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PLANT DISEASE DETECTION USING YOLOV11

Dr. P. Maragathavalli[1], Mr. Hariharan.G[2]

Professor, Information Technology, Puducherry Technological University, Puducherry, India[1]

M. Tech Student, Internet of Things, Puducherry Technological University, Puducherry, India[2]

Abstract: Plant diseases threaten global food security, especially in high-demand crops like tomatoes and potatoes. Early and accurate detection is vital to minimize yield loss and maintain produce quality. Traditional methods, such as manual inspection, are often slow, error-prone, and require expert knowledge. With advancements in AI and computer vision, automated systems now enable faster and more accurate disease identification.

This project uses the YOLO v11 algorithm, an advanced real-time object detection model, to detect diseases in tomato and potato plants. YOLO v11 improves feature extraction, detection precision, and localization, even under changing lighting and noisy backgrounds. By training on a diverse dataset of healthy and diseased plant images, the system can accurately differentiate between infections.

The enhanced accuracy reduces false positives and negatives, ensuring more reliable detection. Early identification allows farmers to apply timely treatments, reducing pesticide use and preventing crop losses. Overall, this AI-powered system boosts agricultural productivity and promotes sustainable farming.

Keywords: YOLO v11, plant disease detection, tomato, potato, AI, computer vision, real-time object detection, crop management, agricultural sustainability, early intervention, precision agriculture.

I. INTRODUCTION

Plant diseases caused by fungi, bacteria, viruses, and nematodes can severely reduce crop yield, quality, and sometimes cause total loss. They affect various parts of the plant, showing symptoms like discoloration, wilting, lesions, and stunted growth. Environmental factors like moisture, temperature, and soil conditions influence their spread. Control measures include crop rotation, resistant varieties, proper irrigation, and timely treatments. Modern technologies like AI and computer vision enable early detection and better management.

Tomato Diseases:

Tomatoes are affected by Early Blight, Late Blight, Fusarium Wilt, Verticillium Wilt, and Tomato Mosaic Virus, leading to wilting, decay, and yield loss. Management focuses on early detection, resistant crops, and integrated pest strategies.

Potato Diseases:

Potatoes suffer from Late Blight, Early Blight, Black Leg, Fusarium Wilt, and Potato Virus Y, causing foliage decay and poor tuber quality. Using resistant varieties, crop rotation, and AI-driven monitoring helps minimize damage and boost productivity.

II. MOTIVATION

- **Critical Need for Early Detection:**

Early identification of plant diseases is vital to prevent large-scale crop loss and maintain food security.

- **Limitations of Traditional Methods:**

Manual inspection is slow, error-prone, labor-intensive, and impractical for large-scale farms.

- **Impact on High-Demand Crops:**

Tomatoes and potatoes are essential food crops globally, and diseases affecting them cause major economic losses.

- **Advancements in AI and Computer Vision:**

Modern technologies like YOLO v11 offer faster, more accurate, and real-time plant disease detection compared to traditional methods.

- **Reduction in Pesticide Use:**

Early and precise detection reduces unnecessary pesticide applications, lowering costs and environmental damage.

- **Improved Farmer Decision-Making:**

AI-based detection systems empower farmers with timely, reliable information, improving crop management strategies.

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- **Scalability and Accessibility:**
The YOLO v11 model is efficient and can be deployed on mobile devices, making it accessible even to small-scale farmers.
- **Contribution to Sustainable Agriculture:**
This project supports sustainable farming by enhancing crop productivity and minimizing resource wastage through smart interventions

III. LITERATURE REVIEW

1. Shanthi D. L., Vinutha K., Ashwini N., and Saurav Vashistha, "Farming as a cornerstone of economic development: Addressing tomato crop losses through CNN-based disease detection," 2024. The study highlights that over 25% of tomato production is lost annually due to diseases and proposes CNN models like AlexNet and VGGNet-16 for early and accurate disease detection to minimize economic losses.
2. Djalal R. Hammou and Mechab Boubaker, "Tomato plant disease detection and classification using convolutional neural networks," 2021. The work addresses food security issues by leveraging CNN architectures such as DenseNet169 and InceptionV3 for early disease detection using the PlantVillage dataset.
3. Preeti Baser, Jatinderkumar R. Saini, and Ketan Kotecha, "TomConv: A CNN-based model for early detection of tomato diseases," 2023. The proposed TomConv model achieves 98.19% accuracy, outperforming other models in classifying diseased tomato leaves with fewer layers and simplified structure.
4. Fizzah Arshad and Muhammad Mateen A., "PLDPNet: A hybrid deep learning framework for potato leaf disease prediction," 2023. A novel ensemble model combining VGG19, Inception-V3, and vision transformers enhances the accuracy and robustness of potato disease detection.
5. Junzhe Feng and Bingru Hou, "Detection of potato late blight using an improved ShuffleNetV2 model," 2023. The improved model achieved 94% classification precision with reduced inference time, effectively identifying potato late blight and enhancing CPU efficiency.
6. Md. Ashiqur Rahaman Nishada, Meherabin Akter Mitua, and Nusrat Jahan, "Deep learning advancements in crop leaf disease identification: A review," 2023. This review discusses how deep learning methods improve plant disease detection through automatic feature extraction and increased research efficiency.
7. Omneya Attallah, "Optimized deep learning model for potato leaf disease prediction," 2023. The study presents an AI-powered CNN model that improves early potato disease detection by applying data augmentation and transfer learning, promoting sustainable agriculture.

IV. LIMITATIONS IN EXISTING SYSTEM

1. **Slow and Manual Process:**
Traditional disease detection relies heavily on manual inspection, which is time-consuming, labor-intensive, and prone to human error.
2. **Dependence on Expert Knowledge:**
Accurate diagnosis often requires experienced professionals, which is not feasible for all farmers, especially in rural areas.
3. **Low Accuracy in Early Stages:**
Manual and basic machine learning techniques often fail to detect diseases accurately in their early stages, leading to larger crop losses.
4. **Environmental Sensitivity:**
Existing models can struggle under varying conditions like changes in lighting, background noise, and plant appearance.
5. **Limited Generalization:**
Many models are trained on specific datasets and do not perform well when exposed to new types of diseases or different plant species.
6. **High False Positives and False Negatives:**
Traditional methods often result in misclassifications, either marking healthy plants as diseased or missing diseased plants, affecting treatment accuracy.
7. **Resource Intensive:**
Some deep learning models require high computational power and may not be suitable for real-time use in farm fields without expensive hardware.
8. **Insufficient Dataset Diversity:**
A lack of diverse, annotated datasets can limit model performance, causing poor detection across different geographic regions and plant varieties.

V. PROPOSED SYSTEM

The proposed system leverages the YOLO v11 algorithm for detecting plant diseases in tomatoes and potatoes, using its efficient object detection capabilities to provide real-time disease identification. YOLO (You Only Look Once) is a state-of-the-art model known for its high speed and accuracy in detecting multiple objects within images. The introduction of YOLO v11 further enhances its feature extraction, detection precision, and localization of disease-affected areas, ensuring that even subtle disease symptoms can be accurately identified. This capability makes it ideal for agricultural settings, where timely disease detection is critical to prevent crop damage. By training the YOLO v11 model on a diverse dataset of both healthy and diseased plant images, the system can effectively differentiate between various plant infections. The model is robust enough to handle challenging conditions, such as fluctuating lighting and noisy backgrounds, which are common in real-world agricultural environments. This training process ensures that the system can identify diseases with high accuracy, leading to fewer errors in disease classification and more reliable detection results. With such high precision, farmers can respond quickly and accurately, applying treatments before the diseases spread. The improved accuracy offered by YOLO v11 directly contributes to better crop management by reducing false positives and false negatives. Fewer misidentifications result in more effective disease monitoring, which in turn minimizes unnecessary pesticide applications and prevents crop loss. This not only benefits the environment but also reduces the financial burden on farmers. The system's real-time disease detection capability empowers farmers to make informed decisions, enhancing agricultural productivity and contributing to food security by ensuring healthier crops and more sustainable farming practices.

1. **Data Collection:**
   Data collection is the initial step in training a machine learning model, especially for plant disease detection. In the context of the YOLOv11-based system, data is sourced from Kaggle's open-source repositories, which host large, diverse datasets of images from agricultural settings. These datasets often contain a variety of healthy and diseased plant images, with detailed annotations for specific diseases like bacterial wilt, late blight, and early blight in crops such as tomatoes and potatoes. The availability of diverse datasets enables the model to learn from different plant conditions, including various stages of infection, lighting conditions, and environmental backgrounds. This extensive data collection is crucial for ensuring that the model generalizes well across various real-world scenarios, providing reliable disease detection across different climates, geographical regions, and plant types.
2. **Pre-processing:**
   Pre-processing is a critical step that prepares raw data for model training. For images, this often includes resizing, normalization, augmentation, and sometimes color-space conversion. In the case of YOLOv11, image resizing ensures that all input images are uniform in size, allowing the neural network to process them efficiently. Normalization adjusts pixel values so that they are within a consistent range, typically between 0 and 1, enhancing the model's performance. Data augmentation techniques such as rotation, flipping, and scaling are applied to artificially increase the diversity of the dataset, preventing overfitting and improving generalization. This process ensures that the data is clean, consistent, and ready for feature extraction and model training.
3. **Feature Extraction Used in YOLOv11:**
   Feature extraction is a key step in enabling the YOLOv11 algorithm to identify plant diseases in images. Unlike traditional machine learning models that rely on handcrafted features, YOLOv11 uses deep learning techniques to automatically learn relevant features from the data. Through convolutional layers, the model extracts hierarchical features that capture the fine-grained details of the plant images. These include edges, textures, and more complex patterns related to the disease's impact on the plants. YOLOv11 uses advanced techniques like depth-wise separable convolutions, which reduce computational complexity while enhancing the extraction of spatial features. These extracted features, including both low-level patterns and high-level contextual relationships, are crucial for detecting the specific areas affected by disease, making the model capable of accurate real-time disease detection even in challenging environmental conditions.
4. **Model Creation Using YOLOv11:**
   The model creation step in YOLOv11 involves designing the architecture and configuring it for plant disease detection. YOLOv11, a state-of-the-art object detection algorithm, is based on a convolutional neural network (CNN) that is specially designed for speed and efficiency. It consists of a series of convolutional layers, activation functions, and pooling layers that progressively refine the feature maps from input images. YOLOv11 incorporates various improvements over its predecessors, including enhanced feature extraction, better detection precision, and the ability to localize the regions of interest (disease-affected areas) within the images. During model training, YOLOv11 learns to predict bounding boxes around objects of interest, in this case, areas where plant diseases are present. The system is trained on a large dataset of annotated plant images, which helps it learn to identify disease-specific patterns in tomato and potato plants. Hyperparameters such as learning rate, batch size, and epochs are tuned to optimize model performance, ensuring that the model can detect diseases accurately and efficiently in new images.

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5. **Test Data:**
   Once the model is trained, it is essential to evaluate its performance using test data. Test data is a separate subset of the dataset that the model has not seen during the training phase. The purpose of using test data is to assess how well the model generalizes to new, unseen examples. In the context of plant disease detection, the test data would consist of images of tomato and potato plants, both healthy and diseased, taken under different environmental conditions. The model's predictions on the test data are compared to the actual labels to compute performance metrics such as accuracy, precision, recall, and F1-score. This evaluation helps identify the model's strengths and weaknesses, including its ability to detect diseases, minimize false positives, and avoid false negatives. By testing on a diverse set of data, the model's robustness is ensured, ensuring reliable performance in real-world agricultural scenarios.
6. **Prediction:**
   Prediction is the final step where the trained YOLOv11 model is deployed to detect plant diseases in real-time. Given an input image of a tomato or potato plant, the model performs object detection by identifying and localizing the areas affected by diseases. Using the learned features, YOLOv11 predicts the presence of specific plant diseases by outputting bounding boxes around infected areas along with the corresponding class labels (disease type). The model also provides a confidence score for each prediction, indicating the likelihood of the disease's presence in the detected region. This allows farmers to quickly identify problem areas in their crops and take timely action. YOLOv11's real-time processing ensures that predictions are made efficiently, enabling immediate decision-making for crop management. By leveraging the model's high prediction accuracy, farmers can reduce pesticide use, prevent crop loss, and ensure higher-quality produce, thereby contributing to more sustainable agricultural practices.

VI. DESIGN AND ARCHITECTURE

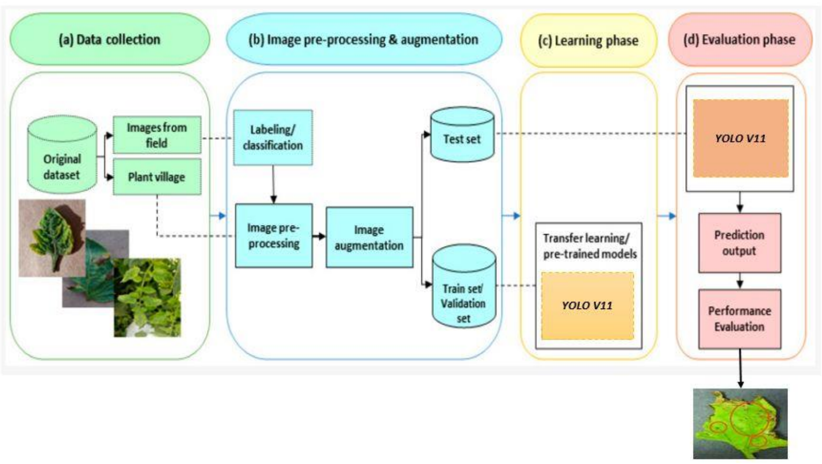

Fig 1: Architecture diagram

- **Data Collection :**

Collect images from an original dataset, field images, and PlantVillage dataset.

- **Image Pre-processing & Augmentation :**

Label and classify images.
Apply image pre-processing techniques.
Perform image augmentation.
Split data into test set and train/validation sets.

- **Learning Phase :**

Use transfer learning with pre-trained models (YOLO V11).
Train the model with prepared datasets.

- **Evaluation Phase :**

Test the trained YOLO V11 model.
Generate prediction outputs.
Perform performance evaluation of the model.

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VII. IMPLEMENTATION STEPS

Data Collection & Pre-processing:
Collect tomato and potato plant images (healthy and diseased) from sources like Kaggle, then preprocess by resizing, normalization, and augmentation to improve data quality.
Model Creation using YOLO v11:
Build and configure the YOLO v11 model, which uses deep convolutional layers for feature extraction and real-time object detection of diseased areas.
Training the Model:
Train YOLO v11 on the preprocessed dataset by tuning hyperparameters (like learning rate and batch size) to optimize detection accuracy.
Testing and Evaluation:
Evaluate the model's performance using unseen test data with metrics like accuracy, precision, recall, F1-score, and confusion matrix analysis.
Real-time Prediction and Deployment:
Deploy the trained model to predict plant diseases in real-time, providing bounding boxes and disease classifications to assist farmers with timely intervention.

VIII. EXPERIMENTAL RESULTS

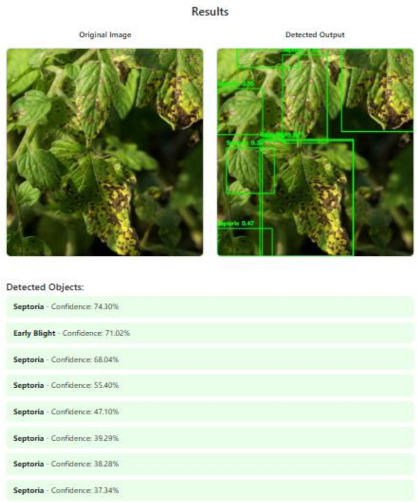

Fig 2: Tomato leaf result

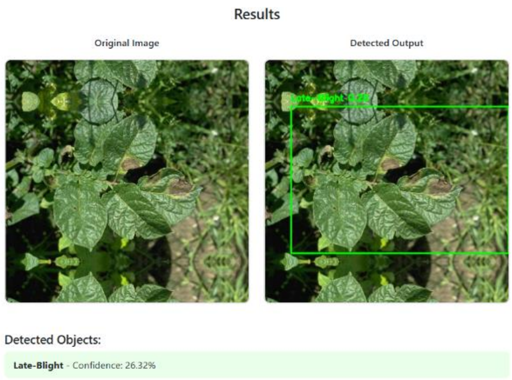

Fig 3: Potato Leaf result

IX.CONCLUSION

The YOLO v11-based system marks a major advancement in detecting diseases in tomato and potato plants. Early, accurate disease detection is crucial for minimizing crop loss and ensuring food security. Traditional manual methods are slow, error-prone, and require expert knowledge.

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YOLO v11 leverages real-time object detection to identify diseased areas quickly and precisely. Using a large and diverse image dataset, it distinguishes between infections even in challenging conditions. This improves detection accuracy and reduces false positives and negatives. Integrating YOLO v11 promotes sustainable farming by lowering pesticide use and minimizing losses. It offers farmers a scalable, practical, and cost-effective tool for crop protection. Future improvements could focus on expanding datasets to include more species and diseases. This will help the model generalize better across different agricultural environments.

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