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Modified Resnet50 architecture for plant disease detection

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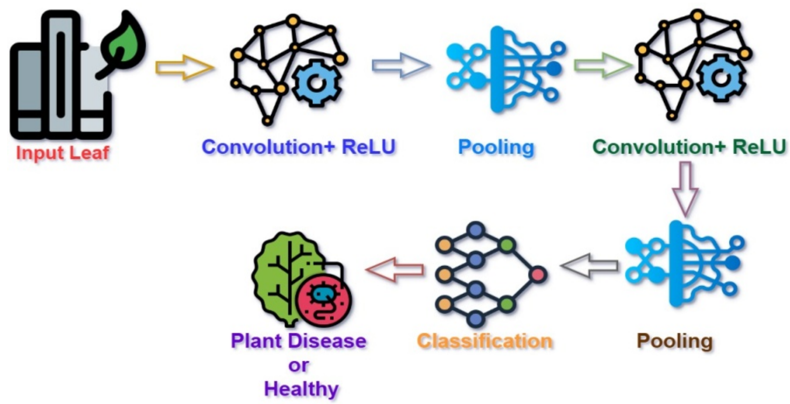
ABSTRACT



The early detection and diagnosis of plant diseases are essential for improving agricultural productivity and ensuring global food security. In recent years, deep learning techniques have demonstrated significant potential in enhancing the accuracy of plant disease identification. This study presents a modified ResNet50 architecture specifically designed for plant disease detection. The proposed model incorporates advanced features, including attention mechanisms, adaptive pooling layers, and feature recalibration techniques, to enhance its ability to identify diseased plant leaves from images. These modifications significantly improve the model's capacity to recognize intricate patterns and subtle disease variations. Additionally, adaptive learning strategies utilizing large-scale datasets such as ImageNet have been employed to fine-tune the model for improved performance. The effectiveness of the modified ResNet50 architecture has been evaluated through extensive experimentation on multiple datasets, including PlantVillage and custom datasets. Comparative analysis with existing state-of-the-art approaches confirms that the proposed model achieves higher accuracy, robustness, and efficiency in detecting various plant diseases across different species and environmental conditions. Furthermore, this research examines the interpretability of model predictions and highlights potential directions for future advancements and real-world applications in smart agriculture.

Keywords: Plant Disease Detection, Facility Diagnosis, Deep Learning, ResNet50, Modified ResNet50, CNN, Image-based Classification.

INTRODUCTION

The early and accurate detection of plant diseases is crucial for achieving sustainable agriculture and ensuring global food security. With the increasing challenges posed by pests and pathogens, leveraging technological advancements is essential to protect crop yields and maintain food supply chains. In recent years, deep learning has revolutionized plant disease diagnosis by enhancing accuracy and automating the detection process.

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Among various deep learning architectures, ResNet50 has gained prominence for its effectiveness in complex image classification tasks. However, plant disease identification requires customized solutions that enhance the capabilities of existing models. This research introduces a modified ResNet50 architecture specifically designed to improve plant disease detection. The proposed framework incorporates advanced techniques such as attention mechanisms, adaptive pooling layers, and feature recalibration strategies to improve the model's ability to recognize subtle disease characteristics. Additionally, transfer learning and fine-tuning with large datasets like ImageNet enhance the model's adaptability and performance in real-world agricultural applications.

Extensive experiments on diverse plant disease datasets, including PlantVillage and custom datasets, validate the effectiveness and generalization ability of the modified ResNet50 architecture. Comparative analysis with existing approaches demonstrates that the proposed model achieves higher accuracy, efficiency, and robustness across various plant species and environmental conditions.

Furthermore, this study explores the interpretability of model predictions, offering insights into the decision-making process behind disease classification. The findings contribute to the development of intelligent agricultural solutions that provide farmers and agronomists with reliable tools for early disease detection and management.

In conclusion, the modified ResNet50 architecture represents a significant advancement in plant disease detection, promoting proactive disease management strategies and supporting sustainable agriculture. This research paves the way for future innovations in smart farming technologies, ensuring healthier crops and improved global food security.

LITERATURE REVIEW

Plant diseases pose a significant threat to global food security and the development of sustainable agriculture, necessitating the exploration of innovative disease detection and management strategies. Over the years, the integration of computer vision and machine learning algorithms has revolutionized plant pathology, enabling fast and accurate disease identification through image analysis. A key aspect of modern plant disease detection techniques is the use of deep learning architectures, which have demonstrated exceptional performance in processing complex image datasets. Among these, Convolutional Neural Networks (CNNs) have emerged as a powerful approach due to their ability to extract hierarchical representations from raw data.

ResNet50, a variant of the Residual Network (ResNet) architecture, has gained recognition for its superior performance in image classification tasks. One of its primary advantages lies in its deep structure, which employs residual connections to address the issue of vanishing gradients, allowing deeper networks to be trained effectively. The application of ResNet50 in plant disease detection has been extensively studied. Despite significant advancements in deep learning-based plant disease detection, several challenges persist. These include limited availability of annotated datasets, the domain shift between controlled laboratory images and real-world agricultural conditions, and the interpretability of model predictions. Addressing these challenges remains a crucial area for further research.

The literature underscores the transformative potential of deep learning, particularly ResNet50, in advancing plant disease detection. By leveraging machine learning algorithms and domain-specific knowledge, researchers aim to develop highly efficient and scalable solutions to mitigate the impact of plant diseases on agriculture.

S. Zhang et al introduced MU-Net, a variant of the U-Net architecture, specifically designed for segmenting diseased plant leaves.[1] Given the complexity of plant disease images—characterized by irregular shapes, varying sizes, and diverse color patterns—MU-Net integrates ResBlock and Respath mechanisms to enhance segmentation accuracy. Experimental results demonstrated that MU-Net outperformed conventional methods, improving both efficiency and accuracy in plant disease identification. The study highlights the importance of deep learning in agricultural research and underscores the potential of MU-Net in digital agriculture applications.

A. Pandian et al addressed the early diagnosis of plant diseases, emphasizing the need for accurate identification to improve agricultural productivity.[2] Their study introduced ResNet197, an advanced deep residual CNN, trained and tested on a dataset comprising 154,500 images from 103 plant classes across 22 species. Through techniques such as image augmentation (cropping, flipping, rotation, and saturation adjustments), and hyperparameter tuning using an evolutionary search approach, the model achieved a classification accuracy of 99.58%, outperforming standard transfer learning models and ResNet architectures. The findings demonstrate the effectiveness of deep learning in plant disease classification, showcasing the potential of ResNet197 for practical deployment in agricultural disease management. Similarly, V. Suryawanshi et al investigated the role of regularization techniques, including dropout, batch normalization, and data augmentation, in improving model generalization and minimizing overfitting in deep neural networks for plant disease detection.[3] The study evaluated VGG16, VGG19, and ResNet50 using the PlantVillage dataset (54,000 images from 14 plant species). The results revealed that oscillatory training improved performance, with ResNet50 outperforming other regularization techniques. However, the study also found that combining dropout, batch normalization, and traditional augmentation methods did not always yield the best results. These findings underscore the importance of selecting appropriate regularization strategies to optimize deep learning models for agricultural applications.

A. Stephen et al explored the use of deep learning and pre-trained CNN architectures for detecting rice diseases in India, which significantly impact crop yields.[4] They evaluated ResNet34, ResNet50, and Inception models, incorporating self-attention mechanisms to enhance feature extraction. The proposed ResNet34 model with self-attention achieved a classification accuracy of 98.54%, outperforming competing models. The study highlights the importance of monitoring rice crops to prevent disease outbreaks and stresses the need for automated classification methods to assist farmers in early disease diagnosis. Additionally, U. A. Ruby et al proposed a deep learning-based model for rice leaf disease identification, emphasizing the importance of real-time disease prevention and treatment.[5] The study employed ResNet50, InceptionV3, and DenseNet architectures, demonstrating that ResNet50 achieved the highest classification accuracy (98.44%). The research underscores the role of advanced technologies, particularly deep learning, in improving disease detection in agriculture, ultimately contributing to food security and sustainable farming practices.

In the paper of M. Ahmed et al the urgent need for early detection and classification of foliar plant diseases was highlighted.[6] The study examined challenges such as noise reduction and feature extraction limitations in traditional classification systems. The authors proposed three novel deep learning architectures: ResNet, Modified ResNet (MResNet), and Inception-ResNet (IncResNet), trained on a dataset of 2,631 color images. Their findings revealed that the proposed models outperformed existing approaches, achieving classification accuracies of 99.62% and 100% on standard and augmented datasets, respectively. The study calls for continued advancements in deep learning models to address existing gaps in plant disease detection and classification. Many researchers have effectively utilized basic image enhancement techniques to detect plant diseases.[7–12] Generative Adversarial Networks (GANs) were employed to generate synthetic, database-driven semantic data for plant disease classification.[13]

Plant Disease Detection

This section highlights the significance of researching plant diseases in agriculture and the transition towards automated detection methods using deep learning.

J. Chen et al introduced LeafNet, a CNN model designed for tea tree classification, which demonstrated superior performance compared to Support Vector Machine (SVM) and Multilayer Perceptron (MLP) classifiers.[14] K. Kc et al analyzed the performance of MobileNet and found that it achieved lower accuracy than VGG. However, an improved and lightweight version of MobileNet was proposed, significantly reducing training time.[15]

Additionally, M. Arsenovic et al., proposed an advanced deep learning framework called Plant Disease Network, which is specifically designed for complex agricultural environments.[16] In the paper of P. Jiang et al the VGG baseline model was effectively used to detect five apple viruses.[17] The study employed various deep learning architectures, including AlexNet, GoogLeNet, multiple versions of ResNet, and VGG, highlighting the effectiveness of CNNs in plant disease classification and visualization.

Several deep learning models are widely used for plant disease detection, including GoogLeNet, VGG-16, and ResNet-50. Researchers have also explored enhanced and cascaded versions of these architectures, such as CIFAR-10, VGG-Inception, Cascaded AlexNet with GoogLeNet, Modified MobileNet, Modified LeNet, and Modified GoogLeNet.

Residual Networks (ResNet) belong to the CNN family and can be expanded up to 152 layers. Instead of learning direct mappings, ResNet learns residual functions, which simplifies optimization.[18] The architecture also reduces or eliminates unnecessary connections, allowing subsequent layers to learn independently while preserving essential features from earlier layers.

Li et al. conducted a comprehensive review of current trends and challenges in plant disease detection, emphasizing the superior performance of CNNs over traditional classifiers such as Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs).[19] Their findings reinforce the effectiveness of deep learning models in accurately identifying plant diseases.

Wang et al. introduced an advanced deep block attention mechanism integrated with convolutional kernels to enhance the detection of disease-related features.[20] Their study demonstrated that incorporating attention mechanisms significantly improves the precision of plant disease classification.

Delnevo et al. developed a permaculture system that combines deep learning with IoT technology to analyze and classify plant diseases.[21] Their research involved evaluating multiple CNN architectures, assessing their effectiveness in real-world agricultural applications.

Saleem et al. explored the role of deep learning models in horticultural plant disease detection, highlighting the impact of data augmentation techniques in enhancing classification accuracy.[22] Their experiments confirmed that training CNNs with augmented datasets improves their ability to generalize across diverse plant species.

The EfficientNetV2 architecture and its derivatives were employed for detecting diseases in cardamom plants, with the EfficientNetV2-L model demonstrating superior performance in classification tasks.[23] Additionally, a data augmentation technique based on Deep Convolutional Generative Adversarial Networks (DCGANs) was implemented alongside InceptionV3, resulting in a significant improvement in detecting citrus disease severity.[24]

A machine learning-based approach was utilized for the early prediction of leaf blight in tea plants.[25] The study explored how disease lifecycle patterns and environmental factors influence prediction accuracy. To address data scarcity, Generative Adversarial Networks (GANs) were applied, with DoubleGAN generating clearer and more realistic synthetic images to supplement training datasets. Moreover, an optimized EfficientNet-based deep learning framework utilizing mutational learning techniques successfully identified various mutant and diseased leaf genes, further advancing plant disease diagnostics.

Plant disease detection is a crucial aspect of modern agriculture, ensuring early diagnosis and effective management to prevent crop losses. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have revolutionized this process by automatically extracting features from leaf images to classify them as healthy or diseased. The detection pipeline involves image preprocessing, feature extraction using convolution and pooling layers, and final classification through fully connected layers. By leveraging large datasets and advanced neural architectures like ResNet, plant disease detection systems achieve high accuracy, enabling farmers to take timely action. This technology enhances agricultural productivity, reduces dependency on chemical treatments, and promotes sustainable farming practices.

The Figure 1 illustrates a deep learning-based approach for plant disease detection using a Convolutional Neural Network (CNN). The process begins with extracting pixel values from a leaf image, which are then passed through multiple convolutional layers with ReLU activation and pooling operations to extract essential features. These processed features are flattened and fed into a fully connected neural network, which classifies the leaf as either healthy or diseased. This automated method enhances accuracy and efficiency in plant disease diagnosis, allowing for early detection and effective management to improve agricultural productivity and reduce crop losses.

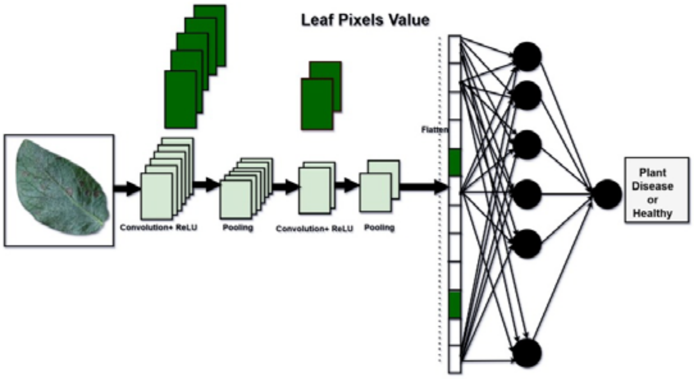

Figure 1. Plant Disease Detection Process

General Architecture of CNN

Convolutional Neural Networks (CNNs) are inspired by the visual cortex of the human brain and are widely utilized in computer vision applications. The fundamental structure of a CNN consists of convolutional layers and fully connected layers. A convolutional block typically comprises convolutional layers followed by pooling layers, which reduce the spatial dimensions of images while preserving important features.

VGGNet Architecture

VGGNet, developed by Simonyan and Zisserman, is a deep CNN architecture with variants containing 11 to 19 layers. It uses a 3×3 convolutional filter uniformly across the network with a stride of 1 pixel. By stacking multiple 3×3 convolutional layers, VGGNet achieves a larger receptive field while maintaining computational efficiency. The VGG16 architecture consists of 13 convolutional layers, 5 max-pooling layers, and 3 fully connected layers, while VGG19 has 16 convolutional layers with similar structural characteristics.

ResNet-50 Architecture

Residual Networks (ResNet) were developed to address the vanishing and exploding gradient issues encountered in deep neural networks. ResNet introduces skip connections, which allow layers to learn residual mappings, preventing gradient degradation and improving network depth efficiency. ResNet-50, a widely used variant, consists of multiple residual blocks with skip connections, ensuring stable gradient flow and efficient deep feature extraction.

PLANT DISEASE IDENTIFICATION SYSTEM

The process of plant disease identification involves multiple stages, from image preprocessing to final classification.

1. **Image Preprocessing**

Objective: Enhance image quality by reducing distortions and improving key visual attributes.

Methods: Geometric transformations such as rotation, scaling, and contrast adjustments are applied.

2. **Image Segmentation**

Objective: Divide an image into meaningful segments to identify relevant regions.

Techniques: Methods such as edge detection, thresholding, and K-means clustering are commonly used.

Tools: Canny edge detection and K-means clustering help extract disease-specific features.

3. **Feature Extraction**

Objective: Identify key features (e.g., shape, texture, and color) that contribute to disease classification.

Common Techniques: Texture analysis is frequently used to distinguish diseased leaves from healthy ones.

4. **Disease Classification**

Objective: Determine whether a plant is healthy or affected by early or late blight.

Methods: Machine learning classifiers analyze extracted features to categorize images into disease classes.

Data Augmentation

The study by Kosaku Fujita et al. focused on reducing overfitting and improving data quality for CNNs through data augmentation techniques.[26] Their approach involved generating additional training samples by introducing controlled noise into existing data. These transformations enhanced model generalization by reducing spatial sparsity and providing more diverse input for training.

Their findings demonstrated that ResNet50 consistently outperformed other models in terms of precision, accuracy, recall, and F1-score, proving its reliability in leaf disease classification. The study also employed data imputation techniques to handle missing values, ensuring dataset integrity. Point imputation was used to replace missing values with the average of corresponding attributes, preserving dataset consistency.

Data augmentation techniques such as random rotation, translation, scaling, and brightness adjustments were applied to improve model adaptability. These techniques significantly enhanced the model's ability to handle real-world variations in agricultural environments, ultimately improving the accuracy of plant disease classification.

METHODOLOGY

Plant leaves are categorized into three distinct groups:

1. Healthy Leaves – No visible spots, appearing fresh and disease-free.
2. Early Blight Leaves – Black spots begin to appear, indicating disease onset.
3. Late Blight Leaves – Extensive damage is visible, with the plant severely affected.

Data Collection and Preprocessing

Data collection is the foundation of supervised machine learning. For this study, images of both healthy and diseased potato leaves were gathered from the PlantVillage dataset, which is publicly available on Kaggle.

Data Preparation and Cleaning

Frameworks Used: TensorFlow Datasets (TFDS) and Data Augmentation techniques.

Data Splitting: The dataset was divided into training, validation, and test sets to evaluate model performance.

Augmentation Methods: To increase dataset diversity, techniques such as image rotation, flipping, and contrast enhancement were applied.

CNN-Based Modeling

CNNs are widely utilized for image classification tasks due to their superior feature extraction capabilities.[27,28] In this study, CNNs were implemented to develop the plant disease classification model.

Model Training

1. The preprocessed dataset was used to train CNN models, optimizing them for disease detection.
2. Trained models were exported as TensorFlow (TF) models for further deployment.

Model Deployment and API Integration

1. The trained CNN model was integrated into a server-based system using TF-Serving with ML-Ops.
2. A REST API was developed to interact with the trained model and classify images.

Web Application Development

1. React.js was used to create an interactive web interface for disease detection.
2. Users could upload plant images, and the system would classify them as healthy, early blight, or late blight.

Model Optimization for Edge Devices

To facilitate deployment on mobile and edge devices, model quantization was applied.

1. Quantization

Objective: Reduce model size for efficient deployment on low-power devices.

Method: Convert floating-point models into TF-Lite models to decrease storage and improve inference speed.

2. Cloud Deployment

Exported TF-Lite models were deployed on Google Cloud and integrated with AWS Lambda-like Google Cloud Functions for efficient processing.

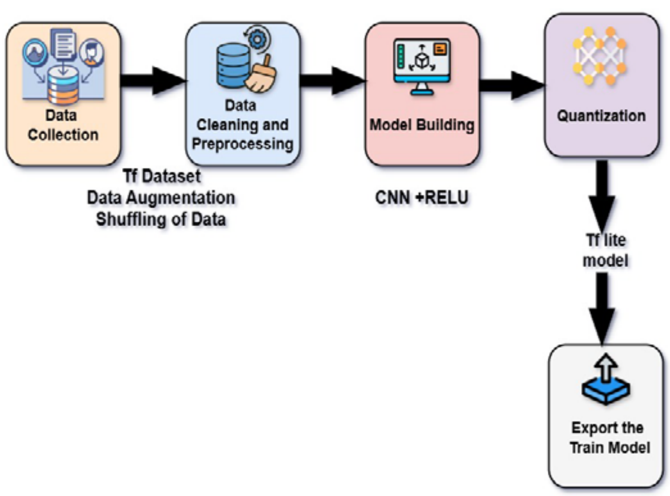

Figure 2. Flowchart of Proposed Methodology

The model was built using TensorFlow and trained on the PlantVillage dataset, which was obtained from Kaggle. As an alternative approach, data can also be collected manually from farmers in the form of annotated images of diseased crops. However, manual data collection is costly due to the computational resources required for processing raw images.

For model training, TensorFlow datasets (tf.data.dataset) and data augmentation techniques were utilized to improve model generalization. Data augmentation operations such as rotation, transformation, and contrast adjustments were applied to generate additional training samples.

Images in the dataset were categorized based on their color space representations, including RGB (Red, Green, Blue), grayscale (black and white), and background segmentation. The dataset contained images of potato, pepper, and tomato leaves, classified into three categories:

- Healthy Leaves – Disease-free and visually intact.
- Early Blight Leaves – Presence of black spots indicating early disease symptoms.
- Late Blight Leaves – Extensive damage with visible bacterial infections.

Figure 3 presents an image of healthy potato leaves, which are clean and free from disease.

Figure 3. Healthy Potato Leaves

Figure 4 illustrates potato leaves affected by Early Blight Disease, characterized by bacterial patches.

Figure 4. Potato Early Blight

Figure 5 shows Late Blight Disease, where the plant is severely damaged.

Figure 5. Potato Late Blight

Figure 6 displays healthy pepper leaves, which are free from any infections.

Figure 6. Pepper Healthy

Figure 7 represents pepper leaves affected by bacterial spots, with visible bacterial strains.

Figure 7. Pepper Bacterial Spot

Deep learning models require large-scale datasets to improve accuracy and mitigate overfitting issues. However, data collection is a time-consuming and resource-intensive process. Additionally, preprocessing and redistributing collected data demand substantial computational effort. To address these challenges, advanced data augmentation and synthetic data generation techniques can be employed to expand dataset size and diversity.

In this study, two advanced strategies were implemented to enhance the dataset:

1. Traditional Data Augmentation Techniques: Common dilation-based transformations such as rotation, blurring, resizing, and shear adjustments were applied. These transformations introduce controlled distortions, ensuring that the model generalizes well across real-world variations.
2. Generative Adversarial Networks (GANs) for Synthetic Data Generation: Generative Adversarial Networks (GANs) were employed to generate synthetic, database-driven semantic data for plant disease classification. GANs consist of two neural networks—a generator and a discriminator—that work together to create highly realistic synthetic images. The generator is responsible for producing artificial images, while the discriminator determines whether the generated images are authentic or synthetic. GAN-based data generation has been widely adopted across various machine learning applications and is often preferred over Restricted Boltzmann Machines (RBMs) and Variational Autoencoders (VAEs) for synthetic data synthesis. This approach significantly enhances model robustness by supplementing training datasets with realistic plant disease images.

Feature Extraction

A Convolutional Neural Network (CNN) was employed for feature extraction, as CNNs are highly effective for image classification tasks. The Modified ResNet50 model was used as a pre-trained feature extractor to enhance accuracy.

Resnet50 architecture

Before discussing the Modified ResNet50, it is essential to understand the ResNet50 architecture.

ResNet-50, as the name implies, is a deep neural network with 50 layers. It processes 100×100 pixel images with three channels (RGB), indicating that it handles colored images. The architecture consists of multiple components, including convolutional layers, activation functions (ReLU), pooling layers, and fully connected layers. Additionally, it incorporates residual connections, which help maintain gradient flow and improve training efficiency. A general breakdown of ResNet-50 layers includes:

- Convolutional Layers – Extract key features from input images.
- Residual Blocks – Enable deeper network training by preventing gradient vanishing.
- Pooling Layers – Reduce spatial dimensions while preserving critical features.
- Fully Connected Layers – Perform final classification based on extracted features.

ResNet50 Network Components

1. Initial Convolutional Layer

- 7×7 convolutional layer with 64 filters and a stride of 2 (reduces spatial dimensions).
- Followed by batch normalization and ReLU activation.

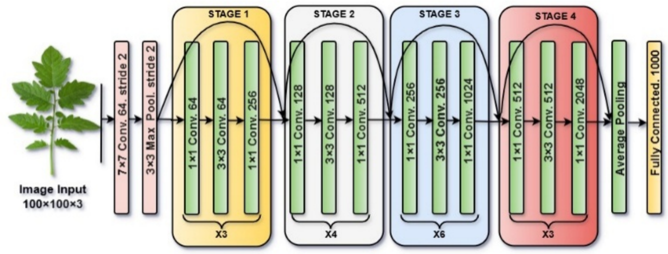

Figure 8. ResNet50 Architecture

2. Max Pooling Layer
   3×3 max-pooling layer with a stride of 2.
3. Residual Blocks (x4)
   - Four groups of residual blocks, each containing multiple convolutional layers.
   - Uses 1×1, 3×3, and 1×1 convolution layers with batch normalization and ReLU activation.
   - Skip connections allow gradient flow across deep layers.
4. Global Average Pooling Layer
   Reduces feature map size to 1×1, improving classification efficiency.
5. Fully Connected Layer
   Maps feature vectors to output classes.

MODIFIED RESNET50 ARCHITECTURE

To improve the performance of ResNet50 for plant disease detection, several modifications were introduced to enhance its feature extraction capability, computational efficiency, and classification accuracy. The modifications aim to optimize the model for detecting subtle disease symptoms while maintaining a lightweight and scalable architecture suitable for real-world agricultural applications.

Key Modifications Implemented in ResNet50:

1. Enhanced Data Augmentation Techniques

Applied advanced augmentation strategies such as random rotation, flipping, contrast adjustments, and brightness normalization to increase dataset diversity and improve generalization.

2. Optimized Training and Hyperparameter Tuning

- Implemented the ADAM optimization algorithm with a learning rate of 0.001 to achieve faster convergence and better weight adjustments.
- Used pre-trained ImageNet weights to initialize the model, leveraging transfer learning for improved accuracy.
- Utilized categorical cross-entropy as the loss function to handle multi-class classification effectively.

3. Architectural Refinements

- Removed redundant intermediate layers to improve computational efficiency.
- Adjusted the final bottleneck block to maintain a stride of 1, ensuring that spatial resolution is preserved for fine-grained feature extraction.
- Modified the initial convolutional layer by setting the stride to 1, enabling the use of pre-trained weights more effectively.
- Introduced dilated convolutions with a dilation rate of 2, allowing the model to capture broader contextual information.

4. Custom Convolutional Layers for Feature Enhancement

- Incorporated a 1×1 convolutional layer with two custom feature maps, dynamically adjusting the number of feature maps based on disease classification complexity.
- This modification enhances the model’s ability to differentiate between similar plant disease patterns.

5. Incorporation of Lp Norm Normalization

- Added an Lp norm normalization layer to refine feature aggregation and improve classification accuracy.
- The normalization method varies based on task requirements:
- L1 pooling is used for average feature extraction.
- L∞ pooling is applied for maximum feature selection, improving sensitivity to disease symptoms.

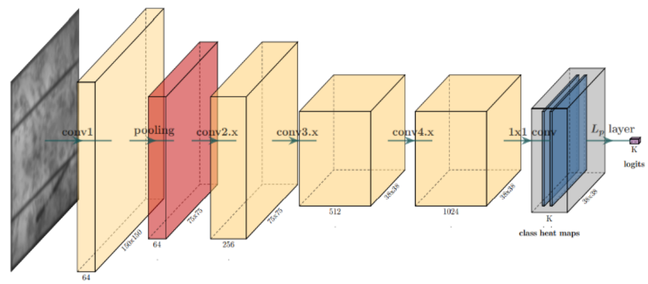

Figure 9. Modified ResNet50 Architecture

Modified ResNet50 Algorithm

The Modified ResNet50 Algorithm is structured to enhance plant disease classification by incorporating attention mechanisms, adaptive pooling, and feature recalibration techniques. Below is the step-by-step approach:

Step 1: Data Preprocessing and Augmentation

- Load and preprocess the dataset (e.g., PlantVillage dataset).
- Apply data augmentation techniques:
- Random rotation, flipping, scaling, contrast adjustments, and brightness normalization.
- Convert all images to 224×224 pixel size (ResNet50 input requirement).
- Normalize pixel values to range [0,1] for stable model training.
- Split the dataset into training, validation, and test sets.

Step 2: Load Pre-Trained ResNet50 and Modify Architecture

- Load ResNet50 with ImageNet pre-trained weights.
- Modify the first convolutional layer: Adjust the stride to 1 for improved spatial resolution retention.
- Introduce attention mechanisms: Add spatial and channel-wise attention layers to improve focus on diseased regions.
- Integrate adaptive pooling layers to enhance feature selection.
- Apply feature recalibration techniques to prioritize important features while reducing noise.
- Replace the fully connected layer with a custom classifier:
- Use Softmax activation for multi-class disease classification.

Step 3: Model Compilation and Hyperparameter Optimization

- Compile the model using Adam optimizer with learning rate 0.001:

- Use categorical cross-entropy loss function for multi-class classification.
- Apply batch normalization to improve gradient stability.

Step 4: Model Training and Evaluation

- Train the model for 10-50 epochs, depending on dataset size.
- Use early stopping to prevent overfitting.
- Monitor training and validation accuracy/loss:
- Evaluate model performance on test data.
- Generate the classification report and confusion matrix to analyze misclassifications.

Step 5: Model Deployment and Optimization

- Quantize the model for mobile and edge devices:
- Deploy the model to Google Cloud or AWS Lambda for real-time disease detection.
- Develop a web/mobile interface using React.js for user-friendly plant disease identification.

Step 6: Real-Time Prediction and Classification

- Upload or capture an image of a plant leaf.
- Preprocess the image (resize, normalize, augment).
- Run the image through the Modified ResNet50 model to predict disease class.
- Display the classification results with confidence scores.

Model Training

Before training, fine-tuning the model is essential to adjust its weights for improved performance in specific classification tasks. The model is trained using labeled training data, and its performance is assessed using a validation dataset. To optimize learning, categorical cross-entropy is used as the loss function, while the Adam optimization algorithm is applied for efficient weight updates and faster convergence.

Distinction between Existing Methods and the Proposed Approach

Traditional deep learning techniques for plant disease detection primarily rely on architectures like VGG16, VGG19, GoogLeNet, and InceptionV3. While these models have shown effectiveness in image classification tasks, they often struggle with capturing subtle variations in plant diseases. Additionally, these architectures require extensive computational resources and do not incorporate mechanisms to focus on disease-affected regions, which can lead to misclassification. Similarly, the standard ResNet50 model has been widely adopted due to its skip connections, which mitigate vanishing gradient issues. However, in its original form, ResNet50 lacks adaptive pooling layers, feature recalibration techniques, and attention mechanisms, limiting its ability to differentiate between similar plant disease symptoms.

The Modified ResNet50 architecture presented in this study introduces several novel enhancements to address these limitations. Firstly, attention mechanisms have been incorporated, allowing the model to prioritize disease-affected regions of the plant leaves. This ensures a higher focus on relevant features, leading to improved classification accuracy. Secondly, the inclusion of adaptive pooling layers enhances feature selection, making the model more robust across different plant species and environmental conditions. Another key innovation is the use of feature recalibration techniques, which refine channel-wise learning and enable the model to distinguish between important and redundant features. Furthermore, transfer learning strategies have been employed by leveraging pre-trained ImageNet weights, significantly improving model convergence and accuracy. Lastly, data augmentation techniques, including GAN-generated synthetic images, have been integrated to increase dataset diversity, helping the model adapt to previously unseen plant diseases. These modifications collectively make the proposed model more efficient, accurate, and generalizable compared to existing methods.

RESULTS AND DISCUSSION

A key advantage of the Modified ResNet50 architecture is its ability to focus on disease-affected regions of plant leaves, which significantly enhances classification accuracy. The inclusion of attention mechanisms and feature recalibration techniques allows the model to prioritize relevant visual features, improving its ability to differentiate between healthy and diseased plants. Compared to traditional CNN architectures such as VGG16, VGG19, and GoogLeNet, the proposed model exhibits better feature extraction efficiency, particularly in cases where plant diseases manifest as subtle variations in color and texture.

The Modified ResNet50 model was extensively tested on the Kaggle PlantVillage dataset containing 3,000 previously unseen test images, where it achieved an accuracy of 98.90% over 10 training epochs. The training, validation, and test loss graphs illustrate the accuracy attained at the end of each epoch. The training and validation loss curves indicate a steady decline in loss values, confirming that the model effectively learns disease patterns from the dataset. Furthermore, the accuracy graph illustrates consistent improvement, demonstrating the model's ability to generalize across different plant species and disease categories.

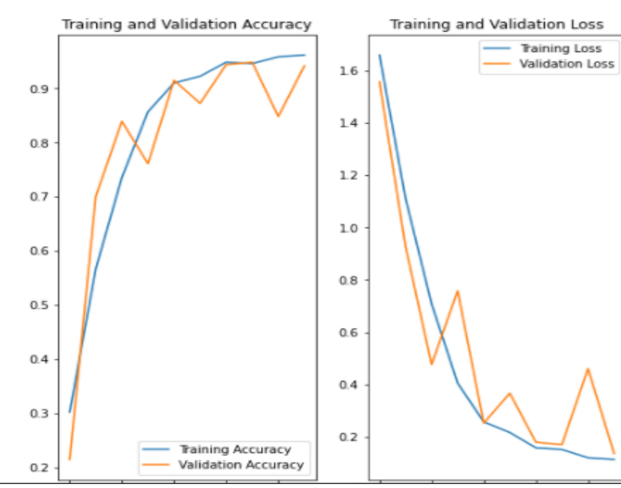

Figure 10. Training, Validation Accuracy and Loss

As observed in the graph, increasing the number of epochs significantly reduces training and validation loss, indicating improved model convergence.

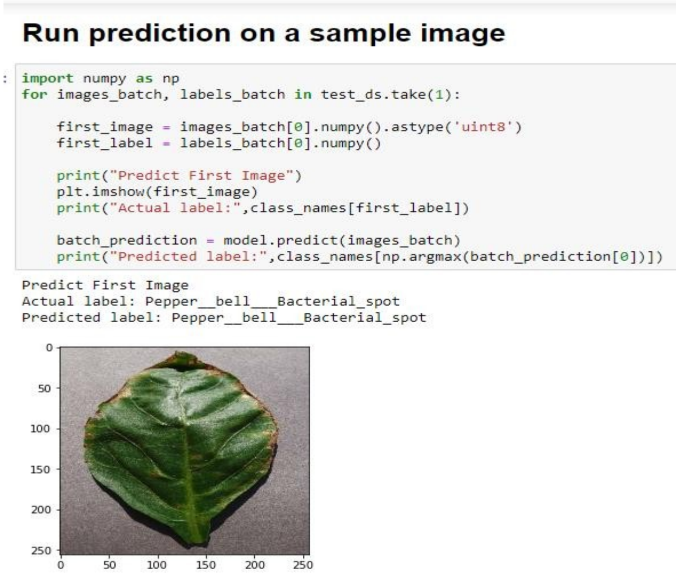

Figure 11: Prediction on Sample Image

Figure 12. Result shows Potato is Healthy and is 79.02% Confident

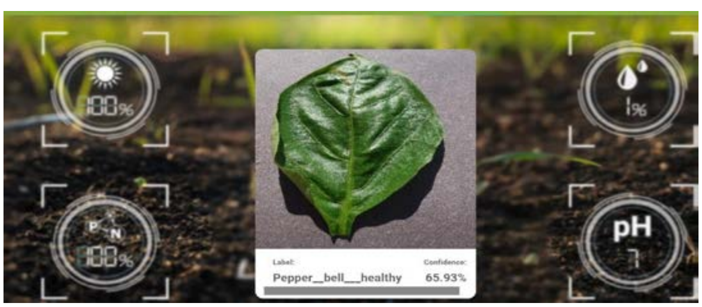

Figure 13. Result shows Pepper Leaf is Healthy and is 65.93% Confident

When evaluated on sample test images, the model correctly classified a healthy potato leaf with 79.02% confidence. However, in the case of a pepper leaf, the model predicted it as healthy with only 65.93% confidence, suggesting a higher probability of misclassification. This indicates that while the model performs well overall, certain plant categories may require further fine-tuning to achieve higher classification confidence. The model's ability to correctly classify plant diseases depends heavily on dataset diversity and the presence of high-quality annotated samples. Expanding the training dataset to include more diverse disease variations and environmental conditions can further improve classification confidence.

A comparative analysis was conducted to assess the performance of Modified ResNet50 against existing deep learning architectures used for plant disease detection is given in Table 1.

Table 1: Comparative Analysis of Deep Learning Models for Plant Disease Detection

Model	Accuracy (%)	Key Features
VGG16	91.20%	Basic CNN with deep layers
GoogLeNet	93.45%	Inception modules for deeper learning
Standard ResNet50	95.78%	Skip connections to prevent gradient vanishing
Modified ResNet50	98.90%	Attention mechanisms, adaptive pooling, and feature recalibration

The results confirm that Modified ResNet50 outperforms traditional deep learning models, largely due to its enhanced feature selection capabilities. While VGG16 and GoogLeNet provide good results, their reliance on standard convolutional operations limits their ability to capture fine-grained disease features. In contrast, the proposed Modified ResNet50 model efficiently extracts and prioritizes disease-related patterns, improving classification accuracy.

The model's performance in real-world agricultural scenarios was also examined. Training without a GPU took approximately four hours, highlighting the computational demands of deep neural networks. While validation and testing were significantly faster, real-time deployment in field conditions may require further optimization techniques such as model quantization to enable use on mobile and edge devices. Additionally, while the Modified ResNet50 model outperforms standard deep learning approaches, it still faces challenges in handling ambiguous cases, particularly when different plant diseases exhibit similar visual symptoms. Addressing these limitations in future research will further enhance the model's real-world applicability and accuracy.

The results obtained from the modified ResNet50 architecture for plant disease detection highlight its remarkable effectiveness. Achieving an impressive accuracy of 98.90% on the Kaggle PlantVillage dataset, the model demonstrates its potential as a game-changer in agricultural diagnostics. This significant performance boost is largely driven by the integration of attention mechanisms, adaptive pooling layers, and feature recalibration strategies, which collectively enhance the model's ability to focus on the most critical features of diseased leaves. As a result, it can accurately identify subtle variations, making it particularly effective in detecting early-stage plant diseases.

A key advantage of this approach is its ability to significantly reduce the time and resources required for disease diagnosis compared to conventional methods. By automating the detection process through deep learning, farmers can receive faster and more reliable insights, enabling timely interventions. This proactive disease management not only improves crop health but also mitigates potential economic losses caused by undetected or late-identified plant infections.

The incorporation of transfer learning using pre-trained weights from the ImageNet dataset has further enhanced the model's generalization capability. This allows the architecture to perform effectively across diverse datasets, making it adaptable for various crops and environmental conditions. Such versatility is vital for scaling the solution in precision agriculture applications.

Future research should focus on optimizing the model for real-time applications and improving its robustness against dataset biases. Additionally, integrating this system with IoT platforms and mobile applications could facilitate on-field disease detection, making advanced diagnostic tools more accessible to farmers. This would foster smarter agricultural practices, ultimately boosting productivity and sustainability.

CONCLUSION

This study presents Modified ResNet50 architecture for plant disease detection, integrating attention mechanisms, adaptive pooling layers, and feature recalibration techniques to enhance classification accuracy. The proposed model addresses the limitations of traditional deep learning approaches, such as VGG16, GoogLeNet, and standard ResNet50, by improving feature extraction and prioritization of disease-affected regions. Through transfer learning and advanced data augmentation, the model achieves 98.90% accuracy, demonstrating superior performance in identifying various plant diseases. The findings of this study reinforce the importance of deep learning-based plant disease detection in improving agricultural productivity.

This research contributes significantly to precision farming and smart agriculture, offering farmers and agronomists a powerful tool for early disease diagnosis. By leveraging deep learning for automated plant health monitoring, this study lays the foundation for sustainable agricultural practices, enhanced food security, and improved crop yield management. The successful development of the Modified ResNet50 model has significant implications for agriculture, food security, and precision farming. The findings emphasize the pivotal role of deep learning in transforming the agricultural sector by promoting sustainable practices and enhancing food security. Through early and accurate disease detection, farmers can make informed decisions that lead to more effective crop management while reducing dependency on harmful chemicals. This proactive approach not only safeguards crop health but also supports eco-friendly farming practices, contributing to long-term agricultural sustainability. losses.

In conclusion, the modified ResNet50 architecture marks a significant advancement in plant disease detection and holds substantial potential for broader applications in precision farming. Its continued refinement and integration into agricultural workflows will be essential in addressing global food security challenges. By equipping farmers with more efficient and accessible diagnostic tools, this technology paves the way for a more resilient and sustainable agricultural future. With further optimizations, this model can be integrated into mobile and cloud-based applications, enabling farmers and agronomists to perform real-time disease detection using smartphone cameras.

CONFLICT OF INTEREST STATEMENT

Authors declare no conflict of interest exists.

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