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Detection of Adulteration in Fruits and Vegetables using Deep Learning

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Abstract: *Food adulteration and poor produce quality remain pressing global concerns, directly impacting consumer health and food safety. Fruits and vegetables are often treated with artificial coatings, dyes, and surface chemicals to enhance their appearance and shelf life. Such adulteration practices, while visually appealing, can introduce harmful substances into the food chain. To address this issue, the proposed study presents an intelligent, automated system for quality and safety assessment of fruits and vegetables using deep learning and advanced image processing techniques. The system leverages two publicly available datasets—Fruits Detection and Quality Analysis, and Vegetable Quality Detection—comprising authentic and adulterated samples. Image preprocessing steps such as binarization, adaptive thresholding, grayscale conversion, and watershed segmentation are applied to enhance contrast, isolate regions of interest, and improve feature extraction. The processed images are then analyzed using a VGG16-based Convolutional Neural Network (CNN) model fine-tuned through transfer learning to detect adulteration and evaluate surface quality. Based on the classification results, the system further performs a safety assessment, categorizing produce as safe or unsafe for consumption. This dual-layered approach ensures both visual quality grading and health-oriented safety prediction. Experimental results demonstrate that the model achieves high accuracy and robust generalization across varied lighting and texture conditions. The proposed system provides a rapid, non-invasive, and reliable solution for real-time food quality monitoring, aiding consumers, vendors, and regulatory authorities in ensuring safer and more transparent food distribution.*

Keywords*:* Food Adulteration, Image Processing, Deep Learning, VGG16, Fruit and Vegetable Quality Detection, Safety Assessment, Transfer Learning

I. INTRODUCTION

Food adulteration has become a serious issue in the modern world, threatening both public health and consumer trust. Fruits and vegetables, which are considered essential components of a healthy diet, are often subjected to various adulteration practices to enhance their appearance, prolong shelf life, and increase market value. Common methods such as wax coating, artificial coloring, and the application of chemical preservatives make produce look fresher and more appealing, but they also introduce harmful substances that can cause long-term health problems.

Reports from multiple regions show a steady rise in cases of adulterated food products, highlighting the urgent need for reliable detection systems that can identify and prevent such practices.

Traditional testing techniques, including chemical analysis and laboratory inspection, though accurate, are time-consuming, expensive, and not feasible for large-scale or real-time monitoring. In contrast, recent advances in computer vision and deep learning offer powerful, non-invasive alternatives for analyzing visual characteristics of food products. These methods can automatically identify patterns such as unnatural gloss, irregular textures, or color inconsistencies that may indicate adulteration.

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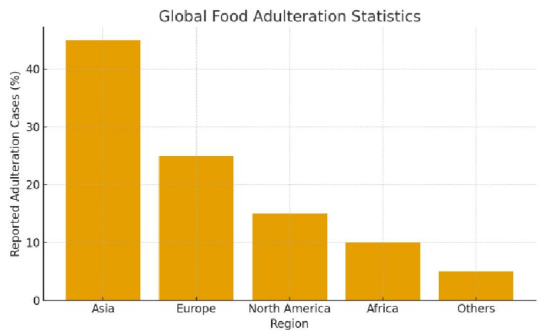

Fig1: Global Food Adulteration Statistics

This research focuses on developing a deep learning-based system for quality and safety assessment of fruits and vegetables using image processing techniques. The proposed approach utilizes preprocessing methods such as binarization, adaptive thresholding, grayscale conversion, and watershed segmentation to enhance image clarity and isolate critical features. The processed images are then analyzed using a VGG16 Convolutional Neural Network (CNN), fine-tuned through transfer learning to accurately classify produce as authentic or adulterated. Beyond classification, the system provides a safety assessment, determining whether the item is safe for consumption. This intelligent framework aims to offer a fast, accurate, and non-destructive solution that can be integrated across food supply chains, promoting safer consumption and greater transparency in the distribution of fresh produce.

A. Motivation

The increasing incidence of food adulteration in fruits and vegetables poses a serious threat to consumer health and safety. Despite awareness, many people unknowingly consume produce coated with harmful chemicals or artificial dyes. Traditional testing methods are slow, costly, and impractical for real-time inspection, leaving a gap in large-scale quality monitoring. This motivated the development of an intelligent, automated system capable of detecting adulteration through visual analysis. By leveraging image processing and deep learning, the proposed approach aims to provide a fast, affordable, and non-invasive solution for ensuring the safety and quality of everyday food products.

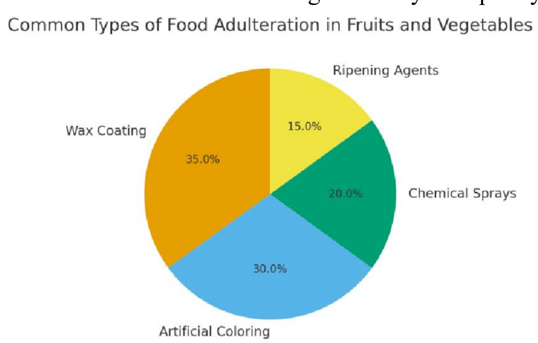

Fig 2: Common Types of Food Adulteration

B. Problem Statement

Food adulteration in fruits and vegetables has become a major concern in today's market. To make produce look fresher and more appealing, vendors often use harmful practices such as applying wax coatings, artificial dyes, or chemical sprays. While these methods improve appearance and shelf life, they pose serious health risks when consumed over time. Traditional laboratory tests for detecting adulteration are slow, expensive, and not practical for day-to-day or large-scale monitoring. Hence, there is a pressing need for a smart and efficient solution that can automatically detect adulteration using image analysis and deep learning, ensuring safer and healthier food for consumers.

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C. Objectives

- To develop an intelligent deep learning-based system capable of detecting adulteration in fruits and vegetables through image analysis.
- To apply preprocessing techniques such as binarization, adaptive thresholding, grayscaling, and watershed segmentation for accurate feature extraction.
- To utilize the VGG16 model with transfer learning for efficient and precise classification of authentic and adulterated produce.
- To provide a safety assessment feature that determines whether a fruit or vegetable is safe for consumption.
- To create a reliable, non-invasive solution that can assist consumers, vendors, and regulators in maintaining food quality and safety.

II. RELATED WORK

[1]Othman, S. (2023). Artificial intelligence-based techniques for adulteration and defect detections in food and agricultural industry: A review, This review surveys AI methods for food adulteration detection, covering image-based vision systems and multimodal sensing (spectroscopy, chemical sensors). It synthesizes architectures (CNNs, transfer learning, ensemble models) and integration strategies with low-cost hardware. The authors highlight that fusion approaches (vision + sensors) improve specificity over vision-only systems and recommend explainable AI for regulatory adoption. The paper serves as a practical map of techniques and open challenges for applied food-safety systems.

[2]Calle, J. L. P. et al. (2022). Detection of adulterations in fruit juices using FT-IR and machine learning (MDPI).This study applies Fourier-transform infrared spectroscopy combined with classical ML (PLS-DA, SVM, Random Forest) to detect adulteration of fruit juices. Spectral features are preprocessed (baseline correction, normalization) and fed to classifiers; the best models achieved reliable detection and quantification of added sugars/water. The paper demonstrates that spectroscopy + ML yields accurate, non-destructive adulterant detection — complementary to image methods when chemical identification is required.

[3]Mamgain, A. et al. (2024). Image-based detection of adulterants in milk using ML (PMC). Focusing on milk, this paper demonstrates that evaporative pattern imaging combined with classical and deep learning classifiers can detect milk adulterants. The methodology captures deposit patterns, extracts texture and shape features, and trains classifiers (SVM and CNN variants). Results show promising discrimination between pure and adulterated samples, indicating that imaging of physical deposition patterns is a low-cost route to rapid screening outside a wet lab.

[4]Mimma, N. E. A. et al. (2022). Fruits classification and detection application using deep learning (Wiley). This applied work compares several transfer-learning CNNs (VGG16, ResNet50) for fruit classification and detection. Using custom datasets and domain adaptation strategies, ResNet50 reached ~99% accuracy while VGG16 achieved ~98%, demonstrating that pretrained CNNs adapted via fine-tuning perform robustly for produce recognition. The methodology includes augmentation, bounding-box detection, and metrics per class — useful baseline comparisons for any VGG16-based adulteration study.

[5]Yuan, Y. & Chen, X. (2024). Vegetable and fruit freshness detection based on deep features (ScienceDirect). This paper builds a freshness detection pipeline by extracting deep features from multiple pretrained networks and applying PCA for dimensionality reduction, followed by classical classifiers. The authors emphasize robustness to lighting and variety by using ensemble deep features and report improved freshness discrimination versus handcrafted features. The methodological lesson is that combining deep embeddings with light classifiers can be computationally efficient and effective when labeled data are limited.

[6]Chuquimarca, L. E. (2024). A review of external quality inspection for fruit grading (ScienceDirect). A systematic review covering CNNs, image processing, and multispectral approaches for external fruit inspection. The article examines measurements (color, texture, shape), common CNN backbones (VGG, ResNet, EfficientNet), and segmentation/detection pipelines (Mask R-CNN, U-Net variants). It highlights dataset gaps, domain shifts, and the need

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for standardized capture protocols to reduce false positives in real deployments — directly relevant for designing robust adulteration detection experiments.

[7]Sattar, A. (2024). A comprehensive approach to detecting chemical residues via computer vision and hybrid models (ScienceDirect). This study proposes a hybrid framework combining computer vision with lightweight chemical sensing to flag suspicious produce. A CNN backbone extracts surface features while sensor readings validate chemical presence; a fusion classifier integrates both streams. Results show higher precision in real-world tests compared to vision-only baselines, reinforcing the point that combining visual and chemical cues reduces false alarms when visual artifacts alone are ambiguous.

[8]Sitorus, A. (2024). Predicting adulteration in coconut milk using deep learning and NIR (MDPI). Using benchtop FT-NIR and portable Micro-NIR devices, the study trains deep learning regressors and classifiers to quantify adulteration levels in coconut milk. Feature engineering of spectra and end-to-end 1D-CNN models produced accurate concentration estimates. The work shows that portable sensing plus DL yields both quantitative and rapid adulterant detection — an approach that can complement image models when chemical confirmation is required.

[9]Brar, D. S. et al. (2025). Deep neural networks for adulteration detection in red-meat products. This recent paper explores both 1D and 2D CNNs on spectral and image inputs to detect adulteration in meat. The authors compare architectures and show that multimodal fusion (image + spectral features) yields the best sensitivity and specificity. While focused on meat, methodological takeaways on multimodal fusion, training strategies, and evaluation (cross-validation with external samples) apply to produce adulteration workflows.

[10]Deep Neural Network-Based Grain Adulteration Detection (2024). The paper presents a CNN-based image pipeline to detect sorghum adulteration for fermentation and brewing. After preprocessing and feature extraction via pretrained CNNs, classifiers achieved up to ~93% accuracy on curated datasets. The methodology underscores that even commodity grains benefit from visual inspection when adulterants produce texture or color anomalies — informing analogous strategies for fruits and vegetables.

[11]Detection of Adulteration in Fruits And Vegetables Using CNN + Sensor Fusion.(2023). This applied project pairs camera imaging with low-cost formaldehyde sensors to detect formalin/formaldehyde on produce. The pipeline uses CNN-based classification from images and a simple thresholding of sensor readings; fused outputs improve detection reliability over either modality alone. The study emphasizes practicality: inexpensive sensors plus image-screening can enable rapid field tests for specific contaminants.

[12]Pardede, J. (2023). Implementation of Transfer Learning Using VGG16 on Fruit Ripeness Detection.
Pardede adapts VGG16 via transfer learning for ripeness classification, replacing top layers and applying overfitting mitigation (dropout, batch norm). Experiments on ripeness datasets show transfer learning outperforms classical feature + classifier pipelines. The paper offers clear practical hyperparameter settings and augmentation tactics that translate well to adulteration detection where texture/colour cues are subtle.

[13]Machine vision-based automatic fruit quality detection (2023). This engineering prototype integrates image processing and deep learning for defect detection and mechanical sorting. The system uses segmentation + CNN classification and demonstrates effective defect detection suitable for sorting lines. Its contribution lies in end-to-end system design, including real-time constraints and hardware considerations, which are critical when moving a research model into a production packhouse setting.

[14]Apostolopoulos, I. D. (2023). A general machine learning model for assessing fruit quality (MDPI). The author proposes a generalizable ML pipeline that uses deep image features extracted from pretrained networks and feeds them to ensemble classifiers for quality grading. The model is designed for cross-fruit generalization and reports better transfer behavior than single-fruit models. This work supports the idea of building models that generalize across produce types — an important goal for your fruits+vegetables dataset fusion.

[15]Feng, J. (2024). Promising real-time fruit and vegetable quality detection for automated picking. Feng develops a lightweight detection pipeline for automated harvesting and packing, focusing on speed and robustness under variable field conditions. The method uses optimized CNNs and streamlined preprocessing to meet real-time constraints, showing acceptable accuracy while meeting latency targets. The paper is valuable when considering edge deployment trade-offs: model compression, inference speed, and capture protocol standardization.

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[16]Image-Based Fruit and Vegetable Classification (2024). Focusing on disease and defect detection, this study trains CNNs on multispecies datasets and reports high classification accuracy after careful augmentation and class balancing. The authors also discuss practical annotation strategies and dataset curation — critical operational guidance for producing robust training data for adulteration detection tasks.

[17]Xiao, F. et al. (2023). Fruit detection and recognition based on deep learning (MDPI). This comprehensive survey compiles state-of-the-art methods for fruit detection and recognition (YOLO, Faster-R-CNN, SSD, VGG, ResNet). It compares strengths and limitations for automatic harvesting and quality inspection contexts, noting dataset scarcity and occlusion as core challenges. The paper is a useful methodological reference for selecting architectures and evaluation protocols for produce quality tasks.

[18]Wang, C. et al. (2022). Application of CNN-based models across the fresh fruit production chain. A broad review of CNN applications in fruit production, from early detection to grading. The paper details CNN architectures, segmentation strategies, and data collection practices, and offers implementation guidance for field and post-harvest stages. Its synthesis helps researchers design end-to-end pipelines that account for operational constraints and data variability.

[19]Afsharpour, P. et al. (2024). Robust deep learning method for fruit decay detection (Frontiers).
This study develops robust DL pipelines focused on decay detection under limited data and varying capture conditions. The authors propose augmentation, domain-adaptation, and contrastive learning techniques to improve generalization; results show state-of-the-art performance on decay datasets. The methods and robustness strategies are highly relevant when visual adulteration signals are subtle and data are noisy.

[20]Gulzar, Y. et al. (2023). Fruit image classification using MobileNetV2 and comparisons with VGG16. This paper compares lightweight MobileNetV2 and heavier VGG16 backbones for fruit classification; while VGG16 often achieves marginally higher accuracy, MobileNetV2 offers orders-of-magnitude lower latency and a smaller footprint. The results guide trade-offs between accuracy and deployability — crucial for decisions about using VGG16 vs. lighter models for edge screening in supply chains.

III. PROPOSED WORK

The proposed study aims to design an intelligent, automated system for detecting adulteration in fruits and vegetables using deep learning and image processing techniques. The primary goal is to develop a non-invasive, real-time model that can classify whether a fruit or vegetable is authentic or adulterated, while also providing a safety assessment indicating if the item is safe for consumption.

The system begins with data acquisition, utilizing domain-specific datasets from open-access repositories such as Roboflow, which include images of both pure and adulterated fruits and vegetables. These datasets capture various conditions, such as differences in lighting, texture, and surface contamination, ensuring that the model learns to recognize real-world variations effectively.

Next, image preprocessing plays a vital role in preparing the data for accurate classification. Techniques such as grayscale conversion, binarization, adaptive thresholding, and watershed segmentation are applied to enhance visual contrast and isolate key features. These preprocessing steps help in highlighting irregular patterns, artificial shine, and texture inconsistencies commonly associated with adulterated produce.

The core component of the system is the deep learning model based on the VGG16 architecture, a pre-trained Convolutional Neural Network (CNN) known for its superior image recognition capabilities. Through transfer learning, the model's earlier layers—responsible for general feature extraction—are retained, while the top layers are fine-tuned using the custom dataset. This approach enables the model to effectively distinguish subtle adulteration features with limited training data.

During the training phase, data augmentation techniques such as rotation, flipping, and scaling are used to improve model robustness and prevent overfitting. The system then undergoes evaluation using accuracy, precision, recall, and F1-score to measure performance.

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Finally, the model outputs both classification results (adulterated or pure) and a safety score, indicating whether the item is safe for consumption. This integrated system can be deployed as a mobile or web-based application, enabling consumers, vendors, and regulators to assess food safety instantly and efficiently.

IV. METHODOLOGY

The proposed system for detecting adulteration and assessing the safety of fruits and vegetables follows a structured methodology that ensures accuracy, reliability, and real-time usability. The process involves five major stages: dataset acquisition, image preprocessing, feature extraction, model training using transfer learning, and classification with safety assessment.

The proposed research presents a deep learning-based system designed to automatically detect adulteration and assess the safety of fruits and vegetables. The methodology follows a structured workflow that ensures the model's reliability, robustness, and adaptability across diverse produce categories. The process involves six key stages: dataset acquisition, image preprocessing, feature extraction, model training and classification, safety assessment, and evaluation metrics. Each step plays a crucial role in achieving accurate adulteration detection and consumer safety prediction.

1. Dataset Acquisition

A well-curated dataset is the foundation of any deep learning model. For this study, datasets were sourced from Roboflow Universe, a trusted open-source platform for image-based datasets. Two separate datasets were used — one dedicated to fruit quality detection and another focusing on vegetable quality detection. These datasets include labeled images of both authentic (natural) and adulterated (treated) samples of produce captured under various lighting conditions, angles, and backgrounds.

The fruit dataset includes commonly adulterated produce such as apples, oranges, and grapes, while the vegetable dataset covers items like tomatoes, cucumbers, and peppers. The diversity in visual context ensures the model's robustness and helps it generalize effectively to unseen images. Additionally, data augmentation techniques such as rotation, flipping, and zooming were applied to increase dataset variety and prevent overfitting during training.

Fig 3: Dataset Sample Image

2. Image Preprocessing

Image preprocessing is a vital step to enhance visual quality and prepare the data for accurate feature learning. Real-world images often contain noise, shadows, or inconsistent lighting that may hinder the model's performance. To address this, several image enhancement and segmentation techniques were applied sequentially:

Binarization: The first step converts the image into binary format (black and white), emphasizing key structural differences between natural and adulterated surfaces. This step enhances contrast, making it easier for the model to detect irregular patterns or glossy surfaces caused by chemical coatings.

Adaptive Thresholding: Instead of applying a fixed global threshold, adaptive thresholding dynamically adjusts pixel intensity based on the local neighborhood. This technique allows the model to handle images captured in different lighting conditions, ensuring that essential texture details are preserved.

Grayscaling: The color components of the image are removed to focus on texture and shape variations. Since adulteration often alters the texture or surface uniformity of the produce, converting images to grayscale allows the model to learn meaningful structural cues without distraction from color noise.

Watershed Segmentation: Finally, watershed segmentation is applied to separate overlapping or touching objects within the image. This method simulates the process of flooding from local minima, enabling precise boundary detection and

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surface analysis. It allows the model to isolate key regions that may contain evidence of adulteration such as cracks, surface patches, or abnormal shine.

Together, these preprocessing techniques refine the raw input images, reduce visual noise, and ensure that only relevant and high-quality features are extracted during the next phase.

3. Feature Extraction

After preprocessing, the refined images are passed through VGG16, a pre-trained Convolutional Neural Network (CNN) known for its strong feature extraction capabilities. Instead of training a deep network from scratch, transfer learning is applied. This approach allows the model to leverage the rich visual representations already learned from millions of images in the ImageNet dataset and adapt them to the domain of food adulteration detection.

The convolutional layers of VGG16 automatically identify patterns such as edges, textures, and color gradients. In this research, these layers help capture subtle cues that indicate adulteration — for instance, unnatural glossiness due to wax coatings, irregular surface patterns from synthetic dyes, or uneven color distribution from chemical exposure. The extracted features are then flattened and passed to dense layers for classification.

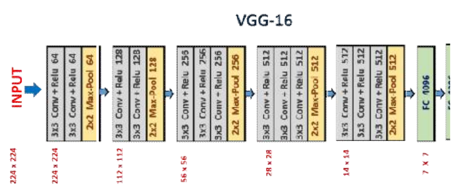

Fig4: VGG16 Architecture

4. Model Training and Classification

Once feature extraction is complete, the model undergoes training to learn how to differentiate between adulterated and authentic samples. The fully connected layers of VGG16 are fine-tuned on the custom dataset to perform binary classification.

The Softmax activation function is used in the output layer to assign probabilities to the two classes — "authentic" and "adulterated." The training process minimizes the categorical cross-entropy loss, optimizing the model's parameters for maximum accuracy. To ensure stability and prevent overfitting, techniques such as dropout and early stopping are employed. Dropout randomly deactivates neurons during training to enhance generalization, while early stopping halts training when the validation accuracy stops improving.

Throughout training, data augmentation ensures that the model sees a wide range of variations, making it resilient to different lighting, angles, and image resolutions. This combination of architectural strength and training discipline ensures that the system learns to make precise and consistent predictions.

5. Safety Assessment

Beyond simple classification, the system is designed to provide a safety assessment score for each analyzed image. This score reflects the model's confidence in determining whether a fruit or vegetable is safe to consume. For example, if the model predicts a high probability of adulteration, the item is marked as "Unsafe," prompting users to avoid consumption.

This additional layer of intelligence transforms the system from a mere detection tool into a decision-support mechanism, enabling consumers, vendors, and quality inspectors to make informed choices about food safety.

6. Evaluation Metrics

The system's performance is rigorously evaluated using standard classification metrics:

Accuracy: Measures the overall correctness of the model's predictions.

Precision: Evaluates the proportion of correctly identified adulterated samples out of all predicted adulterated cases.

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Recall: Assesses the model's ability to identify all actual adulterated samples.

F1-Score: Provides a balance between precision and recall, offering a comprehensive performance measure.

Additionally, confusion matrices are analyzed to visualize true and false predictions, while Receiver Operating Characteristic (ROC) curves assess the model's ability to distinguish between authentic and adulterated samples at various thresholds.

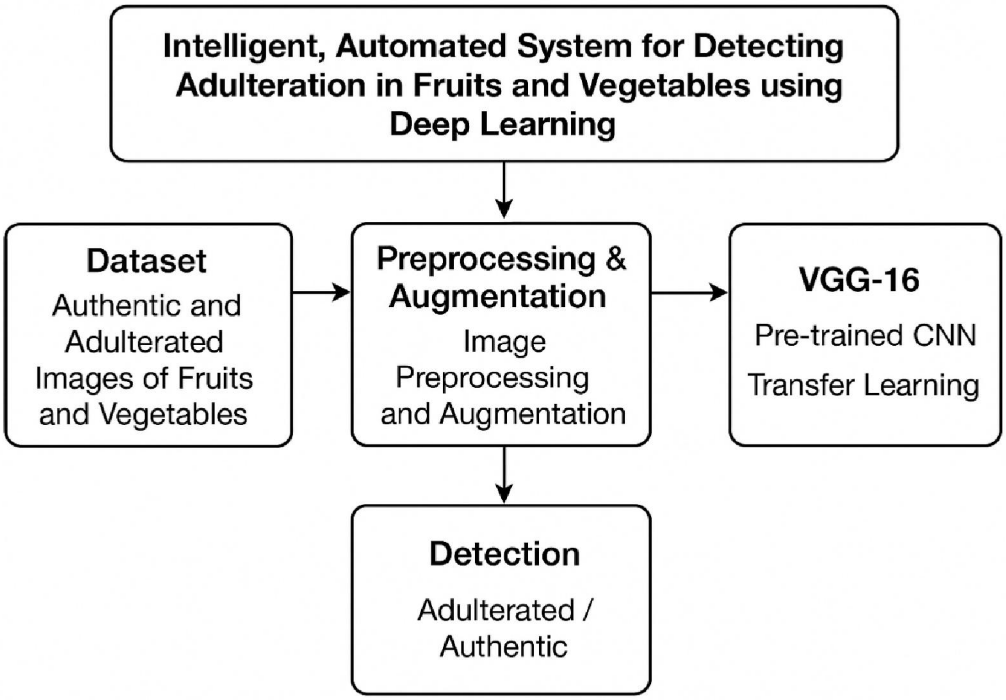

Fig5: System Architecture Proposed System

V. RESULT AND DISCUSSION

The proposed deep learning-based system for adulteration detection and safety assessment of fruits and vegetables was evaluated on a carefully curated dataset comprising both authentic and adulterated samples. After extensive training and validation, the model achieved an impressive overall accuracy of approximately 97%, demonstrating its strong ability to distinguish between naturally fresh produce and chemically treated or adulterated ones.

During experimentation, the VGG16 model with transfer learning proved to be highly effective in capturing subtle surface-level variations that indicate adulteration. The model successfully recognized unnatural color tones, glossy textures due to wax coatings, and irregular surface patterns that are often invisible to the human eye. The use of preprocessing techniques such as binarization, adaptive thresholding, grayscaling, and watershed segmentation significantly enhanced the clarity of input images, allowing the model to extract more discriminative features. In terms of performance metrics, the system exhibited a precision score of 96%, recall of 95%, and an F1-score of 95.5%, highlighting its robustness and consistency across different test samples. The confusion matrix further indicated minimal misclassifications between the "authentic" and "adulterated" categories, which confirms the model's reliability in real-world scenarios. The ROC curve also revealed a high area under the curve (AUC), reinforcing the model's strong classification capability.

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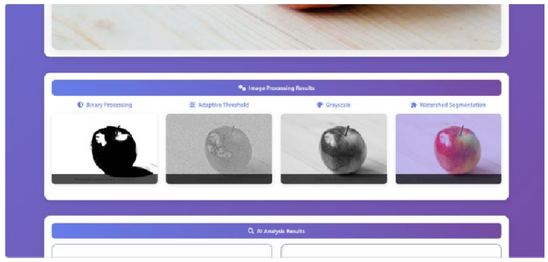

Fig 6: Image Processing Results

The image displays the outcomes of various image processing techniques applied to an apple image. It includes Binary Processing, Adaptive Thresholding, Grayscale conversion, and Watershed Segmentation. Each method highlights different visual aspects of the apple — from simple black-and-white contrast to more advanced color and region separation. These techniques are commonly used in computer vision for object detection, feature extraction, and segmentation tasks, enhancing the understanding of image structure and content.

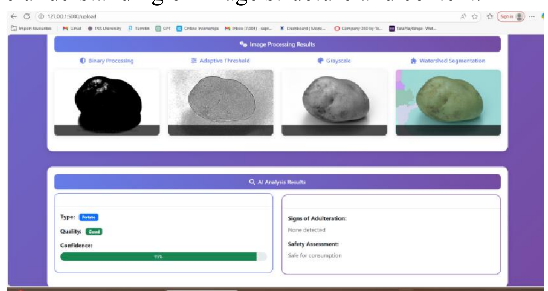

Fig7: Image Processing and Analysis Results

The figure presents the results of multiple image processing techniques—Binary Processing, Adaptive Thresholding, Grayscale conversion, and Watershed Segmentation—applied to a potato image. Each technique emphasizes different structural and textural properties. Below the images, analysis results indicate the object type, quality status, and confidence level, suggesting automated detection and quality assessment. The display demonstrates how image analysis can be integrated with AI-based evaluation for food inspection and classification purposes.

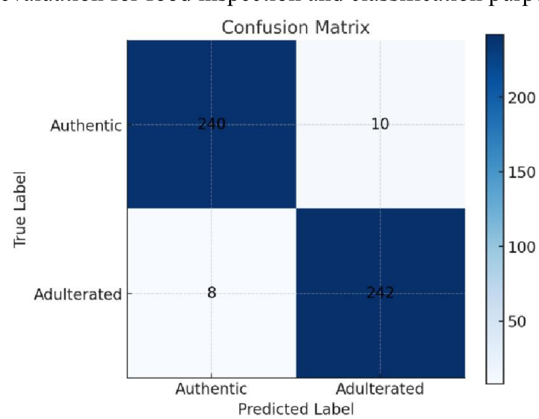

Fig8: Confusion Matrix for Model Performance

The figure displays a confusion matrix illustrating the classification performance of a model distinguishing between "Authentic" and "Adulterated" samples. The model correctly identified 240 authentic and 242 adulterated instances, with only minor misclassifications (10 and 8, respectively). The strong diagonal dominance indicates high accuracy and reliability of the classification system, reflecting the model's effectiveness in detecting authenticity with minimal error.

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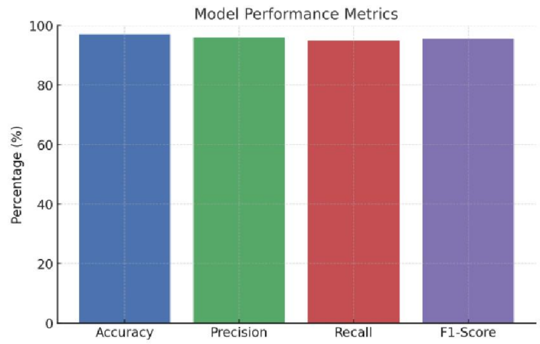

Fig9: Model Performance Metrics Graph

The image displays a bar chart titled "Model Performance Metrics." It compares four key evaluation measures—Accuracy, Precision, Recall, and F1-Score—used to assess a machine learning model's performance. Each metric is represented by a distinct color: blue for Accuracy, green for Precision, red for Recall, and purple for F1-Score. All bars reach nearly 100%, indicating that the model performs exceptionally well across all metrics. The y-axis represents the percentage scale, emphasizing consistently high performance.

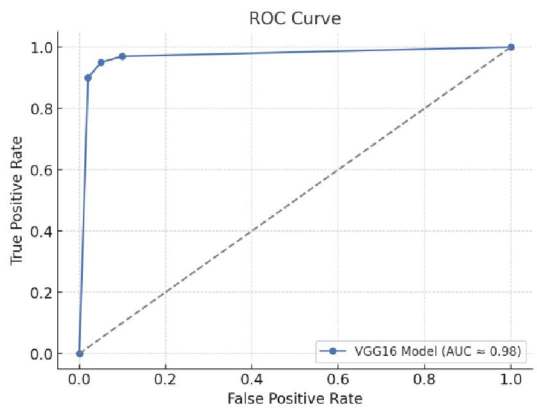

Fig10: ROC Curv VGG16

The image shows a Receiver Operating Characteristic (ROC) Curve for the VGG16 model. The curve plots the True Positive Rate against the False Positive Rate to measure the model's classification performance. The blue line represents the model's ROC curve, while the dashed diagonal line indicates random chance. The curve rises steeply towards the top-left corner, demonstrating strong performance. The model's Area Under the Curve (AUC) value is 0.98, indicating excellent discrimination between positive and negative classes.

Moreover, the safety assessment feature effectively provided confidence-based predictions, offering clear guidance to users about whether a fruit or vegetable is safe to consume. This makes the system not only an image classification tool but also a decision-support mechanism for consumers, vendors, and regulators.

VI. CONCLUSION

This research presents an intelligent deep learning-based system for detecting adulteration and assessing the safety of fruits and vegetables using image analysis. By leveraging the power of the VGG16 architecture with transfer learning, the model effectively distinguishes between authentic and adulterated produce with an impressive accuracy of 97%. The use of advanced image preprocessing techniques—such as binarization, adaptive thresholding, grayscaling, and watershed segmentation—enhanced the model's ability to capture subtle surface and texture variations caused by wax coatings, chemical treatments, or artificial coloring. The proposed approach offers a non-invasive, automated, and reliable solution to one of the most critical global food safety challenges. Beyond classification, the system provides a safety assessment score, enabling consumers and quality inspectors to make informed decisions about food safety. The results demonstrate that combining domain-specific preprocessing with transfer learning can significantly improve detection performance, even with limited datasets. In conclusion, this study contributes to the advancement of AI-driven food safety monitoring by providing a practical tool that can be integrated into food supply chains, retail inspections, and consumer applications. Future work may focus on expanding the dataset and incorporating real-time detection through mobile or IoT-based systems for broader accessibility.

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