Rice Grain Quality Detection

Kailash Bangari[1], Srishti Gurhani[2], Saumya Tripathi[3], Pranav Bansal[4],Prof. Ranjana Agrawal[5]
[1]Student, [2]Student, [3]Student, [4]Student, [5]Faculty
MIT World Peace University, Pune, Maharashtra, India
[1]kailashbangari2002@gmail.com, [2]srishtigurhani@gmail.com,
[3]saumyat2002@gmail.com, [4]pranavb781@gmail.com,
[5]ranjana.agrawal@mitwpu.edu.in

Abstract

Rice is a staple of Indian cuisine and culture, renowned for its multidimensional significance. Beyond its position as a carbohydrate-rich nutritional staple, it incorporates cultural traditions, participating frequently in religious rites and festivals and indicating affluence and auspiciousness. Its versatility in various culinary creations—from scented biryanis to savoury dosas—reflects regional uniqueness while serving as a unifying factor in communal meals. Rice quality is critical since it influences nutrition, market value, and food safety. The detection and assurance of high-quality rice is critical for encouraging better nutrition, fair trade, and safe use. On a self-generated dataset, this work employs a dual-approach strategy to exploit both classic Machine Learning (ML) approaches and advanced Deep Learning (DL) models. Local Binary Pattern (LBP) is used for feature extraction, which is well-suited for capturing image textural features. DenseNet201, known for its robustness in image classification problems, is used as the DL model for rice grain classification. The ability of this network to capture complicated patterns and hierarchical features is likely to aid in accurate grain classification. This paper outlines how rice grain is classified into three sets: good rice, broken rice, and immature rice. The performance of the classifiers based on the feature sets mentioned is also compared. Our system achieves experimental results. The study findings show that the proposed system has the capability and potential to achieve the requirement for rice quality categorization.

Keywords: *rice quality, machine learning(ML), deep learning(DL), Local Binary Patterns(LBP), Densenet201*

1. Introduction

This research aims to completely integrate machine learning (ML) and deep learning (DL) techniques to transform the classification of rice grains. Approach I involves the careful curation of a crucial self-generated dataset that captures the various visual attributes of rice grains, such as differences in size, shape, and texture. Specifically, thresholding is used in segmentation techniques to separate grains from complex backgrounds. After that, the Local Binary Pattern (LBP) technique is used to extract important texture details. The best classification technique is then determined by systematically contrasting several machine learning (ML) algorithms, such as Support

Vector Machine (SVM), k-Nearest Neighbours (KNN), Gradient Boosting (GB), and Decision Trees (DT). Utilising the powerful DenseNet201 DL architecture is Approach II. This deep learning model, which was trained on the self-generated dataset, performs exceptionally well at identifying complex patterns and hierarchical features, which improves the accuracy of rice grain categorization. The project is significant because it has the potential to transform current grain sorting methods and offer a more precise and efficient substitute. It is expected that the research findings would provide significant insights to the food processing and agriculture sectors. The project intends to overcome the inefficiencies present in traditional approaches by promoting breakthroughs in automation and technology-driven grain classification. Due to population increase and rising demand, rice—a vital worldwide staple—must be farmed and processed efficiently. It is accepted that the traditional techniques for classifying rice are labour-intensive and prone to mistakes. This study revolutionises the classification of rice grain quality by utilising cutting-edge technology, especially computer vision and machine learning, to overcome these obstacles. The qualities of size, shape, colour, texture, and milling have a big impact on market value and customer pleasure. These technologies' automated systems have the potential to improve accuracy and efficiency while reducing the subjectivity of humans and time constraints that come with using more conventional approaches. The goal of this research project is to improve rice grain quality categorization by creating a reliable automated system. In order to meet the growing demand for premium rice goods in the international market, it seeks to improve the overall effectiveness of the rice production sector by improving the accuracy of evaluations.

2. Literature review

Many studies have been carried out in order to discover the most efficient technique for recognising rice qualities from a dataset.

The study "Food State Recognition Using Deep Learning" trained a system on food images, identifying 9 states and 18 types of ingredients. Using DenseNet121 fine-tuning, it learned about the food's condition and type. The paper stressed the importance for tasks like automated cooking and aiding the elderly[1].Prajapati and Patel's work on “Algorithmic Quality Analysis of Indian Basmati Rice” relied on image analysis of grain size, shape, colour, and texture. Their method, tested on 100 basmati rice samples, accurately classified them into three quality grades[2].

Kaur and Singh's paper on "Rice Classification and Grading" reviews methods like manual, machine learning, and image processing for these tasks. They advocate for more precise techniques, proposing the use of multi-class SVM as a promising solution to improve rice categorization and grading[3]. In their IJCSE paper "Quality Evaluation of Rice Grains Using Morphological Methods", Ajay, Suneel, Kumar, and Prasad proposed an approach using image traits to classify rice grains into three categories—good, medium, and poor. By extracting details like area, perimeter, axis lengths from grain images, their method achieved an impressive 88% accuracy when tested with a set of 300 rice grain images[4].

Dr. V.K. Banga and Jagdeep Singh Aulakh developed image algorithms to classify rice by size. They convert images to binary form, analyse connectivity and size, create graphs, eliminate smaller grains, and rate quality based on full-length rice count[5]. The paper "Rice Sample Segmentation and Classification Using Image Processing and Support Vector Machine" details how to categorise rice samples by colour and texture traits using image processing and machine learning. It involves steps like noise reduction and using traits for prediction with an SVM, achieving 96.0% accuracy in segmentation and 88.0% in classification across six rice categories[6].

Shrivastava, Pradhan, Minz, and Thakur in "Rice plant disease classification using colour features: a machine learning paradigm" gathered 619 images of diseased rice plants across four classes and used a pre-trained CNN for feature extraction and an SVM for classification. Their model achieved 91.37% accuracy with an 80%-20% training-testing split[7]. V. Lakshmi, K. Seetharaman in "Rice Classification and Quality Analysis using Deep Neural Network" used five rice grain types with 75,000 samples and 17 features. It employed ResNet50 and Xception models for classification, achieving 98.90% and 98.32% efficiency, respectively[8].

While there are numerous approaches for detecting faults in rice, none have classed rice using LBP and Densenet.

3. Materials and Methods

- **Spyder**

  Spyder is a robust environment built-in Python for Python and designed by and for scientists, engineers, and data analysts. It offers a unique amalgamation of a wide-ranging development tool's advanced editing, analysis, debugging, and profiling functionality with the data study, interactive implementation, deep examination, and beautiful visualisation capabilities of a scientific package.

- **Keras**

  Keras is an open-source NN library written in Python. It can be executed on top of Tensorflow Microsoft Cognitive Toolkit, R-language, Theano, or PlaidML. It is developed to enable superior experimentation with DNN. It focuses on being user-friendly, modular, and extensible. It was developed as part of the study effort of project ONEIROS, and its primary author and maintainer is Francois Chollet, a Google engineer.

- **Tensorflow**

  A complete open-source ecosystem for ML is called TensorFlow. TensorFlow, a robust system, handles the complete ML system. However, this course focuses on creating and refining ML models using a specific TensorFlow API.

- **Image processing library: OpenCV**

Open-source Computer Vision (OpenCV) is an image processing and computer vision library mainly developed for artificial vision. It has a BSD license (free for commercial or research use). OpenCV was originally written in C, but currently, it's a whole C++ interface, and there's additionally an entire Python interface to the library. Open-source computer Vision Library, also called OpenCV, is associated with a freeware software package for computer vision. It is used in this project because of its versatility and the fact that it has a C++ interface. OpenCV runs on most major Operating Systems (OS), making it worthwhile to use another computer to program or test.

- **Language: Python**

High-level programming languages like Python are widely utilised in programming. The interpreted language Python has a syntax that lets you utilise programmes written in most other languages, such Java and C++, and it supports a number of programming scripts. The language has structures intended to enable simple programmes at every scale. Python is simple to learn. Writing code in Python is far simpler than in other languages.

- **Training Platform: Google Colab**

Google Colab is an online platform that lets users create, execute, and collaborate on Python code in a web browser. It features a cloud-based Jupyter Notebook interface that makes data analysis, machine learning, and collaborative coding easier by doing away with the requirement for local installations and setups.

4. Proposed Methodology

4.1 Approach 1:

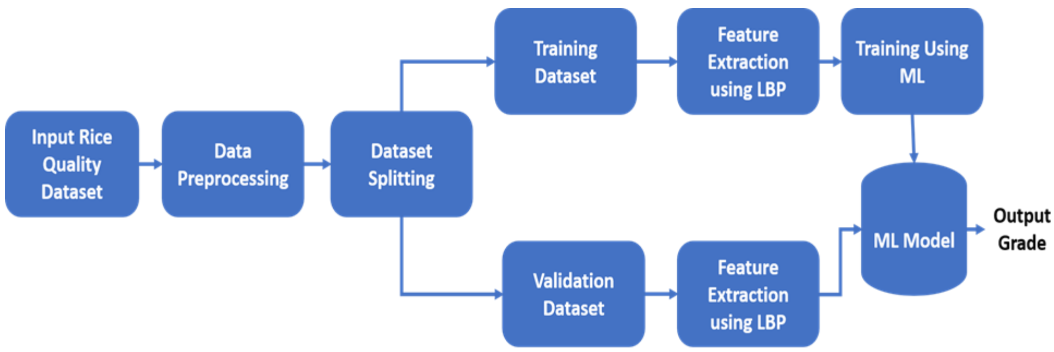


Fig.4.1 Block diagram of the ML based rice grain quality classification

The goal of this project is to create a reliable system for classifying rice grains and a careful pipeline for data processing. To guarantee the robustness of the model, the input dataset is meticulously selected and includes a variety of high-resolution photographs of rice grains. The dataset is preprocessed using segmentation methods and Local Binary Pattern (LBP) feature extraction to improve the separation of grains and backgrounds. Techniques for augmenting data, such flips and zooms, add variety to the training set.

Machine learning algorithms, such as Decision Trees (DT), Gradient Boosting (GB), k-Nearest Neighbours (KNN), and Support Vector Machine (SVM), are used during the training phase. Strong texture descriptor LBP helps extract features by identifying distinctive patterns that are essential for classifying rice grains. This methodical strategy seeks to transform the grain sorting industry by providing a precise and effective substitute for traditional techniques, as well as insightful information to the agricultural and food processing sectors.

4.2 Approach 2:

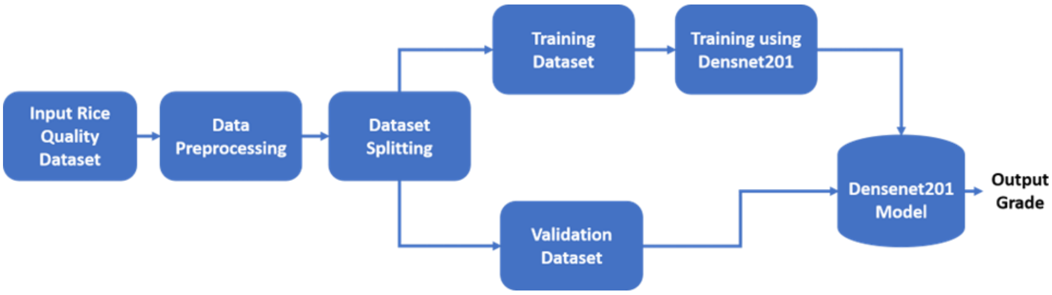


Fig.4.2 Block diagram of the Densenet201 based rice grain quality classification

Transfer learning is a powerful technique for efficient categorization with little data, and it is used in this work. The suggested model, which focuses on Deep Transfer Learning (DTL), uses DenseNet201 and its pretrained weights from the ImageNet dataset. With its unique architecture, DenseNet solves problems such as vanishing gradients, improves feature propagation, and minimises parameters by connecting each layer in a feed-forward fashion. Deeper, more precise, and more effectively trainable convolutional networks are made possible by this method. The DTL model seeks to maximise outcomes through hyper-tuning, demonstrating the possibility of using pre-learned features for better classification results in situations with limited data quantity.

5. Result and Discussion

In this approach, the rice grain quality classification is presented. The results are presented in terms of precision, recall, f1 score and accuracy parameter.

5.1. Results of ML based rice grain quality classification

- **SVM**

The classification report and confusion matrix of SVM algorithm for rice quality grade classification is shown in Fig.5.1.1.

```
SVM Classification Report:
              precision    recall  f1-score   support

     grade 1       0.89      0.94      0.92       132
     grade 2       0.80      0.87      0.83       120
     grade 3       0.74      0.62      0.68       106

    accuracy                           0.82       358
   macro avg       0.81      0.81      0.81       358
weighted avg       0.82      0.82      0.82       358
```

(a)

Fig. 5.1.1. Results of SVM algorithm for rice quality grade classification

Metrics like precision, recall, and F1-score for each class are provided by the SVM Classification Report, which assesses how well a Support Vector Machine model performs on a classification task. The model performs evenly in grades 1, 2, and 3, and its overall accuracy is good (0.82). Recall for grade 2 is 0.87, capturing 87% of real grade 2 cases, while precision for grade 1 is 0.89, suggesting 89% accuracy in positive predictions. Taking into account the class imbalance, macro and weighted averages (0.81) provide an overall performance summary. Taking into account the trade-off between false positives and false negatives, interpretation should be in line with task goals.

- **DT**

The classification report and confusion matrix of DT algorithm for rice quality grade classification is shown in Fig.5.1.3.

```
Decision Tree Confusion Matrix:
 [[128   2   2]
 [  1 104  15]
 [  9  10  87]]
Decision Tree Classification Report:
              precision    recall  f1-score   support

     grade 1       0.93      0.97      0.95       132
     grade 2       0.90      0.87      0.88       120
     grade 3       0.84      0.82      0.83       106

    accuracy                           0.89       358
   macro avg       0.89      0.89      0.89       358
weighted avg       0.89      0.89      0.89       358
```

(a)

Fig. 5.1.3. Results of DT algorithm for rice quality grade classification

The classification report of the Decision Tree model evaluates its performance in a multiclass job. It does exceptionally well in detecting grade 1 cases, with an overall accuracy of 89% (precision: 93%, recall: 97%, F1-score: 95%). While grade 3 displays satisfactory results (precision: 84%, recall: 82%, F1-score: 83%), grade 2 displays balanced performance (precision: 90%, recall: 87%, F1-score: 88%). Values that are weighted-averaged and macro-averaged support the model's consistent 89% accuracy across all classes. The paper offers a brief assessment of the Decision Tree model's advantages and disadvantages.

- **GB**

The classification report and confusion matrix of KNN algorithm for rice quality grade classification is shown in Fig.5.1.4.

```
Gradient Boosting Classification Report:
              precision    recall  f1-score   support

     grade 1       0.95      0.95      0.95       132
     grade 2       0.89      0.91      0.90       120
     grade 3       0.84      0.82      0.83       106

    accuracy                           0.90       358
   macro avg       0.90      0.89      0.89       358
weighted avg       0.90      0.90      0.90       358
```

(a)

Fig. 5.1.4. Results of GB algorithm for rice quality grade classification

5.2. Results of DL based rice grain quality classification

To discuss the results of a Vgg16, Resnet101 and DenseNet201-based rice grain classification system, we typically look at key metrics and performance indicators derived from evaluation techniques such as a classification report or confusion matrix.

- **DenseNet201**

A. Model Summary

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 densenet121 (Functional)     (None, 1, 1, 1024)       7037504

 global_average_pooling2d (  (None, 1024)              0
 GlobalAveragePooling2D)

 dense (Dense)                (None, 128)              131200

 dense_1 (Dense)              (None, 64)               8256
```

```
 dense_2 (Dense)              (None, 3)              195

=================================================================
Total params: 7177155 (27.38 MB)
Trainable params: 7093507 (27.06 MB)
Non-trainable params: 83648 (326.75 KB)
```

B. Classification Report

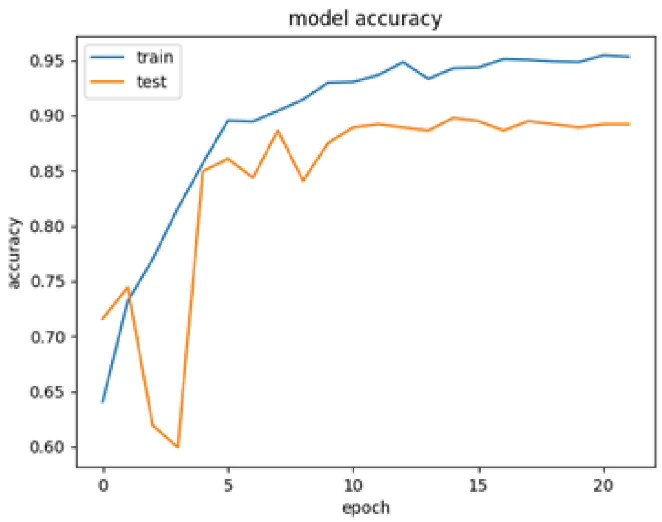
a. Validation results

```
Classification Report
              precision    recall  f1-score   support

     grade 1       0.91      0.95      0.93       132
     grade 2       0.90      0.93      0.91       162
     grade 3       0.77      0.65      0.70        71

    accuracy                           0.88       365
   macro avg       0.86      0.84      0.85       365
weighted avg       0.88      0.88      0.88       365
```

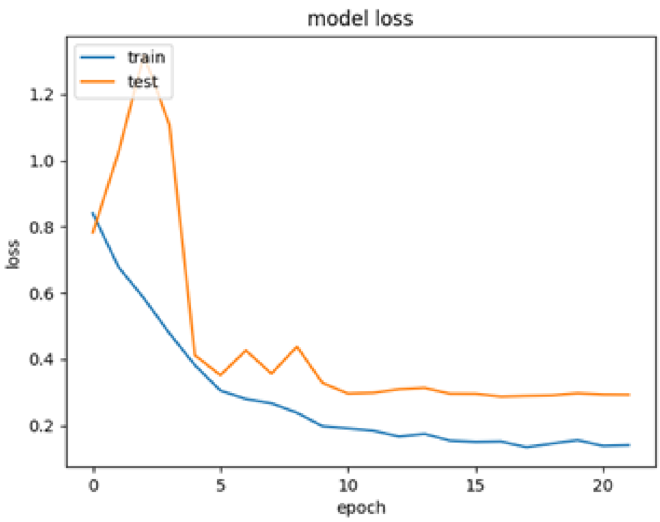
(a)

Fig. 5.2.1. Classification results of Densenet201 algorithm for rice quality grade classification

C. Training progress graph



(a)



(b)

Fig.5.2.2. Training progress graph of Densenet201 algorithm in terms of (a) Accuracy (b) Loss

The overall analysis of the proposed system is tabulated in Table 5.3.

Algorithm	Precision	Recall	F1Score	Accuracy
SVM	0.816654	0.821229	0.816734	0.821229
KNN	0.832033	0.835196	0.831306	0.835196
DT	0.890207	0.891061	0.890354	0.891061
RF	0.926768	0.927374	0.926874	0.927374
NB	0.803897	0.807263	0.801714	0.807263
GB	0.898882	0.899441	0.899085	0.899441
Vgg16	0.78	0.77	0.77	0.77
Resnet101	0.75	0.70	0.67	0.70
DenseNet201	0.88	0.88	0.88	0.88

Table 5.3. Comparative analysis of ML and DL algorithms for rice grain quality classification

The Comparative analysis of the proposed system graphically presented in Fig,5.4.

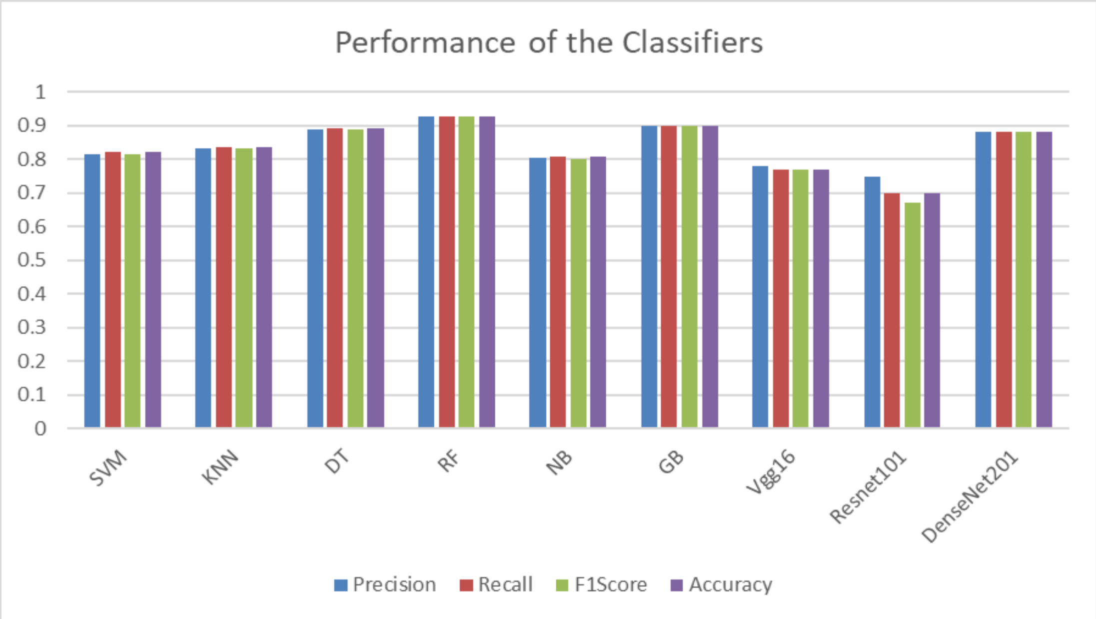


Fig.5.4. Comparative analysis of proposed system

The Densenet201 classifier outperformed all other machine learning and deep learning algorithms for classifying rice grains into good, broken, and immature quality when tested on a self-generated dataset. The accuracy of the Densenet201 method with LBP images as input is 0.88.

6. Conclusion

In conclusion, this study explores the field of rice grain categorization and examines the effectiveness of both conventional machine learning and deep learning techniques. Approach I, utilising machine learning, showcases commendable accuracy through SVM, KNN, GB, and DT, employing a self-generated dataset and Local Binary Pattern for feature extraction. On the other hand, Approach II uses the Vgg16, Resnet101 and DenseNet201 architecture, showcasing deep learning's improved ability to capture complex rice grain patterns. Deep learning is superior at handling complicated visual tasks, highlighting the necessity of context-dependent model selection, whereas machine learning provides clarity. These findings provide insights for crop assessment and quality management, contributing to the rapidly developing field of computer vision in agriculture. This research lays the groundwork for incorporating machine learning and deep learning into useful crop classification applications as the agriculture sector adopts new technology. All things considered, the integration of these approaches not only broadens our comprehension of their respective capabilities but also offers collaborative approaches for upcoming attempts to use artificial intelligence for sustainable crop management.

7. Future Scope

Several directions for further research and development are proposed by the study. Initially, the robustness of the model would be increased by including more diverse images of rice grains in the dataset. Transfer learning can improve accuracy and accelerate convergence when paired with fine-tuning on previously trained models. To improve model understanding, interpretability elements should be integrated and a real-time categorization system should be put in place for on-the-spot processing. Cooperation with agricultural technology platforms and stakeholders, as well as flexibility in classifying grains from different crops to ensure broader applicability. Ongoing improvements in technology-driven agricultural practices would be facilitated by research on sustainable agriculture and constant model monitoring and upgrading.

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