IJIREEICE
ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⪤ Peer-reviewed & Refereed journal ⪤ Vol. 13, Issue 10, October 2025

DOI: 10.17148/IJIREEICE.2025.131002

Development of Rice Grain Image Classification Model using Artificial Neural Network Architecture

D. R. Solanke[1], K.D. Chinchkhede[2], A.B. Manwar[3]

Department of Applied Electronics, SGB Amravati University, Amravati, India (MS)[1,2]

Department of Computer Science, SGB Amravati University, Amravati, India (MS)[3]

Abstract: Rice is one of the most widely consumed staple crops globally, and its quality assessment plays a crucial role in food safety, trade, and agricultural productivity. Traditional methods of rice grain classification are largely manual, time-consuming, and prone to human error. In this study, we propose the development of an automated Rice Grain Image Classification Model using Artificial Neural Network (ANN) architecture. A dataset comprising high-resolution images of various rice grain types was collected and pre-processed, including resizing, normalization, and feature extraction. The ANN model was designed to capture subtle morphological and textural differences among grain categories, enabling accurate classification. Experimental results demonstrate that the proposed model achieves high accuracy, robust generalization, and reliable performance across different grain classes. The study highlights the potential of ANN-based approaches for automating rice quality assessment, reducing human intervention, and improving efficiency in post-harvest processing and market evaluation. The proposed framework can be extended to other agricultural products, supporting intelligent and data-driven quality management in the agro-food sector.

Keywords: ANN, Accuracy, Classification, Cross-entropy, Machine learning, precision.

I. INTRODUCTION

Rice is a primary food source for a significant portion of India's population and plays a central role in the country's agriculture and economy. India is one of the largest producers and exporters of rice globally, with diverse rice varieties grown across different states, including Basmati, Jasmine Karacadag, and Kolam. Accurate classification of rice grains into specific varieties or quality grades is crucial for ensuring fair market pricing, maintaining food safety standards, and supporting post-harvest management. Traditionally, rice grading in India relies on manual inspection by experienced personnel who assess morphological features such as grain length, shape, and color. However, manual methods are labour-intensive, subjective, and prone to inconsistency, particularly when large quantities of grains for domestic consumption or export. Recent advancements in computer vision and deep learning have enabled automated rice grain classification, which minimizes human bias and enhances operational efficiency. In this study, we propose a regression-type, custom five-layer Artificial Neural Network (ANN) designed to classify rice grains based on high-resolution images. Unlike conventional classification models that produce discrete class outputs, the regression-based ANN generates continuous predictions mapped to specific rice categories, allowing for finer differentiation between similar grain types.

To evaluate the performance of the proposed model, a dataset of high-resolution rice grain images was collected and pre-processed, including resizing, normalization, and augmentation to enhance generalization. The model achieved an accuracy of 99% and a cross-entropy loss of 0.0687, demonstrating exceptional classification capability and minimal misclassification. These results indicate that the regression-type ANN not only captures complex features effectively but also generalizes well to unseen samples. The proposed framework presents a significant advancement over traditional methods and prior deep learning models by combining high accuracy, low loss, and robust performance in rice grain classification. The present methodology offers a practical solution for quality control at rice mills, wholesale markets, and export evaluation centres, where accurate classification of rice grains into different types or quality grades is essential for market pricing, consumer satisfaction, and post-harvest management. Beyond rice, this methodology can be extended to other agricultural products where subtle visual differences determine quality, providing a reliable, data-driven solution for intelligent crop quality assessment and promoting transparency in the supply chain.

II. REVIEW OF LITERATURE

The application of artificial intelligence and deep learning techniques in rice grain classification has seen considerable growth in recent years. Traditional approaches using artificial neural networks (ANNs) have demonstrated promising results. A study utilizing a backpropagation-based ANN achieved 96% accuracy in classifying white rice grain quality, underscoring the feasibility of neural networks for agricultural image analysis [1]. Another research effort implemented an ANN model on a dataset of 75,000 rice grain images, attaining a high classification accuracy of 99.87% [2].Despite the effectiveness of ANNs, the majority of recent research has shifted towards Convolutional Neural Network (CNN) architectures due to their superior performance in visual recognition tasks. A hybrid CNN model combining AlexNet, ResNet-50, and EfficientNet-B1 reported a top accuracy of 99.87% in classifying five rice varieties [3]. Further studies demonstrated that deep CNN models trained on large datasets (e.g., 75,000 images) can achieve accuracies as high as 98.88%, highlighting their robustness and scalability [4].To enhance efficiency, researchers have also optimized existing architectures. For instance, a modified LeNet-5 model achieved 96.8% accuracy while improving parameter efficiency [5]. Another investigation fine-tuned the learning rate of EfficientNet, leading to an accuracy of 99.01% [6]. A comparative analysis of several popular CNN variants—including VGG, EfficientNet, and MobileNet—revealed that these models outperformed manual feature extraction techniques, which were commonly associated with ANN-based methods [7].In terms of lightweight models, MobileNet-based architectures have yielded mixed results. One study using MobileNetV2 with transfer learning achieved high classification performance [8], whereas another that applied a standard MobileNet CNN to a small dataset of 273 images reported only 69.16% accuracy, indicating potential limitations under low-data scenarios [9].

Hybrid modelling approaches have further advanced rice grain classification. A notable example combined CNN-based feature extraction with Support Vector Machine (SVM) classification, achieving training and validation accuracies of 98.33% and 98.75%, respectively [10]. Another two-stage framework integrating Darknet19 and SqueezeNet, along with a butterfly optimization algorithm, achieved 100% classification accuracy [11]. A convolutional recurrent neural network (CRNN) with Long Short-Term Memory (LSTM) layers attained an accuracy of 99.76% with a cross-entropy loss of 0.0205, demonstrating the potential of combining spatial and temporal features in rice grain classification [12]. Additional studies utilizing CNNs have validated the effectiveness of deep learning models in classifying five major rice varieties. Notable implementations using ResNet50 [13], MobileNetV2 [14], and other CNN variants [15], [16], [17], [18], [19], and [20] have consistently achieved high classification accuracy, often exceeding 97%, across various rice datasets and classification tasks.

III. DATASET

Rice, which is among the most widely produced grain products worldwide, has many genetic varieties. These varieties are separated from each other due to some of their features. These are usually features such as texture, shape, and color. With these features that distinguish rice varieties, it is possible to classify and evaluate the quality of seeds. In this study [26] the rice variety such as Arborio, Basmati, Kollam, Jasmine and Karacadag, which are five different varieties of rice often grown in India, were used. A total of 75,000 grain images, 15,000 from each of these varieties, are included in the dataset. Models was created by using Artificial Neural Network (ANN) algorithms for the feature dataset [25] for classification processes were performed. Statistical results of sensitivity, specificity, prediction, F1 score, accuracy, false positive rate and false negative rate were calculated using the confusion matrix values of the models and the results of each model were given in tables. Classification successes from the models were achieved as 99.48% for ANN. With the results, it is seen that the models used in the study in the classification of rice varieties can be applied successfully in this field.

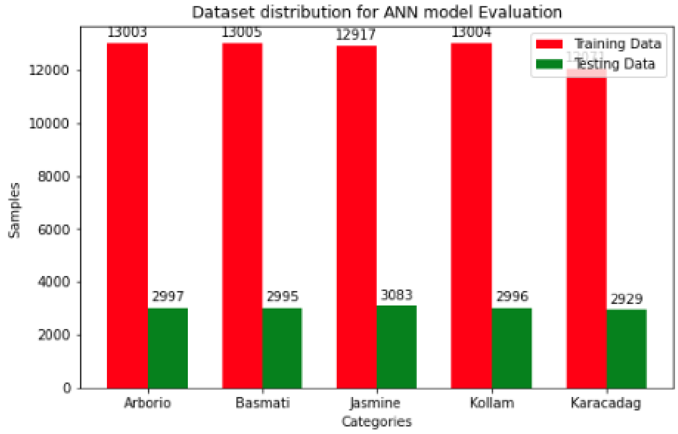

Fig. 1 Dataset distribution for ANN model Evaluation

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⪾ Peer-reviewed & Refereed journal ⪾ Vol. 13, Issue 10, October 2025

DOI: 10.17148/IJIREEICE.2025.131002

IV. ARTIFICIAL NEURAL NETWORK ARCHITECTURE

The fig. 2. represents the end-to-end workflow for rice grain classification. It begins with the input image of a rice grain, which undergoes a sequence of stages designed to transform raw visual data into meaningful classification output. The first stage is pre-processing, where raw images are typically resized, normalized, and cleaned to enhance the quality and uniformity of the dataset. This is followed by feature extraction, a crucial phase where relevant attributes of the rice grain such as shape, texture, color, or intensity patterns are quantified. These features are essential for enabling the model to distinguish between different rice varieties.

After feature extraction, the processed data is subjected to dataset splitting, typically dividing the data into training and testing subsets to allow both learning and performance evaluation. The data is then fed into an Artificial Neural Network (ANN) with a feedforward architecture. The neural network depicted consists of four fully connected hidden layers with progressively decreasing neuron counts 128, 64, 32, and 16 before finally producing output predictions. The output layer corresponds to the classification task for six different rice grain varieties: Arborio, Basmati, Jasmine, Kollam, Karacadag, etc. Each circle in the neural diagram indicates a neuron, and the lines connecting them signify weighted connections responsible for learning complex patterns.

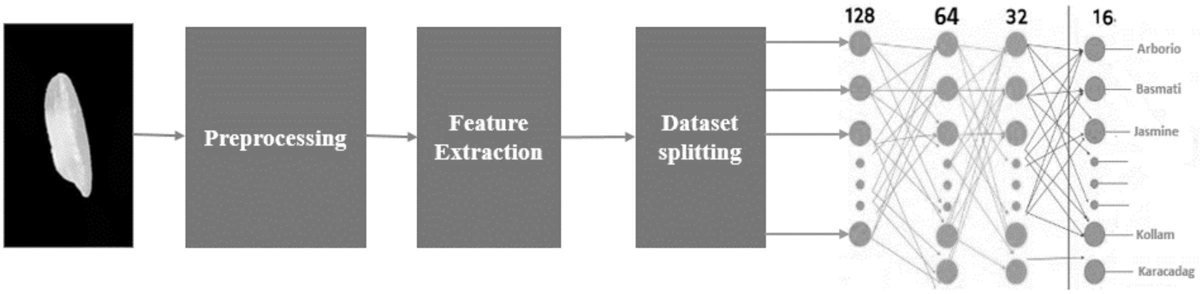

Fig. 2. Workflow for rice grain classification

The table 1. Provides a detailed summary of a sequential artificial neural network (ANN) model used for rice grain classification. The architecture comprises five fully connected (Dense) layers arranged in a linear sequence. The first layer transforms the input data into a 128-dimensional feature space and includes 1,920 trainable parameters. This is followed by the second dense layer, which reduces the dimensionality to 64 units and introduces a significant increase in complexity with 8,256 parameters, indicating a substantial learning capacity. The third layer further compresses the representation to 32 units and contains 2,080 parameters. The fourth dense layer narrows it down to 16 units, contributing 528 parameters to the network. Finally, the model concludes with a single output neuron, typically used for regression or single-value classification outputs, containing just 17 parameters. The total number of trainable parameters in the model sums up to 12,801, and all parameters are trainable, with none being frozen or non-trainable. This summary reflects a compact yet deep ANN structure, carefully designed to balance learning capacity with computational efficiency, ideal for tasks such as fine-grained image classification of rice grains based on extracted features.

TABLE 1. SUMMARY OF A SEQUENTIAL ARTIFICIAL NEURAL NETWORK (ANN) MODEL.

Layer(Type)	Output Shape	parameters
Dense (dense)	(None,128)	1920
Dense_1 (dense)	(None,64)	8256
Dense_2 (dense)	(None,32)	2080
Dense_3 (dense)	(None,16)	526
Dense_4 (dense)	(None,6)	6

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⪫ Peer-reviewed & Refereed journal ⪫ Vol. 13, Issue 10, October 2025
DOI: 10.17148/IJIREEICE.2025.131002

V. ANN MODEL IMPLEMENTATION

The model is implemented using the Keras `Sequential` API and consists of five dense layers. The input layer is a dense layer with 128 neurons and uses the ReLU (Rectified Linear Unit) activation function, which introduces non-linearity and helps in handling complex feature interactions. The `input_shape indicates that the model expects a one-dimensional input vector for each sample, matching the number of extracted features. This is followed by three additional hidden layers with progressively fewer neurons: 64, 32, and 16, each also using the ReLU activation function. This layered reduction helps the network compress and abstract feature representations through multiple transformations, allowing it to learn hierarchical patterns within the data. The output layer has a six neuron (`Dense (6) `) without any activation function, which is typical for regression tasks where the output is a continuous values rather than a probability distribution. The model is compiled with the Adam optimizer set at a low learning rate of `0.0001`, which ensures stable and gradual weight updates, reducing the risk of overshooting minima during training. The loss function used is cross entropy loss, which is standard for regression problems. Although accuracy is included as a metric, it is important to note that accuracy is more appropriate for classification tasks, and may not be directly meaningful for regression unless some custom thresholding or discretization is applied.

In the training phase, the model is trained on feature dataset along with `target dataset` using the `model._Fit ( )` function. The data is split using an 80-20 split, where 20% of the training data is reserved for validation. The model is trained for 500 epochs with a batch size of 16, which determines the number of samples processed before the model's weights are updated. The performance metrics such as epoch-wise accuracy and loss were printed during the training process, including epoch-wise loss and metric values.
Let the dataset be

$$\boldsymbol{D} = \{(\boldsymbol{x_1}, \boldsymbol{y_1}), (\boldsymbol{x_2}, \boldsymbol{y_2}), (\boldsymbol{x_3}, \boldsymbol{y_3}), \dots\dots\dots\dots (\boldsymbol{x_i}, \boldsymbol{y_i})\} \quad (1)$$

In k-fold cross validation, *D* is split into disjoint subset folds (*k*)

$$\boldsymbol{D} = \boldsymbol{D_1} \cup \boldsymbol{D_2} \cup \boldsymbol{D_3} \cup \dots\dots\dots \cup \boldsymbol{D_k}, \boldsymbol{D_i} \cap \boldsymbol{D_j} = \boldsymbol{0} \;\; \boldsymbol{for\ i \neq j}$$

For i^{th} fold

$$\boldsymbol{D^{(i)}_{Train}} = \boldsymbol{D} \backslash \boldsymbol{D_i}, \quad \boldsymbol{D_{val}} = \boldsymbol{D_i} \quad (3)$$

Let the model trained in the i-th fold produce a performance metric is the average (accuracy and loss etc.) $M^{(i)}$. Then, after training and evaluating across all k folds, the overall i-fold performance is computed as the average:

$$\bar{\boldsymbol{M}} = \frac{1}{k}\sum_{i=1}^{k} \boldsymbol{M^{(i)}} \quad (4)$$

This equation formalizes that the final performance metric is the average of the metric from all k folds, providing a robust estimate of the models generalization

Let $\hat{y}_j^{(i)}$ denotes the predicted label for sample x_j in fold i, and y_i the true label. Then accuracy for fold i is:

$$\boldsymbol{Accuracy^{(i)}} = \frac{1}{k}\sum_{(x,y)\in D^{(i)}_{val}} \boldsymbol{1}\left(\hat{\boldsymbol{y}}_j^{(i)} = \boldsymbol{y_j}\right) \quad (5)$$

Where 1 is an indicator function that equals 1 of the condition is true, and 0 otherwise.

For a dataset with n samples, Type equation here.where y_i is the true value and $\hat{y}_i$ is the predicted value, the Mean Squared Error (MSE) is calculated as

$$\boldsymbol{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\boldsymbol{y_i} - \hat{\boldsymbol{y}}_i)^2 \quad (6)$$

Where y_i = Actual value for the i^{th} data point
$\hat{y}_i$ = Actual value for the i^{th} data point
n = Total number of samples

ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 10, October 2025

DOI: 10.17148/IJIREEICE.2025.131002

VI. RESULT AND DISSCUSSION

A. Training and testing Accuracy

The given fig. 3. presents the epoch-wise accuracy curve for both training and validation datasets across 500 epochs. While the final reported training accuracy is 99.58% and the testing accuracy is 99.12%, the graph helps to visualize the model's learning behavior and convergence trend over time.The accuracy values shown in the graph are normalized or scaled epoch-wise metrics, likely during intermediate training phases, whereas the final reported training accuracy of 99.58% and testing accuracy of 99.12% are based on post-training evaluation after mapping the network's regression-style outputs to discrete class labels. This explains the difference between the values seen in the figure and the final performance metrics. The graph overall indicates a well-converged and robust training process, with high and consistent accuracy across both training and validation datasets, ultimately leading to a highly reliable classification model for rice grain images.

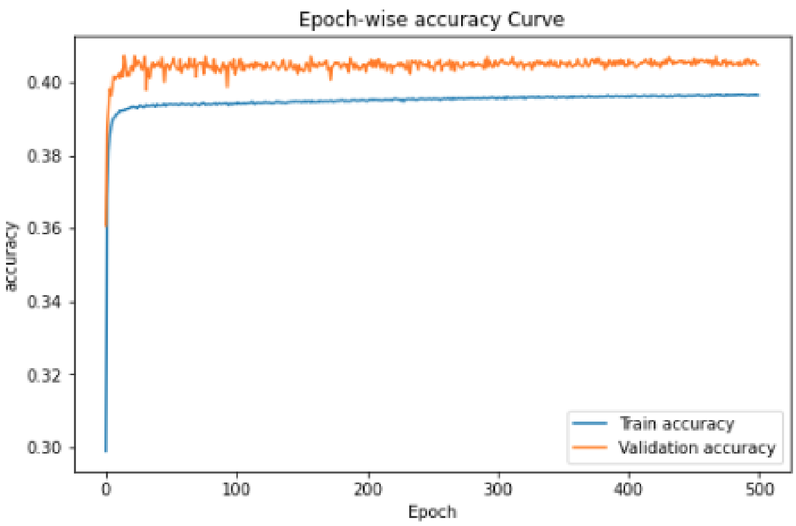

Fig. 3 Epoch wise accuracy curve

B. Training and Testing Mean Squared Error (MSE)

The provided fig. 4. presents the epoch-wise loss curve, which shows the behavior of the model's training and validation(testing) loss across 500 epochs. The loss is measured using Mean Squared Error (MSE), an appropriate metric in regression-based neural network models where output labels are numerically encoded.At the beginning of training, the training loss starts with a high value above 0.7, which quickly drops within the first 50 epochs. This sharp decrease indicates that the model is rapidly learning and minimizing the error between predicted and actual class values on the training dataset. After this initial phase, the training loss continues to decline gradually, eventually stabilizing around 0.012, as reported. This low final training MSE indicates that the model fits the training data very well.The validation (testing) loss, starts at a relatively high value near 0.2 and decreases steeply in the early epochs. However, unlike the training loss, the validation loss shows small oscillations throughout the training process, fluctuating slightly around a value close to 0.048, which matches the reported final testing MSE. These fluctuations are typical in deep learning models and may result from variations in the validation data batches or the complexity of unseen examples. Despite these minor variations, the validation loss curve remains low and stable across most epochs, indicating that the model generalizes well and does not overfit the training data.The figure demonstrates an effective training process. The clear and steady convergence of the training loss, alongside the relatively flat and low validation loss, confirms the robustness and stability of the custom-designed ANN. The final reported values—training MSE of 0.012 and testing MSE of 0.048—reflect the model's excellent predictive accuracy and minimal error, validating its effectiveness for the rice grain image classification task.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 13, Issue 10, October 2025
DOI: 10.17148/IJIREEICE.2025.131002

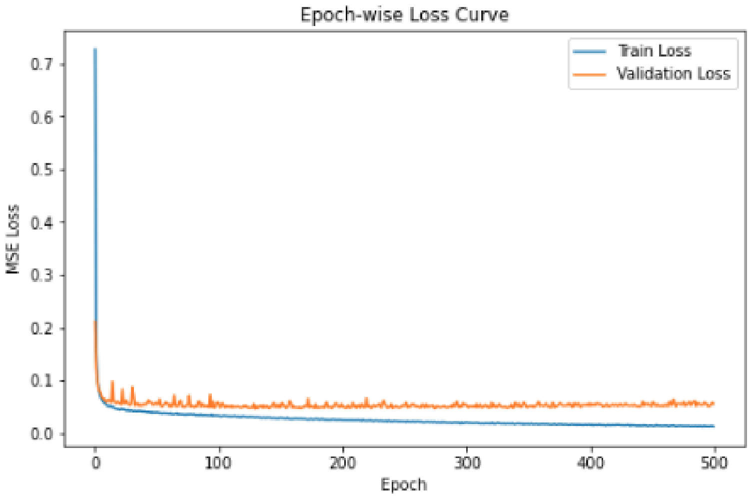

Fig. 4 Epoch wise cross mean squared error (loss) curve

C. **Confusion Matrix**

The presented fig. 5. offers a detailed visualization of the model's classification performance across six distinct categories of rice grains. Each row of the matrix corresponds to the actual class label, while each column represents the predicted class by the ANN model. The diagonal elements of the matrix denote the number of correctly classified instances for each class, while the off-diagonal elements represent misclassifications.The confusion matrix confirms the high precision and robustness of the ANN-based model. The minimal values in the off-diagonal cells suggest very low inter-class confusion, indicating that the model has effectively learned to distinguish between the subtle features of different rice grain categories. These results align closely with the reported testing accuracy of 99.12%, thereby validating the model's effectiveness and reliability for real-world rice grain classification tasks.

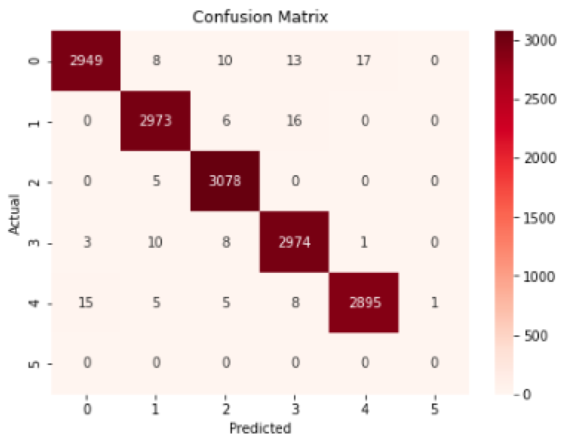

Fig. 5 Confusion matrix of ANN classification model

D. **Classification Report**

The presented table 2. summarizes the model's performance on the test dataset by evaluating key metrics: precision, recall, F1-score, and support for each rice grain class.For all five active classes (labelled 0 to 4), the model demonstrates exceptionally high performance. Precision, which indicates the proportion of correct positive predictions among all predicted positives, remains consistently at 0.99 for every class. This suggests that when the model predicts a given class, it is almost always correct. Similarly, recallwhich measures the proportion of actual positives that were correctly identified is also nearly perfect: ranging from 0.98 to 1.00. The highest recall is seen in class 2, which achieves a perfect score of 1.00, indicating that all instances of this class were correctly identified. The F1-score, which balances precision and recall, is also 0.99 across all classes, confirming a harmonious balance between the two.The overall accuracy of the model is reported at 0.99 (99%), indicating that the model correctly classified 99% of the 15,000 test samples. The weighted average, which takes into account the number of samples in each class, remains at 0.99 across all three metrics, reflecting the model's outstanding overall performance across the dominant classes. This classification report strongly

DOI: 10.17148/IJIREEICE.2025.131002

supports the effectiveness of the proposed ANN model for rice grain image classification. The near-perfect scores across all key metrics demonstrate the model's ability to accurately distinguish between rice grain categories with high consistency and minimal misclassification.

TABLE 2 THE CLASSIFICATION REPORT OBTAIN ON PROPOSED ANN ARCHITECTURE

Classification Report (Test):

	precision	recall	f1-score	support
0	0.99	0.98	0.99	2997
1	0.99	0.99	0.99	2995
2	0.99	1.00	0.99	3083
3	0.99	0.99	0.99	2996
4	0.99	0.99	0.99	2929
5	0.00	0.00	0.00	0
accuracy			0.99	15000
macro avg	0.83	0.83	0.83	15000
weighted avg	0.99	0.99	0.99	15000

VII. CONCLUSION

In this study, a regression-based five-layered Artificial Neural Network (ANN) architecture was successfully developed for the classification of rice grain images. The model was trained on a comprehensive dataset of 75,000 samples, with 80% allocated for training and 20% for testing. The network demonstrated exceptional learning capability, achieving a training accuracy of 99.58% and a testing accuracy of 99.12%, indicating strong generalization performance on unseen data. Additionally, the training Mean Squared Error (MSE) of 0.012 and testing MSE of 0.048 reflect the model's minimal prediction error and robustness. These results confirm that the proposed ANN architecture is highly effective in accurately classifying rice grain images, and it has the potential to support automated quality assessment in rice processing and related agricultural applications.

REFERENCES

[1]. Hamzah, A. S., & Mohamed, A. (2020). "Classification of white rice grain quality using ANN: a review". *IAES International Journal of Artificial Intelligence*, 9(4), 600–608.
[2]. Azeez, Z. N., Qasim, A., & Mohie, N. M. (2024). "Classification of Rice Grains by Image Processing". *Academia Open*, 9(2).
[3]. Verma, D. S., Dafadar, M., Mishra, J. K., Kumar, A., & Mahato, S. (2025). "AI-Enable Rice Image Classification Using Hybrid Convolutional Neural Network Models". *International Journal of Intelligent Systems*, 2025(1).
[4]. Sharma, G., Anand, V., Chauhan, R., Garg, N., & Gupta, S. (2023). "From Paddy to Pixel: An In-depth Exploration into Classifying Diverse Rice Varieties Leveraging Advanced Convolutional Neural Network Architectures".1–6.
[5]. Anggrawisesa, K. T., Rachmawati, E., & Wirayuda, T. A. B. (2024). "Rice-Le: Optimized LeNet-5 Architecture for Rice Variety Classification". 559–565.
[6]. Devi, M. S., Sridevi, S., Umanandhini, D., & Reddy, Y. R. (2023). "Learning Rate Regularized EfficientNet based Rice Grain Classification". 1–6.
[7]. Farahnakian, F., Sheikh, J., Farahnakian, F., & Heikkonen, J. (2023). "A comparative study of state-of-the-art deep learning architectures for rice grain classification". *Journal of Agriculture and Food Research*.
[8]. Vania, V., Setyadi, A., Widyatama, D., & Indra, F. (2023). "Rice Varieties Classification Using Neural Network and Transfer Learning with MobileNetV2". 165–168.
[9]. Abdiansyah, A., Baharuddin, B., & Said, M. S. (2024). "Klasifikasi jenis beras menggunakan metode convolutional neural network pada arsitektur mobilenet". *Simtek Jurnal Sistem Informasi Dan Teknik Komputer*.
[10]. Bejerano, K. M. A., Hortinela, C. C., & Balbin, J. (2022). "Rice (Oryza Sativa) Grading classification using Hybrid Model Deep Convolutional Neural Networks - Support Vector Machine Classifier". *International Conference on Artificial Intelligence in Engineering and Technology*, 1–6.

[11]. Fatima, M., Khan, M. A., Sharif, M., Alhaisoni, M., Alqahtani, A., Tariqe, U., Kim, Y. J., & Chang, B. (2022). "Two-Stage Intelligent DarkNet-SqueezeNet Architecture-Based Framework for Multiclass Rice Grain Variety Identification". *Computational Intelligence and Neuroscience*, 2022, 1–13.

[12]. Dhiman, M., Churh, C. C., Kusal, R., Anupam, P., & Kumar, K. (2023). "Deep Learning-Based Classification of Rice Varieties from Seed Coat Images" (pp. 71–80). *Springer International Publishing*.

[13]. Rayudu, M. S., Pampana, L. K., Myneni, S., & Kalavari, S. (2023). "Rice Grain Classification for Agricultural Products Marketing-A Deep Learning Approach". 1–4.

[14]. Saxena, A., T, A., & Sincy, R. (2023). "Harnessing Deep Learning for Precise Rice Image Classification: Implications for Sustainable Agriculture". 557–564.

[15]. Busi, R. A., Prasanna, V. L., Singla, B., Kishore, T. Y., Santhi, V., & Sainath, Y. (2024). "Rice Grains Detection, Classification, and Quality Prediction Using Deep Learning". *International Journal for Science Technology and Engineering*, 12(3), 2230–2239.

[16]. Busi, R. A., Prasanna, V. L., Singla, B., Kishore, T. Y., Santhi, V., & Sainath, Y. (2024). "Rice Grains Detection, Classification, and Quality Prediction Using Deep Learning". *International Journal for Science Technology and Engineering*, 12(3), 2230–2239.

[17]. Rani, R., & Gupta, S. (2024). "Deep Learning-based Identification of Rice Varieties: A CNN Approach". 798–802.

[18]. Gilanie, G., Nasir, N., Bajwa, U. I., & Ullah, H. (2021). "RiceNet: convolutional neural networks-based model to classify Pakistani grown rice seed types". *Multimedia Systems*, 27(5), 867–875.

[19]. Pillai, R., Chauhan, R., Rawat, D., & Gupta, R. (2023). "CNN-based Approach for Classification of Rice Varieties". 1–5.

[20]. Kamran, R., Abu Saima, M., Naz, N., & Athar, A. (2023). "Classification of Rice Varieties using Convolution Neural Networks". 1–6.

BIOGRAPHY

Prof. D. R. Solanke received his Master's degree in Science in Applied Electronics discipline from PG Deptt. of Applied Electronics, Faculty of Science and Technology, SGB Amravati University Amravati, Maharashtra (India), in the year of 1997. He has also passed and qualified UGC NET and SET exams in 2013.Currentaly working as Assistant Professor in the Department of Applied Electronics, at SGB Amravati University Amravati, Maharashtra state of India. He has published 39 research papers in International, National Journals, Proceedings and conferences. He has 06 design patents and 03 Publication patents in his credit. Also he Copyrighted 02 research articles, 06 textbooks in AI domain and Advanced Microcontrollers. His current research interests including Embedded Systems, Internet of Things (IoT), Soft Computing.

Prof. K. D. Chinchkhede obtained his Master's degree in Engineering in Electronics & Telecommunications discipline from Govt. College of Engg, Amravati, Maharashtra (India), in Faculty of Engineering and Technology from Amravati University, in the year of 2010. Currently working as Assistant Professor in the Department of Applied Electronics, at Sant Gadge Baba Amravati University Amravati, Maharashtra state of India. He has published several research papers in International, National Journals, Proceedings and conferences. He has 03 design patents in his credit. His current research interests including Digital Signal Processing, Soft Computing, Data Analysis and Financial Modelling

Prof. (Dr.) A. B. Manwar received his Master's degree in Computer Science from Amravati University, Amravati, Maharashtra (India), in the year 1994. He has been awarded with doctoral (PhD) degree from Sant Gadge Baba Amravati, Amravati, Maharashtra. He has also passed UGC SET and GATE exam. Currently working as Associate Professor in the Computer Science Department and holding the charge of Head, Department of Mathematics, at SGB Amravati University, Amravati, Maharashtra, India. He has published several research papers in National, International journals, proceedings and conferences. His research interest is in the areas of Information Retrieval, Cross Language IR, and AI in Financial domain.