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Research paper

A CNN-LSTM-based Approach for Classification and Quality Detection of Rice Varieties

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Abstract

Rice is one of the most important staple crops in the world and provides millions of people with a significant source of food and income. Problems related to rice classification and quality detection can significantly impact the profitability and sustainability of rice cultivation, which is why the importance of solving these problems cannot be overstated. By improving the classification and quality detection techniques, it can be ensured the safety and quality of rice crops, and improving the productivity and profitability of rice cultivation. However, such techniques are often limited in their ability to accurately classify rice grains due to various factors such as lighting conditions, background, and image quality. To overcome these limitations a deep learning-based classification algorithm is introduced in this paper that combines the power of convolutional neural network (CNN) and long short-term memory (LSTM) networks to better represent the structural content of different types of rice grains. This hybrid model, called CNN-LSTM, combines the benefits of both neural networks to enable a more effective and accurate classification of rice grains. Three scenarios are demonstrated in this paper including CNN, CNN in combination with the transfer learning technique, and CNN-LSTM deep model. The performance of the mentioned scenarios is compared with the other deep learning models and dictionary learning-based classifiers. The experimental results demonstrate that the proposed algorithm accurately detects different rice varieties with an impressive accuracy rate of over 99.85%, and 99.18% to identify quality for varying combinations of rice varieties with an average accuracy of 99.18%.

1. Introduction

Rice is a staple food for billions of people worldwide and is a primary source of carbohydrates, protein, and essential nutrients for many populations. The global rice market is estimated to be worth over $720 billion, making it one of the most important commodities in the world [1-2]. Rice classification is a crucial step in the rice value chain, as it helps to identify various types of rice based on their properties, such as size, shape, color, texture, and cooking characteristics. The accurate classification of rice varieties can help identify those that have low levels of contaminants, ensuring their safe consumption. By accurately classifying different rice varieties, the industry can improve the quality and safety of rice products, reduce food wastage, and ensure consumers can make informed decisions about the rice they purchase and consume [3-4]. The traditional categorization methods for classifying rice varieties rely on manual visual inspection, which can be time-consuming, subjective, and prone to errors due to human factors such as fatigue, inexperience, and bias. Researchers have adopted advanced classification methods, leveraging signal processing techniques to extract key features from rice grain images using image processing, machine learning, and deep learning. These features are then used to train models for accurate rice variety classification. One of the key advantages of using signal processing techniques for rice classification is their ability to automatically extract key features from images, reducing the need for manual inspection and reducing the risk of error due to human factors [2, 5-6]. Machine learning and data mining techniques have been utilized in rice processing to increase classification speed and accuracy [4-6]. In recent years, deep learning-based techniques have become more prevalent in the field of rice classification. These models are particularly well-suited for image classification tasks due to their ability to effectively extract and process visual features. These features can be used to classify complex rice samples with many variables accurately. In [7], a real-time, non-contact rice quality grading method was proposed using deep learning. The system captured rice images, which were preprocessed and fed into a deep-learning network. The model was trained on a rice dataset and applied transfer learning to identify areas of interest. It was tested on two standard datasets and a real-time scanning prototype, achieving satisfactory results. In [8], a method to detect fraud in rice varieties, seeds, and flour, was proposed using a camera to capture images of rice samples. A convolutional neural network (CNN) classified the samples into five categories, identifying one lower-quality variety as counterfeit and the others as original. In [9], an image processing algorithm using a backpropagation neural network (BPNN) with feature selection was proposed to classify five rice types. The method utilized 36 features from RGB, HSI, and HSV color spaces, achieving high accuracy in rice variety. In [10], a deep learning approach using ResNet20 was developed to classify rice grains based on size, color, shape, and surface. The method effectively identified brown Basmati, Kolam, Parmal, White Basmati, and Wild rice, aiding in the pricing of agricultural products based on quality standards. In [11], a study on identifying 13 Iranian rice varieties using image processing and artificial neural networks (ANN) showed a non-linear relationship between rice characteristics like color, texture, and morphology. The decision algorithm (DA) achieved less than 90% accuracy, while the ANN demonstrated higher classification. In [12], a CNN-based algorithm was developed for the automatic identification and counting of rice crop generative sprouts. The model, trained on a large dataset of images taken under various environmental conditions using a mobile phone, achieved accurate results, offering the potential for automating this process and reducing manual labor. In [13], features such as color, morphology, and shape were extracted from rice images and used for classification using MLP and neuro-fuzzy models, proving the algorithm's effectiveness. In [14], a non-destructive rice variety classification algorithm was developed using hyperspectral imaging and a CNN model, improving classification accuracy by capturing spatial and spectral features of rice grains. A pre-trained deep model combining InceptionV3 and InceptionResNetV2 is introduced in [15] to classify five rice varieties, achieving high accuracy with the RiceNet system. In [16], two CNN-based methods were proposed for classifying five rice types, one using transfer learning with a pre-trained VGG16 network and the other combining the method with VGG16, both achieving high accuracy in recognizing broken or fine rice seeds.

In this paper, a new approach to rice classification using deep learning models is presented, focusing on the structural features of different rice varieties. A powerful deep learning model, known for excelling in computer vision tasks such as data classification, is employed. The proposed approach utilizes a CNN deep model, which has demonstrated the ability to learn rich representations of images and perform well with new data. The transfer learning technique is considered in each proposed scenario [17], which can be particularly useful when labeled data is limited. By starting with a pre-trained model, the new model can leverage prior knowledge, reducing training time and resource requirements. Additionally, the paper employs a Long Short-Term Memory (LSTM) network [18], a neural network architecture widely used in sequential data processing. By combining CNNs and LSTMs, the model can capture both low-level and high-level features and learn complex relationships between them. The LSTM component allows the model to capture long-term dependencies and temporal patterns, which is particularly beneficial for tasks involving time-series data, such as speech recognition or weather prediction. Furthermore, a deep model based on ResNet50 and Xception was developed to categorize five different rice varieties, including Arborio, Basmati, Ipsala, Jasmine, and Karacadag, into categories and quality levels of best, good, and fine. The model used 17 features, including 13 morphological and 4 shape features, and achieved high classification efficiency [19]. Lastly, a CNN-based deep model for classifying rice products in Vietnam into whole and broken rice categories was designed. This model's results were compared to other machine learning classifiers, such as Support Vector Machine (SVM) and K-Nearest Neighbors (K-NN), using Histogram of Oriented Gradients (HOG) features. The models were evaluated on a dataset consisting of rice sample images from various sources to assess their efficiency and accuracy in predicting the rice categories [20]. The proposed method evaluates different scenarios, including CNN, CNN combined with transfer learning (CNN-TL), and CNN with long short-term memory (CNN-LSTM). Its performance is compared with existing methods, such as machine learning-based, dictionary-based, and deep learning models. The method is resilient to rotations and lighting changes, as it extracts deep model-based features that are resistant to these challenges. It focuses on classifying five rice varieties from northern Iran: Tarom, Shiroodi, Fajr, Neda, and Behnam. This approach offers several key contributions to agriculture as:

- Proposing a hybrid CNN-LSTM model for rice quality detection, addressing key challenges in data imbalance, feature representation, and model complexity.
- Optimizing the CNN model with a multi-attention mechanism to improve classification accuracy and model performance.
- Leveraging the LSTM network to capture both low-level and high-level features, enabling the model to learn complex relationships within the data.
- Utilizing transfer learning to fine-tune the CNN model, improving the generalization and performance of rice quality classification tasks.
- Demonstrating the model's adaptability across different scenarios and its ability to classify rice varieties with high accuracy, even under varying conditions.
- Providing a scalable and efficient solution for rice classification and quality detection, with practical applications in agricultural settings.
- Introducing a method for determining rice purity by accurately identifying the purity percentage of different rice varieties and their mixtures.

The proposed method offers significant contributions to agriculture, potentially driving innovation in rice quality detection and classification. It serves as a valuable resource for researchers and practitioners, with the potential for advancements in agricultural technologies. The paper outlines the rice classification process in Section 2, presents the deep learning-based method in Section 3, and provides experimental results in Section 4, demonstrating the method's effectiveness. Section 5 concludes with a summary of the findings and highlights the method's importance in rice grading and quality assessment.

2. Data Processing Steps

Rice is vital to the Iranian economy, ranking fifth globally in production and consumption. Accurate rice classification is crucial for ensuring quality, safety, and optimizing the rice value chain, from production to consumption. It helps identify rice types, improves storage and processing, reduces losses, boosts farmer productivity, and benefits rice businesses. The proposed method includes steps like database collection, pre-processing to improve classification accuracy, and deep model design, with specific details provided below.

2.1. Database Collection

The process of creating an imaging database for rice classification involves several steps. First, samples are collected from various rice varieties commonly consumed in northern Iran, including Tarom, Shiroodi, Fajr, Neda, and Behnam. High-resolution cameras and appropriate lighting are then used to capture clear images of the rice grains. A specialized LED light tent (23cm×23cm×23cm) is designed, equipped with two 23cm LED strips to ensure uniform lighting and prevent shadows. A 5cm circular opening holds the imaging device, such as a smartphone, to capture the images. Rice samples are evenly distributed in the box using a 50g measuring cup. A Sony Imaging Camera with a 300imx sensor and 19-Megapixel resolution is used for image capture [21, 22]. Figure 1 illustrates the LED light tent setup.

Two methods for image acquisition in rice classification are individual sampling and bulk sampling. This paper uses the individual sampling method, where single rice grains are placed on the surface. Figure 2 compares the two techniques. Each image is labeled with the corresponding rice variety, creating a labeled dataset. A total of 2000 images across five rice varieties were collected, providing a sufficient dataset for deep analysis.

2.2. Data Preprocessing

Pre-processing is crucial for ensuring the quality and accuracy of images used in rice classification. It involves steps such as image resizing, color space conversion, noise reduction, and feature extraction. Resizing standardizes image dimensions, improving model performance by reducing input variability. Color space conversion ensures uniformity, minimizing the impact of lighting differences. Noise reduction enhances image quality, making them more suitable for machine learning. In this paper, images are resized to 256×256, and a median filter is applied to reduce noise and shadow effects, enhancing classifier accuracy and algorithm performance.

2.3. Data Augmentation
Large-scale AI applications, such as image classification, require large public datasets for model training. However, collecting and labeling these datasets can be costly and resource-intensive. This highlights the need for efficient methods to gather, process, and label data to reduce the time and resources required for effective models. Smaller datasets limit model performance and may only represent a subset of the underlying patterns. In rice classification, a large amount of labeled, pre-processed data is needed, which can be time-consuming and expensive.

Large datasets are essential to optimize deep model performance, but challenges exist in collecting and labeling them. Advanced computational resources are also required. To address these issues, data augmentation techniques can be used to increase dataset size and avoid overfitting artificially. This paper employs data augmentation to generate more data for each class. Techniques such as mirroring, scaling, shifting, rotation, and noise addition enhance dataset diversity, improving model performance [23-27]. Figures 3 shows the example of augmented rice images for Tarom, demonstrating the effectiveness of this approach.

Figure 1. The box designed for imaging from rice varieties.

(a) (b)

Figure 2. Two types of rice imaging: a) Individual rice grains, b) Bulk rice grains.

2.4. Cross Validation for Evaluation
K-fold cross-validation is a key evaluation method in rice classification, helping to address training model limitations and providing a better understanding of the model's generalization to new data. It involves dividing the dataset into multiple partitions, using each as a validation set once while the others are used for training. This approach enhances the evaluation's robustness and accuracy, and helps identify overfitting or underfitting. In this study, 5-fold cross-validation was used, with 70% of the data for training and 30% for validation. The model's performance was assessed across all five partitions, and the final accuracy was the average of the class accuracies. This method ensures a comprehensive evaluation of the model's generalization ability.

3. Deep Model Architecture
In recent years, deep learning techniques like CNNs have gained popularity in data classification, especially for image tasks, due to their ability to extract and process visual features effectively. These techniques can significantly improve rice classification accuracy and speed. The success depends on selecting appropriate CNN architectures and hyperparameters. The proposed method combines CNN with LSTM to form a hybrid CNN-LSTM model, which classifies input images after CNN processing. Transfer learning is also used to enhance generalization by leveraging a pre-trained model. Block diagrams of the methods (CNN, CNN-TL, and CNN-LSTM) are shown in Figure 4.

3.1. CNN Deep Model
CNNs are deep learning models ideal for image classification tasks [25, 27-28]. CNNs are designed to identify patterns and features in images by applying a series of convolutional operations. These operations help the network extract important features from input data. CNNs are widely used in both image processing and signal classification.

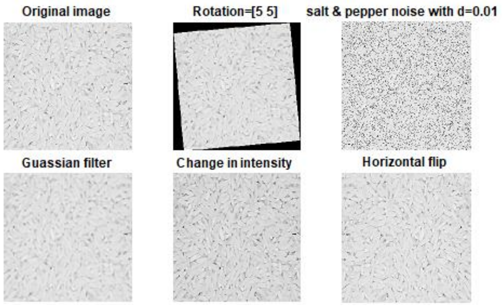


Figure 3. A sample of the Tarom rice cultivar and its transformation based on data augmentation technique.

The model consists of convolutional layers, pooling, and fully connected layers. Convolutional layers extract features by applying filters to the input data while pooling layers reduce the size of the output matrix to improve efficiency. Fully connected layers then classify the extracted features. Proper hyperparameter tuning is critical for optimizing CNN performance, as incorrect settings can lead to overfitting or underfitting. Key hyperparameters include learning rate, batch size, weight decay, and regularization strength, which impact the model's accuracy, precision, and recall. These hyperparameters are discussed in the next sections.

3.2. LSTM Network

LSTM networks are ideal for handling variable-length input sequences and capturing complex temporal patterns, making them suitable for tasks like video classification or sentiment analysis [29-31]. Unlike other recurrent networks, LSTMs efficiently learn long-term dependencies by using multiple memory cells with separate update mechanisms. This paper combines LSTMs with CNNs to enhance rice classification by capturing both low-level and high-level features. The LSTM network includes layers like the input layer, LSTM cells (with input, output, and forget gates), and the output layer. A sequence folding layer is also used for classifying event sequences, where each neuron represents a probability distribution over the entire sequence. The LSTM network is trained using key parameters such as input embedding, the number of layers and cells, timesteps, learning rate, and batch size. L2 regularization helps prevent overfitting. Proper hyperparameter tuning is crucial to optimize performance, minimize overfitting, and improve generalization.

3.3. Transfer Learning Technique

Transfer learning is particularly useful for large-scale datasets or high-dimensional data [32-34]. Training models from scratch is time-consuming and computationally expensive, so using pre-trained models can accelerate training and enhance performance on new tasks. Pre-trained models, having learned from large datasets, offer improved generalization and can transfer learned knowledge to a new model, boosting its performance. Additionally, transfer learning allows us to leverage the strengths of existing models, such as those trained on diverse image datasets, to extract relevant features for new data. Overall, transfer learning reduces training time, saves computational resources, and enhances model performance, making it a valuable tool for CNN deep models.

4. Results and Discussions

The input rice images are pre-processed and augmented before being classified by a fine-tuned CNN model into five categories: Tarom, Shiroodi, Fajr, Neda, and Behnam. The CNN, CNN-TL, and CNN-LSTM architectures are compared with traditional classifiers like MLP, RNN, the dictionary learning-based algorithm from [21], and the GMM-based classifier from [22]. Transfer learning is used in the second scenario to address high-dimensional data fitting, and LSTM is employed to capture long-term temporal dependencies and handle variable-length input data. The proposed solution is validated through experiments with various parameter settings and evaluation measures.

4.1. Details of Simulation

To evaluate the proposed rice cultivar classifier, 2000 color images (256 × 256 pixels) were recorded for each rice type and processed with a median filter to reduce noise and improve accuracy. Three deep model scenarios were used: 1) CNN, trained from scratch; 2) CNN-TL, fine-tuned using transfer learning; and 3) CNN-LSTM, combining CNN for feature extraction and LSTM for classification. Key parameters, such as architecture, hyperparameters, and pre-processing techniques, were considered. The batch size of 128 was used, but adjustments were made for optimal performance. Learning rates were tuned for each scenario to balance training accuracy and convergence. The settings for each model configuration are summarized in Tables 1 and 2.

The proposed approach uses a flexible framework for rice cultivar classification, employing a CNN model with the Adaptive Moment Estimation (Adam) optimizer. Adam computes adaptive learning rates for each parameter, aiding the training of deep networks. The learning rate and decay rate for Adam were set to 10-4 and 0.9, respectively. For the CNN-LSTM scenario, the Stochastic Gradient Descent (SGD) optimizer was used, where model parameters are updated in small steps based on the negative gradient. A balanced batch size and learning rate are critical for stable training and avoiding overfitting. The LSTM network configuration is outlined in Table 3.

The proposed algorithm was trained on a computer with high-performance hardware, specifically, an Intel Xeon E5 2600 CPU with 16 cores and a clock speed of 3.20 GHz. The computer is also equipped with 3.20 GB of RAM, which is a sufficient amount for running deep-learning models. Additionally, the algorithm was trained on a Linux machine with 192 GB of DDR4 RAM, which is a high amount of RAM suitable for running larger models and larger datasets, and for running multiple instances of the algorithm in parallel. It also uses sparse principal component analysis (SPCA) and sparse structured principal component analysis (SSPCA) to reduce dimensionality and improve classification accuracy and efficiency. The algorithm in [22] combines fractal and texture features with a GMM classifier for classifying four rice cultivars. Sparse structured principal component analysis is used to reduce feature dimensions, achieving precise classification with reduced computational time.

4.2. Performance Evaluation

In classification problems, evaluation metrics such as accuracy, sensitivity, specificity, positive prediction rate, and F-Measure are essential for assessing model performance. These metrics provide insights into the model's strengths and weaknesses. Accuracy reflects the classifier's ability to correctly identify the actual class, while specificity measures its capacity to distinguish true categories. A positive prediction rate indicates the percentage of correctly labeled images, sensitivity assesses the recognition of different classes, and F-Measure balances precision and recall. These metrics, defined in this manuscript, facilitate a comprehensive evaluation and comparison of the rice classifiers:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Spe = \frac{TN}{TN + FP} \tag{2}$$

$$Ppr = \frac{TP}{TP + FP} \tag{3}$$

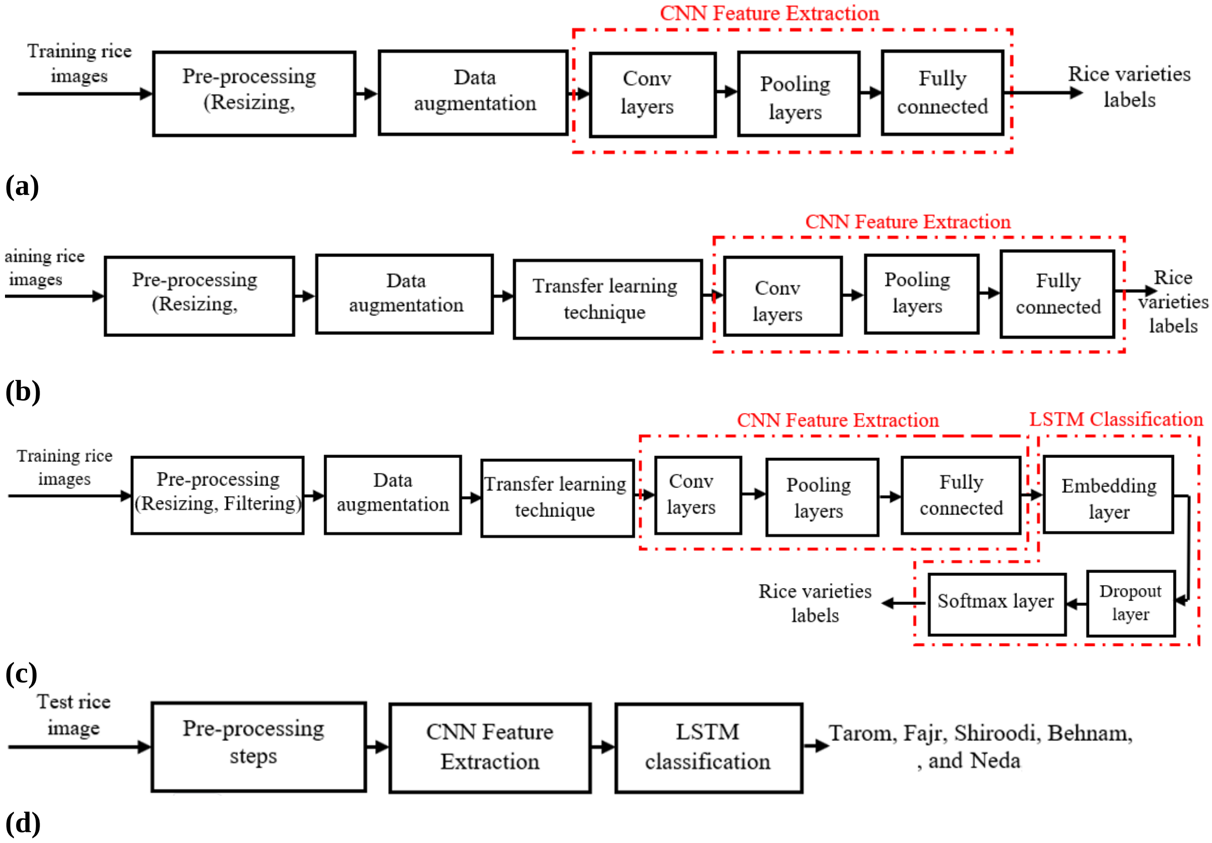


Figure 4. The block diagram of the proposed rice classifier based on different scenarios: a) CNN deep model, b) CNN in combination with transfer learning technique (CNN-TL), c) Hybrid CNN deep model with LSTM network and transfer learning technique (CNN-LSTM), and d) Test procedure in the last scenario.

Table 1. The hyperparameters set for different deep model's scenarios.

	Epochs	Optimizer	Batch Size	Kernel size	Activation function	Learning rate	Weight decay	#of parameters	# of layers
MLP [13]	1000	SGD	32	12	Sigmoid	10^{-4}	-	~	4
Resnet34 [10]	100	Adam	10	3×3	Non-Linear	2×10^{-4}	10^{-4}	0.60M	34
RNN	20	Adam	64	3×3	Sigmoid	10^{-3}	10^{-4}	0.30M	10
CNN (Scenario 1)	250	Adam	128	3×3	Sigmoid	10^{-3}	10^{-4}	0.80M	20
CNN-TL (Scenario 2)	250	Adam	128	3×3	Sigmoid	10^{-3}	10^{-4}	0.90M	20
CNN-LSTM (Scenario 3)	250	SGD	64	3×3	Sigmoid	10^{-4}	10^{-4}	0.90M	20

Table 2. The configurations of each scenario of CNN deep model in the proposed rice classification algorithm.

No. of Layers	Name of layer	CNN (Scenario 1)	CNN-TL (Scenario 2)	CNN-LSTM (Scenario 3)
1	Input image	256×256×3	256×256×3	256×256×3
2	Sequence folding layer	-	-	256×256×1
3	Conv2D/ReLU/Normalization	Kernel size [3,3],256×256×1, Stride 1	Kernel size [3,3], 256×256×1, Stride 1	Kernel size [3,3], 256×256×1, Stride1
4	Pooling	Kernel size [2,2], 256×256×64, Stride2	Kernel size [2,2], 256×256×64, Stride2	Kernel size [2,2], 256×256×64, Stride2
5	Conv2D/ReLU/Normalization	Kernel size [1,1], 64×64×64, Stride 1	Kernel size [1,1], 64×64×64, Stride 1	Kernel size [1,1], 64×64×64, Stride 1
6	Pooling/padding	Kernel size [2,2], 64×64×128, Stride2	Kernel size [2,2], 64×64×128, Stride2	Kernel size [2,2], 64×64×128, Stride2
7	Conv2D	Kernel size [3,3], 32×32×128, Stride 1	Kernel size [3,3], 32×32×128, Stride 1	Kernel size [3,3], 32×32×128, Stride1
8	Pooling	Kernel size [2,2], 32×32×256, Stride 2	Kernel size [2,2], 32×32×256, Stride 2	Kernel size [2,2], 32×32×256, Stride2
9	Sequence unfolding layer	-	-	32×32×256
10	Flattening	-	-	192×192
11	LSTM	-	-	4096
12	Fully Connected	4096	4096	4096
13	ReLU	~	~	~
14	Dropout	~	~	~
15	Fully Connected	4096	4096	4096
16	ReLU	~	~	~
17	Dropout	50% dropout	50% dropout	50% dropout
18	Fully Connected	1000 fully connected layer	1000 fully connected layer	1000 fully connected layer
19	softmax	~	~	~
20	Classification Output	~	~	~

Table 3. Representation of optimized hyperparameters of the LSTM network employed in scenario 3.

	Epochs	Learning rate	Batch size	No. of nods	Interpolate method	Dropout rate	Dimension of hidden state	No. of units in fully connected layer
LSTM	100	10^{-4}	64	40	N/A	50%	200	40

$$Sen = \frac{TP}{TP + FN} \tag{4}$$

$$F - Measure = 2\frac{Ppr \times Sen}{Ppr + Sen} \tag{5}$$

TP, TN, FP, and FN represent True Positive, True Negative, False Positive, and False Negative rates, respectively. TP indicates correctly detected classes, TN represents correctly identified negatives, FP counts false positives, and FN denotes false negatives. Higher TP and TN rates with lower FP and FN rates indicate better classification. These metrics enable a thorough evaluation and comparison of classifier performance, with high scores across all metrics reflecting accuracy and effectiveness.

4.3. The Proposed Rice Classification Based on Different CNN Scenarios

Preprocessing is vital for image classification, as depicted in Figure 4. Steps include resizing, normalization, and median filtering, followed by CNN blocks extracting deep features. These features pass through fully connected layers, with a softmax function estimating class probabilities. The 5-fold cross-validation approach (Section 2.4) divides training data into five groups, iteratively training on four and validating on one. Performance metrics—accuracy, specificity, positive predictive value, sensitivity, and F-Measure—are detailed in Table 4. The Friedman test [39] assesses algorithm efficiency, calculating $\rho-$Values compared to a 0.05 significance level. The lower $\rho-$Value indicates significant differences. Table 5 shows the CNN-LSTM algorithm achieves the best performance, with $\rho-$Values below 0.05, confirm its superiority over alternative methods, including dictionary-based and traditional algorithms.

The CNN-LSTM model demonstrates high accuracy and stability in rice classification, as shown in Table 6. The confusion matrix highlights minimal misclassification, and metrics like specificity, prediction rate, sensitivity, and F-Measure confirm its effectiveness. Figure 5 illustrates the training and testing accuracy and loss, offering insights into the model's learning process and optimal hyperparameters.

Table 4. The overall performance of various rice classifiers, as measured by Accuracy, Specificity, Positive Prediction Rate, Sensitivity, and F-Measure metrics.

		Acc (%)	Spe (%)	Ppr (%)	Sen (%)	F-Measure (%)
MLP [13]	Tarom	94.24	94.89	93.49	94.31	93.89
	Shiroodi	95.39	94.80	94.57	93.43	93.99
	Fajr	94.98	94.32	94.53	94.91	94.72
	Neda	95.62	95.49	94.58	94.96	94.77
	Behnam	95.87	95.44	94.32	94.70	94.51
CNN [6]	Tarom	97.53	97.46	97.56	98.11	97.83
	Shiroodi	97.89	97.70	98.15	97.43	97.79
	Fajr	97.39	97.64	97.21	97.41	97.31
	Neda	97.88	97.47	98.22	97.58	97.89
	Behnam	97.82	97.78	97.84	97.69	97.76
RNN	Tarom	95.86	96.05	96.70	95.96	96.34
	Shiroodi	95.51	94.07	96.04	96.54	96.29
	Fajr	96.74	96.13	95.78	96.27	96.02
	Neda	95.85	95.91	95.91	96.41	96.16
	Behnam	95.77	95.82	96.75	96.53	96.64
GMM-based [21]	Tarom	93.81	93.61	94.23	93.13	93.68
	Shiroodi	93.58	93.24	93.21	93.14	93.17
	Fajr	93.25	93.53	93.28	94.36	93.82
	Neda	94.17	93.31	93.16	93.79	93.47
	Behnam	94.06	94.11	93.77	93.28	93.52
Dictionary learning-based [22]	Tarom	93.35	93.43	94.33	94.34	94.33
	Shiroodi	93.41	94.65	93.56	94.45	94.00
	Fajr	93.87	93.83	93.54	94.22	93.88
	Neda	94.11	93.43	95.02	93.98	94.49
	Behnam	93.21	93.18	93.43	93.56	93.49
CNN (Scenario 1)	Tarom	98.32	98.16	98.78	98.49	98.63
	Shiroodi	98.80	98.69	97.98	98.21	98.09
	Fajr	99.13	98.55	98.65	98.64	98.64
	Neda	98.64	98.48	97.93	99.10	98.51
	Behnam	98.33	98.67	98.80	98.64	98.72
CNN-TL (Scenario 2)	Tarom	99.61	100	99.85	99.23	**99.54**
	Shiroodi	99.65	99.49	99.67	99.21	**99.44**
	Fajr	100	100	99.59	99.32	**99.45**
	Neda	99.63	99.82	99.76	99.40	**99.58**
	Behnam	99.70	99.79	99.85	99.01	**99.43**
CNN-LSTM (Scenario 3)	Tarom	99.68	99.48	100	99.67	**99.83**
	Shiroodi	99.82	99.80	99.80	100	**99.90**
	Fajr	100	99.63	99.69	99.74	**99.71**
	Neda	100	99.56	100	99.83	**99.91**
	Behnam	99.77	99.68	99.81	100	**99.90**

3.4. The Proposed Procedure for Rice Quality Detection Based on Different CNN Scenarios

In many countries, rice is blended with lower-quality varieties due to factors like cost, supply shortages, consumer preferences, or misconceptions. Blending lowers product costs, maximizes retailer profits, and addresses shortages caused by climate change or drought. Some consumers also prefer the taste or texture of mixed rice. Assessing rice purity can be achieved using grain analyzers to measure properties like grain size, impurities, and moisture, or through high-resolution imaging for detailed structural analysis. Signal processing-based methods offer faster, more accurate analysis, enabling real-time monitoring and detailed chemical composition insights, benefiting breeding, quality control, and production processes.

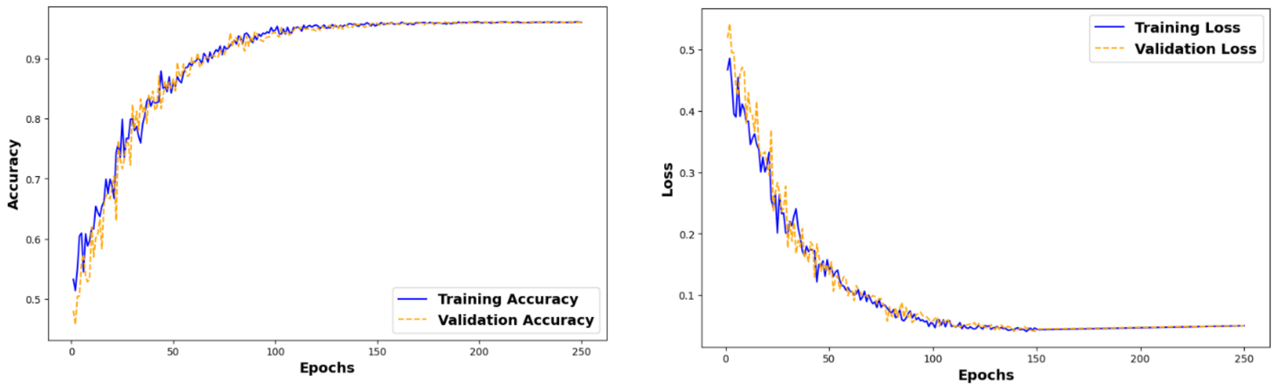
This paper investigates rice cultivar authenticity and classification, focusing on the use of deep learning to detect rice purity after classification. In northern Iran, lower-priced rice varieties, such as Shiroodi, are mixed with higher-quality ones like Tarom for texture, color, and taste. This study examines the purity of Tarom rice mixed with Shiroodi at 10%, 20%, and 40% levels. The authenticity and quality of rice are assessed using a CNN-LSTM classifier, showing remarkable accuracy in detecting rice quality. The success of CNN-LSTM models is due to their ability to learn complex features from large datasets. The paper concludes that the quality of data and model optimization are key to effective machine-learning solutions in rice quality detection. The authenticity of the rice is tested to ensure it meets the required standards, and the results are shown in Figure 6. The results of the proposed CNN-LSTM classifier for rice quality detection are presented in Table 7, highlighting their remarkable accuracy.

Table 5. The results of the Friedman test to analysis the different rice classification algorithms and proposed scenarios.

		Acc (%)	$\rho-$Value	Mean $\rho-$Value	Mean Acc (%)
MLP [13]	Tarom	94.24	0.024	0.0274	95.22
	Shiroodi	95.39	0.026		
	Fajr	94.98	0.027		
	Neda	95.62	0.031		
	Behnam	95.87	0.029		
CNN [6]	Tarom	97.53	0.019	0.0130	97.70
	Shiroodi	97.89	0.009		
	Fajr	97.39	0.016		
	Neda	97.88	0.011		
	Behnam	97.82	0.010		
RNN	Tarom	95.86	0.020	0.0234	95.95
	Shiroodi	95.51	0.018		
	Fajr	96.74	0.029		
	Neda	95.85	0.031		
	Behnam	95.77	0.019		
GMM-based [21]	Tarom	93.81	0.034	0.0324	93.77
	Shiroodi	93.58	0.033		
	Fajr	93.25	0.029		
	Neda	94.17	0.035		
	Behnam	94.06	0.031		
Dictionary learning-based [22]	Tarom	93.35	0.040	0.0382	93.59
	Shiroodi	93.41	0.039		
	Fajr	93.87	0.038		
	Neda	94.11	0.037		
	Behnam	93.21	0.037		
CNN (Scenario 1)	Tarom	98.32	0.009	0.0078	98.64
	Shiroodi	98.80	0.006		
	Fajr	99.13	0.007		
	Neda	98.64	0.008		
	Behnam	98.33	0.009		
CNN-TL (Scenario 2)	Tarom	99.61	**0.004**	0.0042	99.72
	Shiroodi	99.65	**0.003**		
	Fajr	100	**0.005**		
	Neda	99.63	**0.005**		
	Behnam	99.70	**0.004**		
CNN-LSTM (Scenario 3)	Tarom	**99.68**	**0.002**	**0.0018**	**99.85**
	Shiroodi	**99.82**	**0.003**		
	Fajr	**100**	**0.001**		
	Neda	**100**	**0.002**		
	Behnam	**99.77**	**0.001**		

Table 6. Confusion matrix for the CNN-LSTM proposed method for rice cultivars classification.

	Tarom (%)	Shiroodi (%)	Fajr (%)	Neda (%)	Behnam (%)
Tarom (%)	**99.68**	0.00	0.00	0.14	0.18
Shiroodi (%)	0.05	99.82	0.09	0.04	0.00
Fajr (%)	0.00	0.00	**100**	0.00	0.00
Neda (%)	0.00	0.00	0.00	**100**	0.00
Behnam (%)	0.06	0.07	0.06	0.04	**99.77**



(a) (b)

Figure 5. Training progress plots related to, a) the accuracy, and b) the loss function, for the proposed CNN-LSTM model used to resolve the rice classification problem.

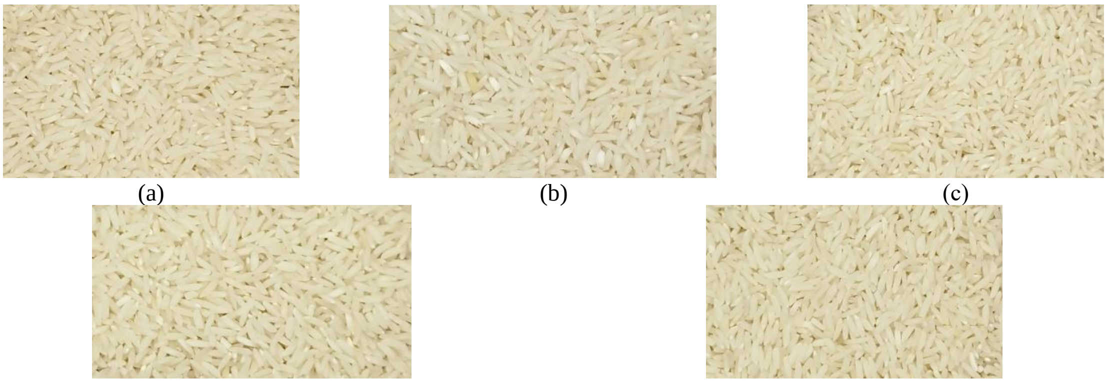


Figure 6. Examples of training data used for rice quality detection, include: a) Tarom1 rice data, b) Shiroodi rice data, c) 90% of grains from Tarom1 in combination with 10% of rice grains from the Shiroodi cultivar, d) 80% of grains from Tarom1 in combination with 20% of rice grains from the Shiroodi cultivar, e) 60% of grains from Tarom1 in combination with 40% of rice grains from Shiroodi cultivar.

Table 7. The statistical test analysis of different rice quality detection scenarios.

		Acc (%)	$\rho -$ Value	Mean $\rho -$ Value	Mean Acc (%)
CNN (Scenario 1)	Tarom	99.07	0.004	0.0055	98.69
	Shiroodi	99.14	0.004		
	Fajr	98.31	0.005		
	Neda	99.28	0.004		
	Behnam	99.33	0.005		
	90% Tarom_10%Shiroodi	98.21	0.007		
	80% Tarom_20%Shiroodi	98.07	0.008		
	60% Tarom_40%Shiroodi	98.18	0.007		
CNN-TL (Scenario 2)	Tarom	99.23	0.003	0.0047	98.99
	Shiroodi	99.49	0.003		
	Fajr	99.54	0.005		
	Neda	99.66	0.005		
	Behnam	99.17	0.006		
	90% Tarom_10%Shiroodi	98.20	0.006		
	80% Tarom_20%Shiroodi	98.32	0.005		
	60% Tarom_40%Shiroodi	98.33	0.005		
CNN-LSTM (Scenario 3)	Tarom	**99.38**	**0.002**	**0.0026**	**99.18**
	Shiroodi	**99.80**	**0.001**		
	Fajr	**99.70**	**0.002**		
	Neda	**99.71**	**0.002**		
	Behnam	**99.80**	**0.003**		
	90% Tarom_10%Shiroodi	**98.27**	**0.004**		
	80% Tarom_20%Shiroodi	**98.36**	**0.003**		
	60% Tarom_40%Shiroodi	**98.41**	**0.004**		

Table 8. Confusion matrix for proposed CNN-LSTM method for rice cultivars classification.

	Tarom	Shiroodi	Fajr	Neda	Behnam	90% Tarom _10%Shiroodi	80% Tarom _20%Shiroodi	60%Tarom_ 40%Shiroodi
Tarom	**99.38**	0.10	0.13	0.09	0.03	0.14	0.04	0.09
Shiroodi	0.00	**99.80**	0.00	0.03	0.00	0.03	0.08	0.06
Fajr	0.03	0.06	**99.70**	0.02	0.04	0.06	0.04	0.05
Neda	0.05	0.07	0.05	**99.71**	0.03	0.02	0.03	0.04
Behnam	0.03	0.05	0.00	0.06	**99.80**	0.02	0.03	0.01
90% Tarom _10%Shiroodi	0.31	0.33	0.21	0.24	0.18	**98.27**	0.28	0.18
80% Tarom _20%Shiroodi	0.29	0.13	0.29	0.17	0.19	0.29	**98.36**	0.28
60% Tarom _40%Shiroodi	0.26	0.22	0.17	0.19	0.16	0.28	0.31	**98.41**

Table 8 shows the confusion matrix for the proposed CNN-LSTM model in detecting rice quality across eight categories of pure and impure rice. The training time for the model depends on factors like dataset size, model complexity, and the training algorithm. Training the model on 70% of the dataset takes about 21 hours, with a runtime of approximately 19 seconds, making it efficient for online applications. The CNN effectively extracts features from rice images, which are then processed by the LSTM network to identify patterns over time, improving classification accuracy and speed. Transfer learning enhances the model's ability to generalize to new, varied data, boosting its performance in real-world applications. This combination of CNN, LSTM, and transfer learning makes the classifier highly accurate and efficient for agricultural use.

While the proposed CNN-LSTM model demonstrates impressive accuracy in controlled experiments, several challenges may arise when deploying the system in real-world agricultural settings. One major challenge is the computational power required for processing bulk samples, especially in environments with limited access to advanced hardware. To address this, edge computing techniques and model compression strategies, such as pruning and quantization, can be employed to reduce the computational load. Additionally, variability in lighting conditions and background noise during image acquisition could impact the model's performance. Employing robust data augmentation techniques and adaptive preprocessing pipelines can help mitigate these issues. Future work will focus on developing hardware-friendly versions of the model to facilitate deployment in resource-constrained settings.

In real-world scenarios, processing high-resolution images of rice grains in bulk could pose computational challenges. Optimizing the model's architecture for deployment on edge devices and exploring lightweight alternatives will be essential steps in future research.

5. Conclusion

Rice classification and quality detection are essential for agriculture, food security, and consumer safety. Rice is a staple food but is also perishable and vulnerable to damage and contamination. Effective rice quality detection is crucial for ensuring food safety and consumer satisfaction. This can be applied in breeding, seed selection, field management, processing, marketing, and food safety. Deep learning algorithms are effective for detecting and classifying rice defects, extracting features from images or spectral data. This paper proposes CNN-based models with transfer learning and hybrid CNN-LSTM models for rice classification and quality detection. The CNN extracts visual features, while LSTM handles temporal data, making the combination effective for sequential tasks. Transfer learning enhances model performance, enabling faster convergence and better generalization. These models classify five rice cultivars and three mixed rice classes in northern Iran. The CNN-LSTM model improves classification accuracy, making it a reliable choice for rice quality detection, as demonstrated through simulations and statistical tests. This approach also evaluates rice purity and quality, highlighting its importance for food safety. In real-world scenarios, processing high-resolution images of rice grains in bulk could pose computational challenges. Optimizing the model's architecture for deployment on edge devices and exploring lightweight alternatives will be essential steps in future research.

Future Work

While this study has demonstrated the effectiveness of the proposed model using rice varieties from northern Iran, we acknowledge the importance of enhancing the model's generalizability. Future work will focus on expanding the dataset to include a more diverse range of rice varieties from different regions globally. This will ensure that the model is applicable across various agricultural practices and addresses challenges specific to different rice-producing areas. Additionally, we aim to explore hardware optimization techniques for more efficient real-world deployment of the system in large-scale agricultural settings. By doing so, we can improve both the model's accuracy and its practical applicability in diverse agricultural environments.

Although the model demonstrates high accuracy, future work will focus on evaluating its computational performance, including processing time, resource consumption, and scalability across various hardware platforms. Optimizing the model for efficiency using techniques such as model compression and parallel processing will also be explored to ensure its applicability in large-scale agricultural settings. By addressing these computational aspects, we aim to enhance the model's real-world feasibility and its potential for widespread deployment in agriculture.

A limitation of this study is the dataset's focus on specific rice varieties. Future work will involve collecting and analyzing a more diverse dataset representing global varieties to enhance the model's generalizability and applicability in diverse agricultural contexts.

Future work will focus on addressing challenges related to the deployment of the system in real-world agricultural settings. Key challenges include hardware limitations, processing bulk samples efficiently, and ensuring scalability across different agricultural operations. Optimizing the system for handling large datasets and ensuring timely

processing will be prioritized. Strategies such as hardware acceleration, distributed computing, and batch processing techniques will be explored to improve the system’s efficiency and feasibility for large-scale agricultural environments.
While deep learning models like the CNN-LSTM often provide excellent performance, their "black-box" nature can make them difficult to interpret. To address this limitation, future work will focus on enhancing the model's interpretability. Techniques such as activation maps, feature importance analysis, and model explanation methods like SHAP and LIME will be explored to provide transparent insights into the model's decision-making process. This will improve the understanding and trust in the proposed solution, especially for real-world agricultural applications.

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رویکردی ترکیبی مبتنی بر یادگیری عمیق برای طبقه‌بندی و تشخیص کیفیت انواع برنج

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چکیده:

برنج یکی از مهم‌ترین محصولات غذایی جهان است که منبع قابل توجهی از غذا و درآمد را برای میلیون‌ها نفر فراهم می‌کند. مشکلات مرتبط با طبقه‌بندی و تشخیص کیفیت برنج می‌توانند تأثیر چشمگیری بر سودآوری و پایداری کشت برنج داشته باشند، از این رو اهمیت حل این مشکلات قابل انکار نیست. با بهبود تکنیک‌های طبقه‌بندی و تشخیص کیفیت، می‌توان ایمنی و کیفیت محصولات برنج را تضمین کرد و بهره‌وری و سودآوری کشت برنج را ارتقا داد. با این حال، چنین تکنیک‌هایی اغلب در توانایی طبقه‌بندی دقیق دانه‌های برنج به دلیل عوامل مختلفی مانند شرایط نوری، پس‌زمینه و کیفیت تصویر محدودیت دارند. برای غلبه بر این محدودیت‌ها، در این مقاله یک الگوریتم طبقه‌بندی مبتنی بر یادگیری عمیق معرفی شده است که از قدرت شبکه‌های عصبی پیچشی (CNN) و شبکه‌های حافظه کوتاه‌مدت بلند (LSTM) برای نمایش بهتر محتوای ساختاری انواع مختلف دانه‌های برنج بهره می‌گیرد. این مدل ترکیبی که CNN-LSTM نام دارد، مزایای هر دو نوع شبکه عصبی را برای طبقه‌بندی مؤثرتر و دقیق‌تر دانه‌های برنج ترکیب می‌کند. در این مقاله سه سناریو شامل استفاده ازCNN ، ترکیب CNN با تکنیک یادگیری انتقالی، و مدل عمیق CNN-LSTM بررسی شده است. عملکرد این سناریوها با دیگر مدل‌های یادگیری عمیق و طبقه‌بندهای مبتنی بر یادگیری دیکشنری مقایسه شده است. نتایج تجربی نشان می‌دهند که الگوریتم پیشنهادی انواع مختلف برنج را با دقت قابل توجهی بیش از ۹۹/۸۵٪ شناسایی می‌کند و کیفیت را برای ترکیبات مختلف برنج با میانگین دقت ۹۹/۱۸٪ تعیین می‌کند.

کلمات کلیدی: طبقه‌بندی برنج، تشخیص کیفیت، شبکه عصبی پیچشی، حافظه کوتاه‌مدت بلند، یادگیری انتقالی.