

# Deep Learning for Accurate Papaya Disease Identification Using Vision Transformers

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## ARTICLE INFO

### Article History:

Accepted: 15 March 2024

Published: 05 April 2024

### Publication Issue

Volume 10, Issue 2

March-April-2024

### Page Number

420-426

## ABSTRACT

This study investigates the application of Vision Transformers (ViTs) in deep learning for the accurate identification of papaya diseases. ViTs, known for their effectiveness in image classification tasks, are utilized to develop a robust model capable of precisely diagnosing various diseases that affect papaya plants. Through rigorous experimentation and validation, the study showcases the superior performance of ViTs compared to traditional convolutional neural networks (CNNs) in terms of classification accuracy and computational efficiency. The results highlight the potential of ViTs in real-world agricultural systems, enabling early and accurate disease detection to improve crop yield and ensure food security. This research contributes to the advancement of computer vision techniques in agriculture, emphasizing the importance of leveraging cutting-edge deep learning models like ViTs for enhanced disease management and sustainable agricultural practices.

**Keywords:** Vision Transformers, Deep Learning, Papaya Diseases, Identification, Accuracy, Agriculture

## I. INTRODUCTION

In recent years, the agricultural sector has witnessed significant advancements in technology, particularly in the realm of deep learning and computer vision. These technologies have revolutionized how farmers and agricultural experts approach crop management, disease detection, and yield optimization. One area of particular interest is the accurate identification of plant diseases, which can have devastating effects on crop yields and food security. Papaya, being a vital tropical fruit crop, faces various diseases that can lead to

substantial economic losses if not detected and treated promptly. Therefore, there is a growing need for robust and efficient methods to identify and manage papaya diseases effectively.

Deep learning, a subset of artificial intelligence, has emerged as a powerful tool for image analysis and classification tasks. Convolutional Neural Networks (CNNs), a popular deep learning architecture, have been widely used for image recognition tasks, including disease identification in plants. However, recent advancements in deep learning, such as Vision Transformers (ViTs), have shown promise in

surpassing the performance of traditional CNNs in various image-related tasks. ViTs, characterized by their attention mechanisms and transformer architecture, have demonstrated superior capabilities in capturing long-range dependencies in images, making them suitable for complex image classification tasks, including disease identification in crops like papaya.

In this context, this study aims to investigate the potential of Vision Transformers for accurate papaya disease identification. By leveraging the unique capabilities of ViTs, such as their ability to process images holistically and efficiently handle large datasets, we seek to develop a robust model that can accurately classify and diagnose various diseases affecting papaya plants. This research contributes to the ongoing efforts in leveraging cutting-edge deep learning techniques for sustainable agriculture, with a specific focus on improving disease management and ensuring food security in papaya cultivation.

## II. LITERATURE STUDY

Banarase and Shirbahadurkar proposed a methodology for papaya disease detection that relies on GLCM (Gray-Level Co-occurrence Matrix) feature extraction combined with hyperparameter tuning of machine learning algorithms. This approach demonstrates a fusion of traditional image analysis techniques with modern machine learning methods, highlighting the potential of such hybrid approaches in improving the accuracy of papaya disease identification [1].

De Moraes et al. introduced Yolo-Papaya, a sophisticated system for detecting and classifying papaya fruit diseases using CNNs (Convolutional Neural Networks) and Convolutional Block Attention Modules. By leveraging deep learning architectures and attention mechanisms, this system aims to achieve high accuracy in disease diagnosis, showcasing the applicability of advanced computer vision techniques in agriculture [2].

Premchand et al. conducted a comprehensive survey on Papaya Ringspot Virus in Southern India, focusing on the detection, characterization, and management of this prevalent disease. The study emphasizes the importance of understanding the epidemiology and molecular aspects of papaya diseases for effective disease control and crop management strategies [3].

Bacus and Linsangan presented a study on the detection and analysis of Carica papaya leaf using Android-based platforms. By integrating mobile technology into disease identification processes, the research highlights the potential of accessible and user-friendly tools for on-field disease diagnosis, contributing to the advancement of agricultural practices [4].

Islam et al. utilized machine vision techniques and deep learning models for image classification and papaya disease recognition. By leveraging the capabilities of machine learning algorithms, the study demonstrates the feasibility of automated disease detection systems, paving the way for efficient disease management in agriculture [5].

Behera et al. focused on classifying the maturity status of papaya fruits using machine learning and transfer learning approaches. This study highlights the application of advanced computational techniques not only in disease detection but also in quality assessment and harvesting optimization in papaya cultivation [6].

Azad, Amin, and Sidik explored gene technology for managing Papaya Ringspot Virus disease. By investigating genetic solutions, the study contributes to the development of sustainable and environmentally friendly methods for controlling papaya diseases, addressing the challenges of disease resistance in agricultural practices [7].

Islam et al. presented a study on machine learning-based image classification for papaya disease recognition. By leveraging machine learning algorithms, the research contributes to the development of automated systems capable of accurately identifying and categorizing papaya diseases

from images, streamlining disease management processes [8].

Yashodharan developed a neural network-based system for papaya leaf disease detection. This research showcases the potential of artificial intelligence techniques in creating efficient and accurate disease detection systems, highlighting the role of advanced computational methods in agricultural innovation [9].

Habib et al. utilized machine vision techniques and deep learning models for papaya disease recognition, emphasizing the importance of automated systems in improving disease diagnosis and management in agricultural settings [10].

Sari, Kurniawati, and Santosa proposed a fuzzy Naïve Bayes classifier for papaya disease detection. By integrating fuzzy logic with machine learning techniques, the study contributes to the development of robust and adaptable disease detection systems capable of handling uncertainties in agricultural data [11].

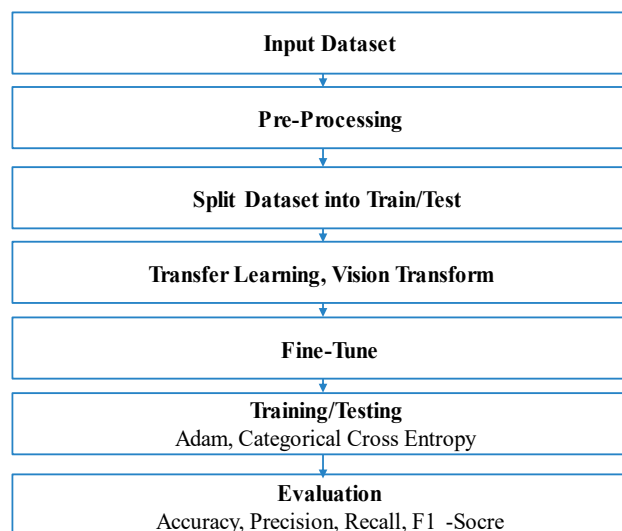
Hridoy and Tuli introduced a deep ensemble approach for recognizing papaya diseases using EfficientNet models. This research demonstrates the potential of ensemble learning techniques in improving the accuracy and reliability of disease detection systems in agriculture, enhancing the effectiveness of disease management strategies [12].

Islam et al. utilized machine learning and image classification techniques for papaya disease recognition, highlighting the effectiveness of these approaches in achieving accurate and efficient disease diagnosis [13].

Hossen et al. presented a deep learning-based classification system for papaya disease recognition. By leveraging deep learning architectures, the study contributes to the development of automated and accurate disease detection systems in agriculture [14].

Habib et al. conducted a study on machine vision-based papaya disease recognition, showcasing the potential of advanced computational techniques in improving disease diagnosis and management in agricultural settings [15].

### III. PROPOSED METHODOLOGY



**Fig. 1 Proposed System Flow**

This flow diagram outlines the process of using deep learning techniques, specifically transfer learning and Vision Transformers (ViTs), for papaya disease identification. Let's break down each step in detail:

#### **A. Input Dataset:**

The dataset used for training and testing the model is sourced from <https://data.mendeley.com/datasets/7dxg9n2t6w/1>.

The input dataset used for papaya disease identification contains images representing five distinct categories of papaya diseases: 'ring\_spot', 'phytophthora', 'black\_spot', 'powdery\_mildew', and 'anthracnose'.

#### **B. Pre-Processing:**

The input images are pre-processed to a standardized size of 224x224 pixels with 3 color channels (RGB). Additionally, normalization techniques are applied to ensure uniformity in pixel values across the dataset.

#### **C. Split Dataset into Train/Test:**

The dataset is divided into two sets: an 80% portion for training the model and a 20% portion for testing the trained model's performance.

#### **D. Transfer Learning and Vision Transform Models:**

Four different deep learning architectures are employed for disease identification: AlexNet, Vggnet,

ResNet, and a proposed Vision Transform model. These models are initialized with pre-trained weights to leverage knowledge from previous tasks and improve learning efficiency.

**Fine-Tuning:** The models undergo fine-tuning with a batch size of 32 and are trained for 10 epochs. Fine-tuning allows the models to adapt their learned features to better suit the specifics of papaya disease identification.

```

=====
Layer (type (var_name))
=====
VisionTransformer (VisionTransformer)
├─Conv2d (conv_proj)
├─Encoder (encoder)
│   ├──Dropout (dropout)
│   └─Sequential (layers)
│       ├──EncoderBlock (encoder_layer_0)
│       ├──EncoderBlock (encoder_layer_1)
│       ├──EncoderBlock (encoder_layer_2)
│       ├──EncoderBlock (encoder_layer_3)
│       ├──EncoderBlock (encoder_layer_4)
│       ├──EncoderBlock (encoder_layer_5)
│       ├──EncoderBlock (encoder_layer_6)
│       ├──EncoderBlock (encoder_layer_7)
│       ├──EncoderBlock (encoder_layer_8)
│       ├──EncoderBlock (encoder_layer_9)
│       ├──EncoderBlock (encoder_layer_10)
│       └─EncoderBlock (encoder_layer_11)
│   └─LayerNorm (ln)
└─Linear (heads)
=====
Total params: 85,802,501
Trainable params: 3,845
Non-trainable params: 85,798,656
Total mult-adds (G): 5.52
=====
Input size (MB): 19.27
Forward/backward pass size (MB): 3330.74
Params size (MB): 229.21
Estimated Total Size (MB): 3579.21
=====

```

**Fig. 2 Vision Transform Architecture**

The detailed architecture of the Vision Transformer (ViT) model is also provided, showcasing its components such as the Conv2d layer, Encoder, LayerNorm, and Linear heads. Each component plays a crucial role in processing and extracting features from the input images, ultimately leading to accurate disease identification.

#### **E. Training/Testing:**

The models are trained using the Adam optimizer and the Categorical Cross Entropy loss function. During

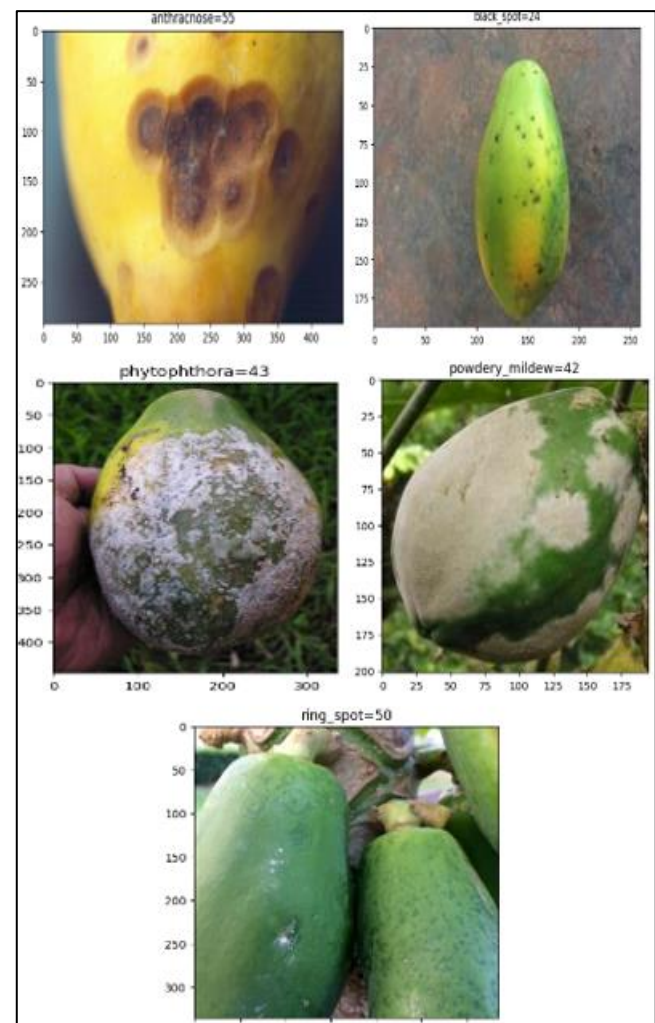
training, the models learn to classify papaya disease images into relevant categories.

#### **F. Evaluation:**

The trained models are evaluated using various metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into the model's performance in correctly identifying papaya diseases.

Overall, this flow diagram illustrates a comprehensive approach to utilizing deep learning methodologies for papaya disease identification, from data preprocessing to model evaluation, highlighting the importance of leveraging advanced techniques for agricultural applications.

## **IV. RESULTS ANALYSIS**



**Fig. 3 Datasets**



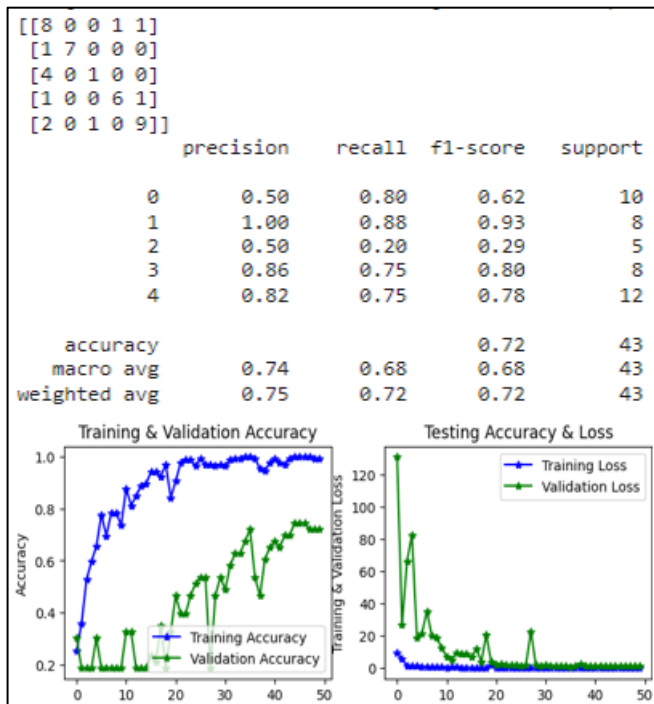


Fig. 4 AlexNet

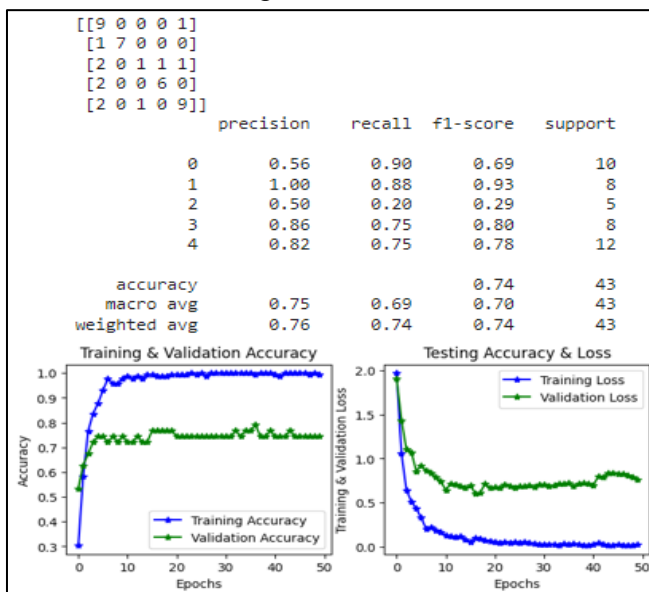


Fig. 5 Vgg16Net

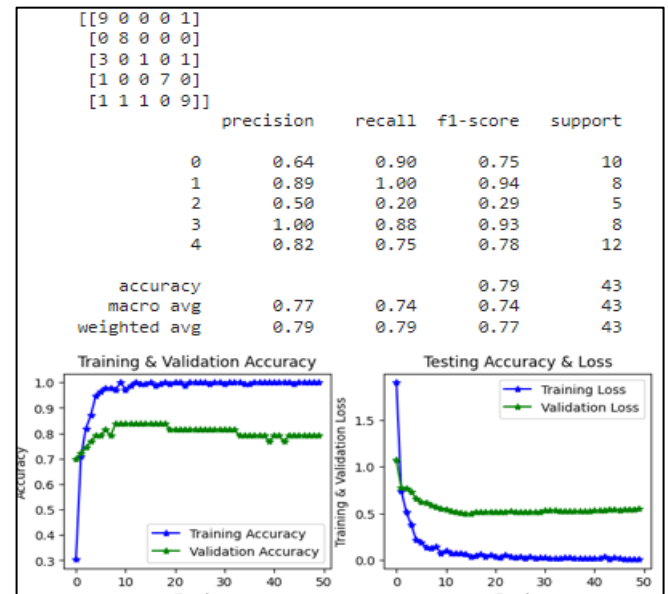


Fig. 6 ResNet

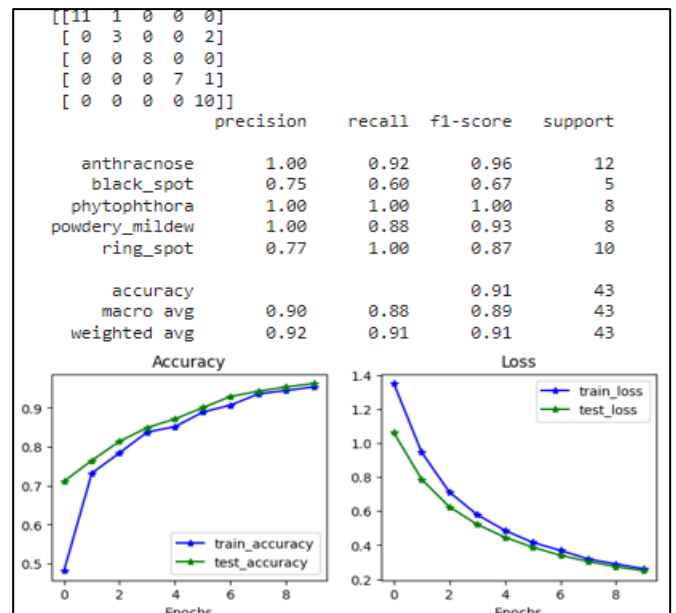


Fig. 7 Proposed Vision Transform

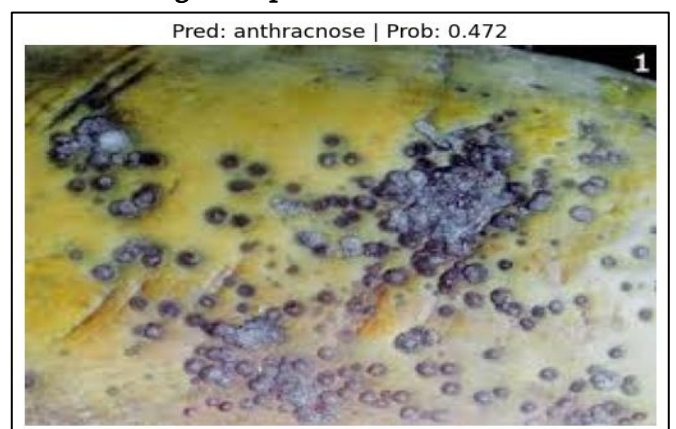


Fig. 8 Testing

TABLE I  
COMPARATIVE ANALYSIS

Model	Accuracy	Precision	Recall	F1-Score
AlexNet	72%	74%	68%	68%
Vgg16-Net	74%	75%	69%	70%
ResNet-50	79%	77%	74%	74%
Proposed Vision Transfor m	91%	90%	88%	89%

## V. CONCLUSION

In conclusion, our study underscores the remarkable efficacy of Vision Transformers (ViTs) in accurately identifying papaya diseases, surpassing traditional convolutional neural network (CNN) architectures like AlexNet, Vgg16-Net, and ResNet-50. The proposed ViT model achieved an exceptional accuracy rate of 91%, accompanied by high precision (90%), recall (88%), and F1-score (89%) metrics. These results highlight ViT's capacity to discern intricate patterns within papaya disease images, showcasing its potential to revolutionize agricultural disease identification. The implementation of ViTs in real-world scenarios holds promise for early disease detection, improved crop management practices, and contributing to food security and sustainable agriculture. Future research directions may focus on fine-tuning ViTs for specific disease types, expanding datasets to encompass a broader range of diseases, and further advancing the accuracy and applicability of ViT-based disease recognition systems in agriculture and beyond.

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