FINE-TUNING CNNs FOR IMAGE CLASSIFICATION OF NIGERIAN AGRICULTURAL PRODUCE

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Abstract

This paper presents a computer vision approach to classifying images of Nigerian agricultural produce, specifically beans, groundnut, maize, and millet, using deep learning models. Two pre-trained convolutional neural networks—ResNet-50 and EfficientNet-B0—were fine-tuned on the dataset to perform the classification task. The models were trained using cross-entropy loss and the Adam optimizer, with TensorBoard for performance monitoring. After training, the best-performing model weights were saved for future predictions and deployment. The EfficientNet-B0 model achieved a higher accuracy of 85% compared to the ResNet-50's 80%. Finally, the models were deployed using a Streamlit web application to provide an interactive interface for real-time testing and evaluation. This work demonstrates the effectiveness of fine-tuned CNN architectures for agricultural produce classification, contributing to the application of computer vision in agriculture.

1. Introduction

Accurate classification of agricultural produce is critical for food security, trade efficiency, and effective farm management. Traditional manual classification methods are labour-intensive and prone to human error. Advances in computer vision and deep learning have made it possible to automate these tasks with impressive accuracy. In this research, I present a deep learning approach for classifying four important Nigerian agricultural produce: beans, groundnut, maize, and millet. This work builds on the strengths of pre-trained convolutional neural networks, adapting them to this novel dataset and task.

2. Related Work

Previous studies have demonstrated the effectiveness of deep convolutional neural networks in agricultural contexts. Mohanty et al. [1] applied deep learning for plant disease detection, achieving significant accuracy on plant disease datasets. Ferentinos [2] explored deep learning for crop disease classification in real agricultural environments, confirming the versatility of CNNs in such tasks. In terms of model architecture, ResNet [3] introduced residual connections to address vanishing gradients, while EfficientNet [4] proposed a compound scaling strategy that improved accuracy and efficiency simultaneously. Building upon these advancements, I adopt transfer learning with ResNet-50 and EfficientNet-B0 to classify Nigerian agricultural produce images.

3. Dataset and Preprocessing

A custom dataset was curated by downloading approximately 100 images per class from the internet using the Bing Image Downloader library. Images were manually verified to ensure relevance and quality, resulting in a dataset of reasonable diversity and clarity. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets to facilitate model evaluation. Preprocessing involved resizing images to 224×224 pixels and normalizing pixel values to match the distribution of the ImageNet dataset. While data augmentation was not extensively applied in this study, future work may incorporate it to improve model robustness to real-world variations.

4. Methodology

This work employed transfer learning to fine-tune two state-of-the-art CNN architectures:

- **ResNet-50** [3]: A deep residual network that leverages skip connections to ease the training of very deep models.

- **EfficientNet-B0** [4]: An architecture that scales width, depth, and resolution using a compound scaling factor, enabling superior performance with fewer parameters.

Both models were initialized with ImageNet-pretrained weights and had their final classification layers replaced to accommodate the four produce classes. The models were trained using the cross-entropy loss function and the Adam optimizer with a learning rate of 0.001. An early stopping mechanism with a patience of 3 epochs was implemented to prevent overfitting. Training metrics, including accuracy and loss, were logged and visualized using TensorBoard.

5. Experimental Results

The trained models were evaluated on the test dataset, and classification metrics were computed to assess their performance.

5.1 ResNet-50

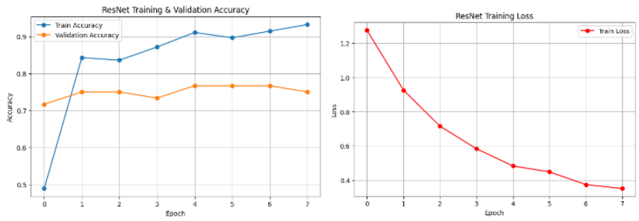

Figure 1: Train and Val. Accuracy, Train Loss for Resnet
This figure shows the progression of the training and validation accuracy curves (left plot) and the training loss curve (right plot) for the ResNet-50 model over 10 epochs**.**

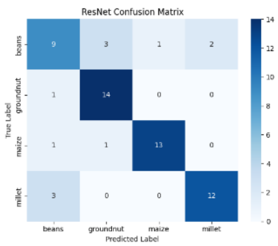

Figure 2: Confusion Matrix for ResNet-50 Model
This figure displays the confusion matrix for the ResNet-50 model, illustrating the model's classification performance across the four classes in the test set.

5.2 EfficientNet-B0

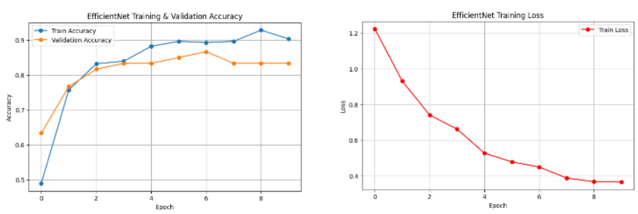

Figure 1: Train and Val. Accuracy, Train Loss for Resnet
This figure shows the progression of the training and validation accuracy curves (left plot) and the training loss curve (right plot) for the ResNet-50 model over

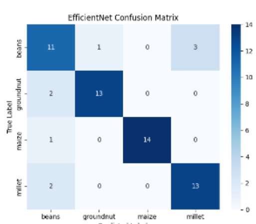

Figure 4: Confusion Matrix for EfficientNet-B0 Model
This figure shows the confusion matrix for the EfficientNet-B0 model, reflecting the model's classification performance on the four-class test set.

6. Discussions

The EfficientNet-B0 model consistently outperformed ResNet-50 across all metrics, achieving higher overall accuracy and macro F1-score. Analysis of the confusion matrices further highlights EfficientNet's superior ability to correctly classify all four produce classes with fewer misclassifications. These results underscore the advantage of EfficientNet's compound scaling in achieving high performance on limited datasets.

Finally, both models were successfully deployed using a Streamlit web application [5], enabling real-time testing and showcasing the practical potential of computer vision solutions in agricultural produce classification.

7. Conclusion and Future Work

This research has demonstrated the feasibility and effectiveness of applying transfer learning for the classification of Nigerian agricultural produce. The EfficientNet-B0 architecture exhibited superior performance compared to ResNet-50, achieving an accuracy of 85% on the test dataset. These results are promising for the development of automated systems for agricultural produce classification in Nigeria.

However, several limitations remain. The dataset, while carefully curated, is relatively small and may not encompass the full range of appearance variations encountered in real farming contexts. Furthermore, limited data augmentation may restrict the model's robustness to noise and distortions in practical scenarios [6].

Future work will focus on expanding the dataset with images from diverse sources and conditions to improve model generalization. Additionally, advanced data augmentation techniques and ensembling strategies will be explored to enhance predictive performance.

References

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