A Survey on Comprehensive Rice Grain Quality Analysis using Machine Learning

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Abstract - *Rice, the most extensively cultivated crop in India, plays a crucial role as a primary dietary staple. It feeds a significant portion of the global population and underscores its pivotal position in ensuring food security. Approximately 70% of the Indian population consumes rice twice daily. The quality of rice is determined by various attributes that influence its taste, appearance, texture, and suitability for different culinary purposes. The quality of rice grains holds paramount importance in determining consumer satisfaction and economic value. In earlier times, identifying rice quality relied on manual inspection conducted by human inspectors an approach that was both time-consuming and prone to low accuracy. However, there are still difficulties in creating quick and inexpensive methods for assessing the features of commercial rice grain quality. Therefore, it is good to use machine learning algorithms. This adoption of machine learning not only ensures food security but also modernizes the agricultural landscape of India.*

***Key Words*: Rice, Rice grain quality, supervised machine-learning algorithm, quality grading.**

1.INTRODUCTION

The primary source of agricultural revenue in our nation is grains. While grains are growing, farmers pay the most attention to yields. However, quality becomes the main priority when rice is processed and sold. Various pollutants, like as stones, weed seeds, chaff, and cracked seeds, may be present in that grains. Grain quality testing is currently not highly automated, with the majority of the work being done by humans. This manual process can lead to worker fatigue and increase both the cost and duration of testing. To address these issues, a machine learning model for assessing and identifying quality grades has been developed. This model utilizes features such as major and minor axis parameters, size, eccentricity, roundness and area, employing image processing and other technologies. Grains are a crucial crop in our nation, and their quality significantly impacts agricultural income. However, the level of automation in grain quality testing remains limited, primarily relying on manual labour.

The assessment of grain quality is still only partially automated, the majority of the work is still done by humans. Rice is particularly important, being one of the most consumed cereal grains in India. The quality of grains greatly affects both the national and international rice market. This identification process is presently carried out manually by human inspectors, which guarantees a certain level of accuracy [5]. However, it requires a lot of work, takes a lot of time, and is judgment-based. For identifying the rice quality, a sample of rice must be separated into the following six categories: complete rice, cracked rice, paddy, stones, and foreign items.

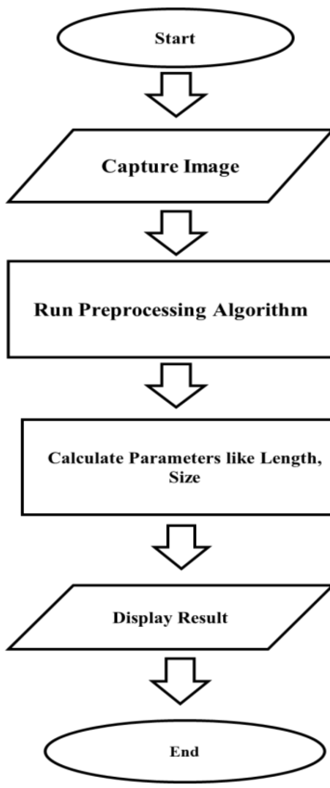

Fig -1: Flow chart of complete process

Manual testing is both laborious and time-consuming, and it provides no practical means to discover low-quality grains in the market. Additionally, it is expensive, complex and relies on complex manual analysis involving factors like working conditions, human error, cleaning rates, and salvage recovery. At present, the manual analysis of grain type, grading, and quality evaluation features is being used. Impurities like stones, sand particles, damaged seeds, and broken granules, referred to as adulteration, can also negatively impact rice quality. However, the primary factor affecting grain sales is its quality.

Manual inspections conducted by human inspectors are less reliable, increasing the risk of impurity mix-ups and a decline in rice quality. These inspections are also subject to operator concentration and time constraints, and sample testing methods can be costly [3]. Analyzing product quality is crucial in the agricultural industry. In the previous days, methods for rice grain quality analysis included manual inspection and grading based on visual appearances such as size, shape, and color. An expert technician assesses the grain seed's quality visually. However, the outcomes of such an evaluation are comparative, inconsistent, and time-consuming. Since the technician's attitude also affects quality, a new and improved technique is required for that and the complete process for that is shown in Fig-1.

2.RELATED WORK

De Oliveira Carneiro [1] have successfully tackled the challenge of finding the quality of milled rice grains by using the methods, non-destructive technologies and machine learning algorithms. They employed algorithms like Artificial Neural Networks and decision tree algorithms to forecast the grain quality. The experimentation involved a dataset that encompassed various moisture contents of milled rice grains. By employing non-destructive technologies like near infrared spectroscopy, they collected crucial data on the physicochemical properties of the grains. The team utilized machine learning algorithms to predict grain quality based on input variables such as whole grain yield, defects, and moisture content. Their findings revealed that leveraging machine learning algorithms alongside non-destructive technologies provided a faster and more precise approach to predicting milled rice grain quality. Their method successfully predicted the physicochemical properties of rice grains with high accuracy, offering great potential for minimizing losses and enhancing efficiency in the rice industry. The proposed approach stands out for its speed and precision in determining milled rice grain quality. Moreover, by employing non-destructive technologies, it aids in reducing losses and optimizing operations within the industry. However, it is important to remember that this method focuses mainly on rice grains and may not be applicable to other grain types. Furthermore, variations in moisture content can affect the accuracy of predictions.

Aznan, A. [2] To tackle the challenge of studying how consumers perceive different types of commercial rice grains, researchers devised a digital approach. They developed a machine learning algorithm that utilizes dimensional morphological parameters to classify rice grains based on their visual appearance. The study involved capturing images of 15 samples using two different lightbox systems under controlled lighting conditions. By training and testing their machine-learning model with this dataset, the authors achieved high accuracy in identifying grain quality and classifying various rice grain types. They concluded that their proposed method is both reliable and robust, making it suitable for classifying different commercially available rice grains worldwide. Their method has certain advantages. It is not dependent on specific camera settings and can be used with various types of cameras. However, there are limitations to their approach. It is sensitive to lighting conditions and camera settings, which may result in misclassification when applied to a new dataset collected under different conditions.

X. Ju [3] A novel approach has been developed to solve the constraints of established biochemical methods for rice quality evaluation, such as complex sample preparation, time-consuming, and low accuracy in recognizing various rice species and adulteration. This method utilizes Headspace-gas chromatography-ion mobility spectrometry (HGC-IMS) to detect the uncertain flavor compounds present in five different types of rice. The identification of these rice types is achieved by generating ion migration fingerprint spectra using a semi-supervised generative adversarial network (SSGAN). By replacing the discriminator’s output layer with a soft max classifier, the GAN is extended into a semi supervised GAN. Through semi supervised training, the parameters of the network are improved by semi-supervised training, and the trained discriminant network is used to efficiently categorize HGC-IMS pictures.

Detecting adulterated rice is a significant challenge in the food industry, according to C. Li's research [4]. In their study, they proposed a comprehensive approach that combines terahertz spectroscopy and pattern recognition algorithms to identify adulterated rice samples. To conduct the experiment, they used a terahertz time domain spectroscopy system and applied various preprocessing techniques such as Savitzky Golay filtering, standard normal variate, first derivative, and baseline correction to the obtained spectral data. For categorization and screening of rice grain samples, they employed chemometric methods including principal component analysis, partial least squares discriminant analysis(PLSDA), genetic algorithm, support vector machine, and backpropagation neural network. The experiment's dataset included 150 rice specimens with varying percentages of contaminated rice. The researchers used pattern recognition algorithms and terahertz spectroscopy to detect adulterated rice. The support vector machine method, combined with the first derivative pretreatment, yielded the highest accuracy in distinguishing adulterated rice. This non-destructive and fast method offers precise results. However, it is important to note that the equipment and expertise required for this method may not be readily accessible in all settings.

The authors of this study developed a vision-based system that addresses the time-consuming process of manually evaluating rice quality. By analyzing the weight ratios of each kind, their suggested automated method can categorize various types of defective rice kernels and evaluate their quality.The suggested multi-stage workflow begins with a detection and separation approach of rice kernels with varied flaws, followed by a weight-per-pixel metric for estimating weight ratios of each type of kernel. X. Wang [5] conducted experiments using a dataset of 322 rice pictures, which were shuffled randomly and classified into training data, validation data, and test data for 5 times. They compared their model with other models, including Yolov5, EfficientDet-D2, and DynamicHead+Resnet50+ATSS.The experimental setup included a block diagram and an architecture diagram. The authors found that their proposed system outperformed other models in terms of classification accuracy and weight estimation. The merits of the proposed method include its ability to accurately classify and evaluate the quality of rice kernels, while the limitations include the requirement for high quality.

M.J. Asif [6] To categorize various kinds of rice and assess its quality, an image-processing approach was presented. To accomplish classification, the method used principal component analysis with canny edge detection. To validate the system, 100 images were captured for each of the following rice varieties: Super Colonel, Khushboo, Basmati, Kainat Sailla, and Old Awami. The results showed that this simple and portable system is both efficient and effective in analysing rice grain quality and distinguishing between different varieties. However, it's worth noting that the experiment only tested five varieties of rice grains. To further enhance the efficiency of the proposed system, implementing algorithms such as General Hough transform (GHT) could be explored.

In a study led by Y. N. Wan [7], the goal was to create an automated machine vision system for examining rice quality. The objective was to accurately categorize rice kernels based on their visual appearance. To achieve this, the researchers presented range selection sorting, which they integrated with tabular list boxes in a user-friendly windows graphical user interface (GUI). This approach aimed to make grain quality inspection more convenient and accessible.

To identify each rice kernel from its backdrop, the system used a variety of image processing techniques, including histogram and threshold approaches. The studies were carried out by utilizing 67 different kinds of rough rice (paddy) obtained directly from local farmers throughout the harvest season. For testing purposes, the rice was repeatedly placed in a humid environment to cause cracked kernels. Impressively, the system achieved an average processing speed of over 1200 kernels per minute for online rice quality inspection. The proposed method offers several advantages, including exceptional accuracy, quick processing speed, and convenient grain quality inspection. However, there are a few limitations to consider. Firstly, the method requires specific software for rice quality inspection. Additionally, consistent results can only be achieved in a controlled environment.

C. Kurade [8] presented a cost-effective and automated system for evaluating the quality of rice using image processing techniques and machine learning algorithms. The author extracted structural and geometric data from 3081 photos of 8 distinct rice grain kinds using a Raspberry Pi-based image collecting module. Using the Watershed technique, the images were processed, and a variety of characteristics based on geometry, size, morphology, color, and roughness were extracted. To classify the rice types, eight machine learning models were employed, and their efficiency was assessed in terms of F1 score, recall, accuracy, and precision.

Among the various algorithms tested, the Random Forest (RF) classifier had the best performance, achieving an accuracy of 76% (F1-score). The authors suggested that incorporating training on various deep learning models like Efficient Net, Inception V3, Res Net, and Mobile Net could potentially enhance the current accuracy. An advantageous aspect of this proposed method is its low cost, portable nature which can be easily implement with a setup cost of USD 50 only. However, it's important to note some limitations of the method such as the requirement for including samples of the same rice varieties grown in different regions and years within the sample pool. Samples from types that are comparable but subjected to various seasonal or environmental conditions should also be taken into account.

The quality of alloy materials heavily relies on the shape, size, and color of their grains. Mingchun Li [9] introduced a GF-RCF network that utilizes multi-level loss from feature to effectively detect grain boundaries in metallographic images of Al-Mg-Si alloy. One notable benefit of this method is its ability to accurately identify grain boundaries even when they are not clearly visible, there-by enhancing the accuracy of grain size evaluation and reducing the time and cost needed for manual annotation. It is important to remember that this approach has certain limitations, such as its dependence on the image quality inputted into the network and the requirement for a significant amount of annotated data for training purposes. Despite these limitations, the propose-d method holds promise in improving the overall grain quality in alloy materials by offering an efficient and precise means of detecting grain boundaries.

Y. Teng [10], The goal of this paper was to examine the decision and actions of government entities, farmers, and consumers in regard to agricultural product quality and safety. To analyse this, an evolutionary game theory model was developed, simulating interactions among these three groups and studying ideal scenarios for government safety supervision, farmers use of green pesticides, and consumers purchase of safe agricultural products. The experiment utilized MATLAB simulation software with varying initial proportions and parameter changes to observe the evolution process and outcomes. The findings highlight the crucial role played by the government in promoting the safe production of agricultural goods and fostering collaboration across multiple departments. This proposed approach offers a valuable theoretical frame work for understanding how different stake holders in the agricultural sector make decisions. To conduct the experiment, we utilized MATLAB simulation software. We manipulated the initial proportions and related parameters to observe how the process and outcome evolved. Our findings indicate that government intervention is pivotal in promoting safe agricultural product manufacturing and fostering collaboration among various departments. This proposed method offers a valuable theoretical framework for comprehending the decision-making processes of diverse stakeholders within the agricultural sector. However, it's essential to acknowledge that our approach has limitations, such as oversimplifying real world complexities, which warrants further empirical validation.

Chengcheng lei [11] This study focuses at the regional and temporal patterns of grain production in China, as well as the effect caused by various factors on total and per capita output. Furthermore, it investigates the factors behind China's grain production for different types of growth orientations. The paper briefly mentions the production of high quality grain with geographical indications in certain regions of China. However, its primary research question does not specifically address grain quality. Instead, the paper provides valuable insights into the spatial temporal pattern of grain production.

According to Zhengjun Qiu and colleagues [12], they aimed to improve the identification of rice seed varieties by combining hyperspectral imaging with convolutional neural networks. Their deep learning algorithm identified seed variety within two spectral regions using complete spectra. The experiment involved a dataset of 10,000 rice seed images, which were split into training, validation, and testing sets. The authors compared the results of their deep learning approach with support vector machine (SVM) analysis and k-nearest neighbours (KNN) methods. The researchers discovered that the deep learning approach showed superior performance compared to the other two methods, particularly when more training samples were used. They also highlighted the advantages of their proposed method, such as its ability to automatically learn features and its potential for exploring various feature combinations with additional training data. They acknowledged that the need for a sizable quantity of training data and the possibility of overfitting are only the drawbacks of the method.

Yan Wang [13] utilized a technique called inductively coupled plasma mass spectrometry with tandem mass spectrometry (ICP-MS/MS) to develop a method for tracing the origin of rice. They employed multielement principal component analysis to analyse the element composition of rice samples from different sources. By using an algorithm that involved principal component analysis and cluster analysis, they were able to determine the origin of the rice samples. The suggested technique's benefits include its accuracy in classifying rice samples according to their site of production, while its drawbacks include the necessity for additional validation and process optimization.

Lin Lu [14] aimed to address the challenge of ongoing analysis and monitoring of quality of rice in Southern China. Their suggestion was to use principle component analysis (PCA) to make the data less dimensional while preserving the most important details. Various rice quality indices, including amylose content, translucency, alkali spreading value, brown rice yield, cracked rice, grain length, length width ratio, and chalkiness, roughness, size, eccentricity, were used in the experiment. Through their research, the authors discovered that PCA was effective in differentiating the local quality of Southern rice and provided insightful information regarding the overall quality indices for this region's rice One advantage of the method is its ability to reduce data size while preserving relevant information. However, it has some drawbacks, such as requiring a large dataset and the risk of losing data during the dimension reduction process.

To tackle the problem of microbial contamination in rice, Ji Hae Lee [15] conducted a study to evaluate- the effectiveness of using high hydrostatic pressure and atmospheric pressure plasma. The researchers proposed an experimental approach where they subjected rice samples to these treatments and assessed their physicochemical properties and levels of microbial contamination. To measure the pH and sugar content, they utilized high performance liquid chromatography and a pH meter respectively. The study's conclusions demonstrated that microbial contamination in rice could be reduced by both atmospheric pressure plasma treatments and high hydrostatic pressure, with atmospheric pressure plasma being more successful than high hydrostatic pressure.

"Multivariate Analysis of Phenotypic Diversity of Rice (Oryza sativa L.) Landraces from Lamjung and Tanahun Districts, Nepal" in this paper Anup Dhakal [16] The goal of the study was to increase the phenotypic variety of rice landraces in the Lamjung and Tanahun Districts of Nepal by finding suitable parents for hybridization. To determine which traits were most important and guide the selection of parents for transgressive segregation, researchers utilized multivariate analysis techniques like principal component analysis and Mahalanobis distance. They used an alpha lattice designwith two different replications to collect data on 13 quantitative features from 30 rice landraces. Five major main components, notably those connected to yield, yield-related variables, and rice characteristics (PC1), were shown to have a substantial impact on the variance. This approach effectively identifies potential parent combinations for hybridization and helps choose desirable landraces for breeding programs. However, further validation and testing are necessary with a larger sample size under different environmental conditions.

Shakeel Ahmed Soomro [17] In a study titled "Mathematical modelling and optimisation of low-temperature drying on quality aspects of rough rice" researchers explored the challenge of maintaining the quality attributes of rough rice during the drying process. They examined how temperature, duration, and velocity influenced hardness, head rice yield (HRY), lightness, and cooking time using response surface methods with a central composite design (CCD). The experiments involved using a low-temperature dryer to dry rough rice at various temperatures and durations. The results demonstrated that low-temperature drying significantly impacted the quality attributes of rough rice. The optimal conditions for low-temperature drying were found to be a temperature of 40°C, a duration of 6 hours, and an air velocity of 0.5 m/s. The research says, drying rice at moderate temperatures can be a good way of retaining the quality of the grain while it's being dried.

By employing grain appearance and milling yields as variables, Pedro Sousa Sampaio [18] sought to evaluate the prediction power of artificial neural networks (ANN) and multiple linear regression (MLR) in identifying rice biochemical components and pasting parameters and it is also says all the following details about samples collection of rice.

In a study titled "Use of Artificial Neural Network Model for Rice Quality Prediction Based on Grain Physical Parameters," the authors examined 66 rice samples from the "Portuguese Rice Breeding Program". They found that the ANN algorithms, which were developed using grain physical data to predict rice biochemical and pasting characteristics, had substantial regression coefficients. These findings have the potential to enhance rice quality during breeding and processing, because they make it possible to precisely measure the many physicochemical properties of rice.

The goal of Koan Sik Woo's [19] investigation was to ascertain how best to prepare rice/adzuki bean mixes and their antioxidant content. They recommended setting up the experiment to look at the qualitative characteristics and antioxidant activity of various combinations of rice and adzuki beans. The cultivars Vigna angularis var. Nipponensis cv. Arari and cv. Geomguseul and cv. Geomguseul rice were used in the experiments by the authors.The researchers analysed the polyphenol and flavonoid content of the mixtures, along with their water binding, waterswelling, water solubility, and viscosity properties. They discovered that including adzuki beans increased the overall levels of polyphenols and flavonoids. Additionally, using a high pressure rice cooker method produced mixtures with higher antioxidant activities and superior quality characteristics. Hence, further investigation is indispensable to ascertain whether these discoveries can be universally extrapolated to encompass other assortments of beans and diverse geographical regions.

In the rice grain filling stage, Jae-Ryoung Park [20] describes the screening and identification of genes that impact grain quality and sales of grains. In addition to gaining knowledge about how climate change affects rice production and grain quality, the scientists sought to find genes linked to spikelet fertility and rice quality at high temperatures. They identified potential genes for amylose production and breakdown using quantitative trait locus mapping on a double haploid line. The researchers discovered that the manifestation of these genes exhibited a correlation with attributes of grain quality, including the content of amylose, the consistency of gel, and the length of the grain. The suggested approach has various advantages, including the use of a double haploid line for genetic study and the discovery of potential genes linked to spikelet fertility and grain quality at high temperatures. However, a constraint arises as the research was executed within the confines of controlled experimental circumstances and might not entirely embody the intricacy of natural surroundings.

Zhyldyzai Ozbekova [21] set out to research the ability of fluorescence spectroscopy in order to promptly and non-destructively detect the moisture content and water activity of rice. Researchers conducted a study on the potential of fluorescence spectroscopy in order to expeditiously and non-invasively assess the moisture content. They used principal component analysis (PCA) and partial least discriminant analysis (PLSDA) to analyse differences in fluorescence spectra and divide rice spicemens based on their moisture content and place of cultivation. In order to standardize the fluorescence spectra, a distinct algorithm was formulated utilizing the programming language MatLab.

The experimental procedure comprised the examination of diverse rice samples possessing varying levels of moisture and originating from distinct cultivation sites, employing a fluorescence spectrophotometer. The findings demonstrated that the utilization of fluorescence spectroscopy in conjunction with multivariate analysis possesses the capability to effectively forecast the moisture content and water activity of rice, alongside the capacity to classify various classifications of rice.

3.RESULT ANALYSIS

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

After reviewing numerous papers, we discovered that various algorithms had been proposed, and different models had been utilized with varying parameters. To the best of our knowledge, we conducted a comparative analysis of these different parameters and compiled the results into the following table:

Table-2: Performance evaluation of rice grain quality analysis on several 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, 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 extent, Shape	RF LR DT SVM	77.00 73.80 67.60 77.35
[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	80.6 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, Width, Aspect ratio, Spatial extent	SM with CCD	73.93
[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.

4.CHALLENGES AND GAPS

By studying above papers, it becomes evident that the challenges in rice grain quality analysis are multifaceted and often revolve around achieving full automation with a high degree of accuracy while considering various factors that influence rice quality. One fundamental difficulty resides in the pursuit of total mechanization, in which the entirety of the procedure, encompassing the compilation of data and the evaluation of excellence, necessitates a harmonious integration within a framework of machine learning. Addressing these challenges is crucial not solely to streamline the evaluation process of rice quality, but also to augment the overall effectiveness and productivity of the rice production and processing sectors.

5.CONCLUSION

This survey paper has shed light on the existing models employed for rice grain quality analysis. By illuminating the current models used for analysing rice grain quality, this survey paper has highlighted their contributions and drawbacks. These limitations include a restricted focus on particular parameters and a decreased level of precision. Thus, it is imperative that we modify the current approaches to overcome these challenges. Our aim is to create a pioneering model that not only resolves the deficiencies of previous techniques but also provides a more inclusive and precise evaluation of rice grain quality. Our aspiration is to provide a significant contribution to improving the methodologies used to assess rice grain quality. We're doing this by integrating a wider range of parameters and advanced techniques, which will revolutionize the field. Our proposed model ensures reliable and robust results for researchers and stakeholders alike.

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