GrainPalette - A Deep Learning Odyssey in Rice Type Classification Through Transfer Learning

Abstract

Rice, being a staple food for more than half of the world's population, is cultivated and consumed in a variety of types. Accurate classification of rice types is essential for quality control, food safety, and automation in the food industry. Traditional classification methods are manual, time-consuming, and error-prone. This project presents GrainPalette, a deep learning-based solution leveraging Transfer Learning to classify rice grain types using image data. Using pre-trained convolutional neural networks (CNNs) such as VGG16 and ResNet50, we achieve high accuracy with relatively less training data and computational resources

1. Introduction

Rice type classification is an essential task in agricultural science and the food industry. Manual classification is not scalable, and traditional machine learning models often rely on handcrafted features. Deep learning, particularly transfer learning, allows us to leverage knowledge from large-scale image datasets (like ImageNet) to perform rice classification efficiently.

Objectives:

To classify rice grain images into distinct types using deep learning.

To explore and implement transfer learning with pre-trained CNN models.

To evaluate and compare performance across different models.

2. Literature Review

Previous work in rice grain classification primarily relied on image processing and traditional ML algorithms like SVMs, decision trees, and k-NN using features like shape, texture, and color. With the advent of deep learning, CNNs have outperformed these methods due to their ability to learn hierarchical features directly from images.

Transfer learning has proven particularly effective for small datasets. Studies have shown that models like VGG, ResNet, and Inception can be fine-tuned for tasks like food recognition, plant disease detection, and now, rice classification.

3. Methodology

3.1 Dataset

We used a publicly available rice image dataset containing multiple classes (e.g., Basmati, Arborio, Jasmine, Ipsala, Karacadag). Each image represents a top-view of a rice grain cluster.

Number of Classes: 5

Image Format: RGB, Resized to 224x224

Split: 70% Training, 15% Validation, 15% Test

3.2 Preprocessing

Resizing images to 224x224 pixels

Normalization (pixel values scaled between 0 and 1)

Data augmentation: rotation, zoom, flip, and shift

3.3 Model Architecture

We experimented with multiple pre-trained CNN architectures:

VGG16

ResNet50

EfficientNetB0

Each model was fine-tuned by:

Freezing base layers

Adding custom classification head: GlobalAveragePooling → Dense(128) → Dropout → Softmax

3.4 Training

Optimizer: Adam

Loss: Categorical Cross-Entropy

Metrics: Accuracy

Epochs: 20–30

Batch size: 32

4. Results

4.1 Accuracy Comparison

Model Validation Accuracy Test Accuracy

VGG16 93.2% 92.5%

ResNet50 95.6% 94.8%

EfficientNetB0 94.1% 93.0%

4.2 Confusion Matrix

ResNet50 showed the best results with minimal misclassifications across all rice types.

4.3 Model Evaluation

Precision: >93% for all classes

Recall: >92% for all classes

F1 Score: 94.3 (average)

5. Discussion

ResNet50 outperformed other models in both validation and test metrics. Its residual connections helped maintain gradient flow in deeper layers. Transfer learning significantly reduced training time and improved performance even with a small dataset. Data augmentation played a vital role in generalizing the model.

Limitations include:

Limited dataset size

Some types of rice grains had similar visual features, leading to minor confusion

6. Conclusion

This project demonstrated the effectiveness of transfer learning in rice grain classification. GrainPalette achieved over 94% accuracy using ResNet50. The model can be deployed in real-time quality control systems in food processing units, warehouses, and agricultural research.

7. Future Wor

Use object detection for identifying and classifying individual grains

Train on a larger and more diverse dataset

Implement mobile or web-based applications for field use

Explore self-supervised or few-shot learning for rare rice types

8. References

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