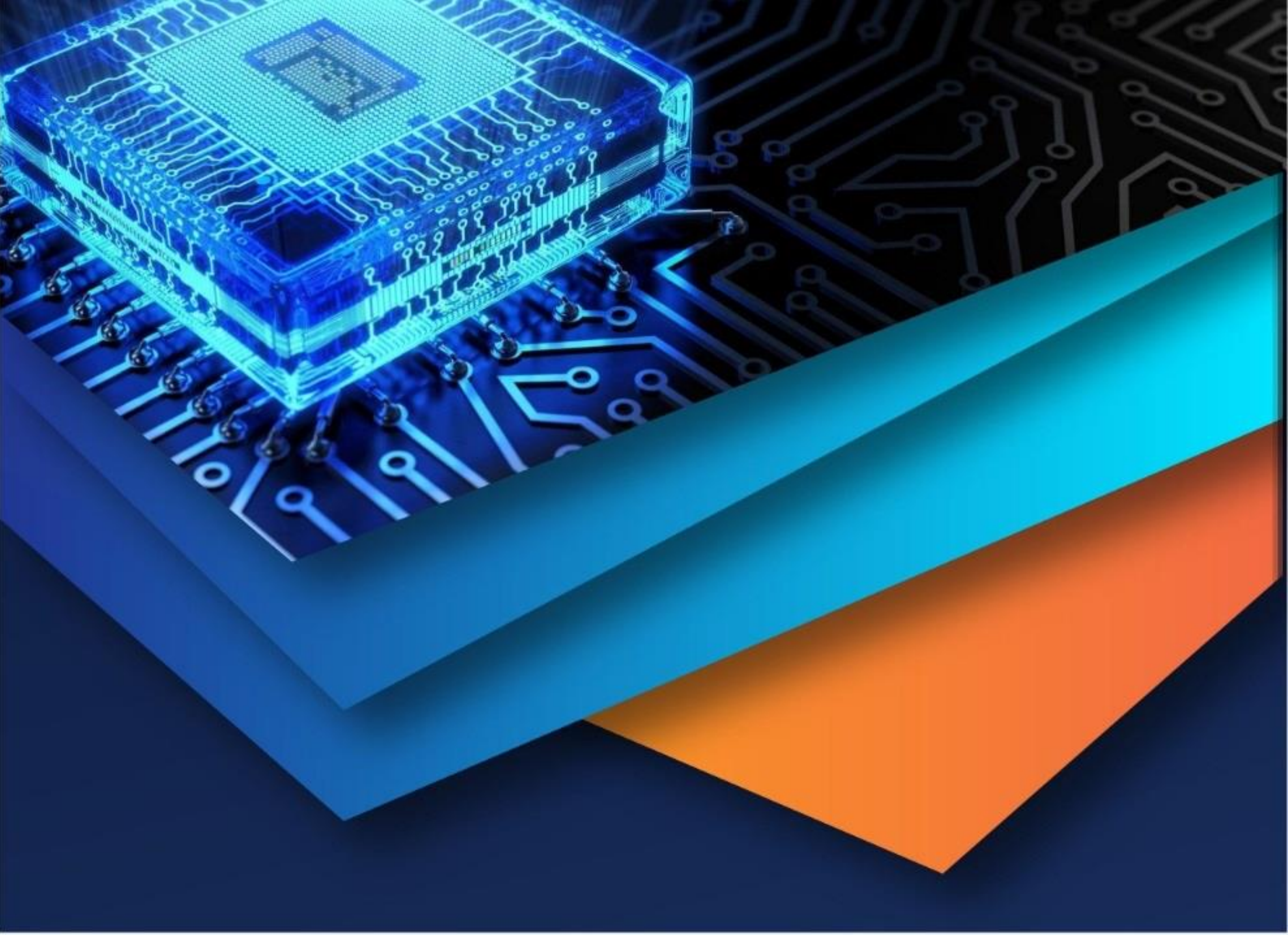

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