RICE CLASSIFICATION USING DEEP LEARNING

Tejpreet Bal, Amey Brahme, Jason Xu, Harshil Patel

University of Calgary

ABSTRACT

Rice, a crucial dietary staple for a significant portion of the global population, varies in types and qualities, impacting both agricultural practices and consumer choices. This study delves into rice variety classification using diverse machine learning and deep learning models, aiming to enhance accuracy and efficiency in image-based classification tasks. Leveraging a dataset from Kaggle comprising various rice variants, we explore the efficacy of convolutional neural network architectures such as CNN, ResNet18, ResNeXT, and VGG. Through extensive experimentation, we unveil ResNeXT as the most promising model, achieving exceptional accuracy rates. However, VGG exhibited subpar performance, warranting further investigation into architectural intricacies. This research contributes valuable insights into optimizing model selection and design for rice classification tasks, with implications for agricultural practices and food processing industries.

1. INTRODUCTION

Rice, a staple for over half of the global population, serves as a primary dietary component in Asia, Africa, and Latin America, offering vital nutrients and sustenance [1], [2]. The diverse grains and textures of rice cater to various culinary needs, from short-grain sushi rice to long-grain basmati, reflecting regional and cultural preferences. Major rice-producing countries, including China, India, and Indonesia, contribute significantly to the global rice supply [3], [4]. Quality variations exist among producers, with some specializing in higher-quality or specialized rice varieties [3], [4].

Rice classification guides farmers in selecting the most appropriate varieties for their distinct regions, refining crop management techniques, and bolstering yields [1]. Following this, it facilitates seamless transactions by providing traders with essential insights into rice quality and attributes, ensuring fair pricing and effective trade agreements [1], [5]. Moreover, a nuanced understanding of rice characteristics is essential for food processors to produce top-quality products that resonate with consumer preferences. Additionally, the diverse nutritional profiles of different rice types empower individuals to make informed dietary decisions tailored to their health needs [6]. Finally, rice classification supports ongoing research and development endeavors by enabling the creation of new varieties adapted to specific environmental conditions or with improved nutritional content [1].

The classification task utilized a publicly accessible dataset sourced from Kaggle, specifically targeting diverse rice variants. By employing prominent convolutional neural network architectures, including CNN, ResNet18, ResNeXT, and VGG, our objective is to investigate and evaluate their effectiveness in improving performance for image classification.

2. RELATED WORK

Various machine learning (ML) and deep learning (DL) techniques have been utilized in several studies to advance rice variety classification [7]. The LR model, combined with ML and DL methods, achieved a 97.9% accuracy [8]. A Quantized Neural Network (QNN) was developed, resulting in a classification accuracy of 99.87% [9]. Using a DL network named PCANet along with hyperspectral imaging (HSI), a classification accuracy of 98.57% was achieved [10]. A comparative study between ANN, DNN, and CNN conducted by [11] found the CNN model to be the most effective. An 86% classification accuracy was achieved by implementing a CNN model [1], while various ML models were contrasted by [12], with the RF model demonstrating the best performance. Combining HSI and CNN, [13] reached a classification accuracy of 31.09%. Additionally, [14] evaluated various ML models, with the RF model achieving a classification accuracy of 97.99% using morphological features. Employing a Transfer Learning (TL) approach with the AlexNet TL model, [15] achieved a classification accuracy level of 98.2%. These studies collectively demonstrate the diverse methodologies and high accuracies achievable in rice variety classification, offering valuable insights for further research and practical applications in agriculture and related fields.

3. MATERIALS AND METHODS

The classification task was undertaken using a publicly accessible dataset obtained from Kaggle, comprising many images depicting various rice variants [16]. Due to Kaggle's established reputation as a dependable source of data and the dataset's suitability for our objectives, it was deemed appropriate for model training and subsequent evaluation.

In establishing a baseline accuracy, a conventional Convolutional Neural Network (CNN) architecture was initially employed. CNNs were selected owing to their intrinsic capability to acquire hierarchical features, exploit translation invariance, and leverage parameter sharing, all of which are instrumental in image classification tasks. Subsequently, to evaluate the potential for performance enhancement, the ResNet18 architecture and a two convolution layer CNN were adopted. This decision was predicated upon its relatively shallow design, integrating residual connections and skip connections. These architectural components endow ResNet18 with an augmented capacity for generalization and deeper feature representation learning.

ResNeXT was employed to augment learning capacity. Noteworthy for introducing cardinality parameters, ResNeXT facilitates parallelized computations, thereby enhancing learning capacity without substantial increments in computational cost. Additionally, it offers improved generalization, a crucial aspect in model performance evaluation.

Visual Geometry Group (VGG) architecture was also incorporated into our study. Renowned for its sequential arrangement of convolutional layers followed by max-pooling, VGG was chosen to exploit its effective learning rate. The deliberate selection of these models was aimed at exploring diverse architectural paradigms to discern their respective efficacy in our classification task.

An additional convolution layer in the CNN should be able to improve accuracy by increasing feature extraction. The first layer of the CNN usally only captures the basic features like edges and textures. Additional convolutional layer can extra more features in a spatial hierarchy structure and improve the model’s ability to recognize objects in relation with each other and capturing relationships that are not apparent at lower levels. However, there will be more computational demand and more prone to overfit when adding an additional convolutional layer.

Employing a diverse range of architectures and design principles facilitates performance comparison, offering insights into the effectiveness of different architectural paradigms for the given problem.

The images underwent preprocessing for each model, which included resizing to dimensions of 224x224 pixels, background removal, and conversion to grayscale. Subsequently, the dataset was divided into training, testing, and validation sets, following a split of 60% for training, 20% for testing, and 20% for validation.

4. RESULTS

In this study, we conducted rice image classification using five different models: a regular CNN model, a CNN model with two convolution layers (CNN2), ResNet18, ResNeXT, and VGG. Each model underwent training for 10 epochs. The results obtained from the experimentation are summarized in the Figures and Table below.

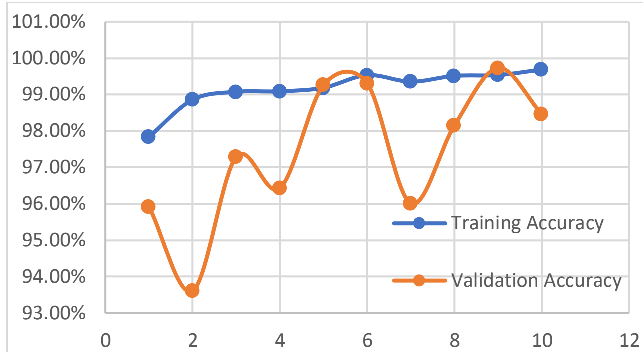

Figure 1A: ResNeXT Training and Validation Accuracy

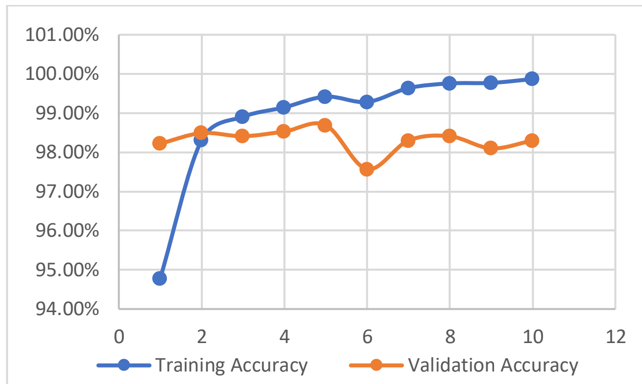

Figure 1B: ResNeXT Training and Validation Accuracy

The final accuracies for all models can be found in table 1.

Table 1: Accuracy Score for each Model

	Training Accuracy	Validation Accuracy	Testing Accuracy
CNN - Base	99.87%	98.30%	98.30%
CNN2 - Two Convolution Layers	99.81%	98.45%	98.39%
ResNet18	99.68%	98.47%	98.20%
ResNeXT	99.67%	99.73%	99.81%
VGG	19.88%	20.00%	20.00%

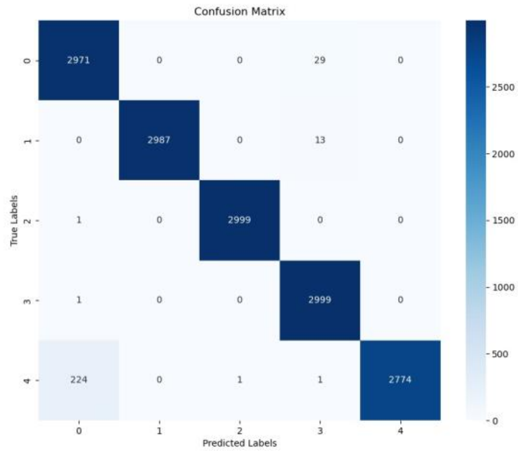

Fig. 2A. Heatmap of testing results using the RestNet18 model

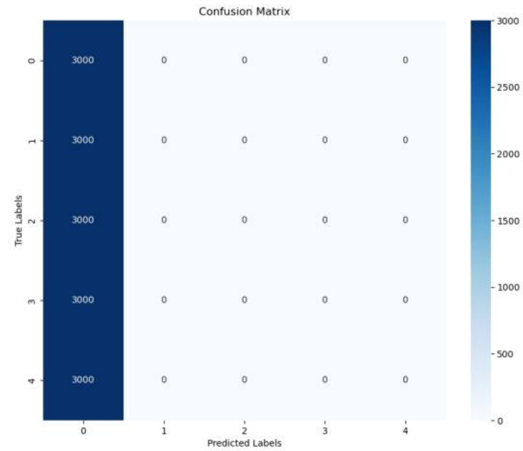

Fig. 2D. Heatmap of testing results using the VGG model

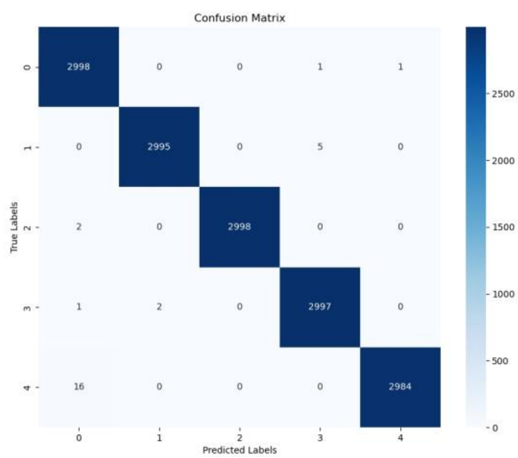

Fig. 2B. Heatmap of testing results using the ResNext model

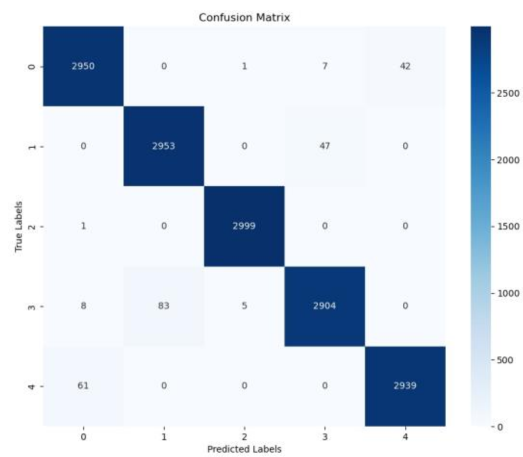

Fig. 2C. Heatmap of testing results using the CNN (with only 1 convolution layer)

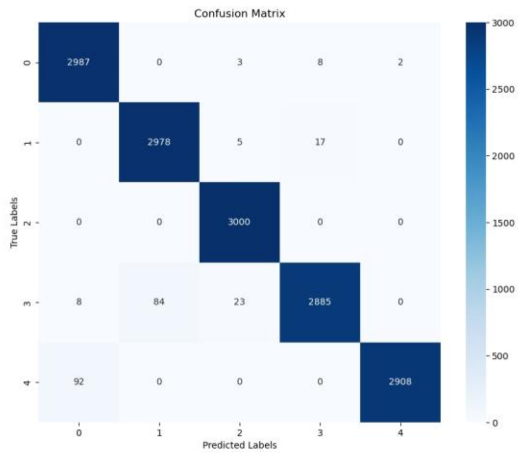

Fig. 2E. Heatmap of testing results using the CNN (with 2 convolution layer)

5. DISCUSSION

The performance metrics reveal significant variations among the models. ResNeXT emerged as the most promising model, achieving an exceptional testing accuracy of 99.81%. This was comparable to the existing literature review which has the max accuracy of 99.87%. Surprisingly, VGG exhibited dismal performance, with both training and testing accuracies hovering around a mere 20%.

The underperformance of the VGG model necessitates a more comprehensive analysis. Several factors contributing to its disappointing results can be attributed to its deep architecture, which may hinder effective generalization. Unlike overfitting, where both training and testing accuracies are high, the issue appears to lie in errors possibly stemming from improper initialization of the model's numerous parameters.

The CNN2 model, despite having two convolution layers, achieved accuracy metrics comparable to the baseline CNN model. This finding indicates that adding additional convolution layers did not significantly enhance the model's performance in this context.

The ResNeXT model consistently outperformed other models across all metrics, showcasing remarkable training, validation, and testing accuracies. This consistency suggests the robustness and efficacy of the ResNeXT architecture for rice image classification tasks.

While ResNet18 demonstrated high training and validation accuracies, its testing accuracy was slightly lower in comparison. This discrepancy suggests a potential slight overfitting tendency in ResNet18, wherein the model may have memorized features specific to the training set, impacting its generalization on unseen data.

Across all models, the training and validation accuracies were consistently high and closely aligned, indicating effective training without significant overfitting on the training data.

6. FUTURE WORK

The stark contrast between the performance of VGG and other models underscores the importance of selecting appropriate architectures and optimizing hyperparameters for the task at hand. In future experiments, exploring alternative architectures or fine-tuning the existing VGG model parameters may be warranted to improve its performance. Additionally, investigating the impact of different data augmentation strategies and regularization techniques could help mitigate overfitting and enhance the VGG model's generalization capabilities.

7. CONCLUSION

In conclusion, this study delves into the critical task of rice classification using convolutional neural network architectures. Through comprehensive experimentation and evaluation, ResNeXT emerges as a standout performer, showcasing exceptional accuracy in distinguishing rice variants. The comparative analysis highlights the importance of selecting appropriate architectures and optimization strategies tailored to the task at hand. Surprisingly, VGG's underperformance prompts further investigation into its architecture and parameter initialization. The findings underscore the significance of robust model selection and optimization techniques in achieving accurate rice classification. Moving forward, future research should focus on refining existing models, exploring alternative architectures, and optimizing hyperparameters to enhance performance and broaden the applicability of rice classification techniques in agricultural and related domains.

14. REFERENCES

[1] R. Singh, N. Sharma, and R. Gupta, “Rice type classification using proposed CNN model,” 2023, pp. 1–6. doi: https://doi.org/10.1109/ViTECoN58111.2023.10157073.

[2] K. Ahmed, T. R. Shahidi, I. Alam, and S. Momen, “Rice leaf disease detection using machine learning techniques,” 2019, pp. 1–5. doi: https://doi.org/10.1109/STI47673.2019.9068096.

[3] Murat Koklu, I. Cinar, and Yavuz Selim Taspinar, “Classification of rice varieties with deep learning methods,” *Computers and Electronics in Agriculture*, vol. 187, p. 106285, 2021, doi: https://doi.org/10.1016/j.compag.2021.106285.

[4] B. Verma, "Image processing techniques for grading & classification of rice," 2010, pp. 220–223. doi: https://doi.org/10.1109/ICCCT.2010.5640428.

[5] J. K. Shwetank, "Review of rice crop identification and classification using hyper-spectral image processing system," *International Journal of Computer Science*, vol. 1, Art. no. 1, 2010.

[6] N. H. Son, "Deep learning for rice quality classification."

[7] R. Pillai, N. Sharma, R. Chauhan, D. Rawat, and R. Gupta, "CNN-based approach for classification of rice varieties," 2023, pp. 1–5. doi: https://doi.org/10.1109/INCOFT60753.2023.10425548.

[8] R. Ruslan, S. Khairunniza-Bejo, M. Jahari, and M. F. Ibrahim, "Weedy rice classification using image processing and a machine learning approach," *Agriculture*, vol. 12, Art. no. 5, 2022, doi: https://doi.org/10.3390/agriculture12050645.

[9] M. Tasci, A. Istanbullu, S. Kosunalp, T. Iliev, I. Stoyanov, and I. Beloev, "An efficient classification of rice variety with quantized neural networks," *Electronics*, vol. 12, Art. no. 10, 2023, doi: https://doi.org/10.3390/electronics12102285.

[10] S. Weng *et al.*, "Hyperspectral imaging for accurate determination of rice variety using a deep learning network with multi-feature fusion," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*, vol. 234, p. 118237, 2020, doi: https://doi.org/10.1016/j.saa.2020.118237.

[11] Murat Koklu, I. Cinar, and Yavuz Selim Taspinar, "Classification of rice varieties with deep learning methods," *Computers and Electronics in Agriculture*, vol. 187, p. 106285, 2021, doi: https://doi.org/10.1016/j.compag.2021.106285.

[12] P. Saxena, K. Priya, S. Goel, P. K. Aggarwal, A. Sinha, and P. Jain, "RICE VARIETIES CLASSIFICATION USING MACHINE LEARNING ALGORITHMS.," *Journal of Pharmaceutical Negative Results*, vol. 13, pp. 3762–3772, 2022, Available: https://ezproxy.lib.ucalgary.ca/login?url=https://search.ebscohost.com/login.aspx?direct=true&db=a9h&AN=171925730&site=ehost-live

[13] I.Chatnuntawech, "Rice classification using spatiospectral deep convolutional neural network," 2018.

[14] İ. Çınar and M. Koklu, "Identification of rice varieties using machine learning algorithms," *Journal of Agricultural Sciences*, vol. 28, Art. no. 2, 2022, doi: https://doi.org/10.15832/ankutbd.862482.

[15] Pandia Rajan Jeyaraj, Siva Prakash Asokan, and E. Rajan, "Computer-assisted real-time rice variety learning using deep learning network," *Rice Science*, vol. 29, Art. no. 5, 2022, doi: https://doi.org/10.1016/j.rsci.2022.02.003.

[16] M. KOKLU, "Rice Image Dataset," *www.kaggle.com*. https://www.kaggle.com/datasets/muratkokludataset/rice-image-dataset/code (accessed Apr. 07, 2024).