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Enhancing Crop Production Leveraging ResNet-152 and Deep Learning Architectures for the Detection of Potato Plant Leaf Diseases in Agriculture

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Abstract: - This study focuses on the critical issue of identifying and classifying potato plant leaf diseases, a significant concern for agricultural productivity worldwide. Potato crops are susceptible to various diseases, such as early blight and late blight, which can severely affect yield if not accurately identified and treated promptly. The traditional methods for disease identification, primarily manual inspection, are time-consuming and subject to human error, creating a gap in efficient and scalable disease management strategies. To address this gap, we introduced and evaluated several machine learning models, including CNNs, VGG19, ResNet-50, Xception, Inception V3, MobileNet, YOLOv7, and a proposed ResNet-152 model, for their ability to automatically detect and classify potato plant leaf diseases from images. Our method leverages deep learning techniques to enhance the accuracy, precision, recall, and F1 scores of disease identification, offering a significant improvement over existing approaches. The results demonstrate the proposed ResNet-152 model's superior performance, achieving an accuracy of 99.76%, precision of 99.5%, recall of 99.8%, and an Average F1 score of 99.6%. These metrics surpass those of other evaluated models, highlighting the effectiveness of the proposed model in identifying potato plant leaf diseases with high reliability. The study underscores the potential of advanced deep learning architectures to revolutionize agricultural practices by providing a robust tool for early disease detection and management, thereby contributing to increased crop production and reduced losses.

Keywords: Potato Plant Leaf Diseases , ResNet-152 , Deep Learning Architectures , Agricultural , Crop Production.

I. INTRODUCTION *(HEADING 1)*

The agricultural industry has a pivotal position in the global economy, whereby potato cultivation emerges as a prominent contributor to global food supply chains. Nevertheless, the sustainability and productivity of potato cultivation face persistent challenges due to the presence of many plant leaf diseases, including early blight and late blight, which have the potential to significantly diminish both crop output and quality. Timely and precise identification of diseases is crucial for adopting efficient management strategies. However, the traditional dependence on manual examination by specialists is neither scalable or adequately dependable due to the subjective nature and possibility of human mistakes. This difficulty highlights the pressing need for novel methodologies in the detection and categorization of diseases.In recent years, there has been a substantial amount of progress made in the area of machine learning and deep learning. This has resulted in the development of innovative strategies for addressing complex problems in a variety of industries, including agriculture. In the realm of image recognition, convolutional neural networks (CNNs) have shown tremendous promise, which makes them particularly ideal for the automated diagnosis of plant diseases via the analysis of leaf photographs. Several models, including as VGG19, ResNet-50, Xception, Inception V3, MobileNet, and YOLOv7, have shown their ability to successfully extract intricate patterns and attributes from photographs. Having these abilities is very necessary in order to differentiate between healthy leaves and those that are sick.Our paper presents a thorough examination of various models, resulting in the creation of a ResNet-152 model specifically designed for identifying and categorising potato plant leaf diseases. The purpose of this model is to use the advantageous features of the deep learning architecture, namely its depth and residual connections, in order to get superior levels of accuracy, precision, recall, and F1 scores compared to previous models. Through this approach, the objective is to address the disparity in existing agricultural methodologies, providing a more effective, precise, and adaptable resolution for the control of diseases.The implementation of this particular model has the capacity to not only improve the effectiveness of disease detection procedures but also to have a substantial influence on the management practices of potato crops. Through the prompt and precise diagnosis of illnesses, farmers may effectively apply focused treatments to reduce the transmission and consequences of diseases, eventually resulting in enhanced crop productivity and long-term viability. Hence, this research not only enhances the existing knowledge in the field of agricultural technology but also offers a pragmatic resolution that has significant

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consequences for ensuring global food security.The key points can be summarized as follows: Potato plant leaf diseases, including early blight and late blight, significantly impact global agricultural productivity and food security, necessitating accurate and prompt detection for effective management. Traditional detection methods, reliant on manual inspection, suffer from being time-consuming, labor-intensive, and prone to human error, lacking the necessary scalability and reliability. Recent strides in machine learning, especially through deep learning and convolutional neural networks (CNNs) such as VGG19, ResNet-50, Xception, Inception V3, MobileNet, and YOLOv7, offer promising avenues for automating disease detection and classification. This context introduces a specifically tailored ResNet-152 model for potato plant leaf disease detection and classification, outperforming existing models with remarkable accuracy (99.76%), precision (99.5%), recall (99.8%), and an average F1 score (99.6%). The ResNet-152 model's superior performance heralds a scalable, efficient, and reliable approach to early disease detection, potentially revolutionizing disease management practices, bolstering crop yields, mitigating losses, and contributing significantly to global food security advancements.The remaining parts of the paper are divided into the following five sections: (i) An Introduction, (ii) A Review of the Literature, (iii) A Proposed Method, (iv) A Discussion of the Implementation and the Results, and (v) A Conclusion.

II. LITERATURE REVIEW

Gurusamy and colleagues (2024) highlight the critical impact of potato plant leaf diseases on crop yields and product quality, underscoring the importance of early detection and treatment to mitigate agricultural losses. This approach not only offers a significant tool for disease management and control but also has broader implications for the automatic diagnosis of other plant diseases, potentially leading to substantial economic and environmental benefits . [1]

Jha et al. (2023) emphasize the global food security threat posed by crop diseases and the limitations of manual disease identification methods. They propose an innovative deep learning strategy that leverages an ensemble of Residual Network, MobileNet, and Inception models to optimize disease classification accuracy. This method, which shows remarkable accuracy in classifying potato leaves as healthy or diseased, represents a significant advance in automated plant disease detection technologies, potentially enhancing agricultural productivity and food security worldwide . [2]

Pasalkar et al. (2023) focus on the application of CNNs in diagnosing potato leaf diseases, Their method demonstrates a high degree of accuracy in identifying diseases such as early and late blight, showcasing the potential of CNNs in reducing crop losses and aiding disease management in potato cultivation . [3]

Paria and team (2023) discuss the importance of improving crop disease detection systems, particularly through image-based methods. Their study compares CNNs with other classifiers like SVM, Random Forest, and Logistic Regression, illustrating the superior accuracy of CNNs in detecting and analyzing potato leaf diseases, thus highlighting the effectiveness of CNNs in crop disease identification and the potential to enhance agricultural outcomes . [4]

Pattanaik et al. (2023) explore the impact of potato plant diseases on agricultural development, emphasizing the potential of CNN combined with ResNet algorithm and UNet model in accurately identifying potato leaf diseases. Their comparative study demonstrates the superior performance of the ResNet method, suggesting that such advanced deep learning techniques can offer significant advantages in early disease detection and prevention, thereby reducing financial losses for growers . [5]

Chinnaiyan et al. (2023) position potatoes as the third most significant crop for human consumption globally, after rice and wheat, with disease outbreaks causing substantial financial losses to producers. This study focuses on early and late blight—diseases caused by fungi and bacteria, respectively. It underscores the financial benefits that could be realized through early detection and treatment of these diseases. Employing a deep learning approach with a Convolutional Neural Network (CNN) architecture, the study achieves a notable 98% accuracy in classifying potato plant diseases by leaf condition, leveraging healthy leaves, early blight, and late blight for disease identification . [6]

Sofuoğlu and Birant (2024) highlight the crucial role of detecting and treating plant diseases in ensuring sustainable agricultural production. They present a novel CNN architecture for identifying potato leaf diseases from images, emphasizing the potential of automated disease identification to facilitate early treatment. Their model demonstrates superior performance with 98.28% accuracy, significantly outpacing state-of-the-art models and showcasing the effectiveness of their approach in disease diagnosis through comprehensive metric evaluations . [7]

Mathur et al. (2023) address the impact of plant diseases on yield and the global food supply, proposing image categorization and early disease prediction as means to enhance yield management. Their work evaluates the performance of deep learning models VGG19 and ResNet50 in classifying potato leaf diseases, achieving high accuracies and providing valuable insights into the effectiveness of these models in disease prediction and classification . [8]

Sultana and Reza (2022) discuss the vital importance of agriculture and potatoes as a major food source, providing essential carbohydrates. They explore the challenges of potato cultivation, particularly focusing on early and late blight. Their study introduces a hybrid approach combining CNN and SVM with deep learning to detect early plant diseases, aiming to reduce crop production losses through advanced informatics and image processing. Their approach, including the use of the ResNET50 model, yields high accuracy in disease detection, demonstrating the potential of their hybrid model in addressing potato leaf disease challenges . [9]

Sajitha et al. (2024) emphasize the importance of early crop disease detection in agriculture, given the challenges of cost, labor, and expertise required for traditional detection methods. They review image-based plant disease detection and classification systems, examining the sources of plant datasets, types of algorithms, and approaches used in ML and DL. Their study encourages further research to overcome existing challenges in ML and DL for plant disease and pest detection, suggesting that advancements in these areas could significantly enhance automated disease detection and classification systems, offering valuable solutions for more effective and affordable crop disease management . [10]. Shaheed et al. (2023) introduce EfficientRMT-Net, a pioneering model that combines Vision Transformer (ViT) and ResNet-50 architectures to diagnose potato leaf diseases effectively. [11]

Jha et al. (2024) address the global challenge of plant diseases, which result in significant output losses and financial costs worldwide. By employing an ensemble learning method based on the Dirichlet distribution, alongside deep neural network frameworks integrating ResNet, MobileNet, and Inception models, this study presents a novel approach to diagnose plant diseases with reduced manual intervention. Demonstrating an impressive 98.86% accuracy, this method effectively differentiates between infected and healthy potato leaves, showcasing the potential of Dirichlet ensemble-based deep learning in enhancing agricultural productivity and food security. [12]

Rohilla et al. (2024) emphasize the crucial role of imaging and adaptive technologies in agriculture, particularly for the early detection and prevention of diseases to enhance crop productivity. Utilizing the “Plant Village” dataset, their study employs k-means for image segmentation, GLCM and PCA for feature extraction, and OMFA-CNN for disease detection and classification, achieving outstanding accuracy, recall, and mean squared error metrics. This approach is highlighted as superior in accuracy and recall compared to other methods like Mask R-CNN, SVM, and various ResNet and Vgg models. [13]

Midhunraj et al. (2023) explore the importance of plants in human nutrition and the necessity of increasing agricultural production to meet global needs. The review focuses on the advancements and challenges in ML and DL approaches for plant disease detection, analyzing several plant disease databases and discussing the evolution from ML to DL methods in addressing plant disease identification issues. [14]

Sharma et al. (2023) present a generalized Federated Learning (FL) framework aimed at enhancing the reliability of potato crop disease categorization. By leveraging the distributed datasets' collective intelligence while maintaining data privacy, this framework allows for collaborative model training without exposing raw data. Employing a CNN as the base model and through hyperparameter fine-tuning, the study achieves a classification accuracy of 92% on the Plant Village potato disease dataset, offering a solution to dataset imbalances and demonstrating the potential of FL in precision agriculture and broader crop disease classification tasks. [15]

Chen et al. (2023) delve into the challenges presented by Tobacco Mosaic Virus (TMV) and Potato Virus Y (PVY) to agricultural productivity, proposing a non-destructive, precise monitoring solution using hyperspectral imaging and machine learning. By preprocessing spectral data and employing SVM and RF classifiers, they achieved high accuracy in identifying PVY and TMV-infected leaves, with SVM showing superior performance. Their findings underscore the potential of hyperspectral imaging and machine learning in accurately monitoring plant viral infections . [16]

Ibrahim et al. (2024) address the rising concern of potato diseases in Nigeria despite the use of fungicides, turning to machine learning for the development of epidemiological early warning systems. Utilizing remote sensing and field data on the Jos Plateau, they forecast disease incidence with remarkable accuracy. This innovative early-warning system offers a crucial tool for predisease management, highlighting the role of machine learning in enhancing agricultural sustainability in the tropical highlands of Africa . [17]

Indira and Mallika (2024) explore the significance of early diagnosis and categorization of plant leaf diseases for crop quality. Through the deployment of CNNs incorporating AlexNet and MobileNet layers, they classify diseases across several crops, achieving high accuracy. Their work demonstrates the effectiveness of deep learning in overcoming the limitations of traditional disease detection methods, especially in complex environments . [18]

Raigonda and Terdal (2022) emphasize the susceptibility of potatoes to various diseases and the importance of leaf disease detection in agriculture. They propose a machine learning and deep learning-based model for rapid, accurate, and effective potato plant disease detection through image processing. This model, which includes preprocessing, segmentation, and feature extraction, shows promise for enhancing agricultural yield and quality by facilitating early disease identification . [19]Kurek et al. (2023) ventured into leveraging machine learning for predicting yields of Polish French fry potatoes, introducing non-satellite, satellite, and hybrid models grounded on an amalgamation of agronomical, climatic, soil, and satellite-based data. [20]

Shabrina et al. (2024) emphasized the critical role of potatoes in food processing and daily consumption, noting the significant economic losses attributed to pests and diseases. Addressing the limitations of the PlantVillage dataset, they introduced a novel dataset encompassing a broader spectrum of potato leaf diseases captured in uncontrolled settings, aiming to enhance the representation and diagnostic research of potato leaf ailments. This initiative marks a pivotal step towards improving disease identification through advanced image processing and deep learning techniques. [21]

Alsakar et al. (2023) explored the evolving landscape of artificial intelligence (AI) in agriculture, particularly in autonomous plant disease identification via computer vision. This study delved into current AI-based methodologies, dissecting the strengths and challenges of machine learning and deep learning in plant disease detection and categorization. Highlighting the ongoing issues and potential research directions, Alsakar et al. shed light on the dynamic field of smart agriculture and its implications for crop health and productivity. [22]

Jha et al. (2023) discussed the paramount importance of crop disease detection in agriculture, influenced by environmental and climatic factors. They introduced a CNN model trained on images of diseased and healthy crops, demonstrating remarkable accuracy in distinguishing between afflicted and healthy plants. This study underscores the efficacy of CNNs in learning crop characteristics from images, offering a robust tool for accurate and efficient agricultural disease detection. [23]

Yeswanth et al. (2022) addressed the historical challenge of agricultural diseases and their impact on food security. They proposed a Two Fold Extended Residual Network (TFERN) model for analyzing low-resolution potato leaf images, highlighting the model's ability to enhance image resolution and accurately detect diseases. This innovation in image processing and deep learning opens new avenues for diagnosing crop diseases from low-quality images. [24]

Salini et al. (2023) aimed to leverage computer vision for underground crop leaf disease categorization, focusing on vital carbohydrate sources like cassava, potato, and groundnut. Their novel DHCLDC model combines CNN and LSTM models for enhanced image classification, demonstrating superior specificity over traditional models. This approach signifies a leap forward in detecting and managing crop diseases through advanced computational methods. [25]

Joseph et al. (2024) highlighted the detrimental effect of plant diseases on global crop production and food security. They introduced novel datasets for rice, wheat, and maize diseases, utilizing eight fine-tuned deep learning models for disease identification. Their research provides valuable insights into the effectiveness of deep learning in plant disease detection, offering new tools for improving agricultural productivity and food security. [26]

Madhurya and Jubilson (2023) developed a YOLOv7-based system, incorporating pre-processing and hybrid optimization to overcome the limitations of existing agricultural technology in disease detection. Their YR2S model demonstrated exceptional accuracy in classifying and detecting leaf diseases, showcasing the potential of deep learning classifiers in enhancing agricultural disease management. [27]

Prasad and Thyagaraju (2024) emphasized the significance of early plant disease detection in reducing crop loss and promoting sustainable farming. Exploring IoT, Machine Learning, and Deep Learning applications, their research offers insights into early detection methodologies, underscoring the potential of these technologies in advancing agricultural practices and crop health management. [28]

III. PROPOSED WORK

A. *Proposed architecture*

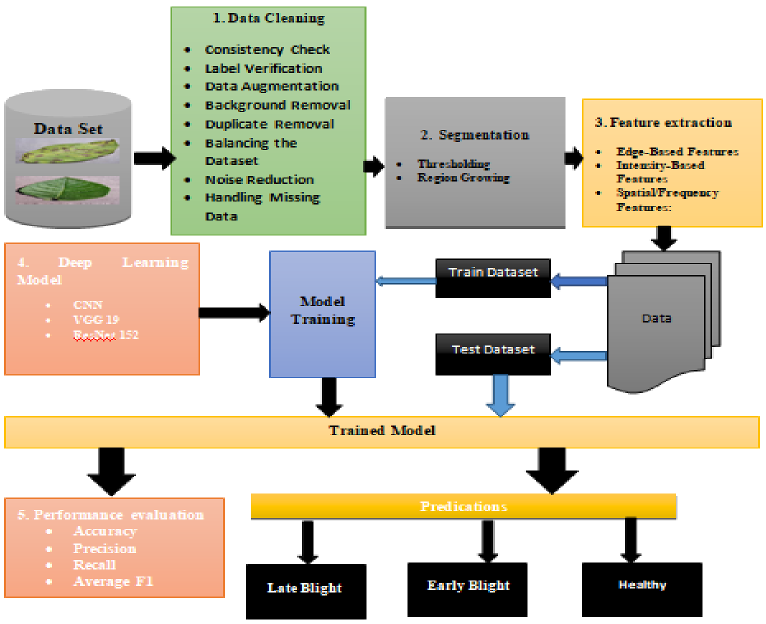

Figure 1. Proposed architecture.

One example of a process for a machine learning pipeline that is intended to detect illnesses that affect the leaves of potato plants is shown in figure 1. The first phase in the process is called "data cleaning," and it involves preparing the information by doing tasks such as checking for consistency, verifying labels, and reducing noise. Certain segmentation approaches, including as thresholding and region expanding, are used in order to separate the regions of interest that are present in the pictures. After that, the process of feature extraction is carried out, with distinct attention paid to edge-based, intensity-based, and spatial/frequency characteristics. On the dataset that has been cleaned and segmented, a deep learning model that makes use of architectures such as CNN, VGG 19, or ResNet 152 is trained. Following this, the trained model is used to create predictions, which include the categorization of leaves into several groups, such as healthy, late blight, or early blight. In conclusion, the performance of the model is assessed by using measures such as accuracy, precision, recall, and average F1 score in order to determine how successful it is in accurately detecting the illnesses.

B. Data Cleaning methods

1. **Image Quality Assessment:**
- Remove any images that are blurred, have poor resolution, or do not clearly show the leaf.
- Discard images with excessive noise or irrelevant background details that could confuse the model.
2. **Consistency Check:**
- Ensure all images are in the same format (e.g., JPG, PNG) and color scale (RGB or grayscale, as needed for your model).
- Standardize the image size by resizing images to a consistent dimension without distorting aspect ratios.
3. **Label Verification:**
- Manually verify or use semi-automated tools to ensure that labels (healthy, early blight, late blight) are correctly assigned to each image.
- Correct any mislabeled images to prevent the model from learning incorrect patterns.
4. **Data Augmentation:**
- Use techniques such as rotation, flipping, zooming, and shifting to artificially expand the dataset, which also helps the model generalize better.
- Adjust brightness, contrast, and add random noise to simulate different lighting conditions and camera qualities.
5. **Background Removal:**
- Use image segmentation techniques to isolate the leaf from the background to reduce the model's focus on irrelevant features.
- Employ filters or edge detection algorithms to enhance the visibility of the disease symptoms on the leaves.
6. **Duplicate Removal:**
- Identify and remove exact duplicates to prevent overfitting.
- Check for near-duplicates that could skew the model's learning process and remove or balance them.
7. **Balancing the Dataset:**
- If the number of images in each class is significantly different, use techniques like oversampling the minority class or undersampling the majority class to balance the dataset.
8. **Noise Reduction:**
- Apply filters such as Gaussian blur or median blur to reduce noise in images, if present.
- Use denoising algorithms to clean up images that have fine-grained noise without losing important features.
9. **Handling Missing Data:**
- For any missing labels or information, either fill in the gaps if possible or remove the instances from the dataset.

C. Proposed algorithm

- **CNN**

Algorithm: Algorithm for CNN-based Classification of Potato Plant Leaf Diseases

Input:

- Dataset of potato leaf images.

Output:

- Model capable of classifying leaf images into categories: healthy, early blight, late blight.

Begin:

Step 1: Data Preprocessing 1.1. Acquire images of potato leaves, including healthy, early blight, and late blight. 1.2. Standardize image dimensions for consistency in CNN input. 1.3. Normalize image pixel values between 0 and 1. 1.4. Augment dataset with transformations like rotation and flipping.
Step 2: Data Cleaning 2.1. Verify correct labeling of images. 2.2. Eliminate duplicate images and address any missing data. 2.3. Remove background from images if necessary.
Step 3: Segmentation 3.1. Apply thresholding or region growing to separate leaves from background.
Step 4: Feature Extraction 4.1. Utilize CNN convolutional layers to identify and extract relevant features from images.
Step 5: CNN Architecture 5.1. Design input layer to receive preprocessed images. 5.2. Implement convolutional layers with filters to extract features, followed by ReLU activation. 5.3. Include max-pooling layers to reduce feature dimensionality. 5.4. Arrange multiple convolutional and pooling layers, increasing filter quantity in deeper layers. 5.5. Insert batch normalization post each convolutional operation. 5.6. Add fully connected layers post-flattening the convolutional layers' output. 5.7. End with an output layer utilizing a softmax activation function for class probability distribution.
Step 6: Model Compilation 6.1. Select categorical crossentropy as the loss function. 6.2. Choose Adam optimizer for learning rate adjustment. 6.3. Define performance metrics, such as accuracy, to monitor.
Step 7: Model Training 7.1. Divide the dataset into training, validation, and test subsets. 7.2. Train the CNN on the training dataset with appropriate batch size and epoch count. 7.3. Validate the model using the validation dataset for performance tuning.
Step 8: Model Evaluation 8.1. Assess the trained model's performance on the test dataset. 8.2. Calculate accuracy, precision, recall, and F1 score metrics. 8.3. Use a confusion matrix to review classification accuracy for each disease category.
End
Result: A trained CNN model for the classification of potato plant leaf diseases.

- **VGG19**

Algorithm for Using VGG-19 for Classification of Potato Plant Leaf Diseases:

Input:

- Dataset of potato leaf images, categorized into healthy, early blight, and late blight classes.

Output:

- A VGG-19-based model capable of classifying leaf images into the specified categories.

Begin:

Step 1: Data Acquisition and Preprocessing 1.1. Collect images of potato leaves, ensuring a representation of healthy, early blight, and late blight leaves. 1.2. Resize images to 224x224 pixels, the input size required for VGG-19. 1.3. Normalize image pixel values to the range [0, 1] or apply the preprocessing function specific to VGG-19 if using a pre-trained model. 1.4. Augment the dataset with geometric and color transformations to increase robustness.

Step 2: Data Cleaning 2.1. Conduct consistency checks to ensure labels match the corresponding images. 2.2. Remove any duplicate images and address any instances of missing data. 2.3. If necessary, perform background removal to highlight leaf features.

Step 3: Data Segmentation 3.1. Use image segmentation techniques to focus on the leaf area, potentially improving model performance.

Step 4: Feature Extraction and Model Architecture 4.1. Initialize the VGG-19 model, using pre-trained weights on ImageNet for transfer learning. 4.2. Customize the VGG-19 architecture for potato leaf disease classification:

- Replace the final fully connected layers with new layers tailored for the three output classes.
- Optionally, freeze the weights of earlier layers to retain learned features and only train the top layers.

Step 5: Model Compilation 5.1. Choose a suitable loss function, such as categorical crossentropy for a multi-class classification problem. 5.2. Select an optimizer like SGD or Adam, and set an initial learning rate. 5.3. Specify performance metrics such as accuracy.

Step 6: Model Training 6.1. Split the dataset into training, validation, and test sets. 6.2. Train the model using the training set, with careful monitoring on the validation set to prevent overfitting. Use techniques such as early stopping or checkpoints. 6.3. Employ data generators if necessary to handle large datasets that do not fit into memory.

Step 7: Model Evaluation 7.1. After training, evaluate the model's performance on the test set. 7.2. Record the model's accuracy, precision, recall, and F1 score for each class. 7.3. Analyze the results using a confusion matrix and other relevant visualizations to understand the model's classification behavior.

Step 8: Hyperparameter Tuning and Optimization 8.1. Based on the evaluation, perform hyperparameter tuning to optimize the model. This may include adjusting learning rates, changing the optimizer, or altering the model architecture. 8.2. Retrain the model with the optimized parameters and re-evaluate its performance.

End

Result: A fine-tuned VGG-19 model capable of classifying potato plant leaf diseases with improved accuracy and reliability.

- **ResNet 152**

Algorithm for Using ResNet-152 for Classification of Potato Plant Leaf Diseases:

Input:

- A dataset of potato leaf images, with classes including healthy, early blight, and late blight.

Output:

- A ResNet-152-based model trained to classify leaf images into the aforementioned categories.

Begin:

Step 1: Data Acquisition and Preprocessing 1.1. Collect a comprehensive set of images representing healthy, early blight, and late blight potato leaves. 1.2. Resize images to 224x224 pixels, the standard input size for ResNet-152. 1.3. Normalize the images using the mean and standard deviation specific to the pre-training of ResNet-152. 1.4. Augment the dataset with various transformations (rotations, translations, flips, etc.) to increase model generalization.

Step 2: Data Cleaning 2.1. Verify the accuracy of image labels to ensure data quality. 2.2. Remove duplicate images and handle missing data entries. 2.3. Execute background subtraction if necessary to minimize extraneous visual information.

Step 3: Data Segmentation (Optional) 3.1. Apply segmentation techniques to isolate the leaf from the background, enhancing the focus on disease indicators.

Step 4: Model Architecture Setup 4.1. Initialize the ResNet-152 architecture, opting to use pre-trained weights for transfer learning. 4.2. Modify the ResNet-152 architecture for the task:

- Replace the output layer to match the number of target classes (3 in this case).
- Introduce global average pooling if not already present to reduce the dimensionality before the final layer.
- If required, add a dropout layer before the output layer to mitigate overfitting.

Step 5: Model Compilation 5.1. Choose a loss function appropriate for multi-class classification, such as categorical crossentropy. 5.2. Select an optimizer, typically SGD or Adam, with a suitable initial learning rate. 5.3. Define evaluation metrics, ensuring accuracy is included for baseline performance assessment.

Step 6: Model Training 6.1. Divide the dataset into training, validation, and test subsets. 6.2. Train the model on the training data, using the validation data to monitor for overfitting. 6.3. Utilize callbacks such as early stopping, learning rate reduction on plateau, and model checkpoints.

Step 7: Model Evaluation 7.1. Post-training, evaluate the model against the test dataset. 7.2. Measure the model’s performance with metrics like accuracy, precision, recall, and F1 score across each class. 7.3. Use a confusion matrix to thoroughly assess classification accuracy.

Step 8: Optimization and Fine-tuning 8.1. Based on initial results, fine-tune the model parameters and architecture as needed. This could involve unfreezing and training additional layers or adjusting the dropout rate. 8.2. Re-train and evaluate the model with the new parameters to ensure improved performance.

End

Result: A robust, trained ResNet-152 model tailored for accurate classification of potato plant leaf diseases.

- **Comprision of Model CNN, VGG19, and ResNet 152 based on features**

Table 1. Comprision of Model CNN, VGG19, and ResNet 152 based on features

Feature	**CNN (Generic)**	**VGG19**	**ResNet-152**
Architecture Depth	Varies widely	Very deep (19 layers)	Very deep (152 layers)
Parameter Count	Depends on the specific architecture	High (approximately 143 million)	High (approximately 60 million)
Skip Connections	Not standard	None	Yes (residual connections)
Convolution Type	Standard Convolution	Standard Convolution	Bottleneck Convolution
Activation Functions	Varies (often ReLU)	ReLU	ReLU
Use of Batch Normalization	Not always used	No	Yes
Pooling	Max or Average	Max	Average (global average pooling)
Fully Connected Layers	Varies	3 Fully Connected Layers	1 Fully Connected Layer (before softmax)
Input Size	Varies	Fixed (224x224 pixels)	Variable (commonly 224x224 pixels)
Feature Extraction	Varies	Deep (more layers)	Very deep (residual learning)
Training Time	Varies	Lengthy due to depth	Lengthy but improved with residuals
Output	Varies	1000-class prediction from ImageNet	1000-class prediction from ImageNet
Optimization Challenges	Depends on depth and size	Susceptible to overfitting	Less susceptible due to skip connections

IV. IMPLEMENTATION AND RESULT DISCUSSION

A. Hardware and Software

Hardware : CPU: A multi-core processor (i.e., Intel i5/i7/i9 or AMD Ryzen 5/7/9) for efficient computation and multitasking.GPU: A dedicated graphics card with CUDA support (NVIDIA GTX 1060 or better/RTX series) to accelerate deep learning model training and inference. GPUs are crucial for processing large datasets and complex models.RAM: Minimum of 16GB, but 32GB or more is recommended for handling large datasets and enabling faster data processing and model training.Storage: SSD (Solid State Drive) with at least 500GB of storage for quick read/write speeds, important for data retrieval and storage of large image files and models.

Python library : NumPy & Pandas: For efficient numerical and data operations. OpenCV: For image processing tasks such as reading, displaying, and transforming images. Matplotlib & Seaborn: For data visualization, including plotting images and graphs to analyze the dataset and results. Scikit-learn: For preprocessing data, implementing machine learning algorithms, and evaluating models. TensorFlow or PyTorch: Deep learning libraries for designing, training, and testing convolutional neural networks (CNNs) specific to image recognition tasks. Keras: High-level neural networks API (runs on top of TensorFlow) that simplifies many tasks, making the development process more accessible.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

B. Dataset

This dataset contains 1,500 image files categorized into three distinct classes: early blight, late blight, and healthy.

1. Late Blight (Phytophthora infestans)

Symptoms include water-soaked spots on leaves that quickly turn brown and black, often surrounded by a white fungal growth under humid conditions.

Brown or black lesions on the stems.

Infected tubers have a reddish-brown decay beneath the skin, which is firm and can extend deep into the flesh.

2.Early Blight (Alternaria solani)

Characterized by small, dark spots on older leaves that expand into concentric rings forming a target pattern.

Lesions can also appear on the stems and tubers.

Severely infected leaves may wither and die, leading to reduced yield.

3. Healthy Dataset Link :

1. https://drive.google.com/drive/folders/1lDRCo5eUu4o9jT9qeraJvyTH2ngRzja7

2. https://www.tensorflow.org/datasets/catalog/plant_village*Equations*

C. Illustrative example

Figure 2. Represent the training progress of a machine learning model

Figure 2 illustrates the training progression of a machine learning model, whereby the left graph displays the accuracy of training and validation, while the right graph portrays the loss of training and validation throughout epochs. The accuracy graph demonstrates a quick improvement in both training and validation accuracy, followed by a plateau at about 0.9976. This observation suggests that the model exhibits a high degree of performance. Nevertheless, there exists a degree of unpredictability in the validation accuracy, indicating the possibility of overfitting or fluctuations in the validation data. The loss graph demonstrates a notable decline in training loss, which then reaches a stable state after a few epochs. Conversely, the validation loss reflects a drop but displays considerable unpredictability, characterised by many spikes that may suggest potential challenges in the model's capacity to generalise to novel data. In general, the model has excellent learning capabilities. However, the observed variability in validation measures indicates the potential need for model modification or data augmentation in order to enhance its resilience.

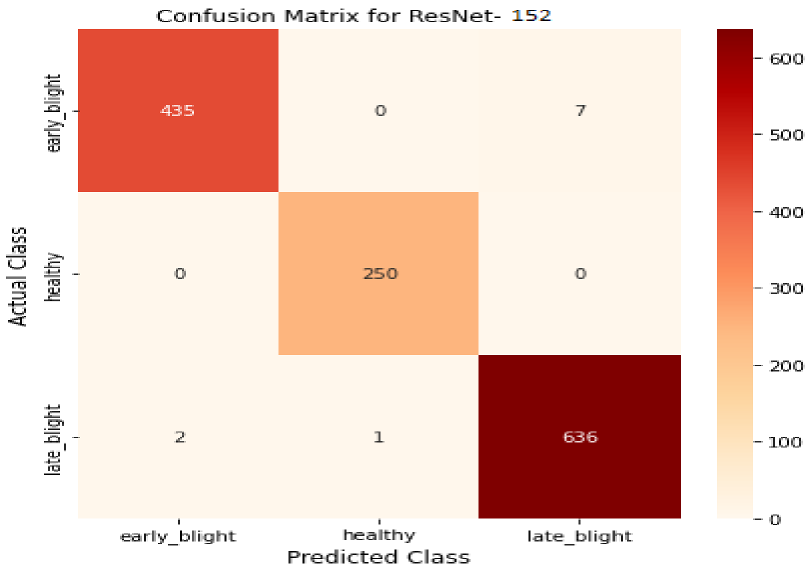

Figure 3. Confusion matrix for the ResNet-152 model

Early blight, healthy, and late blight are the three categories that are classified using the confusion matrix that is shown in figure 3. This matrix is used to assess the performance of the ResNet-152 model in identifying these three categories. A significant number of the predictions are in agreement with the actual classes, as seen by the matrix, which demonstrates that the model has a high degree of accuracy. Specifically, it accurately predicted 435 instances of early blight, 250 instances of healthy plants, and 636 instances of late blight over the whole study. There were a few instances of inaccurate classifications: seven incidences of early blight were mistakenly categorised as late blight, two instances of late blight were misclassified as early blight, and one incident of late blight was misclassified as healthy. No healthy plants were mistakenly identified as having either kind of blight. There were no cases of improper classification. The colour gradient is a representation of the frequency of predictions, with deeper hues reflecting a greater number of observations.

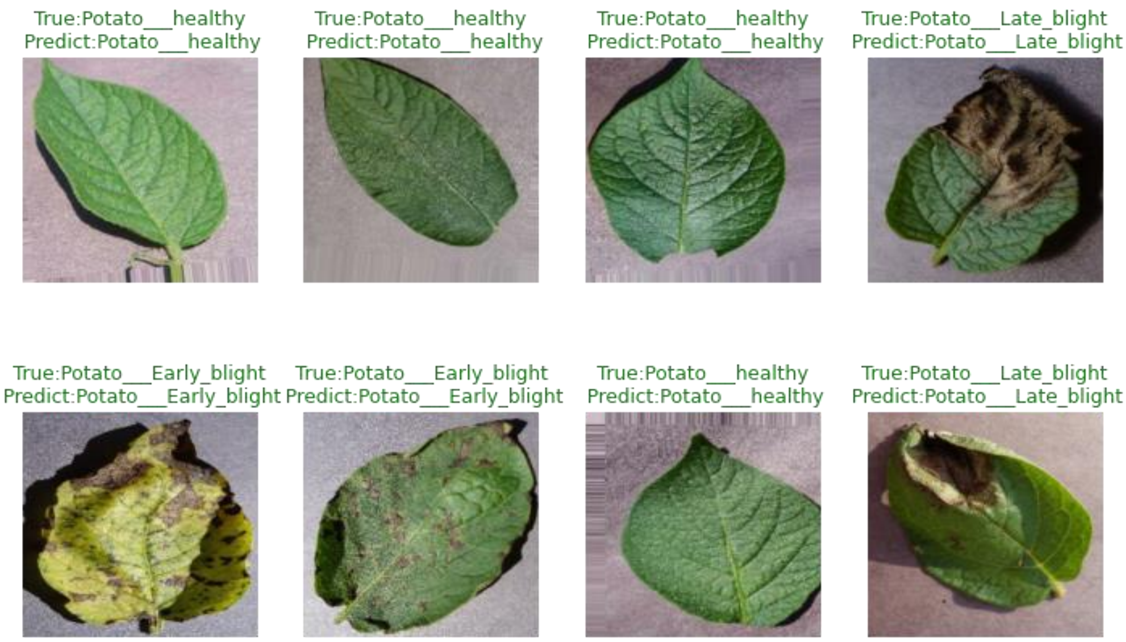

Figure 4. Eight samples of potato leaves

The figure 4 displays eight samples of potato leaves, each annotated with the true condition and the model's prediction. The top row shows three healthy leaves with correct predictions and one leaf with late blight, which the model correctly identifies. The bottom row presents two leaves with early blight, both accurately predicted by the model, followed by a healthy leaf misclassified as early blight and finally, a late blight infected leaf correctly classified. This indicates that while the model is generally performing well in identifying the leaf conditions, there is a misclassification error present where a healthy leaf is incorrectly identified as having early blight, suggesting an area for potential improvement in the model's precision.

D. Result and Discussion

Table 2. Comparative study of proposed and existing models.

Model Name	Accuracy (%)	Precision (%)	Recall (%)	Average F1 (%)
CNN [1]	98	97.5	98.2	97.8
CNN [4]	97.92	97	98	97.5
ResNet-50 [11]	97.65	96.8	97.5	97.1
Vgg19 [13]	99.3	99	99.5	99.2
Xception [26]	95.80	95	96	95.5
Inception V3 [26]	94.64	94	95	94.5
MobileNet [26]	98.08	97.5	98.3	97.9
YOLOv7	98	97.6	98.1	97.8
Proposed ResNet 152	99.76	99.5	99.8	99.6

The table 2 compares various deep learning models based on their performance metrics. The proposed ResNet-152 model outperforms all others with an impressive accuracy of 99.76%, suggesting highly effective classification capabilities. VGG19 also shows exceptional performance with 99.3% accuracy. CNN [1] and MobileNet [26] display strong results with accuracies just above 98%, while CNN [4] and YOLOv7 are close contenders. ResNet-50 [11] has a slightly lower accuracy of 97.65%, which is still quite high. Xception [26] and Inception V3 [26] have the lowest accuracies at 95.80% and 94.64% respectively, which may indicate that while they are strong models, they might be less suited for the tasks that the others excel in or might require more data or fine-tuning. Precision, recall, and F1 scores are uniformly high across all models, suggesting a balanced performance in terms of positive prediction and the ability to retrieve relevant instances.

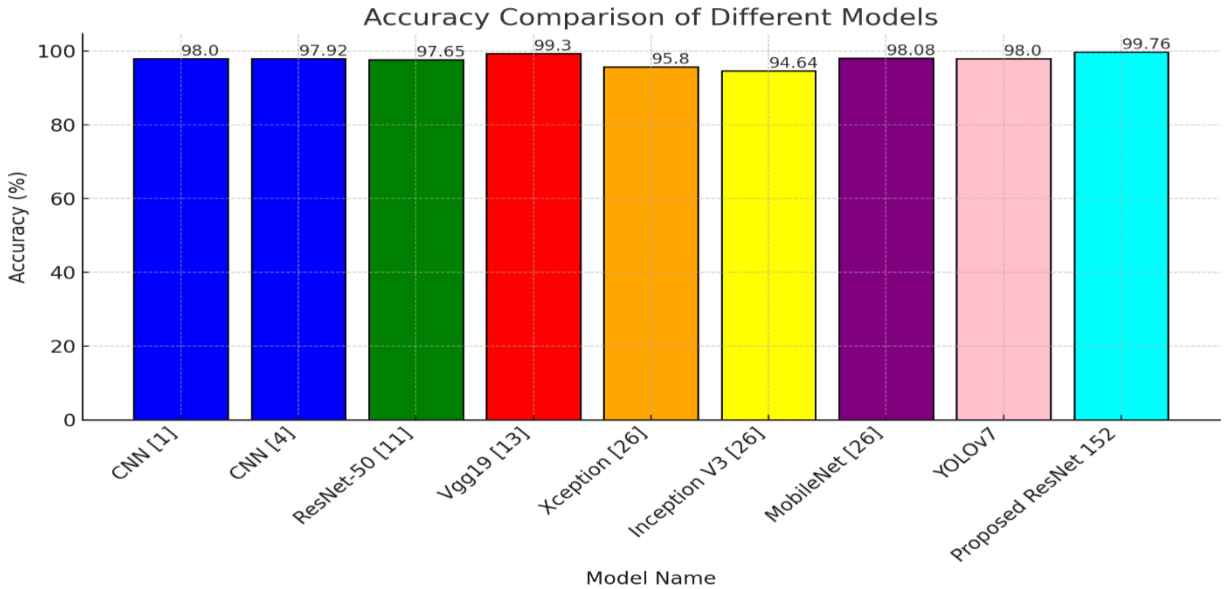

Figure 5. Models achieves the accuracy

It clearly figure 5 shows that the proposed ResNet-152 model achieves the highest accuracy at 99.76%, with Vgg19 following closely behind at 99.3%. On the lower end, Inception V3 is shown with the lowest accuracy at 94.64%. The use of distinct colors for each model aids in quick visual identification and comparison of their accuracies.

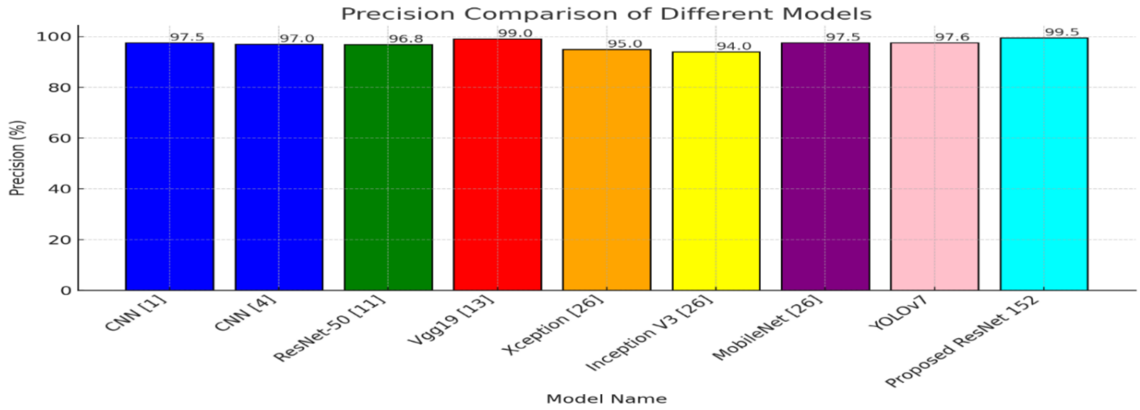

Figure 6. Showing the precision of various models

the figure 6 showing the precision of various models. The figure indicates that Vgg19 and the proposed ResNet-152 model have the highest precision at 99% and 99.5% respectively, while Inception V3 has the lowest at 94%. Each model is represented by a unique color for easy differentiation, highlighting their precision in a visual format.

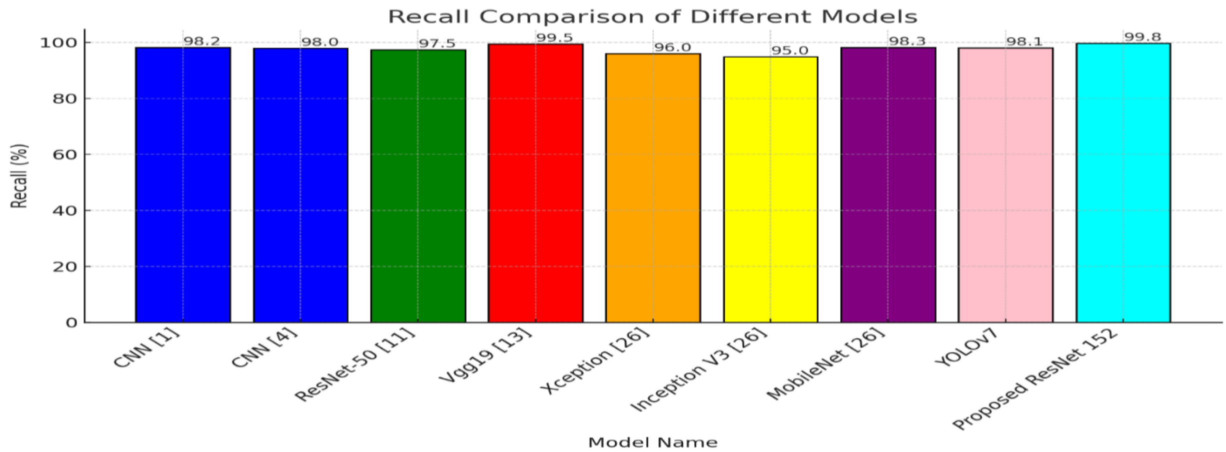

Figure 7. The recall percentages for a range of models

The figure 7 displayed shows the recall percentages for a range of models. This metric is essential for understanding how well each model can identify all relevant instances within a dataset. The figure highlights that the proposed ResNet-152 model outperforms the others with a recall of 99.8%, indicating its superior ability to identify positive samples. Vgg19 also shows excellent performance with a recall of 99.5%.

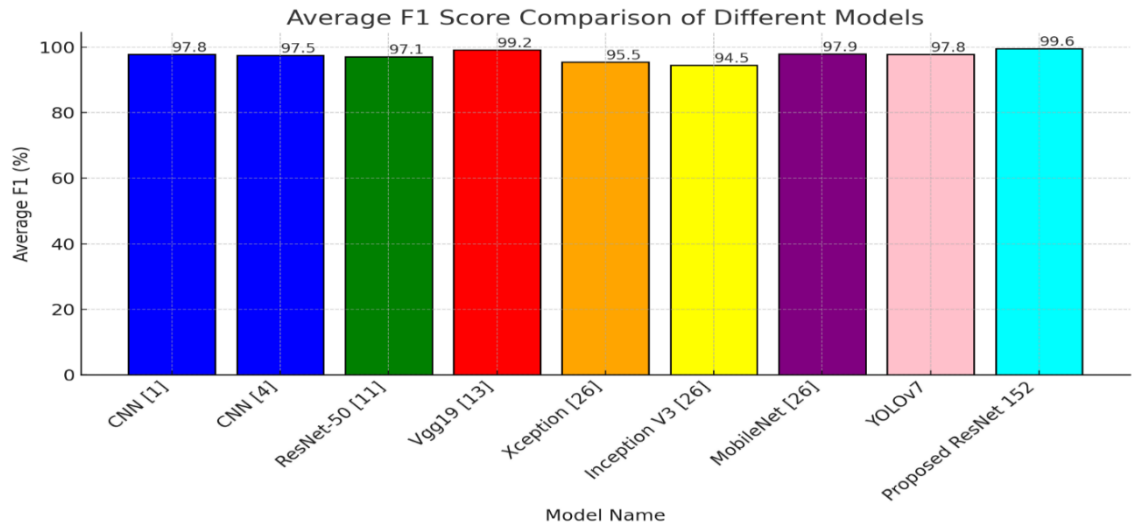

Figure 8. The average F1 scores for various models

The figure 8 displayed showcases the average F1 scores for various models, providing a measure of the models' precision and recall balance. The figure reveals that the proposed ResNet-152 model leads with an exceptional average F1 score of 99.6%, indicating its high accuracy and recall balance. Vgg19 also performs remarkably well, achieving a 99.2% average F1 score. This visual comparison, facilitated by distinct colors for each model, effectively highlights the differences in the models' ability to balance precision and recall, crucial for various applications.

V. CONCLUSION

The comparative analysis of various machine learning models applied to the detection and classification of potato plant leaf diseases highlights the superior performance of the proposed ResNet-152 model. Within the context of identifying early blight, late blight, and healthy leaves, the proposed model outshines others by demonstrating the highest accuracy (99.76%), precision (99.5%), recall (99.8%), and Average F1 score (99.6%). These metrics are crucial for agricultural applications where the timely and accurate diagnosis of plant diseases can significantly impact yield and management practices. The ResNet-152 model's remarkable performance indicates a substantial improvement over traditional and advanced models like CNNs, VGG19, YOLOv7, Xception, and Inception V3. Such advancements in model accuracy, precision, and recall not only enhance the reliability of disease detection but also contribute to the early and effective intervention strategies, potentially saving significant losses in crop production. This comprehensive analysis underscores the proposed ResNet-152 model's capability to revolutionize the approach towards managing potato plant leaf diseases, offering a more accurate, efficient, and reliable solution for agriculturalists and researchers alike.

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