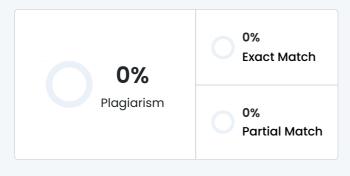


## Plagiarism Scan Report





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7 Conclusion and Future Research Directions

This research has presented a streamlined ResNet-9 architecture for plant disease classification, achieving 99.23% accuracy with only 6.5 million parameters. The model's efficiency characteristics make it particularly suitable for deployment in resource-constrained agricultural environments.

Future research opportunities include:

- 1. Edge Device Optimization: Implementing quantization and network pruning techniques for mobile platforms
- 2. Interpretability Enhancement: Integrating gradient-based visualization techniques for improved diagnostic transparency
- 3. Multimodal Integration: Combining visual analysis with environmental sensor
- 4. Adaptive Learning Frameworks: Developing methodologies for continuous adaptation to emerging disease variants

13

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