ACADEMIC PRESENTATION · SAMPLE

Machine Learning for Early Detection of Crop Disease

Discipline: applied machine learning and computer vision · Task: image-based classification of leaf disease at an early stage · Context: Australian grain and horticulture biosecurity · Approach: a convolutional model benchmarked against a classical baseline

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Agenda

- Problem and motivation
- Aim and research questions
- Data and modelling method
- Results, comparison and deployment
- Recommendations and future work

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Background

- Crop disease reduces Australian yields and export quality
- Manual scouting is slow, costly and inconsistent
- Earlier detection limits spread and unnecessary chemical use
- Bodies such as GRDC and Plant Health Australia prioritise surveillance

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4 Aim and Research Questions

- Aim: assess whether deep learning enables reliable early detection
- Can a convolutional network classify disease from leaf images accurately?
- Does transfer learning outperform a classical baseline?
- Is the model efficient enough for in-field devices?

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Method

- Dataset of 24,000 labelled leaf images, six disease classes plus healthy
- Split: 70 per cent training, 15 per cent validation, 15 per cent test
- Model: EfficientNet-B0 with transfer learning; a support vector machine baseline
- Tools: Python and PyTorch, with augmentation for lighting and rotation

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Results, Model Performance

- Test accuracy of 96.2 per cent across seven classes
- Macro F1 score of 0.95, with precision 0.96 and recall 0.94
- Most errors fell between two visually similar fungal classes
- Inference time of 45 milliseconds per image on a mobile processor

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Results, Model Comparison

- EfficientNet-B0: 96.2 per cent accuracy with 5.3 million parameters
- Support vector machine baseline: 81.4 per cent accuracy on the same test set
- Transfer learning cut training time substantially
- The deep model generalised better to unseen lighting conditions

8 Results, Explainability and Deployment

- Grad-CAM heatmaps localised lesions, supporting user trust
- The model compressed to 12 megabytes for on-device use
- Offline operation suits low-connectivity paddocks
- Confidence thresholds flag uncertain cases for human review

9 Discussion

- High accuracy is promising for early, low-cost detection
- Curated images may overstate real field performance
- Class imbalance and rare diseases remain challenging
- A human-in-the-loop design mitigates automation risk

10 Recommendations

- Validate on multi-season, in-field imagery before any rollout
- Expand data for rare and early-stage disease presentations
- Integrate detection into existing farm-management applications
- Retain agronomist review for low-confidence predictions

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Conclusion

- Deep learning detected crop disease with high accuracy
- It clearly outperformed a classical baseline
- The model is efficient enough for on-device field use
- Field validation and human oversight are the next steps

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