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Exploring the Diversity of Rice Grain Variegation: A Review

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Abstract: Challenges persist in developing a suitable method to distinguish high-quality cultivated rice seeds, which can be estimated based on their characteristics. To prevent rice grain varieties from being incorrectly labeled, the quality and type of rice grains must be accurately identified. In this paper, the classification of rice grains is analyzed, and a study is conducted on various algorithms used at each stage. Generally, visual observations are made by specialists using specialized devices that measure various properties. The resultant data are processed through different stages using multiple algorithms, which are discussed in detail. This study reviews machine learning techniques for differentiating rice seeds based on various algorithms. Each stage is analyzed with distinct objectives, and necessary conclusions are drawn to inform the next stage of research.

Keywords: Classification, Deep Learning, Ensemble Model, Machine Learning, Rice Grain.

1 INTRODUCTION

Rice is a life-giving crop and a key food item consumed by more than half of the world's population [1]. After wheat and corn, rice is the third most widely produced and consumed cereal crop globally. It is a primary source of protein and energy worldwide [2]. The economic importance of rice is further underscored by the fact that one-third of global rice consumption is sourced from international trade, and more than 60% of the world's population resides in Asia. In addition to its economic benefits—such as employment generation and foreign revenue—rice offers numerous nutritional and health advantages. It is a rich source of vitamin B1 and plays a crucial role in regulating blood sugar levels, aiding digestion, and slowing aging. Rice is also extensively used in various industries due to its high starch content [3].

Rice is the primary staple food crop in South India, with various varieties cultivated across different regions to meet the increasing nutritional needs of the growing population [4]. Farmers consistently face significant losses due to multiple factors, including climate change, drought, and issues with seed quality. Currently, Seed Testing Laboratories (STL) are responsible for certifying seed quality, with trained technicians manually conducting purity tests [5]. However, seed classification lacks uniformity across different laboratories due to factors such as technician fatigue, eye strain, and variations in individual judgment [6]. Therefore, automating the identification of rice seed varieties is essential to ensure the quality and germination potential of rice crops.

As stated in [7], rice grain classification is crucial due to the vast number of rice varieties available in the market. Manual classification is a tedious and time-consuming task that necessitates automation through an intelligent system. The classification process involves analysing these features using machine learning techniques. This study identifies and classifies rice grain images through the following steps:

a. Images are captured using a camera.
b. Captured images undergo pre-processing techniques to enhance image quality.
c. Feature extraction is performed on the pre-processed images.
d. The extracted features are fed into the selected machine learning algorithms for classification.

An effective system should be capable of automatically identifying and categorising individual rice grains. The primary process involves collecting a dataset and extracting various parameters of individual rice grains, such as major and minor axes, eccentricity, length, and breadth [8].

2 LITERATURE REVIEW

The input image is ultimately represented as training data, and each grain of rice/picture is mapped to its respective class [9]. Some traditional rice varieties of India, cultivated in different regions, include Basmati, Joha, Jyothi, Navara (unique varieties), Ponni, Pusa, Sona Masuri, Jaya (intermediate varieties), Kalajiri (aromatic), and Boli Palakkad Matta, among others.

Some examples of colored rice varieties include Himalayan red rice, Matta rice, Kattamodon, Kairali, Jyothy, Bhadra, and Asha from the state of Kerala; Rakthashali from Kerala; Red Kavuni, Kaivara Samba, and Mappillai Samba from Tamil Nadu; Kuruvi Kar; and Poongar. The classification of rice plays a key role in research. Manual classification is a tedious and time-consuming task. Automation through an intelligent system is needed to overcome this challenge.

Any rice sample taken for analysis in the system undergoes the following steps: classification, segregation, evaluation, categorisation, and grading. This study's contribution is threefold, as it categorises the algorithms and techniques into five approaches: geometric, statistical, supervised, unsupervised, and deep learning. Deep learning techniques have produced promising findings and have sparked interest in future research. Additionally, these techniques can efficiently separate rice grains into different classes [10]. To guarantee a good yield and quality, rice types must be accurately identified. Grain attributes, such as color, shape, taste, aroma, cooking characteristics, and head rice recovery, are analysed in conjunction with morphological features and visual inspection, which are traditional methods for identifying rice varieties [11]. Some key research questions arose during the study of this topic:

a) What methods and algorithms have been previously suggested for categorising rice?
b) What steps are taken to identify the most suitable method among different types of algorithms?
c) What are the differences between manual and automated rice grading approaches?
d) What could be the best-fit approach that can be extended for further research?

A detailed survey of rice classification techniques is subdivided into Section 3, providing comprehensive knowledge of different types of learning for classifying various rice varieties and offering ideas for further research. Numerous research papers on rice grain classification were analyzed for this study. The collected research articles are categorized according to various methods, including geometric, statistical, machine learning, and deep learning. Furthermore, this study reviews multiple algorithms and techniques for detecting and categorizing rice. Although rice recognition using classic feature extraction has shown encouraging results, the extracted features are often too specific and fail to capture essential characteristics, resulting in significant limitations [12]. Methods for classifying collected research articles have been explained in detail under stages such as screening, eligibility analysis, and data extraction.

Evaluating the quality of rice grains is crucial to meeting customer expectations. Grain quality is determined based on geometric characteristics. The local industry primarily employs mechanical classification techniques to categorize different food grains based on size and shape. Image processing techniques enable the extraction of various features from rice grains, allowing for classification based on shape and geometric properties. Using a binary image, Zhao et al. [13] retrieved 11 geometric properties, such as perimeter, area, circular degree, equivalent diameter, major axis length, stretching of the rectangle's length, maximum inscribed circle, and smallest enclosing circle, from rice kernels. From the grayscale image, texture features, including mean, variance, smoothness, consistency, entropy, and seven statistically invariant moments, were extracted. [14] utilized textural elements for corn image classification, including energy, contrast, homogeneity, correlation, and a Local Binary Pattern (LBP)-based gray-level co-occurrence matrix (GLCM).

These methods can be generally divided into geometry-based, statistics-based, and learning-based approaches, including both unsupervised learning (such as k-means clustering, used for clustering unlabelled data based on similarities) and supervised approaches, such as neural networks, support vector machines, and, more recently, deep learning. Among all the approaches, the supervised approach made the most significant contribution. The improved performance of supervised approaches can be attributed to the use of handcrafted spatial features in conjunction with various classifiers.

3 MACHINE LEARNING APPROACHES

Machine learning approaches can be broadly classified into supervised, unsupervised, and deep learning.

3.1. Unsupervised Learning

Large datasets are not necessary for training classifiers using unsupervised learning approaches. These methods utilize clustering to categorize the data into classes based on their similarity. A clustering-based method for classifying rice is demonstrated in [15]. The authors captured two images of a rice sample consisting of eight different rice varieties. After that, the photos underwent pre-processing using edge detection methods, thresholding, and the elimination of noise and lens distortion. Reliable morphological characteristics of different rice grains, such as average length, shape, and compactness ratio, were obtained once the approaches were implemented.

For every image taken, two dendrograms were created to highlight feature similarities among rice samples, aiding in the classification of short, medium, and long brown and white rice. Principal Component Analysis (PCA) is a dimensionality reduction and machine learning technique used to compress a large dataset into a more compact representation while retaining critical patterns and structures.

One such PCA-based approach to categorizing various Basmati rice varieties was introduced in [16], which, rather than using dendrograms, employed clustering based on K-Nearest Neighbors (KNN), an essential machine learning algorithm. KNN classifies new data by comparing its similarity to existing cases and assigning it to the category with the most similar data. The rice image was pre-processed using KNN clustering, noise reduction, and smoothing. The study experimented with six different types of rice seeds. After segmenting the colored rice image, binarization was performed. Morphological features were then extracted to enhance and clarify the input image. Parameters such as area, major axis length, minor axis length, eccentricity, and perimeter were used for classification. The various rice grain varieties were then clustered using KNN as a classifier. Along similar lines, the authors devised a rice quality classification system that also utilized KNN clustering. Table 1 presents various techniques along with the extracted geometric, texture, and shape features.

Table 1. Feature-based analysis on unsupervised learning and geometric features

Method	Algorithm/Techniques	Extracted Features
S. Mahajan et al. [13]	Edge detection techniques	Geometric Features and Texture Features
J.G.A. Barbedo [14]	GLCM and LBP	Geometric Features and Texture Features
J.P. Shah et al. [15]	Edge detection techniques	Shape Features
T. Bera et al. [16]	PCA-based algorithm + KNN	Shape Features

3.2. Supervised Learning

Supervised learning is a form of Artificial Intelligence in which machines learn from labeled data and predict outcomes based on that information. The labeled data provides the correct results, guiding the machine toward accurate predictions. In supervised learning, the training data serves as a supervisor, instructing the machine to arrive at the correct output. Various morphological features, including seed area, seed boundary, bounding box, width, major and minor axis lengths, thinness ratio, aspect ratio, rectangular aspect ratio, equivalent diameter, filled area, area under the major axis of the ellipse, convex area, solidity, and extent, were extracted from rice images. Additionally, various color features, including hue, saturation, intensity, and the standard deviation of hue in the red, green, and blue color bands, were also extracted.

3.3. Deep Learning Approaches

Deep learning is a subfield of machine learning that utilizes artificial neural networks (ANNs) with multiple layers to process and analyze large datasets of complex data, including images, audio, and text. The field of deep learning has its roots in the study of artificial neural networks. During the 1980s and 1990s, complex neural network architectures such as multi-layer perceptrons (MLPs) and radial basis function networks (RBFNs) were developed. However, it was the advent of powerful computational resources and large datasets in the early 2000s that genuinely enabled deep learning to take off [17]-[21].

An AI model with a high level of abstraction in deep learning can be trained using text, images, sounds, and recognition analysis. Table 2 presents the details of the deep learning algorithms employed and the extracted features. One of the leading deep learning algorithms analysed is the Convolutional Neural Network, which is examined in detail below.

Table 2. Details of Algorithms Used and the Extracted Features

Method	Algorithm/Techniques	Extracted Features
T. Bera et al. [16]	PCA-based algorithm + KNN Neural Networks	Shape features
T.G. Devi et al. [22]	Machine vision algorithm	Physical and chemical features
N. Patel et al. [23]	Neural Networks & Support Vector Machine	Shape features
T.N. Wah et al. [24]	NB Tree & SMO classifiers	Chalkiness and whiteness of grains, along with other morphological features
N.A. Kuchekar et al. [25]	Random Forest classifier, Decision Tree classifier	Shape and geometric features
N.H. Son et al. [26]	Multiclass SVM	Shape descriptors, colour descriptors
Xu Han et al. [27]	BPNN	18 colour features and 21 texture features

3.3.1. Convolutional Neural Network (CNN)

A CNN is a specialized type of deep learning neural network that is particularly well-suited for processing structured arrays of data such as images. The widespread utilisation of CNNs in computer vision is a testament to their effectiveness, with the architecture having become state-of-the-art for a vast array of visual applications, including image classification. CNNs have also demonstrated success in natural language processing, particularly in the realm of text classification [18]-[20]. A CNN is an advanced deep learning neural network specifically designed for image processing. It is particularly adept at detecting patterns in input images, such as circles, lines, faces, eyes, and gradients. This feature significantly enhances the effectiveness of CNNs in computer vision applications. CNNs are feed-forward neural networks that consist of multiple layers, with some models having up to 20 or 30 layers.

The power of CNNs is due to the use of convolutional layers, which can recognise increasingly complex shapes when stacked on top of each other. The applications of CNNs provided an idea for creating the new Scratch Net, thanks to its architecture that can be easily explained to understand the concept clearly. The convolutional layer is the primary layer used to extract different features from the input image, where convolution is performed between the input image and a filter of a specific size M × M. The result is named the feature map, which provides data about the image, including its corners and edges. Afterward, this feature map is applied to different layers to learn several characteristics of the input image.

The pooling layer reduces the information volume and boundary count, which can help prevent overfitting and enhance network performance [18]-[20]. Pooling is divided into two categories:

- Max Pooling: Provides the maximum value within the image area covered by the kernel.
- Average Pooling: Provides the average value within the kernel-covered image area.

The fully connected layer is entirely connected and must be flattened before being fed into the neural network; the entire pooled feature map matrix is transformed into a single column vector. Thus, a model is created by combining the feature map matrix obtained from the fully connected layers using their attributes. The output is then classified using an activation function, such as the Sigmoid Function. Convolutional layers apply filters or kernels to input data, generating features in the process [21].

To evaluate and categorise rice grains, their physical and chemical features were extracted using a machine vision algorithm, which averages the values of the extracted features considered for grading and quality analysis of rice grains [22]. In [23], the extracted shape features of rice are evaluated using Neural Networks (NN) and Support Vector Machine (SVM) algorithms. The results indicate that SVM-based classification outperforms Neural Networks. The work in [24] extracted features that classified nine varieties of rice grains with an accuracy of 95.78% using the Naïve Bayes Tree and Support Vector Machine (SMO) classifiers. These features represent the chalkiness and whiteness of grains along with other morphological features such as area, perimeter, major and minor axes, etc.

Twenty features were extracted using a Random Forest Classifier, and performance metrics, including accuracy, precision, recall, and F1 score, were compared with those of Decision Tree classifiers in [25]. Experimental results show that the Random Forest classifier outperforms the Decision Tree classifier, yielding more accurate results. In the Random Forest classification, the accuracy is 99.85%. In [26], a set of shape and colour descriptors was extracted from each rice grain image. Classification into three types—Basmati, Ponni, and Brown rice—was done using a Multiclass Support Vector Machine. The classification accuracy obtained was 92.22%. Performance was evaluated by extracting features from the 3D reconstructed image of a rice grain and classifying it using a BPNN architecture with 18 color features and 21 texture features [27].

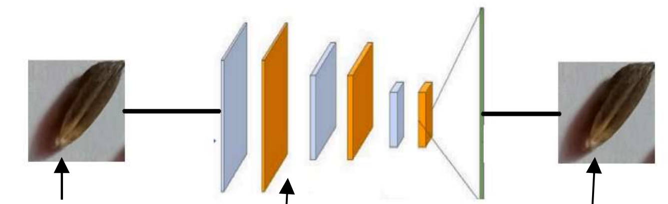

Fig. 1. CNN model in Kauvuni Rice Classification [27]

Fig. 1 illustrates the proposed concept of utilising a CNN model for classifying Kauvuni rice. The model is implemented by adding three convolutional layers and three pooling layers, along with fully connected layers, to perform the classification. To extend the research, a review was conducted on leading pre-trained models, which paved the way to combine the existing architecture with some of the most prominent pre-trained models to propose the new Scratched Net. ResNet, based on the CNN architecture, builds upon the concepts of Inception Networks and Residual Networks (ResNets). It highlights the concept of cardinality to enhance performance and introduces the idea of a divide-transform-merge block. Different versions of ResNet have been proposed to optimise the trade-off between performance and computational cost for various tasks and datasets [26].

3.3.2. Pre-Trained Models

Pre-trained models are neural networks that have been trained on large datasets to perform specific tasks effectively [27]. These models learn complex patterns and features that can be utilised for classification, detection, and other machine learning tasks. This research considers widely adopted pre-trained models—VGG, ResNet, and Inception—which have established benchmarks in the field of computer vision. Table 3 presents the top pre-trained models with ScratchNet models.

Table 3. Top Pre-Trained Models with ScratchNet Models

Model	Variants	Key Features
ResNet (Residual Networks) [28]	ResNet-50, ResNet-101, ResNet-152	• Deep architecture (up to 152 layers). • Residual blocks to enable efficient gradient flow via shortcut connections.
Inception [29]	Inception v3, Inception v4, Inception-ResNet	• Inception modules utilize convolutional filters of varying sizes for multi-scale feature extraction.
VGG (Visual Geometry Group) [30]	VGG-16, VGG-19	• Deep networks with 16 or 19 layers. • Simple and uniform architecture.
EfficientNet [31]	EfficientNet-B0 to EfficientNet-B7	• The compound scaling method optimizes depth, width, and resolution. • Efficient and accurate with fewer parameters.
DenseNet (Dense Convolutional Network) [31]	DenseNet-121, DenseNet-169, DenseNet-201	• Dense connections improve gradient flow and feature reuse. • Reduces the number of parameters.
MobileNet [32]	MobileNetV1, MobileNetV2, MobileNetV3	• Lightweight architecture optimised for mobile devices. • Uses depth-wise separable convolutions.
NASNet (Neural Architecture Search Network) [33]	NASNet-A, NASNet-B, NASNet-C	• Architecture is discovered through reinforcement learning. • High accuracy with efficient performance.
Xception (Extreme Inception) [34]	–	• Fully convolutional architecture based on depth-wise separable convolutions.
AlexNet [35]	–	• It is a simple architecture with eight layers. • Introduced ReLU activation and dropout regularization.
Vision Transformers (ViT) [36]	–	• Transformer-based architecture. • Scales well with large datasets and computational resources.

Table 3 provides an overview of the top pre-trained models, which serve as the foundation for the proposed Scratch Net models, designed for efficient feature classification. Among these, ResNet has been examined in detail. In [28], the architecture of ResNet was analyzed, highlighting its ability to retain and propagate gradients through deep networks using residual layers. ResNet employs skip connections, also known as shortcut connections or identity mappings, which allow gradients to bypass intermediate layers.

This mechanism effectively mitigates the vanishing gradient problem, enabling the successful training of intense networks with up to 152 layers. By facilitating better gradient flow and feature learning, ResNet has demonstrated excellent performance in various computer vision tasks, such as image classification, object detection, and image segmentation [27]. The above analysis supports the creation of customised models—such as Scratch Net—by leveraging the strengths of existing architectures. Moreover, hybrid or ensemble models that combine multiple deep learning techniques are proposed to enhance prediction accuracy and reduce generalization error.

3.3.3. Ensemble Model

Ensemble learning is a machine learning technique that combines multiple models to improve prediction accuracy. It integrates various learners—such as neural networks, decision trees, and regression models—under the premise that a group of models performs better than an individual model. Ensemble methods help address issues such as high variance, underfitting, and overfitting, and apply to tasks including classification, regression, clustering, and more [37]. Ensemble models can also be effectively employed in diverse applications such as short-term forecasting, landslide assessment, and intrusion detection. These models typically employ voting strategies, such as majority or weighted voting, to derive their final predictions.

The study presented in [38] introduces an advanced ensemble methodology called the Ensemble Model of the Stowing and Helping Classifier (EMBBC), which combines decision-making and information-balancing techniques to predict code smells. Four publicly available datasets—Blob Class, Information Class, Long Boundary Summary, and Switch Statement—were used for experimentation. To address class imbalance, the Synthetic Minority Over-sampling Technique (SMOTE) was applied. In [39], an ensemble approach combining K-Nearest Neighbour (KNN), Random Forest, and Ridge Regression (KRR) was proposed. Evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2, were used to compare its performance with other models for yield prediction tasks.

Work in [40] employed multiple machine learning models, including eXtreme Gradient Boosting (XGBoost), K-Nearest Neighbor (KNN), Linear Support Vector Machine (SVM), Naive Bayes, Decision Tree (DT), and Random Forest (RF), to classify potato crop yield and quality. Standard metrics, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and R^2, were used for model evaluation. Table 4 presents the summary of selected ensemble models.

Table 4. Summary of Selected Ensemble Models

Method	Ensemble Model Name	Combinations
Yadav et al. [38]	EMBB Classifier	Bagging and Boosting Classifiers
M. Hasan et al. [39]	KRR	K-Nearest Neighbour, Random Forest, Ridge Regression
S. Tkatek et al. [40]	XGBoost	XGBoost, KNN, Linear SVM, Naive Bayes, Decision Tree, Random Forest

This comparison highlights various algorithmic combinations to identify optimal ensemble strategies for future research. This study reviews a diverse set of algorithms to advocate for ensemble deep learning. The significant contributions are summarised as follows:

- An overview of unsupervised learning and its key challenges.
- Introduction to supervised learning, highlighting its advantages.
- Discussion of deep learning architectures, especially CNN, and their benefits.
- Explore ensemble learning strategies in deep learning.

A comprehensive review to support and justify the proposed research direction.

4 CONCLUSIONS

This study provides a systematic review of various algorithms, including geometric algorithms, machine learning models, deep learning architectures, and ensemble techniques. These reviews offer foundational insights for advancing the research toward efficient classification. The primary objective is to classify rice grain images using appropriate algorithms. The study investigates methods such as the Gray-Level Co-Occurrence Matrix (GLCM), Local Binary Pattern (LBP), and a PCA-based algorithm with KNN for object classification. It also explores diverse feature selection strategies, encompassing geometric, texture, and shape-based features. The study further extends its analysis to machine learning combinations such as:

- PCA with KNN and neural networks,
- Neural Networks with Support Vector Machines (SVM),
- NBTree with SMO classifiers,
- Random Forest and Decision Tree classifiers,
- Multiclass SVM and Backpropagation Neural Network (BPNN).

Additionally, the research examines pre-trained models and custom Scratch Net models, including ResNet, Inception, VGG, EfficientNet, DenseNet, MobileNet, NASNet, Xception, AlexNet, and Vision Transformers (ViT). The findings from this investigation have valuable implications for software developers and researchers, especially in understanding how to mitigate the effects of code smells and improve software quality. Future work could explore a hybrid ensemble strategy to enhance classification accuracy and generalisation. Furthermore, the emphasis on feature selection underlines its importance in building effective ensemble models, encouraging continued research in this area.

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ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTEREST

The authors declare no conflicts of interest related to this study.

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