

Received September 29, 2021, accepted November 18, 2021, date of publication November 23, 2021, date of current version December 10, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3130472

# On the Frontiers of Rice Grain Analysis, Classification and Quality Grading: A Review

SHEIKH BILAL AHMED, SYED FAROOQ ALI<sup>1</sup>, AND AADIL ZIA KHAN

Department of Software Engineering, SST, University of Management and Technology, Lahore 54782, Pakistan

Corresponding author: Syed Farooq Ali (farooq.ali@umt.edu.pk)

**ABSTRACT** Rice is a high valued subsistence crop that feeds more than 3.5 billion of the world population. Its importance can be gauged from the fact that the top five rice exporting countries had a combined net export worth of around 19 billion dollars in 2018. A robust rice grain analysis and classification system can significantly improve performance both in terms of accuracy as well as time. In recent decades, this research area has garnered a lot of attention due to its socio-economic impact. In this paper, we reviewed the work done in image-based rice classification and gradation. The contribution of this study is three-fold. First, it divides the algorithms and techniques of this area into five different approaches namely; geometric, statistical, supervised, unsupervised, and deep learning. Among these, deep learning techniques have shown more promising results and gained attention for future research. Secondly, it divides the rice grain literature historically into three different eras. Thirdly, it summarizes various algorithms and techniques related to rice quality grading and rice disease identification.

**INDEX TERMS** Machine learning, morphological features, quality grading, rice diseases, rice grain.

## I. INTRODUCTION

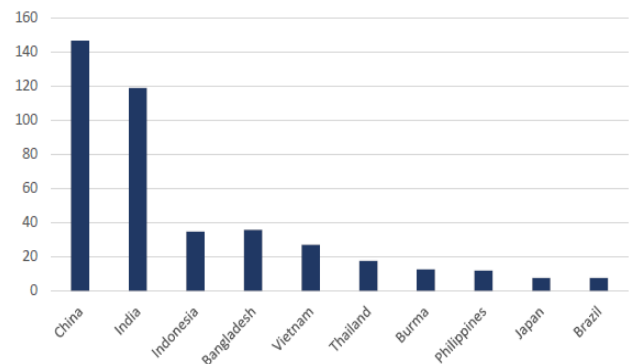
Rice is an important staple food that is harvested from an area spanning 163 million hectares in more than 100 countries to meet the food requirements of around 3.5 billion people worldwide [1], [2]. It is the third highest cultivated product after maize and sugarcane [3]. Rice is cultivated in several areas; with a predominant presence in China, and south and east Asia regions [4]. Moreover, the top five rice exporting countries had a combined export upwards of 19 billion dollars in 2018.<sup>1</sup> The revenue generation,<sup>2</sup> and yield<sup>3</sup> of the top ten rice producing countries is shown in Figures 1 and Figure 2 respectively. For around 520 million people living below the poverty line in Asia, rice meets up to 50% of the dietary caloric requirements. Over the years, rice cultivation has evolved significantly, becoming a primary source of income for around 200 million households across the developing world. Factors such as low cost, easy and quick preparation, and long shelf-life have contributed to its high popularity [5].

The associate editor coordinating the review of this manuscript and approving it for publication was Siddhartha Bhattacharyya<sup>1</sup>.

<sup>1</sup><http://www.worldstopexports.com/rice-exports-country/>

<sup>2</sup><https://www.statista.com/outlook/40060200/121/rice/japan>

<sup>3</sup><https://www.statista.com/statistics/255945/top-countries-of-destination-for-us-rice-exports-2011/>



**FIGURE 1.** Total revenue (in million USD) of top 10 rice producing countries.

While rice has seen an exponential increase in demand, the supply, however, has failed to keep up [6].

Quality of the rice grain is determined by various morphological features such as shape, length, and area, as well as textural features such as chalkiness, and RGB color values [7]. Bulk density is affected by grain shape: the more slender the grain, the more the porosity and less the bulk density [8]. These features are predominantly measured manually in the developing regions. The process is both time consuming as



FIGURE 2. Top 10 rice producing countries in the world. Facts and figures are taken from Statista.

well as error prone and subjective [9]. Hence, there is a need for the development of automated approaches for rice grain analysis, classification, and quality grading [10], [11].

Digital imaging is recognized as a productive technique to automate the process of extracting features from rice grains without physical contact and human intervention [12]. In most of the proposed classifiers, machine vision is used to differentiate between rice varieties based on morphological features such as length, width, area, shape, chalkiness, color, and internal damage of rice [13]. These classifiers achieve their objectives using techniques like RGB color model, histogram, and edge detection [14]. In addition to that, the proposed techniques also help to identify several impurities, such as stones, weed seeds, chaff, and damaged seeds, thereby improving quality of the product sold in the market.

Rice grain analysis, classification, and grading (RGACG) has gained a lot of attention in recent years for datasets generated in a controlled environment. However, the problem seems unresolved for more realistic datasets that include non-uniform lighting, camouflaged grains, and occlusion among rice grains [15]–[17]. Therefore, it becomes crucial to explore the full potential of rice classification, grading and disease classification for real world scenarios [18]–[22].

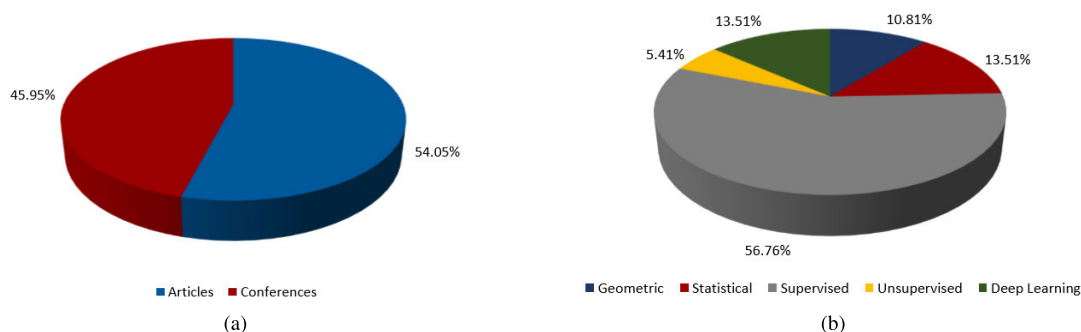
Much work has been done on RGACG in the last two decades. Yet, it becomes difficult to have its comprehensive view unless it has been properly classified approach-wise, citation-wise, and technology-wise. This study also provides the temporal view of the research literature by diving it into three eras, that will help to develop an intuition about the topic and related research challenges and also observe the direction in which the research community is headed.

Fig. 3a gives a breakdown of all the papers that we have reviewed by the publication type, namely; conference or

journal. It further classifies the reviewed papers based on the techniques used by the respective authors. These can broadly be classified into geometric, statistical, supervised, unsupervised, and deep learning based methods. Rest of the paper is organized as follows. In section 3 and 4, we give a detailed survey of the rice classification and grading techniques respectively. We also provide comprehensive literature review on the identification of rice diseases, pests and foreign particles in section 5.

**A. ABBREVIATIONS AND ACRONYMS**

- ANFIS Adaptive Neuro-Fuzzy Inference System.
- CCD Charged Coupled Device.
- CNN Convolutional Neural Network.
- DWT Discrete Wavelet Transform.
- FCM Fuzzy C-means.
- GLCM Grey Level Co-occurrence Matrix.
- HOG Histograms of Oriented Gradient.
- HSI Hue, Saturation and Intensity.
- ISEF Infinite Symmetric Exponential Filter.
- LVQ Learning Vector Quantization.
- MSC Multiplicative Signal Correction.
- NB Naive Bayesian.
- NIR Near Infrared Radiation.
- PCA Principal Component Analysis.
- PNN Probabilistic Neural Network.
- ROI Region Of Interest.
- SNV Standard Normal Variate.
- SRC Sparse Representation Classification.
- UCI University of California, Irvine.
- VGG Visual Geometry Group.



**FIGURE 3. Statistical analysis of research papers a) Distribution of various research publications into conferences and journals b) Distribution of various research publication into different approaches.**

## II. RESEARCH METHODOLOGY

Following are the research questions that guided our study.

RQ1: What are the types of approaches proposed by research community for rice classification?

RQ2: What is the research trend followed by research community chronologically?

RQ3: How automated grading approach presided over manual rice grading?

RQ4: What are the different algorithms and techniques available for automatic identification and classification of rice diseases?

## III. QUALITATIVE ANALYSIS

This study presents two different views for analyzing various research papers related to rice grain classification and grading. The former view classifies 107 research articles into various approaches including geometric, statistical, machine learning and deep learning. While the later highlights the research trends by dividing them into time based eras. Moreover, this study also discusses various algorithms and techniques for rice disease identification and classification.

### A. STAGE 1: SCREENING

We selected 211 articles, published after 1996, from various databases such as IEEE, Springer, Elsevier, ACM based on keywords (“Machine Learning”, “Rice Classification”, “Rice Grading”, “Rice Pests and Diseases” and “Rice Production”) and search criteria. The articles were then refined based on title and abstract. Those articles which complied with rice grain or rice disease classification were included in our study whereas the rest of the papers were excluded. At the end of screening process, 155 papers fulfilled the inclusion criteria.

### B. STAGE 2: ELIGIBILITY ANALYSIS

After shortlisting the papers, we reviewed them in detail to determine their suitability for inclusion in this work. For this purpose, we took into consideration the paper’s contribution to the field, novelty of the solution, and its relevance to rice and pest classification and identification. We identified those articles that were more concentrated on the nature of

approach and its impact on rice grains or their diseases. This further reduced the sample size to 115 papers, which was sufficient enough to culminate conclusions and inferences about the impact of different classification approaches implemented on rice grains or their diseases.

### C. STAGE 3: DATA EXTRACTION

The following information was summarized for each selected paper: (i) type of the algorithm (Geometric, Statistical, Supervised, Unsupervised and Deep Learning), (ii) research trends, (iii) pest and disease classification, and (iv) future works. This information was extracted, analyzed and presented in this manuscript to respond to each research objective.

## IV. APPROACHES OF RICE GRAIN ANALYSIS AND CLASSIFICATION

**Research objective 1:** *What are the types of approaches used for rice classification?*

Over the years, researchers have explored different solutions for rice grain analysis and their classification. These approaches can broadly be classified into geometric, statistical, and learning based approaches including unsupervised (such as k-means, k-NN) as well as supervised (such as neural networks, support vector machines, and more recently deep learning). As seen in Figure 3b, the supervised approach contributed maximum share among all the approaches. The use of handcrafted spatial features in combination with various classifiers helped the supervised approaches to achieve better results. The recent evolution of deep learning can also be observed in this Figure.

### A. GEOMETRIC APPROACHES

Geometric approaches consider the key features of rice grain morphology like compactness, length, and ratios of major and minor axes, slenderness and spread computed on the binary image, for grain classification. Ajay et al. in 2013 presented a quality evaluation method for milled rice [23]. Filtering was first applied to the input rice image in order to remove noise. This was followed by image segmentation to separate connected objects for extracting shape and texture based

features. Minimum rectangular method was then applied to the resultant image to determine the quality of rice grains.

In 1996, Sakai *et al.* presented a rice classification algorithm using image processing [24]. The scanned rice image underwent preprocessing operations including thresholding, smoothing, labeling, searching contours, and filling holes. After that, geometric features including area, maximum length and width, compactness, and elongation of the rice were extracted. Based on these features, the image was classified into brown and polished rice with 95.4% accuracy.

Asif *et al.* introduced PCA based rice grain classification and quality analysis algorithm [25]. Five different types of rice were considered: Super Colonel, Khushboo, Basmati, Kainat, Sella, and Old Awami. Six colored images of different rice varieties were captured with black background from which noise was removed. Canny edge detection and segmentation were applied to these images after binarizing them. Five morphological features were then extracted from these segmented images. PCA was used as a classifier to identify rice variety which resulted in an accuracy of 92.3%.

Vu *et al.* presented a rice variety inspection method using geometrical and morphological features [26]. The rice image, containing 48 rice seeds, underwent a segmentation, followed by seed normalization process. Once the seeds were normalized, morphological and geometrical features were extracted. These features were used with Adaboost classifier which outperformed other classifiers including DT and RF. The geometric features were also used in combination with statistical and learning based approaches specifically deep learning that are also discussed in Sections IV-B and IV-C respectively.

## B. STATISTICAL APPROACHES

Statistical approaches primarily focus on summarizing the data and making inferences regarding the population. The authors in [27] proposed a method for assessing Indian Basmati rice quality. They applied ISEF edge detection algorithm [28], an advanced form of the Canny edge detection algorithm [29], to a greyscale image and extracted geometric parameters including area, major and minor axes lengths, and eccentricity. A histogram was created corresponding to each parameter. The parameter values of rice samples were then compared with the histograms and the rice quality was classified.

In 2014, [18] proposed a rice quality estimation system based on geometric and color features. For the input rice image, the contrast was enhanced and edge detection was then applied. Furthermore, red, green, and blue values of the resultant rice image were extracted and their corresponding histograms were developed. The histogram with maximum readings was used as an appropriate light filter for classification of the rice sample. Along similar lines, [30] proposed a visual framework to classify the varieties of rice seeds using various features including color, size, and shape. Moreover, their framework also distinguished between sticky rice grains and the non-sticky variety using RGB color model and its histogram.

Another method for quality assessment of Indian Basmati rice grains was presented in [31] in which authors applied morphological closing and opening operations [32] to a greyscale image, followed by a top-hat transformation [33]. In doing so, the resultant image was segmented from which major and minor axes lengths of the rice grains were computed and added to their corresponding histograms. The proposed algorithm then classified the rice grains into small, medium, and large. In 2015, [5] proposed an algorithm to classify rice grains using NIR spectroscopy based on starch content. Starch is one of the main components found in rice grains. Three different rice samples (boiled, brown, and raw) were selected and placed in a spectrometer. Ten different reflectance spectra of each rice sample were obtained at a wavelength range of 400-2500 nm. Those spectra were further pushed in for pre-processing techniques, MSC and SNV. PCA with MSC and SNV was repeatedly used until different rice samples were categorized clearly. Then, PCA was used further to classify each rice variety group.

## C. MACHINE LEARNING APPROACHES

Machine learning approach can be broadly classified into supervised, unsupervised, and deep learning [34].

### 1) UNSUPERVISED LEARNING

The unsupervised learning techniques do not require large datasets to train the classifier. These approaches rely on clustering to separate the data into different classes based on their similarities. One such technique for rice classification relying on clustering is presented in [16]. The authors captured two images of a rice sample consisting of eight different rice varieties. The images were then pre-processed with the removal of noise and lens distortion, thresholding, and edge detection techniques. Once the techniques were applied, reliable morphological features of various rice grains were acquired including average length, shape, and compactness ratio. Two dendrograms were developed for each captured image to show similarities of features between rice samples which helped in classifying short, medium, and long brown/white rice.

A PCA based approach for classification of various Basmati rice varieties was introduced in [35] which used KNN based clustering instead of a dendrogram. Rice image was preprocessed for noise removal and smoothing in order to enhance and clarify the input image. The image was then segmented followed by binarization. Once the stated operations were performed, morphological features such as area, major axis length, minor axis length, eccentricity, and perimeter were extracted. KNN was then used as a classifier to cluster the different rice grain varieties. Along similar lines, in [36], the authors devised a rice quality classification system that also used KNN clustering. Six different rice seeds were used for experimentation. The colored rice image was segmented and vital morphological, color, and textural features were extracted from the resultant image which was then given classified using KNN.



In 2016, Watanachaturaporn presented a symbolic regression method for rice identification [37]. Nine morphological and six color features were extracted from the colored Khao Dawk Mali (KDM) rice image. The symbolic regression model was created with Eureqa software [38] using extracted features. These features were added in Equation 1 to calculate the number of KDM rice grains correctly. *MinorAxisLength*, *IntegratedDensity* and *Area* denoted features from rice image respectively.

$$KDM = \logistic(13.38 \times 10^6 \times (MinorAxisLength) \times (IntegratedDensity) - 4008.40 \times 10^9 \times Area) \quad (1)$$

## 2) SUPERVISED LEARNING

In [15], the authors proposed a new approach based on two-layer tan-sigmoid/log-sigmoid neural network [39] for rice seed identification. Various morphological features including area of the seed, seed boundary, bounding box around seed, width, major and minor axes length, thinness ratio, aspect ratio, rectangular aspect ratio, equivalent diameter, filled area, area under major axis of the ellipse, convex area, solidity, and extent were acquired from rice image. In addition to that, various color features including red color band, green color band, blue color band, hue, saturation, intensity, and standard deviation of hue were also extracted. Out of these features, 4 principal components were extracted using PCA to perform dimensionality reduction. These features were used along with neural network for rice seeds classification.

An automatic quality evaluation framework for rice kernels was introduced in [17]. The pre-processing of input rice image was done using background segmentation and color blob extraction [17]. Then, the resultant image was utilized for feature extraction process. The process included the extraction of geometric features of rice via shape descriptor, and acquiring image statistics in RGB and CieLab format [40]. PNN classifier was trained and later utilized for classification. In the same year, an approach was presented for distinguishing rice grains and their quality using pattern classification [41]. The rice grain image was pre-processed using image enhancement techniques. The resultant image was then segmented before the final feature extraction. Under this process, color, textural, and morphological features were extracted. These features along with feed-forward neural network were used for rice grain classification and its quality recognition.

In 2010, Verma proposed an approach for rice grain identification in which rice image, obtained from a flatbed scanner, was pre-processed with several image smoothing operations [42]. Once the operations were performed, the average length, width, and perimeter of the rice grains were extracted and used with the neural network for classification.

The authors of [43] proposed a BPNN based rice classification algorithm using color and texture features. The rice image, obtained from a flatbed scanner, underwent

a background segmentation process. From the resultant image, a total of 60 color and texture features were extracted. These features were passed to four feature selection algorithms, Branch and Bound [44], Standard Forward Sequential [45], Standard Backward Sequential [45] and Plus-1-takeaway-r [46] to acquire 22 optimized morphological feature set that was later used in building BPNN model. Once the BPNN was built, it was evaluated with the test data, resulting in an average of 96.67% accuracy. Similarly, the authors proposed another rice kernel classification algorithm using optimal morphological features and BPNN [47]. The rice image, containing 300 kernels, was acquired from the flatbed scanner using a black background. It was then pre-processed with background segmentation to extract the rice objects. For each rice object, 18 morphological features were extracted. Similar to their previous work, these features were passed to four feature selection algorithms, branch and bound, standard forward sequential, standard backward sequential and plus-1-takeaway-r to acquire six optimized morphological feature set which were later used in building BPNN model. Thus, BPNN was evaluated with the test data, attaining 98.4%. Wenwen *et al.* presented a rice seed identification method using hyperspectral imaging and multivariate data analysis [48]. The hyperspectral images were obtained from a laboratory based imaging system and from those images, spectral data, ranging between 1039 nm to 1612 nm was extracted. The extracted data was then used to build KNN, SVM, RF, PLS-DA, and SIMCA classification models. When the stated models were evaluated, RF performed better classification than others.

In the same year, a NN based approach was presented by Silva and Sonnadara for classification of rice grains [49]. In this approach, the input rice image was pre-processed with several operations: Gaussian filter, morphological opening, contrast stretching, dilation, and erosion. As a result, a unique binary image was produced, containing distinct rice grains' representation. From this image, a total of 34 features (13 morphological, 6 color, and 15 textural) were acquired. PCA was applied to perform dimensionality reduction. As a first step, an individual neural network was created for each feature set, and later the combination of feature set model was implemented yielding an overall classification accuracy of 92% on a dataset which included grain samples from nine rice varieties grown in Sri Lanka.

In 2014, Pazoki *et al.* proposed an approach that extracted 24 color, 11 morphological, and 4 shape features. These features were fed to the neuro-fuzzy network [50] and MLP, attaining accuracy of 99.73% and 99.46% respectively [51]. Singh and Chaudhary presented an efficient technique for the classification of rice grains using BPNN and wavelet decomposition [52]. A total of 45 features (texture, wavelet, and color) were acquired from the rice image. Those features were then given to BPNN. Once the training phase was complete, BPNN was evaluated with test data and according to the study, it classified rice varieties with an accuracy rate of more than 96%. In the same year,

Kuo *et al.* presented a sparse-representation classification (SRC) method using an image processing technique [3]. In this method, the input image was acquired under a controlled lab environment with static lighting conditions. After background segmentation, 9 color, 12 morphological, 7 textural, and 20 Fourier features were acquired. These features were given to SRC classifier. Once the classifier was trained, it was then evaluated on a set of test rice images that classified rice variety with 89.1% accuracy.

It has been observed that occluded and overlapping rice kernels adversely affect classifier accuracy. In [53], this problem was addressed by the use of contour detection and Watershed algorithm [54]. They developed a rice segmentation and classification system based on color and texture features using SVM, achieving an accuracy of 88%. The color and texture features were computed using LBP. In the same year, the authors of [55] introduced a heuristic feature based guided machine vision approach for rice variety classification. Each rice image was converted to grayscale, before applying noise reduction and binarization operations. For detecting edges, the Canny algorithm [56] was applied. Once the pre-processing phase was complete, 10 morphological and 13 color features were extracted. These features along with training data were fed to the ANN model. Once the model was trained, it was evaluated with features from test rice images. In doing so, it classified rice variety with an accuracy rate of 82.21%.

In 2019, Srimulyani and Musdholifah conducted a comparative study which observed that a rice identification system using BPNN outperformed LVQ based approach [57]. In the pre-processing phase, the image segmentation using thresholding and contour tracking was performed. Six color, two texture, and four shape features were obtained from the segmented rice image. These features were fed into both BPNN and LVQ for training and testing. In 2019, Ibrahim *et al.* proposed an approach using morphological and HSV features. These were then fed to a multi-class SVM for rice grain classification [58]. The pre-processing phase consisted of applying Roberts segmentation [59]. Another BPNN based classification method was proposed which predicted rice quality using electronic tongue [60]. The characteristic current and potential arrays were obtained from rice sample which were then converted to peak current and potential phasor plane values as main features. These features were used to train tandem BPNN model. Once the model was trained, it was then evaluated with the extracted features of test rice samples yielding 90% accuracy.

Duong and Hoang presented a rice variety recognition approach based on feature selection [61]. In this approach, the rice image was coded in 8 different color spaces (RGB, HSV,  $I_1I_2I_3$ , Luv,  $YC_bC_r$ , YUV, YIQ). For each coded rice image, histograms oriented gradient (HOG) [62] descriptors were applied to extract different features. Fisher's Scoring [63], a supervised feature selection algorithm, was then applied to each random set of coded features to calculate their score and rank accordingly yielding an accuracy of 93.34%.

This approach helped in reducing dimensions and running time while performing recognition process.

In 2020, the authors presented a feature based cascade network for the classification of rice grains which achieved an accuracy of 97.75% on the UCI dataset [64], [65]. These features included 11 morphological, 18 color, 27 texture, and 24 wavelet while the pre-processing was performed after the conversion of RGB rice image to HSV as the hue channel performed better discrimination between rice kernel and background. The proposed network consisted of four outputs and two hidden layers. Hidden nodes were computed based on the Equation 2. The authors of [66] proposed a rice seeds classification system using spectral and spatial features. The rice image was captured by RGB camera and hyperspectral imaging (HSI) camera. The input images, including RGB and hyperspectral, were normalized using lens distortion and planar calibration techniques. The spatial features (Area, Major Axis Length, Minor Axis Length, Aspect Ratio, Perimeter over Area Ratio and Eccentricity) were extracted from RGB images whereas spectral features were obtained from HSI image. These features were used with Random Forest and classified rice seeds with a test accuracy of 78.8%.

$$N = \frac{I - O}{2} + Y^{0.5} \quad (2)$$

where N, I, O and Y denote number of hidden nodes, input nodes, output nodes and number of training data respectively.

### 3) DEEP LEARNING

In 2017, Patel *et al.* proposed two approaches based on CNN [67] for rice grain classification, one with transfer learning [68] and one without it [69]. Transfer learning consists of CNN models pre-trained from some other related dataset. It is used when datasets of one domain are not sufficiently large to accurately create a model. After pre-processing, 4000 training images were used to train both the CNNs while the testing was performed using 1000 images. It was observed that employing CNN with transfer learning outperformed the other approach. In [70], a rice identification model was introduced using CNN which resulted in 99.52% accuracy. The pre-processing was done with image enhancement operations.

The authors of [71] proposed a rice variety classification system based on the combination of hyperspectral imaging with CNN. The rice image was captured from a visible near-infrared hyperspectral imaging system. The acquired image was corrected and pre-processed with a wavelet transform and image segmentation process. Images with a spectral range of 441-949 nm and 975-1646 nm were selected for training and testing phases. 100-3000 rice samples of every rice variety were used to train SVM, KNN, and CNN whereas a total of 8907 rice seeds were used testing purpose. It showed that CNN classified rice varieties with rice variety with better accuracy than KNN and SVM.

Chatnuntaweck *et al.* developed a mixed rice variety inspection system which classified them using a

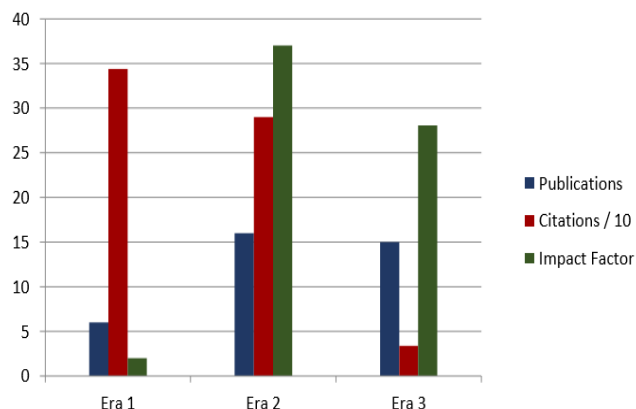
spatio-spectral deep convolutional neural network [72]. A near-infrared hyperspectral imaging system was utilized to obtain spatial and spectral data of the rice sample. The former is based on visual appearance while the latter corresponds to chemical properties. These spatio-spectral data was also known as datacubes as it contained information of two spatial and one spectral dimension. These datacubes were then passed to a deep CNN known as Residual Network (ResNet) [73] that achieved an accuracy of 91.09%. To evaluate the proposed classifier, two different datasets were used; namely processed rice, and paddy rice. One drawback of the proposed approach is that it required the grains to have the same orientation in the image. Another DCNN architecture based rice variety detection system was presented in [74]. The main purpose of this system was to minimize human involvement while attaining maximum level of accuracy in rice variety classification. The colored rice image was first converted to grayscale, followed by segmentation of each rice kernel. It was then processed using simple scaling, mean subtraction and feature standardization to compute dimensionality of the rice kernel which was used to tune CNN network. Furthermore, stochastic gradient descent (SGD), with momentum 0.9 and decay 0.0005, was used to avoid back propagation error and enhance network parameters during training phase. Once the CNN framework was trained, it was employed with test dataset, resulting in 95.5% accuracy rate.

In 2019, the authors of [75] presented rice quality classification algorithm using CNN. Rice objects were detected from the rice image and were cropped according to whole or broken rice. The object was preprocessed with background subtraction operation to eliminate noise and error. Then the processed rice object was fed in to CNN, SVM, and KNN for training purpose. Once the models were trained, they were evaluated with the test data. It showed that CNN delivered better accuracy rates than SVM and KNN in predicting whole and broken rice. Another CNN based rice grain classification algorithm was proposed in [76]. In the algorithm, the rice images were preprocessed with cropping, scaling and auto-alignment operations. Then, marker-based Watershed algorithm [77] was applied to extract area and contour of each rice grain which were then used with ResNet-50 [73] model yielding an accuracy of 80%.

## V. CHRONICLES OF RICE GRAIN ANALYSIS TECHNIQUES: FROM BEGINNING TO DATE

**Research objective 2:** *What is the research trend followed by research community chronologically?*

In this section, we take a bird's eye view of different research trends in this area over the years. Based on the significance of research developments, the literature is divided into three different eras. Supervised approaches are mainly used in Era 1 while Era 2 added more approaches including statistical, unsupervised, and geometrical. Era 3, on the other hand, sees the advent of deep learning. As can be seen in Fig. 4,



**FIGURE 4.** Total number of publications, citations and their cumulative impact factor of Era 1, Era 2 and Era 3.

Era 1 has maximum citations<sup>4</sup> while number of publications and impact factor<sup>5</sup> are highest in Era 2.

### A. ERA 1 (1996-2010)

This Era laid the foundation of algorithms and techniques for rice grain classification. Since this was a time when research on rice classification took root, the immediate goal of the researchers was to improve classification accuracy, even if the running times of the proposed solutions were not optimal. Later eras emphasized on the efficiency of their proposed solutions as well. Table 1 provided an overview of the key papers published in this Era with various attributes, advantages, and limitations. It can be observed that accuracy as high as 94% was achieved using the Probabilistic Neural Network. In this Era, around 72% of the number of publications belonged to supervised learning as can be seen in Fig. 5a.

The authors of [24] presented a rice classification method achieving 95.4% accuracy rate. The method involved rice image being preprocessed with image enhancing operations. Once the image was enhanced, geometric features were extracted, and based upon them, rice image was classified. Liu *et al.* presented an algorithm in which rice seed varieties were identified using a neural network [15]. A total of 21 features including 7 color and 14 morphological ones were extracted from 240 rice kernels and fed to the neural network for training. Once the network was trained, 60 rice kernels were used for the testing phase, yielding an accuracy of 84.43%. The algorithm even performed well on rice grains with a high degree of similarity. Along similar lines, Hobson *et al.* proposed an unsupervised clustering technique for rice classification [16]. The clustering is done based on the morphological features of 8 different rice grains.

In 2008, Agustin and Oh proposed a histogram based quality evaluation framework for milled rice kernels [17]. The color histograms of RGB and Cielab<sup>6</sup> were used to acquire 24 color features of milled rice which were fed to

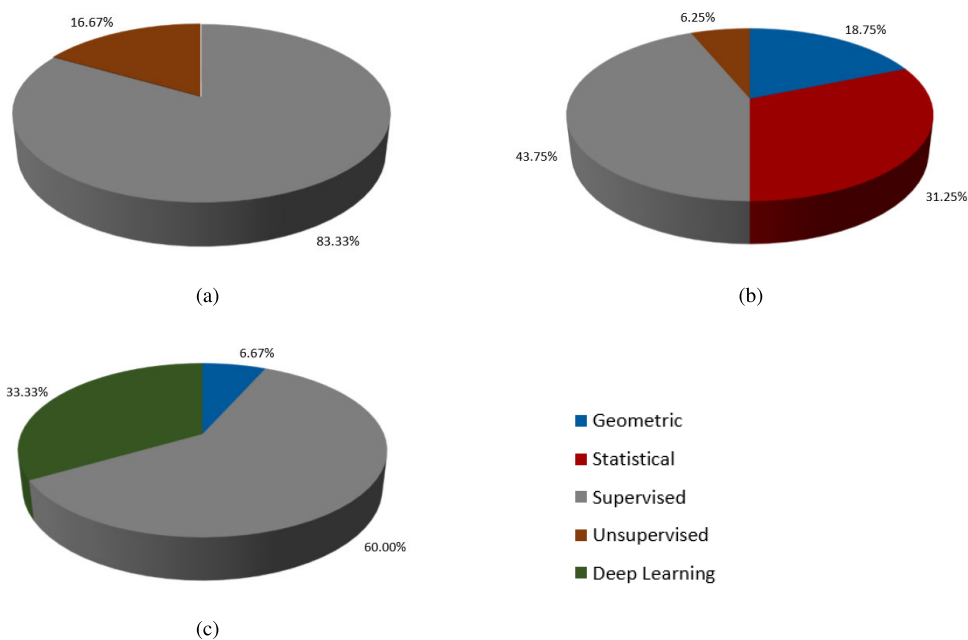
<sup>4</sup><https://libguides.usc.edu/writingguide/citingsources>

<sup>5</sup><https://researchguides.uic.edu/it/impact>

<sup>6</sup>[https://spie.org/publications/fg04\\_p71\\_cielab?SSO=1](https://spie.org/publications/fg04_p71_cielab?SSO=1)

**TABLE 1. Comparison framework of rice grain analysis techniques in Era 1.**

Study	Technique	Training data	Testing data	Accuracy (%)	Advantages	Limitations
[24]	Image Analysis	-	-	94.5	Combined shape and dimension features, better good accuracy	Brown and polished rice only
[15]	Feed forward neural network	240 kernels	60 kernels	84.83	Worked well for rice grains with high similarity	Identifies only six varieties, specific to Zhejiang province
[16]	Digital Image Analysis	-	8	-	Inexpensive hardware, better time efficiency	High resolution image degraded the performance
[17]	Probabilistic Neural Network	17,420	1161	94	Better accuracy results	Cielab color threshold value needed to be selected carefully
[41]	Neural Network	-	60	84.83	Orientation invariant approach	Identified six varieties specific to East-Central India
[42]	Neural Network	7500 - 10000 grains	-	90-95	Better accuracy at nominal cost	Required large data size for training neural network
[78]	Neural Network	280 images	80 grains	80.5	Good percentage accuracy for Premium and Quality-1 Samba rice	Required studio lighting setup, worked only for Samba rice



**FIGURE 5. Percentage distribution of various categories of approaches in a) Era 1 b) Era 2 and c) Era 3.**

Probabilistic Neural Network (PNN). PNN was trained with color features of 17,420 kernels and was tested with 1161 kernels yielding an accuracy of 94%. However, such accuracy rates were highly dependent on the selection of an appropriate Cielab threshold.

In 2010, Shantaiya and Ansari proposed feature based learning system for classification and quality estimation of rice grains [41]. These features which included 9 color and 9 morphological attributes were fed to neural network yielding an accuracy of 84.43%. Similarly, Verma proposed



**TABLE 2. Comparison framework of rice grain analysis techniques in Era 2.**

Study	Technique	Training data	Testing data	Accuracy (%)	Advantages	Limitations
[43]	BPNN	350 kernels	150 kernels	96.67	Better percentage accuracy	Required uniform lighting
[47]	BPNN	1050 kernels	450 kernels	98.40	Better accuracy	Identified one type of rice variety
[80]	Multi-class SVM	400 kernels	400 kernels	86	Low hardware cost	Graded four types of Basmati varieties
[18]	Transparent Image Analysis	-	300 Kernels	91	Delivered better colored rice seeds classification	Performed under laboratory settings
[51]	MLP and Neuro-Fuzzy	300 Grains	150 Grains	98.40 & 99.73	Better accuracy results	Identifies five Basmati rice varieties specific to Guilan and Mazandaran provinces
[35]	Image processing and PCA	-	260 Classic grains, 187 Rozana grains, 339 Mini grains	79	Worked effectively for samples containing less number of rice grain	Limited to Basmati rice only
[81]	SCG-NN	-	-	98.2	Better percentage accuracy	Limited to non-overlapping rice grains
[37]	Symbolic regression	-	3200	86.25	Performed better than PCA-based classification algorithms	Limited to rice varieties of Chachoengsao, Central Thailand
[52]	BPNN	-	400	96	Worked well in any environmental conditions	Classified four rice varieties
[3]	SRC	1350	150	89.1	Classified large number of rice species	Alike rice species degraded the performance

learning based system for the classification of rice grains [42]. The rice image, containing 500 rice kernels, was pre-processed and 10 different features were extracted out of it. Rice grains ranging from 7,500 to 10,000 were used to train the neural network yielding an accuracy of 90-95%.

Pabamalie and Premaratne proposed 21 texture and 10 color based features for the classification of milled rice [78]. These features were given to Neural Network achieving a test accuracy of 80.5% on a data split of 72% for training and 28% for testing. The data set consisted of 360 samples where each sample had an area of  $10 \times 7 \text{ cm}^2$  containing various rice grains. The limitation of this approach was the controlled testing environment having studio light settings.

### B. ERA 2 (2011-2016)

This era is characterized by the diversity of the proposed solutions. Even though supervised learning-based techniques still formed a major chunk, this era also saw novel rice classification proposals relying on unsupervised, geometric, and statistical approaches as shown in Fig.5b. Table 2 provides an overview of the key papers published in this era with various attributes, advantages, and limitations. This era saw an accuracy as high as 99% which was achieved using neuro-fuzzy based system [79].

Rad *et al.* presented a BPNN based classification algorithm [43]. 60 color and texture features were extracted from the segmented rice image and within this feature set, 22 features were used to train and evaluate BPNN. In this

study, features of 350 images were used to train BPNN whereas features of the remaining 150 images were utilized for the testing phase. BPNN classified the test data with an accuracy rate of 96.67%. Similar to their previous work, the same authors presented another rice kernel classification algorithm using optimal morphological features and BPNN, achieving 98.4% accuracy [47]. Here, 1050 kernels were used to train BPNN whereas 450 kernels were used as test data.

In 2013, Kaur and Singh proposed an automated method to classify rice kernels using multi-class SVM [80]. Smoothing, segmentation, and binarization operations were applied to the input rice image before extracting geometric features. The data set including 400 rice kernels was given to the neural network for training using these features. Another 400 kernels were then used for testing our model, which yielded an accuracy of 86%. In the same year, Silva and Sonnadara proposed another neural network based rice grain classification using 34 features [49]. These features, which consisted of 13 morphological, 6 color, and 15 textural ones, were given to a neural network achieving a testing accuracy of 92%. 315 images were used to train the model which was then tested using an additional 68 images. In the same period, Wenwen *et al.* proposed a rice seed cultivar classification system which used a near-infrared hyperspectral imaging technique together with multivariate data analysis [48].

In 2014, Auttawaitkul *et al.* developed a histogram based visual classification system for identifying rice seeds based

on their color and appearance features [18]. Three different color histograms were obtained from the RGB intensity values of the rice image, where each rice image contains several rice grains. The system was tested on a dataset of 300 rice images yielding an accuracy of 91% under a controlled laboratory environment. In the same year, Mahale and Korde introduced a semi-automatic approach based on the edge detection algorithm [82]. After extracting the rice boundaries, the manual measurement of rice length, breadth, and their ratio were made using Vernier Calipers and these were then used for classification.

Pazoki *et al.* introduced MLP and neuro-fuzzy based rice classification algorithm [51] using 39 features. These consisted of 24 color, 11 morphological and 4 shape features. The system was trained and tested using data image repositories of size 300 and 150 respectively. The model achieved accuracy as high as 99.73%. Kambo and Yerpude developed a morphological feature based classification system using k-NN and PCA [35]. The pre-processing was done using smoothing and segmentation techniques. The system achieved an accuracy of 79% on a diverse dataset, consisting of 260 Classic, 187 Rozana, and 339 Mini rice grains.

Mahajan and Kaur [31] proposed a histogram based rice grain classification system in which pre-processing was done using morphological opening and closing operations followed by top hat transformation [31]. Another rice grain classification method was proposed that used only morphological features along with SCG-NN achieving an accuracy of 98.2% [81]. The limitation of this approach included its inability to address occluded and overlapping rice grains.

Priya *et al.* used NIR spectroscopy followed by PCA for rice grain classification [5], [5]. NIR spectroscopy was used to classify rice samples based on the carbohydrate content and starch, present in the rice. It was computed on 250 grams of rice samples within the range of 1100 nm to 2200 nm. In the same year, Zareiforush *et al.* proposed a hybrid automatic system based on fuzzy logic for quality measurement of milled rice achieving an accuracy of 89.8% on unknown milled rice images [83]. Another geometric feature based rice quality and grading system was proposed by Patil achieving an accuracy of 93% [84].

Another work, which relied on feature based symbolic regression algorithm, was proposed to identify adulteration of rice varieties [37]. These features, which consisted of 9 morphological and 6 color features, were extracted from 800 rice grains. Meanwhile, Singh and Chaudhury developed a rice classification technique using BPNN and wavelet decomposition achieving 96% accuracy on a dataset of 400 rice images [52]. The feature vector consisted of 18 color, 24 wavelet, 27 textural and 45 combined attributes. Kuo *et al.* proposed a rice classification system based on SRC and image analysis that used 12 morphological, 9 color, 7 textural and 20 Fourier descriptors achieving an accuracy of 89.1% on a data set of 1500 images [3].

### C. ERA 3 (2017-2020)

This Era marked the application of deep learning approaches for rice grain classification and quality grading as shown in Fig.5c. While deep learning falls under supervised approaches, this study considers it as a separate approach due to its importance and promising results. Table 3 provides an overview of the key papers published in this Era with various attributes, advantages and limitations. It can be observed that the on average, the accuracy achieved in this Era was higher as compared to the previous ones.

In 2017, Lin *et al.* presented an algorithm that utilized Convolution Neural Network (CNN) for rice kernel classification [70] on a training and testing data set of 2854 and 965 images respectively achieving an accuracy of 99.52%. The pre-processing of rice images was done using re-scaling, mean subtraction, and feature standardization processes. In the same year, Patel used VGG-16 on a training and testing dataset of 4000 and 500 segmented rice images respectively achieving a testing accuracy of 94.20% [85].

Asif *et al.* proposed a classification system using PCA that achieved an accuracy of 92.3%. The features used were area, eccentricity, perimeter, length of major and minor axes, eigen values, and eigen vectors [25]. Nagoda and Ranathunga developed a rice segmentation and classification algorithm based on color features using SVM achieving 88.0% accuracy rate [53]. However, for their approach to work, they required a uniform lighting conditions. In the same year, Chatnuntawech *et al.* provided a rice classification algorithm that utilized deep CNN for identification [72]. Even though their classification accuracy was as high as 91.01%, they performed well only for a particular orientation of rice grains. Another DCNN based rice classification system was proposed which predicted rice species with an accuracy of 95.5% [74]. The CNN was trained and tested on 5554 and 1854 images respectively. The addition of Stochastic Gradient Descent approach further enhanced CNN's accuracy.

In 2018, Wijerathna and Ranathunga proposed a rice classification system using ANN which achieved an accuracy of 82.21% [55]. The feature vector consisted of 10 morphological and 13 color attributes. In the same year, Mandal [86] also proposed a rice classification system with 7 morphological features using ANFIS [87] and achieved an accuracy of 98.6%. However, this approach required the rice grains to be non-overlapping and well separated. Vu *et al.* proposed a novel rice variety inspection method using morphological and geometric features [26]. The rice image was segmented and normalized, followed by the extraction of geometric and morphological features of the rice seed. Those features were evaluated using DT, RF [36], and Adaboost classifiers from which Adaboost dominated by achieving a 95% accuracy. Qiu *et al.* presented a hyperspectral-CNN based rice variety classification algorithm [71]. Rice image from the hyperspectral imaging system was pre-processed and segmented from which hyperspectral data was acquired. 100-3000 rice samples were used to build KNN, SVM, and CNN models

**TABLE 3. Comparison framework of rice grain analysis techniques in Era 3.**

Study	Technique	Training data	Testing data	Accuracy (%)	Advantages	Limitations
[70]	CNN	2854 images	952 images	99.52	Attained exceptional accuracy rate.	Supervised training data was used for training.
[85]	VGG-16	4000 images	500 images	94.20	Good accuracy rate	Identifies five different rice varieties
[72]	ResNet (Deep CNN)	2591 datacubes	457 datacubes	91	Features of rice seeds acquired in no time and with no special instructions.	System underperformed with rice seeds in different orientations.
[25]	PCA	-	100 datacubes	92.3	Fast and Easy processing	Limited to non-overlapping of rice grains
[86]	ANFIS	30 images	10 images	98.6	Better accuracy	Limited to non-overlapping of rice grains
[26]	Adaboost	-	-	95.0	Performed better with large number of rice species	Morphological features degraded the performance
[71]	CNN	100-3000 rice samples	8907 rice samples	92.1	Accuracy rate better than KNN and SVM	Identified four rice varieties, specific to Zhejiang province
[74]	DCNN	-	-	95.5	Better accuracy rate	stochastic gradient descent parameters were constant
[61]	HOG and Fisher Score	5255 images	5254 images	93.34	Low computation time	Limited to Vietnam rice seed varieties only
[65]	Cascade Network	280 images	60.0 images	97.5	Better accuracy rate	Small dataset required

while 8907 rice samples were used to evaluate the trained models. CNN outperformed SVM and KNN based techniques by exhibiting a classification accuracy of 92.1%.

Rice variety recognition algorithm based on Fisher's scoring for feature selection was proposed that exhibited an accuracy of 93.34% [61]. A BPNN based rice grain classification method was proposed in [60] which used potential and current phasor plane values to achieve a 90% accuracy. Aukkapinyo *et al.* proposed a rice grain classification method using ResNet-50 which achieved an accuracy of 80% [76]. Another supervised approach using spatial and spectral features was proposed for rice seed classification obtaining an accuracy of 78.8% on a data set of 8640 images [66].

Ibrahim *et al.* proposed an automatic rice classification algorithm using multi-class SVM [58]. The pre-processing underwent image enhancement techniques followed by computation of 4 color and 4 shape based features. Most recently in 2020, another automatic cascade network based rice classification algorithm was developed that used various morphological, color, texture, and wavelet features achieving an accuracy of 97.5% on a data set of 340 images [65].

## VI. AUTOMATED GRADING OF RICE GRAINS

**Research objective 3:** *How automated grading approach presided over manual rice grading?*

As was the case with rice breed classification, manual approaches for rice quality grading are too slow and have

a greater chance for human error. It is therefore essential to automate the process [82]. In this regard, the approach proposed by Mahale and Korde used colored images of rice grains samples which were processed to remove noise using image morphological operations of dilation and erosion [32], followed by segmentation. Later, the edge detection method was applied which computed the boundary of rice grains. Length, width, and their ratio were also computed for rice grain classification. In 2014, Tanck and Kaushal proposed an approach that focused on grading rice quality based on Agmark<sup>7</sup> standards [88]. The colored image was pre-processed with noise removal and image enhancement techniques. The binarization process was then applied to convert it to black and white. By doing so, it aided in more precise extraction of morphological features including area, perimeter, and major axis length that were used for classifying the rice grains.

Zareiforoush *et al.* introduced a hybrid Fuzzy Inference System (FIS) to automate the qualitative grading of milled rice [83]. The RGB rice image, captured from a CCD camera, was converted to grayscale which was then used to calculate the percentage of broken kernels and degree of milling. These two variables were fed to the FIS for qualitative grading purpose, yielding a test accuracy of 89.83%.

<sup>7</sup>[http://agritech.tnau.ac.in/amis/food\\_agmark.html](http://agritech.tnau.ac.in/amis/food_agmark.html)

In [78], an approach based on texture and color features was proposed for milled rice quality recognition. A total of 17 features were extracted for grading the rice grains into Premium, Grade 1, Grade 2, and Grade 3. These 17 features consisted of 7 textural (correlation, energy, homogeneity, maximum probability, inverse different moment, angular second moment and dissimilarity) and 10 color (variance of hue, saturation, intensity, red, green, blue and mean of hue, red, green, blue) which were fed to a Back-Propagation Neural Network (BPNN) that classified the quality of rice grains.

In 2013, an algorithm was proposed in [80] which performed grading and classification of rice using a multi-class SVM. The rice image was pre-processed through image enhancement operations. Unlike previous approaches, the proposed system also took into account the chalkiness of rice grains as a feature, in addition to geometric features.

In 2014, Selvaraju *et al.* presented a novel system for the classification of grades between Basmati rice granules [81]. The rice image was smoothed with median filtering, segmented using adaptive thresholding following by edge detection using the Canny algorithm. Once the edges were identified, morphological features were computed which were then forwarded to train scaled conjugate gradient training based neural network (SCG-NN). After training the network, it was then evaluated with test data which resulted in an accuracy rate of 98.2%.

Patil and Malemath proposed a system that performed quality analysis and rice grading based on geometric features using decision tree [84]. Three different rice varieties were selected for this system. Background noise was removed from the rice image and it was later converted to a binary image using the Otsu method [89]. Each rice grain in the resultant image was segmented and its geometric features were extracted that were then classified and graded.

In 2018, Mandal proposed a rice grading system based on geometric features which were fed to an adaptive neuro-fuzzy inference system (ANFIS) [86]. The proposed solution outperformed KNN and SVM based systems and exhibited an accuracy of 98.6%. The preprocessing was done using the morphological operation of opening to eliminate noise. The benefit of this approach was that unlike [72], it did not require the rice grains to have the same orientation for the classifier to work. Randomly scattered rice grains did not impact classifier accuracy.

## VII. IDENTIFICATION OF RICE DISEASES, PESTS AND FOREIGN PARTICLES

**Research objective 4:** *What are the different algorithms and techniques available for automatic identification and classification of rice diseases?*

Various rice diseases and pests can lead to a loss in annual crop yield, which could be as high as 30% [90]. Misidentification usually leads to incorrect control measures, such as indiscriminate and untimely use of pesticides [91]. It has been observed that untrained farmers, relying on manual methods, often fail to detect the rice crop diseases such as

Leaf blast, Brown spot, Sheath blight, and Leaf scald in a timely manner and subsequently fail to take preventive or corrective measures [92]. Because of this reason, identifying rice diseases through an automated process becomes critical.

Zhou *et al.* in 2013 [93] presented a rice plant hopper classification algorithm based on fractal dimension values and Fuzzy C-means (FCM). The rice image preprocessing stage consisted of smoothing, denoising, color space conversion, frequency domain transformation, and segmentation of ROI. Features based on fractal dimensions were extracted using the Box-Counting Dimension Method and were classified using FCM, achieving a classification accuracy of 63.5%. In 2017, an automated identification algorithm was proposed which identified rice planthoppers using image processing [94]. The rice planthopper image was pre-processed with binarization operation and morphological filtering. Finally, a logical AND operation between the binary and grayscale images were used for insect segmentation. Then the Fourier transform was used to convert the insect image into a frequency domain to quantify its color and texture features. These features were used along with SVM yielding an accuracy of 92%. Table 4 shows the key research papers of various rice diseases, pests and foreign particles.

In [102], the authors presented a statistical approach for grading rice paddy using thermal technology. This approach graded rice paddy quality based on moisture content, maturity and chaff. The thermal rice images were gray-scaled to extract thermal index or pixel intensity. The moisture content was determined using Pearson's correlation coefficient with an accuracy of 92%. The authors also used thermal indexing to determine rice paddy maturity with 90% accuracy and to identify chaff with 100% accuracy. The high accuracies were achieved by trading off the classifier's execution time.

Yao *et al.* developed an application that classified rice disease using shape, color and texture features of rice leaf [91]. Rice bacterial blight (RBLB), rice sheath blight (RSB) and rice blast (RB) diseases were considered in this application. Noise removal and median filtering were applied to the rice images to avoid inaccurate segmentation of disease spots. Then the image was segmented using Otsu's method [89] from which 4 shape features (compactness, roundness, rectangularity and elongation), 60 texture and 3 spatial (H, S, V) feature of the disease spots were extracted and given to the SVM. The classifier yielded an accuracy of 97.2% on a dataset of 216 images.

In 2012, Phadikar *et al.* presented a supervised method for rice disease classification based on morphological alterations [100]. This approach mainly focused on detecting leaf brown spot and blast diseases. The rice leaf image was pre-processed with a mean filtering technique and later Otsu's threshold algorithm was used for segmentation on the hue plane. The segmentation separated infected spot areas on the rice image and then Radial distribution function was applied to color values. These color features were used with Bayes and SVM classifiers on data set of 500 images achieving an accuracy of 79.5% and 68.1% respectively. To overcome the



TABLE 4. Key papers on rice disease classification.

Study	Technique	Training data	Testing data	Accuracy (%)	Advantages	Limitations
[90]	SVM	350 images	150 images	98.6	Extracted features more precisely	Geographically limited to rice diseases of Tamil Nado
[91]	SVM	10 images	34 images	97.2	Better accuracy rate	Alike diseases features degraded application performance
[92]	Resnet-34	86 images	34 images	95.83	Good percentage accuracy	Classified three rice diseases
[95]	DCNN	500 images	-	95.48	No preprocessing operations required	Limited to low dataset
[96]	SVM	280 images	120 images	94.16	Better percentage accuracy, recall rate and precision	Classified three rice diseases only
[97]	Rule Generation	-	500 images	92.29	Low computational complexity	Uniform illumination degraded method's performance.
[94]	Fourier transform	142 images	27 images	92	Low computational cost	Classified one type of pest only
[98]	SVM	105 images	15 images	88.57	Consumed low power and memory	Classified couple of rice diseases only
[99]	MDC and kNN	80 images	35 images	87.02 and 89.23	Classification performed in less time	Identified four types of rice diseases only
[100]	Bayes and SVM	450 images	50 images	79.5 and 68.1	High time efficiency	Couple of diseases were identified, Limited to shadow effect and color distortion
[101]	IPSO	300 images	100 images	84.02	Consumed low computational time	Performance degraded with large datasets

limitation of selecting specific threshold value for segmentation, the authors presented another rice disease detection method using rule and feature selection [97]. In addition to the brown spot and rice blast disease, this work also classified sheath rot and bacterial blight ailments. The rice leaf image was segmented with the proposed Fermi energy-based method which identified the infected region from it. Fifteen color, one position and nine shape features were extracted from the segmented image and given to a rule-based decision system that yielded an accuracy of 92.29%.

In 2016, a new technique was proposed which classified rice diseases using image processing [99]. This technique highlighted four different diseases such as rice blast, rice bacterial blight, rice brown spot and rice sheath rot. At first, the infected rice leaf image was normalized with mean values of R, G and B components and multiplied with the scaling factor to remove the effect of outdoor illumination. The resultant image was converted to  $YCbCr$  color space for segmentation. After segmentation, the mean and standard deviation of R, G and B plane, and ten shape features were calculated from it. These sixteen features were used with minimum distance classifier (MDC) and kNN, yielding an accuracy of 87.02% and 89.23% respectively. Phadikar and Goswami proposed another automated rice disease classification algorithm using vegetation indices based segmentation [103]. Unlike their previous work, the authors focused their work on just two diseases: brown spot and rice blast. The rice disease image

was segmented using four different vegetation index metrics [104] including normalized difference vegetation index, green indexed vegetation index, enhanced vegetation index and soil adjusted vegetation index to extract infected regions. These indices along with five textural features were used along with Otsu's threshold algorithm to classify both rice diseases and achieved an accuracy of 84%.

In 2017, a prototype system was proposed for classification and detection of rice plant diseases [98], including bacterial leaf blight, brown spot and leaf smut. The rice image was converted to the HSV color model from which the saturation component was mainly considered. A mask was then applied to the saturation component of the image, isolating the leaf portion with disease spots from the background. The resultant image was then segmented, using K-means clustering, into 3 different clusters: background, diseased portion and green portion of the leaf. Three segmentation techniques; LAB color space based K-means clustering, Otsu's segmentation, and HSV color space based K-means clustering were then applied to acquire the diseased area on the leaf separately. As a result, three different models were developed containing a combination of various color, shape and texture features. These images were then used to train an SVM with 10 fold-cross validation. The resulting model yielded 88.57% accuracy.

A deep CNN based method was proposed for the identification of rice diseases [95]. This method dealt with 10 rice

disease varieties namely; rice blast, rice false smut, rice brown spot, rice bakanae disease, rice sheath blight, rice sheath rot, rice bacterial leaf blight, rice bacterial sheath rot, rice seeding blight and rice blight wilt. The rice image was preprocessed with scale normalization and mean normalization techniques. Then PCA and whitening techniques were applied to the resultant image to acquire the required feature. This feature was fed into DCNN for training purpose. Once trained, DCNN classified rice diseases with an accuracy of 95.48%.

Sengupta and Das proposed a supervised incremental classifier based on particle swarm optimization (PSO) algorithm for the prediction of rice diseases [101]. A total of 17 shape and texture features of the diseased region were extracted from rice images and were used to train the classifier. Once the classifier was trained, it yielded an 84.02% accuracy rate. Yao *et al.* proposed a microscopy image identification based rice disease detection method using decision tree confusion matrix [105]. Rice disease microscopic image was preprocessed with several image enhancement techniques to locate the infected area. Those techniques include greyscale conversion, histogram equalization, image smoothing, image sharpening, threshold segmentation, inverse contour extraction and distance transformation-Gaussian filtering-watershed (DT-GF-WA) algorithm. 4 shape features (Area, perimeter, ellipticity and complexity) and 3 texture features (entropy, contrast and homogeneity) were then extracted and utilized in decision tree - confusion matrix (DT-CM). 2000 microscopic rice disease images were used for training while 500 images were used for testing purpose. Thus, DT-CM classified rice smut and rice blasts with an average of 94% accuracy rate. Hasan *et al.* introduced a hybrid rice disease detection method using SVM and DCNN [106]. In this method, Inception-V3, one of the deepest and complex CNN architecture, was used to extract features from rice disease images as it does not require the intervention of a handcrafted feature selection algorithm for extraction. Those features were utilized to train multi-class SVM. About 1080 images were used to train SVM whereas 216 images were for testing purpose. SVM classified 9 diseases (Bacterial leaf blight, rice blast, brown spot, false smut, leaf smut, red stripe, leaf scald, sheath blight and Tungro) with 97.5% accuracy rate.

The authors of [96] proposed another method which used textual feature for rice disease classification [107]. Three diseases were considered in this research: brown spot, bacterial leaf blight and false smut. At first, the rice disease image was converted to grayscale and then SIFT transform was applied to extract regions of various diseases from the image. Those sets of regions were forwarded to the Bag of Words (BoW) technique and descriptions were clustered using the K-means clustering algorithm. Then Brute Force matcher histograms and SVM classifier was used to classify these diseases achieving an accuracy of 94.16% on a dataset of 400 images.

Rahman *et al.* presented another CNN based approach for the identification of rice diseases and pests [108].

Six classes of diseases (Bacterial leaf blight, brown spot, sheath blight, sheath rot, neck blast, false smut) and three classes of pests (Brown planthopper, hopper pest and stem-borer) were considered in this paper. Different image transformations such as random rotation ( $-15^\circ$  to  $15^\circ$ ), random distortion, shear transform, vertical flip, horizontal flip, skewing and intensity were applied and the transformed images were stored separately according to their classes. These transformed images were later used to train VGG16, ResNet50, InceptionV3, InceptionResNetV2, and Xception. Each one of them was trained using fine-tuning, transfer learning and training methods. Once trained, they all were evaluated on test data set from which VGG-16 architecture outperformed yielding a 99.53% accuracy rate. Furthermore, the authors also introduced two-stage training for their memory-efficient stacked CNN architecture. Devi *et al.* in 2019, proposed feature based rice disease classification method using various classifiers. Median filtering was applied to eliminate noise from the rice leaf image. Then the K-means clustering was used for the segmentation process. Thirteen features were extracted using a hybrid of SIFT, DWT and GLCM methods. The features were then utilized to train ANN, kNN, multiclass-SVM and Bayesian classifiers. These classifiers were trained with 350 images and were evaluated on 150 images, yielding 86.63%, 96.78%, 98.63%, and 85% accuracy respectively.

In 2020, Sharma *et al.* proposed a rice disease detection method using Bayes and minimum distance classifiers [109]. The rice disease image was preprocessed with grayscale conversion, median filtering and segmentation process. Color, texture, morphological and structural features were extracted and were later fed to Bayes and MDC classifiers for training purpose. 140 images were used for training purpose while 60 images were used for testing purpose. Bayes and MDC classified leaf blast, sheath blight, false smut, stem rot and brown spot with 69% and 81% accuracy, respectively. Patidar *et al.* set forth a deep learning approach in which rice diseases were detected and classified using deep residual learning [92]. This approach mainly focused on leaf smut, brown spot, and bacterial leaf blight rice diseases. The rice image was transformed and normalized so that every pixel attained the same mean and standard deviation. Then these images were given to the Resnet-34 model for training purpose. The classifier was trained with 86 images while it was evaluated on 36 images, yielding 95.83% accuracy.

The authors of [110] presented an automated rice plant disease classification algorithm. The method used color features of diseased rice plant image to classify sheath blight, rice blast, bacterial leaf blight and healthy leaves. So the diseased image was first preprocessed, converting background to black, to minimize complexity and computational cost. The RGB color was fetched from processed image and it was then converted to 13 different color spaces (normalized-RGB, YCbCr, HSV, HSI, CIE XYZ, CIE Lab, CIE Lch, CIE Luv, Hunter-Lab, SCT, opponent, CMY and CMYK). In doing so, a total of 172 features were extracted

including 4 statistical features (mean, standard deviation, skewness and kurtosis). These features were then used to train 7 different classifiers such as SVM, DC, KNN, NB, DT, RF and LR. The classifiers were trained and evaluated with the features of 619 images using 10-fold cross validation. The authors further conducted 10 more trails with different training and testing set upon which the accuracy rates were averaged and considered as final accuracy rate. As a result, SVM dominated with 94.65% classification rate, followed by DC (92.34%) and RF (92.52%). A deep learning method was introduced by [111] which detected rice disease using image processing. It used to identify healthy and unhealthy (brown spot, leaf blast and hispa) rice leaves. The dataset was taken from Kaggle<sup>8</sup> database and some of the images were taken manually. About 70% of the total images were used to train CNN whereas remaining images were used to evaluate trained CNN. Based on a confusion matrix which counts correct and incorrect predictions, an accuracy rate of 90% was attained.

### VIII. CONCLUSION AND FUTURE WORK

This study provides a detailed analysis of existing rice grain classification and quality grading techniques in chronological order and categorizes them into geometric, statistical, supervised, unsupervised, and deep learning approaches. It can be concluded that deep learning approaches generate promising results. It will further pose new challenges in meeting high computational requirements. Moreover, the paucity of datasets poses a big challenge to building accurate deep learning models. The development of large rice grain repositories, in an uncontrolled environment, will gain importance in the coming years. Data sets with non-uniform lighting, occlusion among rice grains, and indistinguishable and camouflaged rice grains will remain a big challenge in future research.

This paper reviews the history of rice grain algorithms starting from 1996 and segments them into three different eras. Each era is demarcated on the basis of some novel researches and developments. It can be concluded that in Era 1 (1996-2010), supervised approaches were dominant, while Era 2 (2011-2016) marked the significance of statistical and geometrical approaches as well. The focus of research took a new turn towards deep learning in Era 3 (2017-2020) which is expected to increase significantly in upcoming years.

Keeping in view the negative impact of rice pests, diseases, and foreign particles, the study further surveys the automated classification techniques proposed in this area. It can be concluded that these can be prevented, or their occurrences can be minimized, through the use of techniques that involve growing the crop in a controlled environment. In recent years, research focus is shifting towards agricultural techniques that are much more efficient as compared to the traditional methods. In this direction, some methods do away with the need for soil as a growth material. These include techniques

like hydroponic<sup>9</sup> and aeroponic.<sup>10</sup> The advantages of using these approaches include i) better utilization of water, ii) more production in lesser space, iii) better use of nutrients, and iv) protection against pests without the need for pesticides. These are more eco-friendly and also maximize profits by reducing costs and increasing the output. Other techniques, like drip irrigation,<sup>11</sup> need soil for growth, but the water delivery mechanism is much more precise leading to water savings by minimizing water wastage and evaporation. Though, the operational and resource cost is low, the water distribution uniformity is poor in drip irrigation. All these techniques (hydroponic, aeroponic and drip irrigation) are managed and monitored by humans due to which there are high chances of error. This is where machine learning approaches would come in handy which not only eliminates human errors but it would perform same human activities with greater precision and high accuracy.

### REFERENCES

- [1] A. G. Laborte, M. A. Gutierrez, J. G. Balanza, K. Saito, S. J. Zwart, M. Boschetti, M. V. R. Murty, L. Villano, J. K. Aunario, R. Reinke, J. Koo, R. J. Hijmans, and A. Nelson, "RiceAtlas, a spatial database of global rice calendars and production," *Sci. Data*, vol. 4, no. 1, Dec. 2017, Art. no. 170074.
- [2] S. Muthayya, J. D. Sugimoto, S. Montgomery, and G. F. Maberly, "An overview of global rice production, supply, trade, and consumption," *Ann. New York Acad. Sci.*, vol. 1324, no. 1, pp. 7–14, Sep. 2014.
- [3] T.-Y. Kuo, C.-L. Chung, S.-Y. Chen, H.-A. Lin, and Y.-F. Kuo, "Identifying rice grains using image analysis and sparse-representation-based classification," *Comput. Electron. Agricult.*, vol. 127, pp. 716–725, Sep. 2016.
- [4] B. S. Chauhan, K. Jabran, and G. Mahajan, *Rice Production Worldwide*, vol. 247. New York, NY, USA: Springer, 2017.
- [5] B. S. Priya, C. Kumaravelu, A. Gopal, and P. Stanley, "Classification of rice varieties using near-infra red spectroscopy," in *Proc. IEEE Technol. Innov. ICT Agricult. Rural Develop. (TIAR)*, Jul. 2015, pp. 13–16.
- [6] S. F. Ali, H. Jamil, R. Jamil, I. Torij, and S. Naz, "Low cost solution for rice quality analysis using morphological parameters and its comparison with standard measurements," in *Proc. Int. Multi-Topic Conf. (INMIC)*, Nov. 2017, pp. 1–6.
- [7] S. Akyol and B. Alatas, "Plant intelligence based metaheuristic optimization algorithms," *Artif. Intell. Rev.*, vol. 47, no. 4, pp. 417–462, 2017.
- [8] D. T. Britt, D. Yeomans, K. Housen, and G. Consolmagno, "Asteroid density, porosity, and structure," Tech. Rep., 2003.
- [9] S. Kaur and D. Singh, "Geometric feature extraction of selected rice grains using image processing techniques," *Int. J. Comput. Appl.*, vol. 124, no. 8, pp. 41–46, Aug. 2015.
- [10] D. A. Garvin, "Building a learning organization," *Harvard Business Review*, Jul./Aug. 1993, vol. 71, no. 4.
- [11] P. Van Mele, "Zooming-in zooming-out: A novel method to scale up local innovations and sustainable technologies," *Int. J. Agricult. Sustainability*, vol. 4, no. 2, pp. 131–142, Jan. 2006.
- [12] K. R. Bhattacharya, *Rice Quality: A Guide to Rice Properties and Analysis*. Amsterdam, The Netherlands: Elsevier, 2011.
- [13] T. Brosnan and D.-W. Sun, "Improving quality inspection of food products by computer vision—A review," *J. Food Eng.*, vol. 61, no. 1, pp. 3–16, Jan. 2004.
- [14] C.-J. Du and D.-W. Sun, "Recent developments in the applications of image processing techniques for food quality evaluation," *Trends Food Sci. Tech.*, vol. 15, no. 5, pp. 230–249, 2004.

<sup>9</sup>is a type of agricultural technique which involves growing plants using soil nutrients and aqueous solvent.

<sup>10</sup>is a technique, similar to hydroponic, where water consumption is further reduced by spraying the roots with water.

<sup>11</sup>is an agricultural technique where water is being dripped on the soil using a system of small plastic pipes.

<sup>8</sup><https://www.kaggle.com/vbookshelf/rice-leaf-diseases>

- [15] Z.-Y. Liu, F. Cheng, Y.-B. Ying, and X.-Q. Rao, "Identification of rice seed varieties using neural network," *J. Zhejiang Univ. Sci. B*, vol. 6, no. 11, p. 1095, 2005.
- [16] D. M. Hobson, R. M. Carter, and Y. Yan, "Characterisation and identification of rice grains through digital image analysis," in *Proc. IEEE Instrum. Meas. Technol. Conf. (IMTC)*, May 2007, pp. 1–5.
- [17] O. C. Agustin and B.-J. Oh, "Automatic milled rice quality analysis," in *Proc. 2nd Int. Conf. Future Gener. Commun. Netw.*, vol. 2, Dec. 2008, pp. 112–115.
- [18] Y. Auttawaitkul, S. Buochareon, T. Maneechukate, and N. Dussadee, "Non-destructive identification of breeder rice seed using transparent image analysis," in *Proc. 4th Joint Int. Conf. Inf. Commun. Technol., Electron. Electr. Eng. (JICTEE)*, Mar. 2014, pp. 1–4.
- [19] J. P. Shah, H. B. Prajapati, and V. K. Dabhi, "A survey on detection and classification of rice plant diseases," in *Proc. IEEE Int. Conf. Current Trends Adv. Comput. (ICCTAC)*, Mar. 2016, pp. 1–8.
- [20] T. Bera, A. Das, J. Sil, and A. K. Das, "A survey on rice plant disease identification using image processing and data mining techniques," in *Emerging Technologies in Data Mining and Information Security*. Singapore: Springer, 2019, pp. 365–376.
- [21] S. D. Khirade and A. B. Patil, "Plant disease detection using image processing," in *Proc. Int. Conf. Comput. Commun. Control Automat.*, Feb. 2015, pp. 768–771.
- [22] S. Kaur, S. Pandey, and S. Goel, "Plants disease identification and classification through leaf images: A survey," *Arch. Comput. Methods Eng.*, vol. 26, no. 2, pp. 507–530, 2019.
- [23] G. Ajay, M. Suneel, K. K. Kumar, and P. S. Prasad, "Quality evaluation of rice grains using morphological methods," *Int. J. Soft Comput. Eng.*, vol. 2, no. 6, pp. 35–37, 2013.
- [24] N. Sakai, S. Yonekawa, A. Matsuzaki, and H. Morishima, "Two-dimensional image analysis of the shape of rice and its application to separating varieties," *J. Food Eng.*, vol. 27, no. 4, pp. 397–407, Jan. 1996.
- [25] M. J. Asif, T. Shahbaz, S. T. H. Rizvi, and S. Iqbal, "Rice grain identification and quality analysis using image processing based on principal component analysis," in *Proc. Int. Symp. Recent Adv. Electr. Eng. (RAEE)*, Oct. 2018, pp. 1–6.
- [26] H. Vu, V. N. Duong, and T. T. Nguyen, "Inspecting rice seed species purity on a large dataset using geometrical and morphological features," in *Proc. 9th Int. Symp. Inf. Commun. Technol. (SoICT)*. New York, NY, USA: Association for Computing Machinery, 2018, pp. 321–328.
- [27] C. V. Maheshwari, K. R. Jain, and C. K. Modi, "Non-destructive quality analysis of Indian basmati *Oryza Sativa* SSP Indica (rice) using image processing," in *Proc. Int. Conf. Commun. Syst. Netw. Technol. (CSNT)*, May 2012, pp. 189–193.
- [28] J. Shen and C. Castan, "An optimal linear operator for edge detection," in *Proc. Conf. Vis. Pattern Recognit.*, 1986, pp. 109–114.
- [29] J. Canny, "A computational approach to edge detection," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. PAMI-8, no. 6, pp. 679–698, Nov. 1986.
- [30] P. Punthumast, Y. Auttawaitkul, W. Chiracharit, and K. Chamnongthai, "Non-destructive identification of unmilled rice using digital image analysis," in *Proc. 9th Int. Conf. Electr. Eng./Electron., Comput., Telecommun. Inf. Technol.*, May 2012, pp. 1–4.
- [31] S. Mahajan and S. Kaur, "Quality analysis of Indian basmati rice grains using top-hat transformation," *Int. J. Comput. Appl.*, vol. 94, no. 15, pp. 42–48, May 2014.
- [32] L. Vincent, "Morphological area openings and closings for grey-scale images," in *Proc. Workshop Shape Picture*. Berlin, Germany: Springer, 1992, pp. 197–208.
- [33] X. Bai, "Image analysis through feature extraction by using top-hat transform-based morphological contrast operator," *Appl. Opt.*, vol. 52, no. 16, pp. 3777–3789, Jun. 2013. [Online]. Available: <http://ao.osa.org/abstract.cfm?URI=ao-52-16-3777>
- [34] S. B. Ahmed, S. F. Ali, J. Ahmad, M. Adnan, and M. M. Fraz, "On the frontiers of pose invariant face recognition: A review," *Artif. Intell. Rev.*, vol. 53, no. 4, pp. 2571–2634, Apr. 2020.
- [35] R. Kambo and A. Yerpude, "Classification of basmati rice grain variety using image processing and principal component analysis," 2014, *arXiv:1405.7626*.
- [36] P. T. T. Hong, T. T. T. Hai, L. T. Lan, V. T. Hoang, V. Hai, and T. T. Nguyen, "Comparative study on vision based rice seed varieties identification," in *Proc. 7th Int. Conf. Knowl. Syst. Eng. (KSE)*, Oct. 2015, pp. 377–382.
- [37] P. Watanachaturaporn, "Identification of rice using symbolic regression," in *Proc. 8th Int. Conf. Inf. Technol. Electr. Eng. (ICITEE)*, Oct. 2016, pp. 1–4.
- [38] R. Dubčáková, "Eureqa: Software review," *Genetic Program. Evolvable Mach.*, vol. 12, no. 2, pp. 173–178, Jun. 2011.
- [39] R. P. Paswan, S. A. Begum, and B. Neog, "Comparison of abilities of different activation functions of artificial neural network to predict crop area and crop production," *Int. J. Pure Appl. Biosci.*, vol. 6, no. 6, pp. 212–220, Dec. 2018.
- [40] S. Bansal and D. Aggarwal, "Color image segmentation using CIE Lab color space using ant colony optimization," *Int. J. Comput. Appl.*, vol. 29, no. 9, pp. 28–34, Sep. 2011.
- [41] S. Shantaiya and U. Ansari, "Identification of food grains and its quality using pattern classification," in *Proc. 12th IEEE Int. Conf. Commun. Technol. (ICCT)*, Nanjing, China, vol. 1114, Nov. 2010, p. 35Shiddiq.
- [42] B. Verma, "Image processing techniques for grading & classification of rice," in *Proc. Int. Conf. Comput. Commun. Technol. (ICCCCT)*, Sep. 2010, pp. 220–223.
- [43] S. J. M. Rad, F. A. Tab, and K. Mollazade, "Classification of rice varieties using optimal color and texture features and BP neural networks," in *Proc. 7th Iranian Conf. Mach. Vis. Image Process.*, Nov. 2011, pp. 1–5.
- [44] P. M. Narendra and K. Fukunaga, "A branch and bound algorithm for feature subset selection," *IEEE Trans. Comput.*, vol. C-26, no. 9, pp. 917–922, Sep. 1977.
- [45] P. A. Devijver and J. Kittler, *Pattern Recognition: A Statistical Approach*. Upper Saddle River, NJ, USA: Prentice-Hall, 1982.
- [46] S. R. Stearns, "On selecting features for pattern classifiers," Tech. Rep., 1976.
- [47] S. J. Mousavirad, F. A. Tab, and K. Mollazade, "Design of an expert system for rice kernel identification using optimal morphological features and back propagation neural network," *Int. J. Appl. Inf. Syst.*, vol. 3, pp. 33–37, Jul. 2012.
- [48] K. Wenwen, C. Zhang, F. Liu, P. Nie, and L. He, "Rice seed cultivar identification using near-infrared hyperspectral imaging and multivariate data analysis," *Sensors*, vol. 13, pp. 8916–8927, Jul. 2013.
- [49] C. Silva and U. Sonnada, "Classification of rice grains using neural networks," Tech. Rep., Mar. 2013, vol. 29.
- [50] Z. Pezeshki and S. M. Mazinani, "Comparison of artificial neural networks, fuzzy logic and neuro fuzzy for predicting optimization of building thermal consumption: A survey," *Artif. Intell. Rev.*, vol. 52, no. 1, pp. 495–525, Jun. 2019.
- [51] A. R. Pazoki, F. Farokhi, and Z. Pazoki, "Classification of rice grain varieties using two artificial neural networks (MLP and neuro-fuzzy)," *J. Anim. Plant Sci.*, vol. 24, no. 1, pp. 336–343, 2014.
- [52] K. R. Singh and S. Chaudhury, "Efficient technique for rice grain classification using back-propagation neural network and wavelet decomposition," *IET Comput. Vis.*, vol. 10, no. 8, pp. 780–787, Dec. 2016.
- [53] N. Nagoda and L. Ranathunga, "Rice sample segmentation and classification using image processing and support vector machine," in *Proc. IEEE 13th Int. Conf. Ind. Inf. Syst. (ICIIS)*, Dec. 2018, pp. 179–184.
- [54] S.-Y. Liu, Y. Chao, T. Zeng, J. Wang, and P. Li, "An improved watershed image segmentation algorithm based on fuzzy threshold," in *Proc. Int. Conf. Appl. Techn. Cyber Secur. Intell.* Cham, Switzerland: Springer, 2019, pp. 1198–1205.
- [55] P. Wijerathna and L. Ranathunga, "Rice category identification using heuristic feature guided machine vision approach," in *Proc. IEEE 13th Int. Conf. Ind. Inf. Syst. (ICIIS)*, Dec. 2018, pp. 185–190.
- [56] D. Sangeetha and P. Deepa, "FPGA implementation of cost-effective robust Canny edge detection algorithm," *J. Real-Time Image Process.*, vol. 16, no. 4, pp. 957–970, Aug. 2019.
- [57] W. Srimulyani and A. Musdholifah, "Identification of rice variety using geometric features and neural network," *Indonesian J. Comput. Cybern. Syst.*, vol. 13, no. 3, pp. 301–312, 2019.
- [58] S. Ibrahim, N. A. Zulkifli, N. Sabri, A. A. Shari, and M. R. M. Noordin, "Rice grain classification using multi-class support vector machine (SVM)," *IAES Int. J. Artif. Intell.*, vol. 8, no. 3, p. 215, Dec. 2019.
- [59] A. Bakhshi, "A comparison among some edge detection methods and region growing algorithm for image segmentation," *Int. J. Comput. Theory Eng.*, vol. 4, Jun. 2012.
- [60] L. Lu, C. Fang, Z. Hu, X. Hu, and Z. Zhu, "Grade classification model tandem BpNN method with multi-metal sensor for rice eating quality evaluation," *Sens. Actuators B, Chem.*, vol. 281, pp. 22–27, Feb. 2019.
- [61] H.-T. Duong and V. T. Hoang, "Dimensionality reduction based on feature selection for rice varieties recognition," in *Proc. 4th Int. Conf. Inf. Technol. (InCIT)*, Oct. 2019, pp. 199–202.



- [62] C. Shu, X. Ding, and C. Fang, "Histogram of the oriented gradient for face recognition," *Tsinghua Sci. Technol.*, vol. 16, no. 2, pp. 216–224, Apr. 2011.
- [63] N. T. Longford, "A fast scoring algorithm for maximum likelihood estimation in unbalanced mixed models with nested random effects," *Biometrika*, vol. 74, no. 4, pp. 817–827, 1987.
- [64] D. Dua and C. Graff. (2017). *UCI Machine Learning Repository*. [Online]. Available: <http://archive.ics.uci.edu/ml>
- [65] K. R. Singh and S. Chaudhury, "A cascade network for the classification of rice grain based on single rice kernel," *Complex Intell. Syst.*, vol. 6, pp. 1–14, Feb. 2020.
- [66] S. D. Fabyi, H. Vu, C. Tachtatzis, P. Murray, D. Harle, T. K. Dao, I. Andonovic, J. Ren, and S. Marshall, "Varietal classification of rice seeds using RGB and hyperspectral images," *IEEE Access*, vol. 8, pp. 22493–22505, 2020.
- [67] Y. Wu, Z. Yang, W. Wu, X. Li, and D. Tao, "Deep-rice: Deep multi-sensor image recognition for grading rice," in *Proc. IEEE Int. Conf. Inf. Automat. (ICIA)*, Aug. 2018, pp. 116–120.
- [68] L. P. S. Thrun, *Learning to Learn*. New York, NY, USA: Springer, 2012.
- [69] N. Patel, H. Jayswal, and A. Thakkar, "Rice quality analysis based on physical attributes using image processing technique," in *Proc. 2nd IEEE Int. Conf. Recent Trends Electron., Inf. Commun. Technol. (RTEICT)*, May 2017, pp. 42–47.
- [70] P. Lin, Y. Chen, J. He, and X. Fu, "Determination of the varieties of rice kernels based on machine vision and deep learning technology," in *Proc. 10th Int. Symp. Comput. Intell. Design (ISCID)*, Dec. 2017, pp. 169–172.
- [71] Z. Qiu, J. Chen, Y. Zhao, S. Zhu, Y. He, and C. Zhang, "Variety identification of single rice seed using hyperspectral imaging combined with convolutional neural network," *Appl. Sci.*, vol. 8, no. 2, p. 212, 2018.
- [72] I. Chatnuntawech, K. Tantisantisom, P. Khanchaitit, T. Boonkoom, B. Bilgic, and E. Chuangsuwanich, "Rice classification using spatio-spectral deep convolutional neural network," *CoRR*, vol. abs/1805.11491, May 2018.
- [73] R. Cristin, B. S. Kumar, C. Priya, and K. Karthick, "Deep neural network based rider-cuckoo search algorithm for plant disease detection," *Artif. Intell. Rev.*, vol. 53, no. 7, pp. 4993–5018, Oct. 2020.
- [74] P. Lin, X. L. Li, Y. M. Chen, and Y. He, "A deep convolutional neural network architecture for boosting image discrimination accuracy of rice species," *Food Bioprocess Technol.*, vol. 11, no. 4, pp. 765–773, Apr. 2018.
- [75] N. H. Son and N. Thai-Nghe, "Deep learning for rice quality classification," in *Proc. Int. Conf. Adv. Comput. Appl. (ACOMP)*, Nov. 2019, pp. 92–96.
- [76] K. Aukkapinyo, S. Sawangwong, P. Pooyoi, and W. Kusakunniran, "Localization and classification of rice-grain images using region proposals-based convolutional neural network," *Int. J. Autom. Comput.*, vol. 17, no. 2, pp. 1–14, 2019.
- [77] H. Gao, P. Xue, and W. Lin, "A new marker-based watershed algorithm," in *Proc. IEEE Int. Symp. Circuits Syst.*, vol. 2, May 2004, p. II-81.
- [78] L. A. I. Pabamalie and H. L. Premaratne, "A grain quality classification system," in *Proc. Int. Conf. Inf. Soc. (i-Society)*, Jun. 2010, pp. 56–61.
- [79] S. Rajab and V. Sharma, "A review on the applications of neuro-fuzzy systems in business," *Artif. Intell. Rev.*, vol. 49, no. 4, pp. 481–510, Apr. 2018.
- [80] H. Kaur and B. Singh, "Classification and grading rice using multi-class SVM," *Int. J. Sci. Res. Publications*, vol. 3, no. 4, pp. 1–5, 2013.
- [81] A. Selvaraju, P. Neelamegam, and K. H. T. India, "Analysis of rice granules using image processing and neural network pattern recognition tool," *Int. J. Comput. Appl.*, vol. 96, no. 7, pp. 20–24, Jun. 2014.
- [82] B. Mahale and S. Korde, "Rice quality analysis using image processing techniques," in *Proc. Int. Conf. Conver. Technol. (ICT)*, Apr. 2014, pp. 1–5.
- [83] H. Zareiforush, S. Minaei, M. R. Alizadeh, and A. Banakar, "A hybrid intelligent approach based on computer vision and fuzzy logic for quality measurement of milled rice," *Measurement*, vol. 66, pp. 26–34, Apr. 2015.
- [84] V. Patil and V. Malemath, "Quality analysis and grading of rice grain images," *Tech. Rep.*, Jun. 2015.
- [85] V. Patel, "Convolutional neural network with transfer learning for rice type classification," *Tech. Rep.*, Sep. 2017.
- [86] D. Mandal, "Adaptive neuro-fuzzy inference system based grading of basmati rice grains using image processing technique," *Appl. Syst. Innov.*, vol. 1, no. 2, p. 19, Jun. 2018.
- [87] D. Karaboga and E. Kaya, "Adaptive network based fuzzy inference system (ANFIS) training approaches: A comprehensive survey," *Artif. Intell. Rev.*, vol. 52, no. 4, pp. 2263–2293, 2019.
- [88] P. Tanck and B. Kaushal, "A new technique of quality analysis for rice grading for Agmark standards," *Int. J. Innov. Technol. Exploring Eng.*, vol. 3, no. 12, pp. 83–85, 2014.
- [89] D. Liu and J. Yu, "Otsu method and k-means," in *Proc. 9th Int. Conf. Hybrid Intell. Syst.*, vol. 1, Sep. 2009, pp. 344–349.
- [90] T. G. Devi and P. Neelamegam, "Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu," *Cluster Comput.*, vol. 22, no. 6, p. 13415–13428, 2019.
- [91] Q. Yao, Z. Guan, Y. Zhou, J. Tang, Y. Hu, and B. Yang, "Application of support vector machine for detecting rice diseases using shape and color texture features," in *Proc. Int. Conf. Eng. Comput.*, 2009, pp. 79–83.
- [92] S. Patidar, A. Pandey, B. A. Shirish, and A. Sriram, "Rice plant disease detection and classification using deep residual learning," in *Proc. Int. Conf. Mach. Learn., Image Process., Netw. Secur. Data Sci.* Singapore: Springer, 2020, pp. 278–293.
- [93] Z. Zhou, Y. Zang, Y. Li, Y. Zhang, P. Wang, and X. Luo, "Rice plant-hopper infestation detection and classification algorithms based on fractal dimension values and fuzzy C-means," *Math. Comput. Model.*, vol. 58, nos. 3–4, pp. 701–709, Aug. 2013.
- [94] J. Wang, R. Kang, K. Chen, D. Liu, and H. Yu, "Automatic identification of Asian rice plant-hopper based on image processing," *Appl. Eng. Agricult.*, vol. 33, no. 5, pp. 591–602, 2017.
- [95] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks," *Neurocomputing*, vol. 267, pp. 378–384, Dec. 2017.
- [96] K. Bashir, M. Rehman, and M. Bari, "Detection and classification of rice diseases: An automated approach using textural features," *Mehran Univ. Eng. Eng. Technol.*, vol. 38, no. 1, pp. 239–250, 2019.
- [97] S. Phadikar, J. Sil, and A. K. Das, "Rice diseases classification using feature selection and rule generation techniques," *Comput. Electron. Agricult.*, vol. 90, pp. 76–85, Jan. 2015.
- [98] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, "Detection and classification of rice plant diseases," *Intell. Decis. Technol.*, vol. 11, no. 3, pp. 357–373, Aug. 2017.
- [99] A. A. Joshi and B. D. Jadhav, "Monitoring and controlling rice diseases using image processing techniques," in *Proc. Int. Conf. Comput., Analytics Secur. Trends (CAST)*, Dec. 2016, pp. 471–476.
- [100] S. Phadikar, J. Sil, and A. K. Das, "Classification of rice leaf diseases based on morphological changes," *Int. J. Inf. Electron. Eng.*, vol. 2, no. 3, pp. 460–463, 2012.
- [101] S. Sengupta and A. K. Das, "Particle swarm optimization based incremental classifier design for rice disease prediction," *Comput. Electron. Agricult.*, vol. 140, pp. 443–451, Aug. 2017.
- [102] S. Bejo-Khairunniza, N. Azman, and N. Jamil, "Paddy grading using thermal imaging technology," *Int. Food Res. J.*, vol. 23, p. S245, Dec. 2016.
- [103] S. Phadikar and J. Goswami, "Vegetation indices based segmentation for automatic classification of Brown spot and blast diseases of rice," in *Proc. 3rd Int. Conf. Recent Adv. Inf. Technol. (RAIT)*, Mar. 2016, pp. 284–289.
- [104] A. Bannari, D. Morin, F. Bonn, and A. R. Huete, "A review of vegetation indices," *Remote Sens. Rev.*, vol. 13, nos. 1–2, pp. 95–120, 1995.
- [105] N. Yang, Y. Qian, H. S. El-Mesery, R. Zhang, A. Wang, and J. Tang, "Rapid detection of rice disease using microscopy image identification based on the synergistic judgment of texture and shape features and decision tree–confusion matrix method," *J. Sci. Food Agricult.*, vol. 99, no. 14, pp. 6589–6600, Nov. 2019.
- [106] M. J. Hasan, S. Mahub, M. S. Alom, and M. A. Nasim, "Rice disease identification and classification by integrating support vector machine with deep convolutional neural network," in *Proc. 1st Int. Conf. Adv. Sci., Eng. Robot. Technol. (ICASERT)*, May 2019, pp. 1–6.
- [107] S. M. T. Islam and B. Mazumder, "Wavelet based feature extraction for rice plant disease detection and classification," in *Proc. 3rd Int. Conf. Electr., Comput. Telecommun. Eng. (ICECTE)*, Dec. 2019, pp. 53–56.
- [108] C. R. Rahman, P. S. Arko, M. E. Ali, M. A. I. Khan, S. H. Apon, F. Nowrin, and A. Wasif, "Identification and recognition of rice diseases and pests using convolutional neural networks," *Biosyst. Eng.*, vol. 194, pp. 112–120, Jun. 2020.

- [109] V. Sharma, A. A. Mir, and D. A. Sarwr, "Detection of rice disease using Bayes' classifier and minimum distance classifier," *J. Multimedia Inf. Syst.*, vol. 7, no. 1, pp. 17–24, Mar. 2020.
- [110] V. K. Shrivastava and M. K. Pradhan, "Rice plant disease classification using color features: A machine learning paradigm," *J. Plant Pathol.*, vol. 103, no. 1, pp. 17–26, Feb. 2021.
- [111] M. A. Rahman, M. S. N. Shoumik, M. M. Rahman, and M. H. Hena, "Rice disease detection based on image processing technique," in *Smart Trends in Computing and Communications: Proceedings of SmartCom*. New York, NY, USA: Springer, 2021, pp. 135–145.



**SHEIKH BILAL AHMED** received the B.S. degree in computer science and the M.S. degree in software engineering from the University of Management and Technology (UMT), Lahore, Pakistan, in 2015 and 2018, respectively. His research interests include computer vision, machine learning, and image processing.



**SYED FAROOQ ALI** received the Ph.D. degree (CS) from UMT, Pakistan, the M.S. degree (CS) from The Ohio State University, Columbus, USA, and the M.S. degree (Hons.) in CS from LUMS, Lahore, Pakistan. During his M.S. degree, he was on LUMS Fellowship. He did his Ph.D. course work and the Ph.D. comprehensive exam at The Ohio State University. He is currently working as an Assistant Professor with UMT. His research interests include computer vision, digital image processing, and medical imaging. He is a reviewer for various IEEE conferences and journals.



**AADIL ZIA KHAN** received the Ph.D. degree in computer science from LUMS, Pakistan. He is currently an Assistant Professor at UMT, Pakistan. His research interests include networked systems and ICTD. More specifically, he has focused on cloud computing and data centers, content centric networks, and peer to peer networking.

...