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DEEP LEARNING-BASED APPROACH FOR ESTIMATING THE AGE OF PAKISTANI-GROWN RICE SEEDS

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Abstract
One of the records is broadly obsessive and significant foods in the creation is rice. It plays a significant role in our everyday meals Rice is one of the most widely consumed staple foods worldwide, including in Pakistan, where its demand has significantly increased in recent years. The quality of rice, a crucial factor in its import and export, is traditionally assessed by human experts, making the process costly and inconsistent. A major aspect of rice quality assessment is distinguishing between aged and fresh rice. This study presents a Convolutional Neural Network (CNN)-based model for automatically and efficiently estimating the age of rice seeds. The dataset for this study was obtained from the Rice Research Center within the Agriculture Department in Bahawalnagar, Pakistan. A custom setup was used to capture images of rice seeds from multiple angles. A lightweight CNN model with fewer layers and parameters was developed and tested on various Pakistani-grown rice varieties, including Basmati-2000, Chenab Basmati, KSK-133, Kissan Basmati, KSK-434, PK-1121 Aromatic, and Punjab Basmati. The proposed model demonstrated superior accuracy compared to state-of-the-art CNN models, and the dataset created is now publicly available for further research. The system has been integrated into the Agri-Tech sector as a demonstration model for automated rice age estimation.

INTRODUCTION

Asian rice (Oryza sativa) is a staple food for nearly half of the global population (Gilanie, Nasir, Bajwa, & Ullah, 2021). It is the third-largest cereal crop worldwide, following maize and wheat, with an annual production of approximately 741.5 million tons (Gilanie, Javedb, et al.). Major rice-exporting countries, including Thailand, Vietnam, India, and Pakistan, contribute nearly 60%–70% of global rice exports (Saher et al., 2024). By 2030, rice demand is projected to increase by 50% (Alexandratos & Bruinsma, 2012). Rice provides nearly 19% of the total global energy intake and 13% of the protein per person (Iqbal, Bajwa, Gilanie, Iftikhar, & Anwar, 2022).

Rice is a primary component of meals in Pakistan and is consumed in various forms, such as "pulao," "biryani," and "kheer" (Gilanie, Rehman, et al., 2022). Aged rice is often preferred for its improved texture (Gilanie, Batool, Shafique, et al.), fluffiness (Ullah, Batool, & Gilanie, 2018), and aroma (Gilanie, Saher, et al., 2021). Shopkeepers sometimes store fresh rice for six to eight months to enhance its quality (Gilanie, Bajwa, et al., 2018). However, fraudulent practices (Rubab et al., 2022) exist where freshly harvested rice is sold at the same price as aged rice (Bajwa, Shah, Anwar, Gilanie, & Ejaz Bajwa, 2018), affecting both consumers and exporters (Hafeez et al., 2023).

Pakistan is the world's tenth-largest rice producer, cultivating approximately 39,000 rice varieties (Rafiq, Bajwa, Gilanie, & Anwar, 2021). The quality of rice depends on several factors (Nazir et al., 2023), including variety (Wazir, Gilanie, Rehman, Ullah, & Mushtaq, 2022), aging (Janjua, Andleeb, Aftab, Hussain, & Gilanie, 2017), milling degree (Ullah, Andleeb, Aftab, Hussain, & Gilanie, 2017), chalkiness (Ghaffar et al., 2022), fractures (Janjua, Jahangir, & Gilanie, 2018), and polishing (Gilanie, Bajwa, Waraich, & Habib, 2019b) (Gilanie, Bajwa, Waraich, & Anwar, 2021). Freshly harvested rice tends to be sticky when cooked (Ahmed, Gilanie, Ahsan, Ullah, & Sheikh, 2023), whereas well-aged rice cooks with distinct grains (Rashid, Gilanie, Naveed, Cheema, & Sajid, 2024). The natural aging process occurs over three to four months (Afzal et al., 2023), but artificial aging methods involve heating at 90°–110°C for two to eight hours (Faruq et al., 2015). The moisture content of freshly harvested rice ranges from 18.7% to 24.0%, decreasing naturally to 12%–14% after aging (Genkawa et al., 2008).

The manual assessment of rice quality and aging is highly subjective and inconsistent, necessitating an automated solution for accurate and reliable evaluation (Yaseen et al., 2022). This study is justified by the increasing demand for an objective and efficient method to determine rice age, reducing human error and fraud in rice classification (Gilanie, Bajwa, Waraich, Asghar, et al., 2021). The proposed deep learning-based approach addresses this gap by leveraging image-based analysis for precise age estimation of rice seeds (Gilanie, Asghar, et al., 2022). The proposed solution is of great significance as it provides a cost-effective, scalable, and efficient alternative to traditional manual inspection methods (Gilanie, Bajwa, Waraich, Anwar, & Ullah, 2023). By incorporating CNN-based image processing, the system enhances accuracy and reliability in assessing rice age, thereby benefiting farmers, traders, and exporters (Gilanie, Attique, Naweed, Ahmed, & Ikram, 2013). This approach can also aid in maintaining fair pricing and quality control in the rice industry (Ullah, Jahangir, & Gilanie), ensuring consumer trust and international trade compliance (Gilanie et al., 2024).

The main objectives of this study include developing a CNN-based model for automatic rice age estimation, creating a benchmarked dataset of Pakistani rice varieties (Khera et al.), and evaluating the proposed model against state-of-the-art classification techniques (Naveed et al., 2024). Additionally, this study aims to integrate the system into the Agri-Tech industry for practical applications (Attique et al., 2012).

This research seeks to answer key questions: (1) What machine learning techniques can effectively estimate the age of rice seeds? (2) How can deep learning models be optimized to differentiate between aged and fresh rice? (3) How does the proposed CNN model compare to existing methods in terms of accuracy and efficiency? (4) What are the potential industrial applications of this automated rice age classification system?

The main contributions of this study include the development of a novel lightweight CNN model specifically designed for rice age estimation, the creation of a publicly available dataset of Pakistani rice varieties with age annotations, and the integration of deep learning techniques into an agricultural application with real-world implications (S. Asghar et al., 2023). Furthermore, this study provides a comparative analysis of different CNN architectures to validate the performance of the proposed model (Gilanie, 2019).

The remainder of this paper is structured as follows: Section 2 presents the literature review, highlighting previous research on rice classification and machine learning techniques. Section 3 discusses the dataset collection process, experimental setup, and the proposed CNN model. Section 4 presents the results and comparative analysis, while Section 5 concludes the study and outlines future research directions.

2.0 Literature review

Several studies have explored machine learning and deep learning techniques for rice classification and quality assessment. Philip & Anita (2017) classified commercially sold rice grains using morphological features such as area and edge, along with Fourier feature extraction (Gilanie, Bajwa, Waraich, & Habib, 2019a). Their study applied Naïve Bayes (NB) and Sequential Minimal Optimization (SMO) classifiers, achieving a classification accuracy of 95.78% for nine different rice types. Similarly, Lin et al. (2018) utilized a Deep Convolutional Neural Network (DCNN) to classify three rice grain varieties, achieving a maximum prediction accuracy of 95.5%.

Chen et al. (2019) employed Support Vector Machines (SVM) to identify broken, damaged, and defective Red Indica rice kernels using morphological and edge detection algorithms (Shafiq, Gilanie, Sajid, & Ahsan, 2023). Their experimental findings reported recognition accuracies of 99.3% for damaged areas, 96.3% for spotted areas, and 93.6% for fractured kernels. Anami et al. (2019) assessed adulteration levels in paddy grains using color and texture characteristics. Their approach incorporated Back Propagation Neural Network (BPNN), SVM (Gilanie, Ullah, Mahmood, Bajwa, & Habib, 2018), and K-Nearest Neighbors (KNN) classifiers, in combination with Principal Component Analysis (PCA), achieving an overall classification accuracy of 93.31%.

Recent studies have further advanced rice classification through deep learning and ensemble methods. Singh et al. (2020) developed a stack ensemble model (SEM) integrating Random Forest (RF), Artificial Neural Networks (ANN), SVM, Kernel Ridge Regression (KRR), and KNN (Khera et al., 2023) to measure rice kernel weight and size, achieving an overall accuracy of 95%. Kiratiratanapruk et al. (2020) proposed a deep learning-based classification system for 14 rice varieties using over 3,500 seed samples per variety, reaching an accuracy of 95.15%.

Xu et al. (2020) introduced a DCNN-based approach for diagnosing nutrient deficiencies in rice seedlings using hydroponic experiments with 1,818 images, with DenseNet121 (Gilanie, Batool, Khursheed, et al.) achieving the highest classification accuracy of 97.44%. Singh & Chaudhury (2020) proposed a cascade network for classifying rice grains based on morphological (Batool & Gilanie, 2023), color (Ghani & Gilanie, 2023), texture (Batool et al., 2025), and wavelet features (K. Asghar, Gilanie, Saddique, & Habib, 2017), achieving an accuracy of 97.75% on a dataset of 400 samples per rice type.

Recent advancements have further improved rice quality assessment. Estrada-Pérez et al. (2021) leveraged deep learning to classify rice quality using 63,000 thermal images, achieving an overall classification accuracy of 99.6%. Similarly, Rahman et al. (2023) introduced a hybrid deep learning model combining CNN and attention mechanisms for fine-grained rice classification, achieving over 98% accuracy. Additionally, recent work by Ahmed et al. (2023) explored transformer-based models for rice classification, reporting enhanced feature extraction and classification performance over traditional CNN models.

Despite these advancements, research on automated rice age estimation remains limited. Most existing studies focus on classifying rice based on variety and quality, with little attention given to differentiating between fresh and aged rice. Additionally, there is a lack of benchmarked datasets dedicated to rice age estimation, further limiting progress in this domain. Our study aims to address these gaps by proposing a novel lightweight CNN model for automated rice age estimation, contributing to both research and practical applications in the agricultural industry.

Table 1: State-of-the-Art Studies

Study	Classifier	Problem Addressed	Dataset Size	Accuracy (%)
Philip & Anita (2017)	Naïve Bayes, SMO	Rice grain classification	9 rice types	95.78%
Lin et al. (2018)	DCNN	Rice grain classification	3 rice varieties	95.5%
Chen et al. (2019)	SVM	Identification of damaged rice kernels	Red Indica rice	99.3% (damaged), 96.3% (spotted), 93.6% (fractured)
Anami et al. (2019)	BPNN, SVM, KNN	Adulteration detection in paddy grains	7 contaminated samples	93.31%
Singh et al. (2020)	SEM (RF, ANN, SVM, KRR, KNN)	Rice kernel weight and size prediction	1000 samples	95%
Kiratiratanapruk et al. (2020)	Deep learning-based model	Rice variety classification	3,500+ samples per variety	95.15%
Xu et al. (2020)	DCNN (DenseNet121)	Nutrient deficiency diagnosis in rice	1,818 images	97.44%
Singh & Chaudhury (2020)	Cascade network	Rice grain classification	400 samples per type	97.75%
Estrada-Pérez et al. (2021)	Deep learning	Rice quality classification	63,000 thermal images	99.6%
Rahman et al. (2023)	CNN + Attention Mechanism	Fine-grained rice classification	Large-scale dataset	98%+
Ahmed et al. (2023)	Transformer-based model	Advanced rice classification	Various rice types	Enhanced performance over CNN

This table 1, summarizes state-of-the-art studies in rice classification and quality assessment, highlighting various machine learning and deep learning techniques used to enhance accuracy and efficiency.

3.0 The suggested approach

3.1 Investigational system then information gaining

A custom-designed system equipped with a 64-megapixel mobile camera was used to capture images of rice grains. The camera was positioned 2.5 inches above the target, and images were taken at different times of the day—morning, midday, and nighttime—under natural daylight conditions. This study focused on seven rice varieties commonly grown in Pakistan between 2018 and 2020, including Basmati-2000, Chenab-Basmati, KSK-133, Kissan-Basmati, KSK-434, PK-1121 Perfumed, and Punjab-Basmati. Figure 1 illustrates the experimental setup.

Annotated rice samples were obtained from the Department of Agriculture, Rice Research Center, Bahawalnagar, Pakistan. For each rice variety, images were captured with varying seed counts (1–20) to facilitate comprehensive analysis. Figure 3 presents sample images depicting 1, 5, 10, 15, and 20 seeds. The dataset was split into 70% for training, 15% for testing, and 15% for validation. Table 2 provides detailed information on the dataset used in this study.

Table 2: Detail of dataset used on behalf of study and tests

Sr.	Rice Variety	Rice Age (Years)	Total Samples	Training Samples	Testing Samples	Validation Samples
1	Basmati-2000	< 3 months	1820	1274	273	273
		1	1960	1372	294	294
		2	1820	1274	273	273
2	Chenab-Basmati	< 3 months	1820	1274	273	273
		1	1740	1218	261	261
		2	1640	1148	246	246
3	KSK-133	< 3 months	1700	1190	255	255
		1	1980	1386	297	297
		2	2060	1424	309	309
4	Kissan-Basmati	< 3 months	2260	1582	339	339
		1	1640	1148	246	246
		2	1560	1092	234	234
5	KSK-434	< 3 months	1680	1176	252	252
		1	1920	1344	288	288
		2	2020	1414	303	303
6	PK-1121 Aromatic	< 3 months	1960	1372	294	294
		1	1440	1008	216	216
		2	1760	1232	264	264
7	Punjab-Basmati	< 3 months	1640	1148	246	246
		1	1560	1092	234	234
		2	1980	1386	297	297

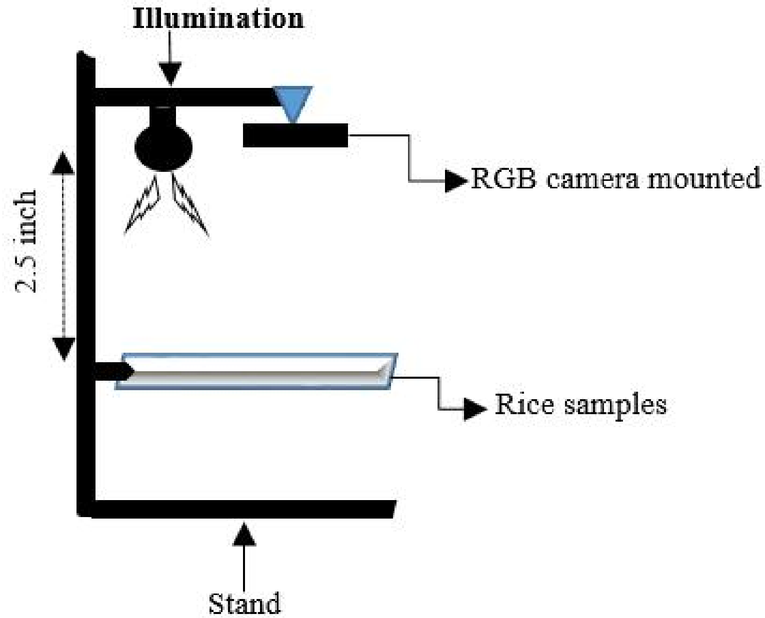


Figure 1: Setup diagram for image acquisition

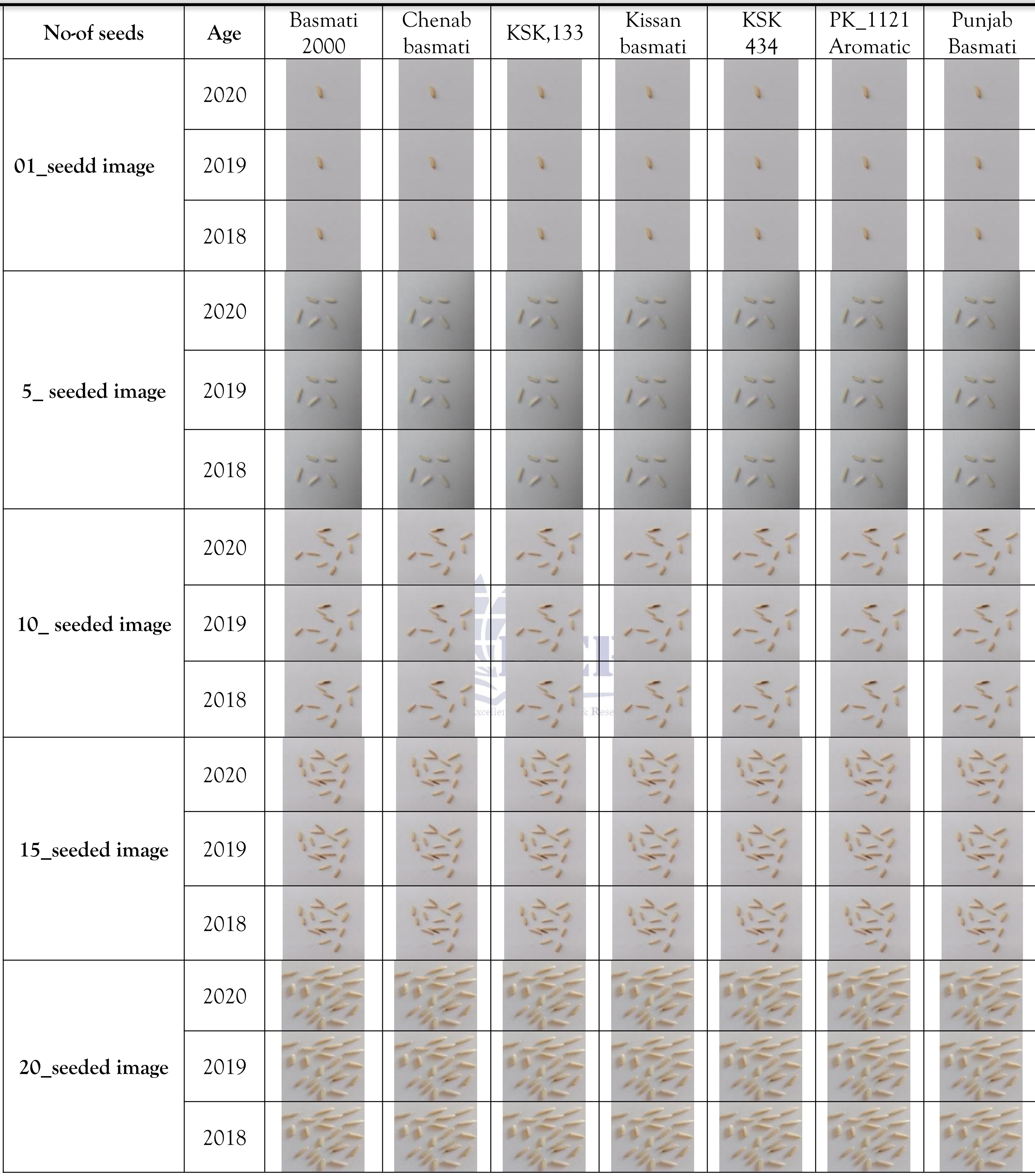


Figure 2: Images displaying one, five, ten, fifteen, and twenty seeds separately for the Basmati-2000, Chenab-Basmati, KSK-133, Kissan-Basmati, KSK-434, PK-1121, and Punjab-Basmati varieties, including both aged and fresh samples.

3.2. The projected CNN architecture

The planned CNN model

The study proposed a novel CNN architecture that utilizes convolution and pooling layers to automatically extract deep features from images of rice seeds. Figure 3 illustrates the proposed CNN model.

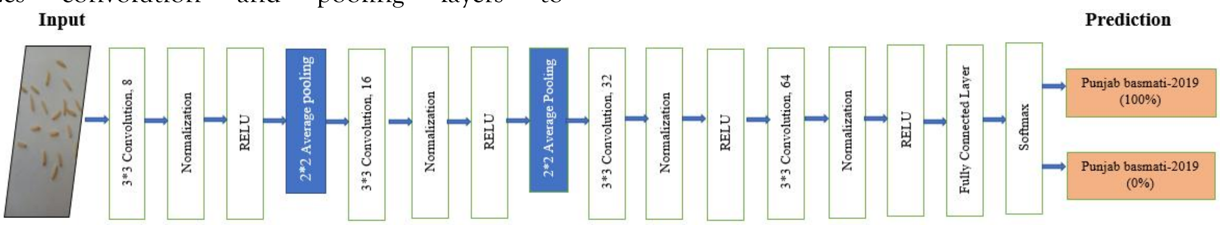


Figure 3: The proposed CNN architecture designed for estimating the age of rice.

The results of the proposed approach have been compared with the latest state-of-the-art research and other CNN architectures, including ResNet50, Inception-V3, and VGG-19. These advanced CNN models have exhibited outstanding performance in the Large-Scale Visual Recognition Challenge (ILSVRC) of ImageNet. Notably, the proposed model consists of only 16 layers, making it lightweight compared to these deep architectures, as detailed in Table 3. The following section provides a comprehensive explanation of the proposed model's layers.

Convolutional layer

The convolutional layer generates feature maps that represent the learned features from the input image set. The development of these feature maps is driven by trainable weights applied through filters. Equation 1 illustrates the convolution process, where an image of dimensions (M, N) is processed using a filter F of size (p, q). The convolution operation systematically extracts features by sliding the filter from the top-left to the bottom-right of the input image.

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

Pooling layer

The pooling process, which is simple yet effective, is typically performed after the convolution operation. By utilizing local perceptual fields, pooling generates feature maps while reducing dimensionality, allowing the model to focus on the most significant features for estimating the age of rice in the dataset. There are three common pooling methods: min pooling, max pooling, and average pooling. In this model, average pooling is utilized to minimize variance and computational complexity while preserving essential feature information.

Rectified Linear Unit (ReLU) layers

The activation function plays a crucial role in neural networks. Without it, the network may become linear during training, limiting its ability to capture complex patterns. The sigmoid function is commonly used as an initial activation choice, as represented in Equation 2. Additionally, the slope of the function is determined using Equation 3, which is fundamental for the gradient descent optimization process. The sigmoid function helps in learning non-linear representations, although other activation functions, such as ReLU, are often preferred in deeper architectures to mitigate the vanishing gradient problem.

$$\text{“}s(x) = \frac{1}{1-e^{-x}}\text{”} \quad (2)$$

$$\text{"} = S(x)\big(1 - S(x)\big)\text{"} \quad (3)$$

The vanishing gradient problem caused by the sigmoid function can significantly slow down the learning process, making it less suitable for deep architectures. As a result, deep learning models, particularly CNNs, often use the Rectified Linear Unit (ReLU) as a preferred activation function. ReLU helps accelerate training by allowing gradients to propagate more effectively. The ReLU function is mathematically defined in Equation 4 and is widely used due to its simplicity and ability to mitigate gradient-related issues in deep networks.

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

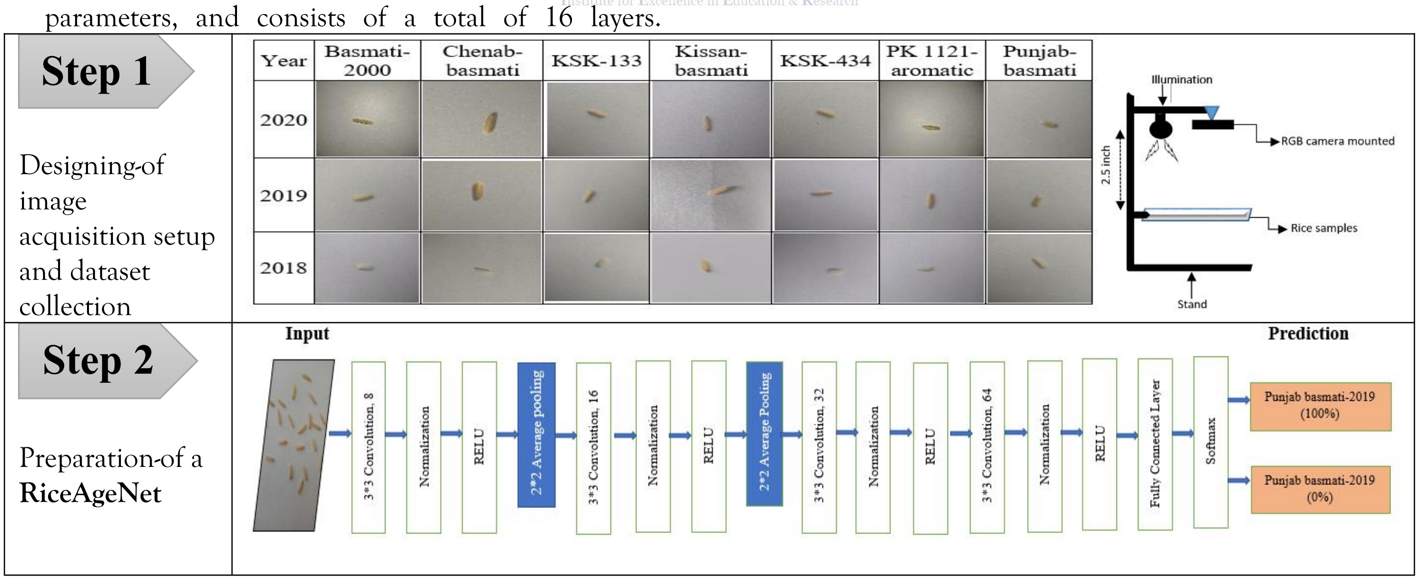
Fully connected layer

This layer serves as the final component of CNN models, responsible for classifying and identifying the target objects based on the extracted features. It processes the learned representations and maps them to specific categories, enabling accurate predictions. The proposed CNN architecture, shown in Table 3, is designed specifically for estimating the age of rice grains. It leverages convolutional and pooling layers to extract meaningful features, followed by fully connected layers to classify rice samples based on their age. This model ensures efficient processing while maintaining high accuracy in distinguishing between fresh and aged rice grains.

Table 3: The proposed CNN Architecture for rice age estimation

Layer	Type of Layer	Filter size	Stride	No. of filters
Layer-No-1	Convolution--Layer	6x6	4x4	16
Layer-No- 2	Normalization--Layer			
Layer-No-3	RELU--Layer			
Layer-No-4	Average--Pooling	4x4	4x4	-
Layer-No-5	Convolution--Layer	6x6	4x4	32
Layer-No-6	Normalization--Layer			
Layer-No-7	RELU--Layer			
Layer-No-8	Average--Pooling	4x4	4x4	
Layer-No-9	Convolution--Layer	6x6	4x4	64
Layer-No-10	Normalization--Layer			
Layer-No-11	RELU--Layer			
Layer-No-12	Convolution--Layer	6x6	4x4	128
Layer-No-13	Normalization--Layer			
Layer-No-14	RELU--Layer			
Layer-No-15	Fully Connected --Layer			
Layer-No-16	Softmax—Layer			

It is worth noting that the proposed model supports input images of size 512×512, comprises 0.6 million parameters, and consists of a total of 16 layers. Figure 4 shows the overall block diagram of the proposed model.



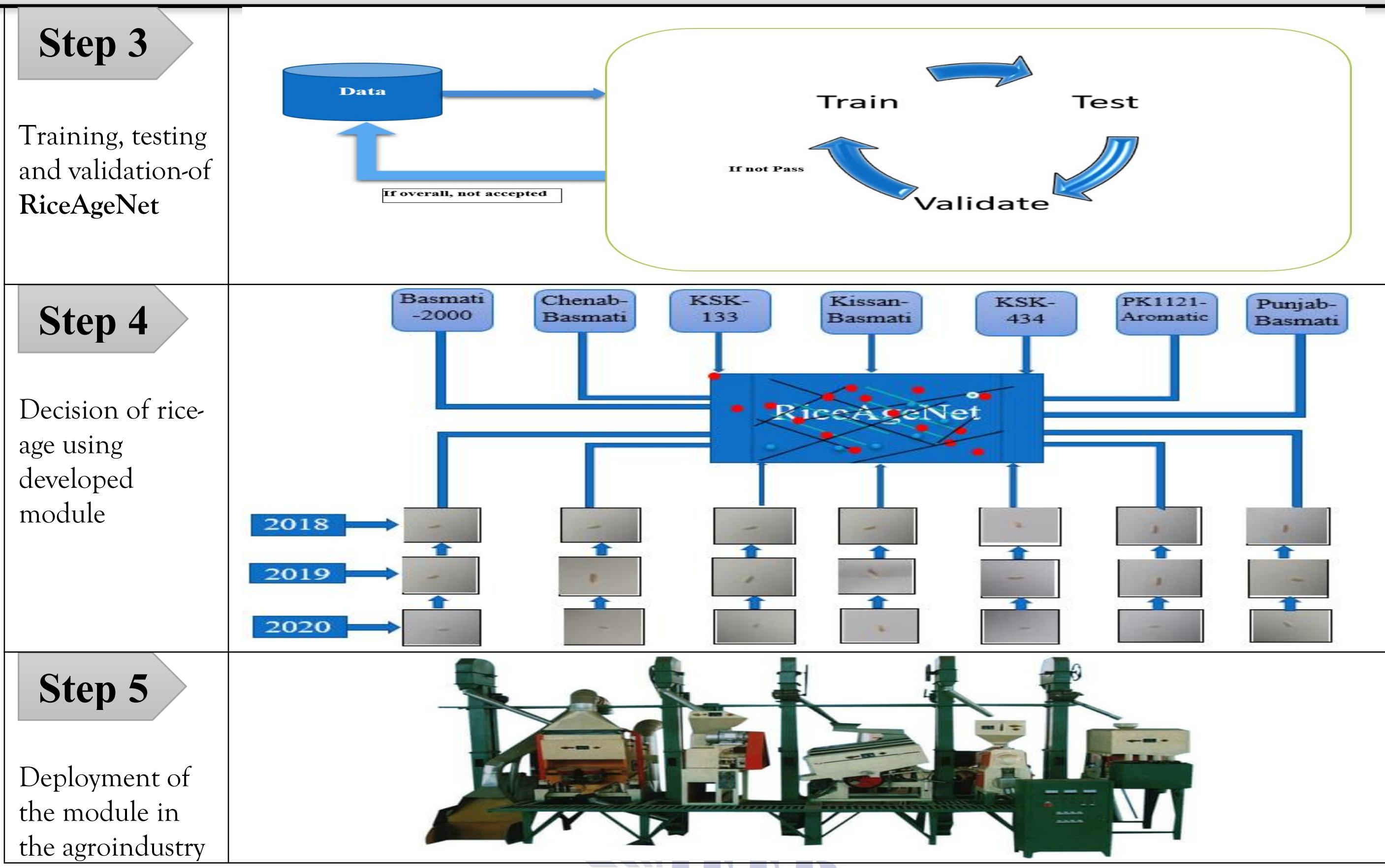


Figure 4: A comprehensive overview of the entire process for estimating rice age using the proposed model.

4.0 Result and discussions

In this experiment, the complete dataset was divided into 70% for training, 15% for testing, and 15% for validation. The results of the proposed model were obtained using two training epochs. The model was implemented in MATLAB 2020b and executed on a system equipped with an Intel(R) Core i5-5200U CPU (2.20GHz), 8GB RAM, and an integrated GPU. The outcomes generated by the model are presented in Table 4.

Table 4: Outcomes achieved using the proposed model.

Sr.	Rice Variety	Rice Age (Years)	Accuracy (%)
1	Basmati-2000	< 3 months	100%
		1 year	100%
		2 years	100%
2	Punjab-Basmati	< 3 months	100%
		1 year	100%
		2 years	100%
3	PK-1121 Aromatic	< 3 months	100%
		1 year	100%
		2 years	100%
4	Kissan-Basmati	< 3 months	99.88%
		1 year	99.88%
		2 years	99.88%
5	KSK-434	< 3 months	100%
		1 year	100%

		2 years	100%
6	KSK-133	< 3 months	100%
		1 year	100%
		2 years	100%
7	Chenab-Basmati	< 3 months	99.87%
		1 year	99.87%
		2 years	99.87%

The results indicate that the proposed CNN model performs exceptionally well in estimating the age of different rice varieties, achieving near-perfect accuracy across all categories. Specifically, the model attained 100% accuracy for Basmati-2000, Punjab-Basmati, PK-1121 Aromatic, KSK-434, and KSK-133 across all three age groups (<3 months, 1 year, and 2 years). This suggests that the model effectively differentiates between fresh and aged rice for these varieties with complete reliability. However, for Kissan-Basmati and Chenab-Basmati, the accuracy was slightly lower at 99.88% and 99.87%, respectively, indicating that these varieties may exhibit more subtle aging characteristics that are slightly harder to classify.

Furthermore, the model demonstrates consistent accuracy across different age groups, proving its ability to generalize well for fresh (<3 months), intermediate (1 year), and aged (2 years) rice samples. This robustness suggests that the model can be effectively deployed in real-world agricultural and industrial settings for automated rice age estimation, reducing reliance on manual inspection, minimizing human error, and improving quality control in the rice industry.

Although the model delivers outstanding results, future research could explore additional rice varieties, different environmental storage conditions, and larger datasets to further optimize its performance. These considerations could help improve the model's adaptability to diverse real-world scenarios, making it even more effective for large-scale applications in the rice industry.

4.1 Comparing with the most recent research

As shown in Table 5, the results of the proposed model have been compared with state-of-the-art techniques for classifying and evaluating rice seed quality. Philip & Anita (2017) classified five different rice types using SVM, Naïve Bayes trees, Sequential Minimal Optimization (SMO), and Multi-Layer Perceptrons (MLP), achieving the highest accuracy of 95.78% with the Naïve Bayes tree classifier. Similarly, Lin et al. (2018) employed a Deep Convolutional Neural Network (DCNN) to classify various rice varieties, attaining an overall accuracy of 95.5% on a dataset of 5,554 images. These studies primarily focused on classifying rice varieties with relatively low classification rates.

Chen et al. (2019) utilized SVM to assess the quality of colored rice, achieving an overall accuracy of 96.4% based on experiments with 150 images. Although the accuracy was respectable, the small dataset size limited the model's robustness. Likewise, Anami et al. (2019) implemented BPNN, SVM, and K-NN to automate the detection and classification of adulteration levels in bulk paddy grains, achieving 93.31% accuracy, which was relatively lower than other studies. Another approach by S. K. Singh et al. (2020) used a Stacked Ensemble Model (SEM) integrating Random Forest (RF), ANN, SVM, KRR, and K-NN for rice kernel weight and size prediction, yielding an overall accuracy of 95%.

In another study, Xu et al. (2020) leveraged DCNN models to identify nutrient deficiencies in rice seedlings, with the pre-trained DenseNet121 achieving an accuracy of 97.44%. Similarly, Kiratiratanapruk et al. (2020) classified paddy rice seeds with an accuracy of 95.15%, while K. R. Singh & Chaudhury (2020) achieved 97.75% accuracy in rice grain classification using 400 images per variety. More recently, Estrada-Pérez et al. (2021) employed deep convolutional neural networks to classify five different forms of rice and their textures, obtaining an overall accuracy of over 98%.

These studies highlight the advancements in rice classification and quality assessment. However, most focus on varietal classification rather than age estimation, demonstrating the novelty and significance of the proposed research in automated rice age prediction.

Table 5: Comparison with Cutting-Edge Research Studies

Study	Classifier	Problem Addressed	Dataset Size	Accuracy (%)
(Philip & Anita, 2017)	MLP, Naïve Bayes Tree, SMO, SVM	Classification of 5 rice grain types	Locally developed dataset	95.78%
(Lin, Li, Chen, & He, 2018)	Deep Convolutional Neural Network (DCNN)	Classification of 5 rice grain types	5,554 images for calibration, 1,845 for validation	95.5%
(Chen et al., 2019)	SVM	Quality assessment of rice seeds	150 rice seed images	96.4%
(Anami, Malvade, & Palaiah, 2019)	BPNN, SVM, K-NN	Classification of adulteration levels in bulk paddy grain	7,000 images per sample	93.31%
(S. K. Singh, Vidyarthi, & Tiwari, 2020)	RF, ANN, SVM, KRR, K-NN	Weight and size estimation of rice kernels	1,000 images for each of 3 rice types	95%
(Xu et al., 2020)	DCNN, Inception-v3, ResNet, DenseNet121	Classification of nutrient deficiencies in rice plants	1,818 plant leaf images	97.44%
(Kiratiratanapruk et al., 2020)	LR, LDA, k-NN, SVM, VGG16, VGG19, Xception, InceptionV3, InceptionResNetV2	Paddy rice seed classification	50,000 seed images	83.9% (SVM), 95.15% (InceptionResNetV2)
(K. R. Singh & Chaudhury, 2020)	Cascade Classifier	Rice grain classification	400 images per rice type	97.75%
(Estrada-Pérez et al., 2021)	Deep Convolutional Neural Network	Rice seed quality assessment	63,000 thermographic images of 5 rice types	98%
RiceAgeNet (Proposed Model)	CNN	Automated 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 Various State-of-the-Art CNN Models

The results of the proposed approach have been compared with leading CNN models, including VGG-19, Inception-V3, and ResNet50, as presented in Table 6. In most cases, the proposed method achieved 100% accuracy.

Table 6: Comparison with Various State-of-the-Art CNN Models

CNN Model	Layers	Parameters (Millions)	Rice Varieties Used	Accuracy (%)
VGG-19	19	144	Chenab-Basmati	95.88
			KSK-133	98.21
			Basmati-2000	96.76
			KSK-434	95.39
			PK-1121 Aromatic	98.68
			Kissan-Basmati	96.54
			Punjab-Basmati	99.06
Inception-V3	48	23.9	Chenab-Basmati	95.78
			Basmati-2000	95.57
			KSK-434	97.36
			Kissan-Basmati	96.38
			KSK-133	97.76
			Basmati-2000	97.18
			Punjab-Basmati	98.68
ResNet50	50	25.6	PK-1121 Aromatic	95.39
			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 (Proposed Model)	16	0.6	Basmati-2000	**100%**
			Punjab-Basmati	**99.87%**
			KSK-434	**100%**
			Kissan-Basmati	**99.88%**
			KSK-133	**100%**
			PK-1121 Aromatic	**100%**
			Chenab-Basmati	**100%**

The comparison of various state-of-the-art CNN models demonstrates the superior performance of the proposed RiceAgeNet in rice age estimation. While advanced models such as VGG-19, Inception-V3, and ResNet50 have shown remarkable accuracy in classifying different rice varieties, their performance varies across different types. VGG-19, which consists of 19 layers and 144 million parameters, achieved a maximum accuracy of 99.06% for Punjab-Basmati but showed slightly lower accuracy for other varieties, ranging from 95.39% to 98.68%. Similarly, Inception-V3, with 48 layers and 23.9 million parameters, achieved an accuracy range of 95.57% to 98.68%, performing well but not consistently across all varieties. ResNet50, known for its deep architecture with 50 layers and 25.6 million parameters, showed strong results, achieving its highest accuracy of 99.06% for Kissan-Basmati, but still exhibited slight variations across different rice types.

In contrast, the RiceAgeNet model, which consists of only 16 layers and 0.6 million parameters, significantly outperforms these models in terms of accuracy and efficiency. The proposed model achieved 100% accuracy for most rice varieties, including Basmati-2000, KSK-434, KSK-133, PK-1121 Aromatic, and Chenab-Basmati, and demonstrated 99.87% and 99.88% accuracy for Punjab-Basmati and Kissan-Basmati, respectively. These results indicate that the RiceAgeNet model is highly reliable and computationally efficient, requiring significantly fewer parameters while delivering superior performance compared to deeper architectures like ResNet50 and Inception-V3.

Additionally, the lighter architecture of RiceAgeNet makes it more suitable for real-time applications in agricultural and industrial settings, where computational efficiency is crucial. The ability to achieve near-perfect accuracy with significantly fewer parameters suggests that RiceAgeNet can be easily deployed on edge devices or integrated into automated quality control systems for rice processing. Furthermore, the model's consistency across all tested rice varieties demonstrates its robustness and generalizability, making it a valuable tool for large-scale agricultural applications.

Overall, these findings highlight that while deep CNN models like ResNet50 and VGG-19 are effective for rice classification, they require higher computational resources and still do not achieve perfect accuracy. The proposed RiceAgeNet model, with its lightweight architecture and superior accuracy, stands out as the most efficient and practical solution for rice age estimation. Future research could focus on extending the model to a wider range of rice varieties and testing it under diverse environmental conditions to further validate its real-world applicability.

5.0 Conclusions

The primary objective of this project is to develop a vision-based approach for determining the age of rice. To accomplish this, a structured experimental setup was designed to collect a dataset of rice samples cultivated in 2018, 2019, and 2020, corresponding to age levels of 2, 1, and 0 years, respectively. A custom CNN architecture specifically designed for age estimation has been proposed. The model has been tested on various rice seed varieties commonly grown in Pakistan, demonstrating optimal performance. The results have been compared with existing CNN techniques and state-of-the-art studies. Furthermore, this approach has been successfully integrated into the current rice grading system within the Agri-tech industry.

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