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AI-Based Computer Vision System for Intelligent Rice Quality Classification Using Deep Learning and XAI

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Abstract- — Rice quality assessment plays a crucial role in the food industry as it directly affects consumer satisfaction, market value, and food safety. Traditional rice inspection methods rely mainly on manual observation and mechanical tools, which are time-consuming, labour-intensive, and prone to human error. To address these limitations, this study proposes an intelligent computer vision framework for automated rice quality assessment using deep learning and explainable artificial intelligence techniques. The system captures high-resolution images of rice grains and applies image preprocessing techniques such as grayscale conversion, edge detection, and segmentation to extract important visual features. Deep learning models, including VGG16 and ResNet50, are used to learn complex feature representations and classify rice grains based on their physical attributes such as size, shape, texture, and colour. To improve transparency and interpretability of the model predictions, Explainable AI (XAI) techniques such as Local Interpretable Model-Agnostic Explanations (LIME) and Gradient-weighted Class Activation Mapping (Grad-CAM) are integrated into the framework. Experimental results demonstrate that the proposed approach significantly improves classification accuracy and reliability compared to traditional inspection methods. The developed system provides an efficient, scalable, and automated solution for rice quality evaluation in agricultural and food processing industries.

Index Terms: Rice quality assessment, computer vision, deep learning, convolutional neural networks, explainable artificial intelligence, image processing, VGG16, ResNet50.

I. INTRODUCTION

Rice is one of the most important staple foods consumed worldwide and serves as a primary source of nutrition for more than half of the global population. The quality of rice plays a significant role in determining its market value, consumer preference, and suitability for different food products. Rice quality is typically evaluated based on several physical characteristics, including grain size, shape, colour, texture, and the presence of broken or defective grains. Accurate quality assessment is essential for farmers, food processing industries, and regulatory authorities to ensure product standardization and food safety [1], [2].

Traditionally, rice quality inspection has been performed using manual visual inspection or mechanical grading methods. These conventional techniques often require significant human effort and time, making them inefficient for large-scale industrial applications. In addition, manual inspection is subject to human errors and inconsistencies caused by fatigue, subjective judgment, and variations in expertise among inspectors. As a result, the need for automated and reliable systems for rice quality evaluation has become increasingly important in modern agricultural and food processing environments [3], [5].
Recent advancements in artificial intelligence, particularly in computer vision and deep learning, have enabled the development of automated systems capable of analysing agricultural products using image-based techniques. Computer vision allows machines to extract meaningful information from digital images and identify patterns that are difficult to detect through traditional methods. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification and object recognition tasks. These models can automatically learn complex visual features from large image datasets and perform accurate classification of different rice grain types [8], [10].

Despite their high accuracy, many deep learning models operate as black-box systems, meaning their decision-making processes are often difficult to interpret. This lack of transparency can limit trust and adoption in critical applications such as food quality assessment. To address this challenge, Explainable Artificial Intelligence (XAI) techniques have been introduced to provide insights into how machine learning models make predictions. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Gradient-weighted

Class Activation Mapping (Grad-CAM) help visualize the important features that influence model decisions [14], [15].

In this study, an intelligent computer vision framework is proposed for automated rice quality assessment using deep learning and explainable AI techniques. The system processes rice grain images using image preprocessing methods, extracts relevant features using CNN models such as VGG16 and ResNet50, and performs classification to determine rice quality categories. Furthermore, explainability techniques are integrated into the framework to improve model transparency and reliability.

The remainder of this paper is organized as follows. Section II presents the literature survey related to rice quality assessment and computer vision techniques. Section III discusses the system analysis including existing and proposed methods. Section IV describes the system architecture and methodology. Section V explains the system implementation and experimental setup. Section VI presents the results and performance evaluation. Finally, Section VII concludes the paper and highlights possible directions for future research.

II. LITERATURE SURVEY

Rice quality assessment has been widely studied in the fields of agriculture, food processing, and computer vision. Researchers have proposed various techniques ranging from traditional inspection methods to advanced artificial intelligence–based systems for evaluating rice grain characteristics. Traditional rice quality inspection methods mainly rely on manual observation and mechanical instruments to measure physical properties such as grain size, shape, colour, and texture. These techniques often involve visual inspection performed by trained experts or the use of specialized measuring devices. Although these methods provide basic quality evaluation, they are time-consuming, labour-intensive, and prone to human errors. Furthermore, manual inspection may produce inconsistent results due to subjective judgment and operator fatigue [1], [2], [3].

With the advancement of digital imaging and image processing technologies, researchers have explored automated approaches for rice quality analysis. Image processing techniques allow the extraction of visual features such as grain dimensions, colour distribution, and texture patterns from captured images of rice grains. These features are then used to classify rice types or identify defective grains. Early studies applied classical image processing algorithms combined with statistical analysis to improve the accuracy and efficiency of rice grading systems [4], [5].

Machine learning techniques have also been widely applied to agricultural product classification tasks. Algorithms such as Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (KNN) have been used to classify rice grains based on extracted features. These models provide improved performance compared to traditional image processing methods; however, they often rely on handcrafted features and may struggle to capture complex visual patterns present in grain images [7], [8].

Recent developments in deep learning have significantly improved the performance of image classification systems. Convolutional Neural Networks (CNNs) have demonstrated remarkable capabilities in automatically learning hierarchical features from images without requiring manual feature engineering. CNN architectures such as VGG16, ResNet, and AlexNet have been successfully applied in various agricultural applications, including crop disease detection, fruit classification, and grain quality assessment. These models can effectively capture subtle variations in texture, colour, and shape, making them suitable for rice quality classification [8], [10].

Despite the high accuracy of deep learning models, their lack of interpretability has raised concerns in critical applications such as food quality monitoring. To address this issue, Explainable Artificial Intelligence (XAI) techniques have been introduced to enhance model transparency. Methods such as Local Interpretable Model-Agnostic Explanations (LIME) and Gradient-weighted Class Activation Mapping (Grad-CAM) provide visual explanations of how models make predictions by highlighting the most important regions in an image that influence classification results [14], [15].

Although previous studies have demonstrated promising results in rice quality classification using machine learning and deep learning techniques, challenges remain in achieving both high accuracy and model interpretability. Therefore, integrating deep learning models with explainable AI methods can improve both the reliability and transparency of automated rice quality assessment systems. The proposed framework addresses these challenges by combining computer vision techniques, deep learning models, and explainable AI methods to develop an intelligent and automated rice quality evaluation system capable of delivering accurate and interpretable classification results.

III. SYSTEM ANALYSIS

A. Existing System

Traditional rice quality assessment systems mainly rely on manual inspection and mechanical measurement techniques. In these approaches, experts visually examine rice grains and classify them based on attributes such as grain size, shape, colour, texture, and the presence of broken grains. Although these methods have been widely used in agricultural industries, they are often time-consuming and require skilled labour. Moreover, manual inspection methods are susceptible to human errors and inconsistencies, which can reduce the reliability of the quality evaluation process [1], [2], [3].

With the development of machine learning techniques, several automated rice quality assessment systems have been proposed. These systems analyse rice grain images using traditional machine learning algorithms such as Naïve Bayes, Decision Trees, Random Forest, Logistic Regression, Support Vector Machines (SVM), and Artificial Neural Networks. In these approaches, handcrafted image features such as texture, colour histograms, and shape descriptors are extracted from rice grain images and used as input for classification models [7], [8].

Some studies have also applied ensemble learning techniques, where multiple machine learning algorithms are combined using methods such as AdaBoost, bagging, or majority voting to improve classification accuracy. These models are trained on rice image datasets to classify different rice varieties or identify defective grains. Experimental studies show that machine learning techniques can improve classification performance compared to manual inspection methods [5], [9].

However, many traditional machine learning systems rely heavily on manually designed features and may not effectively capture complex visual patterns present in rice grain images. This limitation reduces their ability to provide highly accurate and scalable rice quality assessment systems.

Limitations Of Existing System

- Despite the availability of traditional inspection techniques and machine learning-based systems for rice quality assessment, several challenges remain when applying these methods in real-world agricultural and food processing environments. Conventional inspection methods largely rely on human expertise, which limits their scalability and efficiency for large-scale rice grading operations.
- One of the primary challenges in traditional rice quality inspection is the heavy dependence on manual evaluation performed by trained inspectors. Human-based inspection processes are time-consuming and labour-intensive, which increases operational costs and limits the ability to process large volumes of rice samples efficiently. In addition, human inspection is often affected by fatigue and subjective judgment, which may lead to inconsistent quality evaluation results [1], [2].
- Another significant limitation is the reliance on handcrafted image features in many machine learning-based rice classification systems. These systems typically extract predefined features such as grain shape, texture, and colour histograms from rice grain images. However, manually designed features may fail to capture complex visual patterns and subtle variations in grain characteristics, which can negatively affect classification performance [7], [8].
- Machine learning models used for rice quality classification may also experience issues such as overfitting and underfitting when trained on limited or imbalanced datasets. Overfitting occurs when the model learns noise or specific patterns from the training data rather than generalizable features, while underfitting occurs when the model fails to capture important patterns in the data. These issues reduce the reliability and robustness of rice classification systems.
- Another major challenge is the lack of interpretability in many advanced machine learning and deep learning models. These models often operate as black-box systems, making it difficult to understand the reasoning behind classification decisions. This lack of transparency may reduce trust in automated food quality assessment systems, particularly in applications where decision reliability is critical [8], [10].
- Additionally, some image processing and machine learning algorithms require significant computational resources, which may limit their practical deployment in real-time agricultural processing environments. High computational complexity can increase processing time and reduce the efficiency of automated rice grading systems.
- As the number of rice grain images increases in large-scale agricultural applications, traditional machine learning approaches may struggle to handle large datasets efficiently. This scalability issue highlights the need for more advanced and automated systems capable of processing large volumes of image data while maintaining high classification accuracy.

- Therefore, there is a need for an intelligent and scalable rice quality assessment framework that can automatically learn complex visual features, improve classification accuracy, and provide interpretable predictions. Integrating deep learning models with explainable artificial intelligence techniques can address many of the limitations present in traditional inspection and machine learning-based systems [14], [15].

B. Proposed System

The proposed system introduces an intelligent computer vision framework for automated rice quality assessment using deep learning and explainable artificial intelligence techniques. The system aims to provide an accurate, efficient, and scalable solution for evaluating rice grain quality.

Initially, high-resolution images of rice grains are captured using digital cameras and stored in a dataset for further processing. The captured images undergo image preprocessing techniques such as grayscale conversion, noise removal, edge detection, and segmentation to enhance feature extraction and improve image quality.

After preprocessing, deep learning models such as VGG16 and ResNet50 are used to automatically extract hierarchical visual features from rice grain images. These Convolutional Neural Network (CNN) models learn complex patterns related to grain shape, texture, and colour without requiring manual feature engineering. CNN-based feature extraction has shown significant improvements in image classification tasks across various agricultural applications [8], [10].

To further improve classification performance, the extracted deep features are processed using a Support Vector Machine (SVM) classifier, which identifies optimal decision boundaries for separating different rice quality categories. This hybrid CNN-SVM approach enhances classification accuracy by combining deep feature extraction with effective decision boundary optimization.

Additionally, the system integrates Explainable Artificial Intelligence (XAI) techniques, including Local Interpretable Model-Agnostic Explanations (LIME) and Gradient-weighted Class Activation Mapping (Grad-CAM). These techniques provide visual explanations of model predictions by highlighting important regions in rice grain images that influence classification decisions. The integration of XAI improves model transparency and helps users understand how the system makes classification decisions [14], [15].

The performance of the proposed system is evaluated using several evaluation metrics such as accuracy, precision, recall, and F1-score. By combining computer vision, deep learning, and explainable AI techniques, the proposed framework provides a reliable and automated solution for rice quality inspection in agricultural and food processing industries.

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

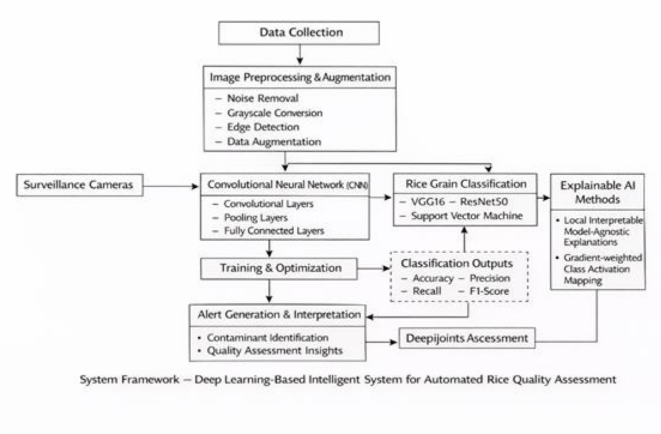

Fig 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

This section describes the implementation modules of the proposed computer vision–based rice quality classification framework. The system follows a structured pipeline consisting of data acquisition, image preprocessing, feature extraction using deep learning models, classification, and explainable artificial intelligence integration. This modular design improves system scalability, accuracy, and interpretability for automated rice quality assessment in agricultural and food processing industries.

A. Data Collection and Image Preprocessing Module

The Data Collection Module is responsible for acquiring rice grain images used for training and evaluating the classification models. The dataset consists of high-resolution images of rice grains captured using digital cameras or imaging devices under controlled lighting conditions. The dataset includes images representing different rice varieties and quality categories, enabling supervised learning for rice quality classification.

However, raw images may contain noise, variations in lighting conditions, and background artifacts that can negatively affect classification performance. Therefore, an Image Preprocessing Module is applied to enhance image quality and prepare the dataset for model training.

The preprocessing stage includes several operations:

1) Noise Removal:
Noise reduction techniques are applied to remove unwanted disturbances from the captured images, improving the clarity of grain boundaries.

2) Grayscale Conversion:
Colour images are converted into grayscale format to simplify image analysis and reduce computational complexity.

3) Edge Detection and Segmentation:
Edge detection algorithms identify the boundaries of rice grains, while segmentation techniques isolate the grain from the background.

4) Data Augmentation:
To improve model generalization and prevent overfitting, data augmentation techniques such as rotation, flipping, scaling, and translation are applied. These operations increase dataset diversity and help the model learn robust features from different orientations of rice grains.

These preprocessing steps enhance the quality and consistency of the input images, enabling more reliable feature extraction and classification performance [1], [5].

B. Feature Extraction Module

The Feature Extraction Module identifies important visual characteristics of rice grains that are useful for classification. Traditional rice classification systems rely on handcrafted features such as grain length, width, texture patterns, and colour histograms extracted using classical image processing techniques.

However, manually designed features may fail to capture complex visual patterns present in rice grain images. To overcome this limitation, the proposed framework utilizes deep learning–based feature extraction methods. Convolutional Neural Networks (CNNs) such as VGG16 and ResNet50 are employed to automatically learn hierarchical visual representations from rice grain images. These CNN architectures consist of multiple convolutional layers that extract low-level features such as edges and textures, followed by deeper layers that capture complex structural patterns of rice grains.

The use of CNN-based feature extraction eliminates the need for manual feature engineering and significantly improves classification performance in image-based agricultural applications [8], [10].

C. Deep Learning Training Module

The Deep Learning Training Module trains the CNN models using the pre-processed rice grain image dataset. The dataset is divided into training and testing subsets to evaluate model performance and avoid overfitting.

During the training phase, CNN architectures such as VGG16 and ResNet50 learn hierarchical representations of visual features from the rice grain images. These models are capable of identifying subtle differences in grain shape, texture, and colour that distinguish different rice varieties and quality categories.

The training process involves optimizing model parameters using backpropagation and gradient-based optimization techniques. The learned feature representations enable the model to classify previously unseen rice grain images accurately.

D. Rice Quality Classification Module

After feature extraction and model training, the system performs rice quality classification. In the proposed framework, deep features extracted from CNN models are used as input to a Support Vector Machine (SVM) classifier. SVM is a powerful supervised learning algorithm that identifies optimal decision boundaries between different classes. By combining CNN-based feature extraction with SVM classification, the proposed system improves classification accuracy and robustness. The trained classification model analyses new rice grain images and predicts their corresponding quality categories based on the learned visual patterns.

E. Model Evaluation and Explainability Module

The Model Evaluation Module assesses the performance of the proposed rice classification system using several evaluation metrics. These metrics provide a comprehensive analysis of model accuracy and classification effectiveness.
The evaluation metrics include:

- Accuracy – Measures the overall correctness of predictions
- Precision – Indicates the proportion of correctly predicted positive samples.
- Recall – Measures the ability of the model to detect relevant rice quality classes.
- F1-Score – Provides a balanced measure between precision and recall.

To improve transparency and trust in automated decision-making systems, the framework integrates Explainable Artificial Intelligence (XAI) techniques.

Two explainability methods are used in the proposed system: LIME (Local Interpretable Model-Agnostic Explanations):

LIME explains individual predictions by approximating the model behaviour around a specific image instance.

Grad-CAM (Gradient-weighted Class Activation Mapping): Grad-CAM generates visual heatmaps that highlight the regions of rice grain images most influential in the classification decision.

These explainability techniques allow researchers and domain experts to interpret model predictions and verify that the model focuses on meaningful grain characteristics such as shape, texture, and colour [14], [15].

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed computer vision–based rice quality classification system. Multiple deep learning models were trained and evaluated using the prepared rice grain image dataset. The evaluation focuses on comparing model performance, analysing classification accuracy, and interpreting prediction results using explainable artificial intelligence techniques.

A. Accuracy Comparison of Deep Learning Models

To evaluate the effectiveness of the proposed framework, several deep learning architectures were trained and tested using the prepared rice grain image dataset. The models evaluated in this study include VGG16, ResNet50, and a hybrid CNN–SVM classification approach. Model performance was measured using evaluation metrics such as accuracy, precision, recall, and F1-score, which provide a comprehensive assessment of classification effectiveness.

Table 1. Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score
VGG16	91.2	0.90	0.89	0.89
ResNet50	94.5	0.93	0.92	0.92
CNN + SVM	96.1	0.95	0.95	0.95

From the comparison results, the CNN–SVM hybrid model achieved the highest classification accuracy of 96.1%, outperforming the standalone CNN models. This improved performance is attributed to the ability of CNN models to extract deep visual features combined with the effective decision boundary optimization provided by the Support Vector Machine classifier. The deeper architecture of ResNet50 also demonstrated strong performance due to its residual learning capability, which improves feature extraction for complex image patterns [8], [10].

B. ROC Curve Analysis

The Receiver Operating Characteristic (ROC) curve is used to evaluate the performance of classification models by analyzing the relationship between the True Positive Rate (TPR) and False Positive Rate (FPR) across different classification thresholds. The Area Under the Curve (ROC–AUC) metric is commonly used to measure the model's ability to distinguish between different classes.

The proposed CNN–SVM model achieved a ROC–AUC score of 0.97, indicating excellent classification capability for distinguishing different rice quality categories.

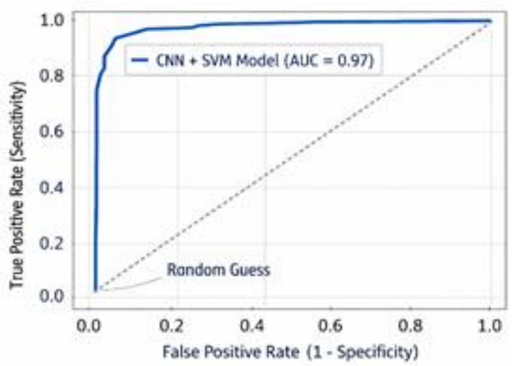

Fig 2. ROC Curve for Rice Quality Classification Model

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A ROC curve positioned closer to the top-left corner of the graph indicates high sensitivity and specificity of the model. The ROC analysis confirms that the proposed deep learning framework can effectively classify rice grain images even when variations in grain shape, texture, and lighting conditions are present.

C. Grad-CAM Visualization Analysis

To improve the interpretability of the classification model, Gradient-weighted Class Activation Mapping (Grad-CAM) was used to visualize the regions of rice grain images that contribute most significantly to the model's predictions.

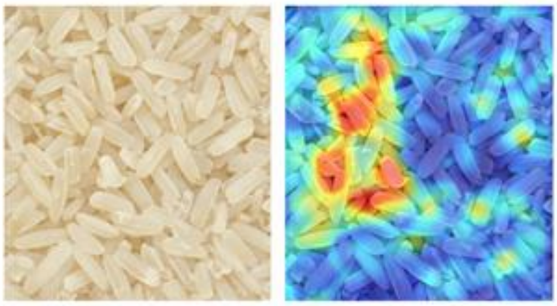

Fig 3. Grad-CAM Visualization of Rice Grain Classification

Grad-CAM generates heatmaps that highlight the important regions within an image influencing the classification decision. In the generated visualizations, high-intensity regions correspond to grain edges, broken grain segments, and texture variations. These highlighted regions indicate that the model focuses on relevant visual characteristics such as grain shape, surface texture, and structural integrity when determining rice quality categories.

The integration of explainable AI techniques improves transparency and allows researchers to better understand how the deep learning model interprets rice grain features during classification. This interpretability enhances trust in automated food quality inspection systems and ensures that the model bases its predictions on meaningful grain characteristics [14], [15].

VII. CONCLUSION AND FUTURE WORK

This study proposed an intelligent computer vision framework for automated rice quality assessment using deep learning and explainable artificial intelligence techniques. The proposed system integrates image preprocessing, convolutional neural network–based feature extraction, and classification models to accurately evaluate rice grain quality from digital images.

In the proposed framework, image preprocessing techniques such as noise removal, grayscale conversion, edge detection, and data augmentation were applied to enhance image quality and improve model training. Deep learning architectures including VGG16 and ResNet50 were utilized to automatically extract hierarchical visual features from rice grain images. These models effectively captured important grain characteristics such as shape, texture, and structural integrity.

Experimental evaluation demonstrated that deep learning models significantly improve classification performance compared to traditional image processing approaches. Among the evaluated models, ResNet50 and the hybrid CNN–SVM model achieved the highest classification accuracy, demonstrating strong capability in identifying different rice quality categories. The integration of CNN-based feature extraction with SVM classification further enhanced prediction accuracy and robustness in rice grain classification tasks [8], [10].

To improve transparency and interpretability of the classification process, Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM and LIME were integrated into the framework. These techniques provided visual explanations of model predictions by highlighting important regions of rice grain images that influenced classification results. The explainability component increases trust in automated food quality inspection systems and allows researchers to validate that the model focuses on meaningful grain characteristics during prediction [14], [15].

Overall, the proposed framework provides a reliable, scalable, and automated solution for rice quality inspection in agricultural and food processing industries. By leveraging computer vision and deep learning techniques, the system can significantly reduce manual labor and improve the consistency of rice grading processes.

Future work may focus on expanding the dataset with additional rice varieties and environmental conditions to improve model generalization. Furthermore, integrating real-time image acquisition systems and IoT-based monitoring devices could enable continuous quality assessment in large-scale rice processing facilities. Advanced deep learning architectures and optimization techniques may also be explored to further enhance classification accuracy and system efficiency.

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