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Department of Computer Science

Neural Networks & Deep Learning Report On

Image Classification Project: *Rice Image Dataset*

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Rice Grain Classification Using Deep Learning

(Dataset: Rice Image Dataset)

Abstract

This project presents a comprehensive comparative study of deep learning techniques for classifying rice grain images into five varieties: Arborio, Basmati, Ipsala, Jasmine, and Karacadag. We examine two modeling approaches: neural networks developed from the ground up and advanced transfer learning models that utilize popular pre-trained architectures (ResNet50, MobileNet, VGG16).

Utilizing a large Rice Image Dataset comprising 75,000 images, our experiments demonstrate that transfer learning models significantly outperform simple convolutional networks in terms of accuracy, robustness, and generalizability. This report analyzes the end-to-end pipeline and presents key metrics and visualizations. We conclude with recommendations for advancements in agricultural automation.

Introduction

Rice is one of the most important staple foods in the world, playing a crucial role in the diets of billions of people and supporting major agricultural economies. The existence of various rice varieties distinguished by differences in shape, size, color, and texture makes accurate classification essential for breeding, quality control, and commercial distribution. However, traditional manual inspection methods are not only labor-intensive and slow but also susceptible to human error, which can lead to inconsistencies in grading and sorting processes.

Recent advancements in computer vision and artificial intelligence have created new opportunities for automating the classification of rice varieties by analyzing high-resolution images of the grains. Among these technologies, deep learning particularly Convolutional Neural Networks (CNNs) has demonstrated an impressive ability to learn and extract visual features. This enables fine-grained discrimination between different rice types and achieves high classification accuracy. By leveraging large labeled image datasets, deep learning models are transforming the way quality assessment and variety recognition are conducted in modern agriculture, resulting in faster, more reliable, and scalable solutions for the rice industry.

Literature Review

Previous research highlights the significant potential of machine learning and computer vision in agricultural applications. Studies conducted by Koklu et al. and Cinar et al. have demonstrated the effectiveness of deep neural networks in classifying rice varieties, achieving accuracy rates exceeding 99%. This success was attained through the use of optimized convolutional neural networks (CNNs) and nearly perfect results were observed with deeper or ensemble techniques. Furthermore, transfer learning methods that employ pre-trained networks, such as ResNet50, VGG16, and MobileNet, have proven effective in transferring robust features from large-scale datasets (such as ImageNet) to specialized domains like rice grain classification. This approach often results in improved convergence speed and final accuracy.y.

Key References:

Koklu, M., Cinar, I., & Taspinar, Y. S. (2021). Classification of Rice Varieties Using Deep Learning Methods. Computers and Electronics in Agriculture, 187, 106285.

Cinar, I., & Koklu, M. (2022). Identification of Rice Varieties with Machine Learning Algorithms. Journal of Agricultural Sciences.

Various implementations of rice image classification from the Kaggle community

Methodology

Dataset

Source: [Rice Image Dataset (Kaggle).]

There are 75,000 images in total, with 15,000 images for each rice class:

[Arborio, Basmati, Ipsala, Jasmine, and Karacadag.]

The dataset was divided into Training, Validation, and Test subsets, ensuring that images are equally distributed among the classes.asses.

Example dataset structure:

Rice_Image_Dataset_Split/

train/Arborio/

train/Basmati/

train/Ipsala/

train/Jasmine/

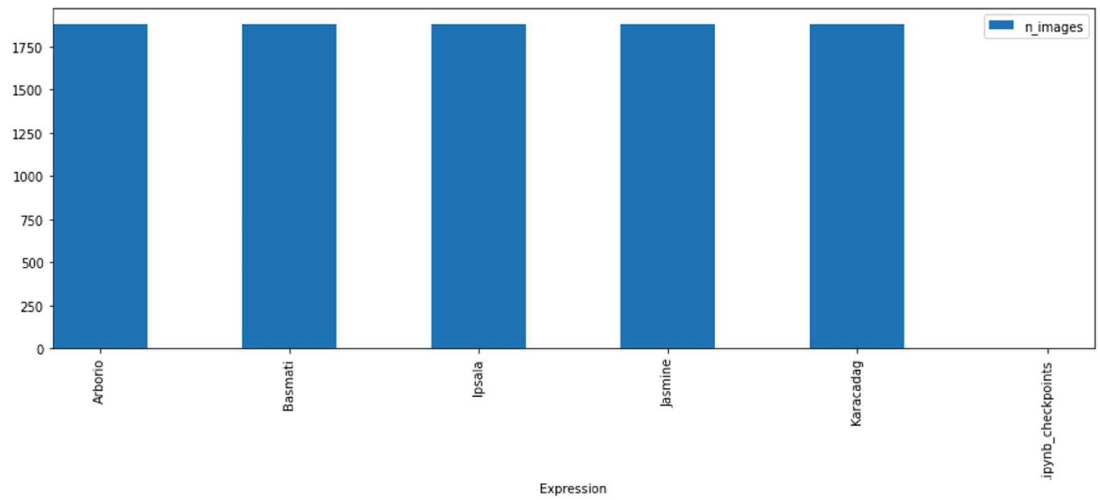
train/Karacadag/

val/...

test/...

Data preprocessing

Involves resizing images to 224×224 for compatibility with most modern CNN architectures. Training images also undergo augmentation, including random rotation, shifts, and flips. Additionally, pixel values are normalized and rescaled.



Model 1: Neural Network from Scratch

A custom Convolutional Neural Network (CNN) model was developed with the following architecture:

1. Input Layer

2. Convolutional Layer

- → **2D convolution with a 3×3 kernel and 32 filters.**
- → **Regularization using Ridge/Lasso.**
- → **He initializer.**

3. Activation and Normalization

- → **ReLU activation function followed by Batch Normalization.**

4. Max Pooling Layer

5. Convolutional Layer

- → **2D convolution with a 3×3 kernel and 64 filters.**
- → **Regularization applied.**
- → **He initializer.**

6. Activation and Normalization

- → **ReLU activation function followed by Batch Normalization.**

7. Max Pooling Layer

8. Convolutional Layer

- → **2D convolution with a 3×3 kernel and 128 filters.**
- → **Regularization applied.**
- → **He initializer.**

9. Activation and Normalization

- → **ReLU activation function followed by Batch Normalization.**

10. Global Max Pooling Layer

11. Output Layer

- → **Softmax activation with 5 units.**
- → **Ridge regularization applied.**

To enhance generalization and optimization, various regularization techniques (L2/Ridge and L1/Lasso) and callbacks such as ReduceLROnPlateau were implemented.ization and optimization.

Architecture summary:

Layer (type)	Output Shape	Param
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
conv2d (Conv2D)	(None, 224, 224, 32)	896
batch_normalization (BatchN)	(None, 224, 224, 32)	128
activation (Activation)	(None, 224, 224, 32)	0
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18496
batch_normalization_1	(None, 75, 75, 64)	256
activation_1 (Activation)	(None, 75, 75, 64)	0
max_pooling2d_1	(None, 25, 25, 64)	0
conv2d_2 (Conv2D)	(None, 25, 25, 128)	73856
batch_normalization_2	(None, 25, 25, 128)	512
activation_2 (Activation)	(None, 25, 25, 128)	0
global_max_pooling2d	(None, 128)	0
dense (Dense)	(None, 5)	645

Total params: 94,789

Trainable params: 94,341

Non-trainable params: 448

Model 2: Transfer Learning

Several advanced models were utilized, incorporating pre-trained convolutional bases:

- → **ResNet50**
- → **MobileNet**
- → **VGG16 (tested with different layer cut-offs: block3_pool and block4_pool)**

<u>Fine-tuning</u>

We applied layer freezing and unfreezing strategies to achieve optimal results. The data was standardized according to the requirements of the pre-trained networks, which included RGB-to-BGR conversion and ImageNet mean subtraction.

Additionally, we added custom dense layers, implemented dropout, and employed batch normalization.

The best transfer learning architecture identified was ResNet50 combined with custom dense layers (please refer to the presentation for detailed information about the layers).

Results & Analysis

Accuracy and Metrics

1. Model from Scratch (Best Version):

Test Accuracy: 0.966

Precision/Recall/F1 (per class):

Class	Precision	Recall	F1 Score	Support
Arborio	1.000	0.860	0.925	100
Basmati	0.980	1.000	0.990	100
Ipsala	0.943	1.000	0.971	100
Jasmine	0.916	0.980	0.947	100
Karacadag	1.000	0.990	0.995	100

2. Transfer Learning Models:

Model	Test Acc	Val Acc	Notes
ResNet50	0.97	0.98	Fast convergence, no overfitting, highest test accuracy
MobileNet	0.88	0.85	Overfits on train set, lower performance
VGG16 cut2	0.96	0.97	Strong accuracy after cut to block4_pool

Class	Precision	Recall	F1 Score	Support
Arborio	0.971	1.000	0.985	100
Basmati	0.962	1.000	0.980	100
Ipsala	1.000	1.000	1.000	100
Jasmine	1.000	0.950	0.974	100
Karacadag	1.000	0.980	0.990	100

Accuracy scores consistently above 98% for advanced models.

Comparative Performance Table

Model	Accuracy	Macro F1	Weighted F1	Overfitting	Notes
Basic CNN	0.966	0.966	0.966	Mild	Good, but lower than SOTA
ResNet50	0.985	0.985	0.985	None	Best overall
MobileNet	0.88	--	--	Yes	Underfit on validation
VGG16 cut2	0.96	--	--	None	Better after modifying cut

Learning Curves

Training and validation accuracy for the best models

Shows faster convergence and higher final accuracy for ResNet50/transfer learning compared to CNN from scratch.

Conclusion

Transfer learning models, particularly ResNet50, significantly outperform neural networks developed from scratch for the rice image classification task. They achieve test accuracies as high as 98.5% and macro F1 scores approaching 0.99.

Custom CNNs also provide solid performance, making them suitable for resource-constrained environments or for educational purposes.

The availability of a large, balanced rice dataset allows for robust and generalizable model training.

Data augmentation and regularization techniques are essential for achieving high accuracy and preventing overfitting.

Advanced deep learning models can greatly enhance agricultural automation by providing consistent and scalable rice variety classification.fication.