Vegetable plant disease classification using mobile convolutional neural network on offline smartphones

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INTRODUCTION

Plant diseases and pest cost the global economy around $220 billion (FAO, 2018).

Most common approaches to dealing with pests and diseases:

- Visual inspection by experts (Barbedo, 2016)
- DNA/RNA techniques (Fang & Ramasamy, 2015).

Plant disease classification is a technological advancement using AI aiding the existing methods.

PROBLEMS

- Over-reliance on data sets taken in controlled conditions i.e. (Plant Village dataset). (Abade et al., 2021)
- Lack of testing on different smartphones in real field conditions.
- Few leafy vegetable disease coverage in datasets.

OBJECTIVES

The main objective of this study was to develop a mobile application for plant leaf disease classification which can work on an offline smartphone device in real field conditions.

Sub objectives

1. To gather a dataset of healthy and diseased plant leaves that represent real field conditions
2. To train existing pre-trained CNN models to be deployed on to an offline smartphone for classification through transfer learning.
3. To test the effectiveness of the trained model on different smartphone devices.

METHODOLOGY

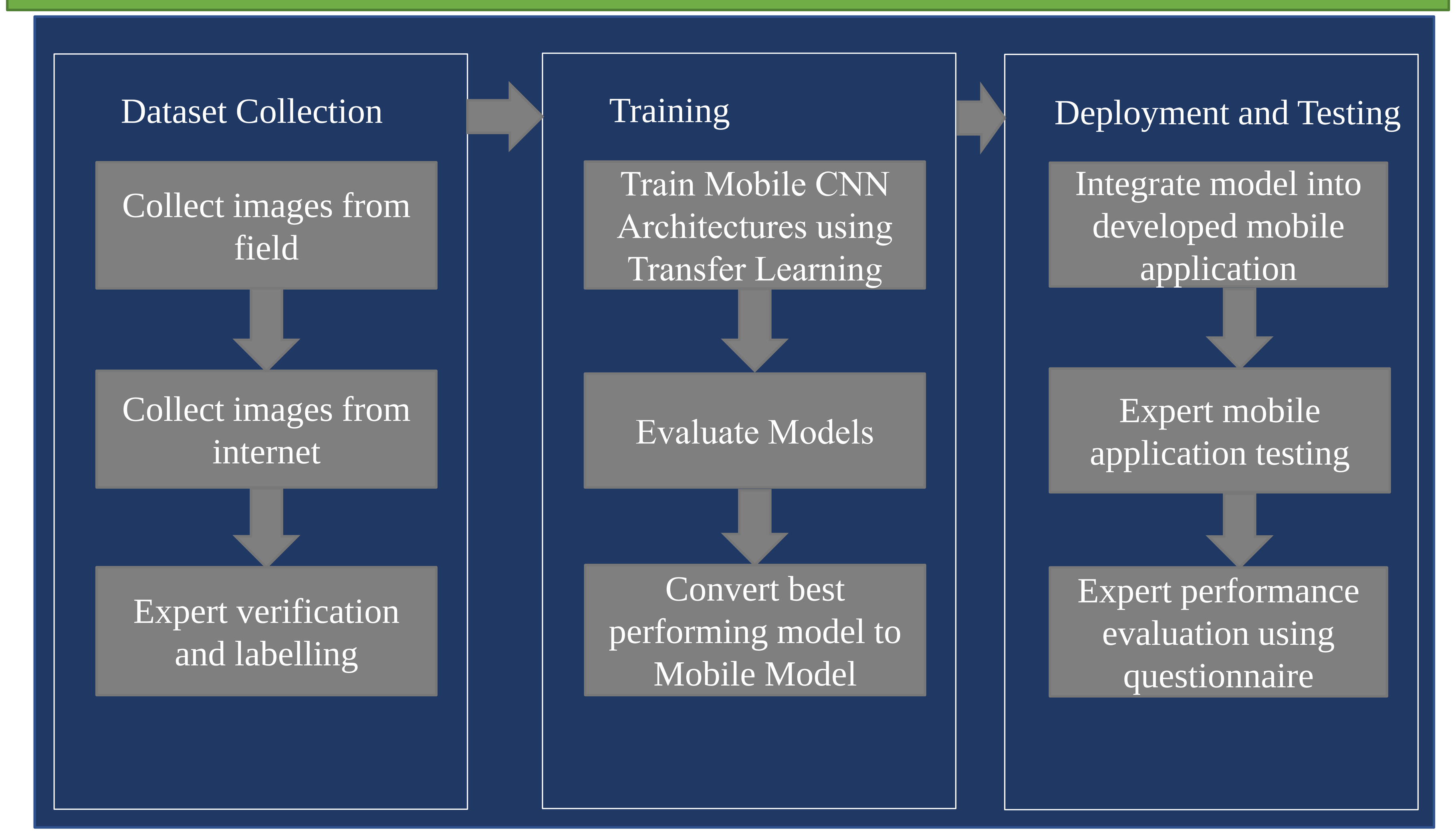

Fig 1: Methodology overview

METHODOLOGY: Collected Images

Fig 2: Cercospora leaf spot

Fig 3: Aphids

Fig 4: Healthy

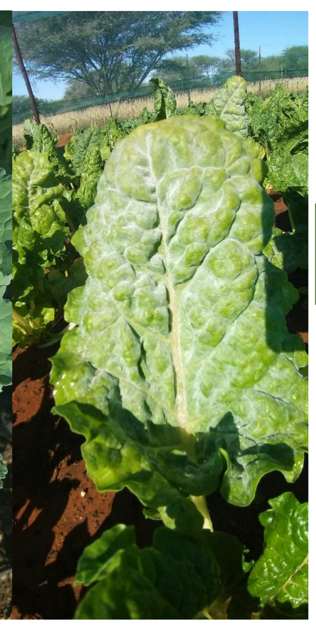

Fig 5: Powdery Mildew

METHODOLOGY: Mobile CNN Models

Name	Pre-trained Dataset	Architecture
Cropnet - ImageNet	ImageNet (Deng et al., 2010)	MobileNet V3
Cropnet – Concat	A concatenation of ImageNet-21K classes and iNaturalist (Van Horn et al., 2018)	MobileNet V3
Cropnet – Cassava_disease_V1	Cassava dataset curated by Makerere University which is divided into 6 classes	MobileNet V3
Efficient Net ImageNet	ImageNet (Deng et al., 2010)	Efficient Net
NasNet ImageNet	ImageNet (Deng et al., 2010)	NasNet

METHODOLOGY: Mobile Application

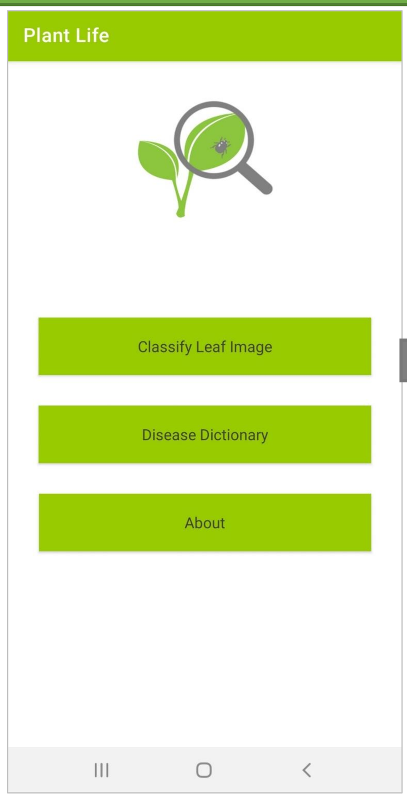

Fig 6: Main Menu

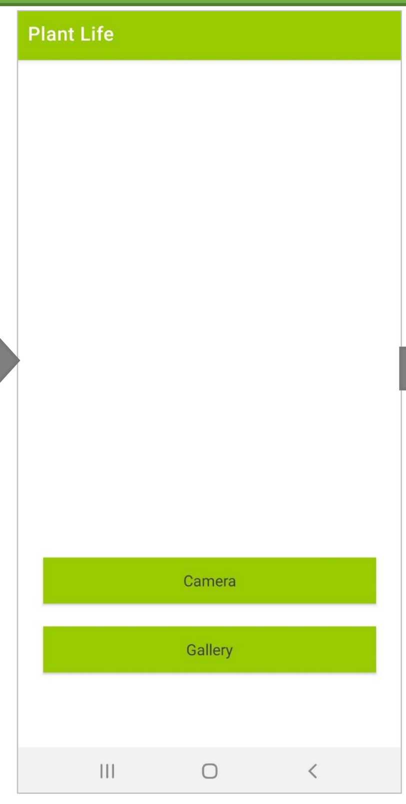

Fig 7:Classification choice

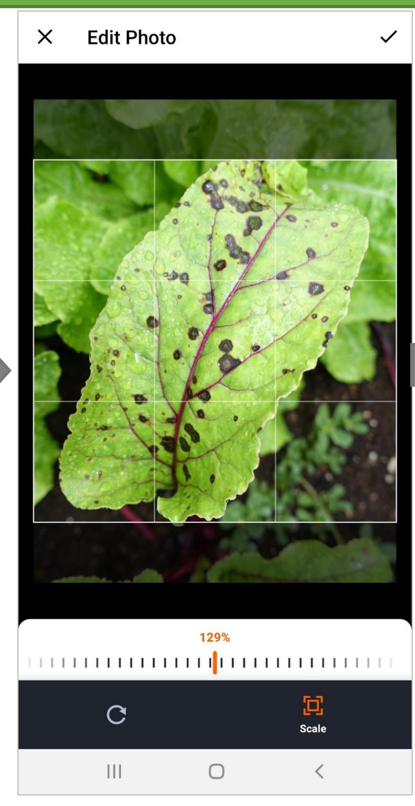

Fig 8: Cropping

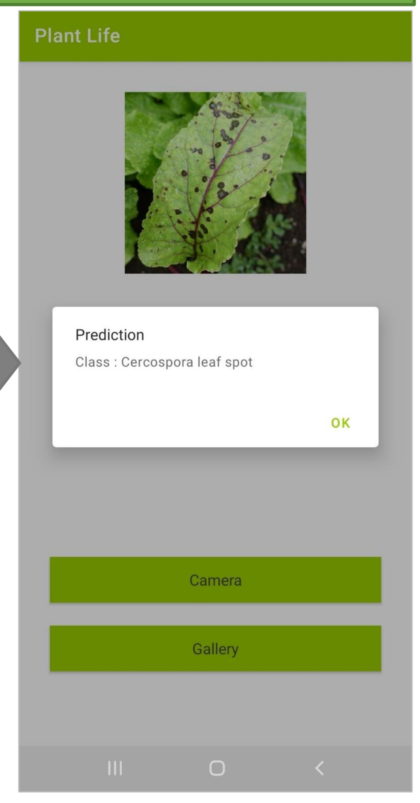

Fig 9: Result

RESULTS

Table 2: Model performances

Model	F1 Score	Precision	Recall	Batch size	Learning rate	Dropout rate
Cropnet Concat	0.9072	0.9189	0.9103	8	0.001	0.5
Cropnet ImageNet	0.9072	0.9094	0.9232	4	0.001	0.5
NasNet ImageNet	0.8659	0.8741	0.8710	8	0.01	0.5
Cropnet Cassava	0.8350	0.8490	0.8180	8	0.001	0.2
EfficientNet ImageNet	0.8234	0.8279	0.8363	16	0.01	0.5

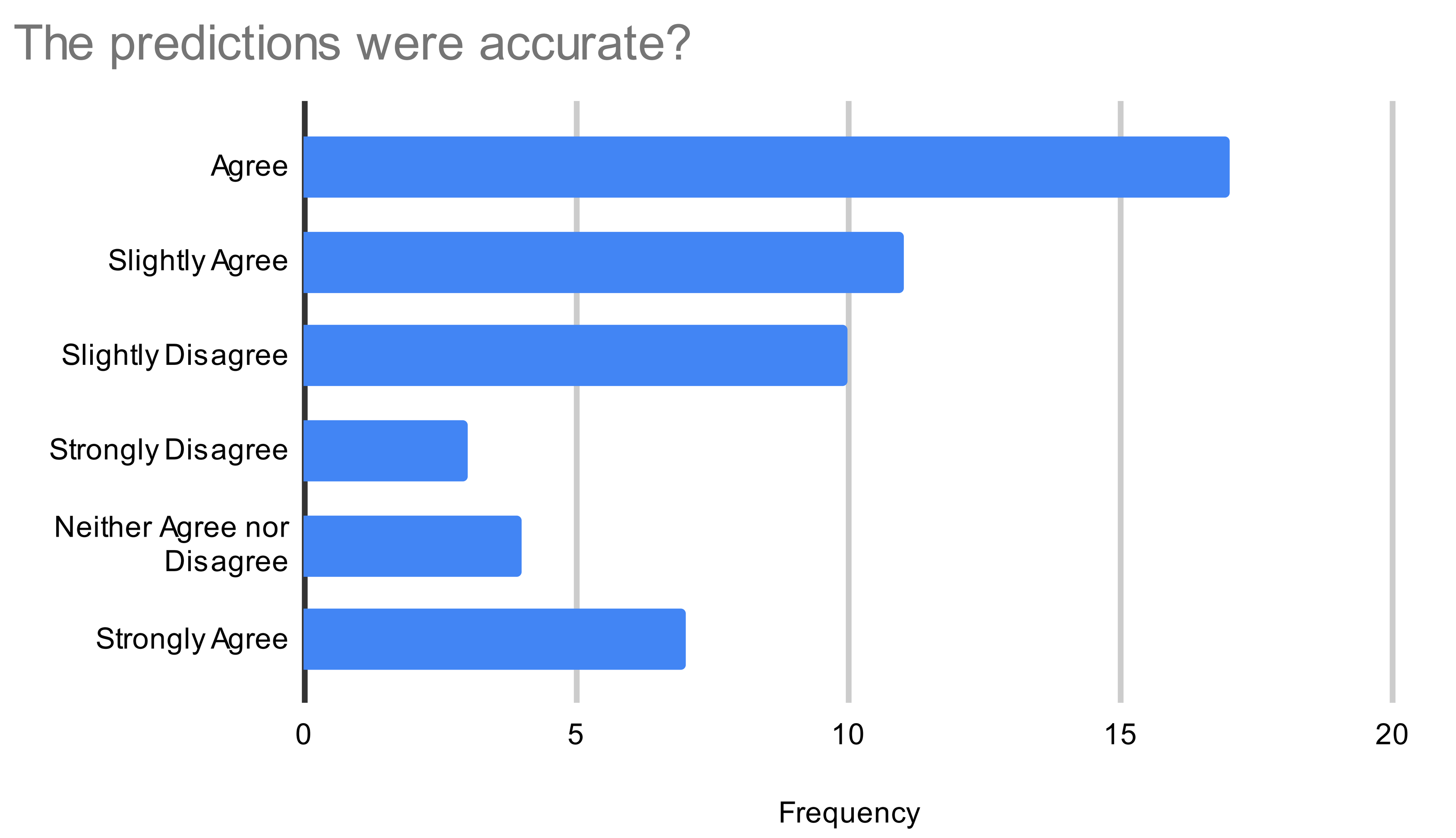

Figure 10: Smartphone prediction accuracy

CONCLUSION

- Trained five pretrained Mobile CNN through transfer on own dataset - 0.9072 F1 score on Cropnet
- Real field acquired dataset translate better to real field conditions - 67% of participants agree the predictions are accurate
- Smartphones can handle offline inferencing efficiently - 75% agreed that the prediction response time was fast
- Future work, expansion to more diseases and more comprehensive experiments to retest in the field.

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