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DETECTING GUAVA DISEASES: A COMPARATIVE ANALYSIS OF MACHINE LEARNING AND DEEP LEARNING TECHNIQUES

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Slide Outline

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- Limitations and Future Scope
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Background and Motivation

- Early and accurate diagnosis of guava diseases is crucial due to the significant environmental and economic impacts of delayed detection

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- In Bangladesh, guava is a staple food, and the productivity of guava crops is essential for food security and economic stability.

- Diseases like canker, mummification, dot, and rust can devastate crops, leading to substantial yield reductions and financial losses. Conventional visual inspections are time-consuming, costly, and often inaccurate.

- Detecting guava diseases using machine learning and deep learning methods is important for effective outbreak management.

Background and Motivation(cont.)

- This project will lead to higher yields and reduced economic losses by enabling early and precise disease detection. It will allow for targeted pesticide use, minimizing environmental damage. Additionally, it will enhance productivity and economic resilience for farmers, contributing to sustainable agricultural practices. By improving disease management, the project will ultimately support food security and economic stability in guava-producing regions.

Objectives

The objectives of this research are as follows:

- Developing an Automated Disease Detection System
- Utilizing Deep Learning Techniques
- Improving Disease Management
- Enhancing Agricultural Productivity
- Addressing Environmental Concerns
- Empowering Farmers
- Knowledge Transfer and Capacity Building
- Contributing to Scientific Knowledge

Literature Review

Work Done	Object(s) Dealt with	Problem Domain	Sample Size	Feature Set Size	Classific ation	Algorithm	Accuracy
Hasan et al. (2022) [6]	Guava	Recognition	550	10	No	AlexNet	83%
Tewari et al. (2023)[7]	Guava	Recognition	527	5	Yes	DenseNet201 Model	96%
Assad S. et al. (2022)[1]	Guava (Leaf)	Recognition	1834	5	Yes	EfficientNet-B3	94%
Mostafa, A.Met al. (2022)[2]	Guava	Recognition	321	5	Yes	ResNet-101	97%
M.Abirami (2017)[3]	Guava (Leaf)	Recognition	465	5	Yes	GLD-Det	97%

Table 1. Overview reviews of Guava disease detection.

Contribution

- Our project focused on Guava Disease Detection, a pioneering effort in Bangladesh's agricultural sector. Employing both traditional machine learning techniques, like SVM, and advanced deep learning methods, including vision transformers and transfer learning, we aimed to develop a precise classification model.

- In the absence of prior research in this area, we created a unique dataset comprising guava leaf images to drive our analysis. By comparing the accuracy and efficiency of different approaches, we aimed to provide actionable insights for improved disease management in guava crops.

Methodology

Overview

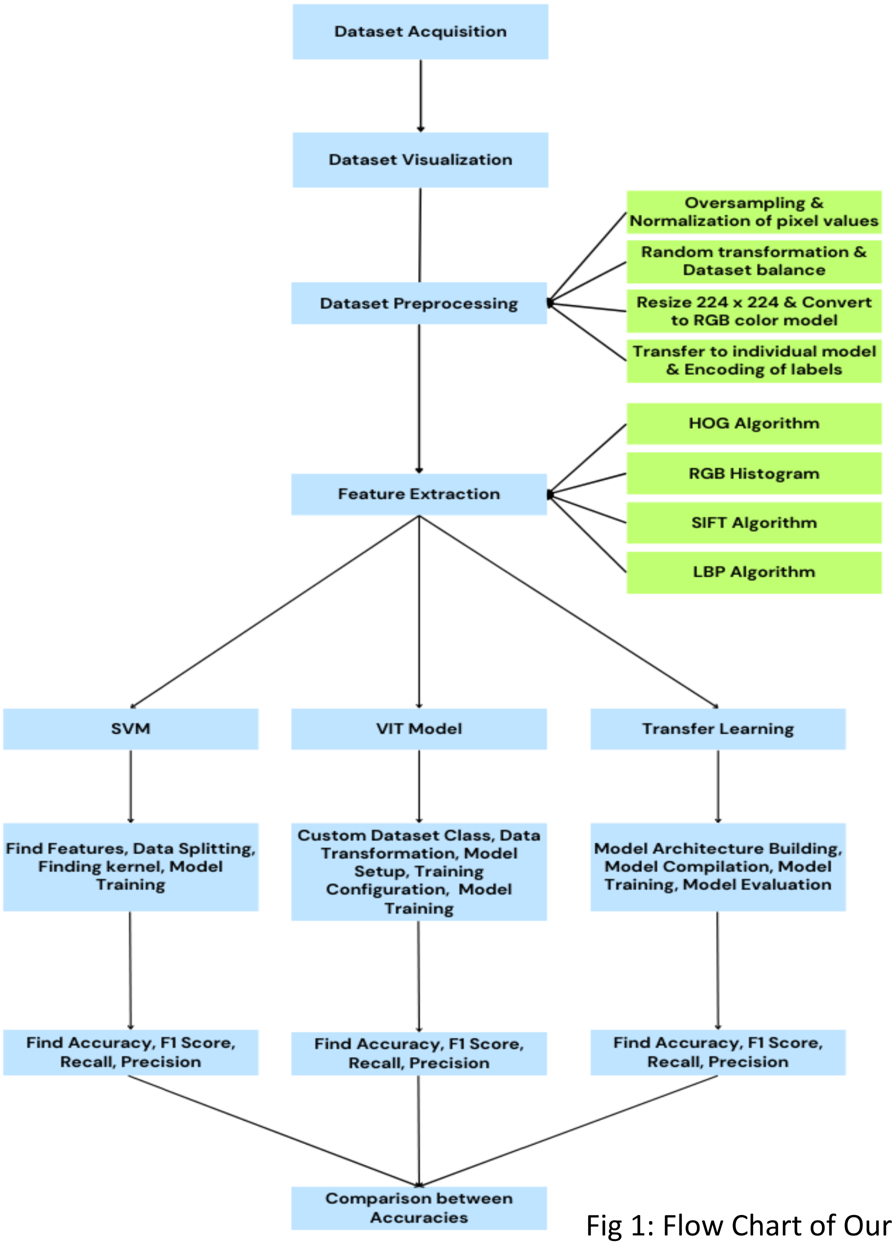

Fig 1: Flow Chart of Our Methodology

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Methodology (cont.)

Dataset Description & Visualization

The dataset comprises 4046 images of guava plants, showcasing manifestations of seven diseases—Styler and Root, Mummification, Dot, Scab, Fresh Guava, Canker, and Phytophthora. These images, sourced from platforms like Kaggle, data.mendeley.com and some were captured using a camera by us.

Fig 2: Set of Diseases and No Disease Guavas

Methodology (cont.)

Data Preprocessing

1. Over Sampling
2. Normalization of Pixel Values
3. Random Transformation
4. Dataset Balance
5. Resize to 224x224
6. Convert to RGB color model
7. Encoding of Labels

Fig 3: Flow Chart of Our Preprocessing Sector

Methodology (cont.)

Feature Extraction

1. SIFT (Scale-Invariant Feature Transform): Identified distinctive key points in images regardless of scale or rotation, aiding in robust feature matching.

2. RGB Histogram: Captured color distribution information across the red, green, and blue channels, providing insights into color composition.

3. HOG (Histogram of Oriented Gradients): Represented image gradients as histograms of oriented gradients, enabling detection of object shapes and textures.

4. LBP (Local Binary Patterns): Encoded texture information by comparing each pixel with its neighboring pixels, facilitating texture classification and analysis.

Methodology (cont.)

Support Vector Classifier

1. Input Image: Original image for classification.
2. Features Extraction: Extract relevant features like edges, shapes, or colors from the image.
3. Feature Vector: Convert extracted features into a numerical feature vector.
4. Training and Classification: Utilize the feature vector to train a model, and then classify them.

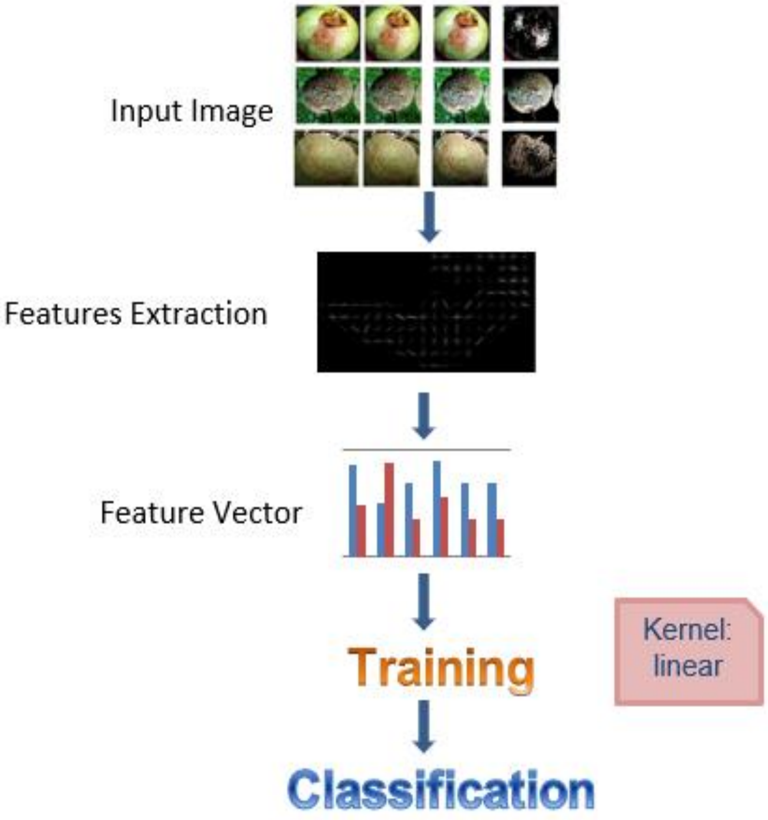

Fig 4: SVM Flow chart

Methodology (cont.)

Vision Transformers

1. Input: Guava images, categorized as healthy or the one of the given 7 diseases
2. Custom Dataset Class: It will be created to handle the loading, transformation, and label encoding of images.
3. Patching: Partition images into small squares
4. Embedding: Enhance squares with content and location information
5. Transformer: Analyze squares to discern disease patterns
6. Output: Classify image as healthy or diseased

Methodology (cont.)

Vision Transformers

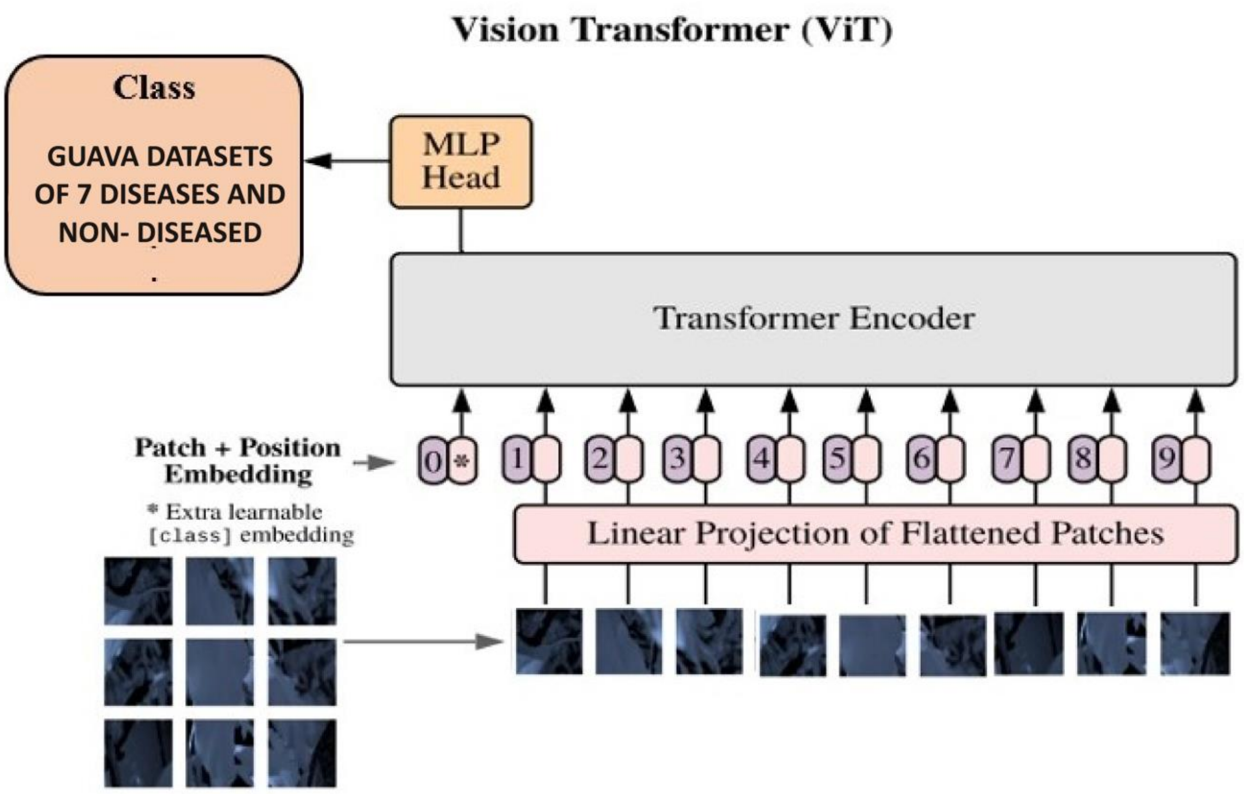

Fig 4: ViT Model

Methodology (cont.)

Transfer Learning

1. Pre-Trained Model: A model trained on generic images learns basic features.
2. Transfer Learning: Adapting a pre-trained model for guava disease detection.
3. Fine-Tuning: Adjusting model layers for disease-specific patterns.
4. Feature Extraction: Extracting basic image features.
5. Disease Detection Training: Training the model to recognize disease patterns.
6. Classification: Classifying new images.

Methodology (cont.)

Transfer Learning

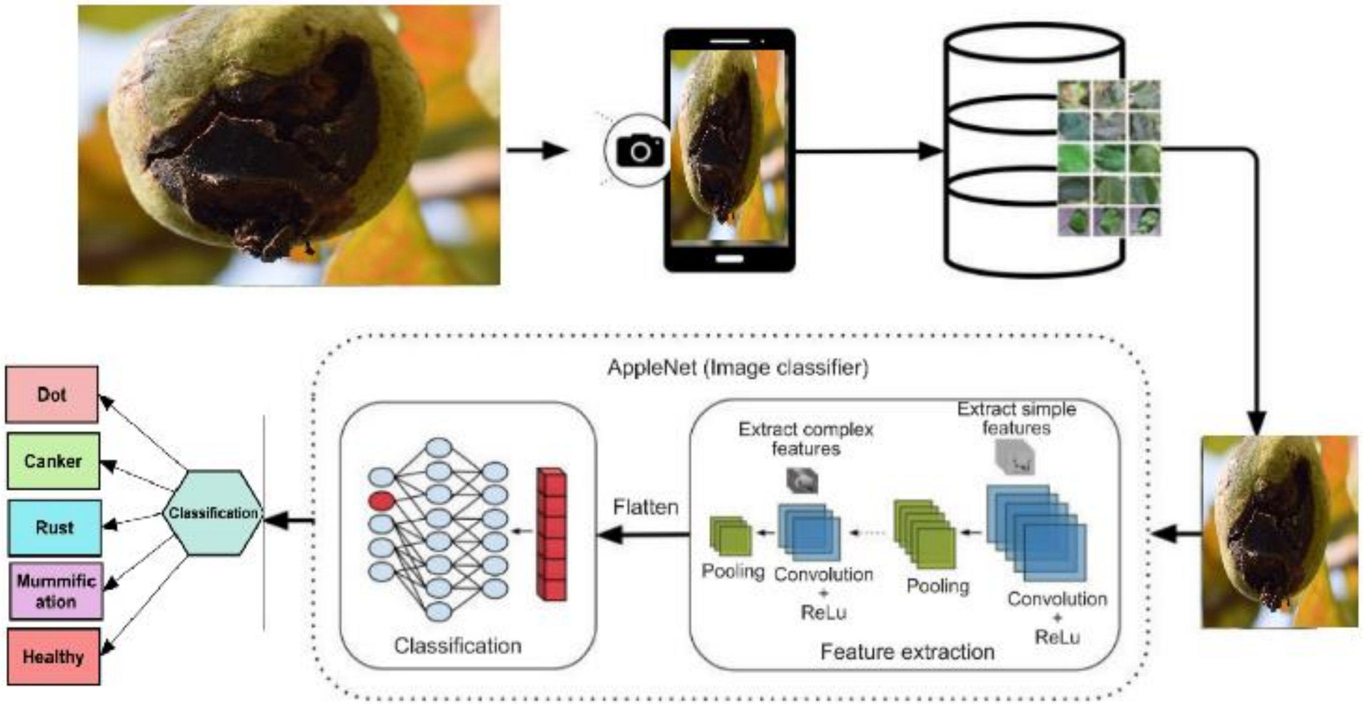

Fig 4: Transfer Learning Model

Results & Discussion

Support Vector Machine

Classification Report:

	precision	recall	f1-score	support
Styler and Root	0.71	0.80	0.75	40
Mummification	0.70	0.70	0.70	40
Dot	0.98	1.00	0.99	40
Scab	0.70	0.65	0.68	40
FreshGuava	0.65	0.65	0.65	40
Canker	0.87	0.82	0.85	40
Phytopthora	0.89	0.85	0.87	40
Rust	0.71	0.72	0.72	40
accuracy			0.78	320
macro avg	0.78	0.77	0.77	320
weighted avg	0.78	0.78	0.77	320

Fig 5: SVM Classification Report

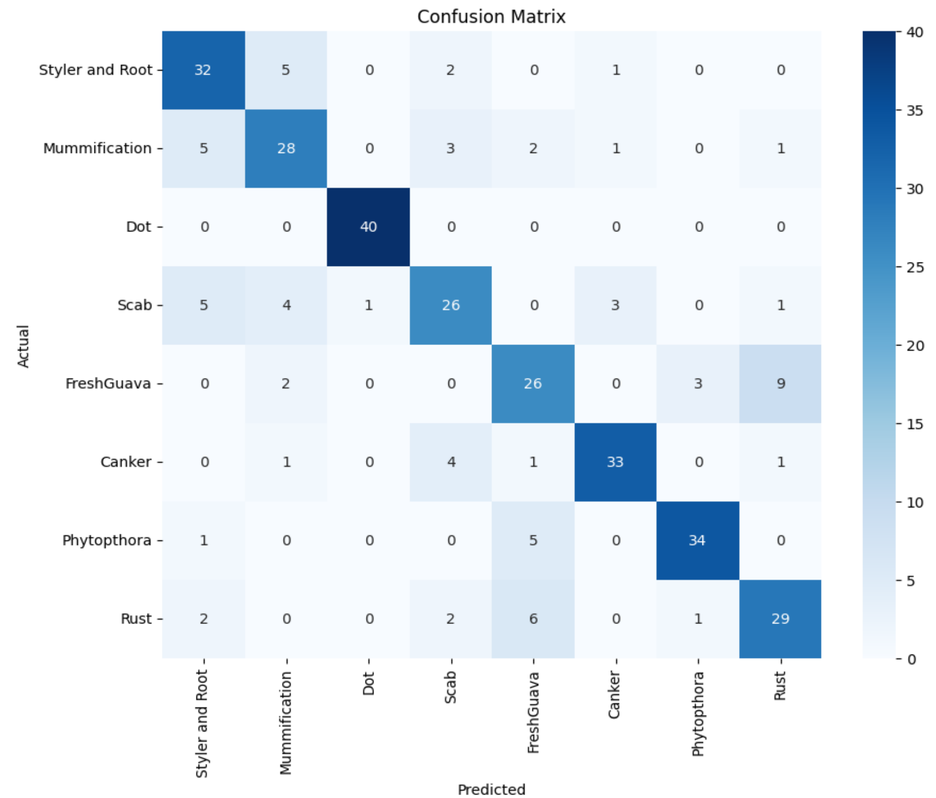

Fig 6: SVM Confusion Matrix

Results & Discussion (cont.)

Support Vector Machine

Metric	Value
Accuracy	0.78
Macro average of Precision	0.78
Weighted average of Precision	0.78
Macro average of Recall	0.77
Weighted average of Recall	0.78
Macro average of F1-score	0.77
Weighted average of F1-score	0.77

Fig 7: SVM Performance

Due to training overfitting, the SVM hasn't performed like the two deep learning models. Even though deep learning models usually perform way more than traditional machine learning, SVM does not very much. Actually, deep learning methods can handle overfitting and underfitting well.

Results & Discussion (cont.)

Transfer Learning

	precision	recall	f1-score	support
Styler and Root	0.95	1.00	0.98	20
Mummification	0.91	1.00	0.95	20
Dot	1.00	1.00	1.00	20
Scab	0.94	0.85	0.89	20
FreshGuava	1.00	0.95	0.97	20
Canker	1.00	0.95	0.97	20
Phytopthora	1.00	1.00	1.00	20
Rust	0.95	1.00	0.98	20
accuracy			0.97	160
macro avg	0.97	0.97	0.97	160
weighted avg	0.97	0.97	0.97	160

Fig 12: Transfer Learning Classification Report

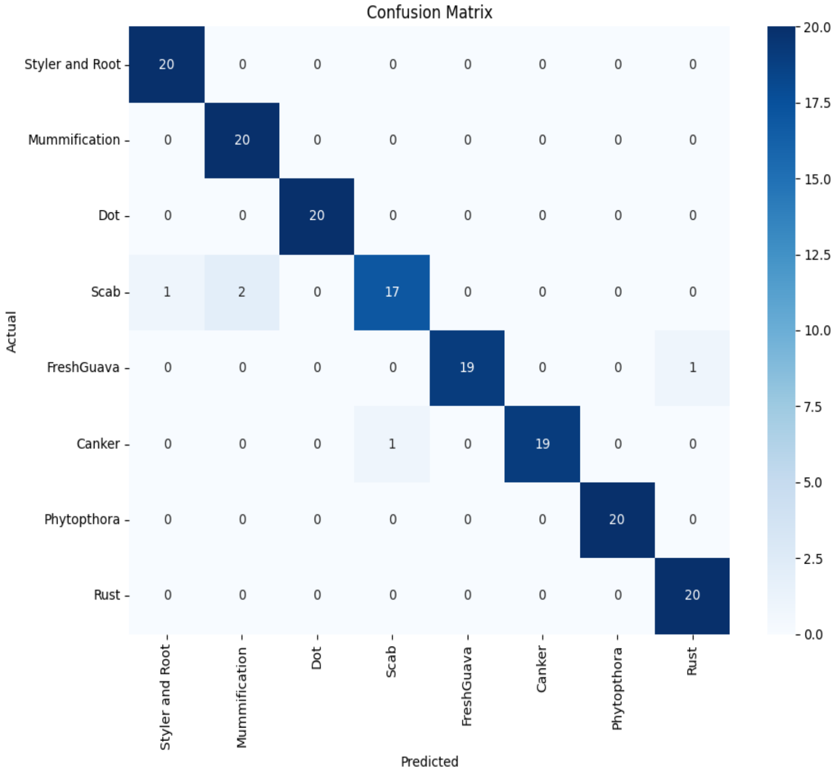

Fig 13: Transfer Learning Confusion Matrix

Results & Discussion (cont.)

Transfer Learning

Metric	Value
Accuracy	0.97
Macro average of Precision	0.97
Weighted average of Precision	0.97
Macro average of Recall	0.97
Weighted average of Recall	0.97
Macro average of F1-score	0.97
Weighted average of F1-score	0.97

Fig 14: Transfer Learning Performance

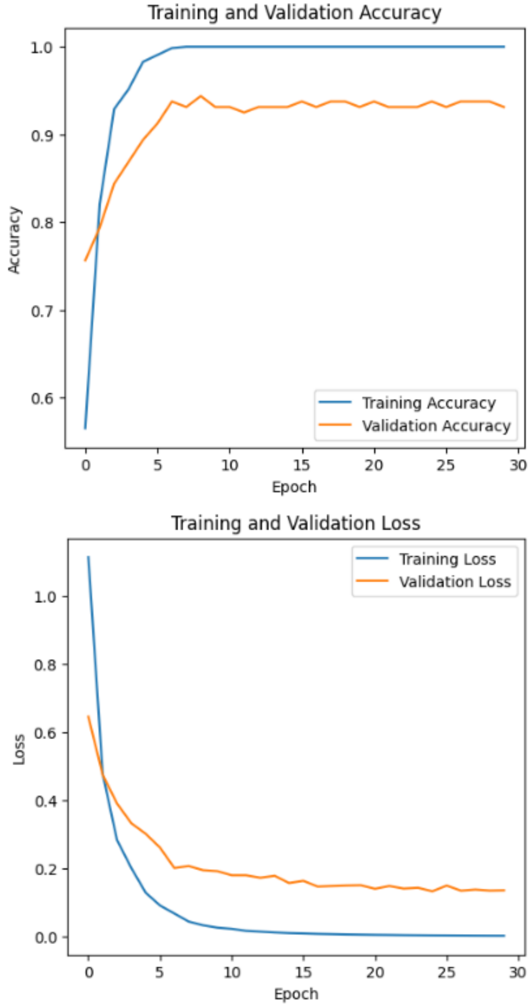

Fig 15: Accuracy & Loss Over Epochs

Results & Discussion (cont.)

Transfer Learning

Transfer learning achieved a high accuracy of 97% due to leveraging pre-trained models on large, diverse datasets. This approach allows the model to utilize already learned features, requiring less training data and computational resources. Fine-tuning these pre-trained models for guava disease detection enables the extraction of high-level features specific to the dataset, resulting in efficient and accurate classification.

Results & Discussion (cont.)

Vision Transformers

	precision	recall	f1-score	support
Canker	0.95	1.00	0.98	20
Dot	1.00	1.00	1.00	20
FreshGuava	1.00	1.00	1.00	20
Mummification	0.95	0.95	0.95	20
Phytopthora	1.00	0.95	0.97	20
Rust	1.00	0.95	0.97	20
Scab	1.00	1.00	1.00	20
Styler and Root	0.95	1.00	0.98	20
accuracy			0.98	160
macro avg	0.98	0.98	0.98	160
weighted avg	0.98	0.98	0.98	160

Fig 8: ViT Classification Report

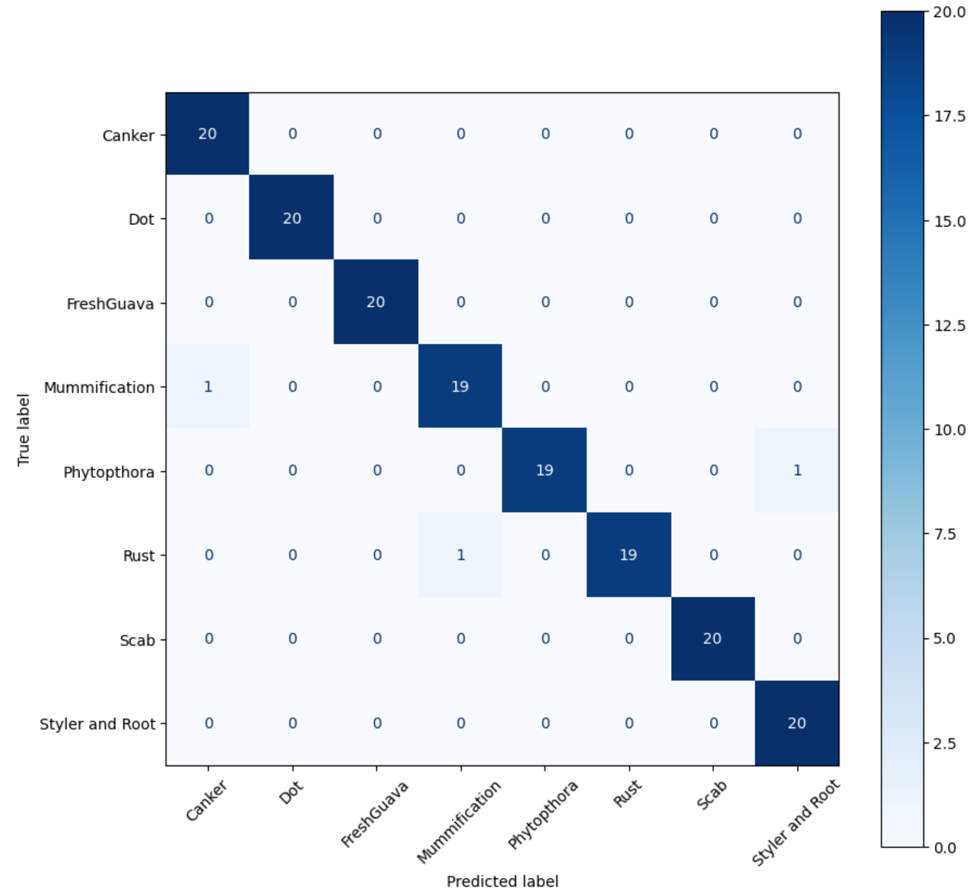

Fig 9: ViT Confusion Matrix

Results & Discussion (cont.)

Vision Transformers

Metric	Value
Accuracy	0.98
Macro average of Precision	0.98
Weighted average of Precision	0.98
Macro average of Recall	0.98
Weighted average of Recall	0.98
Macro average of F1-score	0.98
Weighted average of F1-score	0.98

Fig 10: ViT Performance

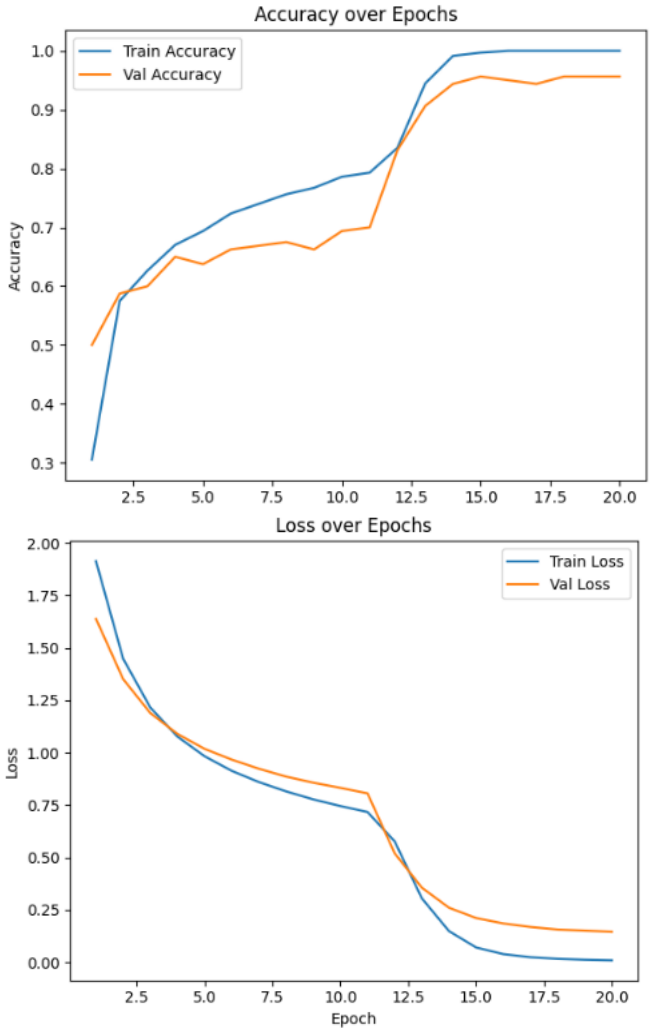

Fig 11: Accuracy & Loss Over Epochs

Results & Discussion (cont.)

Vision Transformers

Vision Transformers (ViTs) achieved the highest accuracy of 98% due to their ability to capture long-range dependencies and contextual information in images. The self-attention mechanism in ViTs allows the model to focus on the most relevant parts of an image, enhancing feature extraction. Additionally, ViTs can handle large-scale data effectively, leading to robust and generalizable models, making them particularly suited for tasks like guava disease detection.

Results & Discussion (cont.)

Comparison

Algorithm	Accuracy (%)
Vision Transformers	98%
Transfer Learning	97%
SVM	78%

Table 2. Comparison Table

We incorporated SVM, Vision Transformers, and transfer learning for guava disease detection. Vision Transformers, capturing spatial relations from raw image pixels, achieved the highest accuracy at 98%. Transfer learning, fine-tuning pre-trained models on large datasets, followed closely with 97% accuracy. SVM, with manually extracted features, attained 78% accuracy.

Results & Discussion (cont.)

Comparison

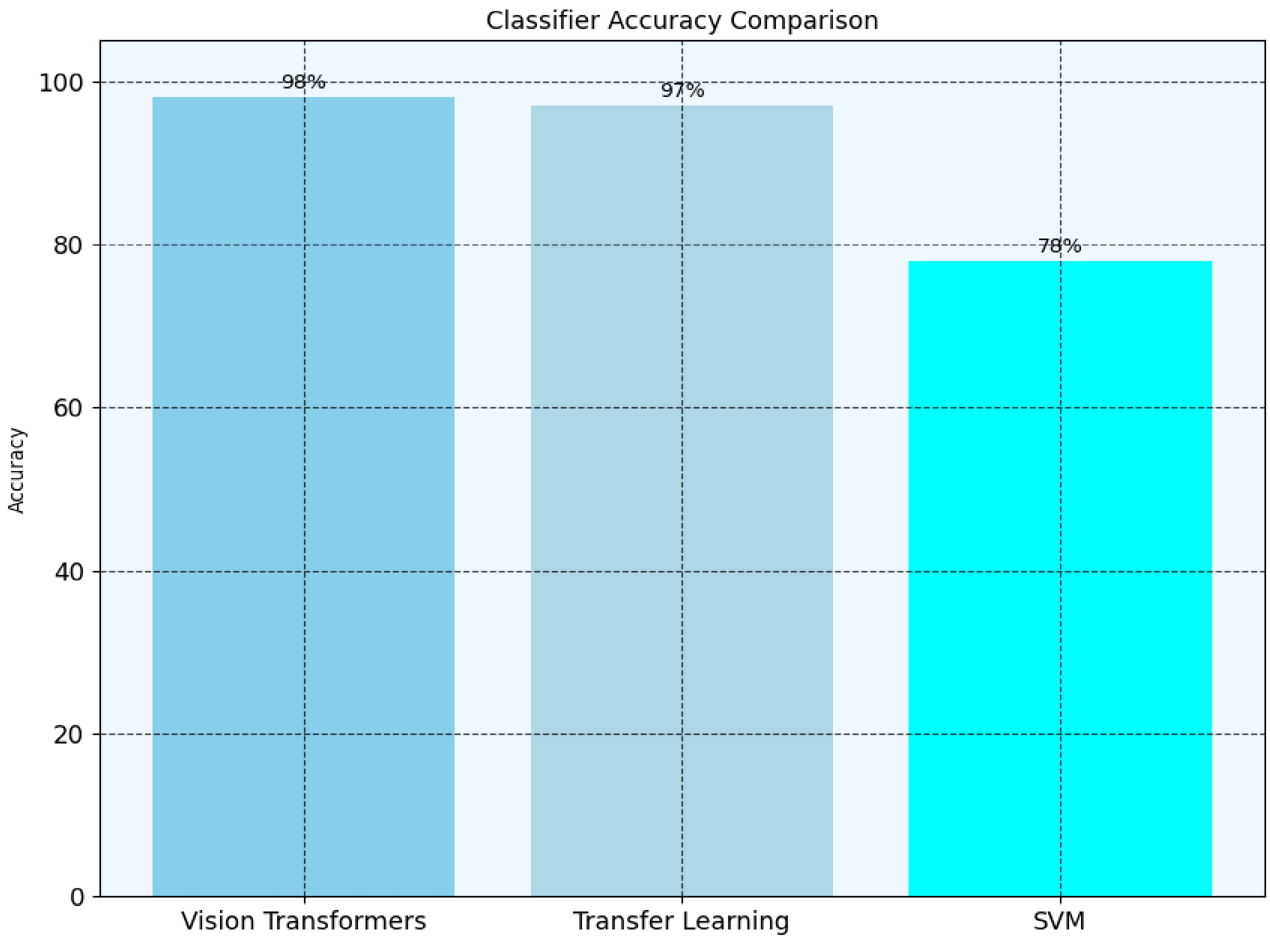

Fig 16: Comparison Histogram

Limitations and Future Scope

Limitations

1. Limited dataset size may hinder model generalization.
2. High computational requirements for training deep learning models.
3. Potential overfitting with insufficiently diverse data.
4. Difficulty in obtaining high-quality annotated data.
5. Limited availability of advanced imaging equipment for data collection.

Limitations and Future Scope (cont.)

Future Works

1. Enhance model architectures by improving deep learning techniques like Transfer Learning and Vision Transformers.
2. Implement fine-tuning strategies such as differential learning rates and layer adjustments.
3. Use advanced data augmentation techniques to improve the dataset and results.
4. Integrate multi-modal data sources like spectral and infrared imaging.
5. Optimize model architectures for real-time deployment on edge devices and IoT systems.
6. Develop compact deep learning models for mobile applications.

Conclusion

In agriculture, accurate and timely plant disease detection is crucial for preventing crop loss and economic damage. Our research highlights the effectiveness of advanced deep learning methods, particularly Vision Transformers (ViT) and transfer learning, in identifying guava diseases with accuracies of 98% and 97%, respectively. These models offer promising solutions for farmers and agricultural stakeholders. Traditional machine learning methods, achieving up to 78% accuracy, remain valuable for foundational insights. Continued research and development are essential for enhancing disease detection and ensuring food security.

Fig 16: Comparison Histogram

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THANK YOU ALL

HAVE A GOOD DAY