Sensors and Materials, Vol. 37, No. 6 (2025) 2447–2461
MYU Tokyo

S & M 4066

Rice Seed Varieties Classified Using Diffusion Convolutional Neural Networks at Various GPS Locations

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(Received May 23, 2025; accepted June 17, 2025)

Keywords: categorization of rice seed varieties, DCNN, 1000 photographs from iPhone sensor camera, comparison of supervised and deep learning algorithms, comparison of publicity data

Photographs of five distinct rice varieties were classified using the new diffusion convolutional neural network (DCNN) technique to create a rice detection system. In this study, we employed a 48-megapixel iPhone 16 Plus camera, which utilizes sensor technology to take 1000 sample photos under various lighting conditions, such as day and night. Regarding the technical approach, a DCNN based on deep learning was used to categorize rice. By calculating the indication of each performance metric, the examined classes generated an overall accuracy of 99.0% using the dataset for training, testing, and validation. In addition, six supervised learning and two deep learning algorithms were tested on these rice varieties and the results were compared. Finally, the practicality of the DCNN tests employing a larger input publicity dataset was assessed, along with their accuracy, loss, and training time. Statistical analysis and comparison showed that our technique achieved a 99% classification rate. They also explain the benefits of DCNN technology compared it with other models, achieving higher performance for agricultural data. On the other hand, integrating GPS into rice seed classification is an actual use of sensor technology, especially in DCNN methodology related to machine learning.

1. Introduction

Rice is one of the world's most essential and ancient crops. It is a staple diet for half of the world's population and has been cultivated for over 5000 years. Approximately 8000–9000 years ago, rice was first cultivated in China, where it is believed to have originated. Since then, rice cultivation has spread to Japan, Southeast Asia, India, and other regions of Asia. Today, rice is grown in over 100 nations and ranks second in cereal production globally after maize. It is a vital component of numerous traditional Asian dishes and is used in various recipes, such as sushi, risotto, and paella. Warm and humid weather, with abundant water, is ideal for rice growth. Rice is a globally produced staple food, with different genetic varieties grown in numerous countries. As different rice varieties are cultivated, identifying specific varieties has become increasingly challenging. Rice classification is one solution to this problem; however, it is time-consuming

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https://doi.org/10.18494/SAM5744

ISSN 0914-4935 © MYU K.K.
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and prone to human error. We developed a smart and intelligent system for classifying rice into distinct major varieties of popular Myanmar rice.

The Association of Southeast Asian Nations (ASEAN) countries, including Indonesia, Vietnam, Thailand, Myanmar, and the Philippines, account for 25% or more of the world's annual rice production, ranking among the top rice-producing countries worldwide. In fiscal year 2022–2023, Myanmar's exports of rice and broken rice reached 2.17 million tons, earning 821.30 million dollars. During this fiscal year, the countries to which Myanmar export rice were mainly China, the Philippines, Spain, Italy, Belgium, Poland, Togo, and Madagascar.

The classification of rice seed varieties is an exploratory research topic. In exploratory research, broad concepts are examined, and why and how things occur are explored. In place of GPS, the novel diffusion convolutional neural network (DCNN) model is utilized to identify multiple types of rice using the dataset of personal rice photos. In machine learning, sensor-based technology is linked to DCNN. The main goal of this study was to determine the effectiveness of rice seed varieties. The remainder of this paper is organized as follows.

- The motivation and contributions of this study are highlighted in Sect. 2, followed by a summary of the relevant literature.
- In Sect. 3, we describe the comprehensive approach, which covers data collection, preprocessing, and the findings of the exploratory data analysis.
- The main conclusions and suggestions are presented in Sect. 4.
- Finally, in Sect. 5, we provide a summary and recommendations for further study.

1.1 Problem statement

Laborers manually examine rice grains. Identifying rice varieties has become increasingly challenging as different types are cultivated. This requires considerable time and is prone to human mistakes. Accordingly, we must develop a system that can quickly and accurately recognize the varieties of rice grains. Specifically, the solution to classifying rice varieties is a mixed strategy based on deep learning techniques. An online/offline intelligent rice classification system is required to evaluate the quality of rice samples. Rice species can then be recognized promptly and precisely.

1.2 Challenges

- For an average individual, visually identifying a specific type of rice is challenging.
- Accurately determining the genus of rice grains requires precise analysis.
- An efficient, affordable, and reliable system for classifying rice types was developed on the basis of computer vision and machine learning techniques.

1.3 This study's primary benefit

An iPhone 16 Plus sensor camera was used to identify different types of rice using the unique DCNN model on a dataset of personal rice images taken under various light conditions. Because of the GPS-generated seed types, a smart recommendation system suitable for many conditions, including soil, longitude, latitude, and states, was created.

2. Literature Review

The first study about point cloud data in three dimensions of rice seed surfaces captured using a Ray Trix light field camera was reported in 2021.(1) Eight distinct rice varieties were classified using an improved Point Net deep learning model with an average classification accuracy of 89.4% following data processing. Furthermore, the second study examined the categorization of rice seed varieties using Soft Independent Modeling of Class Analogy (SIMCA) in combination with near-infrared spectroscopy (NIRS).(2) The method's excellent accuracy rates demonstrated the potential of NIR spectroscopy in seed classification. The third research study employed several methods, such as backpropagation neural networks (BPNNs) and Bayes classifiers, to identify various types of rice seed.(3) The study's objective was to enhance seed quality control by automating the identification of rice seed varieties. In the next study, an image processing method to classify the genotypes of Thai rice seeds was developed.(4) Thailand's rice seed classification automation technique appears to have potential owing to its high classification accuracy. In this research, the authors introduced the Fused Net model, which integrates multiple data modalities, for rice seed classification.(5) The model aimed to improve classification accuracy by combining multiple feature extraction techniques.

A previous study used a five-class dataset comprising data on Indica and Japonica rice, and the ResNet34 model achieved 98.0% classification success.(6) Another study used NIR and HS-SPME–GC–MS to analyze 1399 images of data from 34 classes with an accuracy of 98.0%.(7) The deep 3D-CSAM-2DCNN algorithm achieved a 98% success rate in a trial that used both single and 14 diverse rice types.(8) In this study, a deep convolutional neural network (CNN)-based nondestructive method was developed classifying grains and hyperspectral imagery. With six types of paddy rice data, the accuracy of the suggested technique was 91.09%, whereas SVM with both spatial and spectral information yielded an accuracy of 79.23%.(9) In another investigation, researchers employed a CNN for classification following feature extraction and achieved 88.07% success with 200 data points and three different types of rice.(10)

The results showed that the model is applicable to the identification of not only rice but also other crops. When using 10600 photographs of rice seeds, the residual network yielded an accuracy of 95.13%. Marketing subpar rice as excellent rice is problematic because it damages the finances of farmers and seed producers.(11) Another study used SIMCA and NIRS to analyze 200 data points from 16 classes and achieved an accuracy of 87.16%.(12) The deep CNN algorithm achieved a success rate of 95.5% in the trial, which included 7399 pieces of data and three classes. In Ref. 13, the performance analysis of rice variety classification focuses on misclassifications and several models (LeNet, GoogLeNet, and ResNet) are discussed. In a different investigation of the effects of rising global temperatures on rice productivity and quality, researchers employed a CNN for classification operations following feature extraction, with an overall success rate of 91.33%.(14) Using the SVM technique for classification operations following feature extraction, researchers of the most recent study, which involved 17000 types of *Oryza sativa*, achieved an 83.9% success rate.(15)

In the subsequent study, the 18-layer CNN called Rice Net was investigated to classify seven different types of rice grown in Pakistan.(16) The model outperformed other CNN models such as VGG-19, ResNet50, and Google Net (Inception-V3), achieving a perfect classification accuracy of 100% for each variety.(17) The authors examined many deep learning architectures to classify rice grains, such as ResNet, VGG, Efficient Net, and Mobile Net. According to this study, MobileNet provided faster processing, whereas EfficientNet showed the highest classification accuracy.(18) This study assessed seven machine learning methods for rice variety classification using UAV-based multispectral sensing. These algorithms included neural networks, decision trees, SVM, random forests, naïve Bayes, and logistic regression. It highlighted the significance of feature selection at various phases of development.

After that, the use of automated machine learning (AutoML) and bagging approaches for rice variety classification was examined.(19) Another study showed how well these techniques increase classification efficiency and accuracy. The final part of the literary works is a CNN-based automatic framework for categorizing various rice grain types.(20) The model attained a perfect ROC curve and high accuracy. Furthermore, LIME and SHAP revealed insightful information about the model's decision-making procedure.

Recently, rice quality and classification have been assessed using various digital image attributes. These include the length, perimeter, fracture rate, whiteness, and cracks in the rice grains. Image-processing-based methods can be used to extract different grain product properties. Several machine-learning algorithms have been used to classify these features, including CNN,(9,10,14,20) SVM,(15) LeNet, Google Net, and ResNet.(13) Table 1 summarizes these studies.

3. Materials and Methods

DCNN is a type of machine learning method. Thus, the application of DCNNs is regarded as a form of deep learning, which is followed by machine learning. This is consistent with sensors that classify rice seed varieties using machine learning concepts. Rice grains were gathered from the rice warehouses depicted in Fig. 1. Figure 2 shows the overall process of this investigation, which classifies rice pictures obtained at various GPS locations. The four components of the rice variety classification system are data collection, processing, augmentation, and classification. The DCNN determines the types of rice in a rice image dataset. Finally, the generated results were compared with those obtained using conventional machine learning models.

3.1 Data gathering

In this study, ten varieties of rice were used for classification: white sticky rice, red sticky rice, black sticky rice, Shan rice, Shwe Bo Paw San, Ma Jan Taw rice, Ayeyar Min rice, Ayeyar Padaythar, Shwe War Win, and Lone Thwe Mwe. A 48-megapixel iPhone 16 Plus camera was used to capture 1000 photographs of these different types of rice. Sensor technology is used by the iPhone 16 Plus, especially in its camera system. We created a customized dataset, called the

Table 1
Summary of literature regarding crop variety classification research.

References	Data Pieces	Rice Types	Classifiers	Accuracy (%)
(1)	Point cloud data	8	Point Net deep learning model	89.4
(2)	Kenjing No. 5, No. 6, and No. 9 samples	3	Combined SIMCA and NIRS	90
(3)	Three varieties	3	BPNN and Bayes classifiers	92.68
(4)	Two rice cultivars	2	Color filtering and ratios of physical features	96
(5)	90 distinct types of rice	5	Fused Net model	86.87
(6)	75000	5	ResNet34	98.0
(7)	1399 images	34	NIR and HS-SPME-GC-MS	98.0
(8)	Hyperspectral imaging	14	3D-CSAM-2DCNN	98
(9)	Hyperspectral imaging	6	CNNs	91.09
			SVM	79.23
(10)	200	3	CNN	88.07
(11)	10600	10	Residual network	95.13
(12)	200	16	SIMCA and NIRS	87.16
(13)	7399	3	LeNet, Google Net, and Resnet	95.5
(14)	200	5	CNN	91.33
(15)	50000	14	SVM	83.9
(16)	2000	7	VGG-19, ResNet50, and Google Net	100
(17)	75000	5	ResNet, VGG network, Efficient Net, and Mobile Net models	99.76.
(18)	UAV-based multispectral sensors	3	Neural network (NN) algorithm	80
(19)	3810 data points	2	Light Gradient Boosting Machine - LGBM	93.54
(20)	75000	5	CNN, integration of explainability techniques	98

(a) (b) (c)

Fig. 1. (Color online) (a) Rice store from where the grains were collected, (b) rice varieties, and (c) rice fields.

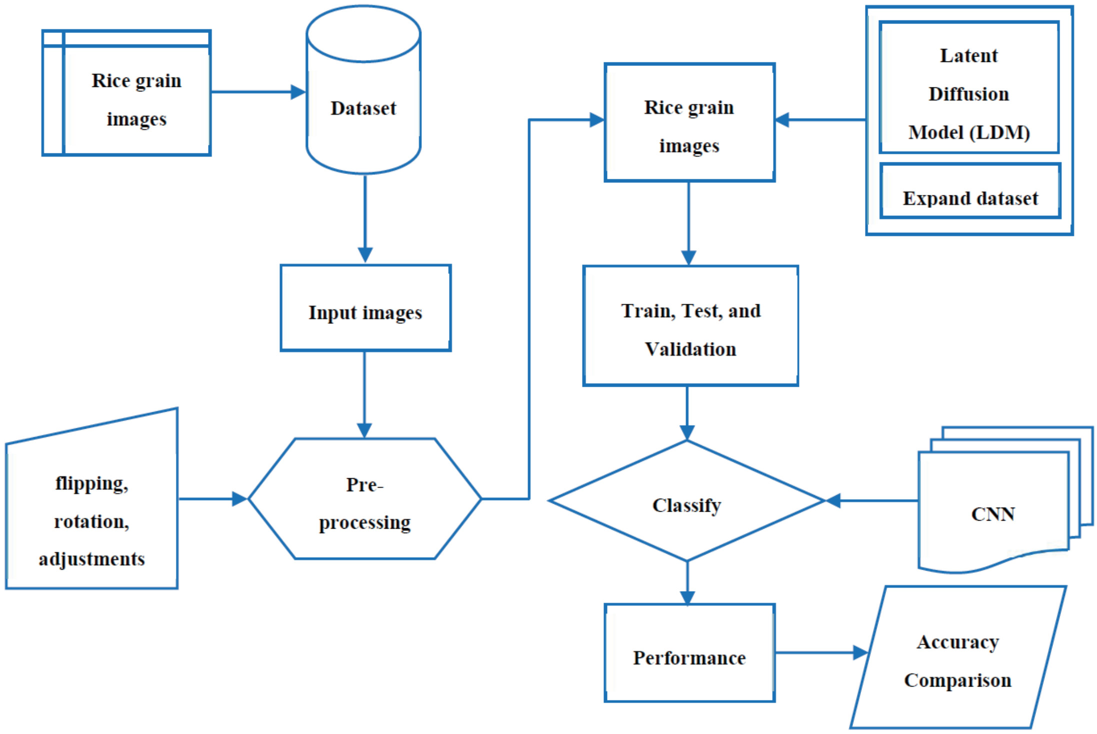


Fig. 2. (Color online) Rice variety categorization diagram using a diffusion CNN with a dataset of personal images.

Dataset of Different Rice Seed Varieties (DDRSV). Data was collected from multiple rice farms in different cities, in collaboration with rice stores. Figure 1 shows the rice stores from which rice grains were collected. Rice grain classification cannot be performed without the cooperation of rice stores, making data support challenging.

We also used various GPS locations to determine the temperature, water availability, and soil conditions in various weather zones. Samples were collected in a wide range of scenarios across different meteorological conditions, such as bright days, light precipitation events, and nighttime, for many periods within the study area to guarantee the flexibility and resilience of our model. These scenarios? were considered during data collection. Table 2 shows the data collected from different longitudes and latitudes in different geographic regions. Rice samples were collected from diverse soil depths in Myanmar's Magway Region, Shan State, Sagaing Region, Mandalay Region, and Nay Pyi Taw Union Territory. The samples of only three types of rice (Ayeyar Padaythar, Lone Thwe Mwe, and Shwe War Win) are shown in Fig. 3 from the numerous images of the various types of rice in the personal dataset.

3.2 Data preprocessing and data augmentation

The images were preprocessed before model training to enhance the model's performance and standardize their dimensions. The images in the DDRSV were enhanced using various

Table 2
Geographical locations, soil depth, latitudes, and longitudes of rice types.

No.	Types of Rice (Myanmar's name)	Types of Rice	Myanmar's State and Division	Latitude and Longitude	Soil Depth Info
1	Sticky Rice (White)	Kauk Hnyin Hsan (White)	Magway Region	20.274°, 94.736°	Thick/Medium
2	Sticky Rice (Red)	Kauk Hnyin Hsan (Red)	Magway Region	20.274°, 94.736°	Thick/Medium
3	Sticky Rice (Black)	Kauk Hnyin Hsan (Black)	Magway Region	20.274°, 94.736°	Thick/Medium
4	Shan Rice	Shan Hsan	Shan State	21.512°, 98.009°	Thick/Medium
5	Shwe Bo Paw San	Paw San Hmwe (Shwebo)	Sagaing Region	21.878°, 95.979°	Medium
6	Ma Jam Taw Rice	A Shay Taw (Ma Jam Taw)	Mandalay Region	20.987°, 95.765°	Thick/Medium
7	Ayeyar Min Rice	E Ya Min Hsan	Mandalay Region	20.987°, 95.765°	Thick/Medium
8	Ayeyar Padaythar	A Yar Pa Da Thar	Mandalay Region	20.987°, 95.765°	Thick/Medium
9	Shwe War Win	Shwe Wa Win	Nay Pyi Taw Union Territory	20.280°, 96.265°	Thick/Medium
10	Lone Thwe Mwe	Lone Thwel Hmwe	Magway Region	20.274°, 94.736°	Thick/Medium

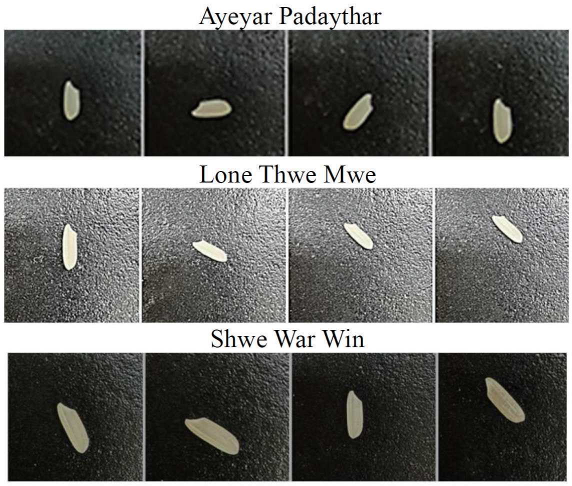


Fig. 3. (Color online) Samples of three different types of rice from the personal DDRSV.

techniques, such as image flipping, random rotation, random brightness adjustments, and contrast enhancement or reduction. These enhancements improved the model's generalization capability, increased its robustness, and helped prevent overfitting or underfitting.

Techniques for data augmentation create fresh training samples from preexisting samples, thereby artificially expanding the dataset size. The model can learn from a wider variety of examples owing to this larger dataset, which lowers the possibility of overfitting and enhances generalization capabilities. A total of 1000 photos were collected. Because the dimensions of the collected data were small, data augmentation was performed on each folder with 200 rice grain subfolders. Figure 4 shows the distribution of classes in the datasets. The DDRSV was then partitioned into training, validation, and test sets at an 8:2:1 ratio. Table 3 provides details on the distribution of rice grain samples.

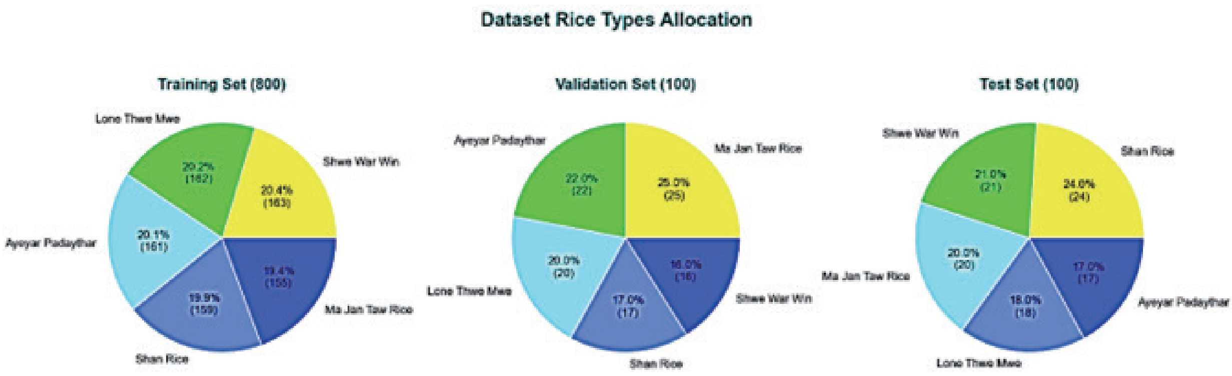


Fig. 4. (Color online) DDRSV's class distribution.

Table 3
Rice image training, testing, and validation.

Dataset	Training	Testing	Validation	Total number of samples
Ayeyar Padaythar				
Lone Thwe Mwe				
Ma Jan Taw Rice	800	100	100	1000
Shwe War Win				
Shan Rice				

3.3 Classification using CNN-combined diffusion model

A generative AI model, a diffusion model, is useful for denoising, feature extraction, and image creation. Diffusion modeling is an advanced technique that uses generative modeling to extract and classify rice grain features. Figure 5 shows the diffusion model architecture of the rice classification process. Overall, there are six steps.

1. Input Layer: This layer provides the model with the image of rice grains.
2. Forward Diffusion: Adding noise extracts the latent space features from the rice image.
3. Reverse Diffusion: The denoised rice image is extracted using U-Nets to eliminate noise.
4. Feature Extraction Module: This module extracts rich features from the bottleneck layer.
5. Classifier Head: CNN classifies the rice grain variety using the extracted features.
6. Output Layer: This layer provides the type of classified rice grain.

Diffusion models are generative models that gradually learn to denoise images, facilitating feature classification and extraction. They extract features from intermediate diffusion process phases and feed them into a CNN classifier for categorization. The latent diffusion model enhances the data for synthetic rice grain images and subsequently classifies them using a CNN for rice seed varieties at different GPS locations. The CNN diffusion model architecture for rice grain classification is shown in Fig. 6, and Table 4 presents the pseudocode for the diffusion CNN model design. Table 5 lists the parameters of the proposed classifier for the rice variety dataset. There are two primary steps in the denoising diffusion probabilistic model, as follows:

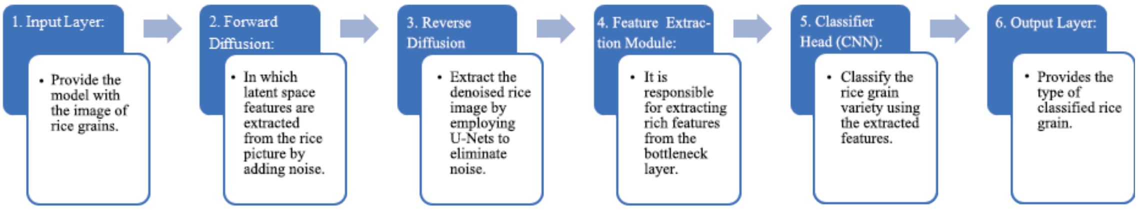


Fig. 5. (Color online) Diffusion model architecture for rice classification.

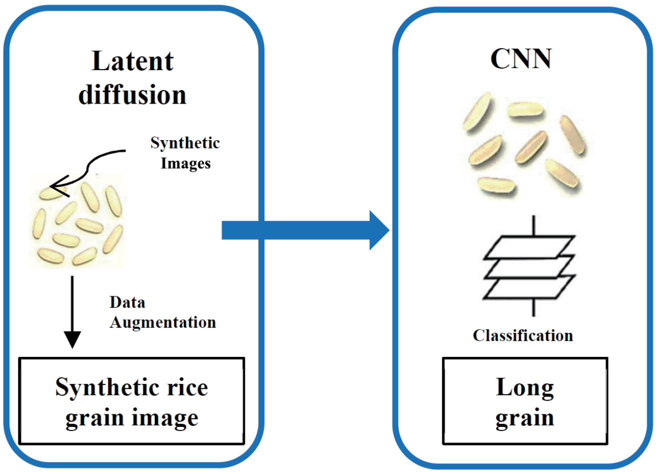


Fig. 6. (Color online) Diffusion CNN model architecture.

Table 4
Pseudocode of proposed model architecture.

Step 1: Diffusion Model for Feature Generation and Enhancement
conditioned_input = prepare_condition (features)

Step 2: CNN Architecture for Classification
CNNInput = Input (shape = EnhancedFeatures.shape)

Step 3: Train the Model
CNNModel.fit(train_generator, epochs=numepochs, validation_data=test_generator, callbacks=[checkpoint_callback, reduce_learning_rate])

Step 4: Generate the Prediction
prediction = Classifier (test_generator, verbose=1)

i. Forward diffusion process: Adds noise to input images.
   - Given an input rice grain image x_0, N: Gaussian noise is added over T timesteps, β_t: a slight variation in noise.
   - The image gradually turns into pure noise.

Table 5
Summary of proposed classifier's parameters for dataset of rice varieties.

Parameter	Description
Input shape	(224, 224, 3)
Batch size	32 and 64
Number of classes	Five rice varieties
Convolution layers	Layers with increasing filters (32 to 64)
Kernel size	(3,3)
Activation function	Relu for hidden layers, SoftMax for output layer
Pooling layer	(MaxPooling2D (pool size = (2, 2)) after each layer
Dropout rate	Dropout (0.5) to prevent overfitting
Fully connected layers	Fully connected layer with 64 and 512 units
Optimizer	Adadelta (learning_rate = 0.01)
Loss function	loss = categorical_crossentropy
Epochs	numepochs = 30
Training	Total training time: 650.36 s (CPU)
Early stopping	Patience = 5

- A Markov chain defines the forward process:

$$q(x_t \mid x_{t-1}) = N\left(x_t \sqrt{1-\beta_t} \cdot x_{t-1}, \beta_t \cdot I\right). \tag{1}$$

ii. Reverse diffusion process: Acquires the capability to eliminate noise and restore the original image.
- A neural network (U-Net) learns to reverse the noise process using $\epsilon_\theta(x_t,t)$.
- The model predicts the noise added at each step and reconstructs the clean image.

$$x_{t-1} = x_t - \beta_t \cdot \epsilon_\theta\left(x_t, t\right) \tag{2}$$

4. Results and Analysis

The model in this study was trained and tested on a PC running on Windows 11 Pro with an NVIDIA GeForce RTX 3080 and 12th Gen Intel(R) Core (TM) i9-12900 at 2.40 GHz. The batch size was eight, with 30 iterations (epochs), and the network input sizes were (224, 224, 3). Setting the initial learning rate to 0.01 and loading pretrained weights into the backbone network initialize the network model. Python 3.13.2 serves as the programming language, while TensorFlow 2.19.0 and the CPU function as the deep learning framework.

In this project, we aim to use DCNNs to classify different types of rice. Table 6 lists the DCNN results of the experiments using statistical classification methods. The rice seed performance on the rice grain dataset is presented. We achieved a very good precision of nearly 100%. Even for the testing dataset, the loss remained below 0.05, indicating excellent performance.

To monitor its performance, we compared the performance of the proposed model with that of eight previously trained models. We created and trained CNN models on our dataset and

Table 6
Performance in terms of accuracy, precision, recall, and F1 score of the proposed model on the rice grain dataset.

Detailed classification report				
Rice grain types	Precision	Recall	F1-score	Support
Ayeyar Padaythar	1.00	1.00	1.00	20
Lone Thwe Mwe	1.00	0.94	0.97	18
Ma Jan Taw Rice	1.00	1.00	1.00	22
hwe War Win	1.00	1.00	1.00	24
Shan Rice	0.94	1.00	0.97	16
Accuracy			0.99	100
Macro avg	0.99	0.99	0.99	100
Weighted avg	0.99	0.99	0.99	100

achieved excellent accuracy in classifying rice varieties. Our findings demonstrate that the DCNN algorithm outperforms the other algorithms in terms of precise grain classification. The results of the tests comparing the deep learning and supervised learning algorithms are shown in Table 7. This advancement can result in an increased farm productivity, enhanced crop management, and improved crop forecasting. Furthermore, Table 8 displays the accuracy, loss, and training duration of the DCNN experiments with various input images.

Figure 7 illustrates the confusion matrix of the model for the test sets. The across-diagonal indicates significantly higher values. The percentage of incorrectly classified samples was lower than that of correctly classified samples. The classification accuracy of the model improved significantly. The confusion matrix for the rice varieties is shown in Fig. 7. This matrix shows a fairly accurate prediction. According to these figures, the current research has excellent accuracy and high applicability. DCNN accuracy, loss, and learning rate are shown in Fig. 8.

The accuracy trend of the model throughout the training times or iterations is shown by an accuracy curve. This demonstrates the accuracy of the model's label prediction. Typically, accuracy is given as a percentage, which shows the proportion of accurate predictions for all guesses. The model achieved an accuracy of 99.00% and a loss of 0.24031. Figure 9(a) shows the training and validation accuracy curves. Figure 9(b) shows the accuracy and loss table.

4.1 Comparative analysis

In the comparative analysis, eight model algorithms were evaluated, and the results were compared with those of previous studies. We compared two deep learning algorithms for Alex Net and Mobile Net to classify rice grain varieties, as shown in Table 7. The accuracy, mean square error (MSE), and R2 scores of the algorithms were also assessed. Additionally, Table 7 presents the results of evaluations of the six supervised learning algorithms: support vector classification, decision tree, gradient boosting regressor, K-nearest neighbors, random forest, and linear regression methods, and two deep learning models: Alex Net and Mobile Net.

Since the DCNN design is scalable, as the amount of rice seed data increases, its performance does not decrease. Finally, an additional large dataset is used to examine the accuracy, loss, and training time of DCNNs. The findings are shown in Table 8.

Table 7
Results of tests comparing algorithms for supervised and deep learning.

Model	Accuracy	MSE	R2_score
Alex Net	0.4399	1.2982	1.2982
Mobile Net	0.4401	1.2982	0.4401
Linear Regression	0.339088	1.376062	0.339088
Random Forest	0.680011	0.666238	0.680011
Gradient Boost	0.753266	0.513717	0.753266
KNN	0.812955	0.389440	0.812955
Decision Tree	0.210399	1.644000	0.210399
Support Vector Classification	1.0000000	1.0000000	1.0000000

Table 8
Comparative findings from an investigation using a larger publicity dataset.

Model	Input Image	Model Accuracy	Loss	Model Training Time
DCNNs	5000	99%	0.02639	9054.19 s

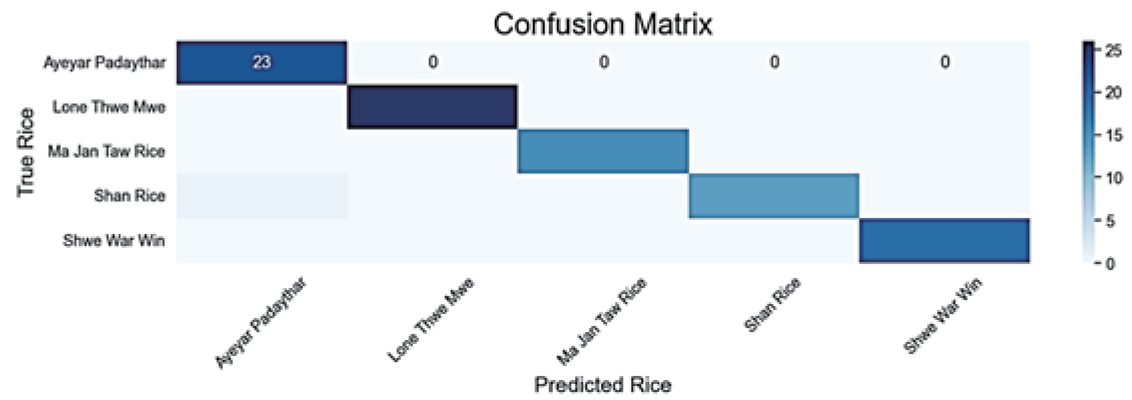


Fig. 7. (Color online) Confusion matrix of the model for the test sets in the comparative experiment.

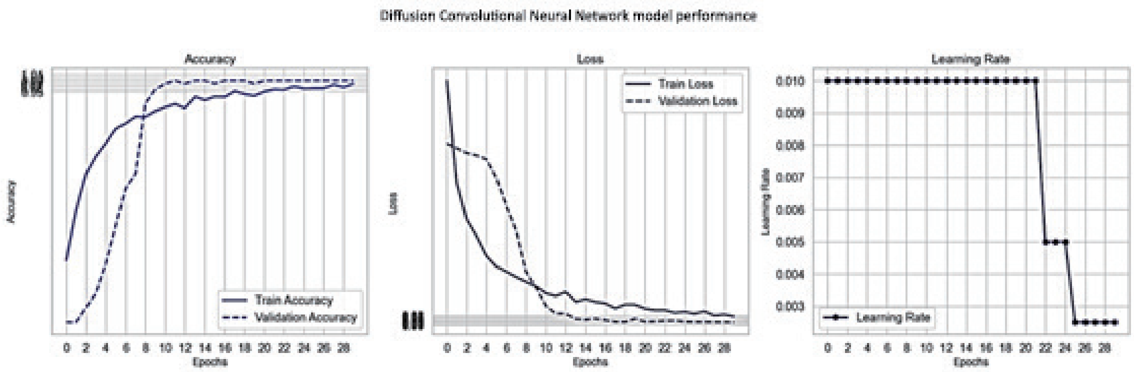
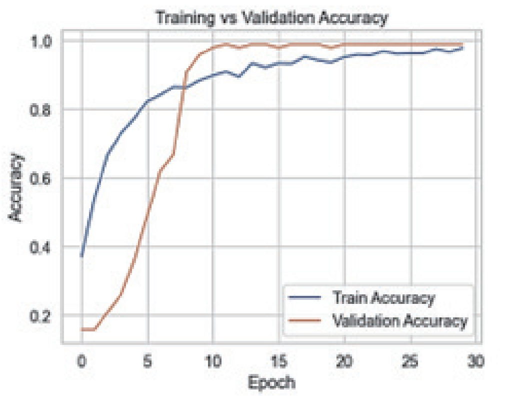


Fig. 8. (Color online) Learning rate, loss, and accuracy of DCNNs.



(a)

	accuracy	loss	val_accuracy	val_loss
0	0.41	2.1616	0.5	1.48533
1	0.62	1.02916	0.46	1.42647
2	0.68375	0.84345	0.58	1.33752
3	0.725	0.690302	0.6	1.18433
4	0.77375	0.604431	0.64	1.01106
5	0.79625	0.53604	0.76	0.849208
6	0.855	0.408527	0.85	0.748471
7	0.84625	0.405904	0.89	0.500573
8	0.84625	0.408724	0.95	0.392318
9	0.865	0.330598	0.96	0.260085
10	0.88875	0.277342	0.95	0.224761
11	0.90125	0.289606	0.98	0.155616
12	0.91875	0.230178	0.97	0.1203
13	0.92625	0.237645	0.98	0.0801301
14	0.92125	0.219192	0.99	0.0686157
15	0.93375	0.176872	0.98	0.0918137
16	0.92625	0.205162	0.98	0.0555959
17	0.93	0.202781	0.97	0.0708862
18	0.9525	0.159725	0.97	0.0705197
19	0.9525	0.131659	0.99	0.0407691
20	0.955	0.12598	0.97	0.0418159
21	0.95375	0.140814	0.98	0.0467159
22	0.94875	0.127403	0.99	0.0271417
23	0.95875	0.126149	0.99	0.0248577
24	0.95875	0.102995	0.99	0.0301251
25	0.95625	0.103453	0.99	0.0314384
26	0.94875	0.128204	0.99	0.0326952
27	0.96	0.126585	0.99	0.0333027
28	0.9675	0.115826	0.99	0.0193601
29	0.9675	0.090953	0.99	0.0242863

(b)

Fig. 9. (Color online) (a) Accuracy curve for training and validation, (b) accuracy and loss table.

Table 9
Outcomes of our study compared with those of other previous studies.

Study	Year	Dataset Used	Method Used	Accuracy (%)	Highlights
Proposed Method	2025	Custom Myanmar Rice Dataset	DCNN (Diffusion CNN)	99	Location-aware, better generalization
Reference (2)	2022	NIRS combined with SIMCA	Principal Component Analysis (PCA)	90	Rapid identification of rice varieties.
Reference (3)	2017	1156 paddy seeds	Back Propagation Neural Network (BPNN)	92.68	Three paddy seeds are effectively identified.
Reference (15)	2020	50000 seeds	SVM method	83.9	Practical design of rice classification.

We used the publicly accessible Rice MSC Dataset, which includes several rice grain photos arranged by variety and was made available by Koklu *et al.*[21] for this research at https://www.muratkoklu.com/datasets/. The comparative experimental results are shown in Table 7. The accuracy, loss, and training time of the DCNN tests using different input images are shown in Table 8. Images of 5,000 rice grains were obtained from another larger publicly available dataset. This study is novel in that it explicitly show the applicability of DCNN in the agricultural area, such as rice seed categorization. A DCNN is a graph that shows the connections between locations and the commonalities among different types of seed. The proposed study's findings are compared with those of the other three previous studies. Table 9 provides the details view of the year, accuracy, highlights, method, and dataset used.

5. Conclusion

In this study, we used a DCNN model to classify different types of rice. To monitor its performance, we compared the performance of the proposed model with that of previously trained models. In a comparative analysis, eight algorithms for the models were assessed, and their performances were compared according to predetermined metrics and standards. The proposed DCNN increased farm productivity, enhanced crop management, and improved crop forecasts.

DCNN lowers the possibility of making mistakes in manual classification. It can accurately identify different types of rice seed when combined with GPS data. Table 6 shows the results. Results from another larger publicity dataset are shown in Table 8. DCNN does well with both its customized dataset and another larger dataset. Lastly, we compared the outcomes of our research with those of previous studies in Table 9.

To sum up, even though this study does not provide details about the sensors used, precision agriculture utilizes GPS data, which has been successfully integrated with DCNN to categorize rice seed types in various places. The DCNN in machine learning is associated with sensor-based technology. We intend to use rice grain classification to distinguish rice types in agriculture, consumer, industry, marketing, export, and factory screening improvement.

In our future study, we intend to incorporate additional data from various geographical regions, creating and distributing extensive datasets to support rice seed categorization research and development, and developing techniques to visualize and interpret model predictions.

Acknowledgments

We sincerely thank Grand-ICT for the assistance. This study was supported by the Ministry of Science and ICT (MSIT), Korea, under the Grand Information Technology Research Center support program (IITP-2025-2020-0-01489), supervised by the Institute for Information & Communications Technology Planning & Evaluation (IITP).

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