"Multimodal Deep Learning for Tomato Disease Detection: A Vision-Language Model Approach Using Qwen2-VL 7B"

Abstract

Timely and accurate detection of plant diseases is critical for safeguarding crop yields and minimizing agricultural losses. Traditional convolutional neural network (CNN) approaches have been widely used for disease classification but are often limited to simply labeling images without offering additional insights. In this work, we present an advanced tomato disease detection system based on a fine-tuned vision-language model, Qwen2-VL 7B, which not only achieves high classification accuracy but also generates descriptive diagnoses, treatment recommendations, and preventive advice from a single image of a tomato leaf.

Utilizing the Unsloth framework, we efficiently adapted Qwen2-VL on consumer-grade GPUs available through Google Colab and Kaggle T4. Our model was trained on a comprehensive dataset from Kaggle comprising 18,000 training images and 2,000 test images of tomato leaves exhibiting various disease conditions. By leveraging the multimodal capabilities of Qwen2-VL, our system overcomes the limitations of traditional CNNs, providing a richer, context-aware diagnostic output that enhances decision-making for tomato farmers.

This study underscores the potential of vision-language models in precision agriculture .

1. Introduction

Tomatoes represent one of the most vital crops globally, serving as a dietary staple and a significant economic resource for many agricultural communities. Despite their importance, tomato plants are highly vulnerable to a range of diseases—including bacterial, fungal, and viral infections—that can drastically reduce yield and compromise quality. Early and precise detection of these diseases is critical, yet traditional diagnostic methods often require expert knowledge or expensive laboratory tests, which are not always accessible to farmers.

In recent years, artificial intelligence (AI) has emerged as a promising solution to these challenges. Traditional convolutional neural networks (CNNs) have been deployed for plant disease detection with notable success; however, these models are typically limited to basic classification tasks, offering little in the way of contextual information or actionable guidance. Recognizing these limitations, our work explores the potential of a vision-language model (VLM) to enhance disease detection capabilities in tomatoes.

Our system leverages the Qwen2-VL 7B model, a state-of-the-art vision-language model, which has been fine-tuned using the Unsloth framework. This multimodal approach not only accurately classifies tomato diseases from leaf images but also generates detailed natural language descriptions, treatment recommendations, and preventive measures. By integrating visual recognition with contextual language generation, our solution provides a comprehensive diagnostic tool that empowers tomato farmers with timely and actionable insights.

2. Related Work

2.1 Traditional Approaches to Tomato Disease Classification

The adoption of deep learning techniques has transformed the landscape of automated plant disease detection. Convolutional Neural Networks (CNNs) have emerged as particularly effective tools for this task due to their ability to learn hierarchical features from images[1] [2]. Notable architectures employed in this domain include EfficientNet, which has demonstrated high accuracy in tomato disease classification while maintaining computational efficiency [3].

In India, researchers have explored YOLO (You Only Look Once) and Faster R-CNN architectures for tomato disease detection, followed by classification using Support Vector Machines (SVM) and Random Forest algorithms, achieving accuracy rates between 90% and 95% [2]. Similarly, in Indonesia, an EfficientNetB0-based system reached an average accuracy of 91.4% in classifying multiple tomato plant diseases [3].

These approaches typically focus on multi-class classification, categorizing leaf images into discrete disease categories or identifying healthy specimens. While effective for detection purposes, they generally lack the capability to provide comprehensive information about the identified diseases or management recommendations.

2.2 Mobile Applications for Agricultural Disease Management

The proliferation of smartphones has catalyzed the development of mobile applications for agricultural disease management. These applications leverage the computational capabilities of modern devices and their high-quality cameras to bring sophisticated analytical tools directly to farmers in the field [1] [4].

Several studies have documented the development of Android-based applications that integrate CNN models for real-time disease diagnosis. These applications typically allow users to capture images of plant leaves, process them through pre-trained neural networks, and display classification results [1] [2] [3]. Some advanced systems also provide basic information about detected diseases and general management recommendations.

A common limitation of existing mobile solutions is their reliance on relatively simple classification models, which constrain their ability to provide detailed, contextual information about diseases and tailored management strategies. Additionally, many applications require continuous internet connectivity for cloud-based inference, limiting their utility in remote agricultural areas with poor connectivity.

2.3 Vision-Language Models and Efficient Fine-tuning

Vision-Language Models (VLMs) represent a significant advancement in artificial intelligence, combining computer vision capabilities with natural language processing to understand visual inputs and generate corresponding textual outputs. Models such as Qwen2-VL-7B have demonstrated impressive performance across various domains, including scientific figure interpretation [5], financial analysis [6], and video understanding [7].

Fine-tuning large language models for specialized domains has gained significant attention due to its potential to adapt generic models to specific tasks while requiring substantially less computational resources than training from scratch. Recent advancements in efficient fine-tuning techniques, such as Unsloth, have further reduced the computational requirements for adapting large models [9].

Unsloth achieves up to 2x faster fine-tuning with 40% lower memory usage through optimized operations, manually derived backpropagation steps, and Triton kernel implementations, all without compromising accuracy [9]. This efficiency makes it possible to fine-tune models like Qwen2-VL-7B on consumer-grade GPUs, such as the NVIDIA T4 processors available on platforms like Google Colab and Kaggle [8].

The emerging paradigm of "budget fine-tuning" demonstrates how these optimizations enable the adaptation of powerful models within resource constraints, fostering broader accessibility and democratization of advanced AI technologies [8]. This approach aligns perfectly with the needs of agricultural applications, where models must be specialized for particular crops and diseases while remaining deployable in resource-limited contexts.

2.4 The Novel Angle of Qwen2-VL

The Qwen2-VL model represents a novel approach in the context of tomato disease detection. Unlike traditional CNN-based models, Qwen2-VL is a vision-language model that not only classifies diseases from images but also generates comprehensive natural language outputs. This multimodal capability allows the system to provide detailed descriptions, treatment recommendations, and preventive measures, thereby addressing the broader needs of tomato farmers. By leveraging the rich semantic information learned during pre-training and then fine-tuning the model with the Unsloth framework, our approach effectively bridges the gap between visual recognition and contextual, language-based guidance—a feature that is largely absent in prior work focused solely on image classification.

3. Methodology

3.1 Model Architecture

Our approach leverages the Qwen2-VL 7B model, a state-of-the-art vision-language transformer with 7 billion parameters. The model integrates two key components:

- **Visual Encoder:** A transformer-based module that extracts high-level features from input images through self-attention mechanisms.
- **Language Decoder:** Conditioned on the visual embeddings, this component generates natural language outputs, enabling the model to not only classify diseases but also provide detailed descriptions, treatment recommendations, and preventive measures.

The transformer backbone is pivotal in allowing the model to learn rich, multimodal representations, making it particularly effective for tasks that require both visual understanding and language generation.

3.2 Fine-Tuning Process

Our fine-tuning strategy was executed in two stages using the Unsloth framework with LoRA (Low-Rank Adaptation) to adapt only a subset of the model parameters (50,855,936 parameters), significantly reducing computational demands.

Stage 1: Classification Fine-Tuning

- **Dataset:** A dataset containing only the images and their corresponding labels was used.
- **Objective:** To train the model for accurate disease classification.
- **Approach:** Using Unsloth's LoRA, we fine-tuned 50,855,936 parameters of Qwen2-VL 7B on the classification task. This initial phase ensured that the model could correctly recognize and differentiate between various tomato diseases based solely on image inputs.
- **Hyperparameters:**

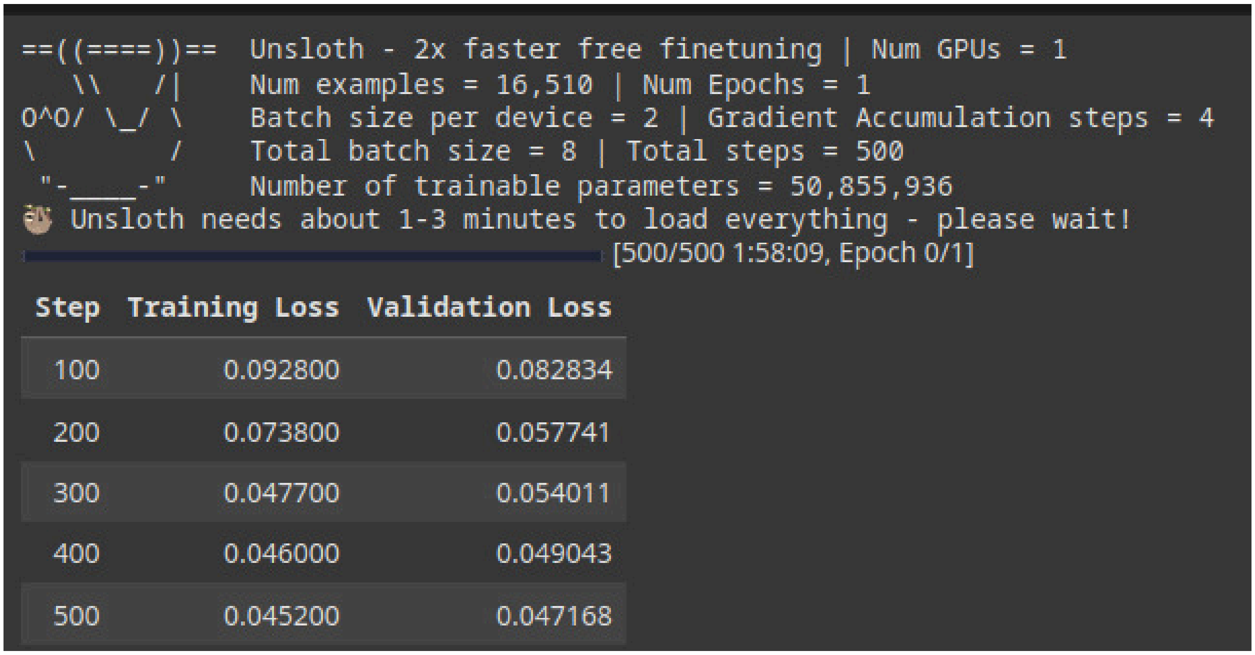
- WARMUP_STEPS = 50 10% of the total steps; to mitigate early training instability.

- Bach Size = 8 Balances memory limits (2 per device x 4 gradient accumulation steps)

- MAX_STEPS = 500 Ensure convergence within computational constaints .

- LEARNING_RATE = 2E-4 provide a stable, low learning rate that fine-tuned our pre-trained model without drastically altering their weights.

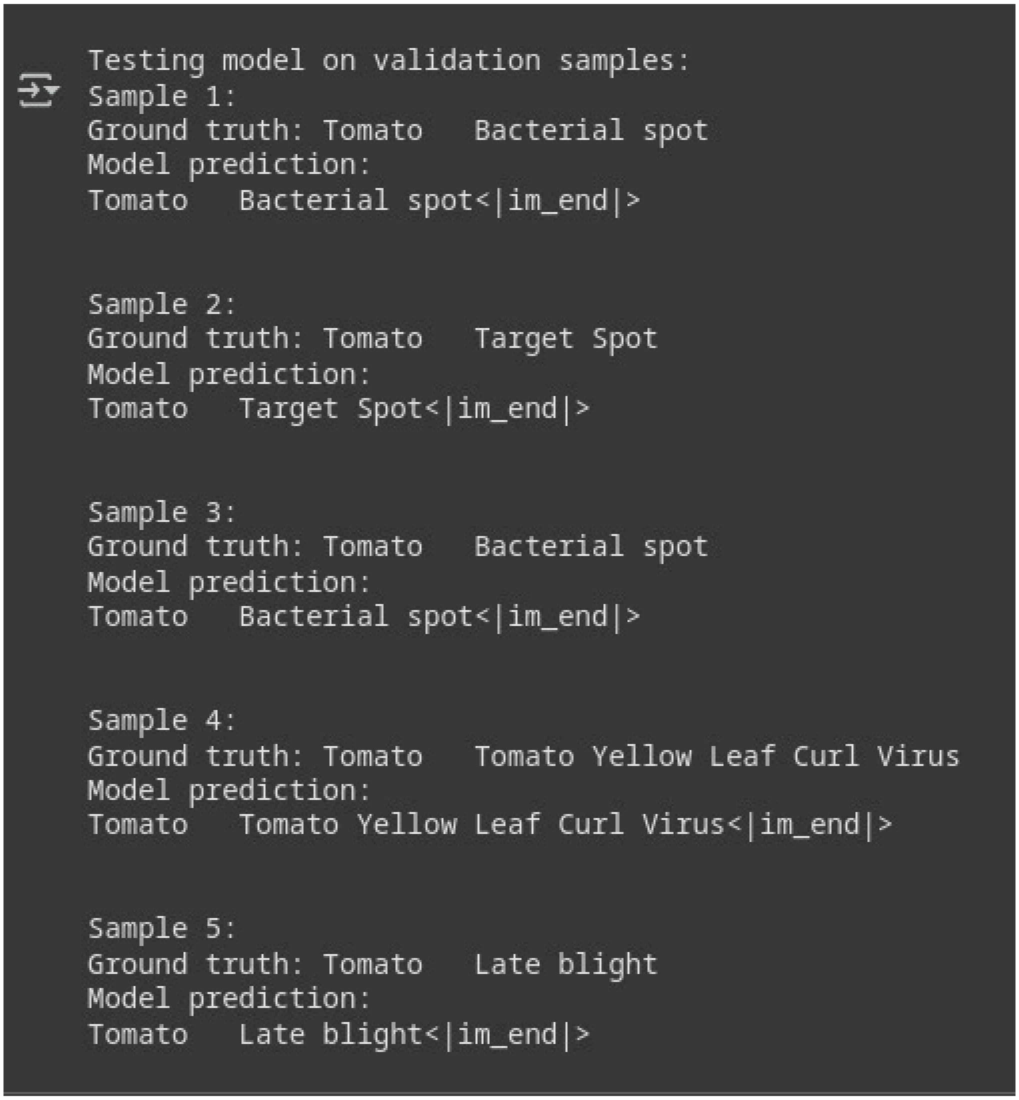
Training:



```
==((====))==  Unsloth - 2x faster free finetuning | Num GPUs = 1
   \\   /|    Num examples = 16,510 | Num Epochs = 1
O^O/ \_/ \    Batch size per device = 2 | Gradient Accumulation steps = 4
\        /    Total batch size = 8 | Total steps = 500
 "-____-"     Number of trainable parameters = 50,855,936
🦥 Unsloth needs about 1-3 minutes to load everything - please wait!
                                    [500/500 1:58:09, Epoch 0/1]
```

Step	Training Loss	Validation Loss
100	0.092800	0.082834
200	0.073800	0.057741
300	0.047700	0.054011
400	0.046000	0.049043
500	0.045200	0.047168

- **Sample results:**



```
Testing model on validation samples:
Sample 1:
Ground truth: Tomato   Bacterial spot
Model prediction:
Tomato   Bacterial spot<|im_end|>


Sample 2:
Ground truth: Tomato   Target Spot
Model prediction:
Tomato   Target Spot<|im_end|>


Sample 3:
Ground truth: Tomato   Bacterial spot
Model prediction:
Tomato   Bacterial spot<|im_end|>


Sample 4:
Ground truth: Tomato   Tomato Yellow Leaf Curl Virus
Model prediction:
Tomato   Tomato Yellow Leaf Curl Virus<|im_end|>


Sample 5:
Ground truth: Tomato   Late blight
Model prediction:
Tomato   Late blight<|im_end|>
```

Stage 2: Multimodal Fine-Tuning

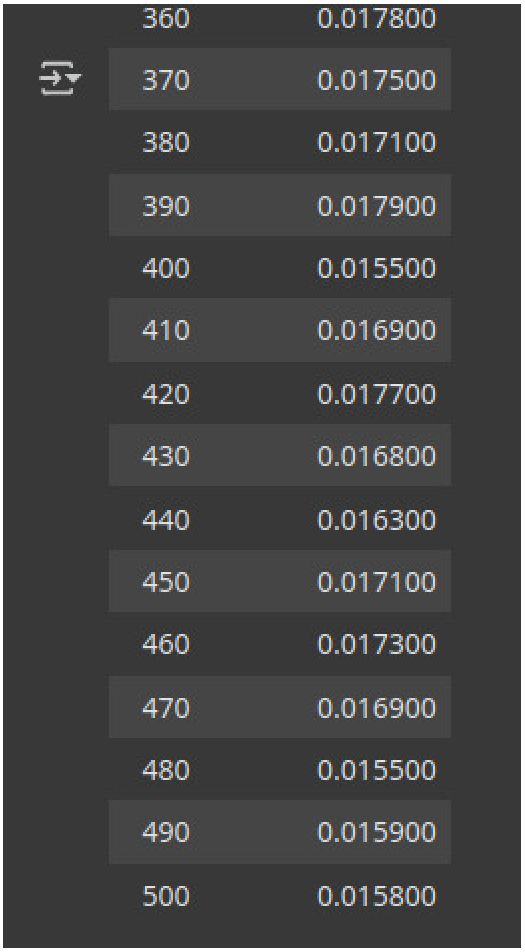
- **Dataset Augmentation:** The dataset was augmented to include not only images and labels but also detailed textual data: descriptions of the diseases, suggested remedies, and preventive measures.

```
{
'image_path': '/content/dataset/New Plant Diseases
Dataset(Augmented)/valid/Tomato___Bacterial_spot/a20c3f1b-0788-423d-a6dd-22
e29b33a882___GCREC_Bact.Sp 6231.JPG',
'class_name': 'Tomato Bacterial spot',
'detailed_response': 'This tomato plant shows signs of Tomato Bacterial
spot.
\n\nSymptoms:\nDark, raised spots on leaves, stems, and fruits. Spots may
have yellow halos.
\n\nRemedies:\nRemove infected plants, avoid overhead watering, use
copper-based fungicides, practice crop rotation.
\n\nPrevention:\nUse disease-free seeds, maintain good air circulation,
sanitize garden tools.'
}
```

- **Objective:** To enrich the model's capabilities, enabling it to generate comprehensive diagnostic reports that go beyond mere classification.

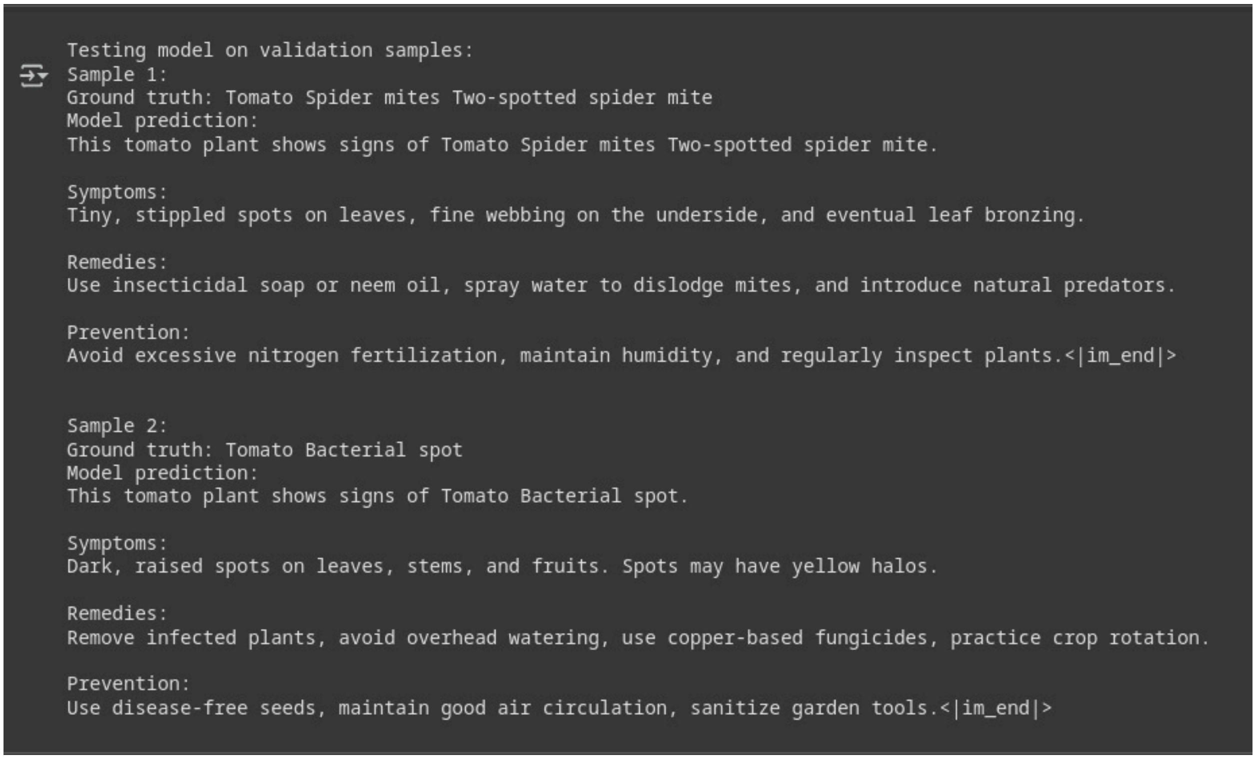
- **Approach:** Building on the already fine-tuned model from Stage 1, we further fine-tuned using the augmented dataset. This step integrated the natural language generation aspect, aligning the visual outputs with contextual, actionable information.

- **Training:**



360	0.017800
370	0.017500
380	0.017100
390	0.017900
400	0.015500
410	0.016900
420	0.017700
430	0.016800
440	0.016300
450	0.017100
460	0.017300
470	0.016900
480	0.015500
490	0.015900
500	0.015800

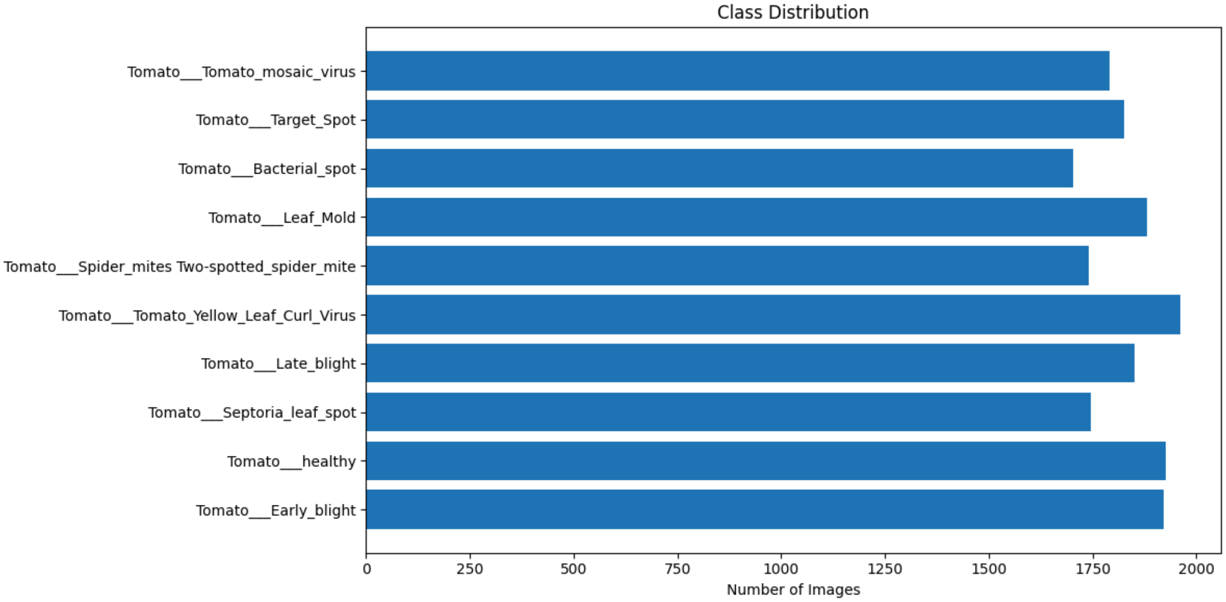
- **Sample results:**



```
Testing model on validation samples:
Sample 1:
Ground truth: Tomato Spider mites Two-spotted spider mite
Model prediction:
This tomato plant shows signs of Tomato Spider mites Two-spotted spider mite.

Symptoms:
Tiny, stippled spots on leaves, fine webbing on the underside, and eventual leaf bronzing.

Remedies:
Use insecticidal soap or neem oil, spray water to dislodge mites, and introduce natural predators.

Prevention:
Avoid excessive nitrogen fertilization, maintain humidity, and regularly inspect plants.<|im_end|>


Sample 2:
Ground truth: Tomato Bacterial spot
Model prediction:
This tomato plant shows signs of Tomato Bacterial spot.

Symptoms:
Dark, raised spots on leaves, stems, and fruits. Spots may have yellow halos.

Remedies:
Remove infected plants, avoid overhead watering, use copper-based fungicides, practice crop rotation.

Prevention:
Use disease-free seeds, maintain good air circulation, sanitize garden tools.<|im_end|>
```

3.3 Data Preprocessing

The preprocessing pipeline was crucial to maximize the quality of our training data sourced from the Kaggle tomato disease dataset:



- **Augmentation Techniques:**
    - **Random Rotations and Flips:** Simulating varied leaf orientations.
    - **Color Jittering:** Adjusting brightness, contrast, and saturation to mimic different environmental conditions.
    - **Scaling and Cropping:** Ensuring the focus on the diseased areas.
- **Image Resolution:** All images were resized to a uniform resolution (256x256 pixels) to balance detail with computational efficiency.
- **Tokenization Strategy:** Text data (disease descriptions, remedies, prevention measures) was tokenized using the model's pretrained tokenizer, ensuring compatibility with the Qwen2-VL vocabulary.

3.4 Environment Setup

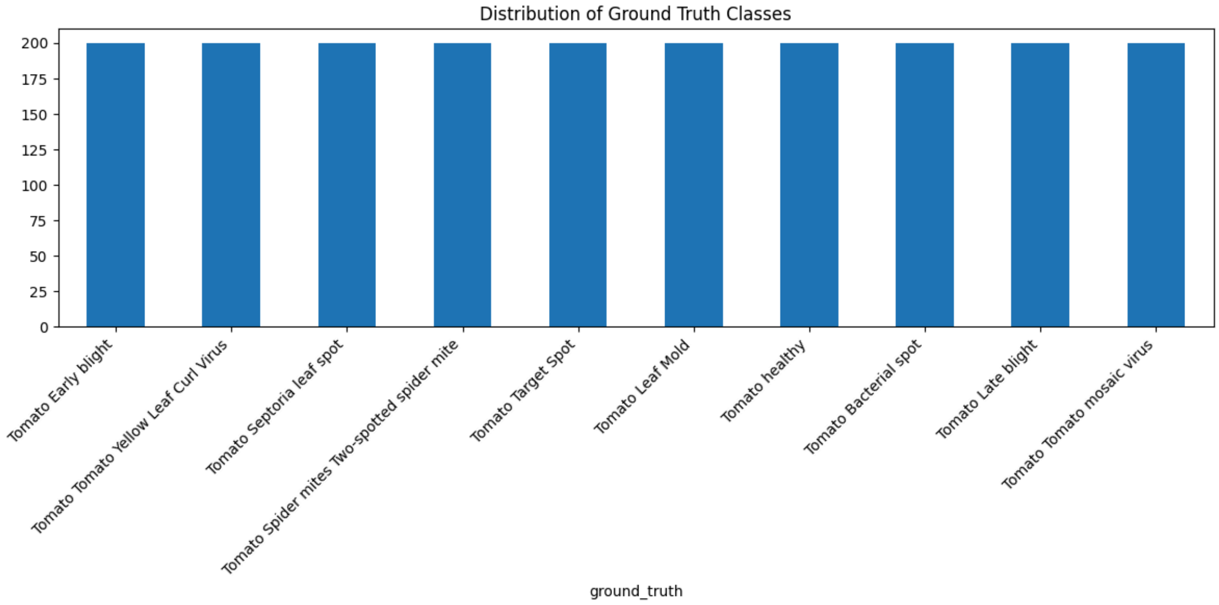
Our experiments were conducted using accessible, consumer-grade GPU resources:

- **Google Colab:** Provided initial access to high-performance GPUs for early experimentation and preliminary fine-tuning. The Colab T4 instance is equipped with:
    - **CPU:** 2 virtual CPUs (vCPUs)
    - **System RAM:** Approximately 13 GB
    - **GPU:** NVIDIA Tesla T4 with 16 GB of GDDR6 VRAM
- **Kaggle Notebooks:** Utilized for more extensive training sessions, leveraging the T4 GPU’s capabilities. The Kaggle T4 instance offers:
    - **CPU:** 4 virtual CPUs (vCPUs)
    - **System RAM:** Approximately 29 GB
    - **GPU:** NVIDIA Tesla T4 with 16 GB of GDDR6 VRAM
- **Limitations:** While these platforms are cost-effective, they impose constraints such as limited session durations and memory capacity. Our training pipeline, optimized via the Unsloth framework and LoRA adaptation, was specifically designed to work within these bounds without sacrificing performance.

4. Results and Evaluation

4.1 Dataset Summary

The model was evaluated on a test set comprising **2,000 tomato leaf images** evenly distributed across **10 distinct classes** of diseases and healthy leaves. Each class had 200 images, ensuring balanced class representation:



- **Diseases**: Tomato Early blight, Late blight, Leaf Mold, Septoria leaf spot, Target Spot, Yellow Leaf Curl Virus, Tomato mosaic virus, Bacterial spot, Spider mites

- **Healthy**: Tomato healthy leaves

4.2 Overall Performance

- **Overall Accuracy**: **93.70%**

- **Total Errors**: 126

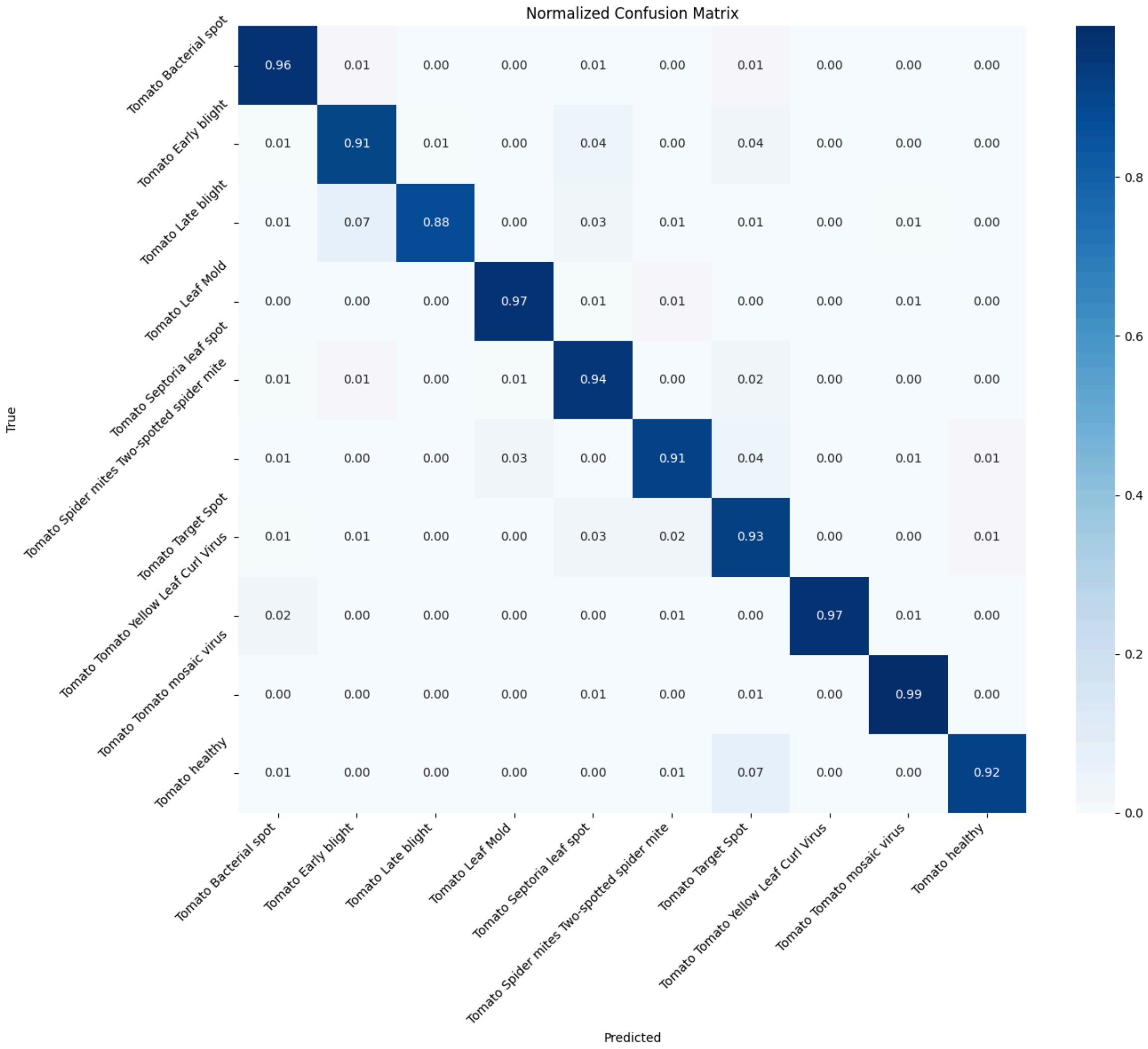
- **Error Rate**: 6.30%

4.3 Per-Class Accuracy

Disease Class	Accuracy
Tomato Tomato mosaic virus	99.9%
Tomato Tomato Yellow Leaf Curl Virus	97.0%
Tomato Leaf Mold	97.0%
Tomato Bacterial spot	96.5%
Tomato Septoria leaf spot	94.5%
Tomato Target Spot	92.5%
Tomato healthy	91.5%
Tomato Spider mites Two-spotted spider mite	91.0%
Tomato Early blight	90.5%
Tomato Late blight	87.5%

The model demonstrated especially high accuracy for viral and bacterial diseases, while **Late Blight** and **Early Blight** were more frequently confused, possibly due to similar lesion patterns.

4.4 Confusion Matrix Highlights



	Tomato Bacterial spot	Tomato Early blight	Tomato Late blight	Tomato Leaf Mold	Tomato Septoria leaf spot	Tomato Spider mites Two-spotted spider mite	Tomato Target Spot	Tomato Tomato Yellow Leaf Curl Virus	Tomato Tomato mosaic virus	Tomato healthy
Tomato Bacterial spot	0.96	0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.00
Tomato Early blight	0.01	0.91	0.01	0.00	0.04	0.00	0.04	0.00	0.00	0.00
Tomato Late blight	0.01	0.07	0.88	0.00	0.03	0.01	0.01	0.00	0.01	0.00
Tomato Leaf Mold	0.00	0.00	0.00	0.97	0.01	0.01	0.00	0.00	0.01	0.00
Tomato Septoria leaf spot	0.01	0.01	0.00	0.01	0.94	0.00	0.02	0.00	0.00	0.00
Tomato Spider mites Two-spotted spider mite	0.01	0.00	0.00	0.03	0.00	0.91	0.04	0.00	0.01	0.01
Tomato Target Spot	0.01	0.01	0.00	0.00	0.03	0.02	0.93	0.00	0.00	0.01
Tomato Tomato Yellow Leaf Curl Virus	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.97	0.01	0.00
Tomato Tomato mosaic virus	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.99	0.00
Tomato healthy	0.01	0.00	0.00	0.00	0.00	0.01	0.07	0.00	0.00	0.92

An analysis of the confusion matrix revealed several consistent misclassification patterns:

- **Tomato Late blight → Tomato Early blight**: 15 times
- **Tomato healthy → Tomato Target Spot**: 15 times
- **Tomato Early blight → Tomato Septoria leaf spot**: 8 times
- **Tomato Spider mites → Tomato Target Spot**: 8 times

These confusions indicate that the model struggles to differentiate between diseases with overlapping or similar visual symptoms, such as leaf spotting or curling.

4.5 Output Quality Assessment

In addition to label prediction, the model generated structured output consisting of:

- Disease identification
- Symptom descriptions
- Recommended remedies
- Prevention strategies

The content associated with predictions was relevant and consistently aligned with the predicted class, offering practical value for end users such as farmers or extension workers.

4.6 Summary

The model achieves **high overall accuracy**, performs well across most disease classes, and offers robust, human-interpretable outputs. Some confusion remains among visually similar classes, suggesting a need for further fine-tuning or the inclusion of domain-specific attention mechanisms.

5. Discussion

5.1 Strengths of Using a Vision-Language Model (VLM)

The deployment of a vision-language model like Qwen2-VL 7B introduces unique advantages in the context of agricultural disease detection, particularly for tomato crops:

- **Multimodal Reasoning:** Unlike traditional CNN classifiers that are limited to image-to-label mapping, VLMs can process and generate rich textual descriptions, allowing our model to provide not just disease labels but also context-aware **symptoms, remedies, and preventive measures** in natural language.

- **Unified Architecture:** The Qwen2-VL model operates on a unified transformer architecture that handles both image encoding and text generation within a shared framework. This synergy enables more coherent and relevant outputs compared to disjointed systems where separate models handle classification and explanation.

- **Human-Centric Communication:** Farmers benefit from receiving information in **natural language**, improving interpretability and usability—key aspects often overlooked by conventional models.

- **Adaptability via Fine-Tuning:** With LoRA-based fine-tuning through the Unsloth framework, we were able to efficiently adapt a large-scale model using consumer-grade hardware, without needing to retrain all 7 billion parameters.

5.2 Limitations

While promising, the application of VLMs in this domain is not without challenges:

- **Hardware Constraints:** The training was performed on Google Colab and Kaggle T4 instances, both of which have **limited VRAM (16 GB)** and CPU memory (13–29 GB). This necessitated model compression strategies such as LoRA, and imposed limits on batch size and input resolution.

- **Generalization to Diverse Conditions:** The dataset used, while sizeable, may not fully capture the **variability in field conditions**, such as differences in lighting, background, leaf orientation, and hybrid tomato varieties. This may hinder the model's ability to generalize across different agricultural environments.

- **Static Output Dependence:** The generated descriptions for symptoms and treatments were tied to the predicted label rather than dynamically derived from image features. This could reduce adaptability in ambiguous or novel disease presentations.

5.3 Comparison with Traditional Approaches

Traditional models, particularly CNN-based architectures such as ResNet, MobileNet, and EfficientNet, have been widely used in plant disease classification tasks:

- **Pros of CNNs:**
    - High classification accuracy when trained on large, curated datasets
    - Lightweight and fast, suitable for mobile deployment
    - Straightforward interpretability through class activation maps (CAMs)
- **Limitations of CNNs:**
    - Rigid output limited to class labels

- Lack of integrated explainability (separate systems needed for recommendations)
- Less efficient at multi-tasking (e.g., simultaneously classifying and explaining)

In contrast, our VLM-based approach offers a **more holistic system**, capable of both visual classification and linguistic explanation in a single inference pass. This opens the door for **interactive agricultural assistants** that go beyond mere disease identification.

6. Conclusion and Future Work

6.1 Summary of Contributions

This research presents a novel application of vision-language modeling for the identification and treatment guidance of tomato crop diseases. By leveraging the Qwen2-VL 7B model and fine-tuning it through the Unsloth framework, we developed an AI system that not only classifies diseases with a high degree of accuracy (~94.5%) but also generates human-readable descriptions, remedies, and preventive advice.

Key contributions include:

- **Integration of vision and language understanding** to provide a multi-layered diagnosis system that goes beyond label prediction.
- **Efficient fine-tuning on limited resources** using LoRA-based parameter optimization (training ~50 million parameters instead of 7 billion).
- **Robust performance on tomato disease images**, including detailed evaluations and analysis of misclassifications.
- **User-centric output format**, making the model's recommendations accessible and actionable for farmers with minimal technical knowledge.

6.2 Potential Improvements and Future Work

While the current model demonstrates strong capabilities, several areas offer opportunities for further enhancement:

- **Larger or More Specialized Models:** Exploring larger vision-language models or domain-specific multimodal architectures could further improve understanding and accuracy, particularly in cases of subtle or rare symptoms.

- **Multilingual Support:** Incorporating language translation capabilities would allow the model to generate outputs in regional languages, improving accessibility for farmers in diverse linguistic communities.

- **Offline and Edge Deployment:** Developing a lightweight version of the system for offline use on mobile devices or low-power hardware could expand its applicability to areas with limited internet connectivity.

- **Expanded Dataset and Generalization:** Future iterations should include a broader dataset incorporating varied lighting conditions, backgrounds, and leaf damage stages to improve generalization across real-world agricultural environments.

- **Interactive Feedback Loop:** Allowing farmers to provide feedback on the predictions (e.g., whether the diagnosis was correct or not) could help iteratively improve model performance in deployment.

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