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Agriculture Disease Classification Using U-Net Architecture

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Abstract: *Understanding and determining the existence of disease in agriculture is important for food security and sustainable agriculture practice. Agricultural activities such as visual inspection is subjective and requires endless hours of work looking over meticulous details which makes it impractical in larger settings. With the development of precision agriculture, automated disease detection systems are gaining popularity as they reduce dependency on manual work and monitoring. This research aims to develop a scalable and robust framework based on deep and traditional machine learning for classifying and detecting diseases in plants.*

As the basis of the method, a U-Net based segmentation model which was designed for biomedical imaging is applied with a segmentation model for capturing spatial precision which needs pixel-level segmentation of fine-grained disease affected spatial details. The segmentation partitions diseased pixel regions to improve subsequent classification. Features of interest, colored histograms, shapes, and textures are extracted, and classification is performed by SVM, RF, and k-NN. Assessment is done based on the amount of accuracy, precision, recall, F1-score, and IoU measurable intersection over union. Using the Plant Village dataset that contains over 54,000 annotated images, experiments run.

Keywords: Plant disease detection, deep learning, U-Net segmentation, image classification, convolutional neural networks (CNN), machine learning, Support Vector Machine (SVM), Random Forest (RF), k-Nearest Neighbors (k-NN), PlantVillage dataset, precision agriculture, feature extraction

I. INTRODUCTION

Agriculture remains a pillar to global food security and the economy, as it supports billions in terms of food and livelihood. Nevertheless, the ever-growing occurrence of crop diseases, comprising of various pathogens such as bacteria, viruses, and fungi, is a critical threat to agricultural productivity and sustainability. Plant diseases must be diagnosed accurately and rapidly to avoid crop loss. Diagnosis relying on visual assessment is often inadequate due to subjective human interpretation, which is not scalable.

Timely and accurate diagnosis of plant diseases is essential to mitigate crop loss, error-prone. Visual assessment suffers from several limitations, including human subjectivity, lack of scalability, and the prevent the misuse of agrochemicals, and support integrated pest and disease management strategies. Delayed or inaccurate detection can lead to significant yield reductions, financial losses for farmers, and environmental degradation due to overuse or misuse of pesticides.

Traditionally, disease diagnosis relies on manual inspection by agricultural experts, which is both time-consuming and requirement for domain expertise, making it impractical for large-scale agricultural monitoring. With the rapid advancements in computer vision and artificial intelligence (AI), automated plant disease detection has emerged as a transformative tool in the field of precision agriculture. AI- based solutions can provide consistent, objective, and real-time diagnostics, thereby reducing dependency on expert supervision.

Among various AI techniques, deep learning—particularly Convolutional Neural Networks (CNNs)—has demonstrated superior performance in complex image recognition tasks. CNNs automatically extract hierarchical and discriminative features from raw image data, making them well-suited for plant disease classification. However, conventional classification approaches often struggle to identify the exact regions affected by disease, limiting interpretability and leading to potential misclassification in heterogeneous image backgrounds.

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To address this limitation, we propose a hybrid framework that integrates U-Net—a state-of-the-art deep learning architecture for image segmentation—with traditional machine learning classifiers, including Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k-NN). U-Net facilitates pixel- level segmentation of disease-affected regions, preserving spatial details through its encoder-decoder structure with skip connections. This preprocessing step enables focused feature extraction from infected areas, enhancing the relevance and quality of input data for classification models.

By isolating the diseased regions before classification, our approach enhances both accuracy and interpretability. The proposed layered system not only localizes disease symptoms but also categorizes them effectively, demonstrating high potential for real-world deployment in smart agriculture applications, particularly for large-scale or resource-limited farming environments.

II. LITERATURE REVIEW

In the last decade, detection of plant diseases has become a very active area of research, primarily because of advances in computer vision and deep learning. More classical methods of image processing that relied on feature engineering and thresholding are slowly being replaced by data-driven approaches that can learn complex patterns from images. Convolutional Neural Networks (CNNs) have emerged as the most popular due to their ability and accuracy in performing visual recognition tasks on diverse datasets.

A foundational work in segmentation-based deep learning is the U- Net architecture, proposed by Ronneberger et al. (2015), originally for biomedical image segmentation. U-Net's encoder- decoder structure, combined with skip connections, allows it to capture both low- level spatial details and high-level semantic features, making it highly suitable for pixel- wise classification tasks. Its application has since extended to agriculture, where precise segmentation of disease-affected regions is crucial for accurate diagnosis.

In a pioneering study, Mohanty et al. (2016) employed standard CNN architectures such as AlexNet and GoogLeNet to classify 38 plant diseases across 14 crop species using the PlantVillage dataset. Although the models achieved impressive classification accuracy (above 99%), they operated on entire leaf images without localizing disease regions, thereby lacking spatial interpretability—a critical factor in real-world disease assessment and treatment planning.

Building on this foundation, Fuentes et al. (2017) developed a region- based CNN (R-CNN) model for real-time tomato disease detection. While their model could detect multiple disease types simultaneously, it faced challenges with overlapping symptoms and background noise, especially under field conditions with complex environments.

To address these shortcomings, subsequent research introduced segmentation as a preprocessing step, enhancing focus on infected regions and reducing background interference. Ferentinos (2018) trained deep CNNs on the full PlantVillage dataset and achieved over 99% accuracy, but the model was computationally intensive and lacked the capability to visually highlight disease- affected areas—an essential requirement for explainable AI in agriculture.

Recent studies have proposed hybrid frameworks that integrate deep segmentation models like U-Net with conventional machine learning classifiers. For instance, Raza et al. (2020) and Zhang et al. (2019) demonstrated that segmenting disease regions before classification significantly improves accuracy, especially in the presence of complex leaf textures or multi-label conditions. By combining the spatial localization power of U-Net with the decision-making robustness of classifiers like Support Vector Machines (SVM), Random Forests (RF), and Decision Trees, these hybrid approaches offer both interpretability and scalability.

This literature trajectory underlines a shift from pure classification toward segmentation-classification pipelines, which not only enhance accuracy but also provide visual interpretability—an increasingly critical criterion for decision support systems in precision agriculture. The promising results from these hybrid models serve as the foundation for our proposed framework.

III. METHODOLOGY AND SYSTEM ARCHITECTURE

A. Dataset

• Decoder (Expanding Path): Transposed convolution (upsampling) layers

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This study utilizes the PlantVillage dataset, a widely recognized benchmark for plant disease classification tasks. The dataset comprises over 54,000 high-quality RGB images of healthy and diseased plant leaves. It covers 14 crop species including tomato, potato, and apple, and represents 38 distinct disease classes, such as bacterial spot, early blight, late blight, leaf mold, and powdery mildew.

All images are captured under controlled conditions with uniform, plain backgrounds and are resized to 256×256 pixels, ensuring consistent input dimensions for model training. To support the segmentation task, a subset of 2,000 images was manually annotated using the LabelMe tool to create binary masks highlighting diseased regions, which were then used to train the U-Net model.

A. Preprocessing

To enhance model generalization and reduce overfitting, several preprocessing steps were applied:

• Normalization: All pixel intensity values were scaled to the [0, 1] range.

• Data Augmentation: Techniques such as rotation, horizontal/vertical flipping, zooming, and contrast adjustments were employed to synthetically expand the dataset.

• Noise Reduction: Gaussian blur was applied to reduce high-frequency noise from image sensors, improving segmentation quality.

B. U-Net Segmentation Model

The segmentation module is based on the U-Net architecture, known for its effectiveness in biomedical and agricultural image segmentation. The model comprises three key components:

• Encoder (Contracting Path): A series of convolutional layers followed by ReLU activation and max pooling, which progressively captures hierarchical features and reduces spatial dimensions.

coupled with skip connections from corresponding encoder layers, enabling recovery of spatial details.

• Skip Connections: Facilitate the fusion of low-level and high-level features, preserving spatial context during upsampling.

Architecture Summary:

• 4 downsampling blocks (convolution + pooling)

• Bottleneck layer with 1024 filters

• 4 upsampling blocks (upsampling + concatenation)

• Output layer with 1×1 convolution followed by a sigmoid activation to produce a binary segmentation mask

The model was trained for 50 epochs using the Adam optimizer, with a Dice Loss function to address class imbalance between background and diseased regions.

C. Feature Extraction and Classification

After obtaining the segmented masks, connected component analysis was applied to isolate disease-affected regions (patches). From these localized regions, the following features were extracted:

• Color Features: Mean and standard deviation of pixel intensities in the RGB channels

• Shape Descriptors: Region area, eccentricity, convexity, and other geometric metrics

• Texture Features: Local Binary Patterns (LBP), Gray-Level Co-occurrence Matrix (GLCM) contrast, and entropy

These feature vectors were input into three traditional machine learning classifiers:

• Support Vector Machine (SVM) with RBF kernel; hyperparameters: $C = 1$, $\gamma = 0.1$

• Random Forest (RF) with 100 decision trees

• k-Nearest Neighbors (k-NN) with $k = 5$, using Euclidean distance

D. Evaluation Metrics

The performance of the segmentation and classification modules was quantitatively evaluated using the following standard metrics:

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• Accuracy (Acc) = (TP + TN) / Total
• Precision (Prec) = TP / (TP + FP)
• Recall (Rec) = TP / (TP + FN)
• F1 Score = 2 × (Prec × Rec) / (Prec + Rec)
• Intersection over Union (IoU) = Area of Overlap / Area of Union

These metrics provide comprehensive insights into the model's ability to localize and classify plant diseases across various classes.

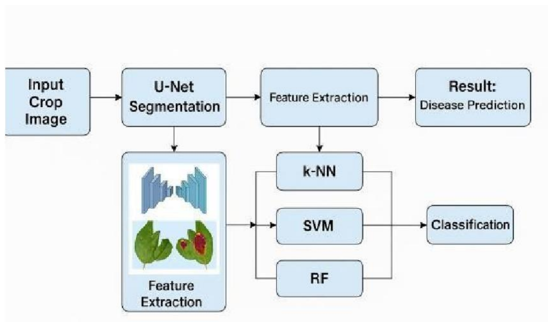

Fig. 3.1 System Architecture

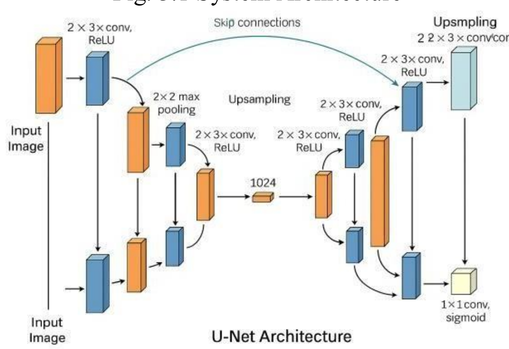

Fig. 3.2 Training Model

IV. EXPERIMENTAL RESULTS

In this study, we proposed a robust and modular framework for automated plant disease detection and classification, combining the U-Net deep learning architecture for pixel-level segmentation with machine learning classifiers for disease identification. By segmenting diseased regions prior to classification, the system enhances the interpretability and relevance of extracted features, resulting in improved classification performance U-Net Segmentation Performance

A. The U-Net model demonstrated strong performance in accurately isolating disease-affected regions in plant leaf images. The evaluation was performed on a test set with ground-truth annotations, using standard segmentation metrics:
• Intersection over Union (IoU): 0.85
• Dice Coefficient: 0.88
• Pixel-wise Segmentation Accuracy: 90.2%

These results indicate that U-Net is effective even in the presence of complex leaf structures or noise, maintaining high fidelity in capturing irregular disease patterns and minimizing false positives.

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B. Classification Performance

The segmented disease patches were processed through three classifiers— Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbors (k- NN). Performance was evaluated using a combination of accuracy, precision, recall, and F1-score, as shown in Table I.

Table I: Classification Metrics Comparison Across Algorithms

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
SVM	92.5	90.3	93.1	91.7
Random Forest	91.1	89.7	91.9	90.8
k-NN	88.4	86.2	87.6	86.9

Among the classifiers, SVM yielded the highest classification accuracy of 92.5%, showing superior generalization on high- dimensional feature vectors derived from the segmented regions. Its robustness to noise and overfitting makes it particularly well-suited for agricultural image classification tasks with limited or imbalanced data.

The Random Forest classifier also performed competitively, offering a balance between interpretability and predictive accuracy. However, it was marginally more susceptible to overfitting, particularly in images with overlapping symptoms or ambiguous feature boundaries.

The k-NN classifier achieved the lowest accuracy among the three due to its sensitivity to noisy features and the absence of learned feature weighting mechanisms. Despite its simplicity, k-NN is less scalable for large datasets or real-time deployment.

IV. RESULT

The test comes about unequivocally approve the proposed frameworks viability incombining U- Net-based division with conventional machine learning classifiers for vigorous plant infection location and classification.. The layered approach— beginning with pixel-wise segmentation of diseased regions, followed by feature extraction and classification—demonstrates notable advantages over conventional end- to-end image classifiers.

The U-Net architecture proved highly effective in isolating disease-affected leaf regions, achieving a Dice coefficient of 0.88 and an Intersection over Union (IoU) score of 0.85. These metrics confirm U- Net's strength in maintaining spatial precision, even in the presence of visually complex or noisy backgrounds. The segmentation step enhances the relevance of extracted features by filtering out irrelevant background content, thereby improving downstream classifier performance.

Among the classifiers, the Support Vector Machine (SVM) consistently outperformed other models, achieving a classification accuracy of 92.5%. Its ability to generalize in high-dimensional feature spaces, especially when training data is limited, makes it a strong candidate for real- world deployment. The Random Forest (RF) classifier also delivered competitive results, with an accuracy of 91.1%, benefitting from its ensemble nature and low susceptibility to noise. However, its performance showed slight degradation in scenarios involving overlapping or visually similar disease patterns.

The k-Nearest Neighbors (k-NN) classifier, while simple and interpretable, critical for agricultural decision support systems.

Future Work

While the current framework provides a strong foundation, several enhancements can be pursued to further improve accuracy, generalizability, and real-world applicability:

• Advanced Segmentation Architectures: Future implementations can incorporate models such as DeepLabV3+, Mask R- CNN, or U-Net++ for improved segmentation performance under natural environmental conditions with varying illumination, occlusion, and backgrounds.

• Transfer Learning and Pretrained Backbones: Leveraging pretrained segmentation networks from domains like biomedical imaging or satellite remote sensing may reduce the need for large annotated datasets and accelerate convergence, especially in resource- constrained training scenarios.
• Lightweight and Real-Time Deployment: For on-field usage, developing lightweight inference pipelines compatible with mobile devices, drones, or edge-computing platforms can enable real-time disease monitoring in remote or rural agricultural settings. Techniques such as model pruning, quantization, and ONNX optimization will be explored to reduce latency and memory footprint.
• Multimodal Fusion: Future versions of the system may integrate environmental demonstrated relatively lower accuracy (88.4%) due to its sensitivity to noise, lack of feature weighting, and increased computational cost during inference. These limitations suggest that k-NN may be less suitable for large-scale or real-time applications.
Overall, the integration of deep segmentation with machine learning classification not only improves accuracy but also enhances model interpretability and domain adaptability, both of which are
factors such as humidity, temperature, and soil data to perform predictive disease analytics, extending its utility from diagnosis to proactive disease management.
By addressing these directions, the proposed framework can evolve into a comprehensive, intelligent, and scalable disease monitoring solution for precision agriculture and smart farming ecosystems.

V. CONCLUSION

In this consider, we proposed a vigorous and measured system for robotized plant malady location and classification, combining the U-Net profound learning engineering for pixel- level division with machine learning classifiers for infection distinguishing proof. By sectioning unhealthy locales earlier to classification, the framework upgrades the interpretability and pertinence of extricated highlights, coming about in progressed classification execution.

Experimental evaluations on the PlantVillage dataset confirmed the effectiveness of this approach. The U-Net model achieved high segmentation accuracy (IoU of 0.85 and Dice coefficient of 0.88), while the Support Vector Machine (SVM) classifier outperformed others with a classification accuracy of 92.5%. This demonstrates the advantage of integrating deep learning-based spatial localization with classical classifiers that perform well in high-dimensional, structured feature spaces.

The framework is highly scalable, computationally efficient, and interpretable, making it suitable for real- world deployment in agricultural decision support systems. It offers significant benefits for large-scale farms, where manual disease detection is impractical, and can serve as a foundation for next- generation precision agriculture technologies.
Future work will focus on expanding the system's capabilities by:
• Incorporating advanced segmentation architectures for improved robustness in real-world field conditions,
• Utilizing transfer learning to reduce annotation overhead,
• Integrating the system with drone-based imaging platforms for large-scale field surveillance,
• And combining visual data with environmental and temporal metadata to support predictive analytics and early disease warnings.
By advancing toward these goals, the proposed solution can evolve into a comprehensive tool for real-time, intelligent crop health monitoring, contributing to sustainable agriculture and food security on a global scale.

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