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

METHODOLOGY: Mobile Application

Table 2: Model performances

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

The predictions were accurate?

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.

REFERENCES


METHODOLOGY: Mobile CNN Models

<table>
<thead>
<tr>
<th>Name</th>
<th>Pre-trained Dataset</th>
<th>Architecture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cropnet - ImageNet</td>
<td>ImageNet (Deng et al., 2010)</td>
<td>MobileNet V3</td>
</tr>
<tr>
<td>Cropnet - Concat</td>
<td>A concatenation of ImageNet-21K classes and iNaturalist (Van Horn et al., 2018)</td>
<td>MobileNet V3</td>
</tr>
<tr>
<td>Cropnet – Cassava_disease_V1</td>
<td>Cassava dataset curated by Makerere University which is divided into 6 classes</td>
<td>MobileNet V3</td>
</tr>
<tr>
<td>EfficientNet ImageNet</td>
<td>ImageNet (Deng et al., 2010)</td>
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<td>NasNet</td>
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</tbody>
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