Classification of Multiple Panamanian Watermelon Varieties Using Convolutional Neural Networks with Transfer Learning

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Abstract: Panama is well regarded as an international exporter of watermelon in the Central American region. Most of the watermelon selection process is made by hand with empirical techniques, based on firmness, color, sound and random sampling from other specimens of the same batch. The overall goal of the project is to have an automated system able to distinguish between watermelon varieties and that is able to classify watermelons that are ready for export or can be sold locally. For this matter, traditional and novel computer vision and spectral pattern recognition algorithms are used.

Objective: Assess the capability of two CNN models pre-trained on VGG19 and EfficientNetB0, are able to classify local watermelon varieties.

Materials & Methods

A data set comprised of watermelon images was created for 3 local export varieties (Joya, Anna, Quetzali) provided by "La Asociación de Productores de Sandía de Exportación Cascajalillo Unido-APSECU". These varieties were selected due to their unique characteristics as: patterns, color hue, size and because of being export quality watermelons [1]. Examples of the varieties of the dataset can be seen in Figure 1a. RGB watermelon images were subsampled, cropped and resized to size of 40x40 pixels, as can be seen in Figure 1b. Figure 2 shows the proposed CNN architecture for variety classification.

Fig 1a. Watermelon varieties used in this study

Fig 1b. Pigment samples for each variety

Model Architecture

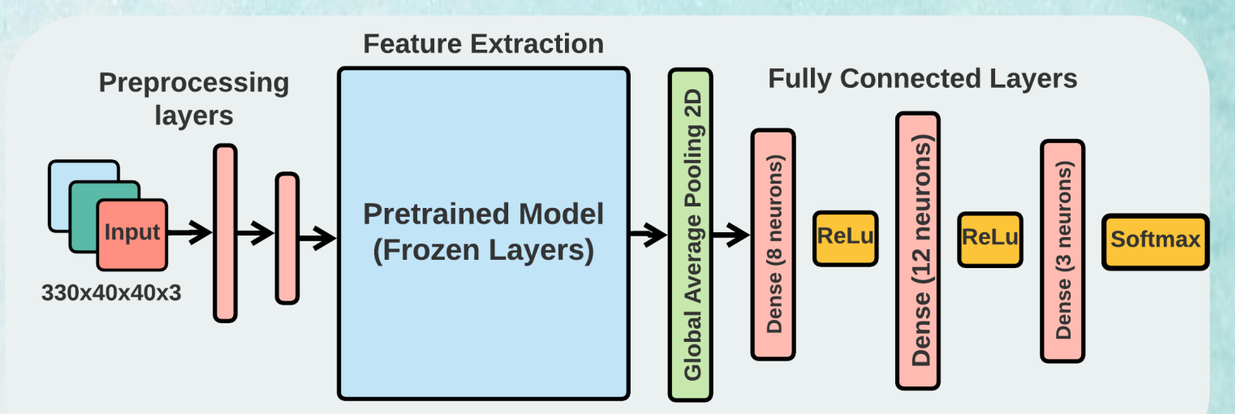

Fig 2. General Architecture used on the study

Results

Based on the works of Pardede [2] and Zhang [3] an initial model was made for early protyping. It included regularization techniques (Dropout and Global Average Pooling layers [4]) and Transfer Learning for Feature Extraction. The final model was optimized in Keras using the Grid Search algorithm while testing 2 pre-trained models (VGG19 and EfficientNetB0 [5]). The results of training the models for 70 epochs with 5-Fold Cross-Validation can be observed in Table 1.

	VGG19		EfficientNetB0	
	Val. Loss	Val. Accuracy	Val. Loss	Val. Accuracy
Fold 1	0.7639	71.21%	0.5172	78.78%
Fold 2	0.4681	89.39%	0.1884	90.90%
Fold 3	0.1997	95.45%	0.1034	96.96%
Fold 4	0.0300	98.48%	0.0796	95.45%
Fold 5	0.1865	93.93%	0.1268	95.45%
Average	0.3295	89.69%	0.2031	91.51%

Table 1. Transfer Learning Results for VGG19 and EfficinetNetB0

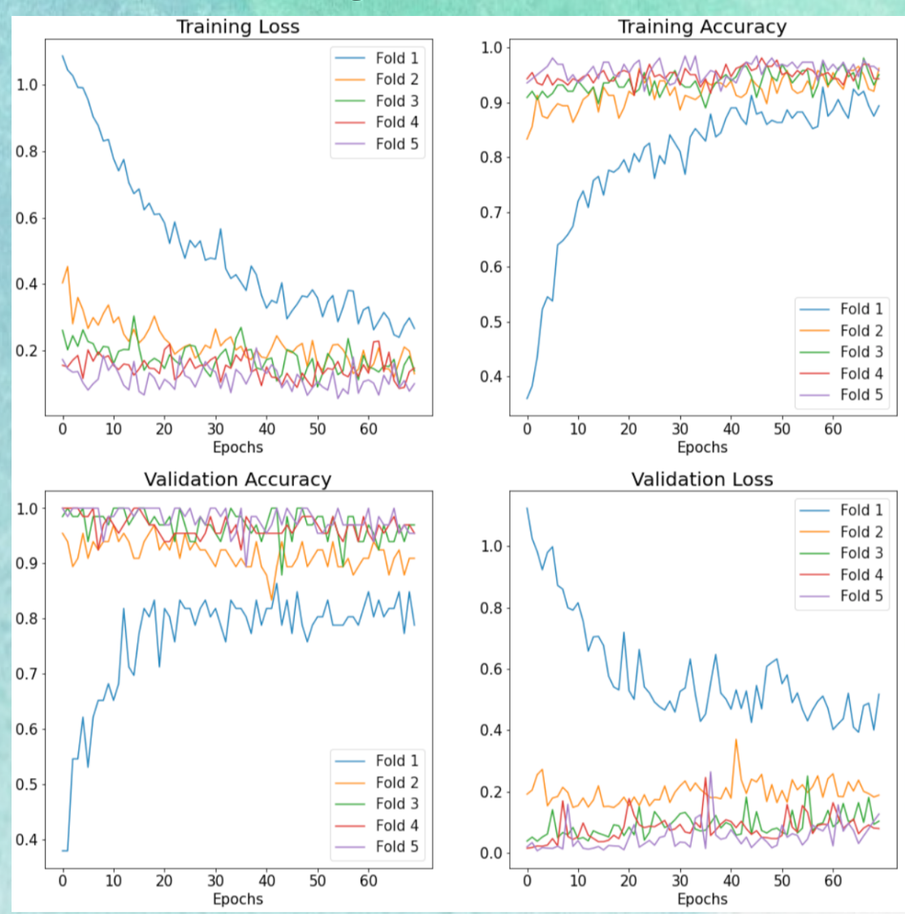

Fig. 3. Resulting Accuracy and Loss Curves for EfficientNetB0

Conclusions

Both models are able to classify the varieties, but show signs of overfitting. Due mostly to having a small dataset (even Data Augmentation was not able to fix the issue), therefore future work will focuse on: 1) using a different pre-processing ROI size (not a fixed 40x40 pixels box) and 2) using other pre-trained models with different optimizers parameters, 3) try different approach with the use of GANs.

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