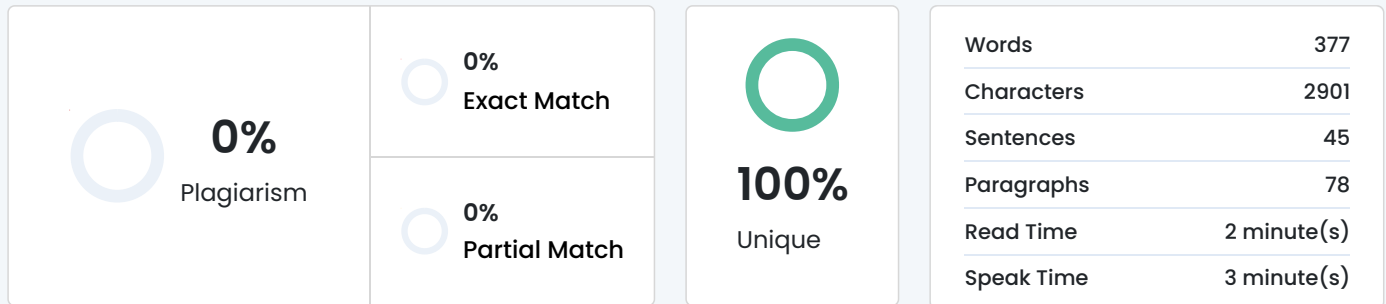


Plagiarism Scan Report



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4.2.2 Advanced Optimization Techniques

The training process incorporated several sophisticated approaches:

1. One-Cycle Learning Rate Scheduling:

- Peak learning rate: 0.01
- Cycle duration: Equal to total epoch count
- Rate adjustment: Cosine annealing

2. Weight Decay Implementation:

- L2 regularization factor: 1e-4
- Reduces overfitting potential

3. Gradient Threshold Application:

- Maximum threshold: 0.1
- Prevents gradient instability

4.2.3 Training Parameters

Parameter Configuration

Batch Size 32

Training Epochs 2

Optimizer Adam

Initialization Random Seed 7

Hardware NVIDIA P100

Table 3: Training parameters configuration

4.2.4 Implementation Specifics

The model was implemented using PyTorch 1.9 with CUDA 11.1 acceleration. Training was performed on Google Colab Pro utilizing P100 GPU resources.

10

5 Experimental Results

5.1 Training Performance Analysis

The model demonstrated efficient convergence characteristics:

Epoch Training Loss Validation Loss Validation Accuracy Learning Rate

1 0.7466 0.5865 83.19% 0.00812

2 0.1248 0.0269 99.23% 0.00000

Table 4: Training performance metrics

5.2 Independent Test Evaluation

The model achieved perfect classification across all 33 test images:

Disease Classification Classification Accuracy

Apple Cedar Rust 4/4

Apple Scab 3/3

Corn Common Rust 3/3

Potato Early Blight 5/5
Tomato Yellow Curl Virus 6/6
Table 5: Test set classification results
5.3 Computational Efficiency Metrics
Performance Metric Measurement
Parameter Count 6,589,734
Model Storage Requirement 25.14 MB
Forward Pass Memory Usage 343.95 MB
Complete Training Duration 20 minutes
Table 6: Computational efficiency metrics
5.4 Comparative Performance Assessment
Architecture Classification Accuracy Parameter Count Training Duration
VGG-16 93.4% 138M 4 hours
ResNet-50 97.3% 25M 3 hours
ResNet-9 99.23% 6.5M 20 mins
Table 7: Comparative performance analysis
11
6 Discussion
6.1 Application Scenarios
The developed model offers potential implementation in several contexts:
1. Mobile Diagnostic Tools: Field-based disease identification for agricultural practitioners
2. Aerial Monitoring Systems: Integration with unmanned aerial vehicles for large-scale assessment
3. Decision Support Systems: Assisting plant pathologists and agricultural extension services
6.2 Implementation Constraints
1. Environmental Variability: Performance may fluctuate under extreme field conditions
2. Classification Limitations: Unable to identify disease conditions absent from training data
3. Image Quality Requirements: Optimal performance requires reasonably clear leaf specimens
6.3 Ethical Framework
1. Data Protection Considerations: Ensuring appropriate safeguards for agricultural data
2. Technology Accessibility: Promoting equitable access across diverse agricultural communities
3. Resource Efficiency: Minimizing computational requirements to reduce environmental impact
12

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