BEAN CROP DISEASE DETECTION USING A MACHINE LEARNING ALGORITHM

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Introduction & Research Area

Research Context

- **Research Area:** Computer Science applied to Agriculture (Image Processing & Machine Learning).
- **Economic Importance:** Agriculture accounts for 50% of Ethiopia's GDP and 80% of employment.
- **The Crop:** Beans are a vital source of protein (approx. 23%) and minerals for millions in Africa.
- **The Threat:** Diseases like Bacterial Blight can cause significant yield loss, threatening food security.

Faba bean crop field in Ethiopia

Problem Statement

Despite the economic importance of beans, productivity is declining due to disease.
Current methods of detection are insufficient.

Manual Detection

Visual inspection by naked eye is prone to error, subjective, and labor-intensive.

Expert Dependency

Farmers often rely on scarce agricultural experts, leading to delays in diagnosis.

Late Intervention

Symptoms are often identified too late, when the disease has already spread, causing irreversible yield loss.

Objectives

Research Question

How can a machine learning algorithm be used to classify bean crop disease effectively?

General Objective

To design a robust model to detect and classify bean crop diseases using machine learning algorithms.

Specific Objectives

- Design a model architecture for disease detection.
- Analyze images to extract features for classification.
- Evaluate the performance (accuracy) of the model.
- Sensitize farmers on the benefits of automated detection.

Scope & Significance

Significance

Increases crop productivity by enabling early treatment. Reduces costs associated with manual expert inspections.

Scope

Specifically focuses on detecting **Bacterial Blight**, **Alternaria Leaf Spot**, and **Halo Blight** in Faba beans.

Limitation

The study is conducted in a laboratory environment. Real-time field implementation via GSM/GPRS is outside the current scope.

Research Design & Sampling

Methodology

Experimental Research: The study employs digital image processing techniques to analyze and classify crop health.

Data Sources

- **Primary Data:** Images collected from EIAR (Ethiopian Institute of Agricultural Research), Debre Zeit center.
- **Secondary Data:** Supplementary images collected from web sources.
- **Sampling:** Targeted Faba bean leaves exhibiting specific disease symptoms vs. healthy leaves.

Data Collection Instruments

Tools & Environment

Camera	TechnoW5 Mobile Camera (13 MP)
Dataset Size	100 Images Total
Split	80 Training / 20 Testing
Environment	Controlled lighting, black background, fixed distance.

Data Preprocessing Tasks

Raw images contain noise and inconsistent lighting. Preprocessing ensures high-quality input for the algorithm.

Scaling

All images are resized to a standard **256 x 256 pixels** to reduce computational load.

Enhancement

Histogram Equalization and **Contrast Stretching** are applied to highlight disease spots.

Color Conversion

Conversion from RGB to **Grayscale** and **HSI** color spaces to isolate intensity from color info.

Analysis Algorithms

1. Segmentation: K-Means

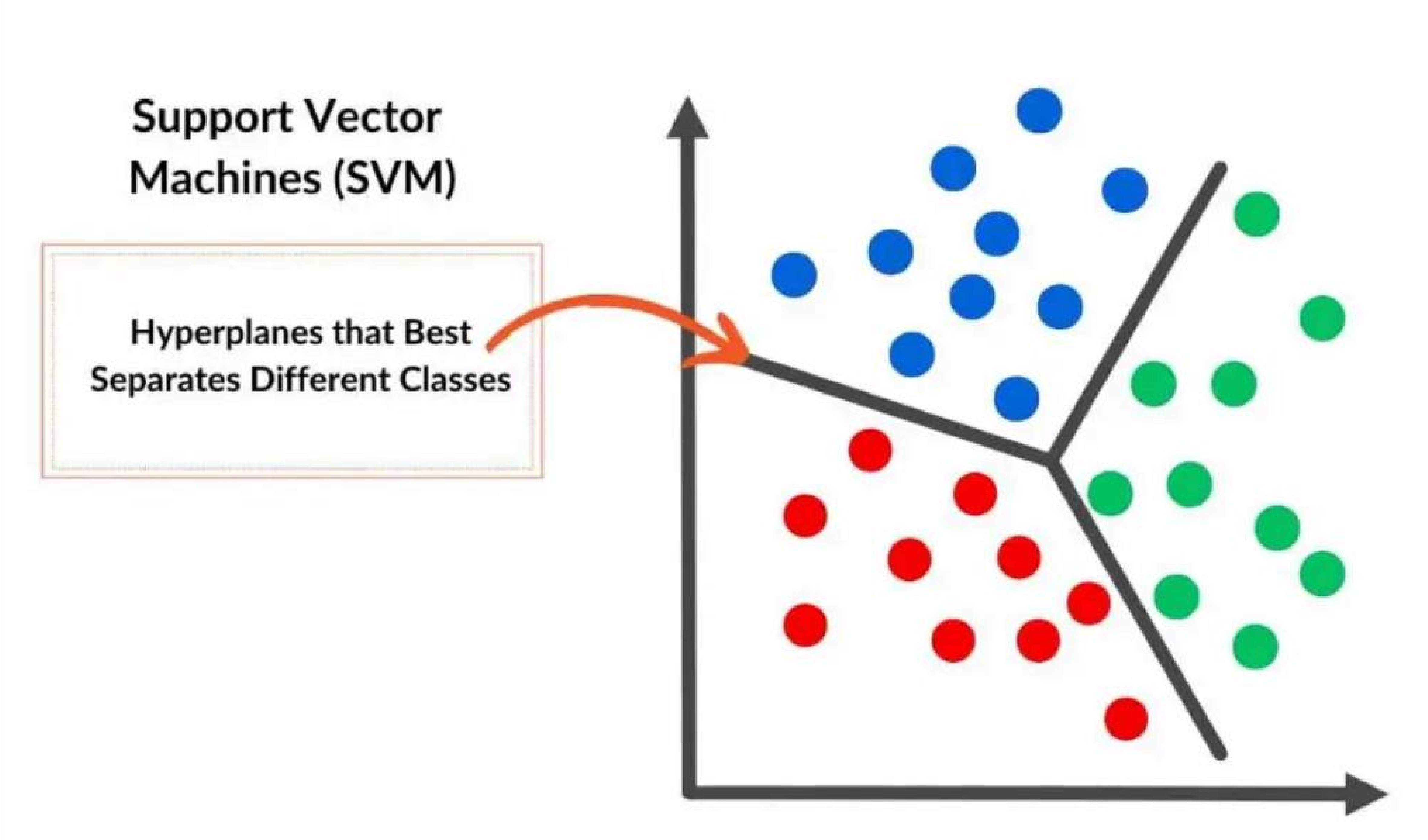
Partitions the image into *k* clusters. Used to separate the diseased leaf area from the healthy leaf and background.

2. Feature Extraction: GLCM

Gray-Level Co-occurrence Matrix extracts 13 texture features (Contrast, Energy, Entropy, Homogeneity, etc.).

3. Classification: SVM

Support Vector Machine. A supervised learning algorithm that finds the optimal hyperplane to separate data classes (Healthy vs. Diseased).



Tools Used in Experimentation

MATLAB R2015b

Primary simulation tool using the Image Processing Toolbox for algorithm implementation.

Microsoft Visio

Used for designing the system architecture and flowcharts.

Adobe Photoshop

Used for initial image formatting and manual cropping preparations.

Performance Measurement

Evaluation Metrics

The model's performance was evaluated using a Confusion Matrix to calculate:

- **TP (True Positive):** Correctly identified diseased leaf.
- **TN (True Negative):** Correctly identified healthy leaf.
- **FP (False Positive):** Healthy leaf misclassified as diseased.
- **FN (False Negative):** Diseased leaf misclassified as healthy.

Formulas

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{Total Samples}} \times 100$$

$$\text{Error Rate} = 100 - \text{Accuracy}$$

Experimental Results

96.77%

OVERALL ACCURACY

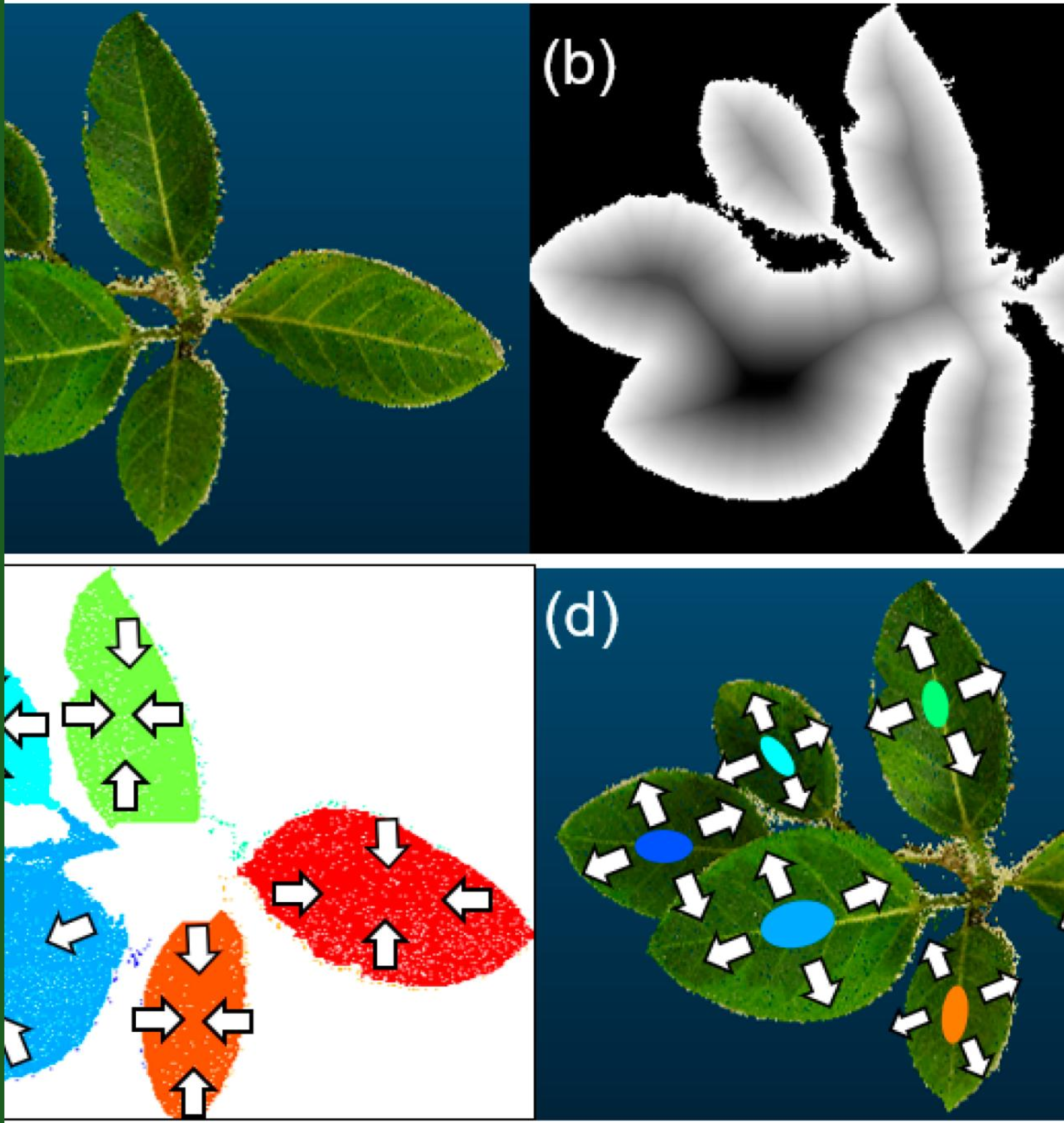
The system correctly classified 96 out of 100 test images.

Detection Accuracy by Disease Class

Conclusion

"The study successfully demonstrated that digital image processing combined with SVM classification is a highly effective method for identifying bean crop diseases."

- Achieved a high accuracy of **96.77%**.
- Provides a viable path for early disease detection systems in Ethiopia.
- Future work can focus on mobile deployment for real-time field use.



Questions?

Thank you for your attention.

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Image Sources

https://groundcover.grdc.com.au/__data/assets/image/0039/579297/220901_rt_faba_ethiopia_3_web.jpg

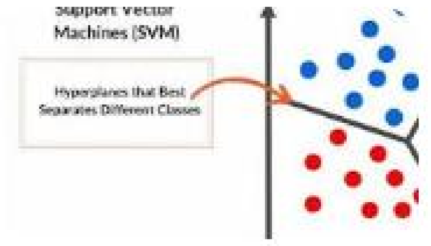
Source: groundcover.grdc.com.au

https://www.growingproduce.com/wp-content/uploads/2020/11/common_bacterial_blight_of_beans_featured.jpg

Source: www.growingproduce.com

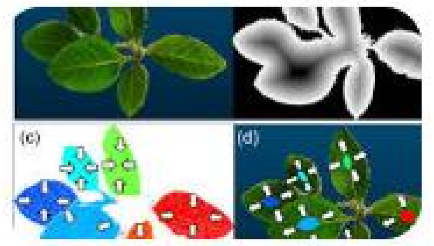
https://etedge-insights.com/wp-content/uploads/2024/06/agri-drone.jpg

Source: etedge-insights.com



https://miro.medium.com/v2/resize:fit:1400/1*qGl9Os6nA82aQrDUhZ7zOQ.png

Source: dilipkumar.medium.com



https://www.mdpi.com/sensors/sensors-18-03576/article_deploy/html/images/sensors-18-03576-g002.png

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