International Journal of Sciences and Innovation Engineering
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
website: www.ijsci.com
Volume 03, Issue 11,November 2026
OPEN ACCESS
E-ISSN : 3049-0251
DOI: https://doi.org/10.70849/ijsci03112677385

AI-BASED FAKE RICE GRAIN DETECTION

Preeti Patil[1], Sahana Kalagudi[2], Sakshi Kamble[3], Sunil Deshanure[4], Arati Patil[5]

[1,2,3,4]*Student, Department of Computer Science and Engineering, Jain College of Engineering and Research, Belagavi, Karnataka, India*

[5]*Faculty, Department of Computer Science and Engineering, Jain College of Engineering and Research, Belagavi, Karnataka, India*

Article Info

Article History:

Published: 01 Nov 2026

Publication Issue:
Volume 03, Issue 11
November 2026

Page Number:
1-8

Corresponding Author:
Preeti Patil

Abstract:

Rice is consumed daily by a large population, and screening the quality and authenticity of rice is important for food safety. This paper describes an image-based system designed to screen rice grains and distinguish between project-defined real rice and suspected fake-rice categories. The system combines image preprocessing, computer vision, and a convolutional neural network (CNN) in a web application. The project dataset contains 4,382 images provided by the project team. A user can submit a rice image through file upload or a camera/webcam interface. The backend prepares the image using resizing, normalization, noise reduction, and enhancement before passing it to the trained CNN. The application then displays the predicted class, a model Accuracy score, and an authenticity oriented report. The system is implemented using Html on the frontend and Python, Flask, and OpenCV on the backend. It is intended as an accessible, non-destructive first-level screening tool. Image-based predictions alone cannot confirm the chemical composition of rice and should not replace laboratory testing. The system is therefore presented as a preliminary visual screening aid; it cannot establish chemical composition, food safety, or authenticity conclusively, and should not replace laboratory testing.

Keywords: rice grain classification, food authenticity, image processing, convolutional neural network, CNN, OpenCV, Flask, visual screening

1. INTRODUCTION

Rice is a staple food for a large part of the world's population and is important to household nutrition and food supply. The quality and authenticity of rice products are consequently relevant to consumers, sellers, and food-supply stakeholders. Visual inspection can help identify noticeable differences among grains, but the result may depend on lighting, image quality, sample arrangement, and the experience of the person performing the inspection.

Computer vision and deep learning provide methods for analyzing images and learning visual patterns from examples. A Convolutional Neural Network (CNN) can learn features such as edges, texture, shape, and local appearance and use these features to assign an image to a learned class. Combining a CNN with a simple web interface can make image classification accessible to users without requiring them to run a model-training program.

This project develops an AI-based Fake Rice Detection application that classifies an input rice image as Real Rice or Fake Rice according to the labels used in the project dataset. The system connects a browser-based interface with a Python/Flask backend, OpenCV image preparation, and a trained CNN. Users can submit an image for analysis and view the predicted category with the score returned by the application.

The intended contribution is an accessible, end-to-end visual classification workflow. The output is a prediction based on the image and training labels; it is not a laboratory determination of rice composition or proof that a sample is safe, genuine, or adulterated. Any consequential food-quality decision requires suitable independent verification.

Copyright © 2026 The Author(s). CC BY 4.0 (https://creativecommons.org/licenses/by/4.0/)

2. LITERATURE REVIEW

Prior research has applied image processing and machine learning to rice-grain classification, quality evaluation, and defect detection. Image-based methods can extract physical characteristics,

while conventional classifiers such as Support Vector Machines (SVMs) have been used to distinguish grain categories. Deep-learning approaches, particularly CNNs, learn visual representations directly from image data and have been investigated for rice classification and quality-related tasks.

The references listed in this paper include studies on CNN-based rice quality assessment, real time rice classification, image-processing methods for physical grain attributes, milled-rice quality evaluation, rice damage classification, SVM-based classification, and non-destructive rice inspection [1]–[10]. These works provide methodological context for applying image analysis to rice. However, the tasks and datasets used by prior studies are not necessarily equivalent to the two project-defined classes Real Rice and Fake Rice.

A key consideration in image-based food inspection is the validity of the labels and evaluation data. A model may perform well on images similar to those used during training but perform less reliably on images captured under different conditions or on unfamiliar samples. In addition, visual appearance alone cannot confirm chemical adulteration. The present project therefore focuses on implementing a convenient image-classification pipeline and treats its prediction as preliminary screening rather than definitive food-authenticity testing.

3. PROBLEM STATEMENT AND OBJECTIVES

3.1 Problem Statement

Fake or plastic rice Grains are mixed with real rice is a serious health issue that people cannot easily detect. Current detection methods are costly and require laboratory testing. Therefore, there is a need for a simple, fast, and affordable solution. This project aims to develop an AI-based system to check the authenticity of rice using images.

3.2 Objectives

The objectives of the proposed project are:

- To provide an accuracy indicating rice is real or fake.
- To build a user-friendly interface for easy image upload and result display.
- To support multiple input methods (webcam, file upload).
- To generate a detailed authenticity report for each sample.

4. PROPOSED SYSTEM

4.1 System Architecture and Workflow

The application consists of a frontend, a Flask backend, an image-preprocessing stage, a trained CNN model, and a result-display stage. The user selects an image file or uses the camera/webcam option supported by the interface. The frontend sends the image to the backend. OpenCV prepares the image, the CNN generates a class prediction, and the backend returns the result for display. The workflow can be summarized as:

Home Page → Rice Image Analysis Page → Choose / Upload Rice Image → Prediction → Accuracy Score / Rice Quality → Display Result and Rice Detection Report

The frontend is developed using HTML and CSS. Python and Flask handle the request and connect the application to the model. OpenCV is used for image preparation. The CNN performs the classification. The exact implementation details of any database or detection-history feature should be stated only if they are present in the final deployed version.

5. METHODOLOGY

The AI-Based Fake Rice Detection system follows the sequence shown in Fig. 1. The process begins at the Home Page and continues to the Rice Image Analysis Page, where an image can be selected or uploaded. The system then produces a prediction, displays the accuracy score and rice quality information, and presents the final result with a Rice Detection Report.

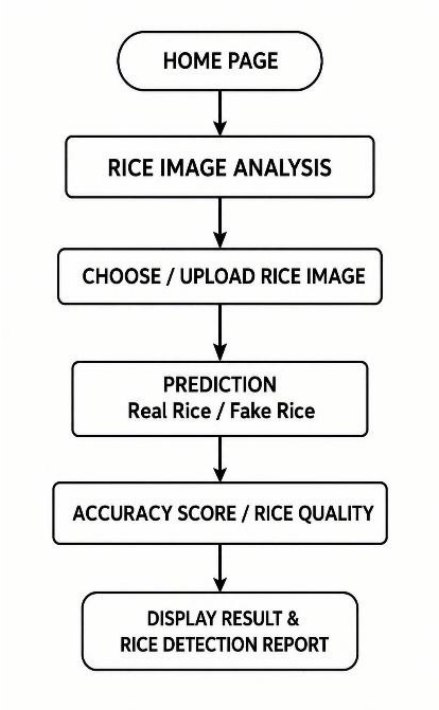

Fig. 1. System flow of the AI-based fake rice grain detection

5.1 Home Page

The process begins with the Home Page of the RiceGuard application. It acts as the main entry point for users who want to check the authenticity of rice grains. The page introduces the purpose of the application and provides access to the rice detection feature. Its interface is designed to be simple and user-friendly so that users can easily understand how to begin the analysis.

The Home Page guides the user to the rice image analysis section, where an image can be selected or captured for examination. It also helps users understand that the application performs image-based screening and provides a preliminary prediction rather than a laboratory-confirmed result.

5.2 Rice Image Analysis

The Rice Image Analysis page provides the main interface for examining a rice-grain image. It allows the user to access the image input options and initiate the detection process. The page is designed to make image submission straightforward, without requiring the user to have technical knowledge of image processing or machine learning.

After opening this page, the user can choose an image from the device or use the available camera or webcam option. Once the image is selected, the user can start the analysis. The submitted image is then passed to the backend processing component, where it is prepared for classification by the trained CNN model.

5.3 Choose / Upload Rice Image

The user selects a rice-grain image from the available files or uploads an image for analysis. The selected image serves as the input for the detection process. A clear image of the rice grain helps the system analyze its visible characteristic.

The quality of the input image is important because factors such as blur, poor lighting, shadows, background colour, and overlapping grains may affect the analysis. After the image is submitted, the system can perform preprocessing operations such as resizing, normalization, noise reduction, and image enhancement, as described in the project workflow. These operations help prepare the image in a consistent format for the classification model.

5.4 Prediction — Real Rice / Fake Rice

After the image has been processed, it is passed to the Convolutional Neural Network (CNN) for classification. The model examines visual patterns in the submitted image and produces a predicted category based on the classes represented in the project dataset.

The application displays the prediction as Real Rice or Fake Rice. These labels refer to the categories defined for this project; they do not independently establish the chemical composition or food safety of the sample. The prediction may also be influenced by the image quality and by how closely the submitted sample resembles the images used to train the model.

5.5 Image Preprocessing and CNN

The detailed project report describes resizing input images to 224×224 pixels and normalizing pixel values by scaling them. It also describes training-time augmentation, including rotation, zoom, and horizontal flipping. At inference time, the image-processing steps should be consistent with those used to prepare the model's training images.

The CNN receives the prepared image and predicts one of the two dataset-defined categories. The application displays the predicted class and an associated score. This score is an output of the model/application and should not be interpreted as measured test accuracy or as a calibrated probability of food authenticity unless such calibration has been established.

5.6 Dataset and Training

The detailed project report describes approximately 3,506 rice images. It reports a 20% validation split, batch size 32, and 10 training epochs. The same report gives a validation accuracy of approximately 99.43% and a validation loss of approximately 0.02997. These figures are reported as validation results from the training process.

A separate project-paper draft mentions a dataset size of 4,382 images. Because the supplied documents differ in their reported counts, the dataset size should be reconciled against the actual dataset folder and training logs before final publication. This paper uses the approximately 3,506image count from the detailed project report and explicitly notes the discrepancy.

The available materials do not establish a separately held-out, independent test set, class-wise test results, or a confusion matrix. Therefore, the reported validation accuracy must not be presented as verified generalization accuracy. For a stronger evaluation, the dataset should be divided into training, validation, and independent test partitions, ensuring that images from the same physical sample or capture session do not leak across partitions.

Table 1: Summary of the project configuration reported in the project documentation

Attribute	Description
Dataset source	Project team dataset
Total images	4,382 images
Classification	Real Rice and Fake Rice
Input type	Rice grain images
Input method	File upload / Camera / Webcam
Image processing	Resizing, normalization, enhancement
Model	Convolutional Neural Network (CNN)
Output	Class and prediction score

Table 2: Tools and technologies used

Component	Technology
Frontend	HTML

Backend	Python, Flask
Image processing	OpenCV
Machine learning	CNN
Input	File upload / Camera / Webcam
Database	Detection records
Development environment	Visual Studio Code
Operating system	Windows

5.7 Evaluation Measures

When an independent labeled test set is available, performance may be evaluated using accuracy, precision, recall, and F1-score:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \qquad \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-score} = \frac{2 \text{Precision} \text{Recall}}{\text{Precision} + \text{Recall}}$$

where *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false positives, and false negatives. The positive class must be defined before calculating these measures. No independent test metrics are claimed in this paper because the supplied materials do not provide the required test predictions and labels.

6. IMPLEMENTATION

The prototype combines a browser-based interface with a Python/Flask backend. The interface supports image input through upload and, where enabled in the application, camera capture. The backend prepares the image using the project's image-processing workflow, invokes the trained CNN model, and returns the predicted class and score for display. The implementation should be checked against the final source code before submission, particularly for any optional features not consistently documented in the report.

The system uses a trained deep learning model to learn visual characteristics from rice images. The trained model is integrated with a Python-based backend, while HTML and CSS are used to develop the user interface. Users can provide rice samples through image upload or webcam-based input. After receiving the input image, the system processes the image, passes it to the trained CNN model, and displays the predicted a class along with the a corresponding accuracy score.

The project documentation identifies Visual Studio Code as the development environment and Windows/Linux as supported operating systems.

- The implementation sequence can be summarized as follows:
- Start the application and open the image-input interface.
- Upload or capture a rice-grain image.
- Validate the image and apply the required preprocessing.
- Resize and normalize the image to match the model input.
- Pass the prepared image to the trained CNN.

Obtain the predicted class and associated Accuracy score. Display the prediction and generate the result report.

7. RESULTS

Theimplementedapplicationdemonstratesanend-to-endworkflowforsubmittinganimage, preprocessing it, performing CNN inference, and displaying a predicted class and score. The project report records approximately 99.43% validation accuracy during training. This result indicates performance on the validation data used in that training procedure; it does not establish performance on unseen, independently collected rice samples.

Prediction quality may be influenced by illumination, blur, background, camera characteristics, grain overlap, dataset diversity, and label quality. The model may also fail to recognize unfamiliar fake-rice materials that are not represented in the training data. The system should consequently be used as a preliminary screening tool, with any important decision confirmed by appropriate reference or laboratory methods.

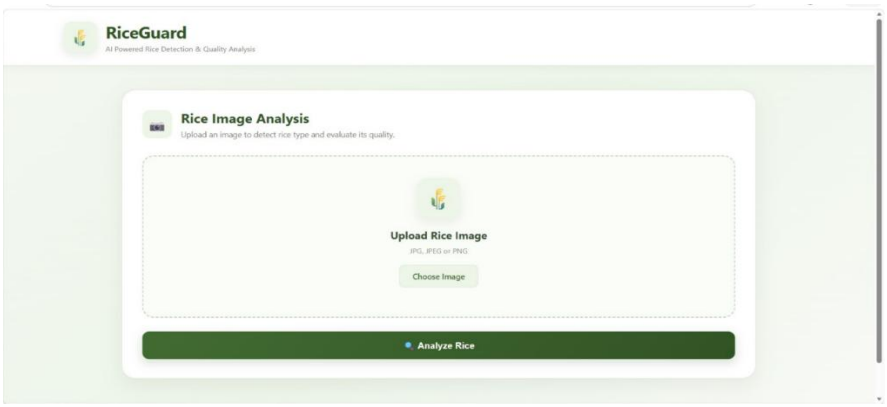

Fig.2. Home page

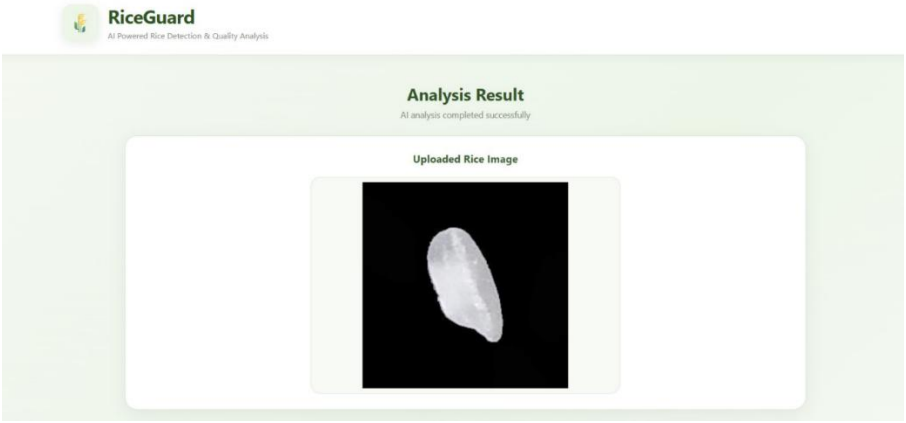

Fig. 3. Uploaded Rice Image



Fig.4. AI-Based Rice Quality Detection and Analysis Result

8. ADVANTAGES AND LIMITATIONS

A. Advantages

The system offers non-destructive, image-based preliminary screening and can return a prediction without requiring the user to inspect every grain manually. The React interface provides a straightforward way to submit images and view results, while Flask and OpenCV connect the interface with the processing pipeline. The design also leaves room for future mobile or edge device deployment.

B. Limitations

The system examines images and cannot determine the chemical composition of rice. Second, an independent held-out test set, confusion matrix, and class-wise test metrics are not documented. The validation accuracy reported during training therefore cannot be treated as independently verified real-world accuracy.

The model is limited to the two classes represented in its training data. Its predictions may be affected by illumination, blur, background, grain overlap, camera characteristics, and variation in rice samples. Most importantly, visual classification cannot establish chemical composition, detect every form of adulteration, or prove that food is safe. The application should be regarded as a preliminary visual screening aid rather than a substitute for laboratory testing.

9. FUTURE SCOPE

Future work can strengthen the system by verifying dataset counts and labels, collecting more diverse images, and creating a separate test set that avoids overlap between samples or capture sessions. Evaluation should include a confusion matrix, precision, recall, F1-score, and class-wise results on independently collected data.

Further improvements may include image-quality checks, testing under different lighting and camera conditions, confidence-score calibration, and deployment on mobile or edge devices. The application could also be extended to additional rice varieties or food products, provided that each new category is supported by a representative, verified dataset and its own evaluation. Collaboration with food-testing experts would help compare visual predictions against appropriate laboratory reference results.

10. CONCLUSION

This paper presents an AI-based rice-image classification application integrating a web interface, Flask backend, OpenCV preprocessing, and a CNN model. It classifies submitted images into the project-defined categories Real Rice and Fake Rice and displays the model's prediction with an associated score. The project uses a dataset of 4,382 images, as reported by the team, and is designed to classify images into the project-defined real-rice and fake-rice categories. The reported validation result is therefore not claimed as verified real-world accuracy. The application demonstrates the potential of computer vision for preliminary visual screening, but it cannot replace laboratory analysis or provide definitive proof of food authenticity.

ACKNOWLEDGMENT

The author acknowledge the Department of Computer Science and Engineering, Jain College of Engineering and Research, Belagavi, and Prof. Arati Patil for her academic guidance and support during the development of this project.

References

[1] S. Suma, M. Narendra, H. Holla, et al., "Intelligent Rice Quality Assessment Using Hybrid CNN-Clustering Approach," *Discover Applied Sciences*, 2025. Full publication details should be verified.

[2] X. Xia, Y. Peng, Z. Chu, et al., "An Overall Real-Time Mechanism for Classification and Quality Evaluation of Rice," 2025. Full publication details should be verified.

[3] "A Comparative Study on Rice Grain Classification Using Convolutional Neural Network and Other Machine Learning Techniques," 2024. Authors and publication details should be verified.

[4] Srikar et al., "Deep Learning-Based Rice Quality Evaluation Using Image Processing for Physical Attribute Analysis," 2024. Full publication details should be verified.

[5] S. Kurade, Meenu, S. Kalra, A. Miglani, et al., "An Automated Image Processing Module for Quality Evaluation of Milled Rice," *Foods*, 2023. Full publication details should be verified.

[6] B. Bhupendra, Kriz Moses, A. Miglani, and P. K. Kankar, "Deep CNN-Based Damage Classification of Milled Rice Grains Using a High-Magnification Image Dataset," *Computers and Electronics in Agriculture*, 2022. Full publication details should be verified.

[7] "Rice Grain Classification Using Convolutional Neural Networks (CNN)," 2021. Authors and publication details should be verified.

[8] I. Ibrahim, N. Zulkifli, N. Sabri, N. Shari, and M. Noordin, "Rice Grain Classification Using Multi-Class Support Vector Machine (SVM)," *IAES International Journal of Artificial Intelligence*, 2019. Full publication details should be verified.

[9] I. Ibrahim, N. Kamaruddin, N. Zabidi, and A. Ghani, "Contrastive Analysis of Rice Grain Classification Techniques: Multi-Class SVM vs Artificial Neural Network," 2020. Full publication details should be verified.

[10] S. Mittal, M. Dutta, and P. Issac, "Non-Destructive Image Processing-Based System for Assessment of Rice Quality and Defects," *Measurement*, 2019. Full publication details should be verified.