PLANT DISEASE SEVERITY DETECTION USING DEEP LEARNING

Problem Statement :

Agriculture plays a pivotal role in global economies and food security. Efficient disease detection and accurate severity assessment are crucial for maximizing crop yield and quality. Traditional methods for disease identification are often labour-intensive, subjective, and prone to errors, necessitating automated and reliable solutions.

Current approaches to plant disease detection rely heavily on visual inspection and expert consultation, which are time-consuming and subjective. Basic image processing techniques have been employed, but they often lack scalability and accuracy. There is a pressing need for automated, accurate, and scalable solutions that can predict disease severity in plants swiftly and effectively.

Objectives

This research aims to develop a robust model utilizing deep learning and machine learning techniques for predicting plant disease severity:

- ❖ Develop a deep learning model capable of accurately identifying and classifying the severity of plant diseases from images.
- ❖ Integrate clustering techniques to enhance model performance, particularly with limited labelled data and complex image backgrounds.
- ❖ Evaluate the effectiveness of the developed model using rigorous validation methods and real-world datasets.

Existing Methods and Gaps in Research

Current practices predominantly rely on manual inspection and basic image processing for disease detection. Previous works in machine learning and deep learning have shown promise, but there remains a gap in predicting disease severity accurately. The research identifies challenges such as limited availability of comprehensive datasets covering all disease severity levels and the variability in disease presentations across different stages.

Key Challenges

- **Limited Labelled Data**: Acquiring a diverse and well-annotated dataset representing various levels of disease severity poses a significant challenge.
- **Variability in Disease Presentation**: Different stages of disease progression can manifest varied symptoms, complicating accurate severity assessment.
- **Real-time Analysis**: The model needs to process and analyse images swiftly to enable real-time applications in agricultural settings.

This study aims to address these challenges by leveraging advanced deep learning techniques to enhance the accuracy and efficiency of plant disease severity detection, thereby contributing to sustainable agricultural practices and food security.

Literature Survey :

1. Wheat Disease Severity Estimation: A Deep Learning Approach

Authors : Sapna Nigam, Rajni Jain, Surya Prakash, Sudeep Marwaha, Alka Arora, Vaibhav Kumar Singh, Avesh Kumar Singh & T. L. Prakasha
Summary : This research paper includes deep learning model accurately estimates stem rust disease severity in wheat, achieving 98.41% training and 96.42% testing accuracy. This CNN-based approach reduces the need for manual labor and conventional methods, enhancing precision agriculture by optimizing pesticide use and predicting crop yields
Published : 19 January 2022
Link : Wheat Disease Severity Estimation: A Deep Learning Approach

2. Recent advances in plant disease severity assessment using convolutional neural networks

Authors : Tingting Shi, Yongmin Liu, Xinying Zheng, Kui Hu, Hao Huang, Hanlin Liu & Hongxu Huang
Summary : This research paper reviews the latest developments in using CNNs for plant disease severity assessment, discussing classical CNN frameworks, improved architectures, and segmentation networks. It highlights key challenges like the need for high-quality datasets and handling complex image backgrounds.
Published : 9 February 2023
Link : Recent advances in plant disease severity assessment using convolutional neural networks

3. A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits

Authors : Celestine Iwendi, Poonam Dhiman, Vinay Kukreja, Poongodi Manoharan, Imed Saad Ben Dhaou, MM Kamruzzaman
Summary : This research paper includes deep learning model using VGGNet and transfer learning effectively categorized disease severity in citrus fruits, achieving accuracy rates of 99% for low, 98% for high, 97% for medium severity, and 96% for healthy conditions. This approach promises improvements in agricultural productivity.
Published: 8 February 2022
Link : A Novel Deep Learning Model for Detection of Severity Level of the Disease in Citrus Fruits

4. Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning

Authors : Guan Wang, Yu Sun, Jianxin Wang
Summary : This research paper presents a method for estimating disease severity using deep learning, specifically focusing on fine-grained disease severity classification using CNNs and transfer learning. The best model achieved an overall accuracy of 90.4% on the test set.
Published : 5 July 2017
Link : Automatic Image-Based Plant Disease Severity Estimation Using Deep Learning

5. Disease detection, severity prediction, and crop loss estimation in MaizeCrop using deep learning

Authors : Nidhi Kundu, Geeta Rani, Vijaypal Singh Dhaka, Kalpit Gupta, Siddaiah Chandra Nayaka, Eugenio Vocaturo, Ester Zumpano

Summary : This paper introduces an automated system for analyzing corn crops to detect, classify, and measure disease severity, and estimate crop loss. Utilizing K-means for data pre-processing and various supervised learning models, including MaizeNet, it achieves 98.50% accuracy. Integrated into a web application, it aids farmers in improving agricultural practices and crop yields.

Published : 17 November 2022

Link : [Disease detection, severity prediction, and crop loss estimation in MaizeCrop using deep learning](#)

6. Plant Disease Severity Assessment Based on Machine Learning and Deep Learning: A Survey

Authors : Demba Faye, Idy Diop, Nalla Mbaye, Doudou Dione, Marius Mintu Diedhiou

Summary : This paper reviews advances in plant disease severity assessment, categorizing methods into expert visual assessment, image processing with ML, and DL. It highlights achievements and challenges, proposing a CNN-based solution for evaluating four common mango diseases in Africa, using a dataset from Senegal.

Published : 9 September 2023

Link : [Plant Disease Severity Assessment Based on Machine Learning and Deep Learning: A Survey](#)

7. AgriDet: Plant Leaf Disease severity classification using agriculture detection framework

Authors : Arunangshu Pal, Vinay Kumar

Summary : In this paper, the AgriDet framework, using INC-VGGN and Kohonen-based deep learning, improves plant disease detection and severity classification, addressing issues of image quality and background complexity. It utilizes image pre-processing and a multi-variate grab cut algorithm for better segmentation, outperforming existing methods in accuracy and efficiency.

Published : 10 January 2023

Link : [AgriDet: Plant Leaf Disease severity classification using agriculture detection framework](#)

8. Identifying plant disease and severity from leaves: A deep multitask learning framework using triple-branch Swin Transformer and deep supervision

Authors : Bin Yang, Zhulian Wang, Jinyuan Guo, Lili Guo, Qiaokang Liang, Qiu Zeng, Ruiyuan Zhao, Jianwu Wang, Caihong Li

Summary : The paper presents the Triple-branch Swin Transformer Classification (TSTC) network, a deep learning framework for classifying plant diseases and their severity

separately. Utilizing multitasks learning and deep supervision, the TSTC network achieves high accuracy (99.00% for disease and 88.73% for severity) on the AI Challenger 2018 dataset, showcasing its potential for intelligent agriculture applications.
Published : 21 April 2023
Link : [Identifying plant disease and severity from leaves: A deep multitask learning framework using triple-branch Swin Transformer and deep supervision](#)

Core Techniques :

- ❖ **Convolutional Neural Networks (CNNs)**: CNNs are specialized neural networks designed for image processing tasks. They use convolutional layers to automatically learn hierarchical representations of features from images, capturing spatial patterns and allowing for effective image recognition and analysis.
- ❖ **Clustering Techniques**: Clustering algorithms like K-means or DBSCAN group similar data points together based on their characteristics, even without labelled data. This can aid in discovering patterns and structures within data, which can subsequently improve the learning process of machine learning models, especially when labelled data is limited.
- ❖ **Classification and Regression**: Classification involves predicting which category or class a data point belongs to, while regression predicts a continuous-valued output. These are fundamental supervised learning tasks used extensively in various applications such as image classification, sentiment analysis, and predicting stock prices.
- ❖ **Transfer Learning**: Transfer learning involves leveraging knowledge gained from a pre-trained model (often trained on a large dataset) and fine-tuning it on a smaller, task-specific dataset. This approach helps in achieving better performance with less labelled data, speeding up training time, and allowing models to generalize well to new tasks or domains.

Methodology :

To achieve detection of plant disease severity using deep learning. Here is a Step-by-Step Approach:
- ❖ **Data Collection**
- ❖ **Data Preprocessing**
- ❖ **Model Development**
- ❖ **Model Training with Transfer Learning**
- ❖ **Implementation**
- ❖ **Model Evaluation**
- ❖ **Real-time Deployment**

1. Data Collection
- ❖ **Sources of Data**: Gather data from publicly available repositories such as PlantVillage and establish collaborations with agricultural institutions to obtain real-field data. This ensures a diverse dataset representing different plant species and environmental conditions.
- ❖ **Data Types**: Collect high-resolution images of both healthy and diseased plants, carefully annotated with severity levels ranging from mild to severe. This comprehensive dataset will enable the model to learn the nuances of disease progression.

❖ **Variability**: Capture images under varying lighting conditions, growth stages, and disease severities to ensure the model's robustness and generalization across different scenarios.

2. Data Preprocessing:

❖ **Image Augmentation**: Augment the dataset by applying techniques such as rotation, scaling, flipping, and cropping. This expands the dataset size and introduces variability, enhancing the model's ability to generalize to unseen data.

❖ **Normalization and Standardization**: Normalize pixel values and standardize image dimensions to ensure consistency across the dataset. This preprocessing step aids in convergence during model training and improves overall performance.

❖ **Annotation**: Manually annotate each image with disease severity levels using expert knowledge or crowd-sourced annotations. This ground truth labelling is crucial for supervised learning and accurate model predictions.

3. Model Development:

❖ **Deep Learning Models**:

➢ **Feature Extraction**: Combine traditional image processing techniques (colour histograms, texture analysis, and shape descriptors) with deep learning methods such as Convolutional Neural Networks (CNNs). CNNs are particularly effective in automatically learning hierarchical features from images, capturing spatial dependencies and fine details related to disease symptoms.

➢ **Custom Architectures**: Design tailored CNN architectures optimized for specific crops and diseases. This customization ensures that the model can effectively differentiate between subtle variations in disease symptoms across different plant species.

➢ **Transfer Learning**: Utilize pre-trained CNN models (e.g., VGG16, ResNet50) trained on large-scale image datasets (e.g., ImageNet) to leverage learned feature representations. Fine-tune these models on the plant disease dataset to expedite convergence and enhance performance.

❖ **Machine Learning Models**:

➢ **Clustering Techniques**: Employ clustering algorithms (e.g., K-means, DBSCAN) to group similar images based on extracted features. This unsupervised learning approach helps in identifying clusters of similar disease patterns, which can be used to augment the labelled dataset.

➢ **Classification and Regression**: Implement supervised learning models such as Random Forest, Support Vector Machines (SVM), and XGBoost to classify images into different severity levels or predict continuous severity scores. These models refine predictions based on the features extracted from the CNNs and clustering results.

4. Model Training with Transfer Learning

❖ **Fine-Tuning**: Fine-tune the pre-trained CNN models using a combination of labelled and pseudo-labelled data generated from clustering. This approach enhances the model's ability to generalize to new instances and improves performance on the specific task of disease severity detection.

❖ **Cross-Validation**: Validate the model's performance using techniques like k-fold cross-validation to ensure robustness and reliability. This step helps in evaluating how well the model generalizes to unseen data and mitigates overfitting issues.

❖ **Training Metrics**: Monitor training using metrics such as accuracy, precision, recall, F1-score, and loss functions (e.g., cross-entropy) to optimize model parameters and assess convergence.

5.Implementation:
- **Frameworks**: Implement deep learning models using popular frameworks like TensorFlow, Keras, or PyTorch, which provide efficient tools for building, training, and deploying neural networks. Use Scikit-learn for implementing traditional machine learning models for comparison and ensemble methods.
- **Cloud Platforms**: Utilize cloud computing platforms such as Google Colab, AWS, or Azure to leverage scalable computational resources for training large-scale models. This ensures faster processing times and efficient utilization of computing resources.

5. Model Evaluation
- **Metrics**: Evaluate model performance using a separate validation set and compute metrics such as accuracy, precision, recall, Area Under the ROC Curve (AUC-ROC), F1-score, and Mean Squared Error (MSE). These metrics provide insights into the model's effectiveness in predicting disease severity levels accurately.
- **Visualization**: Visualize model predictions and compare them with ground truth annotations to identify any discrepancies or areas for improvement. Interpretation of model outputs aids in understanding its strengths and weaknesses.

6. Real-time Deployment
- **Optimization**: Optimize the trained models for real-time deployment by reducing model size and complexity. Use techniques such as model pruning, quantization, and compression to enable efficient inference on edge devices or cloud platforms.
- **Deployment Strategy**: Deploy the optimized models on edge devices within agricultural settings or on cloud platforms for scalable and accessible disease monitoring. Ensure integration with user-friendly interfaces or APIs for seamless interaction and usability.

Expected Outcomes :
1. **Development of a Robust Deep Learning Model**
   - Creation of a deep learning model capable of accurately identifying and categorizing plant diseases based on severity levels.
   - Enhanced accuracy and reliability in disease classification across various crops and environmental conditions.
2. **Improved Model Performance**
   - Implementation of advanced techniques such as clustering and transfer learning to enhance model performance.
   - Optimization of model training processes to achieve higher predictive accuracy and robustness.
3. **Real-Time Disease Severity Detection System**
   - Development of a practical system for real-time detection of disease severity in plants.
   - Deployment of the system to aid farmers and agronomists in timely and effective crop management decisions.

Hardware Requirements :

❖ **Development Environment**:
- ➢ **GPU**: NVIDIA GPUs (e.g., GTX 1080 Ti, RTX 2080, or Tesla V100) for accelerated training.
- ➢ **CPU**: Multi-core processors (e.g., Intel i7/i9, AMD Ryzen 7/9).
- ➢ **RAM**: 16GB or higher.
- ➢ **Storage**: SSDs with at least 512GB.

❖ **Deployment Environment**:
- ➢ **Edge Devices**: Devices with powerful mobile GPUs or dedicated AI processors (e.g., NVIDIA, Jetson, Google Coral).
- ➢ **Cloud Services**: Platforms like AWS, Google Cloud, or Azure with GPU instances.

Innovation and Future Work :

❖ **Integration of Contextual Metadata**
- ➢ Enhance disease severity detection by incorporating contextual metadata such as weather conditions, soil type, and agricultural practices.
- ➢ Explore how environmental factors influence disease progression to improve model accuracy and reliability.

❖ **Development of Explainable AI Framework**
- ➢ Create an explainable AI framework to elucidate the decision-making process of the severity detection model.
- ➢ Provide transparent insights into which features and patterns contribute most to disease severity assessments, fostering trust and usability among stakeholders.

❖ **Integration with IoT for Real-Time Monitoring**
- ➢ Integrate the severity detection system with Internet of Things (IoT) devices for continuous real-time monitoring of plant health.
- ➢ Implement alert systems to notify farmers and agronomists promptly about disease outbreaks or changes in severity levels

Application :

❖ **Agricultural Support**
- ➢ Facilitate early detection and proactive management of plant diseases, assisting farmers in preserving crop health and optimizing yield.
- ➢ Empower decision-making through timely interventions based on accurate disease severity assessments.

❖ **Research Advancement**
- ➢ Provide researchers with advanced tools to study disease progression dynamics and accelerate the development of disease-resistant crop varieties.
- ➢ Foster scientific exploration into the interactions between environmental factors and disease severity for more sustainable agriculture practices.

❖ **Commercial Agriculture**
- ➢ Enhance automated crop monitoring systems for large-scale farms, improving operational efficiency and resource allocation.

➢ Enable precision agriculture practices by integrating real-time disease severity assessments with existing agricultural technologies.

Schedule and Deadline :

❖ **Week 1: Project Setup and Data Preparation**
➢ Set up development environment (e.g., install necessary software tools like TensorFlow, PyTorch).
➢ Gather and preprocess datasets from sources like PlantVillage and agricultural collaborations.
➢ Annotate images with disease severity labels and validate data quality.

❖ **Week 2: Model Development**
➢ Design and implement initial deep learning models (e.g., CNN architectures) for disease severity detection.
➢ Experiment with different model configurations and hyperparameters.
➢ Conduct preliminary training to establish baseline performance.

❖ **Week 3: Model Optimization and Fine-Tuning**
➢ Optimize model performance through techniques such as transfer learning and feature extraction.
➢ Fine-tune models using labelled and pseudo-labelled data, incorporating clustering techniques if applicable.
➢ Validate and refine model parameters based on performance metrics (e.g., accuracy, F1-score).

❖ **Week 4: Evaluation, Deployment, and Research Paper Writing**
➢ Evaluate final models using validation and test datasets to assess accuracy and generalization.
➢ Deploy the trained model for real-time disease severity detection, integrating with IoT devices if planned.
➢ Begin drafting the research paper, including methodology, results, and discussion sections.
➢ Prepare presentations or reports summarizing project findings for stakeholders or academic review.

This proposal leverages CNNs, clustering techniques, and transfer learning to develop a robust system for plant disease severity detection, addressing key challenges in agricultural management.