ENHANCED FRUIT ADULTERATION DETECTION USING FORMALDEHYDE SENSOR AND IMAGE ANALYSIS

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KEYWORDS

Fruit Adulteration, Formaldehyde Detection, Fermion Gas Sensor, Arduino, Machine Learning, Logistic Regression, Support Vector Classifier, Decision Tree Classifier, Random Forest Classifier, KNN Classifier, Deep Learning, YOLOv8, Image Analysis, External Adulteration Detection, Internal Adulteration Detection, Quality Assessment

ABSTRACT

Fruit adulteration poses a significant threat to public health, with prolonged exposure potentially leading to severe health conditions such as cancer. Traditional approaches to identify adulteration utilize either only supervised machine learning techniques or only image processing methods that rely solely on external appearance, leading to limited accuracy. Our research introduces a novel solution integrating a formaldehyde gas sensor to measure formalin levels in fruits, thus enhancing internal adulteration detection. If it is found internally unadulterated, external checks are conducted using images from various angles, with adulteration levels compared against a dataset. We propose a grading scale for fruits: 1) completely unadulterated and safe, 2) externally but not internally adulterated, and 3) internally adulterated, the most severe form. Our approach is applicable for export-grade fruit quality testing, potentially enhancing the market value of organic fruits.

1. Introduction:

Food adulteration has a significant impact on our health. Whether it is the addition of harmful chemicals, dyes, or preservatives, prolonged consumption of adulterated food is highly detrimental to the body. Such food not only loses its nutritional value but also introduces toxins that can lead to various health issues. The presence of chemical adulterants can be particularly dangerous, posing risks of carcinogens that can initiate or promote cancer development. Additionally, the consumption of adulterated food may directly affect our internal organs, potentially leading to heart, kidney, liver disorders, and even organ failure. While some research suggests that food-grade wax used on fruits is safe for consumption, most waxes are mixed with morpholine and its derivatives (MAID), which are applied to ensure even and thin coatings. In the presence of dietary nitrate, morpholine can be chemically transformed into N-nitrosomorpholine (NMOR), a potent carcinogen. Even at low levels, morpholine can impair liver or kidney function, and chronic consumption of wax-coated fruits containing morpholine could slightly increase the risk of cancer in susceptible individuals. Given these significant health risks, there is an urgent need for advanced technologies that can ensure the integrity of the food supply, particularly in detecting adulterants in fruits. Traditional methods of adulteration detection are often labor-intensive, time-consuming, and prone to errors. They tend to focus solely on external or internal adulteration, rarely addressing both. To overcome these limitations, our research proposes an integrated solution that leverages deep learning techniques alongside chemical sensors to improve the accuracy and efficiency of adulteration detection. Specifically, we use deep learning models like YOLOv8 to detect external adulteration, while the Fermion formaldehyde gas sensor is employed to assess internal adulteration. This dual approach enables a comprehensive assessment of fruit quality, addressing both external appearance and internal chemical safety. Our methodology involves training convolutional neural networks (CNNs) on a diverse dataset that includes images of both adulterated and unadulterated fruits. These models learn to identify subtle visual cues indicative of adulteration, such as irregularities in color, texture, and shape. The YOLOv8 model, known for its speed and accuracy in real-time object detection, is particularly well-suited for this task. On the other hand, the Fermion sensor provides a non-contact method for detecting formalin levels in fruits, allowing for quick and non-intrusive assessments. By analyzing the sensor data, our system can accurately quantify the concentration of formalin, a harmful preservative often used illegally to extend the shelf life of fruits. If the formalin levels exceed safe thresholds, the fruit is classified as internally adulterated, and further analysis is halted. For fruits passed as internally unadulterated, external checks are conducted using images from various angles, with adulteration levels computed by the YOLOv8 model. If external adulteration prediction exceeds 60%, the fruit is classified as potentially harmful. This research introduces a novel methodology that not only detects internal and external adulteration but also evaluates the safety of wax coatings on fruits. The ability to differentiate between harmful and permissible coatings ensures that only safe fruits reach consumers. Additionally, our approach considers the effect of a fruit's age on formalin levels, adding a unique dimension to adulteration detection. By offering a holistic solution, our system provides a reliable tool for vendors and consumers alike, helping to ensure food safety and protect public health. The following sections detail our methodology, experimental setup, and results, demonstrating the potential of this integrated approach to revolutionize food safety practices.

2. Literature Review:

This literature review provides a comprehensive overview of recent advancements in detecting fruit adulteration using machine learning techniques. A variety of methods, including sensor-based approaches, image processing, and hybrid techniques, have been explored to accurately identify and quantify the presence of adulterants in fruits. The studies reviewed highlight the potential of machine learning to ensure food safety and protect consumers from harmful substances.

S. Prince Sahaya Brighty, G. Shri Harini, and N. Vishal in "Detection of Adulteration in Fruits Using Machine Learning" have used HCHO Sensor and Raspberry pi3 to detect formalin and value detected is fed to supervised machine learning model. The dataset is validated with the naturally occurring values of formalin in fruits that is collected from the Centre for Food Safety (CFS). Algorithms used are Logistic Regression, Support Vector Machines and K-NN. Best case accuracy of 95% is given by KNN model on test set [1].

S. S. Saha, M. S. Siraj, and W. B. Habib in "FoodAlytics: a Formalin Detection System Incorporating a Supervised Learning Approach" have used HCHO Sensor to detect formalin and value detected is fed to supervised machine learning model. BCSIR chemical kit is used as reference to detect artificially added formalin. Algorithms used are Levenberg-Marquardt algorithm, Polynomial Regression. The system is able to classify between artificially added and naturally formed formalin by applying logistic regression and support vector machines [2].

K. Tabassum, A. A. Memi, N. Sultana, A. W. Reza, and S. D. Barman in "Food and Formalin Detector Using Machine Learning Approach" have first used HCHO sensors to extract values of their color, resistance and mass using a rule-based machine learning approach to identify the fruit. The dataset referred is that of the natural formalin level in fruits which is collected from the Centre for Food Safety (CFS). Algorithms used are Logistic Regression, Naïve Bayes, Support Vector Machines and K-NN with the accuracy increasing respectively [3].

A. M. P. Anjana and K. Pradeepa in "Detecting Food Adulterants Using The Concepts Of Machine Learning" have used image processing and feature matching to detect whether fruit is consumable. The model is first trained using the microscopic image of the consumable apple, open CV and matplotlib generates and extracts the features from the image. The imported library functions for this model are numpy, opencv2 and pyplot from matplotlib [4].

C. R. PH, D. Rakshitha, K. B. Likitha, M. Chetan, and J. J. Jayashubha in "Detection Of Adulteration In Fruits And Vegetables Using Machine Learning" used image processing to sort the fruits. An HCHO sensor is used to measure formalin level. The dataset referred is that of naturally occurring formalin in fruits that is collected from the Centre for Food Safety (CFS). Algorithms used are Logistic Regression, Support Vector Machines and K-NN. For three trials an accuracy of 98.33% was achieved [5].

F. Nowshad, M. N. Islam, and M. S. Khan in "Concentration and Formation Behavior of Naturally Occurring Formaldehyde in Foods" the authors tried to establish a relationship between the rate of decay of fruit and the naturally occurring formaldehyde content. The experimental results of apple, grape, banana, pear, plum, tomato, onion, cauliflower, potato, cabbage, kohlrabi, carrot, radish, cucumber and beetroot were found compatible with results reported by Centre for Food Safety [6].

P. Kogali, A. K, A. M. G, A. Deshpande, S. K in "Detection Of Adulteration In Fruits Using Machine Learning" proposed that a fruit adulteration gadget can be used to classify the fruits and to pick out defected fruit. Image processing is used to get the accurate output. Defected fruit is detected in particular based totally on photo pixels. Logistic Regression, SVM and KNN algorithms are used with highest accuracy of 95% obtained by KNN [7].

M. Sanjitha, A. S. K. Reddy, A. Joshi, A. R. NP, and A. Mahana in "Detection Of Disease And Adulteration In Fruits Using Machine Learning" propose an image pattern classification technique to identify adulteration in fruit with extraction of colour and textural features combined these photos. Photos are processed to extract colour, shape, and textural properties. Finally, a support vector machine classifier is used to categorize these photos. This technique makes use of YOLOv3, YOLOv2 combined with VGG16. Accuracy obtained is 92.7% [8].

C. D. Cortez, F. C. Bato, T. J. G. Bautista, J. M. G. Cantor, C. L. Gandionco III, and S. P. Reyes in "Development of Formaldehyde Detector" have conducted a study whose objective was to design a system that can detect concentration of formaldehyde and indicate if the reading was above or below the permissible level for formaldehyde. The system obtained an average of 98.33% accuracy in measuring formaldehyde concentration level [9].

J. Sampathkumar, M. Rajaganapathy, M. Praveen, and S. Socrates in "Food Adulteration Detection Using Machine Learning" use image processing and microprocessors. They used open cv and matplotlib to extract and concentrate the highlights of the objective. The solution utilized MATLAB and ThingSpeak to convey an arrangement of cloud-associated sensors [10].

K. Goyal, P. Kumar, and K. Verma in "Food Adulteration Detection using Artificial Intelligence: A Systematic Review" emphasize the significance of AI in detecting food adulteration for consumer protection and food quality maintenance. They analyze the role of machine learning and deep learning in assessing food quality, referencing online data sources. The study reviews 112 studies on food adulteration detection, noting the prevalent use of ML and DL approaches and the challenges in technical development [11].

W. Ni and R. Li in "Research on Recognition Technology of Fruit based on Simulated Annealing Algorithm and Neural Network" introduced a fruit grading algorithm using a combination of simulated annealing and neural network models, focusing on apple classification. The study addresses the limitation of BP neural network models by integrating simulated annealing to expand the weight update space for enhanced optimization. It demonstrates improved recognition efficiency compared to conventional BP and RBF neural network algorithms through the proposed approach [12].

H. Mures and M. Oltean in "Fruit Recognition From Images Using Deep Learning" have introduced a high-quality dataset of fruit images and discusses numerical experiments utilizing TensorFlow for fruit detection using neural networks. They identified the need to enhance neural network accuracy by experimenting with network structures, including adding or replacing layers and exploring different activation functions. The solution achieves best test accuracy of 98.53% [13].

Our literature survey provides valuable insights into current fruit adulteration detection techniques, encompassing various methods from image processing and sensor-based approaches to advanced machine learning algorithms. Key findings highlight the effectiveness of combining image analysis with chemical sensors and the use of algorithms like Logistic Regression, SVM, and KNN for detection. We observed that integrating deep learning models offers significant improvements in accuracy. By analyzing these methods, we identified both strengths and limitations, guiding us to refine our approach. Our novel methodology leverages these insights, incorporating best practices and addressing identified gaps to enhance the accuracy and reliability of our fruit adulteration detection system. By incorporating aspects from several reviewed studies, including sensor-based approaches (as seen in papers discussing HCHO sensors) and image processing techniques (like those employing YOLO and other deep learning models), our integrated approach aims to provide a more comprehensive and reliable solution for identifying both internal and external adulteration in fruits. This review not only shapes our product development but also paves the way for innovative improvements in food safety technology.

This literature review helped us identify the gaps and shortcomings in the existing research on this topic. Previous research efforts have primarily concentrated on either internal or external adulteration, neglecting the potential for both to occur simultaneously. Additionally, the impact of fruit age on formalin levels has not been thoroughly investigated in these studies. Image-based methods, while useful for detecting external adulteration, often rely solely on pixel analysis, limiting their accuracy. Moreover, some solutions have been tailored to specific fruits, restricting their generalizability. Furthermore, studies focusing solely on internal adulteration overlook the significance of waxing, a common practice that can pose health risks. By examining the gaps in previous solutions, we establish a foundation for our research and contribute to the development of more robust and effective detection methods.

3. Methodology:

Our research focuses on developing a comprehensive system to detect and assess adulteration in fruits, combining advanced technologies to ensure safety, reliability, and accessibility. Our primary objective is to accurately detect whether a fruit has been adulterated, identifying any harmful substances or alterations that compromise its quality or safety. This detection is crucial for protecting consumer health and ensuring that the food supply remains safe. To achieve this, we integrate the use of the Fermion gas sensor, specifically designed to detect formaldehyde levels in a non-contact manner. This sensor will identify the presence of formalin in fruits or vegetables without requiring any invasive procedures, thereby simplifying the process and enhancing user convenience. In addition to sensor-based detection, our approach leverages image processing technology to identify external adulterations or irregularities. By analyzing visual cues such as color, texture, and shape, the image processing component enhances the accuracy of our adulteration detection, ensuring that even subtle signs of tampering are identified. Another key objective is to ensure that the solution we develop is cost-effective and accessible. By focusing on affordability, we aim to make this technology widely available to vendors, sellers, and buyers in the market, enabling broader adoption and use. This objective is crucial for ensuring that the benefits of this technology can reach all segments of the food industry, from large-scale distributors to small vendors. Furthermore, our system includes the capability to identify harmful and unauthorized wax coatings applied to fruits and vegetables. These coatings, often used for preservation or to enhance appearance, can pose significant health risks if they contain hazardous substances. By detecting such coatings, our system adds an extra layer of safety, protecting consumers from potential harm. In addition to detection capabilities, our system will implement a quality grading system that categorizes fruits and vegetables into one of three defined grades. This grading system is designed to provide clear guidance to both consumers and sellers, helping them make informed decisions based on the quality of the produce. The grading criteria will consider both internal and external factors, offering a comprehensive assessment of each item’s safety and quality. By integrating these technologies and methodologies, our overarching objective is to deliver a robust, reliable, and user-friendly solution for detecting adulteration in fruits, ensuring that consumers have access to safe and high-quality produce. Through this approach, we aim to enhance food safety standards, promote consumer confidence, and contribute to the integrity of the food supply chain.

4. Overview of the System

A. Architecture

The product is a multi-model product using image processing and sensors. The product will use a Fermion sensor to measure the formaldehyde level in that fruit/vegetable. We will then classify the fruit/vegetable into three categories. Grade 1 is when the fruit is of good, unadulterated quality with no external adulteration and is safe for consumption. Grade 2 is when fruit has some external adulteration but not internal adulteration. Grade 3 is when the fruit has internal adulterated and is not safe for consumption. If the formalin level is above the acceptable level permitted in that type of fruit/vegetable as per our machine learning model, then we place it in Grade 3 as it is adulterated. If not, then we check for any external adulteration on the fruit/vegetable using our YOLOv8 model. If there is no external adulteration then we classify it as Grade 1 however if there is, then we classify it as Grade 2.

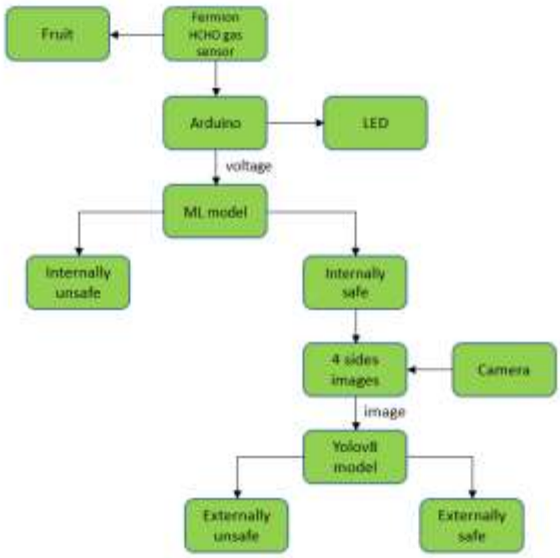

Fig.1: Block architecture diagram for the system

B. Naturally Occurring Formaldehyde

Formaldehyde is a compound that is produced naturally in fruits, vegetables, meats, fish, etc. as a by product of metabolism. In biological specimens, Formaldehyde is produced from methylated compounds and conversion of glycine and serine. The formaldehyde content produced varies in different food items based on the food types and conditions. The dosage of extra formaldehyde can be found by figuring out the natural amount of formaldehyde content in the fruit. We create a system to detect formaldehyde content in a fruit and create a dataset of formaldehyde levels in samples of unadulterated fruit and manually adulterated fruit created by injecting excess formalin.

C. Formaldehyde Detection

We have designed an airtight enclosure to house the fruit or vegetable during the formaldehyde detection process. The sealed environment is essential because the Fermion gas sensor, which is highly sensitive to formaldehyde, requires a controlled atmosphere to accurately measure the gas levels. The Fermion sensor is positioned inside the enclosure, attached to the lid, where it can monitor the air within the container without making direct contact with the fruit or vegetable. The sensor is connected to a microcontroller, such as an Arduino, which captures the formaldehyde levels detected by the sensor and feeds this data into our machine-learning model for analysis.

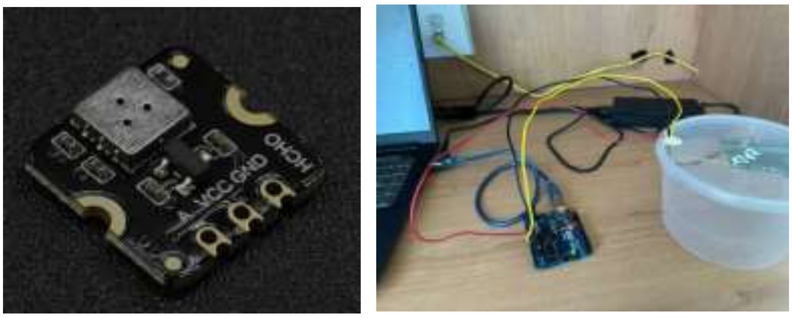

Fig.2: Proposed design for embedding the sensor

D. Model Selection for External Adulteration Check

The YOLOv8 model is a powerful tool for object detection, specifically designed for real-time applications. It's like a super-fast detective that can scan an entire image in a single glance. It can be seen from Table I that YOLOv8n-cls is perfect for deploying on devices with limited resources thanks to its efficiency and small size.

Table 1. An example of a table.

Model	Size (pixels)	Acc Top1	Acc Top5	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	Params (M)	FLOPs (B) at 640
YOLOv8n-cls	224	69.0	88.3	12.9	0.31	2.7	4.3
YOLOv8s-cls	224	73.8	91.7	23.4	0.35	6.4	13.5
YOLOv8m-cls	224	76.8	93.5	85.4	0.62	17.0	42.7
YOLOv8l-cls	224	76.8	93.5	163.0	0.87	37.5	99.7
YOLOv8x-cls	224	79.0	94.6	232.0	1.01	57.4	154.8

In tests using the COCO dataset, YOLOv8n-cls showed impressive results. It's incredibly fast, able to process an image in just 12.9 milliseconds on a regular computer. This means it can detect almost instantly, allowing for quick responses. Despite its small size, it still achieves a decent accuracy of 69% on the COCO dataset, which is more than enough for our purposes. Considering its speed, efficiency, and accuracy, YOLOv8n-cls is the ideal choice for training our image data in real-time.
However, we still compare the results with other commonly used image processing models.

5. Implementation

A. Datasets

In our research, we utilized various datasets tailored to the specific functions of our different models, each serving a unique purpose in the adulteration detection process. The process of data collection was labour-intensive, as we manually gathered and curated datasets to meet our precise requirements.

One of the key datasets is the *Formaldehyde in Food* dataset, published by the Centre for Food Safety (CFS). This dataset provides a list of the acceptable range of formaldehyde levels in various fruits and vegetables, which is deemed safe for consumption. We use this dataset to determine whether a fruit or vegetable is internally adulterated based on its formaldehyde content.

Another critical dataset is *Apples with Wax*, which we constructed manually. This dataset consists of images of apples with and without wax coatings, and it is used to train our YOLOv8 model. The model uses this dataset to classify apples as either externally adulterated or not, based on the presence of wax.

Additionally, we developed the *Apple PPM from Sensor* dataset, which contains over 200 readings of formaldehyde levels in apples. These readings were collected using our Fermion sensor and include data from both known adulterated and unadulterated apple samples. This dataset plays a crucial role in our model's ability to accurately detect internal adulteration in apples based on formaldehyde measurements.

1	fruit_label	input	voltage	state
2	1	3.3	485	0
3	1	3.3	433	0
4	1	3.3	426	0
5	1	3.3	429	0
6	1	3.3	438	0
7	1	3.3	391	0
8	1	3.3	439	0
9	1	3.3	454	0
10	1	3.3	427	0
11	1	3.3	464	0
12	1	3.3	426	0
13	1	3.3	429	0
14	1	3.3	438	0
15	1	3.3	391	0
16	1	3.3	439	0
17	1	3.3	454	0
18	1	3.3	427	0
19	1	3.3	464	0
20	1	3.3	426	0
21	1	3.3	429	0
22	1	3.3	438	0
23	1	3.3	391	0

Fig.3: Snippet from *Apple PPM from Sensor* dataset (0 indicates unadulterated sample)

B. Experimentation

In our study, we embarked on a comprehensive methodology to assess the adulteration status of apple samples. Initially, we employed a Fermion gas sensor coupled with an Arduino system to meticulously gather 200 voltage readings, serving as proxies for formaldehyde levels. Of these, 100 readings were derived from unadulterated apple samples, while the remaining 100 corresponded to adulterated ones. Each subset of 100 readings encompassed 50 instances with an input voltage of 3.3V and another 50 with a voltage of 5V. To ensure data integrity, we computed the average of 10 sensor readings to represent a single value in our dataset, thereby mitigating the impact of outliers. Additionally, we enforced a 10,000 ms interval between consecutive readings.

Following data collection, we proceeded to train various machine learning models, including Logistic Regression, Support Vector classifier, Decision Tree classifier, Random Forest classifier, and KNN classifier, to discern patterns indicative of adulteration. Moreover, we developed sophisticated deep learning models, notably YOLOv8, tailored to identify external adulteration. These models were trained on manually curated datasets of images specifically designed for the task at hand.

Subsequently, we integrated the Random Forest classifier and YOLOv8 model, both yielding superior performance in their respective categories. The integration process involved acquiring four voltage values from the sensor, akin to the previous data collection procedure, along with the input voltage. Leveraging this information, our model predicted the internal adulteration status of the sample. If deemed internally adulterated, the system alerted the user and halted further analysis. Conversely, for samples deemed free from internal adulteration, images of the four sides of the sample were captured and subsequently processed through the YOLOv8 model to detect external adulteration. An aggregate score, derived from the average of the four sides, exceeding 60% was indicative of external adulteration, prompting the classification of the sample as adulterated. Conversely, if the aggregate score fell below the threshold, the sample was deemed safe for consumption.

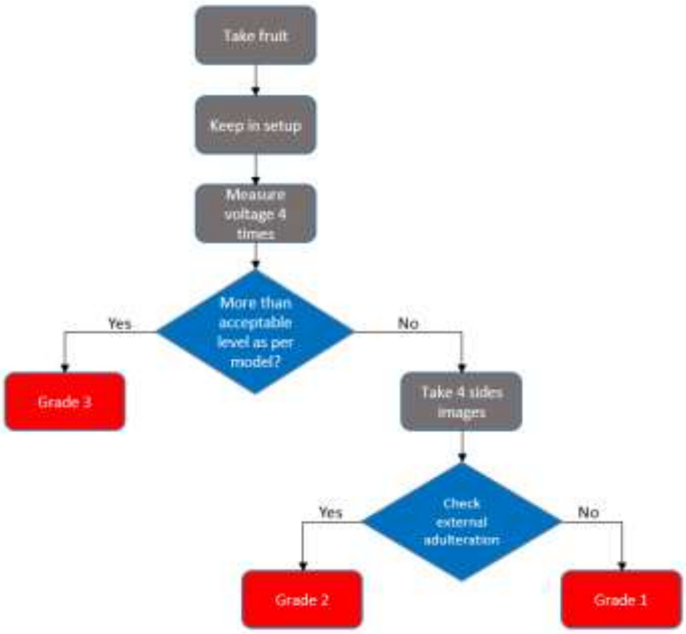

Fig.4: Flowchart diagram for the working of the system

6. Result and Discussion

We implemented our proposed solution using the designed enclosure to hold the fruit and ensure an airtight environment for accurate formaldehyde level detection. The Fermion gas sensor was positioned inside the enclosure, attached to the lid, to sense the air within. Four random readings were taken from the sensor, accounting for outliers, and the average reading was calculated. If the fruit was determined to be internally adulterated based on the dataset, it was excluded from further external adulteration checks. Conversely, if deemed unadulterated, four images were captured from different angles for external adulteration detection. The images were compared with the dataset, and if the average adulteration level exceeded 60%, the fruit was labelled as externally adulterated, indicating potential risks. The experimentation aimed to validate the effectiveness of our approach in detecting and grading adulteration levels in fruits. We also evaluated the accuracies of all the various models and algorithms to determine which one is most suitable for our purposes.

A. Performance of Models for External Adulteration Detection

Table 2: Result Comparison of Various Models used for External Adulteration Detection

Model	Accuracy	Precision	Recall	F1 Score
YOLOv8n-cls	92%	0.98	0.96	0.93
ResNet-50	57%	0.61	0.53	0.59
VGG-19	81%	0.83	0.76	0.82
GoogleNet	85%	0.89	0.82	0.86

For detection of external adulteration, the YOLOv8 model performs much better than the other models. A possible reason YOLOv8 outperforms in fruit adulteration detection could be due to its real-time object detection capabilities, efficient grid-based methodology, and ability to capture spatial context in a single pass. YOLOv8's architecture excels at detecting objects in complex scenes, leading to higher accuracy across various fruits, while other models mentioned in Table II, like ResNet-50's hierarchical feature extraction may struggle with subtle object detection and require more computational resources for optimization.

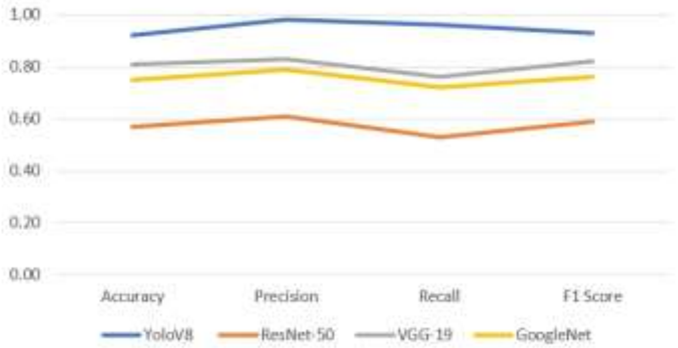

Fig.5: Line graph comparing the metrics of the various models

B. Performance of Models for Internal Adulteration Detection

Table 3: Accuracy results of various algorithms used for internal adulteration detection

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	95%	1.0	0.91	0.95
Support Vector Classifier	88.33%	1.0	0.79	0.88
Decision Tree Classifier	90%	0.96	0.85	0.90
Random Forest Classifier	95%	1.0	0.91	0.95
KNN Classifier	95%	1.0	0.91	0.95

Logistic Regression, Random Forest, and K-Nearest Neighbors (KNN) outperform Support Vector Machine (SVM) and Decision Tree classifiers due to their simplicity, versatility, and ability to capture complex relationships in the data. Logistic Regression is well-suited for binary classification tasks and offers interpretable results, making it a reliable choice for straightforward classification problems. Random Forest combines the strength of multiple decision trees to handle high-dimensional data and nonlinear relationships, providing robust performance and resistance to overfitting. KNN, on the other hand, relies on the proximity of data points to make predictions, making it effective in capturing local patterns and suitable for datasets with varied distributions.

7. Conclusion and Prospects

Our research presents a multi-model system for fruit adulteration detection which effectively combines image processing and sensor technologies to ensure food safety. The core of our approach involves the use of a Fermion sensor to measure formaldehyde levels in produce. Our design incorporates the sensor in an airtight container, aligning with our goal of providing a comprehensive solution for assessing food quality and safety. Our design, integrating YOLOv8 for external adulteration identification has demonstrated strong performance. The use of diverse datasets contributed to the robustness of our models. To classify the produce, our system first evaluates formaldehyde levels using the Fermion sensor. If the levels exceed acceptable limits, the produce is classified as Grade 3 due to internal adulteration. If the formaldehyde levels are within the acceptable range, we then use the YOLOv8 model to detect any external adulteration. If no external adulteration is found, the produce is classified as Grade 1. Conversely, if external adulteration is detected, it is classified as Grade 2. Our methodology leverages advanced technologies to provide a comprehensive solution for detecting both internal and external adulteration. The system's integration of sensor-based measurements and image processing ensures a thorough evaluation of produce quality. It addresses key concerns in the food industry, such as harmful wax coatings and the effects of fruit age on formaldehyde levels, making it a versatile tool for vendors and sellers.

Looking ahead, the future scope of this project includes extending the methodology to a wider variety of fruits, and potentially vegetables. Additionally, developing a user-friendly application to collect and display sensor readings could enhance the system's accessibility and usability. Furthermore, incorporating a fan or ventilation system within the sensor enclosure could improve formaldehyde dispersion and detection efficiency, advancing the overall effectiveness of the adulteration detection process. Overall, our approach offers a promising solution for combating fruit adulteration, contributing to food safety and quality.

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