Detection of Black Pepper Adulteration Using Image Processing Method

Tejaswi Shriram Naik[1], Prof. Sanjay Kumar B M[2], Priyanka KP[3], Shruthi S Nayak[4], Sushmita D[5]
[1]Leader, Srinivas Institute of Technology
[2]Guide, Srinivas Institute of Technology
[3,4,5]Member, Srinivas Institute of Technology
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***Abstract*—Black pepper is most widely used and valued spices worldwide, playing a significant role in culinary, medicinal, and industrial applications. Adulteration, which involves mixing black pepper with cheaper or inferior substances such as husks, stems, or other grains, significantly reduces quality and can potentially pose health risks. This project presents a reliable and automated approach to detect black pepper adulteration using advanced image processing techniques. High-resolution images of both pure and adulterated black pepper samples are captured under controlled conditions. Key features such as color variations, texture patterns, and shape characteristics are extracted and analyzed. the samples and accurately identify adulteration. The proposed method is non-destructive, rapid, and highly effective, offering practical benefits for spice manufacturers, retailers, and quality control laboratories. By providing an automated and precise solution, this study contributes to improving food safety, enhancing quality assurance processes, and ensuring consumer confidence in black pepper products.**

***Index Terms*—Black pepper, adulteration detection, image pro-cussing, feature extraction, machine learning, quality control, food safety, non-destructive analysis.**

I. INTRODUCTION

Black pepper is a commonly consumed spice known for its distinctive flavor, and medicinal value. Because of its high commercial demand, it is often adulterated by mixing low-cost materials such as husks, stems, or other grains, which reduces quality and may raise health concerns.

Con-venational adulteration detection methods, including manual inspection and chemical analysis, are time-consuming. Image processing offers an efficient alternative by examining visual characteristics such as color, texture, and shape from captured images. By combining these features with ml techniques, an automated system can be developed to identify adulterated black pepper samples.

This approach supports faster quality assessment for spice manufacturers and quality control laboratories while maintaining food safety standards. Furthermore, automated detection reduces human error and subjectivity in quality evaluation. Additionally, it enables the analysis of large datasets, allowing for consistent monitoring of spice quality across production batches.

II. LITERATURE REVIEW

Recent advancements in automated spice quality inspection have created a growing need for fast and reliable meth-ods to detect adulteration, leading researchers to focus on image processing, feature extraction, and machine learning techniques. In paper [1], Kumar demonstrated that machine learning models could significantly improve the detection of food adulteration, emphasizing that careful feature selection and essential for accurate results. In paper [2], Singh and Mehta studied image-based classification of peppercorn seeds, showing that color and texture features help distinguish pure and adulterated samples, though their method faced challenges with mixed or subtle adulteration. In paper [5], Anitha proposed a method specifically for detecting black pepper adulteration using image processing, successfully identifying foreign particles under controlled conditions, but performance declined with varying lighting and sample orientations. In pa-per [6], Zhang compared SVM-based classification approaches for food grading, highlighting the importance of selecting suitable features and models for accurate detection. In paper [4], Howard applied YOLO-based object detection for real-time spice inspection, achieving fast automated detection, although small particles and complex backgrounds remained challenging. Similarly, in paper [20], Suresh and Banerjee used YOLO algorithms for real-time spice quality inspection, confirming the benefits of automated detection while noting limitations related to particle size and lighting. In paper [3], Latha explored computer vision techniques for spice quality assessment, emphasizing the role of texture and shape analysis in improving classification accuracy. In paper [8], Reddy investigated texture-based approaches to detect seed adulteration, showing that combining multiple features increases robustness. In paper [9], Sharma applied image segmentation for non-destructive spice adulteration detection, demonstrating automated evaluation methods. In paper [21], Park developed a Mobile Net-based lightweight detection framework for small agricultural objects, allowing efficient implementation, though performance declined with complex or mixed samples. In addition, integrating color, texture, shape, and deep learning enhance spice adulteration detection.

III. PROPOSED APPROACH

The first step of the process is to acquire images of two different types of black pepper samples: pure black pepper and adulterated black pepper. In order to achieve consistent visual quality and minimize the impact of shadows and specular highlights that could distort accurately capturing details of surface textures, it's important to shoot all photographs under controlled conditions with uniform lighting.

A neutral background should be used for photograph shoot-ing, so that no other objects interfere with accurately capturing the images of the black pepper. Each sample should be pho-to graphed multiple times to create a diverse dataset that will allow for adequate learning of many different types of visual patterns within the model. Proper acquisition of photographs is critical for increasing the accuracy rates of detecting the presence of adulterated black pepper from pure black pepper based on visual features.

The reduction of noise caused by camera sensors and/or external lighting on the surface of the photographs is accomplished through appropriate filtering techniques. Contrast enhancement will increase the visibility of surface detail associated with the sample. Color normal-ization will mitigate the effects of environmental lighting conditions on how the sample is colored. In some instances, photographs of coffee beans may be converted to alternate color spaces to emphasize texture in a way that may not be possible using the original photographs taken in RGB color.

IV. METHODOLOGY

The project methodology starts with the collection of datasets which is an important foundation for building detection and classification models. High resolution images of black collected from multiple sources including market vendors and agricultural farms. various sources provide a variation in size, color and texture.

To balance the dataset, both pure and adulterated sample images were included. The individual image files have been tagged with an '" adulterant" 'or '" pure" 'label to correctly identify if an image file contains an adulterant or a pure sample. Correctly tagging images is important for the successful use of supervised learning, as it allows for proper model training by helping the model identify the differences between pure and adulterated black pepper samples.

Next, all images collected are prepared for examination including modifying image size, enhancing image contrast, decreasing image noise, and normalizing pixel intensity.

Then, segmentation is done to separate out the individual pepper-corns from the background of the image, thus allowing the model to concentrate only on the areas of interest within the image. These steps will improve the quality of feature extraction from the images and also will reduce the number of errors that are introduced into the model through particle overlap, inconsistent lighting, and background interference. By generally standardizing the images this way, the model will have a greater chance of recognizing patterns during model training.

The methodology's backbone is comprised of two parts: model training and feature extraction. Model training occurs after the sample features (color, texture, shape, and size) have been extracted from the samples' images. The testing and evaluation component of this methodology measures the effectiveness of the developed system. An unseen sample is processed through the trained models, and the results are com-pared to true labels in order to calculate accuracy, precision, recall and F1-score. The developed system produces reports identifying where and how much adulterants are present. The process is rapid and non-destructive; it allows users to detect black pepper adulteration without using specialized laboratory equipment. The application of this methodology ensures both reliable and scalable detection systems to be used by manufacturers, retailers, and quality control laboratories.

A. Image Acquisition

The images obtained during the process of detecting black pepper adulteration impact on the final results of identifying an adulterated pepper from a pure pepper sample. An extensive number of images will need to be collected for comparison purposes before creating a comprehensive dataset to analyze. Images are collected under controlled lighting to eliminate potential shadowing or reflection problems that may interfere with the accuracy of identifying adulterated pepper samples. A digital camera (standard) or smartphone (high resolution) since either option will be inexpensive and readily available. If possible, several images will also need to be collected from different angles and distances to create a dataset containing sample images with different sizes, shapes, and orientations of the black peppercorns.

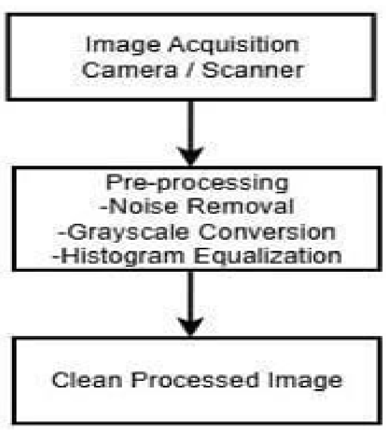

Fig. 1. Image processing

The first step in detecting black pepper adulteration using image processing is capturing clear images of both pure and adulterated samples with consistent lighting and a neutral background. High-quality cameras or scanners are used, and maintaining a standard distance and angle ensures uniformity. Next, noise reduction is applied using filters like median, Gaussian, or bilateral to remove unwanted artifacts while pre-serving edges and textures.

The images are then converted into suitable color spaces, such as grayscale or HSV, and enhanced with techniques like histogram equalization and sharpening to highlight important features. Segmentation separates the pepper particles from the background and any adulterants us-ing thresholding, morphological operations, or edge detection. Finally, feature normalization ensures consistency in particle size, color, and dimensions, preparing the images for accurate analysis and reliable detection.

B. Feature Extraction

After preprocessing, the next step in detecting black pepper adulteration is feature extraction and texture analysis. Feature extraction focuses on identifying distinct visual characteristics that differentiate genuine black pepper from adulterants using texture, shape, and color descriptors [9, 14]. Techniques such as gray level co-occurrence matrix (GLCM), local binary patterns (LBP), and contour analysis are effective for captur-ing subtle variations in texture that are difficult for human inspection [10, 7]. These extracted features help isolate the unique structural details of peppercorns, making it easier for algorithms to classify the samples accurately [6, 9].

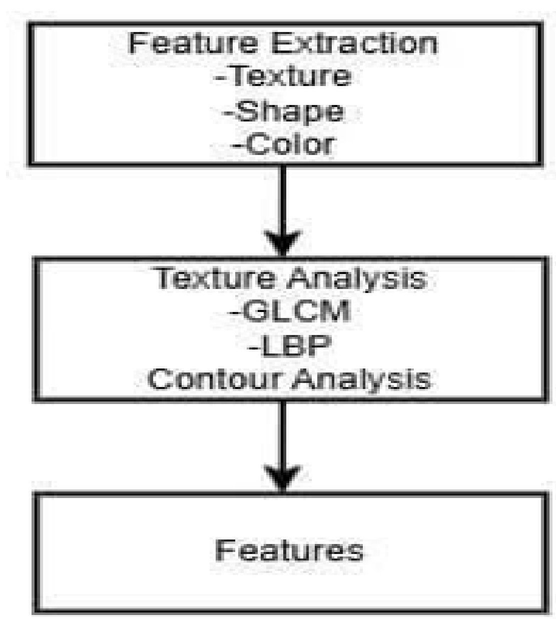

Fig. 2. Texture Analysis

C. Workflow of YOLO8m and MobileNetV2 Models
The workflow of the YOLOv8m and MobileNetV2 models begins with feeding preprocessed images of black pepper samples into the network. In the YOLOv8m model, network that extracts important visual features, followed by a neck layer that combines multi-scale features to improve object detection accuracy.
The head of YOLOv8m then predicts bounding boxes, class labels, and confidence scores in a single forward pass, enabling fast and precise detection of pepper grains and adulterants. In contrast, MobileNetV2 follows a lightweight architecture designed for efficient classification, where depth wise separable convolutions and inverted residual blocks. Together, YOLOv8m provides accurate object-level detection, while MobileNetV2 offers efficient classification, making the combined workflow suitable for real-time and resource-constrained adulteration detection systems.

D. Classification, Evaluation, and Real-Time Deployment
In order to determine if black pepper samples are pure or contaminated, after extraction of features and detection by a deep-learning model, the resultant dataset is classified and classified into various purity levels through a machine-learning/deep-learning model created based on the characteristics that were extracted from the original black-pepper samples, and therefore, the classification of the purity level uses the learned characteristics of the original black-pepper samples to assign a class label to each purity level. Upon completion of the classification, the performance of the entire system was evaluated using established methods of measuring the reliability and accuracy of detection through the use of the accuracy metric, precision metric, recall metric, F1 metric, and confusion matrix.

E. Performance Optimization
Performance optimization is carried out to enhance both the efficiency of black pepper adulteration detection system. During training, learning rate, batch size, and number of epochs are carefully adjusted to ensure stable learn-ing and faster convergence. including image rotation, scaling, and brightness variation, are applied to increase dataset diversity and improve the model's ability to generalize to unseen samples. Model complexity is also optimized by selecting appropriate network depth and fea-ture sizes. which helps reduce computational overhead without compromising detection performance. Continuous validation and monitoring of evaluation metrics guide further refinements during training. These optimization strategies help minimize false detections, improve real-time performance, and make the system suitable for practical deployment in food quality inspection environments.

F. Cross-Verification
Cross-verification is conducted to confirm the robustness and general reliability of the black pepper adulteration detection system. The dataset is systematically divided into multiple subsets for training, validation, and testing to ensure unbiased evaluation. By testing the model on unseen samples, this pro-cess verifies that the system is capable of generalizing beyond the training data. Performance metrics obtained from different data splits are carefully compared to check for consistency and stability. Cross-verification also helps in identifying issues such as overfitting or data imbalance. Through repeated evaluation and comparison, the credibility of the model's predictions is strengthened, making the system more dependable for real-world applications. Additionally, cross-verification enhances confidence in the system by ensuring that the results are not influenced by random data variations. It allows the model's performance to be observed under different training and testing conditions, reflecting real-world usage scenarios. Any significant variation in results highlights areas where further tuning or data improvement may be required. This process supports better model selection by comparing how different configurations perform across multiple evaluations.

V. IMPLEMENTATION

A. Data Collection
Data collection is a critical step in developing a reliable system for detecting black pepper adulteration. Images of both pure and adulterated black pepper are gathered from sources such as local spice markets, laboratories, and controlled sample preparations. Special care is taken to capture the images under consistent lighting and against neutral backgrounds to minimize shadows and reflections.

Multiple angles and distances are used to create a diverse set of images, which helps the system learn effectively. Each image is accurately labeled as pure or adulterated to form a structured dataset.

Fig. 3. Adulterated Sample

B. Image Processing

The process begins with enhancing the quality of captured images by reducing noise and improving contrast, which makes the details of pepper grains more visible. Techniques such as color space conversion, filtering, and image sharpening are applied to highlight important features like texture, shape, and color. Segmentation methods are then used to separate the pepper particles from the background and any adulterants. By processing the images in this way, the system can extract meaningful information that forms the basis for accurate classification and detection.

After segmentation, the processed images are analyzed to extract distinguishing features that help differentiate pure pepper from adulterated samples. These features capture sub-tle variations in surface texture, size distribution, and color patterns that are not easily visible to the human eye. Feature normalization is performed to maintain consistency across different samples and imaging conditions. This structured image processing pipeline ensures that the classification results are reliable and less affected by external factors such as lighting or background variations.

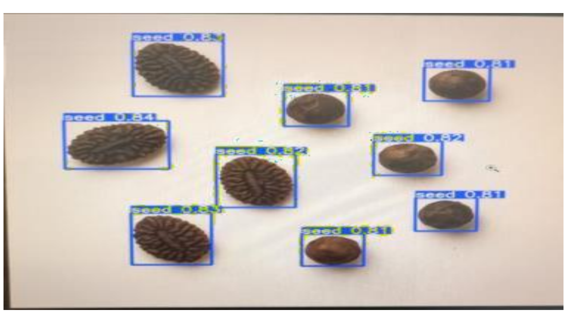

Fig. 4. YOLO Object Detection

C. Model Training

Model training is the process where the detection system learns to differentiate between pure and adulterated black pepper samples. The collected and preprocessed images are fed into deep learning models like YOLOv8m for object detection and MobileNetV2 for classification. During train-ing, the models adjust their internal parameters to recognize patterns, textures, shapes, and colors that distinguish authentic pepper from adulterants. Techniques such as batch processing, learning rate adjustment, and data augmentation are used to improve learning efficiency and prevent overfitting. The model's performance is continuously monitored on a validation set to ensure accurate predictions.

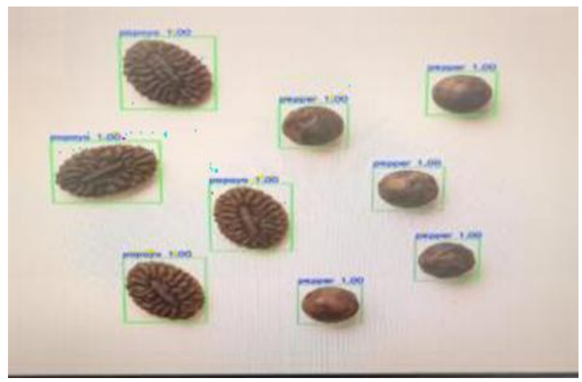

Fig. 5. Final Annotated Output

VI. RESULTS AND DISCUSSIONS

The results of the black pepper adulteration detection system demonstrate the effectiveness of combining image processing with deep learning models. The trained YOLOv8m model accurately detected and localized pepper grains and potential adulterants in the images, while MobileNetV2 successfully classified the samples as pure or adulterated.

The discussion of results shows that the system can handle variations in lighting, particle size, and background, which are common challenges in real-world scenarios. Some minor misclassifications occurred in cases where the adulterants closely resembled pepper. in texture or color, highlighting areas for further improvement. Overall, the system provides a fast, efficient, and practical so-lution for automated adulteration detection, making it valuable for food quality inspection and spice industry applications.

A. Class Distribution of Seeds

Class distribution of seeds shows how the collected images are grouped into different categories. In this project, the dataset contains two classes: pure black pepper and adulterated samples. An almost equal number of images are included in both classes so that the model does not favor one category over the other. This balanced distribution helps the system learn the differences more clearly and produce accurate results during testing. Proper class distribution improves the reliability of the model when it is used on new samples.

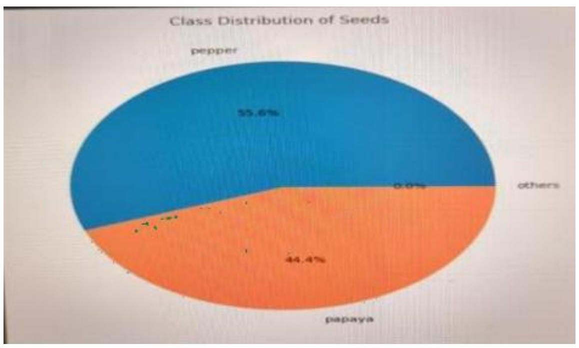

Fig. 6. class distribution

B. classification Reports

The classification report displays the results of the black pepper adulteration detection system for a total of nine seed samples. Each seed is analyzed using both the MobileNetV2 and YOLOv8m models, with the respective confidence scores shown in parentheses. For example, Seed 1 is classified as papaya with a confidence of 1.00 by MobileNetV2 and 0.84 by YOLOv8m. Seeds 1 to 4 are identified as papaya, while Seeds 5 to 9 are classified as black pepper.

Overall, the classification results confirm that the system can accurately identify and separate pure pepper from adulterated samples, supporting its practical application in quality control and food safety. This balance also helps the model generalize better when it is tested on new, unseen samples

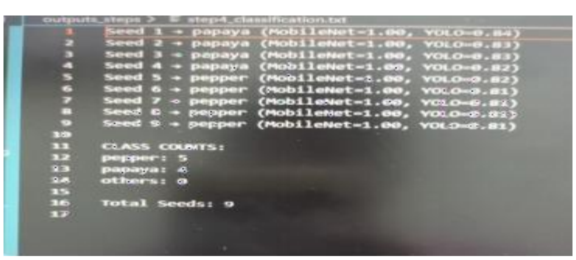

Fig. 7. Text-Based Seed Classification

C. Confidence Graph

A confidence graph is used to show how confidently the model predicts whether a sample is pure pepper or adulterated. During testing, the model assigns a confidence score to each detection, usually ranging from 0 to 1. These scores are plotted on a graph to observe the variation in prediction certainty. Higher confidence values indicate stronger and more reliable predictions by the model. This graph provides a clear visual understanding of the model's decision-making behavior. Sam-ples with consistently high confidence reflect accurate feature learning by the model. Lower confidence scores highlight uncertain cases that may need further inspection or additional training data.

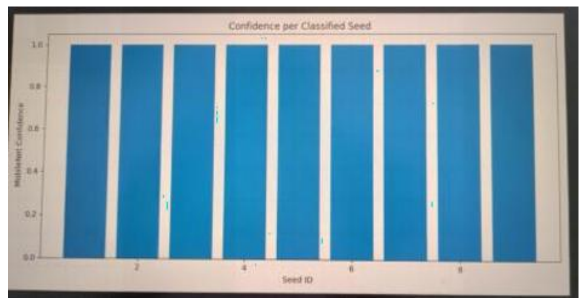

Fig. 8. Confidence Bar Graph

D. Result Table

Table I

Parameter	YOLOv8m	Mobile Net V2
Training Data Samples	2356	18000
Testing Data Samples	588	3900
Number of Epochs	100	12
F1 Score	0.98	0.9983
Recall	0.992	0.9998
Precision	1.00	0.99828
Testing Accuracy (%)	99.2%	99.83%

The table provides a comparison of the performance of two deep learning models, YOLOv8m and MobileNetV2, used to detect adulteration in black pepper samples. It includes details such as the size of the training and testing datasets, the number of epochs used during training, and key performance metrics. YOLOv8m was trained on a smaller dataset but with more training iterations, yet it achieved very high accuracy and perfect precision, highlighting its ability to correctly classify pepper samples even with limited data. On the other hand, MobileNetV2 utilized a much larger dataset, required fewer epochs, and achieved slightly higher accuracy and recall, demonstrating its efficiency when trained on extensive data. Overall, both models are highly effective, each with distinct strengths—YOLOv8m excels with smaller datasets, while MobileNetV2 benefits from larger datasets to enhance performance.

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