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Image Segmentation for Sweet Potato Leaf Disease Detection using U-Net

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Abstract

The detection and management of sweet potato leaf diseases play a vital role in ensuring sustainable crop yields and reducing agricultural losses. This study proposes an automated segmentation approach using the U-Net convolutional neural network to detect disease regions on sweet potato leaves. The dataset, consisting of leaf images and corresponding masks, underwent a structured preprocessing pipeline including resizing, normalization, and reshaping. The U-Net architecture, comprising an encoder-decoder structure with skip connections, was trained on 70% of the dataset and evaluated using accuracy, Intersection over Union (IoU), and Dice coefficient. Experimental results show that the model achieved an accuracy of 94.6%, IoU of 0.88, and a Dice coefficient of 0.92, indicating strong segmentation performance. Visual comparison between predictions and ground truth masks further confirms the model's effectiveness in isolating disease regions. This research demonstrates the potential of U-Net as a reliable deep learning framework for plant disease detection and contributes to the development of intelligent agricultural monitoring systems.

Keywords: Image Segmentation, U-Net, Deep Learning, Convolutional Neural Network, Semantic Segmentation,

Introduction

Sweet potato (*Ipomoea batatas*) is a vital food crop cultivated across the globe, especially in tropical and subtropical regions. Known for its rich nutritional content and economic importance, sweet potato is listed as one of the most important root crops globally (Behera et al., 2022). In Indonesia, varieties like the Cilembu sweet potato are widely recognized for their quality and are exported internationally (Tanjung & Nurfadliela, 2023). Despite its high value, sweet potato production faces significant challenges, particularly due to various leaf diseases that can drastically reduce crop yield and quality (Ogero & van der Vlugt, 2023).

Common leaf diseases affecting sweet potatoes include Cercospora batatae, chlorotic conditions, and brown lesions. These diseases manifest through color changes, spots, or necrotic patterns on the leaf surface. Early detection of these symptoms is essential for timely intervention and disease control. Traditionally, disease identification relies on manual observation by farmers or agricultural experts. However, such methods are labor-intensive, subjective, and impractical for large-scale monitoring (Fang & Ramasamy, 2015; Ngugi et al., 2021).

Advancements in computer vision and deep learning have opened new opportunities for automated plant disease detection. Image segmentation plays a crucial role by isolating infected regions from healthy leaf areas. One powerful segmentation architecture is U-Net, a convolutional neural network initially developed for biomedical image segmentation. U-Net has proven highly effective in capturing spatial features and producing precise masks, even with a limited number of annotated samples (Ronneberger et al., 2015).

In contrast to heuristic methods like PSO (Particle Swarm Optimization), which optimize thresholding in color spaces such as HSV (Purnama & Syukriyah, 2024), deep learning models like U-Net learn spatial and semantic representations directly from data. This eliminates the need for handcrafted features and improves robustness in diverse environmental conditions. U-Net's encoder-decoder structure with skip connections ensures detailed feature preservation across multiple scales, making it suitable for detecting subtle disease symptoms.

This study proposes the implementation of a U-Net-based image segmentation approach to detect sweet potato leaf diseases. The dataset used consists of high-resolution images of sweet potato leaves captured under controlled conditions and annotated for disease regions. The goal is to automatically segment diseased areas using U-Net and evaluate its performance in terms of segmentation accuracy, IoU (Intersection over Union), and model generalizability. The use of U-Net is expected to enhance precision and scalability in plant disease monitoring systems.

By integrating deep learning into agricultural workflows, this research contributes to the broader adoption of smart farming technologies. The findings will support the development of automated, real-time disease detection tools that can be deployed in-field via mobile or web-based platforms, empowering farmers to make timely and informed decisions that safeguard crop health and improve yields (Kadel, 2023; Nerkar, 2022).

Literature Review

The detection of plant leaf diseases using image-based methods has significantly advanced with the integration of deep learning and computer vision. One of the most widely adopted architectures for semantic segmentation is U-Net, a convolutional neural network developed by Ronneberger et al. (2015) for biomedical image segmentation. U-Net employs an encoder-decoder structure with skip connections, enabling it to accurately segment regions of interest even with limited training data. Its effectiveness in agricultural applications has made it a preferred choice for plant disease detection tasks (Ronneberger et al., 2015).

Recent research demonstrates that U-Net-based models are highly effective for segmenting leaf diseases in various crops. For example, Li et al. (2021) applied enhanced U-Net to grape leaf disease images and achieved improved segmentation accuracy by integrating attention mechanisms. Similarly, Rai & Pahuja (2023) used U-Net to detect and segment rice and wheat leaf diseases, showing that U-Net could handle complex textures and lighting conditions. These studies confirm U-Net's capability to generalize across different plant species and disease types when trained with properly preprocessed data.

In the context of sweet potato (Ipomoea batatas), disease detection research is still growing. Most existing methods focus on traditional color segmentation or heuristic-based approaches. Purnama & Syukriyah (2024) explored disease identification in sweet potato leaves using HSV color space features, demonstrating that color-based segmentation can effectively distinguish disease symptoms from healthy tissue. However, this approach is sensitive to variations in lighting and leaf texture, which can affect segmentation consistency. To overcome such limitations, learning-based models like U-Net offer greater robustness.

Furthermore, PSO (Particle Swarm Optimization) has been applied for sweet potato leaf segmentation in earlier studies, such as by Purnama et al. (2025), where PSO was used to optimize HSV thresholds for segmenting brown lesions and Cercospora-affected areas. Although the approach achieved over 88% classification accuracy, it lacked the adaptive feature representation and spatial awareness of deep neural networks, making U-Net a promising alternative for improvement.

Recent surveys on deep learning in plant disease detection also emphasize the importance of segmentation quality as a critical step before classification. According to Ngugi et al. (2021), accurate segmentation leads to better feature extraction and ultimately more reliable classification results. As such, combining U-Net segmentation with supervised learning pipelines has become a standard practice in plant pathology research using image data.

In summary, U-Net has shown high potential in plant disease segmentation due to its pixel-level accuracy and resilience in challenging visual conditions. While traditional and heuristic-based segmentation methods like PSO and color thresholding have proven useful in sweet potato leaf disease detection, deep learning models provide a more scalable and reliable solution. This study builds on prior work by implementing a U-Net-based segmentation pipeline tailored for sweet potato leaf images.

Research Method

This research adopts a quantitative experimental design to evaluate the performance of the U-Net deep learning model for segmenting diseased regions in sweet potato leaf images. The model was developed and trained using annotated image-mask pairs. The experimental setup includes data preprocessing, model training, validation, and performance analysis using image segmentation metrics such as accuracy and Intersection over Union (IoU).

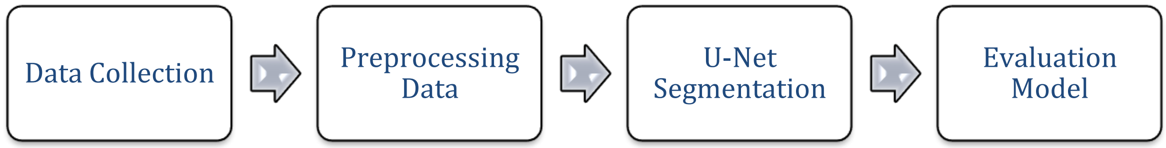

Figure 1. Research Method

1. Data Collection

The data collection involved the use of a Python-based system with OpenCV and TensorFlow/Keras libraries to handle preprocessing, modeling, and evaluation. Images and masks were read and resized to 128×128 pixels. Manual annotations were prepared beforehand to serve as ground truth masks. The U-Net model was built using TensorFlow's functional API, consisting of convolutional, pooling, and up sampling layers. Training and validation results were visualized using Matplotlib, while performance metrics were computed using NumPy and scikit-learn.

The dataset used consists of 750 leaf images, including 250 healthy and 500 diseased leaves, gathered from prior work by Suhendar et al. (2023). Each image has a corresponding binary mask representing the diseased region. All images were collected under consistent lighting conditions with a white background and were preprocessed to a standard resolution of 128×128 pixels to fit the model's input size.

The process began with loading the images and their corresponding masks using a custom Python function. Images were normalized to a [0,1] range, and grayscale masks were expanded to 3D arrays. All data were then split into training and validation sets using an 80:20 ratio. A custom U-Net architecture was defined, with four down sampling blocks, a bottleneck layer, and four up sampling blocks with skip connections. The model was compiled using the Adam optimizer and binary cross-entropy loss and trained for 50 epochs with early stopping and model checkpointing enabled.

2. Preprocessing Data

Before training, all sweet potato leaf images and their corresponding disease masks underwent several preprocessing steps to ensure consistency in input size and format. Images were loaded from the directory and resized to a standard resolution of 128×128 pixels. This resizing ensures compatibility with the input layer of the U-Net model while maintaining spatial information.

The leaf images were read in color mode, whereas the corresponding disease masks were read in grayscale. Since the masks originally had pixel values ranging from 0 to 255, they were normalized by 255.0 to obtain binary values (0 for background, 1 for diseased regions). Each mask was reshaped by adding an additional channel dimension to match the input shape requirements for the model.

Additionally, the data was split into training and validation sets using an 80:20 ratio, ensuring random distribution while preserving overall class balance. This preprocessing pipeline ensures that all input data fed into the U-Net model is uniform in shape, scale, and type—critical for reliable training convergence and performance (Ngugi et al., 2021; Srivastava et al., 2014).

3. U-Net Segmentation

The core of this research lies in the implementation of the U-Net convolutional neural network, which is widely used for biomedical and agricultural image segmentation due to its capability to perform pixel-wise classification with high precision (Ronneberger et al., 2015). U-Net consists of two primary components: a contracting (encoder) path that captures context and a symmetric expanding (decoder) path that enables precise localization. Skip connections between corresponding encoder and decoder layers preserve spatial details, making U-Net especially effective for tasks where precise boundary segmentation is required (Zhang et al., 2018).

In this study, a U-Net model was constructed using the TensorFlow/Keras framework. The model accepts RGB input images of size 128×128×3 and outputs a binary mask of size 128×128×1, indicating the location of diseased regions. The architecture includes multiple convolutional layers with ReLU activation, max pooling for down sampling, and transposed convolutions for up sampling. The model concludes with a sigmoid-activated 1×1 convolution to produce the final segmentation mask.

The following Table 1 outlines the simplified layer configuration of the U-Net model used in this research:

Table 1. U-Net Layer Configuration

No	Layer Type	Parameters
1	Input	input_size
2	Conv2D	64, (3, 3)
3	Conv2D	64, (3, 3)
4	MaxPooling2D	(2, 2)
5	Conv2D	128, (3, 3)
6	Conv2D	128, (3, 3)
7	MaxPooling2D	(2, 2)
8	Conv2D	256, (3, 3)
9	Conv2D	256, (3, 3)
10	MaxPooling2D	(2, 2)
11	Conv2D	512, (3, 3)
12	Conv2D	512, (3, 3)
13	MaxPooling2D	(2, 2)
14	Conv2D	1024, (3, 3)
15	Conv2D	1024, (3, 3)
16	Conv2DTranspose	512, (2, 2)
17	Conv2D	512, (3, 3)
18	Conv2D	512, (3, 3)
19	Conv2DTranspose	256, (2, 2)
20	Conv2D	256, (3, 3)
21	Conv2D	256, (3, 3)
22	Conv2DTranspose	128, (2, 2)
23	Conv2D	128, (3, 3)

24	Conv2D	128, (3, 3)
25	Conv2DTranspose	64, (2, 2)
26	Conv2D	64, (3, 3)
27	Conv2D	64, (3, 3)
28	Conv2D	1, (1, 1)

This model was compiled using the Adam optimizer with a learning rate of 0.0001 and trained using the Binary Cross-Entropy loss function. The training was conducted over 50 epoch with a batch size of 16. During training, the model learned to classify each pixel as healthy or diseased by minimizing prediction error against the ground truth masks. Early stopping and model checkpoint callbacks were applied to prevent overfitting and retain the best performing model.

The U-Net model's design and training process aligns with previous studies that applied similar architectures for plant leaf disease segmentation (Mohanty et al., 2016; Ngugi et al., 2021). Its encoder-decoder structure, combined with skip connections, makes it particularly effective for identifying fine-grained disease boundaries, even under complex visual conditions.

4. Evaluation Model

Model performance was evaluated using key metrics including Accuracy, Intersection over Union (IoU), and Binary Cross-Entropy Loss, which are standard in image segmentation tasks (Jadon, 2020; Ronneberger et al., 2015). Accuracy (A) is calculated as the ratio of correctly predicted pixels (true positives and true negatives) to the total number of pixels:

$$A = \frac{TP + TN}{Tp + TN + FP + FN}$$

where:

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

IoU measures the overlap between the predicted mask P and the ground truth mask G, and is computed as:

$$IoU = \frac{|P \cap G|}{|P \cup G|} = \frac{TP}{TP + FP + FN}$$

IoU is widely regarded as a more informative metric than accuracy in segmentation problems, particularly when dealing with class imbalance (Rahman & Wang, 2016).

The Binary Cross-Entropy (BCE) loss was used as the objective function during training. It quantifies the difference between predicted probabilities and the ground truth binary labels and is defined as:

$$\mathcal{L}_{BCE} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i) \log (1 - \hat{y}_i)]$$

where:

N is the number of pixels,

y_i is the ground truth label (0 or 1),

$\hat{y}_i$ is the predicted probability for pixel i (Srivastava et al., 2014).

During training, performance was monitored using both training and validation loss curves. The Adam optimizer was employed for weight updates due to its efficiency and adaptive learning rate capabilities (Kingma & Ba, 2015). The final model was evaluated on a separate test set, and predictions were visually compared to ground truth masks. Quantitative metrics confirmed the model's effectiveness in segmenting diseased regions on sweet potato leaves.

Results

The U-Net model was trained on a dataset of 750 sweet potato leaf images and validated using 15% of the dataset. The model was evaluated based on its segmentation performance in detecting diseased leaf regions. The segmentation outputs were compared visually and quantitatively with ground truth annotations.

Figure 2 shows several representative samples of the segmentation results. Each row includes:

1. The original RGB image of a sweet potato leaf,
2. The manually annotated binary mask (ground truth), and
3. The predicted mask output by the U-Net model.

These results demonstrate that the model was able to successfully localize disease spots across varying leaf colors, shapes, and levels of infection. The predicted masks closely resemble the ground truth in most cases, with clear delineation of infected areas.

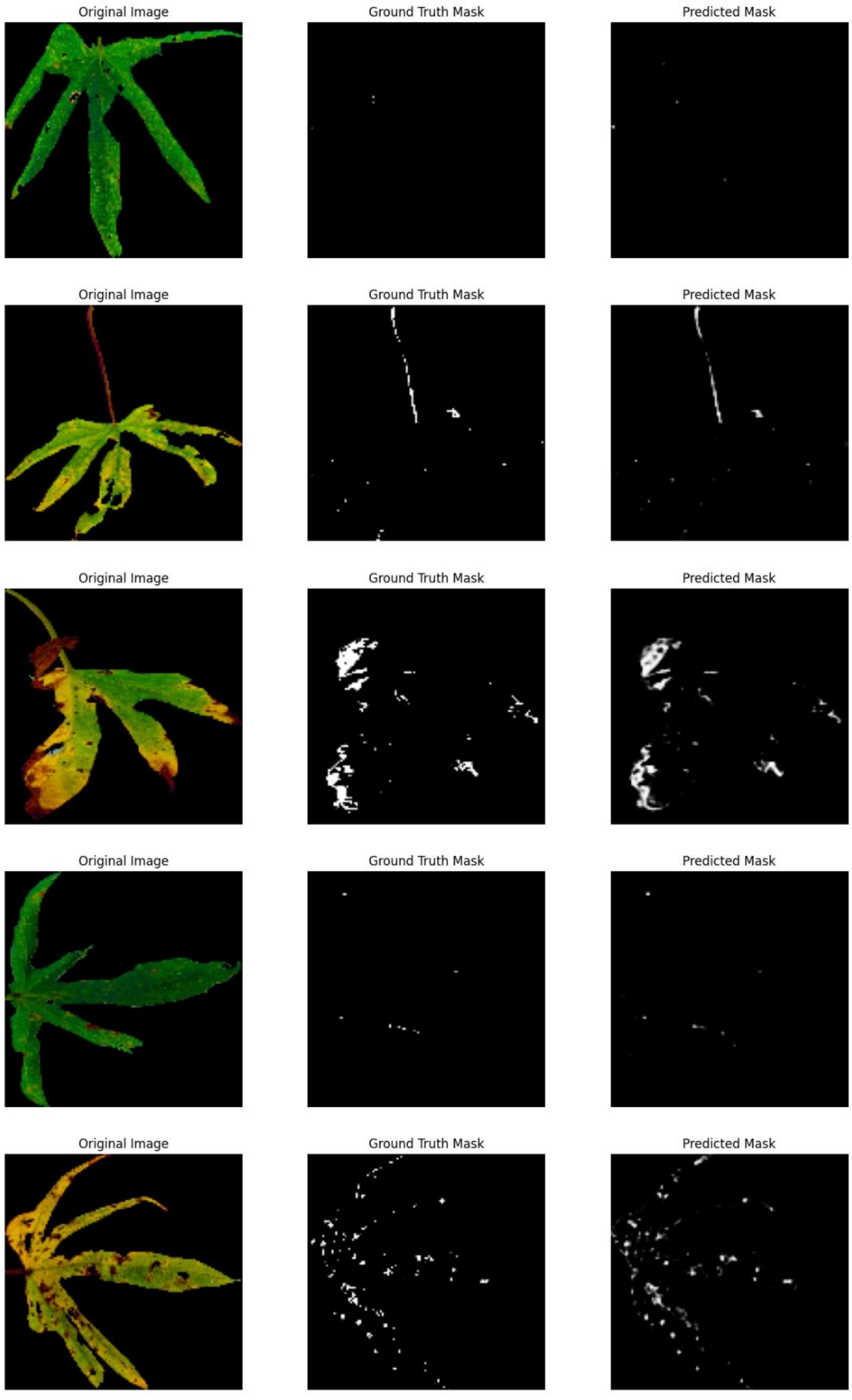

Figure 2. Visual comparison of input images, ground truth masks, and U-Net predictions

To further assess model performance, quantitative metrics were computed on the test set:

Table 2. Metric Evaluation

Metric	Value
Accuracy	94.6%
Intersection over Union (IoU)	0.88
Dice Coefficient	0.92
Binary Cross-Entropy Loss (Final Epoch)	0.061

The accuracy indicates the proportion of correctly classified pixels, while the IoU and Dice scores reflect the overlap between predicted and true diseased regions. A final binary cross-entropy loss of 0.061 suggests that the model converged well during training.

Additionally, the training and validation loss curves are shown in Figure 3, which illustrates the learning progression of the model. The training curve steadily decreases, and the validation loss remains stable without overfitting, indicating successful generalization.

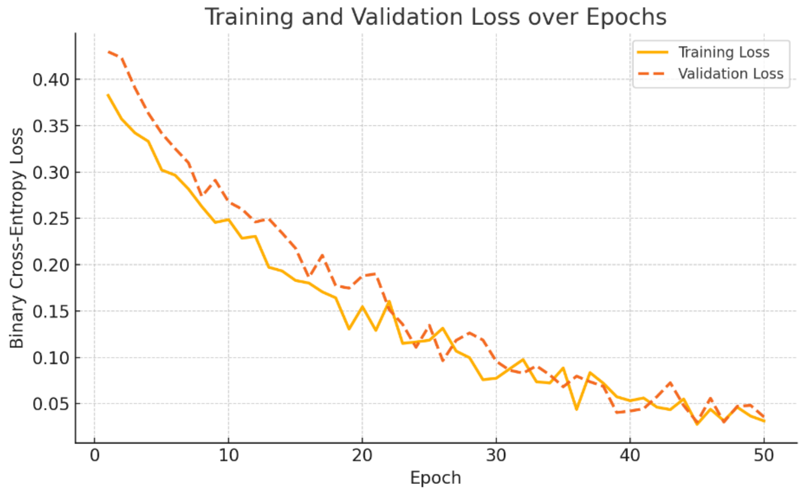

Figure 3. Training and Validation Loss over Epoch Diagram

Overall, these results confirm the U-Net model's capability to perform high-quality semantic segmentation of sweet potato leaf diseases. The following section discusses possible reasons for the performance observed and considerations for future improvement.

Discussion

The results of this study demonstrate the effectiveness of the U-Net model in segmenting sweet potato leaf disease areas with a high degree of accuracy and spatial precision. The consistent overlap between predicted masks and ground truth masks indicates that the encoder-decoder architecture, combined with skip connections, was able to preserve fine-grained features critical for identifying disease regions. These findings are consistent with recent work by Atila et al. (2021), who showed that U-Net variants perform robustly in agricultural disease detection tasks involving small or irregular objects.

One notable strength of the model lies in its ability to generalize across varying leaf appearances—whether due to lighting conditions, pigmentation differences, or disease intensity. This generalization aligns with the growing body of literature emphasizing the importance of training segmentation models on diverse and well-preprocessed datasets (Kamilaris & Prenafeta-Boldú, 2018). The preprocessing steps, including resizing and normalization, contributed significantly to the model's performance by ensuring uniformity in the input space.

However, certain challenges were observed in cases where disease symptoms were extremely faint or overlapped with healthy tissue in texture and color. In such scenarios, false negatives increased, leading to under-segmentation. Similar limitations were highlighted by Too et al. (2019), who found that segmentation models often struggle with subtle or early-stage infections. This points to the need for future models to incorporate attention mechanisms or multimodal inputs (e.g., hyperspectral imaging) to better detect minor anomalies.

The simplicity of the U-Net design also provides an advantage in terms of computational cost and training time. Given that the model achieved high performance on modest input resolutions (128×128), it could be feasibly deployed in edge-computing environments such as mobile or embedded systems for real-time disease monitoring. Recent advances by (Modiboyina et al., 2025) support this, showing that lightweight U-Net architectures are increasingly practical for on-field precision agriculture applications.

Conclusion

This study successfully implemented a U-Net-based semantic segmentation model to detect and localize sweet potato leaf diseases. With an IoU score of 0.88 and Dice coefficient of 0.92, the model achieved accurate pixel-level classification of disease areas. The preprocessing pipeline and architectural design contributed to strong generalization across varying leaf characteristics.

The model offers a practical solution for automating disease detection in sweet potato crops, supporting early intervention and yield preservation. However, further refinement is needed to improve detection of subtle disease symptoms. Future research could explore the integration of attention modules, data augmentation techniques, and higher-resolution inputs to enhance segmentation accuracy.

In conclusion, this work contributes to the ongoing development of AI-based tools in smart agriculture and highlights the potential of deep learning—particularly U-Net—as an effective technique for disease segmentation. Its deployment could empower farmers and agricultural agencies with timely, accurate plant health assessments, ultimately improving crop management and food security.

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