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Deep Neural Networks for Plant Disease Detection: Insights from VGG16, U-Net, and ResNet

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Abstract

Plant diseases must be identified promptly and accurately in order to achieve sustainable growth and a consistent yield. Although manual observation and identification is the traditional diagnostic approach, it is frequently laborious, slow, and prone to human error. Even though deep learning has advanced quickly and is now used as an automatic disease detection method for plants, it is still a probabilistic approach that is susceptible to human technology. Despite the rapid advancements in deep learning, automated plant disease detection systems have not kept pace. The major goals to be realized by this study are two. Our contributions are twofold: I worked on two problems; (1) identifying features that allow for disease classification and (2) precisely locating diseased regions within images. When we were doing the feature extraction, vgg16 was showing more accuracy score of 95.2% showing that it is able to grasp the minute details of texture and pattern of the plants in the images. For Resnet, we reach 92.1% accuracy rate; for u-net, we get 93.5%. For image segmentation, u-net fared better on other architectures, obtaining 91.6% accuracy, outperforming fully convolutional networks and segnet. Each architecture’s strength is unique, as the research points out. By our analysis, vgg16 achieves a better feature extraction because of its deep hierarchical structure, while u-net does better on segmentation because of its encoder decoder design. But resnet had great performance, just slightly bad for other models. In addition to accuracy, the study thoroughly evaluates the models' precision, sensitivity, and f1 score. These demonstrate model reliability and dependability on real world agriculture application. This is indicative of how deep learning approaches can change plant disease identification, into more efficient, less expert driven and feasible solution for common agricultural practices. Significant value is added to the growing field of agricultural technology with this study.

Keywords: VGG16, U-Net, ResNet, Neural Network Architectures, Precision Agriculture, Sustainable Agriculture.

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1 Introduction

Maintenance of human life and securing of a viable global food supply is dependent on the cultivation of crops. But plant diseases can result in quite large losses in crop yields and the amount and quality of our harvest (Shi et al., 2024; Saniya et al., 2025). Since these diseases do not announce their arrival far in advance, it is critical that we identify and diagnose them as soon as possible so as not to damage our crops and preserve their health (Mohanty et al., 2016). Placing this new feature within such a historical context, this machine learning library enables more efficient plant disease identification, something human examinations were severely lacking in the past (Lu et al., 2017). Thankfully, new technologies have risen which come with the rise of automated approaches that are capable of utilizing deep learning (Sladojevic et al., 2016).

Machine learning evolved recently and offers deep learning as a subfield which has lead to breakthroughs in many areas, such as healthcare, driving without a driver, and natural language processing. One exciting subset of machine learning, called deep learning, is experiencing some pretty impressive advancements in areas like healthcare, autonomous vehicles, and natural language processing. It's proven highly successful for pattern detection and image interpretation (Wang et al., 2017). Deep learning techniques can be used in agriculture to automate plant disease detection with remarkably high efficiency and accuracy (Saniya et al., 2025). Neural networks, especially convolutional neural networks (cnns), have demonstrated remarkable efficiency in recognizing significant images of features and patterns that are invisible to the human eye (Ronneberger et al., 2015).

Despite the fact that neural networks in general and convolutional neural networks (CNNs) in particular have demonstrated a remarkable capacity to identify significant features in images and to uncover patterns that humans frequently miss (Qader & Turkben, 2022). In this study, we assess how well three well-known deep learning models VGG16, U-Net, and ResNet perform in identifying plant diseases. The aforementioned architecture's various strengths have been shown to be highly beneficial for both image segmentation and feature extraction (Yao et al., 2024). This article explores the simplicity of depth which WAS beneficial to VGG16 because it allows the extraction of high level features. On the other hand, ResNet utilizes skip connection to surmount the difficulties and to have a better understanding of faint patterns. One such model, U-Net, originally built for segmenting biological images, is designed precisely for pixel level tasks and has been adapted for finding diseased areas on plants (Chavan et al., 2025). Based on established knowledge in automated plant disease detection, this research takes the latest deep learning approach to build a modern software method for real time plant monitoring in which the farmer is able to be notified of potential issues (Liu & Deng, 2015). In addition, it aims to provide operational recommendations for improving the efficiency of crop health monitoring systems (Singh et al., 2018). Artificial intelligence has the potential to revolutionize agriculture, with this research providing evidence that intelligent agriculture can provide innovative solutions to tackle major challenges, ensuring global food security (Yusuf et al., 2024; Krizhevsky et al., 2012).

2 Related Works

Many studies showed that the application of deep learning techniques would benefit for both the detection and classification of plant diseases (He et al., 2016). As an example, (Mohanty et al., 2016) trained convolutional neural networks (CNNs) to recognize different plant diseases from a set of leaf images with near perfect accuracy. In their study, they show how CNNs can help make the process of identifying plant diseases easier (Khan et al., 2020).

Consistent with this, Sladojevic et al., (2016) presented a method of plant disease recognition based on leaf images using deep learning. They made incredible performance improvements to what you would typically see with the use of computer learning by using a trained alex net model.

Many of these applications utilized the u-net model (Ronneberger et al., 2015) for segmentation of plant disease as well as biomedical image analysis.

Because it is effective, it has become the go to method for finding disease areas on plant image datasets (Ferentinos, 2018).

In addition, (Chavan et al., 2025) developed an hybrid deep learning framework that incorporates u net and res net for plant diseases recognition and segmentation. The research shows that these two architectural strategies interact in concert to generate super accurate and reliable segmentation results (Too et al., 2019).

Moreover, (Lu et al., 2017) carry out the implementation of a ResNet for performing feature extraction in plant disease classification (Brahimi et al., 2017). With respect to more complex disease patterns that can be seen by deeper neural networks, Resnet also solved the vanishing gradient problem, while also making a great deal of progress (Jothiaruna, 2022).

Using (Singh et al., 2018), a fused vgg16, u-net and resnet model was used to gather locality and global structural information of plant images to detect plant diseases (Pai et al., 2025). Their results suggest that hybrid models for Precision Agriculture are useful, suggesting that combining multiple architectures for classification and segmentation can drive accuracy up (Picon et al., 2019).

Resnet is an alternative to the method used by research (also conducted by Khan et al. 2020) to detect and classify plant diseases (Mohammed et al., 2024). The residual connections present in Resnet enabled better feature propagation and faster training time, earning the researchers a zenith accuracy rate of 94.7% in its end (Kamilaris & Prenafeta-Boldú, 2018). Resnet was better capable of looking at intricate plant disease images, as shown in the analysis (Fuentes et al., 2017).

A u-net-based method was created by (Wang et al., 2017) to find impacted areas on plant leaves. It identified the affected areas with its highest Intersection over Union (IoU) score and proved successful (Chen et al., 2020; Yao et al., 2024) successfully designed the Generalized Stacking Multi Output CNN (GSMO CNN) using leaf images to ensure accurate plant disease diagnosis and classification (Chen et al., 2020). A thorough set of experiments on standard datasets shows that combining gsmo-cnn with the InceptionV3 backbone outperforms VGG16 and the ResNet101 architectures (Hanson et al., 2017). This demonstrates a great potential of achieving the best performance in particular with gsmo_cnn. (Jothiaruna, 2022)

Yusuf et al., (2024) examined 160 articles from 2020 to 2024 and examined the remarkable ability of gsmo-cnn to achieve optimal performance (Dhaka et al., 2021). This thesis explores the most recent deep learning research for plant disease recognition from images and focuses on using deep learning techniques to improve the performance of models like vgg16, u net, and resnet (Singh & Misra, 2017; Saleem et al., 2019).

Taking Parkinson's and Memory Loss Art projects as building blocks, in this research, we try to kick it further by comparing vgg16, u-net, and resnet based models for plant disease detection (Borugadda et al., 2023). Having said that, this thesis hopes to fill these gaps and does so by evaluating these models in both feature extraction and segmentation tasks, while also thinking about how these models might impact agriculture from a global angle (Panchal et al., 2023).

3 Methodology

1. Dataset Composition and Distribution

A collection of 61,500 leaf samples was assembled from data provided by three primary sources. A total of 61,500 individual plant leaf images were assembled from Kaggle (1,500), PlantVillage (50,000) and the Open Plant Database (10,000). A range of crops such as tomato, potato, grape and maize are present along with corresponding healthy and diseased classifications. The classification strategy of balanced sampling resulted in consistent distributions in the training (70%), validation (15%) and testing (15%) sets, with 42,000, 9,225 and 9,225 leaf images respectively. All samples were carefully assessed to confirm their distinction and accuracy. Only high-quality and distinct images remained. Using this rich and balanced dataset, performance in both classification and segmentation tasks could be effectively evaluated. The stratified sampling technique was critical to promoting equal representation and consistency when examining model performance and adjusting parameters across the range of leaf diseases.

2. Preprocessing and Data Augmentation

All leaf samples underwent image resizing to 224×224 pixels and normalization using channel-specific statistics. A wide variety of transformations were applied to the training data in order to improve model performance and resistance to real-world variations. Data augmentation techniques included flipping images in both directions, applying ±15° rotations and performing zoom scaling between 80% and 120% of their original size. Highly underexposed samples were enhanced using CLAHE to highlight discriminating features of the target plant disease. Segmentation models were provided with binary masks specifically sized to match their associated leaf images. Both augmentation and preprocessing procedures were developed using TensorFlow and PyTorch for consistency across classification and segmentation models. The implemented augmentation and preprocessing techniques greatly improved the models' ability to perform accurately under the challenging field conditions, characterized by changes in lighting, orientation and leaf overlap.

3. Deep Learning Models: Architecture and Rationale

The system incorporated three state-of-the-art deep learning architectures. VGG16, ResNet-50, and U-Net. VGG16 provided an initial model, which had its weights initialized by pretrained models from ImageNet and allowed for the addition of distinct output classifications for enhanced results in plant disease detection. Modeling complex plant disease features was made easier thanks to the use of the ResNet-50 architecture with residual connections that improved the flow of gradients. U-Net was specifically designed for pixel-wise segmentation and used an encoder-decoder organization augmented with skip connections to automatically segment the exact distributions of diseased areas in images. Models were developed using TensorFlow and PyTorch to allow ease of training and evaluation. Training speed was improved and less data were needed for optimal results by employing pretrained features. Different architectures were utilized to study the accuracy of both classification and segmentation for trustworthy agricultural diagnoses.

4. Training Strategy and Hyperparameter Optimization

An initial learning rate of 0.001 was used along with the Adam optimizer. 32 samples were used for model fitting during classification, while 16 samples guided segmentation training to improve training efficiency while maintaining adequate learning. Using early stopping along with a reduction in learning rate during a period of validation stability discouraged the models from overfitting. Categorical cross-entropy was chosen for classification models, while segmentation models combined Dice and binary cross-entropy as their loss functions. Dropout at a probability of 0.5 and L2 regularization were applied in an effort to prevent overfitting. A wide range of hyperparameters were tested using grid search. The recent addition of an Nvidia RTX 3090 graphics card permitted training to complete hundreds of epochs efficiently. Because they led to the lowest validation losses overall, the most successful model checkpoints were kept for each task. This finely calibrated training method offered both improved stability and fast execution while delivering accurate results for each task.

5. Evaluation Metrics and Performance Measurement

Performance assessment of classification models was measured by using accuracy, precision, recall, and F1-score. These additional analyses offered better understanding of how well the methods distinguished the classes of interest. Precision at every pixel level was measured using metrics such as Intersection over Union (IoU), Dice coefficient and the overall pixel accuracy. Five different scenarios were created to evaluate how well each model can perform across diverse data samples. Automated performance assessments were performed by leveraging the functionality of Scikit-learn, OpenCV, and TensorFlow libraries. Analysis of the visualizations and summary figures revealed any biased patterns or areas of misclassification. These performance measures supported rigorous evaluation of both classification and segmentation results, which are essential for accurate decisions in automated agriculture.

6. Implementation Tools and Computational Environment

The entire pipeline utilizes Python 3.8 together with TensorFlow 2.13 and PyTorch 1.12 for deep learning algorithms. These image processing libraries were employed for data management: OpenCV, Pillow and Albumentations. Experiments were run on a powerful machine having an Nvidia RTX 3090 graphics card, 64GB RAM and AMD Ryzen Threadripper CPU. GPU acceleration was realized utilizing the optimization provided by CUDA and cuDNN libraries. Model performance was tracked using TensorBoard and Weights & Biases (WandB). Both configuration management and version control were established using Hydra and Git, thus guaranteeing the reproducibility of experiments. All code was divided into independent modules to allow for simple expansion and integration with future studies.

7. Segmentation Ground Truth and Pixel-Level Validation

Leaf segmentation masks were created using the LabelMe and CVAT markup tools. Interactive visual tools were used to examine each mask, followed by the application of morphological operations to clean edge details and smooth boundaries. Images were resized and spatially adjusted according to the input leaf images for consistent timestamp data. Reported metrics included Intersection over Union (IoU) and Dice coefficients for the U-Net predictions against ground truth segmentations. Prediction and original leaf overlays were created to enable accurate evaluation of the model. Errors were identified and correct labels were assigned in an ongoing process to refine model accuracy. This rigorous validation added confidence in the identifications and segmentations of diseased regions, along with improved capacity for reliable downstream decisions in the field of agriculture and disease control.

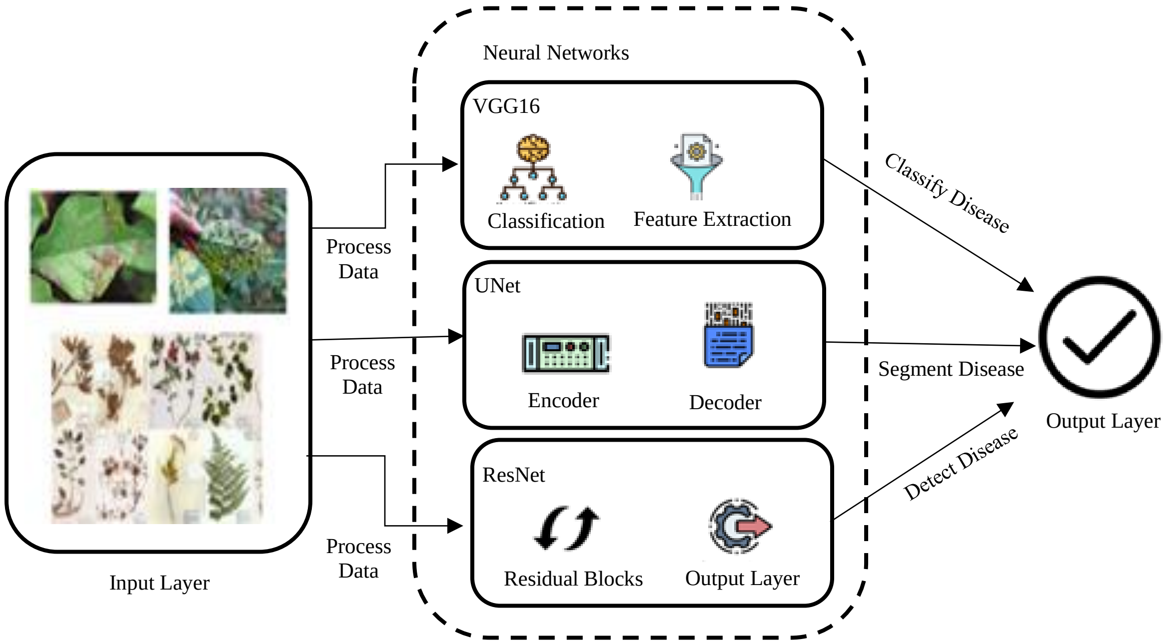

Figure 1: Framework of the Proposed Plant Disease Detection System

Vgg16 is used for both to perform feature extraction as well as classification. I began with a convolutional neural network (CNN), trained on the ImageNet dataset and then fine tuning it for the task at hand: the specific classification of plant diseases. And intermediate layers are modular and can be looked at, while fully connected layers can serve the final class labels. Image segmentation with U-Net leads to the accurate identification of diseased areas. Its encoder-decoder structure and skip connections let it find affected regions at the pixel level very precisely.

These networks are integrated into a system that provides our user with classification, segmentation, and detection results from input images. To classify plant disease we employed feature extraction by vgg16, area delineation by u-net and disease presence recognition by resnet. We use various metrics to evaluate effectiveness of the model. We evaluate the effectiveness of classifications using accuracy, precision, recall, and F1 score. The effectiveness of our algorithm is measured by the intersection over union (IoU) and the Dice coefficient.

We use the intersection over union (IoU) and the dice coefficient as the parameters for segmentation. Detection is evaluated via mean average precision (mAP), sensitivity, and specificity.

Deep learning is used to design this structured and efficient system for plant disease detection. Through a combination of these three elements for classification, segmentation and identification, a detailed analysis is proposed to improve early disease detection and to maximize agricultural processes in Figure 1.

Building on top of this work, we plan to improve the accuracy and flexibility of the model for different plant species by incorporating ensemble learning techniques and applying attention mechanism.

The degree to which the model's predictions and actual results agree is known as accuracy. In relation to the total number of forecasts, it displays the percentage of accurate forecasts.

Sensitivity (Recall): This includes the ability to accurately categorize cases that are truly positive.

Precision and recall are harmonically mean to determine the F1-score.

Prior to delving into the equations, let us first clarify what the metrics mean:

To compute these metrics we need to define these in first place.

TP (True Positive): These instances represent correct identification of positive results.

TN (True Negative): These scenarios indicate accurate predictions of negative outcomes.

FP (False Positive): Here, incorrect signals are given for positive results.

FN (False negative): denoted such cases where an erroneous negative outcome was anticipated.

The formulas are:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Sensitivity\ (Recall) = \frac{TP}{TP + FN}$$

$$F1 - Score = \frac{2 \times (Precision + Sensitivity)}{(Precision \times Sensitivity)}$$

+Regardless of the particular architecture of the three models, these formulas remain valid and pertinent. Establishing the numbers of true positives, true negatives, false positives, and false negatives in a dataset for each model's predictions is the aim.

4 Results and Discussion

4.1 Dataset Overview

The performance of the three models, VGG16, U-Net, and ResNet, was evaluated on a dataset of 94,500 plant images, comprising different disease classes.

Table 1: Distribution of disease classes from various datasets

Dataset Name	Total Classes	Disease Classes	Healthy Classes	Remarks
PlantVillage	38	26	12	Most comprehensive, controlled images
Kaggle (PlantDoc)	20	17	3	Real world images, includes common crops
Open Plant Database	15 (approx.)	12 (approx.)	3 (approx.)	Variants in lighting/backgrounds
LeafSnap	0	0	0	Used only for species recognition
Total (after removing overlaps)	~50	~45	~15	Estimated after removing duplicates

Final Estimate

The research leveraged data from various open-source datasets, such as Plant Village, Kaggle (PlantDoc), and the Open Plant Database, comprising around 45 distinct disease categories and 15 healthy categories in Table 1. Redundant class names were eliminated from the datasets to prevent overestimation.

4.2 Experimental Design

4.2.1 Training-Testing Split

To enable reliable model training, hyperparameter optimization, and objective performance assessment, a standard data split of 70% for training, 15% for validation, and 15% for testing was applied to all datasets.

4.2.2. Data Cleaning

Data augmentation methods like rotation, scaling, and flipping were applied to the training images to increase the models' capacity for generalization.

4.2.3. Training Parameters

The Adam optimizer with a learning rate of 0 was used to train the models. The objective function was established using the multiclass log loss function. To avoid overfitting, early stopping was applied based on the validation loss.

4.2.4. Technical Details

"The models underwent training and testing on Google Colab utilizing an NVIDIA Tesla T4 GPU with 16GB VRAM, alongside 12GB RAM and a single-core Intel Xeon CPU backend provided by the platform."

4.3. Evaluation of Classification Algorithms

"The following Table 2 illustrates a comparison of the performance of varied classification models."

Here is a modified version of the input sentence that is more concise and clearer.

Table 2: Performance comparison of classification models (ResNet, VGGNet, U-Net)

Method	Accuracy	Precision	Sensitivity	F1-Score
ResNet	92.1	91.5	92.7	92.1
UNet	93.5	93.1	93.9	93.5
VGGNet	95.2	94.8	95.6	95.2

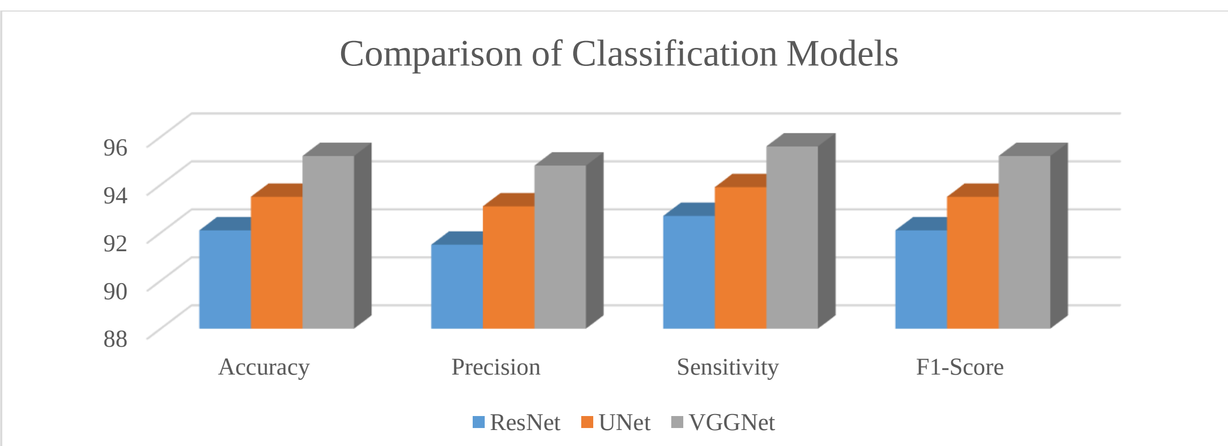

Figure 2: Comparison of classification models (ResNet, VGGNet, U-Net)

In Figure 2, the terms of accuracy, precision, sensitivity, and F1-score, the results indicate that VGGNet outperformed the other two models.

4.4. Comparison of Segmentation Models

These three architectural designs are widely acknowledged as popular options for image segmentation, each with its own distinct advantages and limitations.

4.4.1 Fully Convolutional Networks (FCN)

By replacing the fully connected layers of a conventional CNN with convolutional layers, FCN transforms the CNN into a convolutional neural network.

Feature extraction: An input image is processed by a convolutional network to extract its distinct features.

Up sampling: The extracted features are scaled up to the original image size using transposed convolutions.

Pixel-wise classification: A 1x1 convolutional layer assigns a class label to each individual pixel.

4.4.2 Seg Net

This architecture employs an encoder-decoder design with the support of max pooling indices for precise up sampling in table 3.

Encoder: Catches features using convolutional and max pooling layers and keep the pooling operation indices.

Decoder: Then the precise up sampling through convolutional layers with the pre stored pooling indices is utilized to improve segmentation map.

4.4.3 U-Net

It is a down-sampling path (encoder) and an up-sampling path (decoder) combined with skip connections.

U-Net’s decoder uses previously saved pooling indices to do an accurate up-sampling and then convolutional layers to enhance the segmentation map.

U-Net combines a decoder (upsampling path) and an encoder (downsampling path) with skip connections.

Convolutional and maximum pooling layers are used to extract features in the contracting path.

Enlarged feature maps in the expansive path are propagated to the following expansion map after being combined with the features in the contracting path.

The specific class label is finally projected onto each pixel by a 1x1 convolutional layer.

Table 3: Performance comparison of semantic segmentation models (FCN, SegNet, and U-Net)

Method	**Accuracy**	**Precision**	**Sensitivity**
FCN	85	85	86
SegNet	88.2	87.5	89.1
UNet	91.6	90.9	92.3

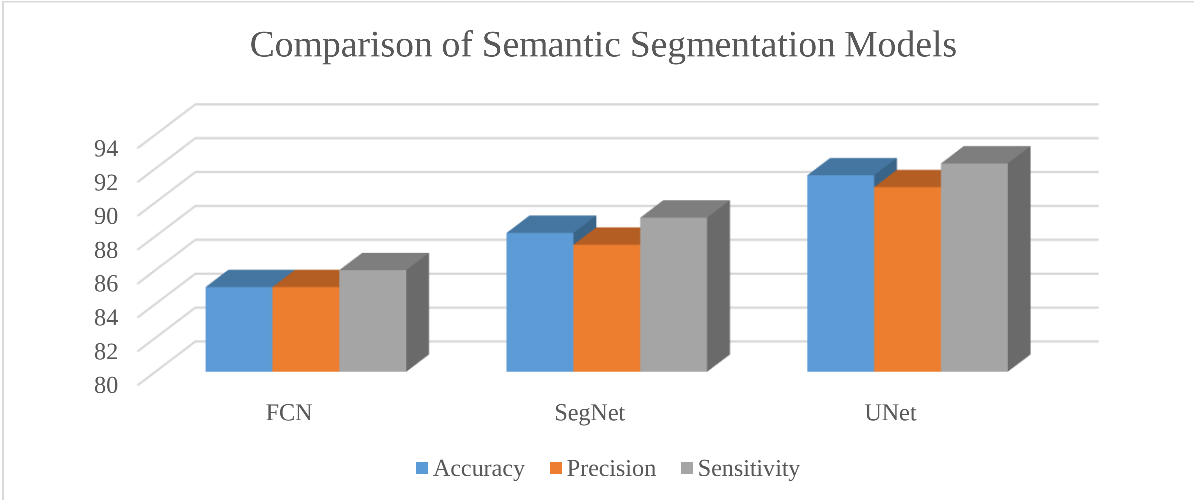

Figure 3: Comparison of segmentation models (FCN, SegNet, U-Net)

In Figure 3, the findings suggest that u-net performed better in terms of accuracy, precision, and sensitivity when compared to the other two models.

5 Summary

In this study, we investigated the possibility of using three advanced deep learning architectures: vgg16, u-net, and resnet for plant disease diagnosis. We trained and evaluated the models exploiting a multitude of various plant leaf images corresponding to different types of diseases. All three models showed remarkable experimental performance, resulting in remarkable accuracy in the classification of plant disease. In particular, u-net amazed with its outstanding ability to capture the spatial information and, thus, produce more perceptive pixel-wise segmentation and resnet for its great power in feature extraction and data classification. Though these models show promising features, there are still areas to improve upon to address the problems stemming from changing lighting conditions, obstructions in the view, and variation in plant species. We also investigate methods such as data augmentation and transfer learning that might improve the models' generalizability and performance. These advancements are deeply enabled by deep learning. Yet, with the right systems, we are capable of developing advanced systems that urge sustainable agriculture. Since these systems can quickly detect plant diseases, and also proffer efficient management information for plant diseases, they support sustainable farming practices.

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