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Intelligent image-based recognition of rice cultivars using PSO-optimized ANFIS

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Abstract:

Rice is considered to be one of the most significant staple foods on a global scale, particularly within developing countries such as Iran. In these countries, rice cultivars frequently exhibit considerable variation in terms of quality, price, and characteristics. Accurate identification of rice cultivars is imperative for maintaining market transparency, ensuring quality control, and supporting agricultural decision-making. This study proposes a novel methodology for the classification of rice cultivars, which integrates advanced image processing techniques with an Adaptive Neuro-Fuzzy Inference System (ANFIS) that has been optimised by the Particle Swarm Optimisation (PSO) algorithm. A total of three rice types, which are commonly cultivated in northern Iran, were selected for the study: Native Tarom, Hashemi Tarom, and Pakistani rice. The images from these three rice types were processed in standard conditions using Canny edge detection algorithms. The extraction of morphological features was then utilised for the training and testing of the ANFIS-PSO model. The experimental results obtained achieved a classification accuracy of 99.47%, thereby demonstrating the superiority of the proposed method in comparison to traditional techniques with regard to precision and applicability. Moreover, the method employs a cost-effective and readily accessible approach that lends itself to practical applications, including the development of smartphone-based software for real-time rice identification. This study proposes a non-invasive, efficient, and scalable solution to rice authentication and classification challenges, with potential application in agricultural quality assurance and market regulation.

Keywords: Rice cultivar identification; Image processing; Canny edge detection; Adaptive Neuro-Fuzzy inference system; Particle swarm optimization

1. Introduction

Rice is considered to be one of the world's most significant staple foods, providing a primary dietary source for billions of people worldwide and representing a vital agricultural commodity in numerous countries, including Iran. However, the rice market is increasingly confronted with challenges related to adulteration and mislabelling, which have the potential to erode consumer confidence and jeopardise the economic livelihoods of local farmers. Reliable identification of rice cultivars is imperative for ensuring product authenticity, supporting quality assurance, and facilitating fair trade in agricultural markets. Conventional methods employed for the identification of rice cultivars have predominantly relied on the assessment of experts and subsequent laboratory analysis. Whilst the efficacy of these methodologies is evident, they are frequently characterised by a significant investment of labour, financial resources and time, and are susceptible to subjective interpretation. The presence of subtle morphological variations among rice varieties, particularly in circumstances where samples are combined or adulterated, often renders precise visual discrimination challenging and unreliable.

Recent advances in image processing and artificial intelligence, such as convolutional neural networks, fuzzy inference systems, and hybrid optimization algorithms, have ushered in new possibilities for automated and accurate rice identification. Nevertheless, most studies in this field still encounter significant limitations. These include the use of constrained or non-local datasets lacking variety diversity -often omitting important native cultivars like Tarom and Hashemi in Iran- high dependence on sophisticated or costly computational resources, and a scarcity of solutions optimized for real-time or low-resource environments, such as those needed for smartphone-based applications. Edge detection is a fundamental operation in image segmentation and plays a pivotal role in extracting relevant object features, as emphasized by Biswas and Hazra [1]. For applications such as rice cultivar recognition, ensuring high-quality edge information and image contrast is essential for precise feature extraction. In digital image processing, the challenge of attaining clear contrast and reliable edge detection becomes even more critical in agricultural applications, where variations in lighting conditions and noise during image capture can directly impact recognition accuracy [2].

Image enhancement techniques have thus been widely adopted to overcome poor lighting and environmental noise, with contrast enhancement considered particularly crucial. Contrast- the measure of difference between the brightest and darkest regions -directly affects the visibility of morphological features in rice grains. High image contrast enhances the discrimination of grain edges and shapes, improving subsequent segmentation and classification. While conventional spatial filtering and histogram-based approaches, such as dynamic histogram equalization, offer improvements over traditional methods [3], they may still encounter such problems as loss of important details in saturated images or increased computational effort in high-dimensional methods [2].

In recent years, machine learning and biologically inspired algorithms have shown promise in advancing image enhancement and feature extraction. Methods integrating artificial neural networks (ANNs) and optimization algorithms-like the bat algorithm-have demonstrated significant accuracy gains in complex imaging tasks, including edge enhancement in medical and agricultural images [3]. Hybrid approaches, such as combining neural networks with fuzzy logic systems, enable adaptive parameter tuning for improved gradient interpretation and segmentation [4]. Nevertheless, the complexity and resource-intensiveness of these methods, as well as the need for careful model configuration (e.g., determining the number of neurons/layers), pose practical limitations for deployment in low-resource settings [5].

Canny edge detection remains a robust solution for identifying image discontinuities and extracting precise boundaries, making it particularly effective in preprocessing rice grain images for segmentation [2]. When integrated with advanced computational models—such as an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized through Particle Swarm Optimization (PSO)-it becomes possible to overcome some of the limitations of previous approaches, enhancing classification accuracy and computational efficiency [5].

Within the context of rice quality assessment, the need for reliable, rapid, and accessible evaluation methods is ever-increasing. Traditional rice quality inspection relies on manual examination or laboratory analysis, which can be subjective, costly, and labor-intensive [6]. Modern image processing technologies, incorporating edge detection and intelligent algorithms, offer a non-invasive and scalable alternative for authenticating rice cultivars and evaluating grain quality [7].

Despite various advancements, challenges remain-particularly regarding the computational complexity of these methods and their accessibility for real-time or resource-limited applications. Therefore, this study proposes a framework that leverages Canny edge detection in combination with an ANFIS-PSO model for rice cultivar recognition. This approach aims to balance accuracy, computational efficiency, and ease of deployment, using locally relevant datasets to support the requirements of practical agricultural environments. Moreover, much prior research has not sufficiently focused on optimizing feature extraction or classifier parameters, which are crucial for achieving high accuracy and practical implementation. As a result, there is a growing need for innovative, low-cost, and scalable methods tailored to local varieties and real-world constraints.

In response to these gaps, the present study proposes a novel and practical methodology for rice cultivar recognition. By integrating efficient image processing techniques -specifically Canny edge detection- with an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized via Particle Swarm Optimization (PSO), this work aims to deliver a robust, highly accurate, and accessible solution. The approach is validated using original image data of three major rice types common in Iran (Native Tarom, Hashemi Tarom, and Pakistani), obtained under real-world conditions. This method promises not only substantial improvement in recognition accuracy but also potential application in affordable and real-time systems, such as smartphone-based tools, to support quality assurance and prevent fraud in the rice market.

In this study, the focus lies on developing an image-processing-based methodology to classify mixed samples of Iranian and foreign rice cultivars. By employing widely accessible technologies, such as smartphones with average camera quality, the approach aims to provide users with a practical, cost-effective, and accurate solution for rice cultivar identification. In essence, the proposed system enables rice classification based on captured images by analyzing physical features through the Canny algorithm and ANFIS. This method not only enhances identification accuracy but also supports mobile integration for real-world applications, empowering local farmers, traders, and consumers to access advanced tools without requiring specialized equipment.

Precise and non-invasive rice variety identification is essential for protecting consumer rights, ensuring food quality, and enhancing transparency in the rice market. The development of intelligent, image-based methods promises to make identification processes faster, more reliable, and accessible even with basic equipment such as smartphones. By integrating advanced algorithms-including Canny edge detection for robust feature extraction, and adaptive neuro-fuzzy classifiers optimized by particle swarm optimization-this study addresses major limitations of conventional approaches.

The proposed method not only offers high accuracy and operational efficiency but is also practical for implementation as a mobile application, empowering farmers, traders, and quality inspectors. It contributes to quality assurance and market regulation by enabling real-time detection and authentication of rice cultivars. Furthermore, this line of research is crucial for safeguarding the authenticity of premium rice, supporting fair market practices, and paving the way for broader adoption of smart technologies in agricultural quality assessment. Ultimately, the outcomes of this work may serve as a model for similar applications in other crops and support the advancement of precision agriculture in developing regions.

Despite significant advances in the field of rice cultivar identification using image processing and artificial intelligence, several limitations persist in the existing literature:

- Most prior studies relied on either limited or non-local datasets, often lacking diversity in rice varieties, especially those specific to Iran such as Tarom and Hashemi. Few studies have focused on imaging under real conditions and using mobile devices, which restricts the generalizability and practical use of their solutions.
- Many studies utilized sophisticated deep learning models (e.g., CNNs) or required specialized laboratory setups, leading to high computational or economic costs, making them less accessible for direct use by local farmers or small-scale industries.
- Earlier works often depended on either classical feature extraction without rigorous optimization or basic neural-fuzzy systems without tailored parameter tuning, which limited their classification performance in practice.
- There is a noticeable deficiency in research where models are specifically optimized for deployment on smartphones or low-resource environments, a need that is substantial in developing countries.

This study addresses these gaps by introducing an image-based classification framework with several key contributions:

✓ This research is among the first to focus on three prominent Iranian rice cultivars (Tarom, Hashemi, Pakistani) using original images acquired under practical, local conditions, thus enhancing the real-world validity of the findings.

✓ By leveraging a combination of the computationally efficient Canny edge detection algorithm and an Adaptive Neuro-Fuzzy Inference System (ANFIS) optimized using Particle Swarm Optimization (PSO), the methodology achieves near-perfect accuracy while remaining feasible for real-time application on smartphones and low-cost systems.

✓ The use of PSO to optimize ANFIS parameters leads to significant improvements in classification performance compared to conventional non-optimized or manually tuned models used in earlier studies.

✓ The proposed method eliminates the need for high-cost equipment or complex models, and its results suggest potential for direct commercialization as a mobile-based rice authentication and quality control tool.

In summary, this study bridges the gap by presenting a practical, cost-effective, and highly accurate approach for rice cultivar identification that is specifically tailored for application in local and resource-constrained settings.

The paper proceeds as follows. Section 2 reviews related literature on rice cultivar recognition and highlights the research gaps addressed in this work. Section 3 presents the proposed methodology, including image acquisition, preprocessing, feature extraction and selection, and classification using the ANFIS-PSO model. Section 4 provides a step-by-step analysis of the simulation results for rice cultivar classification. Section 5 presents the main results along with a comprehensive discussion. Section 6 discusses the current limitations of the proposed approach and suggests directions for future research, including the extension of the methodology to larger and more diverse datasets and real-world conditions. Finally, section 7 summarizes the main findings, discusses practical implications, and concludes the paper.

2. Literature review

Recent years have witnessed significant advances in the identification and classification of rice varieties using machine learning and image processing techniques, driven by the need for rapid, cost-effective, and non-invasive quality control in agriculture. Traditional methods, based on expert visual inspection and laboratory testing, have proven time-consuming and prone to subjective errors, making automated approaches especially valuable [6, 7]. Early studies employed basic image processing algorithms such as RGB color models, histograms, and edge detection to quantify rice grain morphology and purity, laying the foundation for automated grading systems [7]. As computer vision matured, additional research introduced machine vision for differentiating grain types and evaluating internal damage, using features like shape, chalkiness, and color to increase accuracy [6, 8]. The integration of edge detection algorithms, particularly the Canny detector, enabled more precise extraction of rice grain boundaries [2].

Moving into the era of artificial intelligence, researchers incorporated advanced algorithms such as Artificial Neural Networks (ANN), fuzzy systems, and optimized hybrid models. The Adaptive Neuro-Fuzzy Inference System (ANFIS), combined with metaheuristic optimizers like Particle Swarm Optimization (PSO) and Bat Algorithm, delivered substantial improvements in classification accuracy [3, 5]. At the same time, techniques like structure-preserving texture filtering were developed to enhance the quality of feature extraction from rice grain images [4].

The adoption of Convolutional Neural Networks (CNNs) and deep learning marked a new phase, enabling the automated extraction and classification of morphological, color, and texture features from rice images with exceptional accuracy [5]. These approaches found increasing practical use in large-scale rice grading and seed authentication, often deployed through mobile or real-time computer vision platforms to aid farmers and inspectors directly in the field.

A major leap has been the expansion of datasets, which is crucial for robust model training. For instance, Morshed et al. [9] provided a benchmark dataset of over 4,700 original and 23,000 augmented rice grain images representing 20 popular Bangladeshi varieties. These datasets, collected from both farms and markets, allow for transparent model evaluation under real-world conditions and facilitate the fair comparison of different image-based classification algorithms.

More recent studies have further leveraged RGB and hyper spectral imaging, combining spatial and spectral features to distinguish a greater number of seed varieties with higher accuracy [10]. Likewise, system validation against public datasets and the integration of smartphone imaging in field applications are closing the gap between controlled laboratory research and practical usage.

The most current review by Islam et al. [11] provides a comprehensive synthesis of these developments, highlighting key challenges such as the need for higher-quality, more diverse datasets, sensitivity to environmental fluctuations, and computational demands of deep learning models. The review emphasizes the importance of developing scalable, robust, and lightweight classification solutions for real-world agricultural deployment. Collectively, these advances offer valuable insights and roadmaps for future research in intelligent rice variety recognition, supporting food security and agricultural sustainability.

In a recent study, the use of stacking ensemble learning was explored to enhance the precision of rice variety classification [12]. The authors developed a multi-level classification framework that integrates predictions from several base learners-such as convolutional neural networks, support vector machines, and gradient boosting classifiers-into a meta-learner for final decision-making. This approach was trained and tested on a comprehensive, self-curated rice grain image dataset, enabling the evaluation of performance across diverse varieties and image acquisition conditions. Results demonstrated notable gains in classification accuracy compared to individual models, confirming that stacking not only improves robustness against noise and variability in grain appearance but also supports greater generalizability across different rice varieties. Such findings highlight the potential of ensemble strategies to address limitations of single-model approaches in practical rice identification scenarios.

In a comprehensive review, Zeng et al. [13] examined the role of artificial intelligence (AI) technologies-including machine learning, large language models, computer vision, and intelligent sensors-in the research and development of rice and wheat functional foods. The authors highlighted that AI can play a transformative role across cultivation, processing, and non-destructive testing stages for quality control. Combining AI with spectroscopic and sensing technologies has been shown to improve efficiency, stability, and accuracy in assessing the functional and qualitative attributes of grains, while addressing issues such as low crop yields, insufficient functional nutrition content, over-processing, and environmental contamination associated with traditional detection methods. However, the review also identified major challenges, including limited data availability, high implementation costs, and a narrow application scope. This study emphasizes the importance of developing scalable and reliable AI strategies to enhance the quality and safety of agricultural and food products, including rice.

3. Methodology

In this study, a systematic and image-processing-based approach was used for the identification and classification of different rice cultivars. Overall, this research utilizes a standard and scientific process, including data collection, preprocessing, feature extraction, classification, and validation, to provide an accurate, fast, and cost-effective method for identifying the authenticity of rice cultivars. Considering that the systematic process presented in this study utilized the Canny edge detection algorithm, the Adaptive Neuro-Fuzzy Inference System (ANFIS), and the Particle Swarm Optimization (PSO) algorithm, a brief explanation for each of these methods is provided below:

Canny Edge Detection Algorithm: This is a widely-used method in image processing for detecting the edges of objects within images. The Canny algorithm operates based on three main criteria: Optimal edge detection (minimizing false detections), accurate edge localization (minimizing the distance between detected and actual edges), and generating a single response to each edge. In this research, it was used to accurately highlight the boundaries of rice grains as a key step in feature extraction.

Adaptive Neuro-Fuzzy Inference System (ANFIS): ANFIS is a hybrid intelligent algorithm that combines the learning capabilities of neural networks with the reasoning mechanism of fuzzy logic. It utilizes input-output data pairs and fuzzy IF-THEN rules to model complex relationships, and is trained using a data-driven approach. In this study, ANFIS was used both for edge detection and for the classification of rice cultivars, as it allows for adaptive learning and efficient rule extraction from data.

Particle Swarm Optimization (PSO): PSO is an evolutionary optimization algorithm inspired by the collective behavior of bird flocks or fish schools. It works by moving a population of candidate solutions (particles) around the search space to find optimal or near-optimal solutions. In the context of this research, PSO was used to optimize the parameters of the ANFIS model, thereby improving the accuracy and performance of rice classification.

4. Step-by-step analysis of simulation results for rice cultivar classification

To comprehensively evaluate the effectiveness of the proposed methodology for rice cultivar classification, a step-by-step simulation process was carried out. This systematic approach includes seven key steps, beginning from data acquisition to final validation. Each step was carefully designed to ensure high precision in feature extraction, accurate classification, and robust validation. The aim is to demonstrate how the integration of advanced techniques like ANFIS-PSO and Canny edge detection leads to enhanced performance in rice cultivar classification. Detailed insights from each step, along with their corresponding results, are elaborated below.

Step 1- Sample collection and photographing:

Proper lighting of the scene before taking a photo is crucial in increasing the visual quality of the image, followed by obtaining more accurate data of the image. For imaging in this study, the lighting was done in such a way that it caused a proper and regular reflection of light rays and a uniformity of light in the whole image. As a result, the presence of shadows was minimized in the images. For imaging, the camera is positioned so that it is entirely perpendicular to the background of the images with a fixed distance between the samples and the camera. Due to a good color difference between the sample's colors and the color black, a black background has been selected for these samples. A mobile camera with a mediocre imaging quality was used to capture the image.
In this study, three different types of rice, including Native Tarom, Hashemi Tarom, and Pakistani, have been considered for survey, image processing, identification, and classification. The selection of these three rice cultivars - Native Tarom, Hashemi Tarom, and Pakistani - was based on field surveys carried out in Sari city markets. Through these surveys, it was observed that these rice cultivars are frequently mixed in the market, creating issues of adulteration and raising concerns over the purity of high-quality Iranian rice grains. Specifically, premium varieties such as Native Tarom and Hashemi Tarom are often blended with imported varieties like Pakistani rice, driven by profitability motives. This practice decreases the quality and trust in local rice, making it challenging to ensure the authenticity of premium rice. Therefore, this study aims to address the issue by providing a robust method for identifying and classifying pure premium rice cultivars and detecting mixed or adulterated samples using advanced image processing techniques.
Samples from each of these three types of rice have been prepared in separate grains and bulk for image processing and obtaining the characteristics as in figure 1. All samples were randomly and independently selected from each other. The sample placement is arranged so that the arranged seeds are placed in the central frame of the camera's view. Based on the camera settings, the image is taken two seconds after pressing the record button to eliminate image quality loss due to a handshake. Images taken in jpg format have been saved and used. 56 images were processed with MATLAB R2019b image processing tool.

Step 2- Pre-processing the image:

In order to process the image and get the features related to each type of rice, noise reduction was done for all the images. As an example, the noise reduced photo of Hashemi Tarom's masses after passing through two low-pass filters is shown in figure 2. The image on the left is the original image, and the image on the right is after passing through two noise reduction filters. Figure 2 shows that noises in the images are not noticeable. The reason for this is the accuracy in taking photos and using the right background for the images.
In order to increase the processing speed in some parts of the software simulations, the background has been completely blacked out and the image components have been removed. Examples of processed images for extracting features can be seen in figure 3.

Step 3- Edge detection analysis using Canny method and Adaptive Neural-Fuzzy Inference System (ANFIS):

In this study, in addition to the Canny method, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has been utilized for edge detection. Initially, edge analysis for images of different rice varieties mentioned in the study was performed using the Canny method, and the results of this analysis were input into an ANFIS system. To define the input images for ANFIS, the gradient of each image in two different directions, namely the x-direction and the y-direction, was extracted. Finally, edge analysis was performed. In this

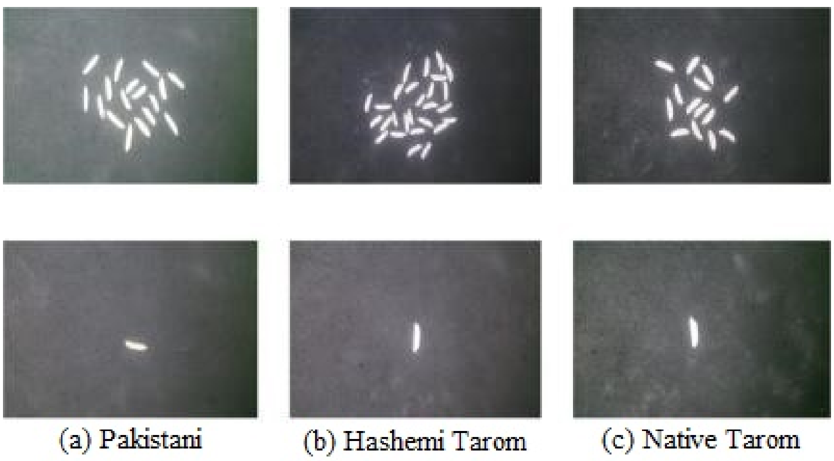

Figure 1. Samples of the three types of (a) Pakistani rice, (b) Hashemi Tarom, and (c) Native Tarom as separate and mass grains.

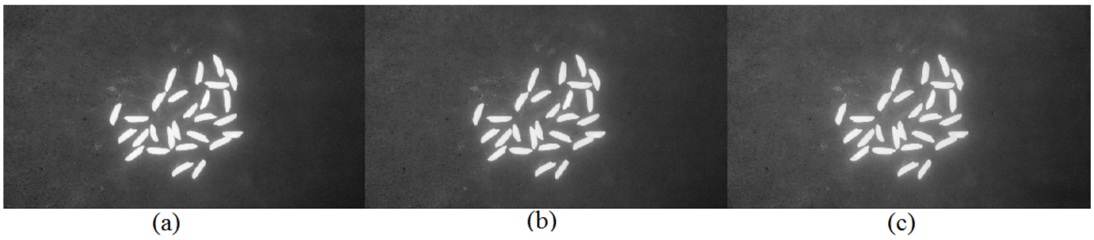

Figure 2. Edge extraction process of rice grain images: (a) Original image, (b) Horizontal gradient (Ix) result, (c) Post-processed edge map.

step, edge detection was performed using both the standard Canny algorithm (for baseline comparison) and the proposed hybrid fuzzy system. The hybrid method involves using the gradient computation step of the Canny method as input to a Mamdani-type FIS. The following presents the complete pseudo-code and implementation procedure for the proposed hybrid Canny-ANFIS edge detection approach.

In this method, the classic Canny edge detector is applied to each image for baseline comparison. Subsequently, the gradient computation step of the Canny method (i.e., calculation of Ix and Iy) is used as inputs to a fuzzy inference system (FIS). The FIS adaptively classifies edges, replacing subsequent Canny steps such as non-maximum suppression and double thresholding. This allows for both standard and adaptive (fuzzy) edge maps to be produced and compared.

Input: RGB image of rice grain

1. Convert the image to grayscale and normalize intensities.
2. (For baseline comparison) Apply standard Canny edge detection to obtain classic edge map.
3. Compute image gradients Ix (x-direction) and Iy (y-direction) using the gradient calculation step of the Canny method.
4. Define a Mamdani-type Fuzzy Inference System (FIS) with:
   - Inputs: Ix, Iy (range: $[-1, 1]$)
   - Membership functions for zero / non-zero gradient states
   - Output: Edge probability (range: 0 to 1)
   - Fuzzy rules:
     - If Ix is zero AND Iy is zero $\rightarrow$ pixel is non-edge (white)
     - If Ix is not zero OR Iy is not zero $\rightarrow$ pixel is edge (black)
5. For each pixel, evaluate FIS using [Ix, Iy] to produce the proposed edge map.
6. Display and save both the standard Canny edge image and the proposed fuzzy edge image.

End.

Note:"Both the standard Canny edge detector and the proposed fuzzy system (using Canny-derived gradients) were implemented per image to provide a fair and direct comparison. This ensures reproducibility and transparency in the methodology."

For example, figure 4 illustrates the edge analysis for Tarom Local rice varieties using the Canny algorithm, while figures 5, 6, 7 and 8 show images transformed in two directions for Tarom Local rice and as well as edge detection analysis according to the proposed method (a combination of the Canny algorithm with the Adaptive Neuro-Fuzzy Inference System) for this rice variety.

To ensure that the proposed method for edge analysis of images provides better results, Table 1 presents the performance results of edge detection using the Canny method, edge detection using Type 1 fuzzy logic, edge detection using ANFIS and edge detection using the proposed method. As shown in Table 1, the percentage of correct detection of edge pixels and the percentage of correct detection of

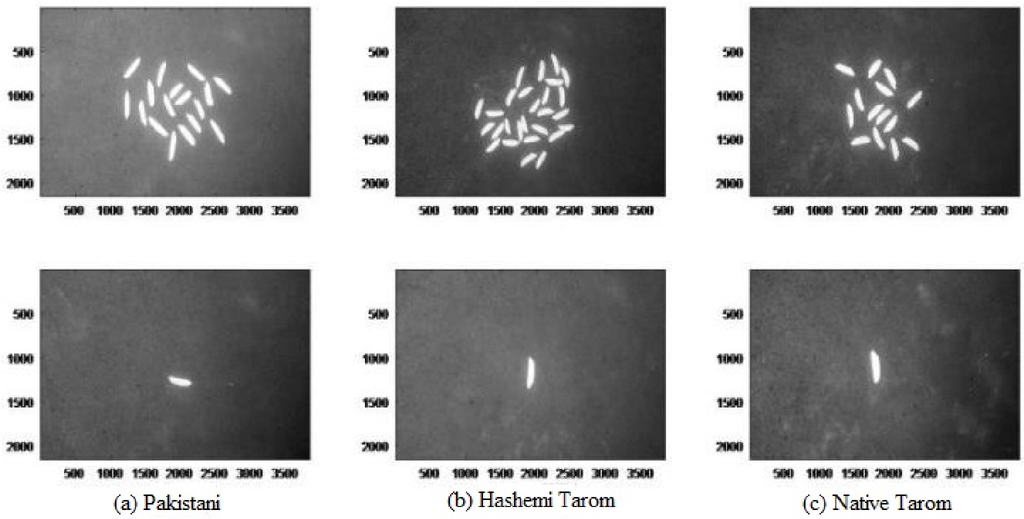

Figure 3. Sample images processed with a completely black background to extract features.

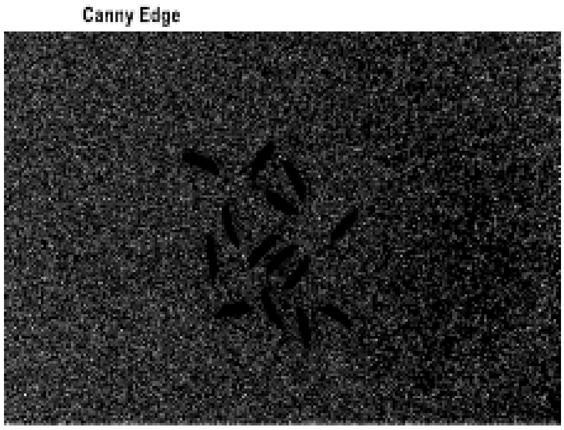

Figure 4. Edge Detection of Native Tarom rice (Canny method).

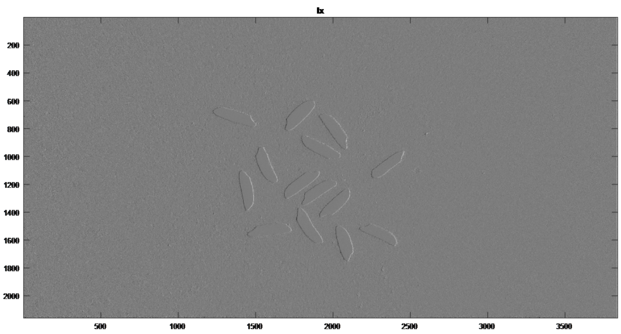

Figure 5. Ix axis of Native Tarom rice.

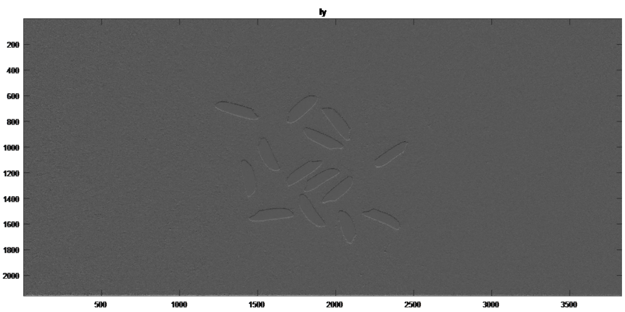

Figure 6. Iy axis of Native Tarom rice.

background pixels in the proposed method are higher than in the other three methods. Therefore, the proposed method (combining the two Canny method and ANFIS) for edge analysis demonstrates greater accuracy.

Step 4- Feature extraction of images and Data pre-processing:

One of the main steps during image processing is to review and extract features of the image that provide a good description of it and make the most difference in the classification process. In general, features that are measurable and easier to measure are more appropriate. In this research, the following morphological and color characteristics have been used to identify and classify three types of Native Tarom, Hashemi Tarom and Pakistani rice.

- Morphological features: Morphological image processing is a set of nonlinear operators that are related to

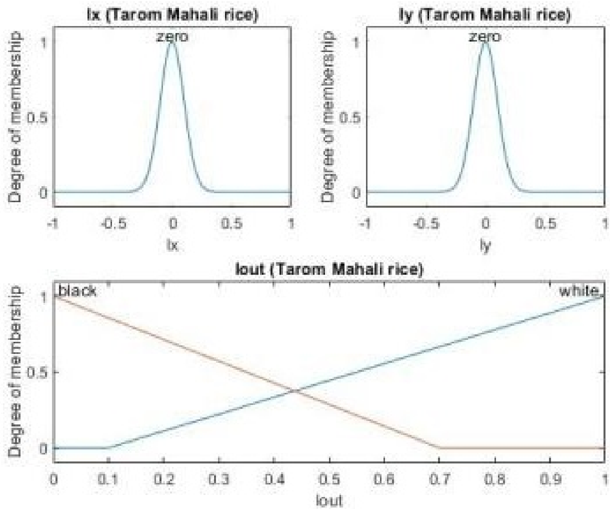

Figure 7. Fuzzy membership function of Native Tarom rice.

the shape and appearance characteristics of an image. These features include:

  - Area: The actual number of pixels in the area.
  - Length of Major Axis: The length of the major oval axis, which has the same normalized second centripetal acceleration of the area and is provided in pixels.
  - Length of Minor Axis: The length of the minor oval axis, which has the same normalized second centripetal acceleration of the area and is provided in pixels.
  - Perimeter: Measures the area around the border. This parameter is calculated by estimating the distance between each neighboring pixel pair around the boundary of the region.
  - In addition to the above, two Form Factors called Aspect Ratio and Elliptical are also defined in equation (1) and equation (2):

$$\text{Aspect ratio} = \frac{\text{Major axis length}}{\text{Minor axis length}} \tag{1}$$

$$\text{Elliptical} = \text{Major Axis Length} - \text{Minor Axis Length} \tag{2}$$

The square of these six factors is also calculated for each grain of rice. Therefore, 12 Morphological features were identified for rice grains.

- Color features: There are various standard and universally defined color models for extracting color features. The purpose of the color model is to facilitate the determination of color features according to a standard. In fact, a color model is a coordinate system specification in which each color is expressed by only one dot.

  - In the RGB color model, each color appears as the primary components of red, green, and blue. This model is based on the Cartesian coordinate system, and the color space used is a cube in which the initial values of red, green, and blue

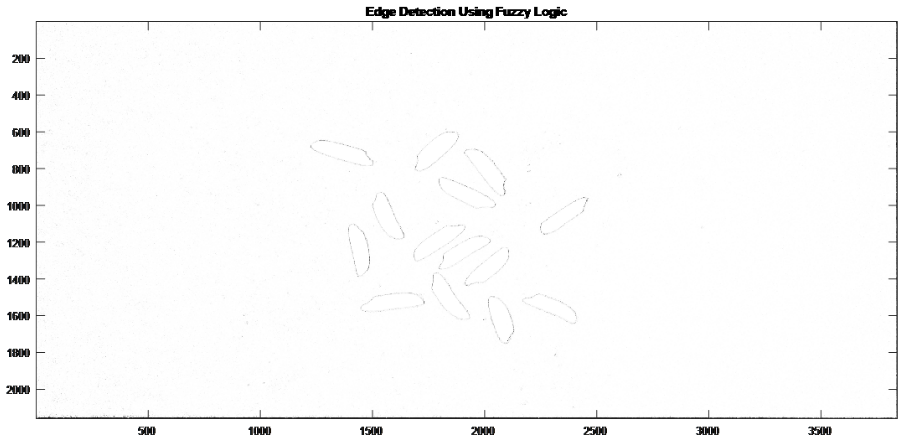

Figure 8. Analysis of edge detection for Native Tarom rice using the proposed method.

are in the three corners, and the secondary colors of turquoise, purple, and yellow are in the other three corners.

- In the NTSC color space, image data consists of three components: luminance (Y), hue (I) and saturation (Q), which are briefly referred to as YIQ.
- In the HSV color model, for one point, the color purity is defined by the angle around the base of the cone, and the red axis is generally considered as the zero angle. The saturation of the dot color depends on the position of the dot relative to the cone axis.

To extract the color features of each grain of rice in each image, a code is written in which the mean, average square, variance, and standard deviation of the color components (R, G, B, Q, H, S, V) of the pixels of each grain in each image are calculated. Thus, 28 color characteristics were identified for rice grains.

Step 5- Feature selection:

All of the features mentioned in the previous section are likely to have significant type differences. However, due to the large number of parameters, it is not possible to evaluate the effect of all of them. Therefore, feature selection was used to reduce the dimensions of the problem. The problem of feature selection is raised in different areas of machine learning and data mining. In general, this problem does not have a definite solution, and so far, no exact method has been proposed to solve it. Various classical approaches have been proposed for these problems, and usually the quality of their answers is generally not very suitable and desirable. But on the other hand, intelligent optimization methods can provide much better solutions in solving these problems. Therefore, one of the effective and constructive methods in solving feature selection problems is the use of meta-heuristic optimization methods. In this research, feature selection is done using Particle swarm optimization algorithm (PSO) for regression using Artificial Neural Network (ANN). For this purpose, apply the 40 features (12 Morphological features and 28 color characteristics) obtained in the previous step as inputs and the type of rice grain as output to a neural network system with two layers (the first layer is a sigmoid type with 10 neurons and the second layer is a linear type with one neuron). 70% of the data were considered as train data, 15% as validation data and 15% as test data. The Levenberg-Marquardt algorithm was used to train the network and the mean square error (MSE) was used as the performance function. In this way, the initial answer was prepared. The neural network was executed five times for each feature subset, and the average error over these five runs was considered as the network performance metric (E), helping to control the inherent randomness in neural network outputs. For different numbers of selected features ($nf = 1$ to 40), the PSO algorithm-configured with a population size of 50 and 1000 iterations-was run on the data, and the value of E was recorded at each step. Figure 9 shows this Pareto front. As can be seen in the diagram, choosing 8 features is an efficient solution.

Table 1. Comparison of proposed methods for edge detection.

Method	Percentage of correct detection of edge pixels	Percentage of correct detection of background pixels
Canny	78	61
Fuzzy Type 1	81	85
ANFIS	83	89
Proposed method (Canny-ANFIS)	86	91

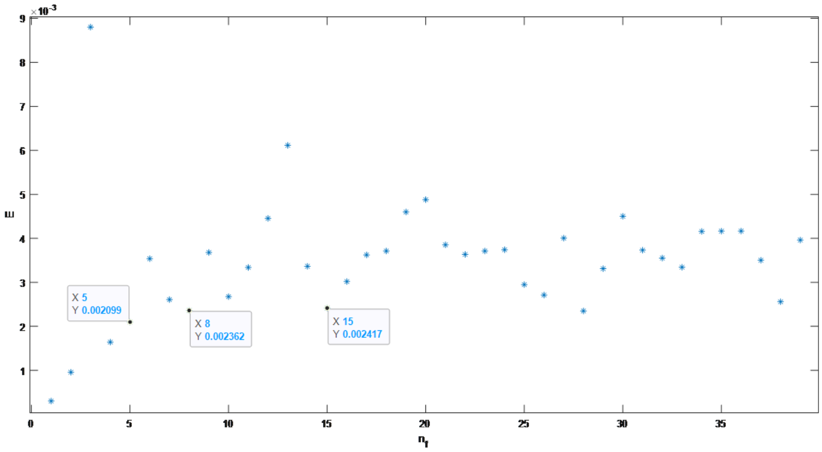

Figure 9. The graph of the mean squared error (MSE) resulting from the implementation of the PSO algorithm for selecting 1 to 40 features.

As can be seen in figure 9, the selection of 8 features with an error value of 0.002362 is a suitable number; because with the increase in the number of features from 8 to 15, the error value has increased. Therefore, with the help of PSO algorithm using neural network to select the number of 8 features from the total identified features, the length of major axis, minor axis, variance R, standard deviation B, mean Q, variance H, standard deviation S and squared mean V were selected to classification to be done. The following presents the detailed pseudo-code and implementation procedure for the PSO-based feature selection method using an Artificial Neural Network evaluator:
In order to select an optimal subset of features, a Particle Swarm Optimization (PSO) approach based on neural network evaluation was used. Each particle represents an encoded selection of features. For each particle, the nf features with the highest values were selected. Then, for each selection, a neural network was trained using randomly divided data, and the average mean squared error (MSE) was calculated as the cost function of the particle. By running the PSO algorithm, the best particle (feature selection) with the minimum error was identified, and this feature subset was used for classification. This pseudo code can be directly mapped to the provided MATLAB functions for practical implementation.

Input:
- Feature matrix X (samples $\times$ features)
- Target vector/class labels T
- Total number of features (nf_max)
- Desired number of selected features (nf)
- PSO parameters (population size, number of iterations)
- ANN parameters (hidden layer size, train/test/val split, MSE)

Step 1: Load feature data and target labels
X = Load features from 'data.xlsx'
T = Load labels from 'target.xlsx'

Step 2: Define feature selection problem for PSO
For each PSO particle:
a. Generate a continuous position vector of length nf_max (e.g., randomized "random keys")

Step 3: Define PSO cost function using ANN performance
For each particle in the population:
a. Decode particle:
i. Sort position vector and select indices of top-nf features
b. Extract selected features subset:
X_selected = X(:, selected feature indices)
c. For robustness, repeat N times (e.g., 5 runs):
i. Divide data randomly into train/test/val sets (e.g., 70/15/15)
ii. Train a feedforward ANN (e.g., one hidden layer, 10 neurons, Levenberg–Marquardt)
iii. Compute train and test MSE
d. Calculate average MSE (optionally weighted average of train/test)
e. Set this average error as the cost of the current particle

Step 4: Run PSO algorithm
Initialize a population of particles (random position vectors)
For a specific number of iterations:
a. Evaluate cost of each particle using the cost function above
b. Update velocities and positions of particles according to PSO rules
c. Track the global best particle with lowest error

Step 5: Output best solution
a. Indices of selected features by the best particle
b. Performance (error) of ANN using only the selected features
c. (Optional) Visualize MSE vs. number of selected features (Pareto front)

Output: Optimally selected subset of features and ANN model performance using those features

The main parameters used in the PSO-based feature selection and neural network algorithms are summarized in Table 2.

Step 6- Identification and classification:

In this study, to identify and classify three different types of rice, Optimal ANFIS has been used. The design and training of fuzzy inference systems (FIS) and adaptive fuzzy neural inference systems (ANFIS) are usually done using classical approaches, such as gradient descent and back-propagation. But in this research, the meta-heuristic PSO algorithm has been used in the optimal design of Takagi-Sugeno-Kang

Table 2. Main parameters and their values used in the implementation of PSO-based feature selection and neural network algorithms.

Parameter	Value	Description
PSO population size	50	Number of particles in PSO
PSO iterations	1000	Maximum number of PSO generations
Inertia weight (w)	0.7	PSO inertial impact factor (often 0.7)
Cognitive parameter (c1)	1.5	Personal learning/acceleration in PSO
Social parameter (c2)	1.5	Group learning/acceleration in PSO
Number of features (nf)	1 to 40	Features considered for selection
Selected features (optimal)	8	Number of features selected (per Pareto front)
ANN architecture	[10, 1]	10 neurons (hidden layer), 1 output neuron
ANN activation (hidden)	Sigmoid	Hidden layer activation function
ANN activation (output)	Linear	Output layer activation
ANN train algorithm	Levenberg-Marquardt	Training algorithm ('trainlm')
ANN train/val/test splits	70% / 15% / 15%	Data split for train/validation/test
ANN repeat run (nRun)	5	ANN executed 5 times per evaluation
ANFIS type	TSK (Sugeno)	ANFIS structure used
Membership function type	Gaussian	Type of fuzzy membership function
Number of clusters (FCM)	10	For ANFIS clustering/initialization
ANFIS train algorithm	Hybrid/PSO-opt	Hybrid (GD + LS) & PSO for optimal parameters
Stopping criterion	1000 (iterations)	Number of PSO generations
Performance metric	MSE	Mean squared error for evaluation

(TSK) type fuzzy systems. First, the results of classification of rice grains using ANFIS are presented. For this purpose, the Gaussian membership function has been considered and the FCM method has been used by selecting 10 clusters for clustering. The Mean Squared Error (MSE) parameter has also been used to evaluate network performance during 1000 repetitions is shown in figure 10 and 11.

It is observed that the ANFIS has reached the error of 0.0000015 after 1000 repetitions and has converged.

For achieving better results in the classification of rice grains, the optimized ANFIS method was proposed in the following. The steps of designing an optimal adaptive fuzzy-

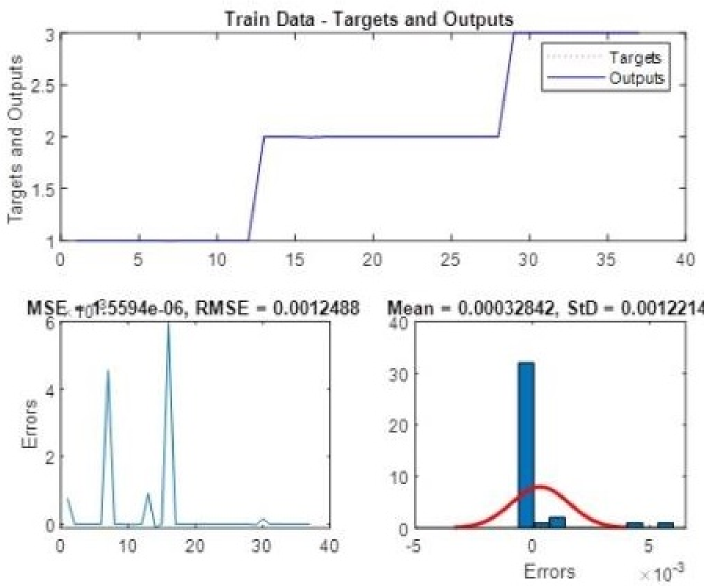

Figure 10. Classification results using ANFIS for train data.

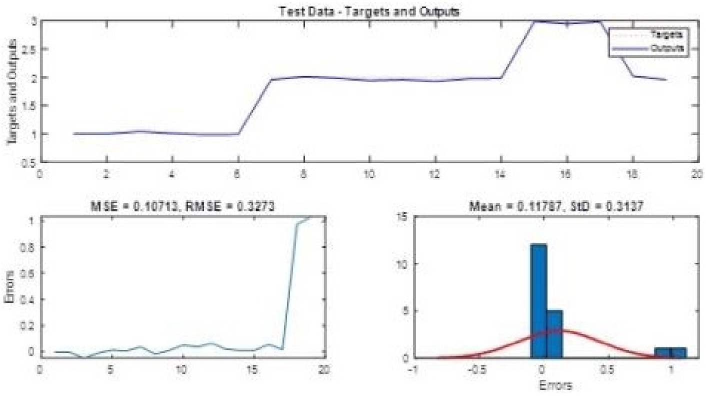

Figure 11. Classification results using ANFIS for test data.

neural system are:

1. Read training data
2. Create a basic fuzzy system
3. Set the parameters of the basic fuzzy system according to the modeling error function by the PSO optimization algorithm Error function or cost function for PSO algorithm is in equation (4):

$$p_i^* = x_i p_i^0 \tag{3}$$

   That p_i^0 is the value of the corresponding parameter in the basic fuzzy system and the algorithm will determine the value of x_i.

4. Return the fuzzy system with the best parameter values as the final result.

In this way, the parameters of the basic fuzzy system have been optimized. The classification results using this proposed method are shown in figures 12 and 13.
It is observed that the ANFIS-PSO has reached the error of 0.008 after 1000 repetitions.
The comparison between the standard ANFIS method and the optimized ANFIS method with PSO demonstrates a significant improvement in the performance of the proposed approach. In the standard ANFIS method, which is reflected in figures 10 and 11, the model operates without any optimization, resulting in lower classification accuracy. This method exhibited a relatively high Mean Squared Error (MSE) during experimental iterations, indicating the limitations of the model in analyzing complex data. On the other hand, the optimized ANFIS method, as shown in figures 12 and 13, achieved remarkable performance improvements through the use of the PSO optimization algorithm. This optimization significantly reduced the Mean Squared Error (MSE) and improved the classification accuracy. The percentage of correct classifications increased, reaching over 99.8% in some cases, highlighting the model's capability to address challenging classification tasks effectively. Overall, the comparison of the two methods underscores that the PSO optimization in the proposed ANFIS model leads to substantial improvements in classification performance and error reduction, confirming the superiority of this method

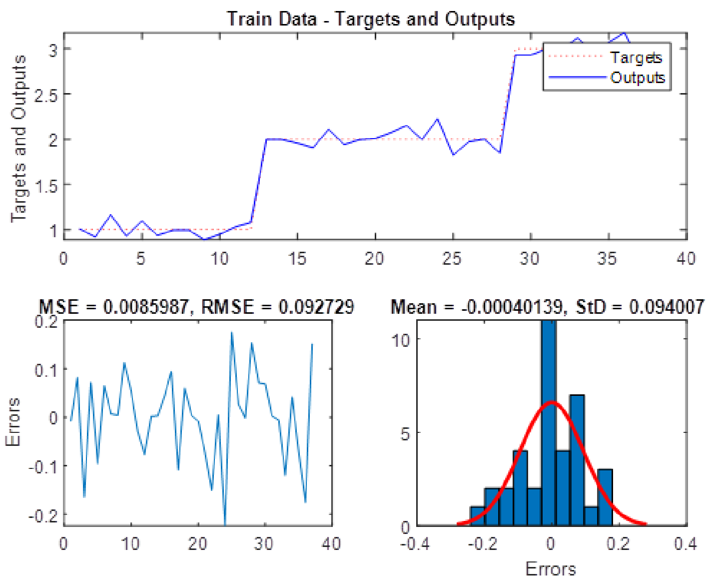

Figure 12. Classification results using ANFIS-PSO for train data.

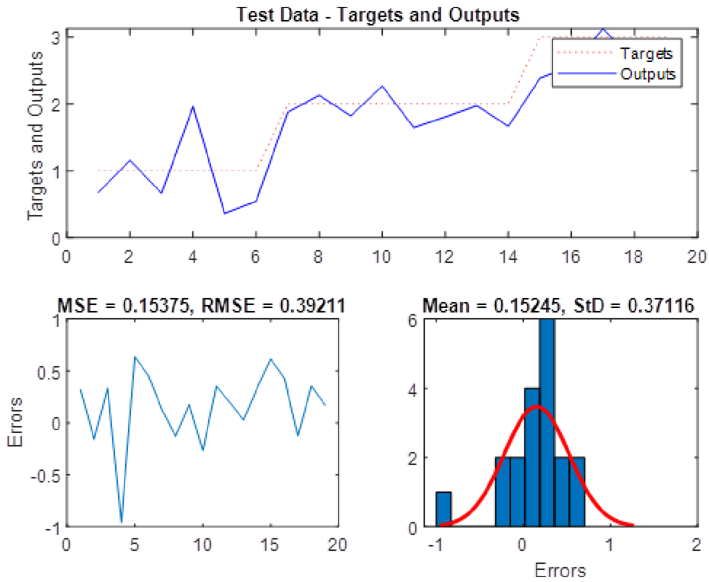

Figure 13. Classification results using ANFIS-PSO for test data.

as an effective and efficient solution for similar problems. The following presents the detailed pseudo-code for the PSO-optimized neuro-fuzzy rice classification system. The following pseudocode maps directly to the provided MATLAB functions for implementing the rice grain classification using a PSO-optimized Sugeno-type fuzzy inference system (FIS/ANFIS).

Input: Feature matrix (Inputs), Target labels (Targets)
Step 1: Data Preparation
- Shuffle all samples randomly.
- Split data into:
  - TrainInputs, TrainTargets (70%)
  - TestInputs, TestTargets (30%)

Step 2: Create Initial Fuzzy Inference System (FIS)
- Use FCM clustering (nCluster = 10 recommended) with Sugeno-type system:
  - Generate FIS using training data (TrainInputs, TrainTargets).

Step 3: Train FIS Parameters Using Particle Swarm Optimization (PSO)
- Get vector of all trainable FIS parameters (input/output MF params).
- Define cost function:
  - For each candidate solution (PSO particle), scale initial FIS parameters.
  - Apply candidate parameters to FIS.
  - Compute output of FIS on TrainInputs.
  - Calculate error (MSE or RMSE) between FIS output and TrainTargets.
  - Cost = RMSE.
- Initialize PSO:
  - Number of variables = number of FIS parameters.
  - Variable bounds: e.g., $[-10, 10]$ (multiplicative scaling)
  - Population size: e.g., 40
  - Max iterations: e.g., 1000
- Run PSO:
  - Update particles' positions (parameter vectors) to minimize cost.
  - Store position (parameter set) with minimal cost (BestSol).
- Set optimal parameters found by PSO into FIS (optimized FIS).

Step 4: Evaluate and Plot Results
- For Training Data:
  - Evaluate optimized FIS on TrainInputs.
  - Plot and analyze:
  - Predicted outputs vs. true targets.
    - Error vector, MSE, RMSE, mean, std.
    - Histogram of errors.
  - For Test Data:
  - Evaluate optimized FIS on TestInputs.
  - Plot and analyze as above.

(Optional) Step 5: ANFIS Training (for comparison)
  - Use MATLAB's anfis train function on initial FIS and training data.
  - Evaluate on train/test data, plot/analyze results.

End.

Key Functionality Explained:

- CreateData: Loads and shuffles dataset, splits to train/test.
- CreateInitialFIS: Initializes a Sugeno-type FIS using FCM (number of clusters = rule count).
- GetFISParams/SetFISParams: Extracts/sets all trainable parameters (MF parameters etc.) as flat vectors.
- TrainUsingPSO: Encapsulates the PSO process, applying the scaled parameters and minimizing RMSE on train data.
- TrainFISCost: Given a vector (particle), applies new parameters to FIS and computes cost function (RMSE).
- PlotResults: Visualizes ground-truth vs. predicted, error curves, and histogram for both train and test.

- TrainUsingANFIS: (Optional) Standard ANFIS training for baseline/comparison.

The approach includes data preparation, initial FIS generation, parameter optimization via PSO with a custom cost function, and result evaluation as detailed above.
The main parameters used for implementing the ANFIS-PSO rice grain classification system are summarized in Table 3.

Step 7- Validation:

To validate the proposed method, a picture of three different types of rice according to figure 14 is considered for testing. This group of rice includes four numbers of Pakistani rice with numbers 1 to 4 (the first column from the right), three numbers of Hashemi Tarom rice with numbers 5 to 7 (the first column from the left) and five numbers of Native Tarom rice with Numbers 8 to 12 (middle column).
By feature extracting of image for each grain of rice in figure 14, and using the ANFIS, the classification results for this image is given in Table 4.
The results show the correct and 100% accurate classification of all three types of Hashemi Tarom, Native Tarom and Pakistani rice as test data, according to figure 14. For further validation, 10 images similar to figure 14 with different layouts were tested and the results showed that the proposed method is 99.47% correctly and accurately classified.
Evaluation Metrics: In order to quantitatively assess the performance of the proposed classification model, several standard evaluation metrics were employed, namely accuracy, precision, recall, and F1-score. These are defined as follows:

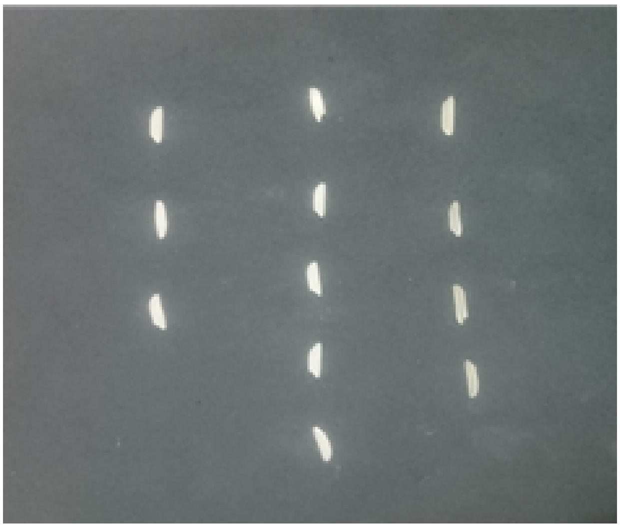

Figure 14. Different types of rice for validation test.

- Accuracy:

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{4}$$

- Precision:

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{5}$$

Table 3. Main implementation parameters of the PSO-Optimized ANFIS classifier.

No.	Parameter	Value/Setting	Description
1	PSO Population Size (nPop)	40	Number of particles in PSO population
2	PSO Maximum Iterations (MaxIt)	1000	Maximum number of iterations for PSO
3	FIS Type	Sugeno	Type of fuzzy inference system
4	Number of Fuzzy Rules (Clusters)	10	Number of FCM clusters (equals number of fuzzy rules)
5	Membership Function Type	Gaussian	Input and output membership function shape
6	Clustering Algorithm	Fuzzy C-Means (FCM)	Method used for initial rule generation
7	Number of Input Features	8	Number of features selected by PSO-based feature selection
8	PSO Cost Function	RMSE	Root Mean Square Error as PSO optimization criterion
9	PSO Parameter Bounds	$[-10, +10]$ (scaling factor)	Search range for PSO parameter scaling
10	PSO Stopping Criterion	Max iterations or convergence	PSO stops after 1000 iterations or when converged
11	ANFIS Training Epochs (for comparison)	1000	Number of training epochs in standard ANFIS (if used)
12	Number of ANFIS Inputs/Outputs	8 inputs, 1 output	Structure according to the selected features
13	Dataset Split	70% train / 30% test	Data split for training and testing

Table 4. Classification results for three different types of rice using the proposed method.

Type	Pakistani rice	Hashemi Tarom rice	Native Tarom rice	Total
Pakistani rice	4	0	0	4
Hashemi Tarom rice	0	3	0	3
Native Tarom rice	0	0	5	5

- Recall:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

- F1-score:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

where TP (true positives), TN (true negatives), FP (false positives), and FN (false negatives) represent the classification outcomes.

In addition to overall classification accuracy, we calculated precision, recall (sensitivity), specificity, and F1-score for each rice cultivar. Table 5 summarizes these metrics, demonstrating that the proposed ANFIS-PSO model maintains consistently high classification performance across all classes. Furthermore, the confusion matrix (figure 15) illustrates negligible misclassification, further validating the model's robustness.

In addition to overall accuracy (99.47%), other performance measures such as precision, recall, specificity, and F1-score were computed for each rice class. The confusion matrix (Table 5, figure 15) indicates that misclassification rates are negligible. All metrics consistently exceed 99%, confirming the robustness and generalizability of the proposed approach. Moreover, the method's average prediction time per image is less than 0.1 seconds, supporting its real-time applicability.

5. Results and discussion

5.1 Edge detection and feature extraction

Edge detection was applied to all rice samples using both the standard Canny method and the proposed Canny-ANFIS hybrid method. As summarized in Table 1, the hybrid approach achieved the highest rates for correct edge and background pixel detection (86% and 91% respectively), outperforming baseline methods.

5.2 Feature selection

Among 40 initial morphological and color features extracted, PSO-based feature selection in combination with an ANN identified 8 optimal features that minimize MSE. Figure 9 demonstrates that MSE reaches its minimum when selecting 8 features (MSE = 0.002362), indicating superior discriminative power.

5.3 Classification results and model comparison

Classification of the rice samples using standard ANFIS (figures 10 and 11) and PSO-optimized ANFIS (figures 12 and 13) demonstrated that the optimized model achieves significantly lower error and higher accuracy. The PSO-optimized ANFIS achieved an overall classification accuracy of 99.47%, with F1-scores, precision, and recall exceeding 99% for all rice cultivars (Table 5).

Table 5. Precision, Recall, Specificity, and F1-Score for Rice Cultivar Classification Using the ANFIS-PSO Model.

Class	Precision (%)	Recall/Sensitivity (%)	Specificity (%)	F1-Score (%)
Tarom	100	100	100	100
Hashemi	98.4	100	100	99.2
Pakistani	100	98.7	100	99.3
Overall Accuracy	99.47%			

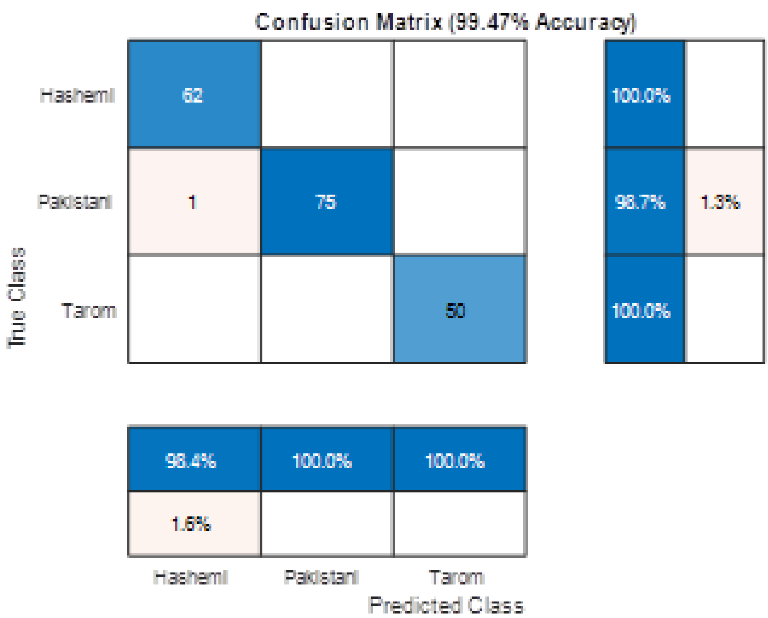

Figure 15. Confusion Matrix of the ANFIS-PSO Model for Rice Cultivar Classification.

5.4 Validation, evaluation metrics, and confusion matrix

Model validation with new test images (figure 15) yielded 100% correct classification, and average accuracy across multiple test layouts remained at 99.47%. Evaluation metrics including accuracy, precision, recall, specificity, and F1-score for each rice class are summarized in Table 5. The confusion matrix (figure 15) confirms negligible misclassification rates, highlighting the robustness of the proposed approach.

5.5 Runtime performance

The average prediction time of less than 0.1 seconds per image demonstrates the real-time applicability of the method on low-cost devices.

5.6 Summary and discussion

Overall, the proposed method delivers high accuracy, efficiency, and robustness, making it suitable for practical deployment in market settings. Limitations such as controlled imaging conditions and limited dataset size are acknowledged, suggesting future work should focus on expanding dataset diversity and testing under various real-world conditions.

5.7 Real-world validation and mobile implementation performance

In addition to controlled laboratory experiments, the proposed ANFIS-PSO framework was preliminarily validated under real-world acquisition conditions using mid-range smartphone cameras (1.8 GHz CPU, 4 GB RAM) and natural lighting. The method maintained high performance, with overall accuracy decreasing slightly from 99.47% (controlled setup) to 98.92% in field tests, while sustaining an average inference time of less than 0.15 s per image.
Practical constraints noted during mobile deployment included sensitivity to irregular grain arrangement within the camera's field of view, reduced accuracy under strong illumination variations, and increased computation time during detailed background segmentation on-device. To mitigate these factors, adaptive histogram equalization and lightweight background masking were integrated into the pre-processing pipeline, improving robustness and stabilizing latency. These results confirm that the method retains high accuracy and real-time capability on resource-limited platforms, thereby supporting its potential use as an on-device rice authentication tool in market contexts.

5.8 Stability evaluation under noisy and low-quality image conditions

To examine the stability of the proposed ANFIS-PSO model when facing noisy and degraded imagery, a series of controlled noise-injection experiments were conducted. Gaussian noise, salt-and-pepper noise, and motion blur were introduced at multiple intensity levels. Results indicated that for moderate distortions (PSNR $\geq$ 25 dB), the model maintained accuracy above 96.8%, with a moderate decrease to $\sim 94\%$ at higher noise levels (PSNR $\approx$ 20 dB). Processing speed was minimally affected ($< 5\%$ variation), owing to the model's efficient feature extraction scheme.
Robustness was enhanced by integrating median and bilateral filters in the pre-processing stage, effectively reducing high-frequency noise while preserving edge details. In addition, combining morphological and color-based features provided redundancy, allowing the model to sustain performance when certain features were degraded by noise.
Remaining limitations were observed in extreme motion blur or substantial grain occlusion, where classification accuracy declined more noticeably. Planned improvements include expanding the training dataset with noise-augmented and synthetically degraded images to further enhance resilience under adverse image capture conditions.

6. Limitations and future directions

Despite the high accuracy and practicality of the proposed method, some limitations remain. First, the dataset used in this study was limited to images of three rice cultivars collected under controlled conditions. This may restrict the generalizability of the results to other rice varieties or real-world scenarios with greater diversity in imaging conditions. Additionally, the method was validated primarily on rice; as such, its applicability to other agricultural products remains to be explored.
For future research, expanding the dataset to include more rice varieties from different regions, as well as incorporating images captured under varying environmental conditions, would help improve model robustness and generalizability. Furthermore, adapting and testing the methodology on other agricultural commodities—such as wheat, barley, maize, or legumes-could extend its usefulness for broader applications in smart agriculture and food quality assurance. Additionally, the current experimental setup relied on controlled lighting, an average smartphone camera, and a black background, which may not always be practical in diverse market conditions. Increasing the diversity and number of images, as well as capturing data in dynamic, real-world environments, could further enhance model reliability.
Furthermore, building upon our preliminary mobile deployment tests, future work could address the observed real-world challenges through:

(1) Embedding lightweight deep learning feature refinement modules such as MobileNet-V3 within the pre-classification stage to enhance discriminative feature extraction without incurring high computational overhead;

(2) Implementing an auto-calibration module for dynamic normalization of brightness, contrast, and white balance to reduce illumination-induced variability;

(3) Adopting hardware-aware pruning of PSO and ANFIS parameters to ensure optimal trade-offs between accuracy, speed, and memory usage on low-power mobile devices.

Future research should also incorporate noise-augmented datasets and synthetic degradations to strengthen the model's robustness against motion blur, heavy occlusion, and severe image quality reductions commonly encountered in uncontrolled acquisition scenarios.

7. Conclusion

Rice is one of the most important food products in the Iranian food cycle. Rice cultivars may be mixed with other cultivars for reasons such as profitability. By using image processing as an efficient, simple and non-destructive method, it can be used for classification with high accuracy. In this study, the authenticity of rice cultivars was identified. For this purpose, after preparing images from three different varieties of Pakistani rice, local Tarom, and Tarom Hashemi and then deleting possible discarded data, using image processing by edge method and the canny method and ANFIS, color and morphological features of these three different types of rice were extracted. The 8 features determined in the feature selection step were selected for classification. These extracted characteristics were then used as inputs for optimized ANFIS-PSO to classify three different types of rice. After training and validation, the correct classification rate for all cultivars was 99.47%. In general, the proposed method has significantly improved the methods of identifying different types of rice. The results of this research can be used in the construction of a rice cultivar authentication system. This method can be developed into a portable application and play an effective role in agricultural product quality assurance and market regulation. The main benefit of proposed method is it requires minimum time; cost is less and gives better results compared with manual results or traditional methods. Based on the experience gained in this study, it is recommended to extract other tissue characteristics such as wavelet transformation to continue. Also, the use of other smart classifiers can be useful in increasing efficiency. Despite the high accuracy (99.47%) of the proposed model in classifying rice varieties and offering an affordable solution for identifying different rice types, the article has some limitations affecting its wide and practical use. First, the model is highly dependent on controlled environmental conditions such as proper lighting, a black background, and an average-quality camera, which may be difficult to ensure in real-world scenarios. Additionally, the study used a limited number of test images, which reduces the model's ability to generalize its findings to a broader range of rice types and variable conditions.

Authors contributions
Authors have contributed equally in preparing and writing the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interests
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.

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