International Journal of Scientific Research and Engineering Development-– Volume X Issue X, Year

Available at www.ijsred.com

RESEARCH ARTICLE OPEN ACCESS

Comparative Analysis of CNN Based Deep Learning Models for Automated Rice Varity Classification

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Abstract:

Rice variety classification is crucial for quality control, yield estimation, and market value assessment. With advancements in deep learning, automated classification using convolutional models has gained importance. This study compares various deep learning models for rice variety classification, evaluating accuracy, efficiency, and robustness. A dataset of rice grain images is used to train and test models, analyzing key performance indicators like accuracy, precision, recall, and F1-score. The impact of data augmentation and transfer learning is also explored. Computational efficiency and training time are assessed for practical applicability. Results show deeper architectures perform better than shallower ones. The study highlights the potential of deep learning in automating classification for agriculture. Future work will focus on hybrid models and advanced feature extraction.

Keywords — **texture, EfficientNet, ResNet.**

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I. INTRODUCTION

Rice classification plays a crucial role in agricultural supply chains and food safety. Traditional methods of classification, which rely on manual inspection, are time-consuming and prone to inconsistencies. With advancements in deep learning, CNNs have emerged as a powerful tool for automated classification, leveraging image data to identify different rice varieties accurately. The study aims to compare different CNN architectures for their effectiveness in rice classification, exploring both simple and advanced models.

The **Aruzz Rice Image Dataset** is a meticulously curated collection of images showcasing 5 well-established rice varieties native to various regions of Bangladesh. This dataset serves as a valuable resource for researchers and developers working on computer vision and agricultural applications, particularly in the classification and recognition of rice varieties.

Dataset Composition:

Rice Varieties Included: The dataset encompasses 5 distinct classes, including: Bashmoti, BR-28, BR-29, Lal Binni, Red cargo

Image Details: The dataset comprises a total of 4,730 original JPG images, each with a resolution of 853 × 853 pixels. Additionally, to enhance the dataset's robustness, 23,650 augmented images have been generated, bringing the total to 28,380 images.

Dataset Structure: To facilitate efficient data management, the dataset is organized the main categories:

Original Images: Contains 4,730 images, organized into 5 sub-directories, each corresponding to a specific rice variety.

Deep Learning is a subset of machine learning that uses multi-layered artificial neural networks to learn and extract features from data. Convolutional Neural Networks (CNNs) are a specialized deep learning architecture designed specifically for image processing and computer vision tasks.

II. LITERATURE SURVEY

Rice classification is essential for ensuring quality, preventing adulteration, and optimizing agricultural processes. Traditional classification methods rely on manual inspection, which is time-consuming and error-prone. Recent studies have explored machine learning (ML) and deep learning (DL) techniques for automating rice variety classification using morphological, shape, texture, and color-based features.

Several studies have used ML algorithms such as K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Support Vector Machine (SVM), and Logistic Regression (LR) to classify rice grains. These methods rely on extracted features such as 12 morphological, 4 shape, and 90 color features**.** One study achieved 99.91% accuracy using Random Forest with a combined feature set, demonstrating the effectiveness of combining multiple features for rice classification.

Deep learning models, especially Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), have been extensively applied for rice classification. A study on nine rice varieties extracted 13 morphological, 6 color, and 15 texture features, showing that texture features contributed the most to classification accuracy. A combined model achieved 92% accuracy, while individual variety accuracies ranged between 68% and 100%**,** highlighting the role of optimized feature selection.

CNN-based models outperform traditional ML models in classifying rice varieties. One study used ANN, Deep Neural Networks (DNN), and CNN for classification, achieving 99.87% (ANN), 99.95% (DNN), and 100% (CNN) accuracy. These findings confirm that deep learning models, particularly CNNs, are highly effective in automating rice classification tasks.

A novel deep learning model**,** RiceNet, was developed using Deep Convolutional Neural Networks (DCNNs) to classify five rice varieties. Additionally, pre-trained architectures such as InceptionV3 and InceptionResNetV2 were fine-tuned with the Adam optimizer (lr = 0.00003)**.** Comparisons with traditional ML models, including HOG-SVM, SIFT-SVM, and Logistic Regression-based methods**,** showed significantly lower accuracies (52%–66%**).** In contrast, RiceNet achieved 94% accuracy, while InceptionV3 and ResNetInceptionV2 achieved 84% and 81.33% accuracy, respectively**.**

III. METHODOLOGY

Deep learning models such as ResNet (Residual Networks) and EfficientNet have gained significant attention for image classification, including agricultural applications like rice grain classification**.** These models offer improved accuracy, efficiency, and generalization capabilities compared to traditional CNN architectures.

ResNet (Residual Networks):

ResNet, introduced by Microsoft Research, revolutionized deep learning by addressing the vanishing gradient problem in deep neural networks. The key innovation in ResNet is the residual connection (skip connection)**,** which allows gradients to flow through the network more effectively, enabling very deep architectures (e.g., ResNet-50, ResNet-101, ResNet-152).

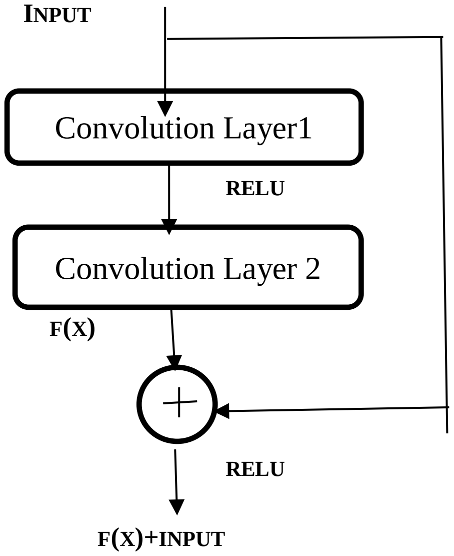

Fig.1 A ResNet Model

EfficientNet:

EfficientNet is a family of CNN architectures developed by Google, designed to improve accuracy and efficiency simultaneously. Unlike traditional CNNs, which simply increase the number of layers, EfficientNet uses a compound scaling method to balance depth, width, and resolution for optimal performance.

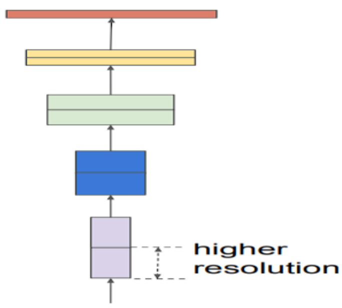

Fig.2 Compound scaling in EfficientNet model.

IV. EXPERIMENTAL SETUP

A. Dataset

The Aruzz Rice Image Dataset is a carefully structured collection of images designed for rice classification research. It consists of 28,380 JPG images, with an original set of 4,730 images captured at a high resolution of 853×853 pixels. To enhance the dataset's robustness, an additional 23,650 augmented images have been generated. The dataset is systematically organized into five subdirectories, each representing a specific rice variety: Bashmoti, BR-28, BR-29, Lal Binni, and Red Cargo**.**

Each image in the dataset captures crucial grain features such as texture, shape, and color variations, making it a valuable resource for machine learning and deep learning applications. The images are labeled according to rice variety, allowing for efficient classification. Since the dataset is primarily used for CNN-based rice variety identification, preprocessing steps like resizing (e.g., 128×128 pixels) may be necessary for optimal model input. The dataset structure ensures easy navigation and facilitates research in food quality control, supply chain automation, and agricultural AI applications**.**

B. Pre-processing

The Aruzz Rice Image Dataset is a structured collection of images designed for rice classification research. It consists of 28,380 images, including 4,730 original high-resolution (853×853 pixels) JPG images and 23,650 augmented images. The dataset is categorized into five rice varieties**:** Bashmoti, BR-28, BR-29, Lal Binni, and Red Cargo, each stored in separate subdirectories for easy organization.

Preprocessing is essential to enhance model performance. Resizing images to 128×128 or 224×224 pixels ensures compatibility with CNN architectures. Normalization standardizes pixel intensity values, while grayscale conversion can simplify computations. Augmentation techniques, such as rotation, flipping, and brightness adjustment, help increase dataset diversity and reduce overfitting.

For better feature extraction, contrast enhancement and background noise removal highlight key grain characteristics. Segmentation techniques isolate individual rice grains, improving classification accuracy. These preprocessing steps optimize the dataset for machine learning (ML) and deep learning (DL) applications, making it useful for food quality control, agricultural automation, and supply chain management. The structured format and preprocessing strategies ensure the dataset's effectiveness in CNN-based rice variety identification.

C. **Implementation details**

Deep learning models for image classification using Convolutional Neural Networks (CNNs). The objective is to develop and compare different CNN architectures to determine the most effective model for classifying rice varieties. The dataset consists of multiple image categories stored in structured directories. A systematic approach is followed, starting from data preparation to model evaluation, ensuring efficient training and fair performance comparison.

Data preparation involves loading images from structured directories, extracting file paths and labels, and organizing the dataset into training (75%), validation (15%), and testing (10%) sets using stratified sampling. Proper dataset management ensures that models are trained on non-overlapping sets, preventing data leakage and improving generalization.

Images are normalized by scaling pixel values to a range of [0,1], which improves training stability. Additionally, data augmentation techniques such as rotation, horizontal flipping, and zooming are applied to increase dataset diversity. TensorFlow's ImageDataGenerator is used for augmentation, applied only to the training dataset, while validation and test sets undergo only rescaling to maintain consistency. Visualization techniques, including class distribution plots and sample image displays, help assess dataset balance and identify potential biases.

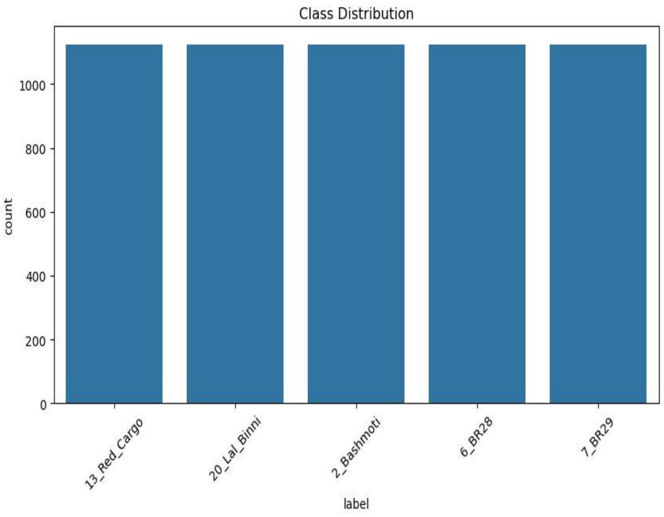

Fig. 3 class distribution plots

Two CNN architectures are developed for comparison: the ResNet model and the EfficientNet model. The ResNet model consists of two convolutional layers with ReLU activation, followed by max pooling layers and a fully connected dense layer, with the final output using softmax activation for multi-class classification. The EfficientNet model features three convolutional layers with batch normalization, dropout layers for regularization, and an increased number of filters, allowing for more complex pattern recognition. Both models are compiled using the Adam optimizer and categorical cross-entropy loss function.

The models are trained using the prepared dataset, with validation accuracy and loss monitored over multiple epochs. The training process includes feeding augmented data in batches, validating performance after each epoch, and adjusting hyperparameters as needed. Overfitting is closely monitored by observing the gap between training and validation loss, with dropout techniques employed to mitigate it. Evaluation metrics such as accuracy, loss, precision, recall, and F1-score provide insights into model performance across different classes

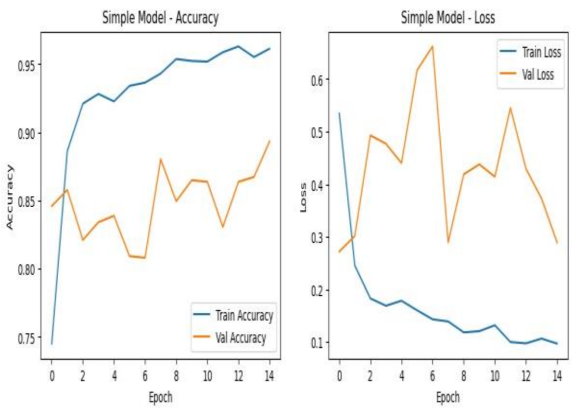

Fig.4 ResNet Model Accuracy and Loss

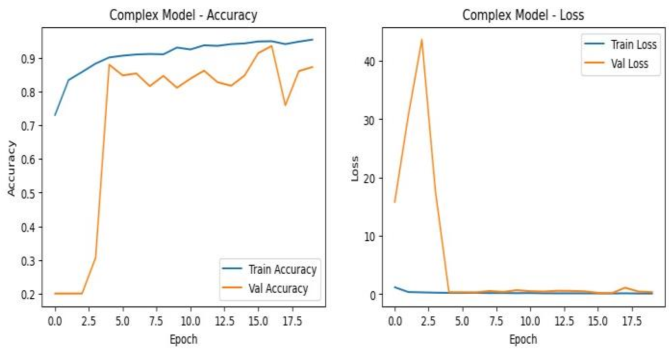

Fig.5 EfficientNet Model Accuracy and Loss

To further analyze model effectiveness, classification reports and confusion matrices are generated, visualizing misclassifications and identifying potential weaknesses. Comparing results, the ResNet model achieves **95.5% accuracy**, while the EfficientNet model reaches **97.4% accuracy**. However, despite its deeper architecture, EfficientNet does not significantly outperform ResNet, indicating possible overfitting or the need for additional fine-tuning.

Fig.6 Misclassification of ResNet Model

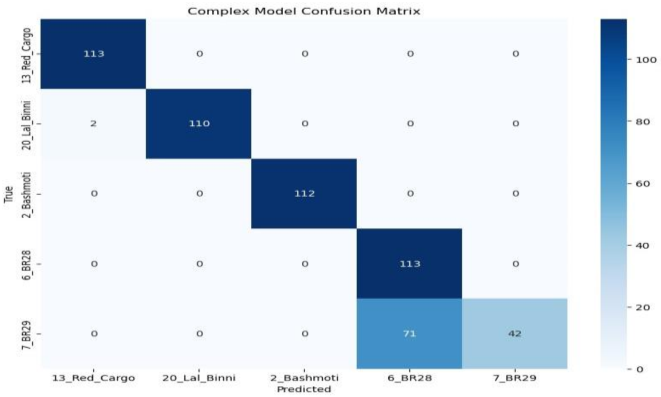

Fig.7 Misclassification of EfficientNet Model

V. EXPERIMENTAL RESULT

The results of this project provide valuable insights into the performance of deep learning models for image classification. The accuracy, loss, and classification metrics indicate how well the models generalize to unseen data. The ResNet model achieved an accuracy of 94.5%, while the more EfficientNet model reached 97.4%, highlighting that deeper networks do not always guarantee better performance without proper tuning. The classification report and confusion matrix further help in understanding the model's strengths and weaknesses. By analyzing precision, recall, and F1-score, we can identify which classes are easier or harder to classify. The visualization of predictions allows us to inspect real-world performance and detect common misclassifications.

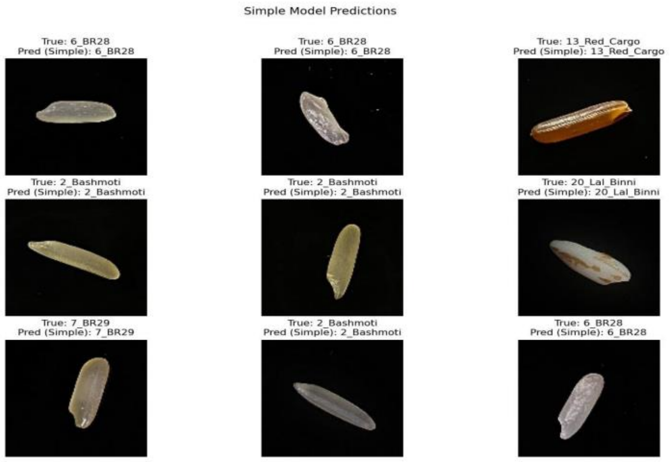

Fig.8 Classification of ResNet Model

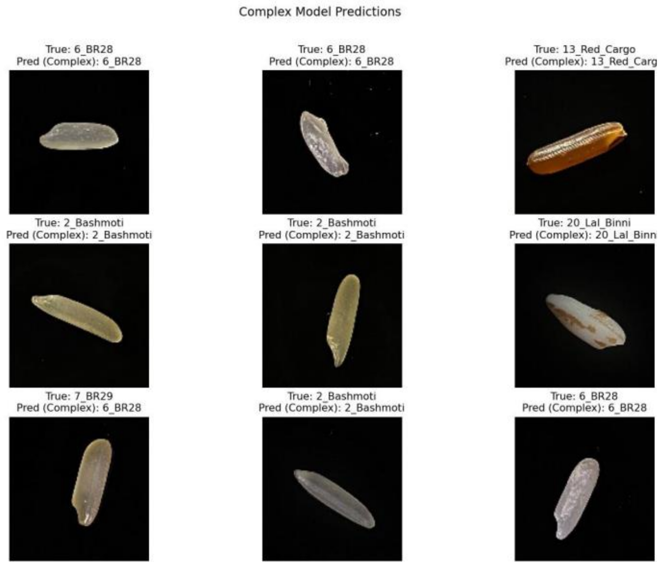

Fig.8 Classification of EfficientNet Model

VI. CONCLUSIONS

This study demonstrates the effectiveness of deep learning models, particularly convolutional neural networks (CNNs), in automating rice variety classification. By evaluating multiple models on a diverse dataset of rice grain images, the research highlights that deeper architectures outperform shallower ones in terms of accuracy, efficiency, and robustness. The study also emphasizes the impact of data augmentation and transfer learning in improving classification performance.

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