

Grain Quality Testing Using Neural Networks

¹V Sahiti Yellanki, ²Srikiran Kavuri, ³K. Anitha, ⁴M. Shara Lydia, ⁵Nagabhairava Srilakshmi, ⁶Manmath Nath Das, ⁷Jyotsnarani Tripathy

^{1,3,4,7} Department of CSE- AIML & IoT, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, Telangana, India

²Department of CICS, University of Massachusetts, Amherst, USA

⁵ Dhanekula Institute of Engineering & Technology, Ganguru, Vijayawada, Andhra Pradesh

⁶ Department of AI & DS, VNR Vignana Jyothi Institute of Engineering & Technology, Hyderabad, Telangana, India

Email : ¹sahiti_y@vnrvjiet.in; ² srikirankavuri@gmail.com; ³ anithakoneru@gmail.com;

⁴sharalydia_m@vnrvjiet.in; ⁵ srilakashmi57@gmail.com; ⁶ manmathnath.das@gmail.com;

⁷jtjyotsna@gmail.com

Abstract

Grain quality plays a crucial role in agriculture, affecting health, economic efficiency, and market pricing. Traditional manual testing methods are often slow, inconsistent, and labour-intensive. This project presents an automated system that leverages image processing and machine learning to transform grain quality assessment and price estimation, offering direct benefits to farmers and stakeholders throughout the supply chain. High-resolution images of grains, captured under controlled lighting conditions, are processed to extract essential features such as size, color, shape, and texture. These are the key features for identifying grain types and evaluating quality metrics like moisture content, protein levels, and impurities. The system utilizes a Multilayer Perceptron (MLP) as its final model for classification and analysis. Trained on extensive datasets of labelled images, the MLP ensures precise grain classification, impurity detection, and quality evaluation. Furthermore, it estimates grain prices based on these quality metrics, enabling farmers to receive fair compensation for their produce and make informed decisions regarding market timing and quality enhancement. By automating grain testing and pricing, this non-destructive approach eliminates human error, preserves grain integrity, and offers a reliable, efficient, and scalable solution. Farmers benefit from quicker quality assessments, enhanced pricing transparency, and reduced reliance on manual testing, empowering them to optimize productivity and profitability in a competitive market.

Keywords: Grain Quality Assessment, Image Processing, Multilayer Perceptron, Impurity Detection, Agricultural Supply Chain, Impurity Detection

1. INTRODUCTION

Grain quality testing is crucial in agriculture, influencing aspects from food safety to economic results, such as ensuring farmers receive fair prices. Traditionally, this process has relied on manual inspection, where trained individuals visually assess grain samples for quality indicators like type, purity, and kernel condition.[1] However, these methods are often slow, labour-intensive, and prone to human error, leading to inconsistencies and inefficiencies in quality control. To tackle these issues, advancements in image processing and machine learning present innovative solutions. Image processing enables the extraction of detailed features from digital images of grains, such as color, shape, texture, and size. These are the essential features for evaluating key quality parameters, including moisture content, protein levels, and the presence of impurities.[2] By combining image processing with machine learning techniques, these features can be analysed to classify grain types, assess their quality, and estimate market prices with high accuracy and consistency. The proposed system aims to integrate image processing with the MLP model to revolutionize grain quality testing and pricing. This approach addresses the limitations of manual inspection, offering a faster, more accurate, and scalable solution. By incorporating a price estimation feature, the system enables farmers to receive fair compensation for their produce while allowing buyers to make informed purchasing decisions.[3] The benefits of this system include reduced labor costs, enhanced consistency in quality assessments, improved pricing transparency, and the ability to efficiently manage large-scale operations. This research not only modernizes grain quality testing but also directly benefits farmers by increasing profitability and reducing reliance on traditional methods, thereby making the agricultural supply chain more efficient and equitable.

2. EXISTING WORK

An extensive review of research on automated grain quality assessment using image processing and machine learning reveals various methodologies, each with unique approaches to enhancing grain classification

accuracy. Grain Quality Detection Using Convolutional Neural Networks [4] study presents a CNN-based approach for automating grain quality detection, with a focus on classifying different grain types and identifying impurities such as stones and damaged kernels. The model leverages CNNs to differentiate between grain types based on features like shape, size, and color. Even while the model achieves great accuracy, noise and lighting changes are problems, and its performance is heavily reliant on the quality of the photos. The study suggests that improvements in pre-processing and robustness under diverse environmental conditions would further enhance the system's practical application in real-world scenarios. Automated Grain Quality Assessment Through Image Processing Techniques [5] research combines traditional image processing techniques with machine learning for grain quality assessment. The system extracts features such as texture, color, and shape from grain images, which are then input into machine learning classifiers to determine the grain's quality. Although cost-effective and functional in controlled environments, this system's reliance on handcrafted features limits its adaptability, especially in complex, real-world scenarios [11]. The study emphasizes that traditional techniques could be supplemented with deep learning methods to improve performance in diverse conditions. A Deep Learning Approach to Grain Quality Analysis Using Transfer Learning [6] paper introduces deep transfer learning for grain quality analysis, adapting pre-trained CNN models to classify grain types and assess quality. The model achieves an impressive classification accuracy of 91.5%, making it particularly effective in situations where labelled data is limited. The transfer learning approach leverages large datasets from related domains, reducing the need for extensive grain-specific labelled data. However, the study notes the computational burden of fine-tuning pre-trained models and suggests optimizing the models to ensure efficiency in low-resource environments.

The traditional methods of grain quality testing [10] are predominantly manual, relying on human expertise to evaluate the grains' physical and chemical properties. Although these methods are widely used, they have several notable limitations: **Manual Inspection:** Grain quality is typically assessed by trained professionals through visual inspection, considering factors such as size, shape, color, and the presence of impurities. However, this process is subjective and heavily reliant on the inspector's experience. Variations in judgment, fatigue, and inconsistency in handling different grain types or quality issues often result in unreliable outcomes [7]. **Laboratory Analysis:** More advanced quality parameters, such as moisture content, protein levels, and the presence of foreign matter, are tested using chemical and physical methods in laboratories. While these methods are highly accurate, they are time-consuming, costly, and require destructive sampling, meaning a portion of the grain must be destroyed to conduct the tests. **Lack of Scalability:** Manual inspection and laboratory-based testing are resource-intensive and do not scale well, especially during peak harvest seasons when large quantities of grain need to be tested quickly [12]. The time and manpower required limit the ability to test large numbers of samples in a short period. **Delayed Results:** Traditional methods often lead to delays between sample collection and the availability of results. This delay can impact key decision-making processes and slow down the grain supply chain, leading to inefficiencies in logistics, processing, and storage [8]. **Non-Uniform Standards:** Assessment standards can vary significantly across regions, organizations, or even individual inspectors. This lack of uniformity can lead to inconsistencies in how grain quality is evaluated, causing confusion and potential disagreements in commercial transactions. While the existing systems are still in use, they are becoming outdated and struggle to meet the demands of modern agriculture [16]. These limitations highlight the need for an automated, accurate, and scalable solution for grain quality testing, capable of delivering faster, more consistent, and reliable results [9].

3. BACKGROUND WORK

Hand By combining cutting-edge image processing methods with machine learning algorithms, the suggested system provides a thorough and automated grain quality checking solution. By utilizing feature extraction methods and training a Multilayer Perceptron (MLP) for classification, this system automates grain type identification and impurity detection, overcoming the limitations of traditional manual inspection methods.

3.1. Image Acquisition

- **High-Resolution Imaging:** The system begins by capturing high-resolution images of grain samples using sophisticated cameras with adjustable focus and exposure settings. This ensures consistent clarity and quality for subsequent analysis.
- **Spectral Imaging:** Techniques like **hyper-spectral imaging** can be employed, capturing detailed spectral information to further enhance accuracy during quality assessments.

- **Uniform Lighting:** Uniform lighting conditions are maintained throughout the imaging process, reducing noise and providing consistent image quality suitable for accurate analysis [13].

3.2. Preprocessing

The captured images are pre-processed to improve their quality and prepare them for feature extraction:

Noise Reduction: Filters like Gaussian blur are applied to remove image noise and preserve the grain details.

Contrast Enhancement: To make grain details easier to see, techniques like histogram equalization are applied to images.

Segmentation: Morphological operations are employed to isolate grain objects from the background, ensuring that only relevant features are extracted for analysis.

Feature Extraction

The system extracts various features from the processed images to distinguish different grain types and detect impurities:

Shape-based Features: These include **mean area**, **perimeter**, and **eccentricity**. The **mean area** and **perimeter** help in identifying grain types and assessing the physical integrity of the grains [14].

Color-based Features: The system uses color histograms to capture the grain's color, which aids in impurity detection and classifying different grain types.

Features of PCA: The grayscale pictures' eigenvalues are extracted using Principal Component Analysis (PCA), which provides information about the structure and form of the grain.

Texture-based Features: Features such as **Haralick features** or **Gabor filters** could be applied (though not implemented in the provided code) to analyze grain surface textures, identifying quality issues such as damage.

Advanced Deep Features: Though not explicitly included in the provided code, advanced techniques like CNN-based feature extraction can be used to capture complex patterns in grain images.

The specific features extracted in the code include:

- Mean area
- Perimeter
- Color channels (Red, Green, Blue)
- Eigenvalues (from PCA)
- Eccentricity (ratio of eigenvalues)

These features are stored in the `grain_feature.pkl` file, which is later used for training the machine learning model.

Data Preparation

The dataset consists of images from different grain categories, such as:

1. **Grain types:** Regular grain (e.g., wheat, rice), damaged grain, broken grain, foreign particles.
2. **Impurities:** Foreign particles like stones, weed seeds, or any grain that is contaminated.

The system processes images into **training and testing datasets**, split using a percentage (typically 70% for training and 30% for testing)[15]. The features for each grain image are extracted and stored in `train_features.csv` (training) and `test_features.csv` (testing).

Model Training

The **Multilayer Perceptron (MLP)** is the primary machine learning model used for classifying grains based on the extracted features. The training process involves:

- **Training MLP on extracted features:** Using features such as **mean area**, **perimeter**, **eigenvalues**, and **eccentricity**, the model learns to classify grains into two categories: **grain** or **not grain** (the impurity category).
- **Model Saving:** The trained MLP model is saved as `mlp_model.h5` and can be reused for future classification tasks.

Classification and Evaluation

Once the model is trained, it is evaluated using a **test set**. The evaluation involves:

- **Accuracy Evaluation:** The model's performance is tested on the `test_features.csv` dataset (testing data), and the accuracy is recorded.
- **Loss Calculation:** The system outputs the **MLP test loss** and **test accuracy** to measure the effectiveness of the trained model.

The **model evaluation** process is logged into the `test_results.txt` file for further analysis and comparison.

Impurity Detection

In addition to grain classification, the system also detects **impurities** using object detection methods. This could include detecting **damaged kernels**, **foreign particles**, and **broken grains** using bounding box detection

and segmentation techniques. Algorithms like **Faster R-CNN** or **YOLO** (though not explicitly implemented in the provided code) can be integrated to identify these impurities in real-time.

Integration and Deployment

Software Architecture

The system is modular, allowing for:

- **Scalability:** It can be adapted to various grain types and environmental conditions.
- **Real-time Processing:** The system is capable of handling large-scale grain analysis in real-time through the application of effective image processing as well as machine learning models.
- **User Interface:** A web-based or desktop interface can be developed to enable operators to upload grain images, view results, and monitor the classification process.

Hardware Compatibility

The system is designed to run on various hardware platforms, making it suitable for deployment in different agricultural settings, from small farms to large processing facilities.

Performance Evaluation

The system is rigorously tested on different datasets:

- **Accuracy:** The accuracy of the model's grain classification and impurity detection.
- **Efficiency:** The system's ability to process images quickly for real-time use in high-throughput environments.
- **Robustness:** The ability of the system to handle variations in image quality, lighting conditions, and grain types.

The performance is assessed using common measures including F1-score, recall, accuracy, and precision. The system is benchmarked against manual inspection methods to demonstrate its efficiency and accuracy in classifying grain types and detecting impurities.

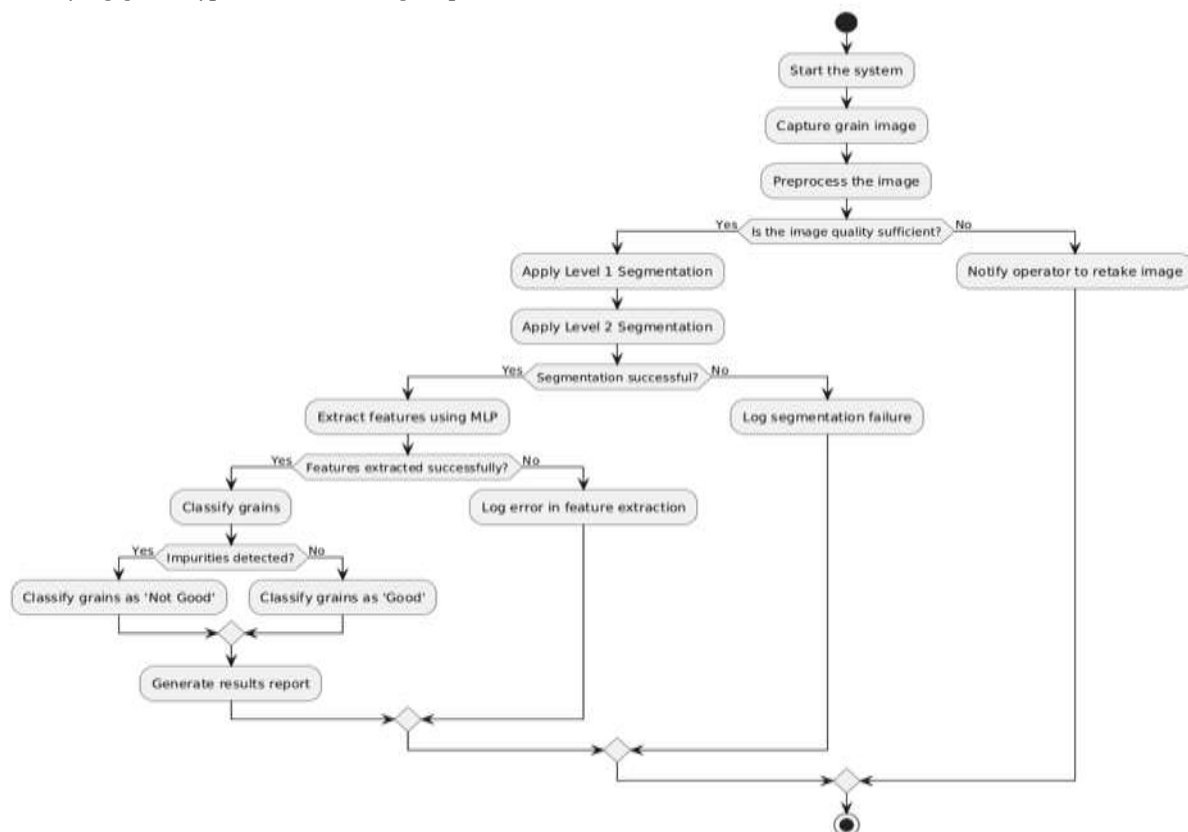


Fig-1 Workflow Diagram

4. IMPLEMENTATION

4.1 Dataset

The dataset is a fundamental component of the proposed computer vision-based grain quality assessment system. It comprises a collection of images meticulously categorized to support the training and evaluation of our models. The dataset is organized as follows:

Dataset Structure:

The images are divided into two primary folders: train and val (validation). This division ensures that the data used for model training is distinct from the data used for performance validation.

Within each folder, images are further categorized into different quality classes, such as high-quality grains, low-quality grains, and grains with impurities. Each class is defined by specific grain characteristics:

High-Quality Grains: Well-formed, healthy grains without visible defects.

Low-Quality Grains: Grains with visible defects, such as discoloration or damage.

Grains with Impurities: Presence of foreign particles or materials such as stones, dirt, or husk.

Image Details:

Photographs of various waste products taken in a variety of settings are included in the dataset. In order to train models that can reliably identify and categorize garbage in practical situations, this diversity is essential.

4.2 Data Preprocessing

- **Image Normalisation:** Images are resized to a consistent resolution and pixel values are normalised to ensure uniform input for model training.
- **Noise Reduction:** Techniques such as filtering and contrast adjustment are applied to enhance image quality and feature clarity.
- **Data Augmentation:** Includes rotations, flips, and crops to artificially expand the dataset and improve model robustness.

4.3 Data splitting

70% of the whole data is used for training, and 30% is used for validation, according to our 70:30 dataset splitting policy. In order to prevent bias and maximize model performance in a variety of settings, this stratified division ensures a strong representation.

4.4 Models

When implementing grain quality testing using neural networks, several types of models can be employed depending on the nature of the data (e.g., images, tabular data, spectral data) and the specific goals of the task (e.g., classification, regression). Here's an overview of the key models that can be used:

Convolutional Neural Networks (CNNs)

Mostly employed for analysing grain picture data and assigning quality ratings like "Good," "Damaged," or "Impure."

Convolutional Layers: Extract forms, edges, and other patterns from pictures.

Layers for Pooling: Reduce the number of dimensions while keeping important aspects.

Map extracted features to output categories using fully connected layers.

Non-linearity is introduced via activation functions (e.g., ReLU, Softmax) to improve decision bounds.

Convolutional layers are used to identify features in grain images. The feature maps are down-sampled by pooling layers, and they are categorized into quality groups by completely linked layers.

Residual Networks (ResNet)

Problems involving deep image classification that calls on strong pattern recognition in grainy images.

Residual Connections: By addressing vanishing gradient issues, these skip connections allow for deeper structures.

Convolutional Blocks: More precise and in-depth feature extraction.

In contrast to dense layers, global average pooling lowers parameters.

A deep network that processes grain images improves feature extraction and classification by preventing learning loss as the number of layers increases through residual connections.

Efficient Net

Scalable and effective method for checking grain quality for mobile applications or systems with limited resources.

For best results, compound scaling strikes a balance between resolution, depth, and width.

Depth-wise Separable Convolutions: Lowers processing costs without compromising precision.

Pre-trained Weights: Uses weights that have already been taught by ImageNet to facilitate transfer learning.

A balanced network that scales effectively is used to process and resize grain images, allowing for great performance on devices with limited resources.

Vision Transformer (ViT)

For advanced image analysis tasks, especially in identifying complex patterns in high-resolution grain images.

Self-Attention Mechanisms: Focuses on important regions of the image.

Positional Encoding: Retains spatial information within the transformer architecture.

Transformer Blocks: Processes image patches as sequences for feature extraction.

Grain images are divided into smaller patches, and each patch is encoded into embeddings. A transformer processes these embedding, focusing on critical areas of the image for quality classification.

MobileNet

Ideal for lightweight applications such as mobile or IoT-based grain quality monitoring systems.

Depthwise Separable Convolutions: Efficiently reduces computation.

Global Average Pooling: Summarizes feature maps into compact representations.

Pretrained Weights: Useful for transfer learning.

Grain images are processed through a compact network with reduced parameters, enabling efficient real-time classification on constrained devices.

4.3 Performance Metrics

Performance metrics provide a quantitative assessment of model effectiveness. Key metrics include accuracy, measuring overall correctness; precision, indicating true positive rate; recall, gauging the ability to identify positives; and F1 score, blending precision and recall.

- The ratio of accurately anticipated occurrences to total instances is known as accuracy.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

- Precision: Reflects the proportion of true positives among the predicted positive instances.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall, also known as sensitivity or true positive rate, is a measure of the proportion of true positives to actual positive cases.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

- The F1 Score provides a harmonic mean of precision and recall, balancing the two measurements.

$$\text{F1 Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

5. RESULT ANALYSIS

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Features: ['MEAN_AREA', 'PERIMETER', 'R', 'B', 'G', 'EIGEN_VALUE_1', 'EIGEN_VALUE_2', 'ECCENTRICITY']
MLP Test Loss: 0.3125
MLP Test Accuracy: 0.9024

```

	precision	recall	f1-score	support
grain	0.89	0.95	0.92	1349
not_grain	0.92	0.83	0.87	875
accuracy			0.90	2224
macro avg	0.91	0.89	0.90	2224
weighted avg	0.90	0.90	0.90	2224

Fig-2 Different Performance Metrics

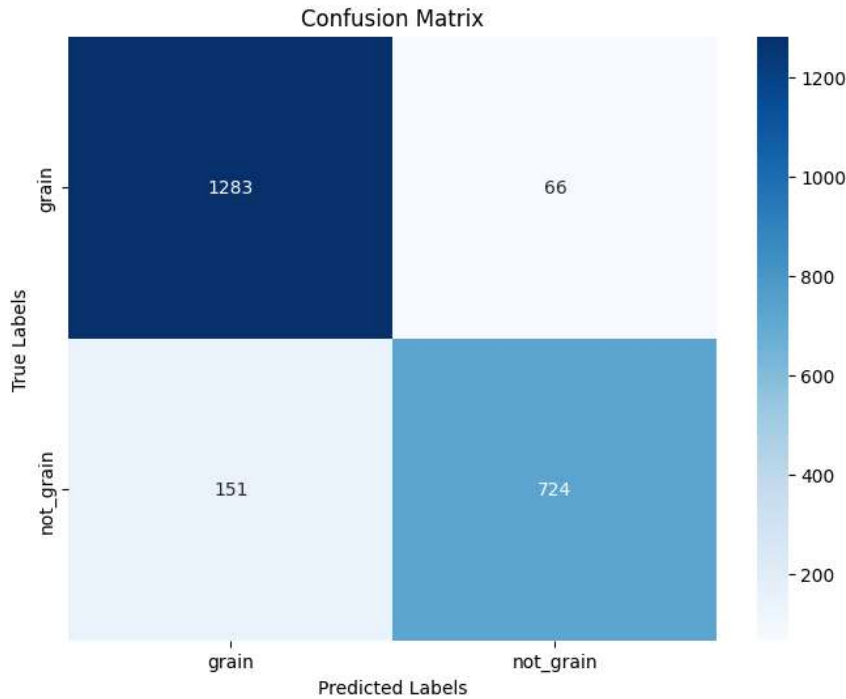


Fig-3 Confusion Matrix

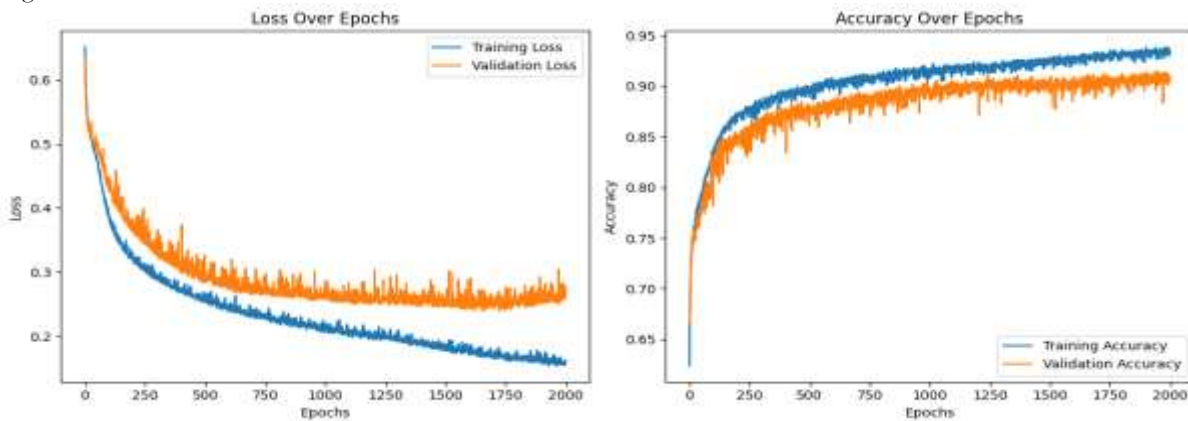


Fig4 Training and Validation Performance

The provided image fig 4 displays the performance metrics for training and validation of the neural network model used in assessing grain quality. Training and Validation Loss Graph (Left Panel) Description: The blue line which consistently decreases indicates training loss over the epochs, signifying that the model is effectively learning from the training dataset. The orange line represents the validation loss, which initially decreases but then levels off with some variations after approximately 500 epochs. Inference: The steady decline in both training and validation loss suggests effective learning. The lack of significant divergence between the two lines implies minimal overfitting, indicating the model retains strong generalization capabilities. Training and Validation Accuracy Graph (Right Panel) Description: The blue line depicts training accuracy, which rises rapidly and consistently, eventually surpassing 0.94. The orange line illustrates validation accuracy, which follows a similar pattern and stabilizes around 0.90, indicating strong performance on new data. Inference: Both lines level off smoothly, indicating the model achieves high accuracy and stable performance. The model's good generalization to test data without noticeable overfitting is confirmed by the near proximity of training and validation accuracy.

6. CONCLUSION

The grain quality assessment system using a Multi-Layer Perceptron (MLP) achieved 90.24% accuracy on 2224 test samples, effectively classifying grains into grain and not_grain. The model showed strong recall for the grain class (0.95) and high precision for the not_grain class (0.92), confirming its balanced performance. With only 2722 trainable parameters and a simple three-layer architecture, the MLP proved both efficient and reliable.

While effective in capturing external features like shape, size, and color, further improvements can be made by incorporating internal features through advanced imaging (e.g., NIR or hyperspectral), adopting more complex models like CNNs, and applying data augmentation to enhance robustness. Overall, the system demonstrates the potential of combining image processing and machine learning for accurate grain classification.

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