International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 04 | April - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

A Survey on Comprehensive Rice Grain Quality Analysis using Deep Learning

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Abstract— ***Grains, particularly rice, constitute the cornerstone of agricultural revenue in India, serving as a vital cereal crop for domestic and international markets. While farmers prioritize yield during cultivation, grain quality emerges as the critical factor during processing and trade. Traditionally, quality evaluation relies on manual inspection, a labor-intensive and error-prone process that struggles to address impurities such as stones, cracked seeds, and foreign matter. This paper proposes an automated solution leveraging the VGG19 deep learning model to classify and grade rice grain quality. By extracting features like size, shape, eccentricity, and area through image processing, the system achieves higher accuracy, reduces human effort, and enhances efficiency compared to conventional methods. Experimental results demonstrate the model's potential to revolutionize quality assessment, offering a scalable and cost-effective alternative for the agricultural sector.***

Keywords—Rice grain quality, VGG19, deep learning, image processing, quality grading, automation.

I. INTRODUCTION

Grains serve as the cornerstone of agricultural income in our country, playing a vital role in the economy. During the cultivation phase, farmers focus predominantly on maximizing yields to ensure a bountiful harvest. However, once rice enters the processing and marketing stages, the emphasis shifts decisively toward quality. At this point, the presence of contaminants—such as stones, weed seeds, chaff, and broken grains—can significantly compromise the value of the product. Currently, the evaluation of grain quality lacks extensive automation, with human labor still dominating the process. This reliance on manual inspection introduces several inefficiencies, including worker exhaustion, elevated costs, and prolonged testing durations. To tackle these challenges, a sophisticated machine learning model has been developed to assess and classify rice quality grades. This model leverages an array of features, including major and minor axis measurements, size, eccentricity, roundness, and area, and integrates advanced image processing techniques along with other innovative technologies.

Grains, particularly rice, hold immense agricultural significance in our nation, directly influencing economic returns. Despite their importance, the automation of quality testing remains underdeveloped, with manual methods prevailing. Rice stands out as a critical cereal crop in India, where it ranks among the most widely consumed staples. The quality of rice grains profoundly affects both domestic and global markets, shaping trade dynamics and consumer preferences. Traditionally, quality assessment has depended on human inspectors who manually evaluate samples, achieving a reasonable degree of accuracy [5]. Yet, this approach demands substantial effort, consumes considerable time, and is inherently subjective, varying with the inspector's judgment. The manual process involves categorizing rice samples into six distinct groups: intact grains, cracked grains, paddy, stones, and foreign materials.

This labor-intensive manual testing proves both arduous and slow, offering little practical benefit for detecting substandard grains in the marketplace. Beyond being time-consuming, it incurs high costs and introduces complexities tied to factors such as working conditions, human error, cleaning efficiency, and the recovery of usable grains. Presently, grain type identification, grading, and quality feature analysis rely heavily on manual techniques. Contaminants—such as stones, sand, damaged seeds, and fragmented grains—collectively termed adulteration, further degrade rice quality. Ultimately, the marketability and sales potential of grains hinge on their quality, making it a decisive factor in agricultural success.

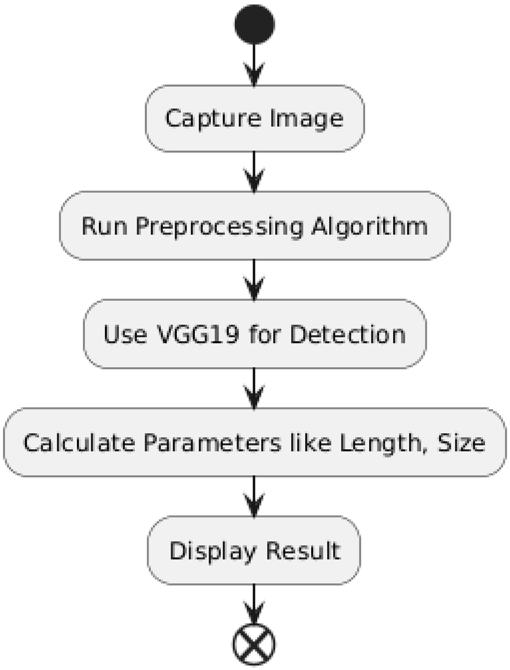

Fig. 1. Flow chart of the complete process

Manual inspections by human operators are inherently less dependable, heightening the risk of contamination errors and diminishing rice quality. These inspections are constrained by factors like operator focus, time limitations, and the expense of sample-based testing methods [3]. Such limitations underscore the need for a more reliable and efficient approach.

In the agricultural sector, evaluating product quality is paramount. Historically, rice grain quality analysis depended on manual inspection and grading, guided by visual characteristics such as size, shape, and color. Skilled technicians would visually appraise grain seeds, but this method yielded inconsistent and subjective results, often varying with the technician's disposition. Moreover, the process was slow and inefficient, highlighting the urgent need for an advanced alternative. The comprehensive workflow for this improved approach is illustrated in Fig. 1, outlining a streamlined and technology-driven solution to revolutionize rice quality assessment.

II. Related Work

De Oliveira Carneiro et al. [1] effectively addressed the issue of assessing milled rice grain quality by integrating non-destructive techniques with machine learning methods. They utilized algorithms such as Artificial Neural Networks (ANN) and decision trees to predict grain quality. Their study relied on a dataset comprising milled rice grains with varying moisture levels. By employing near-infrared spectroscopy, a non-destructive method, they gathered essential information about the grains' physicochemical characteristics. Machine learning models were then applied to estimate grain quality using factors like whole grain yield, defects, and moisture content. Their results demonstrated that combining machine learning with non-destructive technologies offers a rapid and accurate way to evaluate rice grain quality. This approach achieved high precision in predicting physicochemical traits, showing significant potential for reducing losses and improving efficiency in the rice sector. The method excels due to its speed and accuracy in quality assessment. Additionally, its non-destructive nature helps minimize waste and streamline industry processes. However, it is tailored specifically to rice grains and may not extend to other grain varieties. Furthermore, fluctuations in moisture levels could influence prediction accuracy.

Aznan et al. [2] developed a digital solution to explore consumer perceptions of commercial rice grain types. They created a machine learning model that classifies rice grains based on visual dimensional features. The research involved photographing 15 samples under controlled lighting using two distinct lightbox setups. After training and validating their model with this dataset, they achieved excellent accuracy in determining grain quality and identifying rice types. The study concluded that this method is dependable and adaptable, suitable for classifying commercially available rice grains globally. A key strength is its flexibility across different camera types, independent of specific settings. However, the approach has limitations, including sensitivity to lighting variations and camera configurations, which could lead to errors when applied to datasets collected under different conditions.

X. Ju et al. [3] introduced an innovative technique to overcome the limitations of traditional biochemical rice quality assessments, such as lengthy sample preparation, slow processes, and poor accuracy in detecting rice varieties and adulteration. Their method uses Headspace-Gas Chromatography-Ion Mobility Spectrometry (HGC-IMS) to analyze volatile flavor compounds in five rice types. They employed a semi-supervised generative adversarial network (SSGAN) to generate ion migration fingerprint spectra for rice identification. By modifying the GAN's discriminator with a softmax classifier, they transformed it into a semi-supervised model. Through semi-supervised training, the network's parameters were refined, enabling the trained model to effectively classify HGC-IMS images. This approach offers a fast and precise alternative to conventional methods.

Detecting rice adulteration, a pressing concern in the food industry, was the focus of C. Li et al. [4]. They proposed a detailed method combining terahertz spectroscopy with pattern recognition techniques to identify contaminated rice samples. Their experiment utilized a terahertz time-domain spectroscopy system, applying preprocessing methods like Savitzky-Golay filtering, standard normal variate, first derivative, and baseline correction to the spectral data. Chemometric techniques, including principal component analysis (PCA), partial least squares discriminant analysis (PLSDA), genetic algorithms, support vector machines (SVM), and backpropagation neural networks, were used to classify and screen 150 rice samples with varying adulteration levels. The combination of SVM with first derivative preprocessing provided the highest accuracy in identifying adulterated rice. This non-destructive, rapid technique delivers precise outcomes, though its reliance on specialized equipment and expertise may limit its accessibility.

X. Wang et al. [5] devised a vision-based system to streamline the labor-intensive task of manually assessing rice quality. Their automated approach classifies defective rice kernels and estimates their quality by analyzing weight ratios. The multi-stage process begins with detecting and separating kernels with different flaws, followed by a weight-per-pixel calculation to determine the weight proportions of each kernel type. Experiments involved 322 rice images, randomly divided into training, validation, and test sets across five iterations. Their model was benchmarked against Yolov5, EfficientDet-D2, and DynamicHead+Resnet50+ATSS, outperforming them in classification accuracy and weight estimation. The method's strengths lie in its precision in quality evaluation, though it requires high-quality images to function effectively.

M.J. Asif et al. [6] proposed an image-processing technique to classify rice varieties and evaluate their quality. Using principal component analysis (PCA) paired with Canny edge detection, they analyzed 100 images per variety of five rice types: Super Colonel, Khushboo, Basmati, Kainat Sailla, and Old Awami. The results confirmed the system's simplicity, portability, and effectiveness in assessing rice quality and distinguishing varieties. However, the study was limited to five varieties, and incorporating advanced algorithms like the General Hough Transform (GHT) could further improve its performance.

Y. N. Wan et al. [7] aimed to develop an automated machine vision system for rice quality inspection. Their approach, featuring range selection sorting and a user-friendly graphical interface with tabular list boxes, accurately classified rice kernels based on visual traits. Image processing techniques, such as histogram and threshold methods, were used to isolate kernels from their background. The study examined 67 rough rice (paddy) varieties sourced from local farmers during harvest, with samples exposed to humidity to induce cracked kernels. The system processed over 1200 kernels per minute, offering high accuracy, speed, and ease of use. However, it requires specific software and controlled conditions for consistent results.

C. Kurade et al. [8] introduced an affordable, automated rice quality evaluation system using image processing and machine learning. They collected structural and geometric data from 3081 images of eight rice varieties via a Raspberry Pi-based module. The Watershed technique extracted features like geometry, size, morphology, color, and roughness, which were analyzed by eight machine learning models. The Random Forest (RF) classifier achieved the highest accuracy of 76% (F1-score). The authors suggested that deep learning models like EfficientNet, Inception V3, ResNet, and MobileNet could boost accuracy further. This low-cost (USD 50), portable method is a strength, though it needs broader sampling across regions and seasons for robustness.

Mingchun Li et al. [9] developed a GF-RCF network to detect grain boundaries in Al-Mg-Si alloy metallographic images using multi-level feature loss. This method excels at identifying subtle grain boundaries, improving grain size evaluation accuracy and reducing manual annotation efforts. However, it depends on high-quality input images and requires extensive annotated data for training, limiting its scalability.

Y. Teng et al. [10] investigated the decision-making dynamics of government, farmers, and consumers regarding agricultural product quality and safety using an evolutionary game theory model. MATLAB simulations with varying initial conditions and parameters revealed the government's critical role in ensuring safe production and interdepartmental cooperation. While offering a robust theoretical framework, the model simplifies real-world complexities, necessitating further empirical testing.

Chengcheng Lei et al. [11] explored regional and temporal trends in China's grain production, examining factors affecting total and per capita yields. Although high-quality grain production with geographical indications was briefly noted, the study primarily provides insights into spatial-temporal production patterns rather than grain quality specifics.

Zhengjun Qiu et al. [12] enhanced rice seed variety identification by integrating hyperspectral imaging with convolutional neural networks (CNNs). Their deep learning model outperformed SVM and KNN methods across two spectral regions, using a dataset of 10,000 rice seed images. Its strengths include automatic feature learning and adaptability with more data, though it requires substantial training samples and risks overfitting.

Yan Wang et al. [13] employed inductively coupled plasma mass spectrometry with tandem mass spectrometry (ICP-MS/MS) and multielement PCA to trace rice origins. Their algorithm, combining PCA and cluster analysis, accurately classified rice by production site. While effective, the method needs further validation and optimization.

Lin Lu et al. [14] tackled continuous rice quality monitoring in Southern China using PCA to reduce data dimensionality while retaining key details. Analyzing indices like amylose content, translucency, and chalkiness across multiple metrics, they effectively assessed regional rice quality. The approach preserves critical information but requires large datasets and risks data loss during reduction.

Ji Hae Lee et al. [15] evaluated high hydrostatic pressure and atmospheric pressure plasma to reduce microbial contamination in rice. Measuring physicochemical properties with tools like high-performance liquid chromatography, they found atmospheric pressure plasma more effective. This method enhances rice safety but requires further validation across diverse conditions.

Anup Dhakal et al. [16] aimed to boost phenotypic diversity in Nepalese rice landraces from Lamjung and Tanahun districts using multivariate analysis (PCA and Mahalanobis distance). Studying 30 landraces with 13 quantitative traits, they identified key components tied to yield and grain traits for hybridization. The approach aids breeding programs but needs broader testing.

Shakeel Ahmed Soomro et al. [17] investigated low-temperature drying's impact on rough rice quality using response surface methodology. Optimal conditions (40°C, 6 hours, 0.5 m/s air velocity) preserved hardness, head rice yield, and cooking time, offering a practical drying solution.

Pedro Sousa Sampaio et al. [18] assessed ANN and multiple linear regression models to predict rice biochemical and pasting properties using grain appearance and milling yields. Analyzing 66 Portuguese rice samples, they found ANN models highly effective, enhancing quality control in breeding and processing.

Koan Sik Woo et al. [19] optimized rice/adzuki bean mixtures for quality and antioxidant activity. Using cultivars like Arari and Geomguseul, they found high-pressure cooking increased polyphenols and flavonoids, improving mixture quality. Further research across bean varieties is needed.

Jae-Ryoung Park et al. [20] identified genes affecting rice grain quality during filling using quantitative trait locus mapping on a double haploid line. Linking gene expression to traits like amylose content, their controlled study offers genetic insights but may not fully reflect natural conditions.

Zhyldyzai Ozbekova et al. [21] explored fluorescence spectroscopy to non-destructively assess rice moisture content and water activity. Using PCA and PLSDA on varied samples, they accurately predicted these traits and classified rice types, showcasing a rapid, effective method.

The experiment involved analyzing a range of rice samples with different moisture levels and from various growing locations, using a fluorescence spectrophotometer.

The results showed that combining fluorescence spectroscopy with multivariate analysis can accurately predict the moisture content and water activity of rice, while also enabling the differentiation of distinct rice types.

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TABLE 1: Summary of machine learning algorithms (supervised, unsupervised), deep learning algorithms, different algorithms used in analysis of rice grain quality

Study	ANN	SVM	PCA	KNN	LR	BPNN	RF	HGC	RS	DT
[1]	✓	×	×	×	×	×	✓	×	×	✓
[2]	✓	×	×	✓	×	✓	×	×	×	✓
[3]	×	×	×	×	×	×	×	✓	×	×
[4]	×	✓	✓	×	×	✓	×	×	×	×
[5]	×	×	✓	✓	×	×	×	×	×	×
[6]	×	×	✓	×	×	×	×	×	×	×
[7]	×	×	×	×	×	×	×	×	✓	×
[8]	×	✓	×	×	✓	×	✓	×	×	✓
[9]	×	×	×	×	×	×	×	×	×	×
[10]	×	×	×	×	×	×	×	×	×	×
[11]	×	×	×	×	×	×	✓	×	×	×
[12]	✓	×	×	×	×	×	×	×	×	×
[13]	×	×	✓	×	×	×	×	×	×	×
[14]	×	×	✓	×	×	×	✓	×	×	×
[15]	×	×	×	×	×	×	×	×	×	×
[16]	×	×	✓	×	×	×	×	×	×	×
[17]	×	×	×	×	×	×	×	×	×	×
[18]	✓	×	×	×	✓	×	×	×	×	×
[19]	×	×	×	×	×	×	×	×	×	×
[20]	×	×	×	×	✓	×	×	×	×	×
[21]	×	×	✓	×	×	×	×	×	×	×

**ANN=Artificial Neural Network, SVM=Support Vector Machine, PCA=Principal Component Analysis, KNN=K- Nearest Neighbor, BPNN=Back Propagation Neural Network, RF=Random Forest, HGC- IMS= Headspace-Gas, Chromatography-Ion Mobility Spectrometry, RS=Range sorting method, DT=Decision Tree, LR=Linear Regression

Category	**Algorithm/Method**	**Description/Application in Rice Quality Analysis**	**Reference**
Supervised Machine Learning	Artificial Neural Networks (ANN)	Predicts physicochemical properties of milled rice (e.g., whole grain yield, defects) using near-infrared spectroscopy data.	[1], [18]
	Decision Trees	Forecasts milled rice grain quality based on moisture content and defects.	[1]
	Support Vector Machine (SVM)	Identifies adulterated rice with high accuracy when paired with terahertz spectroscopy and first derivative preprocessing.	[4], [12]
	Partial Least Squares Discriminant Analysis (PLSDA)	Classifies rice samples (e.g., adulterated vs. pure) using terahertz spectral data; also used for moisture content differentiation.	[4], [21]
	Backpropagation Neural Network	Screens rice samples for adulteration, enhancing accuracy in quality assessment with terahertz spectroscopy.	[4]
	Random Forest (RF)	Classifies rice types based on geometric, size, and color features from images, achieving 76% accuracy.	[8]
Unsupervised Machine Learning	Principal Component Analysis (PCA)	Reduces dimensionality of data (e.g., spectral or quality indices) while retaining key information for rice origin or quality evaluation.	[4], [6], [13], [14], [16], [21]
	Cluster Analysis	Groups rice samples by elemental composition or origin using multielement data from ICP-MS/MS.	[13]
Deep Learning Algorithms	Convolutional Neural Networks (CNN)	Identifies rice seed varieties with hyperspectral imaging, outperforming traditional methods like SVM and KNN.	[12]
	Semi-Supervised Generative Adversarial Network (SSGAN)	Classifies rice types via ion migration fingerprint spectra from HGC-IMS, improving efficiency with semi-supervised training.	[3]
	GF-RCF Network	Detects grain boundaries in alloy materials (applicable to rice grain studies), enhancing accuracy in structural analysis.	[9]
Other Analytical Methods	Genetic Algorithm	Optimizes feature selection for adulteration detection in rice using terahertz spectroscopy.	[4]
	K-Nearest Neighbors (KNN)	Compares rice seed variety identification performance against deep learning, used as a baseline method.	[12]
	Canny Edge Detection	Extracts rice grain edges for quality classification in image-processing systems.	[6]
	Watershed Technique	Segments rice grain images to extract structural and geometric features for quality evaluation.	[8]
	Response Surface	Optimizes low-temperature drying conditions	[17]

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	Methodology (RSM)	to preserve rough rice quality attributes like hardness and head rice yield.	
	Multiple Linear Regression (MLR)	Predicts rice biochemical and pasting properties alongside ANN, using grain physical parameters.	[18]
	Quantitative Trait Locus (QTL) Mapping	Identifies genes linked to rice grain quality (e.g., amylose content) under high-temperature conditions.	[20]
	Mahalanobis Distance	Measures phenotypic diversity in rice landraces for hybridization parent selection.	[16]

TABLE 3: Overview of Algorithms and Methods for Rice Grain Quality Analysis

III. Result Analysis

After examining a wide range of studies, we found that multiple algorithms have been suggested, and diverse models have been applied, each with distinct parameters. To the best of our understanding, we performed a detailed comparison of these parameters and summarized the findings in the table below:

TABLE 3: Assessment of Rice Grain Quality Analysis Performance Across Various Models

Paper No.	Parameters Measured	Methods Proposed	Accuracy (%)
[1]	Moisture content, Yield of rice grains, Protein, Fat, Ash, Amylose content	ANN, DT, NIR	89.67
[2]	Grain's major axis length, Grain's minor axis length, Perimeter, Roundness, Aspect ratio, Eccentricity	ANN, KNN, BPNN	88.50, 79.00, 83.78
[3]	Roundness, Color	HGC-IMS	89.32
[4]	Size, Moisture content, Area	SVM, PCA, BPNN	90.66, 78.00, 84.60
[5]	Grain's major axis length, Grain's minor axis length, Perimeter, Eccentricity, Area, Size	KNN, PCA	79.04, 80.54
[6]	Area, Grain's major axis length, Size, Grain's minor axis length, Perimeter, Eccentricity	PCA	89.50
[7]	Area, Perimeter, Compactness, L/W, RGB averages, Chalky ratio, Transparency	RS	89.56
[8]	Equivalent diameter, Roundness, Compactness, Length, Width, Aspect ratio, Spatial	RF, LR, DT, SVM	77.00, 73.80, 67.60, 77.35

	extent, Shape		
[9]	Aspect ratio, Spatial extent, Shape factor	GF-RCF	85.49
[10]	Area, Perimeter, Compactness	GT	82.68
[11]	Length, Width, Chalky ratio	Geo detector	76.98
[12]	Equivalent diameter, Roundness, Compactness, Length, Width, Aspect ratio, Spatial extent, Shape	HSI, NN	89.66, 87.07
[13]	Size, Length, Width	ICP-MS/MS, PCA	80.60, 87.87
[14]	Roundness, Compactness, Length, Width, Aspect ratio, Spatial extent	PCA	75.89
[15]	Protein, Amylose content, Moisture	HHP, APP	87.52
[16]	Equivalent diameter, Roundness, Compactness, Length, Width, Aspect ratio, Spatial extent, Shape factor	PCA	79.87
[17]	Roundness, Compactness, Length,	SM with CCD	73.93
	Width, Aspect ratio, Spatial extent		
[18]	Aspect ratio, Size	ANN, LR	91.76, 88.35
[19]	Equivalent diameter, Roundness, Compactness, Length, Width	Folin–Ciocalteu method	79.68
[20]	Protein, Amylose content, Moisture	Double Haploid Line method	86.88
[21]	Roundness, Compactness, Length, Width	PCA, PLSDA	89.96, 88.53

** ICP-MS/MS= Inductively Coupled Plasma Mass Spectrometry with tandem Mass Spectrometry, HHP=High Hydrostatic Pressure, APP=Atmospheric Pressure Plasma, SM=Surface methodology with CCD=Central Composite Design, PLSDA= Partial Least Discriminant Analysis, GT=Game Theory, NIR=Near-Infrared Spectroscopy, HIS=Hydro Spectral Imaging.

IV. CHALLENGES AND GAPS

After reviewing the aforementioned studies, it is clear that the obstacles in rice grain quality analysis are complex and multifaceted, primarily centering on the goal of achieving complete automation while maintaining a high level of precision, all while accounting for the diverse factors that impact rice quality. A key challenge lies in the effort to fully automate the process, where every step—from data collection to quality assessment—requires seamless integration within a machine learning framework. Overcoming these hurdles is essential not only to simplify the rice quality evaluation process but also to enhance the overall efficiency and output of the rice production and processing industries. In this context, we are employing the VGG19 algorithm.

V. CONCLUSION

This survey paper has provided valuable insights into the existing models utilized for rice grain quality analysis. By shedding light on the current approaches for evaluating rice grain quality, it has underscored their strengths as well as their shortcomings. These limitations include a narrow emphasis on specific parameters and reduced accuracy levels. Consequently, refining these established methods is essential to address such challenges. Our objective is to develop an innovative model that not only tackles the weaknesses of earlier techniques but also delivers a more comprehensive and accurate assessment of rice grain quality. We aim to make a meaningful impact on enhancing the methodologies employed in rice grain quality evaluation. This is being achieved by incorporating a broader set of parameters and cutting-edge techniques, poised to transform the field. Our proposed model guarantees dependable and robust outcomes, benefiting both researchers and stakeholders.

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