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Qeios

Peer Review

Review of: "Plantation Monitoring Using Drone Images: A Dataset and Performance Review"

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1. Scientific and Methodological Rigor

Strengths

The manuscript successfully develops a structured UAV-based monitoring system, which:

Introduces an annotated dataset containing RGB drone images labeled with three health categories.

Explores deep CNN architectures, benchmarking seven well-known models on the proposed dataset.

Evaluates object detection models (YOLO variants) for individual tree identification.

Applies data augmentation strategies, including horizontal flip and random rotation.

Areas for Improvement

Mathematical Justification of CNN Models: The study should provide a formal mathematical representation of how CNN models process spatial patterns in drone images.

Computational Complexity Analysis: A Big-O complexity evaluation comparing shallow vs. deep CNN models would clarify the trade-offs between accuracy and computational efficiency.

Feature Selection Analysis: Investigate which features (e.g., color histograms, texture, spectral indices) contribute most to tree health classification.

A relevant study on machine learning optimization for precision agriculture can be cited:

https://doi.org/10.54216/JAIM.060205.

2. Experimental Validation and Comparative Benchmarking

Strengths

The study evaluates model performance using:

A curated dataset containing 9,534 tree annotations from 255 drone images.

Train-test split (204 images for training, 51 for testing) to assess generalization.

 doi.org/10.32388/MKWYCE

Multiple CNN architectures, reporting performance metrics such as accuracy and loss.

Areas for Improvement

Statistical Significance Testing: Conduct Wilcoxon signed-rank tests or ANOVA to confirm whether differences in CNN performances are statistically significant.

Comparison with Transformer-Based Models: Include Vision Transformers (ViTs) or Swin Transformers, which have outperformed CNNs in remote sensing applications.

Robustness to Different Vegetation Types: Assess how the model performs on diverse crops beyond mango plantations.

A study on deep learning-based forecasting for smart agriculture can be referenced: https://doi.org/10.54216/MOR.030203.

3. Theoretical Contributions and Algorithmic Justification

Strengths

The manuscript provides:

A new benchmark dataset for tree health classification using UAV images.

Insights into overfitting challenges, highlighting the performance gap between shallow and deep networks.

A performance evaluation of YOLO-based tree detection models, demonstrating that YOLO v8 with pre-trained weights achieves 69% accuracy.

Areas for Improvement

Explainability of CNN Predictions: Utilize SHAP (Shapley Additive Explanations) or Grad-CAM to highlight which parts of the tree images influence classification decisions.

Convergence Analysis of CNN Models: Provide learning curve visualizations for all models to illustrate how accuracy improves across epochs.

Multi-Objective Optimization for Model Selection: Investigate whether evolutionary algorithms (e.g., NSGA-II, Particle Swarm Optimization) could optimize CNN hyperparameters.

A study on adaptive optimization in deep learning-based classification can be cited: http://dx.doi.org/10.1109/ACCESS.2021.3106233.

4. Visualization and Interpretability

Strengths

The manuscript includes:

Confusion matrices and performance tables summarizing model accuracy.

Loss vs. accuracy curves for multiple CNN architectures.

Sample annotated drone images showing different tree health classes.

Areas for Improvement

Visualization of Feature Importance:

Use heatmaps to illustrate which features contribute most to classification.

Incorporate spatial distribution maps to show patterns in tree health categories.

Comparison of CNN Decision Boundaries:

Provide activation maps to explain differences between shallow and deep CNNs.

Show YOLO object detection visualizations, comparing how different versions localize trees.

A study on visual interpretability in CNN-based remote sensing can be referenced:

http://dx.doi.org/10.3390/math10203845.

5. Practical Applications and Future Research Directions

Strengths

The study highlights:

Potential applications in real-time agricultural monitoring.

Feasibility of UAV-based tree health classification for low-resource farmers.

Opportunities for open-source development, encouraging further research in plantation monitoring.

Areas for Improvement

Scalability to Large-Scale Plantation Monitoring: Assess whether the proposed approach can be applied to larger farms or commercial forestry projects.

Integration with IoT and Smart Farming Systems: Explore how UAV-based monitoring can integrate with IoT sensors and real-time alert systems.

Exploring Federated Learning for Privacy-Preserving AI: Investigate how federated models can enable decentralized tree health monitoring while preserving farmer data privacy.

A study on real-time AI deployment in sustainable agriculture can be referenced:

http://dx.doi.org/10.1007/s00704-022-04166-6.

6. Conclusion

Strengths

Summarizes the impact of UAV-based CNN classification for tree health assessment.

Demonstrates the importance of deep feature extraction for plantation monitoring.

Highlights the potential of open-source datasets for advancing research in precision agriculture.

Areas for Improvement

Addressing Model Limitations:

Discuss data imbalance and its impact on classification performance.

Acknowledge potential generalization issues when applying the model to different regions or climates.

Future Research Recommendations:

Investigate semi-supervised learning approaches to reduce reliance on labeled data.

Explore hybrid CNN-Transformer architectures to balance feature extraction efficiency with model interpretability.

Declarations

Potential competing interests: No potential competing interests to declare.