International Journal of Computational Intelligence in Control

RiceAgeNet: Age Estimation of Pakistani Grown Rice Seeds using Convolutional Neural Networks

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Abstract. Rice is one of the most common and important food all over the world. In Pakistan, it is also an important part of our daily meal. Rice demand has increased significantly recently. Its quality is one of the main factors, considered, while its import and export, which is evaluated manually by the human experts in Pakistan, hence making quality assessment process a costly, and unreliable. This necessitating an automated solution to analyze as well as distinguish between the old and new rice, a one of the factors, affecting rice quality. The purpose of this research is to present an automated, reliable, robust, efficient, and cost-effective solution through Convolutional Neural Network (CNN) based model to estimate the age of a rice seed. For research and experiments, annotated sample rice seeds have been collected from Rice Research Center, Department of Agriculture, Bahawalnagar, Pakistan. Rice seeds images are obtained using specific designed setup, which consists of different angle and no. of seeded images. A light-weighted with lesser number of layers and parameters CNN based model has been specifically designed. The proposed model has been evaluated on most Pakistani grown rice seeds, i.e., Basmati-2000, Chenab-basmati, KSK-133, Kissan-basmati, KSK-434, PK-1121 Aromatic, and Punjab-basmati. The obtained results have been compared with the state-of-the-art recent studies and CNN based models. The developed dataset is made public for the researcher community, and this study is currently integrated with agri-technology industry for auto estimation of rice age as a demo version.

Keywords: Rice age estimation, convolutional neural network, Pakistani grown rice.

1.0 Introduction

Oryza sativa (Asian rice) belongs to the grass species. It is consumed all over the world, especially in Asia. It is the third-largest cereal crop in the world after sugarcane and maize. The average production of rice is 741.5 million. Thailand, Vietnam, India, and Pakistan are among the dominant countries in the global rice market and contribute about 60% to 70% of the total global exports (Gilanie, Nasir, Bajwa, & Ullah, 2021; Memon, 2013). About 7.4 billion populations, i.e., probably half of the world's population eat rice as part of its vital diet. Rice demand is expected to rise by 50 percent in 2030 (Alexandratos & Bruinsma, 2012). Rice provides almost 19% of global human per capita energy and 13% of per capita protein that is increased with time. It is good in nutritional value, low in fat, has no additives, and is a source of vitamins and minerals. Rice protein ranks among cereals high in nutritional quality, the protein content is modest. The average person in some parts of Asia eats rice 40-60kg per year.

In Pakistan, rice is the main item of the meal and is the basic ingredient of almost every meal. Using rice, many dishes like "biryani", "pulao", "saffron rice", "kheer", "zarda rice" etc. are made almost in every home on special occasions in sub-continent of Asia. In addition to consuming and its cooking in usual ways, there are many other rice-based foods and drink products, prepared for human consumption including noodles, bread, cakes, etc. At the time of cooking, the aged rice is cooked separated, fluffy, perfect, and gives a high-quality aroma, which makes difference between new and old rice. Shopkeepers purchase new rice and store it for 6-8 months to have its better quality. In the fraudulent activity, shopkeepers may sell new rice at the price of the old one.

Pakistan is the 10th largest producer of rice worldwide. There are more than 39,000 different rice varieties harvested all over the world. Several factors affect the rice quality, which includes taste, aroma, variety, aging, whiteness, shape, milling degree, chalkiness, and cracks & polishing. The rice with more age cooks fine, with separate grains, while freshly harvested rice when cooked may become sticky. Rice quality depends upon two factors, i.e., agricultural, and post-harvest effect. Factors which affect the rice quality and its diversity, are summarized in Figure 1.

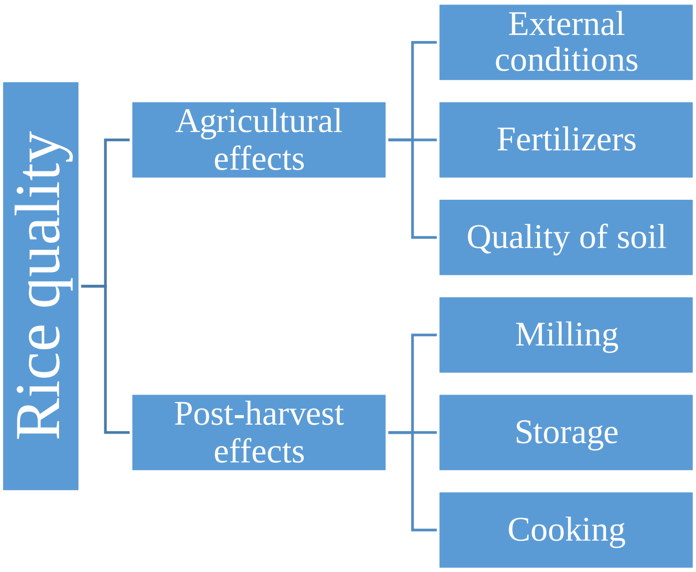


Figure 1: Rice quality factors

Rice is also cultivated in many areas of Pakistan, major areas include Kasur, Sialkot, Wazirababd, Sheikhupura, Gujrat, Jhang, Okara, Bahawalnagar, Chiniot, Sargodha, D. G. Khan, Rahim Yar khan, Gujranwala, Khanewal, Faisalabad, Larkana, Dadu, Shikarpur, Thatta, Badin, Jacobabad, Kashmor, Tando Muhammad Khan, Jaffaraabad, Nasirabad, Usta Muhammad, Peshawar, Charsadda, Noshera, Swabi, Kohat, and Mardan. The famous rice types cultivated include Basmati, Super Basmati, Punjab Basmati, Chenab Basmati, Kissan Basmati, Pukhraj, Arize, Shahanshah, Kainat, Kernel, Super, etc.(Khan, Gao, Abid, & Shah, 2020; Rafi et al., 2013).

The aging of rice is a process in which physical and chemical properties change with the passage of time. Adhesion to lips, hardness, cohesiveness of mass, tooth pull, and loose particles are directly correlated with the age of a rice seed. These changes affect the pasting, gel properties, flavor, and texture of cooked rice. The quality and effectiveness of aging dependsupon rice types, storage, and milling treatments. Rice storage after harvesting for three to four months is simply a natural aging method, which has a great impact on the quality of rice grains in connection with their cooking. In an artificial aging process, fresh paddy rice is kept under 90°–110°C temperature for 2-8 hours. This is the same as rice is kept for 14 months, however, its chemical and physical properties are affected by heat treatment and changes are different than natural aging (Faruq, Prodhan, & Nezhadahmadi, 2015).

The rice verities are classified into three groups, i.e., long-grain, medium-grain, and short-grain according to their width to length ratio. For newly harvested rice, the level of moisture content is 18.7% to 23.5% and 21.5% to 24.0 % for long grains and medium grains respectively(Genkawa, Uchino, Inoue, Tanaka, & Hamanaka, 2008).

The higher the moisture level of rice seeds is the poorer quality after cooking, as lower moisture level avoids shattering of rice seeds. In 3 to 4 months of a natural aging process, the moisture level is automatically reduced to 12% to 14%(Shafiekhani, Wilson, & Atungulu, 2018). Aged rice prices are 3 to 4 times higher than freshly harvested rice because natural aging improves and intensifies the characteristics of its taste, aroma, and cooking. Basmati rice is the most acclaimed fragrant rice used in Pakistan. Basmati and kernel rice are internationally renowned for their excellent cuisine and eating qualities combined with a very good aroma. The rice quality evaluation is very important in the present time for Pakistan to improve its exports ratio.

The experts and the sellers currently observe the aged rice. More often sellers sell new rice at the price of old one. Due to a lack of knowledge about the rice texture, color, silhouette, and size, the buyers must purchase (even substandard rice), advised by the sellers. Old rice is used in rice packing industries of Pakistan. The identification of an aged rice from newly harvested one is done through human experts or operators. Fraudulent packing may involve the mixing of old and newly harvested rice seeds, resulting in an effect on import/export ratios. Information of grain types and quality is required at several stages during grain handling operation for automated packing procedures. Unlike most other industrial products, the shape, size, color, and texture of agricultural products are not governed by new techniques in Pakistan. It has become a challenging task for the machine vision system to recognize and classify rice seed's age and quality in automated and reliable manners. The present grain handling system, of course, requires a visual inspection, hence, is monotonous and time-consuming.

Researchers used many machine-learning algorithms, i.e., support vector machine (SVM), Bayesian's algorithm, fast Fourier transformation, fuzzy logic, Random Forest (RF), Artificial Neural Network (ANN), Kernel Ridge Regression (KRR), Kernel Nearest Neighbor (K-NN), and deep learning models to classify and access the rice types and quality respectively(Gilanie, Attique, Naweed, Ahmed, & Ikram, 2013; Gilanie, Bajwa, et al., 2021; Gilanie, Bajwa, Waraich, & Habib, 2019a, 2019b; Gilanie et al., 2018). However, unfortunately, in Pakistan, all this work is on manual basisunder help of human experts. Thus, an automatic system can prevent human errors in the quality evaluation process, which may become an alternative to manual inspection of rice grain samples.

The literature revealed that most of the work done in this domain belongs to the classification of rice into different rice types with little work on rice quality estimation. Literature also established that no benchmarked dataset is available for the researcher community to perform experiments. These issues motivated us to introduce anautomated, light-weighted, reliable, efficient, and cost-effective system, which can estimate the age of rice to facilitate the people and agricultural industry.

The rest of the article is arranged as follows; reviewed literature is presented in section 2, while material and methods consisting of image acquisition setup detail and the proposed CNN architecture is the part of section 3. Results and their discussions are positioned in section 4, while conclusions are placed in section 5.

2.0 Literature review

In a study (Philip & Anita, 2017), the authors classify commercially available rice grains. They used morphological features including area, perimeter, etc. Fourier features are also extracted from the images of rice grain. This study classifies nine (09) varieties of rice grains with an accuracy of 95.78% using the Naïve Bayes (NB) Tree and Sequential minimal optimization (SMO) classifiers. In another article(Lin, Li, Chen, & He, 2018), Deep Convolutional Neural Network (DCNN) is used to classify three distinct groups of rice grains. The prediction accuracy results for test datasets by PHOG-KNN, PHOG-SVM, GIST-KNN, and GIST-SVM models were 89.1, 76.9, 90.6, and 92.1%, respectively. The highest prediction accuracy of DCNN is 95.5%.Similarly, in a study (Chen et al., 2019),SVM has been used for the inspection (damaged, broken, and flawed rice kernels) of Red indica rice. Broken parts are detected by edge detection and morphological methods. The experimental results show that the recognition accuracy for broken kernels, chalkiness, and damaged and spotted areas reached 99.3%, 96.3%, and 93.6%, respectively.A research (Anami, Malvade, & Palaiah, 2019), has identified adulteration levels from the images of paddy grains using color and texture features. Seven adulterated bulk paddy samples have been used and each of the samples is prepared by mixing a premium paddy variety with the identical looking and commercially inferior paddy variety at five different adulteration levels of 10%, 15%, 20%, 25%, and 30%. Three classification models, i.e., Multilayer Back Propagation Neural Network (BPNN), SVM, and KNN along with Principal Component Analysis (PCA) and Sequential Forward Floating Selection (SFFS) methods of feature reduction have been used. Overall, an adulteration classification accuracy obtained is 93.31% using the BPNN and PCA.

In this article (S. K. Singh, Vidyarthi, & Tiwari, 2020), researchers measured the weight and size of rice seeds using a machine learning stack ensemble model (SEM). A sample of 55 grains obtained from US grown rice cultivars Jupiter, calhikari, and CL153 has been used in this study. SEM model consists of RF, ANN, SVM, KRR, and K-NN. Dataset is divided into three parts, i.e., 40%, 40%, and 20% for training, testing, and validation respectively. The SEM predicted average lengths of 1000 rice kernel samples, i.e., 4.69mm, 5.81mm, and 6.37mm, which is very close to their respective measured lengths, i.e., 4.66mm, 5.87mm, and 6.41mm respectively. The overall accuracy of their proposed system is 95%.In another article (Kiratiratanapruk et al., 2020), a method for the classification of 14 rice varieties has been proposed. Over 3,500 seed samples of each rice variety have been used. The dataset was divided into three (03) groups. Overall, their model achieved maximum accuracy of95.15%.

Deep convolutional neural networks (DCNNs) have been used for the diagnosis of nutrients deficiencies present in rice images by the researchers (Xu et al., 2020). Dataset of 1818 images belonging to 10 different classes of nutrient deficiencies has been obtained through hydroponic experiments. The images were divided into training, validation, and test sets in a 3:1:1 ratio. All the DCNNs obtained accuracies of 90%, while DenseNet121 achieved maximum accuracy of 97.44 %.In another paper (K. R. Singh & Chaudhury, 2020), the researchers proposed a method to classify rice grain. Four types of rice varieties were classified. A dataset consisting of 400 images (100 images of each rice type) has been used for research and experiments. Morphological, color, texture, and wavelet features have been used. Dataset has been divided into 70%, 15%, and 15% for training, testing, and validation respectively. The overall accuracy achieved is 97.75%.In the most recent study (Estrada-Pérez et al., 2021), different types of rice qualities have been classified using deep learning neural network. A total of 63000 thermal images have been used for research and experiments. The overall accuracy of rice classification is 99.6%, while pure or adulterated rice samples have classification accuracy of98.8%.

3.0 The proposed methodology

3.1 Experimental setup and data acquisition

The rice grains images have been obtained through a designed setup, which consists of a 64-megapixel mobile camera. The camera is mounted at a height of 2.5 inches above the targeted object. The images were taken under natural lighting conditions during morning, afternoon, and evening hours. In this research activity, 07 rice seed types have been selected from each of the year-2018, year-2019, and year-2020, which are mostly cultivated in Pakistan. These rice seeds include Basmati-2000, Chenab-basmati, KSK-133, Kissan-basmati, KSK-434, PK-1121 Aromatic, and Punjab-basmati. The experimental setup is shown in Figure 2. Annotated rice samples have been collected from the Rice Research Center, Department of Agriculture, Bahawalnagar, Pakistan. For each of the rice type, we collected mixed no. of seeded (1-20) images for experiments. Samples images of 1, 5, 10, 15, and 20 seeds are shown in Figure 3. The whole of the dataset has been divided into 70%, 15%, and 15% for training, testing, and validation respectively. Table 1 contains information on the dataset used for experiments.

Table 1: Detail of dataset used for research and experiments.

Sr.	Rice type	Rice age (Year)	Total samples used for experiments	No of samples used for training	No of samples used for testing	No of samples used for validation
1	Basmati-2000	0 (age less than 03 months)	1620	1134	243	243
		1	1960	1372	294	294
		2	1820	1274	273	273
2	Chenab-basmati	0 (age less than 03 months)	1820	1274	273	273
		1	1740	1218	261	261
		2	1640	1148	246	246
3	KSK-133	0 (age less than 03 months)	1500	1050	225	225
		1	1780	1246	267	267
		2	1860	1302	279	279
4	Kissan-basmati	0 (age less than 03 months)	2060	1442	309	309

		1	1640	1148	246	246
		2	1560	1092	234	234
5	KSK-434	0 (age less than 03 months)	1680	1176	252	252
		1	1920	1344	288	288
		2	2020	1414	303	303
6	PK-1121 Aromatic	0 (age less than 03 months)	1960	1372	294	294
		1	1440	1008	216	216
		2	1760	1232	264	264
7	Punjab-basmati	0 (age less than 03 months)	1640	1148	246	246
		1	1560	1092	234	234
		2	1980	1386	297	297

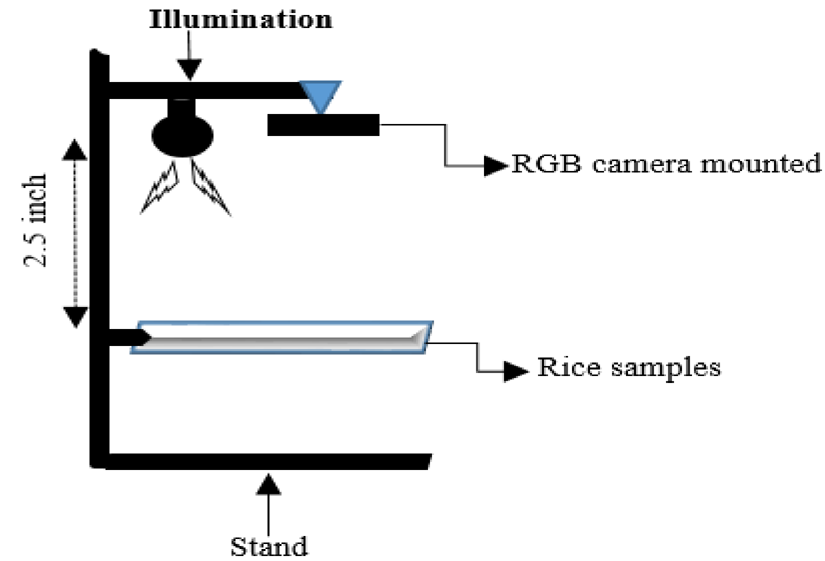
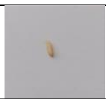
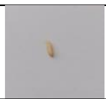
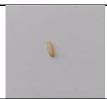
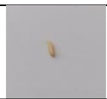
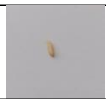
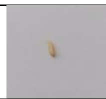
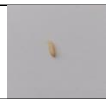
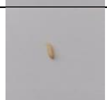
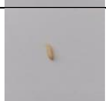
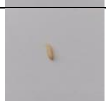
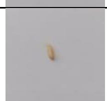
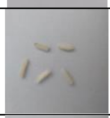
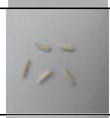


Figure 2: Setup diagram for image acquisition

No of seeds	Age	Basmati-2000	Chenab-basmati	KSK-133	Kissan-basmati	KSK-434	PK-1121 Aromatic	Punjab-basmati
01 seeded image	2020							
	2019							
	2018							
5 seeded images	2020							
	2019							

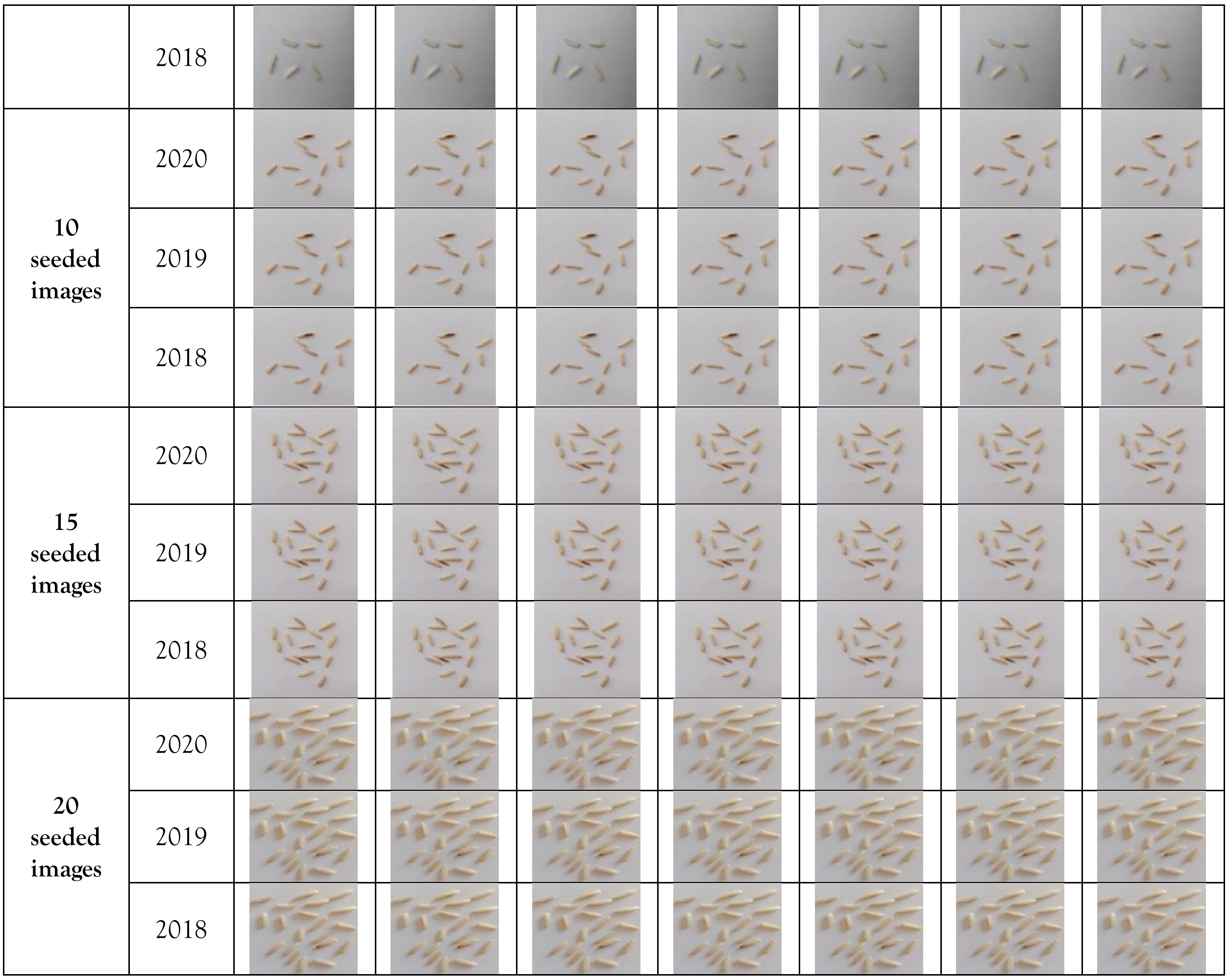


Figure 3: 01 seeded, 05 seeded, 10 seeded, 15 seeded, and 20 seeded images of old and new of each of the Basmati-2000, Chenab-basmati, KSK-133, Kissan-basmati, KSK-434, PK-1121, and Punjab-basmati

3.2. The proposed CNN architecture

The proposed CNN model

In this research work, a new CNN architecture, which extracts deep features from rice seed images in automated manners through convolution and pooling process, has been designed. The proposed CNN model is represented in Figure 4.

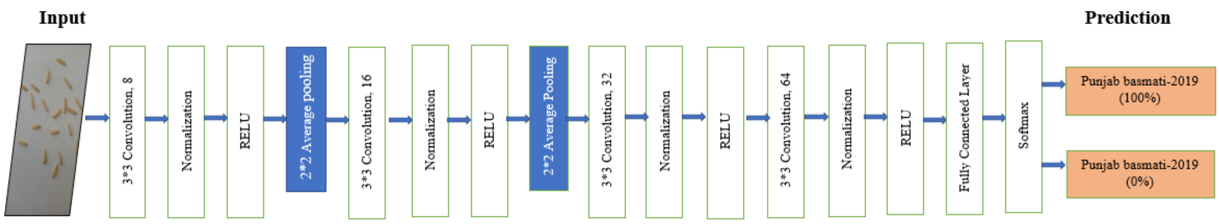


Figure 4:The proposed CNN architecture for rice age estimation

Results obtained with the proposed method have also been compared with the state-of-the-art recently conducted studies and different CNN models, i.e., VGG-19, Inception-V3, and ResNet50. These state-of-the-art CNN models have achieved excellent performance in Image Net Large Scale Visual Recognition Challenge (ILSVRC). It is noteworthy to mention here that the proposed model is composed of only 16 layers as represented in Table 2, which are less as compared to state-of-the-art CNN models. A detailed description of the proposed model layers is as follows.

Convolutional layer

Features maps, which represent learned features from the input set of images, are generated through the convolutional layer. Trainable weights help filters to generate feature maps. Given an image *Img* with dimension (*M*, *N*) with filter *F* of size (*p*, *q*), the convolution method is represented in Equation No. 1. Feature maps have been generated through a convolutional process starting from top left to bottom right of the input *Img*.

$$conv = (Img * \mathrm{F})(\mathrm{x,y}) = \sum_M \sum_N I\,(x-p, y-q)F(p,q) \tag{1}$$

Pooling layer

Generally, pooling operation is performed after the convolution process, it is simple and effective. Feature maps with local perceptive fields are produced by pooling operation. The main contributing features, which helped the model in age estimation of rice from dataset have been extracted using pooling layer, it is also used to reduce dimensions of the extracted features. Although, there were three options, i.e., minimum, maximum, and average for pooling. However, to reduce variance and computation complexity, average pooling words well, so used in this model.

Rectified Linear Unit (ReLU) layer

This layer has a vital role in neural networks. Matrix multiplication of a network, under training, may cause the network to become linear if the activation function is not used. The sigmoid function is generally used as an activation function, represented using Equation No. 2. The gradient is calculated using Equation No. 3; however, its gradient descent algorithm mostly uses the sigmoid function.

$$s(x) = \frac{1}{1-e^{-x}} \tag{2}$$

$$S'(x) = S(x)(1 - S(x)) \tag{3}$$

Sigmoidal function caused gradient vanishing problem, and this problem leads to the slow learning process, which is why it is not used in deep architectures. Thus, the Rectified Linear Unit (ReLU) is often a good choice for deep architectures especially CNN. The formula of ReLU is calculated using Equation No. 4.

$$ReLU(x) = max(x, 0) \tag{4}$$

Fully connected layer

Mostly, this layer is the part of CNN models at their end, which is used for recognition of the targeted objects.

Table2: The proposed CNN Architecture for rice age estimation

Layer	Type of Layer	Filter size	Stride	No. of filters
Layer No. 1	Convolution Layer	3x3	2x2	8
Layer No. 2	Normalization Layer	-	-	-
Layer No. 3	RELU Layer	-	-	-
Layer No. 4	Average Pooling	2x2	2x2	-
Layer No. 5	Convolution Layer	3x3	2x2	16
Layer No. 6	Normalization Layer	-	-	-
Layer No. 7	RELU Layer	-	-	-
Layer No. 8	Average Pooling	2x2	2x2	-
Layer No. 9	Convolution Layer	3x3	2x2	32
Layer No. 10	Normalization Layer	-	-	-
Layer No. 11	RELU Layer	-	-	-
Layer No. 12	Convolution Layer	3x3	2x2	64
Layer No. 13	Normalization Layer			
Layer No. 14	RELU Layer			
Layer No. 15	Fully Connected Layer			
Layers No. 16	Softmax Layer			

It is worth stating here that the proposed model has a total of 16 number of layers, with 0.6million parameters, and can receive images of size 512x512 as input. An overview of the whole process of rice age estimation using the proposed model is shown in Figure 5.

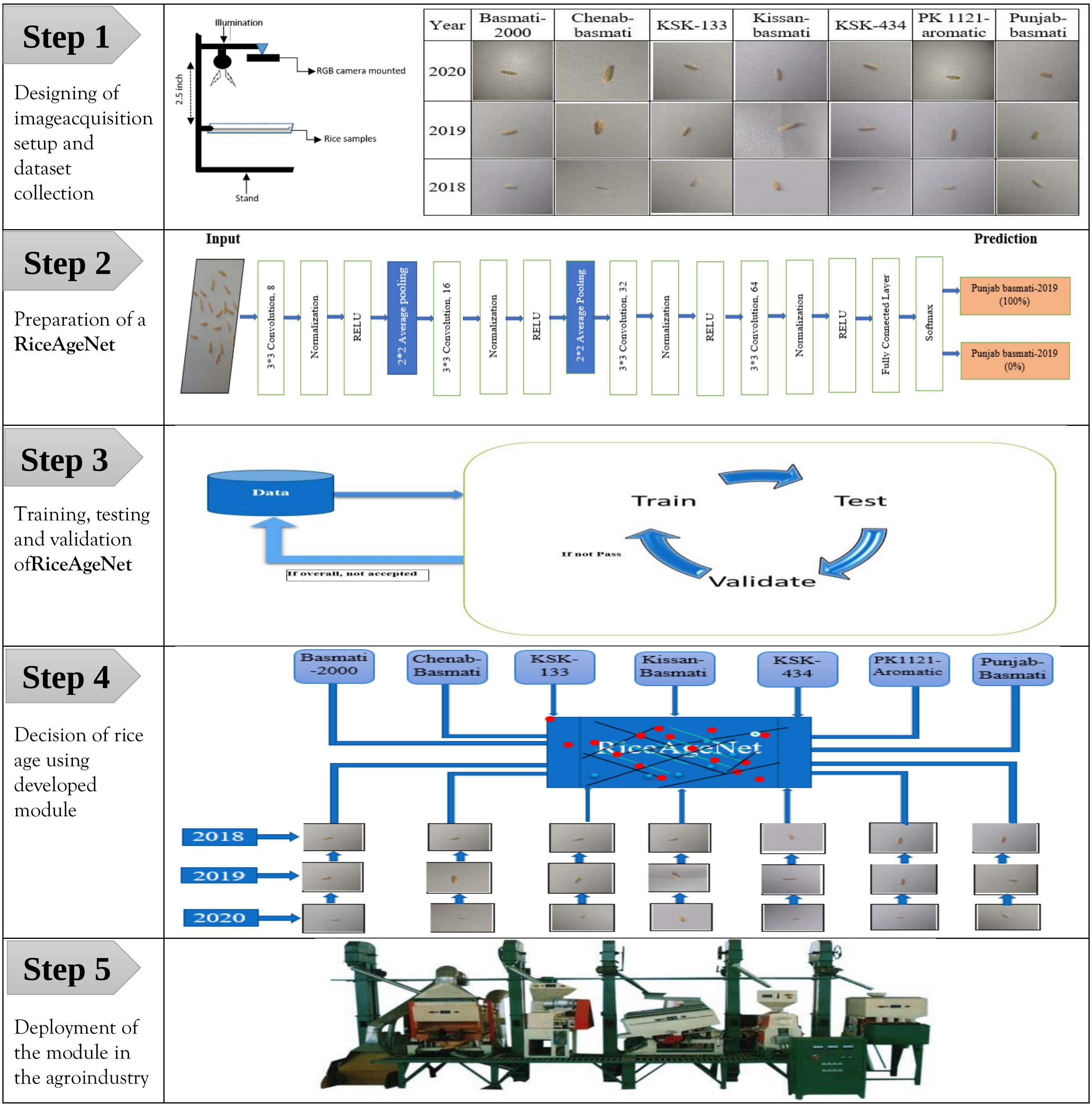


Figure 5: An overview of the whole process of rice age estimation using the proposed model.

4.0 Result and discussions

In this experimental work, the whole of the dataset is divided into 70%, 15%, and 15% for training, testing, and validation respectively. The results obtained through the proposed model are configured with two (02) epochs selected in experiments. The simulation environment used is MATLAB 2020b on Intel(R) Core (TM) i5-5200U CPU @2.20GHz-2.20GHz processor with 8GB RAM and built-in GPU. The results shown in Table 3 have been obtained through the proposed model.

Table 3: Results obtained through the proposed model.

Sr.	Rice type	Rice age (Years)	Accuracy
1	Basmati-2000	0 (age less than 03 months)	100%
		1	
		2	
2	Chenab-basmati	0 (age less than 03 months)	99.87%
		1	
		2	
3	KSK-133	0 (age less than 03 months)	100%
		1	
		2	
4	Kissan-basmati	0 (age less than 03 months)	99.88%
		1	
		2	
5	KSK-434	0 (age less than 03 months)	100%
		1	
		2	
6	PK-1121 Aromatic	0 (age less than 03 months)	100%
		1	
		2	
7	Punjab-basmati	0 (age less than 03 months)	100%
		1	
		2	

4.1 Comparison with state-of-the-art studies

The results obtained through the proposed model have been compared with the results obtained through state-of-the methods of rice seed classification and quality assessment as shown in Table 4.

(Philip & Anita, 2017)used multi-layer perceptron, naive Bayes tree, sequential minimal optimization, and SVM for the classification of five rice types. Naive Bayes tree classifier achieved the highest accuracy of 95.78%.(Lin et al., 2018) used a deep convolutional neural network architecture for rice types of classification. The overall achieved accuracy was 95.5% on 5554 images. These studies have been performed for the classification of rice types with not so high classification rates.

(Chen et al., 2019)obtained overall accuracy of 96.4% on colored rice for their quality assessment using SVM. They used 150 images for research and experiments. Although, a reasonable accuracy, however, use of 150 images only could not ensure the robustness of the proposed model.(Anami et al., 2019)achieved 93.31% accuracy for automated recognition and classification of adulteration levels from bulk paddy grain using BPNN, SVM, and K-NN. The achieved measures are not so high. Similarly, in another study,(S. K. Singh et al., 2020) the method of weight and size of rice kernels using RF, ANN, SVM, KRR, and K-NN with overall achieved accuracy, i.e., 95% has been proposed. In the study (Xu et al., 2020),diagnosis of nutrient deficiencies in rice seeds using deep convolutional neural networks has been proposed. Maximum accuracy achieved through a pre-trained model, i.e., denseNet121 is 97.44 ± 0.57.

In another study (Kiratiratanapruk et al., 2020), classification of paddy rice seed has been performed 95.15% accuracy based result.(K. R. Singh & Chaudhury, 2020)obtained 97.75% accuracy for the classification of rice grain on 400 images of each rice type. In the most recent study (Estrada-Pérez et al., 2021), five different types of rice verities and their floor are used to classify through thermal imaging using a deep convolutional neural network. The overall achieved accuracy is above 98%.

Table 4: Comparison with state-of-the-art studies

Study	Classifier	Problem addressed	Dataset	Evaluation measure (Accuracy %)
(Philip & Anita, 2017)	Multi-layer perceptron, Naive Bayes Tree, Sequential Minimal Optimization, SVM	05 Rice Grain types of Classification	Locally developed	95.78%
(Lin et al., 2018)	Deep convolutional neural network (DCNN)	05 Rice Grain types of Classification	5554 images for calibration 1845 images for validation	95.5%
(Chen et al., 2019)	SVM	Quality assessment of rice seeds	150 images of rice seeds	96.4%
(Anami et al., 2019)	BPNN, SVM, K-NN	adulteration classification from bulk paddy grain	7000 pictures of each sample	93.31%
(S. K. Singh et al., 2020)	RF, ANN, SVM KRR, K-NN	weight and size estimation of rice kernels	1000 images of each of 3 rice types	95%
(Xu et al., 2020)	Deep convolutional neural network (DCNN), Inception-v3, ResNet, and DenseNet121	Rice Nutrient Deficiencies classification	1818 photographs of plant leaves	97.44%
(Kiratiratanapruk et al., 2020)	LR, LDA, k-NN, SVM VGG16, VGG19, Xception, InceptionV3, and InceptionResNetV2	Development of Paddy Rice Seed Classification	50,000 seeds images	83.9% on SVM 95.15% on InceptionResNet V2
(K. R. Singh & Chaudhury, 2020)	Cascade classifier	rice grain classification	400images of each rice type	97.75%
(Estrada-Pérez et al., 2021)	Deep convolutional neural network	quality of rice seeds	63000 thermographic images of 5 different rice types	98%
RiceAgeNet	CNN	Age estimation of rice seeds	Basmati-2000=5400 Chenab-basmati=5200 KSK-133=5140 Kissan-basmati=5260 KSK-434=5620 PK-1121 Aromatic=5160 Punjab-basmati=5180	≅100%

4.2 Comparison with state-of-the-art different CNN models

The results obtained through the proposed method are also compared with state-of-the-art different CNN models, i.e., VGG-19, Inception-V3, and ResNet50as represented in Table 5. The proposed method in most aspects achieved perfect accuracy, i.e., 100%.

Table 5: Comparison with the state-of-the-art CNN based models.

State-of-the-art CNN models	Layers	Parameters (Millions)	Rice types used for experiments	Accuracy
VGG-19	19	144	Basmati-2000	96.76
			Chenab-basmati	95.88
			KSK-133	98.21
			Kissan-basmati	96.54
			KSK-434	95.39
			PK-1121 Aromatic	98.68
			Punjab-basmati	99.06
Inception-V3	48	23.9	Basmati-2000	95.57
			Chenab-basmati	95.78
			KSK-133	97.76
			Kissan-basmati	96.38
			KSK-434	97.36
			PK-1121 Aromatic	95.39
			Punjab-basmati	98.68
ResNet50	50	25.6	Basmati-2000	97.18
			Chenab-basmati	98.96
			KSK-133	98.68
			Kissan-basmati	99.06
			KSK-434	99.04
			PK-1121 Aromatic	98.68
			Punjab-basmati	97.18
RiceAgeNet	16	0.6	Basmati-2000	100%
			Chenab-basmati	99.87%
			KSK-133	100%
			Kissan-basmati	99.88%
			KSK-434	100%
			PK-1121 Aromatic	100%
			Punjab-basmati	100%

Conclusion

In this study, the main aim is to suggest a system that can estimate the age of rice using machine vision. For this purpose, the dataset of rice samples cultivated in the years 2018, 2019, and 2020 having age levels 2, 1, and 0 years respectively have been obtained through a designed setup. A CNN architecture designed specifically to estimate the age has been proposed. The proposed model come up with ideal results when evaluated on most Pakistani grown rice seed types. Results are compared with state-of-the-art studies and CNN methods. This model has also been integrated into the existing Agri-industry of rice grading.

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