Software Impacts 20 (2024) 100654

Contents lists available at ScienceDirect

Software Impacts

journal homepage: www.journals.elsevier.com/software-impacts

Original Software Publication

Rice-ResNet: Rice classification and quality detection by transferred ResNet deep model

Mohammadreza Razavi [a], Samira Mavaddati [b], Ziad Kobti [c], Hamidreza Koohi [c,*]

[a] Computer Engineering Department, Shomal University, Amol, Iran
[b] Electronic Department, Faculty of Engineering and Technology, University of Mazandaran, Babolsar, Iran
[c] School of Computer Science, University of Windsor, Ontario, Canada

ARTICLE INFO

Keywords:
Rice quality detection
ResNet Model
Transfer learning
Python
Open-source

ABSTRACT

Efficient classification and quality assessment of rice varieties are essential for market pricing, food safety, and consumer satisfaction in the global rice sector. Leveraging pre-trained ResNet architectures, Rice-ResNet significantly enhances feature extraction, ensuring accurate classification and quality detection of rice cultivars. This system, accessible in Python repositories, promises improved crop management and yield. Despite requiring real-world implementation, Rice-ResNet marks a significant advancement in rice classification, fostering enriched digital experiences.

Code metadata

Current code version	V1.1
Permanent link to code/repository used for this code version	https://github.com/SoftwareImpacts/SIMPAC-2024-91
Permanent link to reproducible capsule	https://codeocean.com/capsule/3242936/tree/v1
Legal code license	MIT License
The code versioning system used	GitHub
Software code languages, tools, and services used	Python
Compilation requirements, operating environments, and dependencies	Refer to the README file in the repository
If available, link to developer documentation/manual	Non
Support email for questions	m.r.razavi@outlook.com

1. Introduction

Rice, a staple food worldwide, plays a pivotal role in global sustenance. Beyond its nutritional significance, rice is a vital agricultural commodity, contributing substantially to the livelihoods of farmers. However, ensuring the safety and quality of rice crops remains paramount. Buyers' rejection poses financial risks, underscoring the need for accurate and efficient rice quality detection techniques. In recent years, rice classification and quality assessment have emerged as critical research domains [1–3]. Traditional methods, reliant on visual and olfactory cues, prove time-consuming and unreliable, especially for novice buyers [4,5]. To address this, data mining and machine learning techniques have been harnessed to enhance recognition speed and accuracy. By analyzing recorded images, these approaches extract color-based, morphological, and texture-based features, enabling precise rice classification and quality evaluation. Deep learning (DL), a subset of machine learning and artificial intelligence, finds widespread application in diverse fields, including signal processing, visual recognition, and texture analysis. However, constructing effective DL models remains challenging due to the dynamic nature of real-world data. Researchers have leveraged computer vision algorithms to assess rice quality, focusing on aspects like purity and recognition [6–8]. These endeavors are crucial for successful commercial trading and sustainable rice development [9–11]. Despite its significance, the field of rice quality research remains relatively unexplored. Further investigations are essential to unlock the full potential of rice production and enhance global food security.

DOI of original article: https://doi.org/10.1016/j.eswa.2024.123276.
The code (and data) in this article has been certified as Reproducible by Code Ocean: (https://codeocean.com/). More information on the Reproducibility Badge Initiative is available at https://www.elsevier.com/physical-sciences-and-engineering/computer-science/journals.
* Corresponding author.
E-mail addresses: m.r.razavi@outlook.com (M. Razavi), s.mavaddati@umz.ac.ir (S. Mavaddati), kobti@uwindsor.ca (Z. Kobti), koohi@uwindsor.ca (H. Koohi).

https://doi.org/10.1016/j.simpa.2024.100654
Received 16 April 2024; Received in revised form 28 April 2024; Accepted 3 May 2024

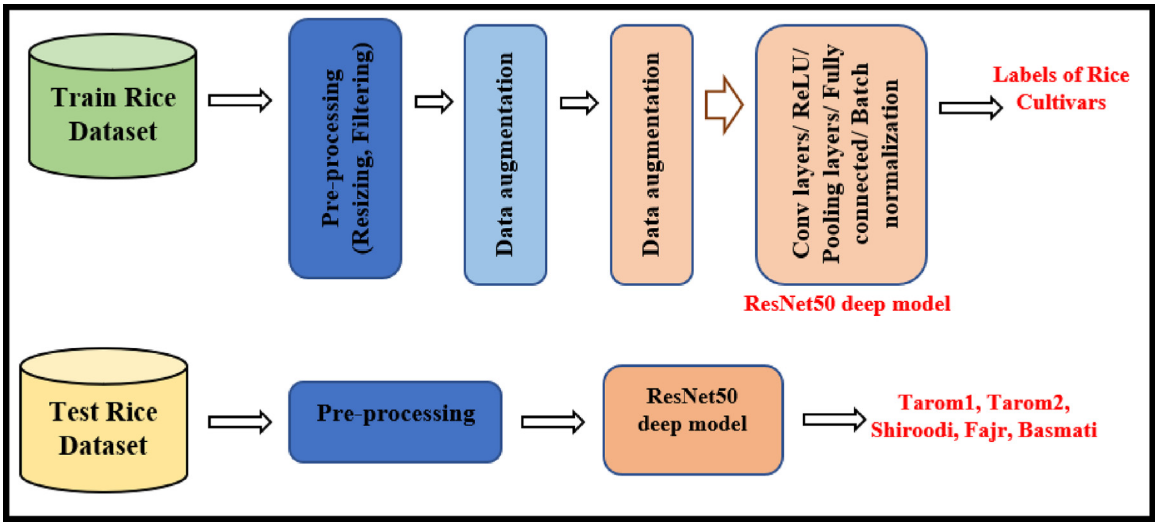

Fig. 1. The block diagram of Rice-ResNet model.

This paper serves as a practical guide, emphasizing the implementation of a pre-trained transferred deep model provided by ResNet50 named Rice-ResNet [12]. This innovative approach to rice classification is introduced by leveraging deep learning models, specifically emphasizing the structural characteristics of diverse rice varieties. The Rice-ResNet harnesses a potent deep-learning model, renowned for its prowess in various computer vision tasks, including data classification. In computer vision, particularly in rice classification, a widely adopted deep learning model is the residual neural network (ResNet). ResNet is meticulously designed to acquire rich image representations and exhibits robust generalization capabilities when faced with novel data, rendering it particularly suitable for rice categorization. The ResNet architecture addresses the challenge of vanishing gradients encountered in deep convolutional neural networks (CNNs) during training on extensive image datasets. It achieves this through a mechanism known as residual learning, which facilitates error propagation across network layers. For rice classification, ResNet combines convolutional layers, down-sampling layers (such as max-pooling), and fully connected layers. Additionally, it employs various other techniques to learn powerful representations from rice images. In this study, the Rice-ResNet architectures, including ResNet50, and a transfer learning-based version of ResNet50 are evaluated [12]. The software components of Rice-ResNet play a crucial role in its functionality and performance. This architecture is based on Python code. Deep Learning Framework specifies the framework to provide pre-implemented layers, optimizers, and utilities for building neural networks.

The data preprocessing procedure describes how rice grain images are preprocessed e.g., resizing, normalization, augmentation. Data quality significantly impacts model performance. Training Pipeline explains how Rice-ResNet is trained. This includes loading data, defining the model, compiling it, and training with labeled samples.

Model evaluation details how the model is evaluated using different measures such as accuracy, precision, and recall. Also, deployment and inference discuss how the Rice-ResNet system deploys for real-world use will be a web service, mobile app, or embedded system.

2. Rice-ResNet architecture

The Rice-ResNet system aims to enhance rice classification rates by employing pre-processing techniques such as resizing, denoising, and median filtering, primarily focusing on creating an accurate deep ResNet-based classifier for label extraction from recorded images. Researchers manually captured image data due to the absence of a dedicated rice variety database [12]. They designed a photography LED light tent (23 cm × 23 cm × 23 cm) to capture rice grain features precisely. Using two LED strips along the box's inner and upper sides, they ensured consistent lighting and minimized shadows. A 5 cm circular opening in the upper panel held the camera for image recording and bulk sampling was employed to create high-quality datasets for rice classification. The input rice image is subsequently classified into five distinct categories by the trained model including Tarom1, Tarom2, Shiroodi, Fajr, and Basmati, and has the highest consumption observed in northern Iran. In the Rice-ResNet classification system, a ResNet50 deep model is pre-trained on an extensive dataset with labeled examples. Subsequently, it is fine-tuned on a smaller dataset to enhance its performance. This dual-step process significantly reduces the time and resources needed for developing new models. Moreover, it capitalizes on the insights gained from the pre-trained model. The benefits of this approach extend beyond efficiency. It improves model performance by mitigating overfitting and enhancing robustness, particularly when dealing with scarce labeled data for novel tasks. Furthermore, it enables us to overcome the limitations of less complex models by facilitating continued learning and fine-tuning on fresh datasets. In the Rice-ResNet system, the transfer learning technique was employed during the training process of deep models to enhance classification accuracy and expedite model training. Fig. 1 shows a schematic diagram of the Rice-ResNet system [12].

The significant contributions of the Rice-ResNet system are discussed in the following. More details about the novelties and the application of this system in agriculture can be reviewed in detail in [12].

The paper presents a novel approach to detecting the quality of rice, which involves addressing the imbalanced nature of the rice data. The Rice-ResNet approach effectively tackles the challenges associated with rice classification, including data imbalance, representation, and model complexity. The development of deep ResNet models with the multi-attention mechanism, trained with annotated data, enhances the performance of classifiers. Furthermore, the study leverages the benefits of transfer learning to design a fine-tuned ResNet model. The deep model can accurately classify rice categories under multiple scenarios, highlighting its efficiency and ability to adapt to varying situations. The Rice-ResNet system provides an effective scalable solution for enhancing the performance of this classification task, with potential applications in the agricultural industry. The presented algorithm can determine the purity percentage of rice varieties and the purity percentage of rice types mixed in different ratios, with great accuracy.

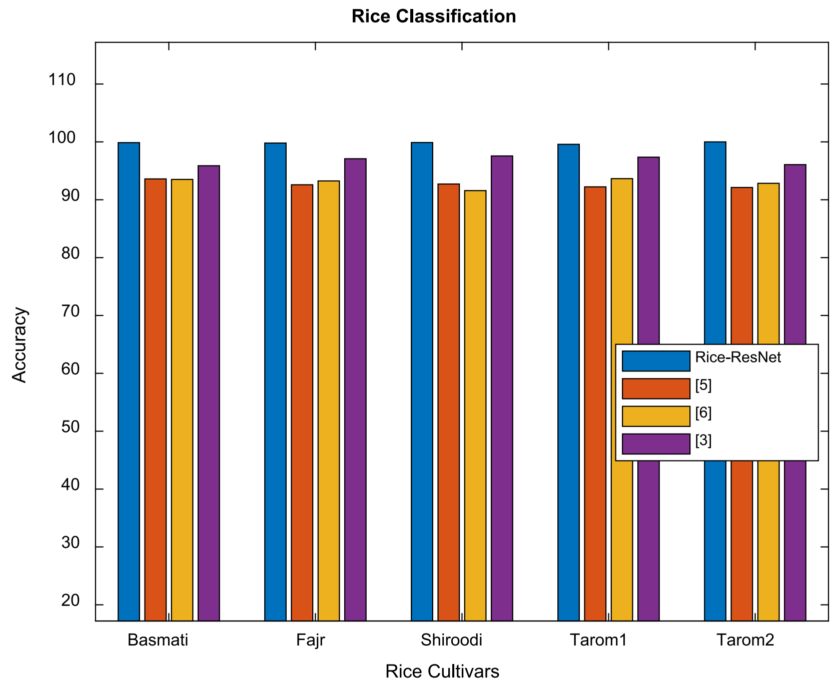

Fig. 2. The experimental results of the Rice-ResNet classifier.

3. Experiments and results

To evaluate the efficiency of the Rice-ResNet, 2500 color images with a size of 100 × 100 pixels were recorded for each type of rice cultivar. The ResNet model layers were trained using the adaptive moment estimation (Adam) optimizer, which is a popular method for updating the weights of a deep network during training [13,14]. Adam is well-known for its capability to converge to a solution quickly. This paper analyzes the performance of the rice classifier using various evaluation metrics such as accuracy, specificity, positive prediction rate, sensitivity, and F-measure. To assess the efficiency of Rice-ResNet, the following metrics are examined: overall accuracy, specificity, positive predictive value, sensitivity, and F-Measure score. The results are presented in Fig. 1. These results show the effectiveness of the presented classifier on different rice types with high accuracy. The Rice-ResNet provides a potential solution for rice purity detection. The obtained results support the ability of the Rice-ResNet classifier to accurately classify different rice types and detect the purity percentage of different rice types mixed in different ratios.

The paper also assesses the efficiency of the Rice-ResNet procedure for rice quality detection. This can be important in different situations, such as when mixing rice with a lower-quality variant to reduce the overall cost, particularly when it comes to retailers who wish to maximize their profits. Therefore, it is crucial to be able to accurately evaluate rice quality to avoid potential issues related to lower-quality rice being used in the production process. The paper assesses the authenticity of Tarom1 rice mixed with Shiroodi rice varieties, at various percentages of combined rice, 15%, 30%, and 45% of Shiroodi rice cultivar. This is performed to determine the purity of the rice mixture, ensuring that it meets the required standards. The results of the Rice-ResNet classifiers to identify the rice quality are presented in Fig. 2. The presented deep learning models, using the ResNet architecture, were shown to be an effective method for solving the rice classification and quality detection problem. The architecture could learn highly complex and hierarchical features from large datasets of rice images (see Fig. 3).

4. How to utilize rice-ResNet

Utilizing Rice-ResNet involves several steps to harness its power for rice classification and quality detection. Here's a guide on how to make the most of this architecture. Rice-ResNet is a custom deep-learning architecture based on pre-trained ResNet models. It has been fine-tuned specifically for rice classification and quality assessment. The architecture leverages feature extraction capabilities from ResNet while enhancing feature selection through self-attention mechanisms. Load the pre-trained ResNet50 model using a deep learning framework like TensorFlow. Fine-tune the ResNet50 by training it on the rice dataset. Using transfer learning, most layers are frozen, and only the final layers are updated for rice-specific features. In the hyperparameter tuning step, the hyperparameters such as learning rate, batch size, and optimizer are experimented with. Remember that real-world implementation involves addressing challenges like scalability, robustness, and computational efficiency. Rice-ResNet represents a significant advancement, and its adoption can lead to enriched experiences in rice classification and crop management in the digital era.

The implementation of Rice-ResNet is made accessible through two Python repositories hosted on GitHub and CodeOcean. Both repositories are listed in the Code metadata Table. The code comprises two primary scripts: one for the ResNet50 deep model and another for the group Rice-ResNet based on the transferred ResNet50 deep model. Comprehensive explanations are provided both in the README file and within the scripts themselves. To utilize Rice-ResNet, the following steps can be followed:

1- The Rice dataset should be cloned to your local machine.
2- Create a virtual environment to manage your Python dependencies.
3- Install the required packages by executing the specified command.
4- Modify the parameters in the main functions of the scripts to align with your dataset and preferences. Detailed guidance on this can be found in the README file and within the scripts themselves.
5- Run the scripts according to your specific needs.

By following these steps, you can effectively leverage Rice-ResNet for rice classification and quality detection.

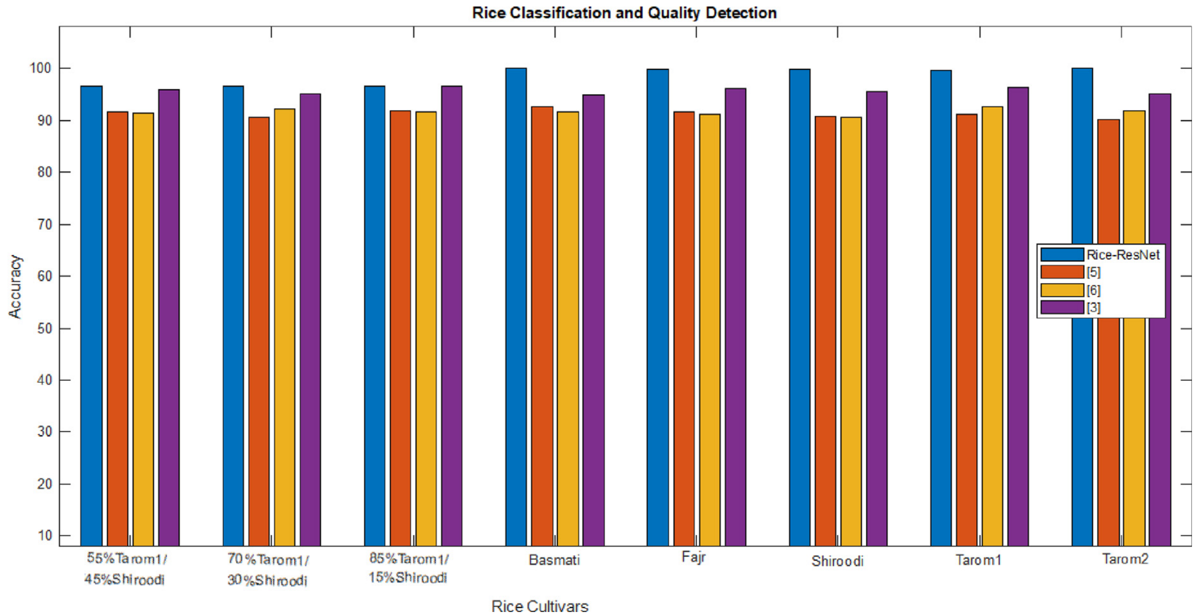

Fig. 3. The experimental results of the Rice-ResNet classifier for rice quality detection.

5. Impact overview

Regarding the experimental results presented in [12], the Rice-ResNet has successfully improved both the classification and quality detection of rice cultivars rather than state-of-the-art methods. The implementation of the Rice-ResNet classifier is available in GitHub and CodeOcean repositories for public usage. The study's findings may have significant implications in the fields of food technology, agriculture, and computer science. This system can potentially benefit the rice industry and lead to the development of efficient and accurate rice identification and classification systems. Moreover, this work can contribute to the advancement of deep learning techniques and their applications in various fields. The software makes the impact choices. The efficient code ensures faster training and inference. Well-structured software allows easy scaling to larger datasets or more complex models. This maintainable code simplifies future updates and bug fixes. Also, leveraging existing libraries and tools saves time and benefits from community contributions. The success of the Rice-ResNet system not only depends on its architecture but also on the robustness and efficiency of the software components.

6. Possible applications and future development

Assessing and identifying the quality of rice holds significance across various domains such as agriculture, ensuring food security, and consumer safety. Rice stands as a pivotal crop globally, serving as a primary sustenance, energy source, and income generator for millions of people. However, given its susceptibility to spoilage and contamination throughout processing, storage, and transit, maintaining rice quality proves paramount in guaranteeing food safety and consumer satisfaction. The proposed software aimed at rice quality assessment can find application in multiple domains, spanning from breeding and seed selection to field management, processing, marketing, and food safety protocols. Engineered with a focus on learning intricate image representations and adeptly applying them to novel datasets, Rice-ResNet emerges as a reliable tool for rice classification. In particular, the combination of residual learning and a well-structured architecture enables Rice-ResNet to achieve high accuracy in rice classification tasks, even in the presence of noisy or ambiguous examples. By leveraging transfer learning and ResNet, the fusion not only can enhance the performance of rice classifiers but also can accelerate and refine the training process, culminating in the development of more precise and resilient rice quality assessment systems.

CRediT authorship contribution statement

Mohammadreza Razavi: Software, Data curation. **Samira Mavaddati:** Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Ziad Kobti:** Writing – review & editing, Supervision, Resources. **Hamidreza Koohi:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] L. Tang others, Food security in China: A brief view of rice production in recent 20 years, Foods 11 (21) (2022) http://dx.doi.org/10.3390/foods11213324.

[2] S. Wan, S.H. Chang, C.T. Peng, Y.K. Chen, A novel study of artificial bee colony with clustering technique on paddy rice image classification, Arab. J. Geosci. 10 (9) (2017) http://dx.doi.org/10.1007/s12517-017-2992-2.

[3] I. Cinar, M. Koklu, Classification of rice varieties using artificial intelligence methods, Int. J. Intell. Syst. Appl. Eng. IJISAE 7 (3) (2019) 188–194, http://dx.doi.org/10.1039/b000000x.

[4] Samira Mavaddati, Rice classification and quality detection based on sparse coding technique, Int. J. Eng. Trans. B Appl. 31 (11) (2018) http://dx.doi.org/10.5829/ije.2018.31.11b.15.

[5] S. Mavaddati, S. Mavaddati, Rice classification with fractal-based features based on sparse structured principal component analysis and Gaussian mixture model, Technol. J. Artif. Intell. Data Min. 9 (2) (2021) 235–244, http://dx.doi.org/10.22044/jadm.2021.9583.2090.

[6] P.R. Jeyaraj, S.P. Asokan, E.R. Samuel Nadar, Computer-assisted real-time rice variety learning using deep learning network, Rice Sci. 29 (5) (2022) http://dx.doi.org/10.1016/j.rsci.2022.02.003.

[7] S. Pradana-López, A.M. Pérez-Calabuig, C. Rodrigo, M.A. Lozano, J.C. Cancilla, J.S. Torrecilla, Low requirement imaging enables sensitive and robust rice adulteration quantification via transfer learning, Food Control 127 (2021) http://dx.doi.org/10.1016/j.foodcont.2021.108122.

[8] P. Shrivastava, K. Singh, A. Pancham, Classification of grain s and quality analysis u sing deep learning, Int. J. Eng. Adv. Technol. 11 (1) (2021) 244–250, http://dx.doi.org/10.35940/ijeat.A3213.1011121.

[9] M. Koklu, I. Cinar, Y.S. Taspinar, Classification of rice varieties with deep learning methods, Comput. Electron. Agric. 187 (2021) http://dx.doi.org/10.1016/j.compag.2021.106285.

[10] R.A. Dar, et al., Classification of rice grain varieties using deep convolutional neural network architectures, SSRN Electron. J. (2022) http://dx.doi.org/10.2139/ssrn.4129838.

[11] A.P. Shaji, S. Hemalatha, Data augmentation for improving rice leaf disease classification on residual network architecture, in: IEEE International Conference on Advances in Computing, Communication and Applied Informatics, ACCAI 2022, Institute of Electrical and Electronics Engineers Inc., 2022, http://dx.doi.org/10.1109/ACCAI53970.2022.9752495.

[12] M. Razavi, S. Mavaddati, H. Koohi, ResNet deep models and transfer learning technique for classification and quality detection of rice cultivars, Expert Syst. Appl. 247 (2024) http://dx.doi.org/10.1016/j.eswa.2024.123276.

[13] D.P. Kingma, J. Ba, Adam: A method for stochastic optimization, in: The 3rd International Conference on Learning Representations, ICLR, 2015, [Online]. Available: http://arxiv.org/abs/1412.6980.

[14] P. Harar, J.B. Alonso-Hernandezy, J. Mekyska, Z. Galaz, R. Burget, Z. Smekal, Voice pathology detection using deep learning: a preliminary study, in: International Conference and Workshop on Bioinspired Intelligence, IWOBI, Funchal, Portugal, 2017, http://dx.doi.org/10.1109/IWOBI.2017.7985525.