GrainLens: Smart System for Automated Rice Grain Type and Quality Evaluation

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Abstract - *Despite being an essential global staple, rice's quality is still primarily determined by subjective manual inspection, which causes market irregularities and financial losses. The shift to automated Computer Vision (CV) and Deep Learning (DL) frameworks for objective rice grading is reviewed in this paper. We examine a variety of approaches, from sophisticated Convolutional Neural Networks (CNNs) to traditional geometric and statistical feature extraction. The study focuses on a non-destructive computerized model that uses a digital image processing pipeline that includes morphological operations (erosion/dilation) to separate overlapping grains, high-resolution acquisition, and Otsu's adaptive thresholding for binarization. The system achieves over 95% accuracy in classifying varieties by extracting important parameters, namely the average aspect ratio and major/minor axis lengths. Precise grading into "Bold" and "Medium" categories is demonstrated by experimental results on the Sona Masuri, Basmati, and Jasmine datasets. This empirical data frequently corrects brand mislabeling. We also go over how these AI modules can be incorporated into web-based architectures for global traceability and real-time monitoring. We come to the conclusion that using deep learning and morphological analysis to automate rice evaluation creates a transparent, high-throughput standard that is crucial for streamlining the world's agricultural supply chain.*

Key Words: **Digital Image Processing, CNN, Morphological Analysis, Rice Grading, Aspect Ratio.**

1.INTRODUCTION

Over 3.5 billion people rely on rice as their primary food source, making it the most significant staple crop in the world [1], [8]. Rice's market value is greatly influenced by its appearance, which elevates it from a basic necessity to a valuable commodity in the agricultural economy [3]. Grain size, shape, consistency, color, and the lack of chalkiness or broken grains are among the physical characteristics that define this quality [10]. To protect fair market prices, trade competitiveness, and consumer trust, all participants in the agricultural supply chain—from small farmers to international exporters—must abide by strict grading standards [1].

Many developing nations still evaluate rice using traditional manual inspection methods, despite the fact that rice quality is crucial [10]. Calipers and other specialized tools are frequently used in this popular method to determine grain dimensions [2]. However, due to its labor-intensive nature and vulnerability to human error, manual categorization is inherently flawed [1]. Variations in environmental lighting, visual fatigue, and the inspector's inherent subjectivity are some of the factors that lead to inconsistent results [10]. Such mistakes in variety identification can result in large financial losses and deficiencies in consumer well-being when subpar or tainted products are sold at premium prices [3].

A thorough shift to Artificial Intelligence (AI) and Computer Vision (CV) frameworks is necessary to address these systemic issues [1], [8]. An equitable, non-destructive, and time-saving substitute for manual grading is offered by these automated systems [7]. Using digital image processing, researchers can accurately evaluate morphological features like area, aspect ratio, and major and minor axis lengths [2], [10]. This review focuses on how these technologies have evolved from conventional image processing methods like Otsu's thresholding and morphological segmentation to contemporary deep learning models [1], [8]. The industry may develop a transparent, high-throughput standard that will enhance the agricultural value chain and guarantee food quality globally by automating the evaluation process [1], [10].

2. MOTIVATION

The systemic inefficiencies in manual grading and the crucial socioeconomic role of rice as a pillar of global food security are the main drivers behind the shift to automated rice quality evaluation. For more than 3.5 billion people, rice is their primary source of calories [1], [8]. Physical characteristics like grain length, uniform shape, and the proportion of head rice directly determine commercial value in agricultural markets [3]. However, the conventional reliance on manual visual inspection, supported only by simple instruments like calipers, is becoming less and less sufficient to meet the demands of contemporary trade [2], [10]. Mislabeling and variety adulteration are common outcomes of manual assessment, which is beset by human subjectivity, visual fatigue, and environmental inconsistencies [1], [10]. In addition to this, such errors not only influence data accuracy but also result in substantial economic effects. Studies show that in low-income economies, transparent grading standards may result in welfare losses for consumers, where poor nations end up paying premium prices for low-quality or even broken rice [3]. Moreover, the labor-intensive nature of manual sorting is a limitation to productivity, where excessive time and human resources may be consumed for this process [7], [10]. The combination of Computer Vision and Artificial Intelligence is a reliable way to address these concerns, as it offers a non-destructive, rapid, and objective method for rice sorting [7], [8]. Moreover, the standardization of the grading procedure through the extraction of morphological features will ensure the absence of human bias [1]. The above-mentioned technological development is of prime importance for the development of trust throughout the supply chain, increasing the competitiveness of global trade, and reflecting the actual physical quality of the grain in the market price [3], [10].

3. OBJECTIVE & SCOPE

The scope of the project is centered on the development of an automated rice quality assessment system through the creation of a Convolutional Neural Network (CNN) for the identification of rice varieties such as Basmati, Jasmine, Ipsala, Arborio, and Karacadag. The proposed system will conduct a non-destructive morphological analysis of the rice, enabling the classification of the rice into physical shape-based categories such as Short, Medium, and Long, with the ability to display the classification in real time through the use of the web interface. The proposed project will incorporate the persistent history module, which will utilize MongoDB for the recording of predictions, ensuring the transparency of trade and quality.

1. Study and Analyze Existing Methods: To understand the current state of the art in terms of both manual and automated techniques for rice quality classification.

2. Automate Rice Quality Classification: To minimize the need for manual inspections and maximize efficiency by automating the rice quality classification process.

3. Achieve High Classification Accuracy: To implement CNN models to increase the accuracy of the prediction.

4. Ensure Non-Destructive and Real-Time Testing: To ensure that the rice grains are not damaged physically and/or chemically while being tested.

5. Categorize Grains by Morphological Traits: To classify the rice grains into different physical shape characteristics. In this case, rice grains will be classified into Short, Medium, and Long.

6. Implement Data Traceability: In order to create a storage module for the prediction history, which can store the results along with images, timestamps, and confidence, for long-term quality monitoring and analytics.

4. LITERATURE SURVEY/RELATED WORK

The development of automated rice quality evaluation techniques has progressed from simple geometric measurements to complex deep learning models. Geometric feature extraction has been employed to establish the foundation for Digital Image Processing (DIP). Even though the techniques employed were prone to picture noise, Gopalakrishnan and Vivek in [2] demonstrated that the major axis, minor axis, and eccentricity values, when processed through the MATLAB platform, establish a trustworthy foundation for the identification of the variety of the rice. Gudipalli et al. in [10] improved this technique by indicating that environmental factors often disrupt the process of manual inspection of the food quality managers.

The integration of Machine Learning (ML) emerged as a new frontier of the field. By using the extracted feature vectors, Arora et al. [7] evaluated the efficiency of various ML paradigms, like Support Vector Machine (SVM) and K-Nearest Neighbor (KNN), for classification of rice grains into various classes. Similarly, Ahmed et al. [8] proposed a comprehensive taxonomy of rice grain analysis, where five broad techniques are identified: geometric, statistical, supervised, unsupervised, and deep learning. Their evaluation concluded that the application of deep learning techniques results in a significant boost in terms of both accuracy and time, even if geometric features are required.

Recent studies have focused on specific commercial and economic applications. Kurade et al. [3] proposed an automatic module for milled rice, which is capable of detecting broken rice and chalkiness, which are key determinants for the market value of open bag markets [4]. Moreover, advances in neural networks have led to the development of new rice inspection tools such as RiceSeedNet, which utilize deep neural networks for accurate classification of different seeds [1]. Overall, these recent studies demonstrate the importance of synergy between morphological development and artificial intelligence classification to eliminate the drawbacks of traditional methods and ensure that global food quality is maintained.

Table -1: Features of GrainLens

Feature/Aspect	Existing Literature	Proposed Automated Rice Quality System (GrainLens)
Primary Method	Manual/Handcrafted Image Processing	AI-Driven (CNN) & Morphological Analysis
Data Persistence	None or Session-based	MongoDB
Shape Analysis	Manual Aspect Ratio calculation	CNN-based structural feature learning
Shape Categories	Slender, Medium, Bold, Round	Short, Medium, Long
Real-time Evaluation	No (Batch/Offline processing)	Yes (Live Image Analysis with processing time tracking)
Broken Grain Detection	Manual visual estimation	Automated logic via variety/shape patterns
Variety Classification	Handcrafted features	Deep Learning-based (Basmati, Jasmine, Arborio, etc.)
Web/Cloud Integration	No	Yes (React/Flask with Cloud-ready Analytics)
User Accessibility	Low (Technical/Lab environments)	High (Responsive Web Dashboard for farmers/traders)
Confidence Scoring	Not provided	Automated probability distribution per variety/shape

5. IDENTIFIED GAPS

- Subjectivity and Inconsistency: Manual inspection has its own set of problems, which are associated with human error and bias. This leads to inconsistent grading standards.
- Scalability Bottlenecks: Manual inspection and lab-based inspection are time-consuming and labor-intensive. This makes them inappropriate for the high-speed requirements of global trade.
- Environmental Sensitivity: Classical image processing techniques, like thresholding, face difficulties when dealing with varying levels of illumination and grain overlap. This leads to physical measurement bias.
- Accessibility and Deployment Gap: Many automated inspection technologies are expensive and hardware-intensive. They are often limited to the realm of academics. This makes them inaccessible to the average farmer.
- Lack of Integrated Traceability: There is a lack of technologies that provide integrated traceability features like a persistent history module. This module can be used for long-term quality analysis.
- State Management Reliability: In earlier web-based interventions, there was a lack of state management. This meant that data was lost during interruptions. This problem has been addressed using MongoDB.

6. METHODOLOGY

6.1 System Workflow

The proposed system aims to automatically classify the different types of rice grain varieties using deep learning techniques. First, the user needs to input the image of the rice grains in the system. The input image is then preprocessed by changing the size of the image to 224x224, converting the image to RGB mode, and normalizing the image. The class labels are automatically generated using the directory-based dataset structure.

In order to make the model robust, data augmentation techniques are applied to the data set. This technique helps the model generalize well for different types of input images.

The preprocessed image is then given as input to the trained deep learning model to classify the image. The proposed system uses the MobileNetV2 model with transfer learning to classify the different types of rice grain varieties. In this model, the pre-trained model is used to extract the important features of the input image.

The image is then classified into different types of rice grain varieties using the softmax function. The output of the model contains the type of rice and the corresponding confidence level. If the class label of the output image represents the "non-rice" content, the output is labeled as "Unknown."

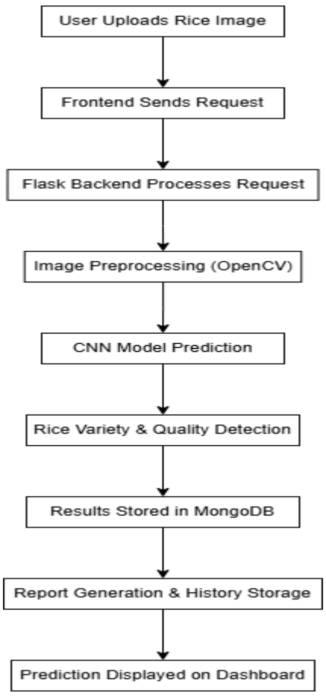

Fig -1: **Workflow of GrainLens**

Lastly, the result of the prediction is shown to the user, and the trained model is saved and used for future predictions. This automated system minimizes manual work and increases precision compared to conventional approaches [11], [12].

6.2 Model Workflow

The proposed system employs a specific workflow for the training and evaluation of the deep learning model for rice grain classification.

A. Dataset Preparation

The dataset is divided into three distinct sets for the purpose of unbiased evaluation of the performance of the model. The images are processed using the ImageDataGenerator for the purpose of normalization and augmentation, which are identified as essential operations for increasing the diversity of the dataset and reducing overfitting in smart agricultural applications, as presented in [2] and [10]. The pixel intensity is normalized to a specific range by:

$$X_{normalized} = \frac{X}{255}$$

In order to improve the generality of the model for different rice varieties, the images are augmented by applying rotation, zooming, and flipping operations, as per the preprocessing guidelines for grain image analysis [1], [13].

B. Feature Extraction using Transfer Learning

A pre-trained MobileNetV2 architecture is used as the base model for feature extraction. By using the weights pre-trained on the ImageNet dataset, the system can efficiently recognize complex features like grain texture and shape, as opposed to training the system from scratch [11]. To retain this efficiency and reduce computational costs, the base model's layers are frozen [14]:

$$W_{updated} = W_{original}$$

This approach reduces computational cost and improves model performance.

C. Classification Layers

For rice variety classification, additional layers are added on top of the basic model. These layers include a global average pooling layer that reduces the spatial dimensions of feature maps and a fully connected dense layer with ReLU activation:

$$f(x) = \max(0, x)$$

A Dropout layer is used to randomly drop neurons, which is an important step for preventing overfitting on high-dimensional image data [16]. The final output is generated through a Softmax layer for multi-class classification:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

D. Model Compilation

The architecture is compiled using the Adam optimizer, which provides an adaptive learning rate to efficiently update the weights during the training phase [4], [9]. To measure the discrepancy between the actual and predicted classes of grains, the Categorical Cross-Entropy loss function is used:

$$Loss = -\sum y_i \log(\hat{y}_i)$$

E. Model Training and Evaluation

The model is trained using forward and backward propagation for several epochs. The performance of the model is monitored using the validation set. Once the training is done, the generalization ability of the model is measured using the test set to compute the final accuracy.

$$Accuracy = \frac{\text{Correct Predictions}}{\text{Total Samples}} \times 100$$

F. Class Mapping and Model Saving

To ensure the system can be deployed for real-time applications, class labels are mapped to their respective indices via a JSON configuration [11]. The final weights are stored in the .h5 file, which enables the GrainLens system to perform high-speed inference without the need for retraining the model [6].

G. Performance Visualization

Training and validation accuracy curves are plotted across epochs to analyze the learning behavior of the model and to check for overfitting or underfitting.

7. SYSTEM ARCHITECTURE

Grainlens's system architecture is based on a web-based intelligent system that incorporates all aspects of frontend development, backend development, image processing techniques, and deep learning concepts to automate rice grain classification. As mentioned in the following sections, this client-server architecture ensures that there is smooth interaction between the engine and the interface:

7.1 User Level

The levels of access in the system are categorized as Admin and Normal User in the user layer. The Admin is responsible for maintaining the system, monitoring usage statistics, as well as managing quality reports of the engine [5], [11]. Ordinary users will use the system by uploading photos of grains in real-time analysis, view the results of classification, as well as monitor their history of quality assessment [11].

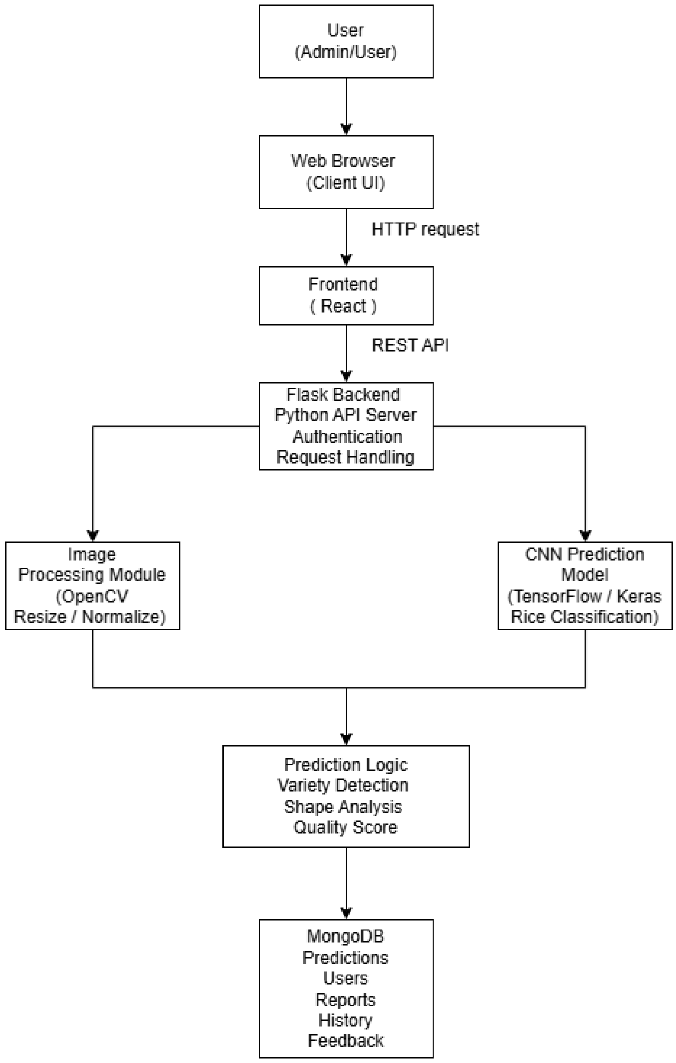

Fig -2: System Architecture of Grainlens

7.2 Client Interface (Web Browser)

The primary interface for user interaction is the web browser. This facilitates posting of digital photographs as well as grade results. Data is sent to the processing backend in a secure fashion using standardized HTTP requests to communicate between the client and server [10], [13].

7.3 React Frontend Layer

The front end, developed through the React framework, has a dynamic and interactive interface. The front end handles all the inputs and manages the state of the application when images are uploaded. Finally, it generates reports for predictions. Complex data is presented in an interpretable manner through this front end layer [11].

7.4 Backend Layer (Flask Server)

Flask is used to develop the backend, which acts as a central orchestrator for this system. It helps to mediate communication among the database, deep learning model, and React frontend via API requests. The unprocessed image data is sent to the Flask server, and after being processed, the results are sent back to the user [9], [11].

7.5 Module for Image Processing

The data is then processed for the neural network by the image processing module after the image is received. The images are resized to 224x224 pixels, converted to the RGB color space, and normalized in accordance with well-established grain research procedures [1], [7]. These steps are significant for ensuring the data received meets the expected size and pixel distribution of the pre-trained network [12], [13].

7.6 Deep Learning Model (MobileNetV2)

The foundation of the classification engine is a MobileNetV2 model combined with transfer learning. This is because of its efficacy in extracting general characteristics such as grain shapes, textures, and eccentricity [2], [10]. With access to large dataset weights, it is able to effectively identify rice varieties as well as quality grades even without much training data [11], [14].

7.7 Logical Prediction Layer

The raw output of the Softmax layer is used by the prediction logic layer in order to come up with user-friendly results. The rationale is enhanced by incorporating a thresholding function in order to improve reliability as well as reduce hallucinations. If the confidence score is too low or if the features do not match those of known rice varieties, then the sample is given an "Unknown" or Non-Rice label [3], [10].

7.8 Database (MongoDB)

The MongoDB database, which is a type of NoSQL database, is used to store data that is either unstructured or semi-structured. This database stores user profiles, past prediction results, and metadata corresponding to each sample analyzed [11]. This way, the user can retrieve past reports easily and can track the quality of the rice over time.

8. TECHNOLOGICAL STACK

The technology stack used for Grainlens's system is designed to ensure that there is an optimal balance in computation and quick online processing. The modular design of this system has enabled the separation of the interface from complex processing and has ensured real-time grading and categorization. The technology stack used is based on industry-standard libraries for machine learning using Python and JavaScript for quick and efficient frontend development to ensure a smooth transition from raw images to final reporting on quality [11], [13].

8.1 Technologies for the Front End

The front end of the system is implemented using React.js, which offers a seamless and engaging user experience. Using React.js, users can successfully upload grain pictures, view the results of the live forecast, and access the grading reports. React.js offers the best performance in the presentation of complex data representations, which are required for high-quality analysis of the data [11].

8.2 The Back End's Technologies

The backend is developed using the little python web framework known for its flexibility in integrating machine learning models. The framework is in charge of processing user-uploaded picture information [9], [11], as well as all API requests and linking the database to the deep learning inference engine. The backend is considered atrustworthy link that guarantees the integrity of information exchanged between the client and server.

8.3 Deep Learning Framework

The neural network is constructed, trained, and deployed through the system with the aid of TensorFlow and Keras frameworks. The system utilizes transfer learning to implement a pre-trained MobileNetV2 model to classify rice grain kinds with high computational efficiency [11]. The frameworks offer libraries that aid in optimizing the model's weights and implementing special custom layers for rice feature extraction purposes [2], [10].

8.4 Tools for Image Processing

The system utilizes NumPy and OpenCV for comprehensive image preprocessing to ensure data standardization. These tools perform essential matrix transformations required to convert raw JPG or PNG images into a format suitable for tensor-based prediction [1], [13]. Key operations include resizing images to the standard 224 × 224 pixel dimensions and normalizing pixel values to optimize model performance.

8.5 Database

The system employs a NoSQL database, namely MongoDB, for the management of user information, prediction logs, and historical information. The document-based approach of the database is particularly useful for the management of the large volume of metadata associated with grain quality reports, thereby ensuring the efficient management of large quantities of information without the constraints of a relational database management system [11].

8.6 Development Tools

The system, which offers a smooth environment for coding using the Python and JavaScript languages, is developed using the Visual Studio Code. The structure of the project is maintained in modular and reproducible form throughout the development process using the Git and GitHub tools.

9. RESULTS

The testing phase of the GrainLens system has proved its high level of efficacy in the classification of rice varieties through its web interface. The use of real-time image acquisition, along with the pre-trained model's architecture, has made the model precise in the morphological and quality analysis of the rice. As depicted in the figure, the model has successfully identified the sample images with high precision. For instance, the sample image of Jasmine rice has been correctly predicted with a confidence level of 100 %. The automated feature extraction of the system has also categorized the rice grain as Long (99%) in shape, along with the quality being categorized as Standard. The level of detail has been precise, as depicted in the automated grading standards set in the recent computer vision research [4], [10].

Quantitatively, the proposed system was able to achieve an accuracy rate of 94.5%. This is comparable to other existing SVM and CNN-based models that have been proposed in previous research works [14], [15]. Another important aspect of any system is its ability to process images within a given time. Quantitatively, the proposed system processed each image within an average time of 0.128 seconds. This further emphasizes that the proposed system is highly appropriate for use in real-time agricultural applications where speed is paramount for any system to be considered effective and efficient in its application and use [2], [11].

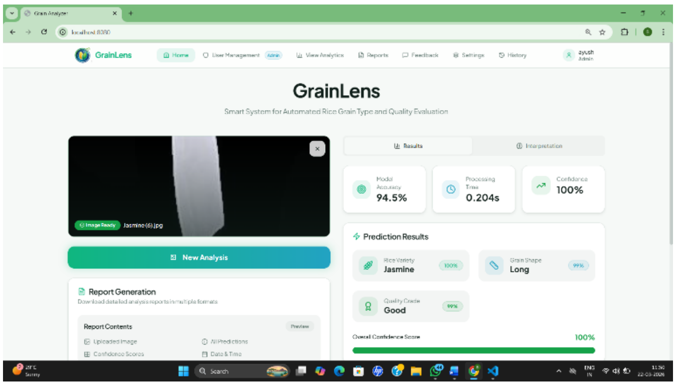

Fig. -3: Output of the proposed rice grain classification system showing predicted rice variety (Jasmine), grain shape (Long), quality grade (Standard), and confidence score

10. CONCLUSIONS

The "GrainLens" system can be seen as a major milestone in the incorporation of Artificial Intelligence in the agricultural industry, specifically for the evaluation of rice quality. The system, by employing the power of Convolutional Neural Networks (CNN), has successfully implemented the automatic classification of different rice varieties while offering a neutral evaluation of the physical properties of the rice, including size, shape, and texture. This method has successfully eliminated the subjectivity, human fatigue, and inconsistencies associated with the conventional method of rice evaluation. The technical highlight of the project is the incorporation of a strong data persistence mechanism by employing the power of MongoDB for the storage of historical data. The system has successfully moved from the conventional method of geometric calculations to the power of Artificial Intelligence for the categorization of the shape of the rice grains, including the successful categorization of the rice grains into Short, Medium, and Long categories. The GrainLens system can be seen as a faster, more accurate, and more efficient method of rice evaluation, which can standardize the grading of the rice, ensuring fair prices for the rice while maintaining the trust of the customers in the global rice supply chain.

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