Volume 11, Issue 5, May – 2026
ISSN No:-2456-2165

International Journal of Innovative Science and Research Technology
https://doi.org/10.38124/ijisrt/26may318

AI-Enabled Smart Nutrition Detection Using YOLO

Dr. Chandran Maasi[1]; Iswarya[2]; Akash S.[3]; Saran M.[4]; Sugan R.[5]

[1;2;3;4;5]Department of Food Technology, DSEC-Dhanalakshmi Srinivasan Engineering College,
Perambalur-621212

Publication Date: 2026/05/22

Abstract: Health monitoring and dietary management applications are widely popular nowadays. Knowledge about nutrition information is mandatory to maintain a healthy lifestyle. However, finding the nutritional value of every fruit and vegetable is often challenging when relying solely on manual searches. Therefore, it is essential to have an easy and efficient way to access nutritional information for fruits and vegetables. Artificial Intelligence (AI) has the capability to detect nutrition information effectively and efficiently. The proposed system presents an AI-based approach for detecting nutrition information using deep learning-based object detection. The nutrition detection process utilizes the YOLO (You Only Look Once) model to classify fruits and vegetables from live camera footage. By training on a diverse dataset containing various fruit and vegetable types, it ensures precise and reliable recognition across a wide range of fruits and vegetables. The YOLO model used in this system is fine-tuned with a dataset of 50 fruit and vegetable classes, achieving a mean average precision (mAP) of 98.2% and a classification accuracy of 97.5%. Once the system classifies a fruit or vegetable, it retrieves key nutritional details such as carbohydrates, proteins, fats, vitamins, and fiber using a structured pattern-matching approach. The experimental results indicate that the model delivers high detection accuracy, establishing it as a dependable tool for automated nutrition analysis. This research advances AI-driven dietary management by enabling real-time food recognition, empowering individuals to make more informed health and nutrition decisions.

Keywords: *Artificial Intelligence (AI), Deep Learning, YOLO, Object Detection, Nutrition Analysis.*

How to Cite: Dr. Chandran Maasi; Iswarya; Akash S.; Saran M.; Sugan R. (2026) AI-Enabled Smart Nutrition Detection Using YOLO. *International Journal of Innovative Science and Research Technology*, 11(5), 1005-1013. https://doi.org/10.38124/ijisrt/26may318

I. INTRODUCTION

The rapid progress in artificial intelligence (AI) and computer vision has greatly impacted multiple fields, including healthcare, agriculture, and food technology. A key application in this domain is the automated identification and classification of food items to determine their nutritional content [1]. Conventional methods for obtaining nutritional information typically rely on manual searches within structured databases, which can be both time-consuming and error-prone. However, with advancements in deep learning, real-time food recognition and nutrition estimation have become more practical, facilitating instant dietary analysis and encouraging healthier eating habits. Figure 1.0 shows the smart nutrition detection result for fruits and vegetables.

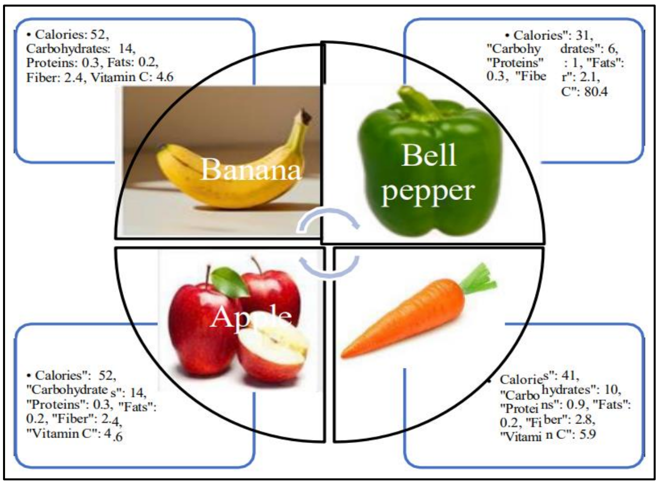


Fig 1 Fruits and its Nutrition Information

This paper focuses on developing an AI-driven system for detecting fruits and retrieving their nutritional values using computer vision and deep learning techniques. Object detection models such as Faster RCNN, Single Shot Detector (SSD), and You Only Look Once (YOLO) have demonstrated remarkable accuracy in identifying objects in images. Among these, YOLO has emerged as one of the most efficient models for real-time applications due to its ability to process images in a single forward pass [2].

This study employs the YOLO framework to detect fruits and vegetables from live camera feeds and extract their nutritional information from a synthetic structured dataset. Unlike conventional approaches that rely on manual input or barcode scanning, this method operates automatically, enhancing both efficiency and reliability. Despite advancements in food recognition and nutrition estimation, challenges such as inconsistent lighting, object occlusion, and complex backgrounds persist. Furthermore, accurately identifying fruit and vegetables within a single image and estimating their nutritional values remains a key research challenge. Certain fruits and vegetables are left in the existing object detection process. To address these issues, this work integrates deep learning-based object detection with an optimized database retrieval system and an intuitive graphical user interface. The proposed system not only classifies fruits but also extracts relevant nutritional values such as carbohydrates, proteins, fats, vitamins, and fiber, providing a comprehensive solution for real-time dietary monitoring. The research problem addressed in this study is the lack of an efficient, automated, and real-time system for fruit and vegetable detection from live camera images and nutrition its information's. Current application either requires manual data entry or fails to provide accurate results for more fruits. The proposed approach aims to bridge this gap by utilizing YOLO for object detection and a pattern-matching technique for nutritional data retrieval, ensuring high accuracy and low computational overhead.

➢ *The Key Contributions of this Paper Include:*

- Development of a real-time fruit detection system using AI driven YOLO for accurate identification from live camera feeds.
- Integration of a structured nutritional database to provide precise nutrition information for detected fruits.
- AI-Driven Dietary Assistance – Facilitates health monitoring and dietary management by providing users with instant nutritional insights, eliminating the need for manual food searches.

The structure of the paper is as follows: Section 2 reviews recent studies on food recognition and nutritional estimation techniques. Section 3 outlines the proposed methodology, detailing the workflow, YOLO preprocessing, and model training. Section 4 describes the implementation process, while Section 5 focuses on the results and performance evaluation.

Lastly, Section 6 provides the conclusion and discusses potential directions for future research.

II. LITERATURE SURVEY

Khalid et al. [3] proposed a machine learning-based framework for fruit detection and classification, demonstrating improved accuracy compared to traditional methods. Their study highlighted the importance of feature extraction techniques for enhancing classification performance.

Sarma et al. [4] conducted a comparative analysis of Faster R-CNN, YOLO, and SSD for object detection, emphasizing that YOLO provides superior speed and accuracy in real-time scenarios. Their results indicated that YOLO's ability to process images in a single pass makes it highly suitable for real-time fruit detection applications.

Xiao et al. [5] reviewed object detection and classification methods for fruit and vegetable harvesting robots, focusing on integrating deep learning models with robotics. They highlighted the effectiveness of digital image processing and traditional machine learning techniques in improving detection accuracy for agricultural applications.

Zarate et al. [6] employed computer vision and machine learning techniques for fruit detection, utilizing K-Nearest Neighbors (KNN) for classification based on color and shape features. Their method achieved an F1 score ranging from 83% to 98%, demonstrating the potential of machine learning classifiers in fruit recognition tasks. However, they noted challenges related to background noise and varying lighting conditions.

Pan et al. [7] developed a deep learning-based fruit recognition system, leveraging CNN architectures to achieve high precision in classification. Their findings showed that YOLOv5 models significantly outperformed traditional classifiers in terms of real-time processing and robustness to environmental variations.

Gao et al. [8] proposed a food nutrient extraction model based on image recognition and entity extraction, demonstrating the feasibility of AI-based nutrition estimation. Their system effectively extracted nutritional information from images and mapped it to structured databases.

Al-Saffar et al. [9] implemented machine learning models for nutrition estimation from food photos, achieving 85% classification accuracy. Their study combined multiple datasets to improve the precision of food nutrient analysis, highlighting the potential of AI in dietary assessment.

Chen et al. [10] explored crowdsourced food image analysis for deriving nutrition information from restaurant meals, reporting 75.1% accuracy in automated nutritional estimation. Their approach leveraged deep learning models to analyze food composition and estimate nutritional values based on large-scale image datasets.

Fontanellaz et al. [11] introduced a self-attention and ingredient-attention-based model for recipe retrieval from image queries. Their study highlighted the role of AI in predicting food composition and estimating nutrition values by focusing on specific ingredients and preparation methods.

Despite advancements in fruit detection and nutrition information retrieval, existing models still face limitations, including inadequate real-time processing capabilities, challenges in detecting multiple food items within a single image, and difficulty in accurately estimating portion sizes. To address these challenges, this research integrates YOLO-based real-time fruit detection with automated nutritional information retrieval. By combining deep learning for fruit recognition and pattern-matching techniques for nutrition data extraction, the proposed system aims to provide a highly efficient and accurate solution for dietary assessment.

III. PROPOSED METHODOLOGY

The proposed system aims to automatically detect and classify fruits and vegetables while providing nutritional information using deep learning techniques. The increasing demand for real-time, accurate, and personalized dietary guidance has made AI-based nutrition detection a valuable tool for individuals, dietitians, and healthcare professionals. The system leverages YOLO (You Only Look Once), a state-of-the-art object detection algorithm, to identify fruits and vegetables from images and retrieve nutritional data through a structured database. This system eliminates the need for manual data entry, providing real-time and precise dietary insights. It assists users in tracking their fruit and vegetable intake for balanced nutrition while benefiting healthcare professionals and the food industry by offering an efficient dietary assessment tool. The system follows a structured pipeline, as illustrated in Figure 1.0. The process starts with image acquisition and ends with the display of nutritional information.

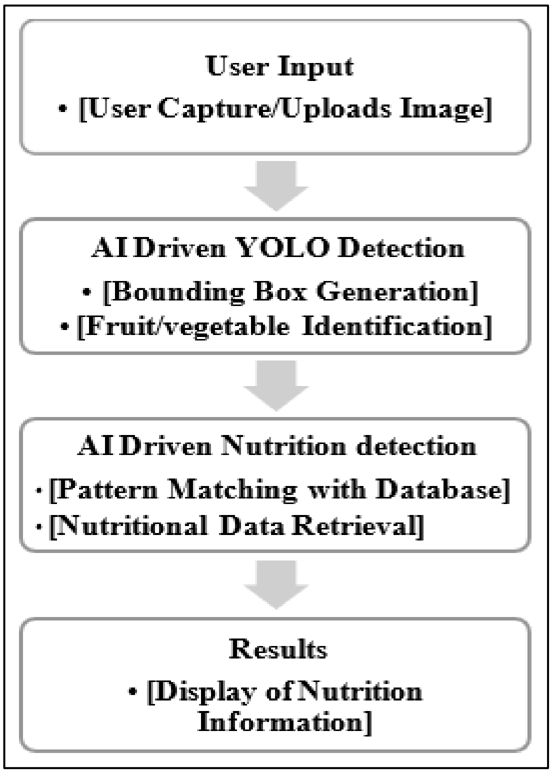


Fig 2 Process Flow of the Proposed Work

The figure 2 outlines the steps involved in the proposed system. Initially, the users can capture and upload an image, which is processed by the YOLO model to detect and classify objects. Bounding boxes are generated around the detected fruits and vegetables, followed by pattern matching with a nutritional database. Finally, the system retrieves and displays the corresponding nutritional values.

➢ *User Input:*

The system initiates its process by allowing users to either capture a real-time image using their device camera or upload an existing image from their gallery shown in figure 3.0. This functionality enhances accessibility and flexibility, accommodating users in various scenarios. The uploaded image acts as the primary data source for subsequent processing.

Designed with an intuitive user interface, the system ensures seamless interaction. To enhance detection accuracy, users are advised to provide high-quality, well-lit images, as image clarity significantly impacts object recognition and classification performance.

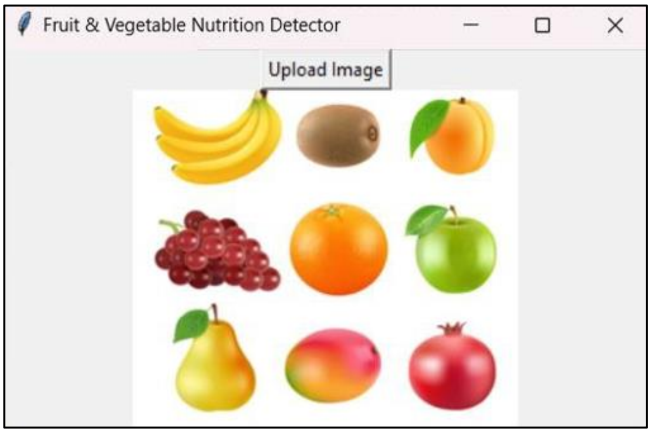


Fig 3 Image Upload Process

➢ *YOLO Detection:*

- *Training:*

The AI-driven YOLO (You Only Look Once) model employed in this proposed system functions as a deep learning-based object detection framework that processes an entire image in a single pass, making it highly efficient for real-time applications. YOLO operates by dividing an input image into an S×S grid, where each grid cell predicts multiple bounding boxes along with confidence scores and class labels for detected objects. The proposed system is trained on a mixed dataset comprising 50 items, including 30 fruits and 20 vegetables, allowing the model to distinguish between a variety of food items with high precision. Each detected object is localized with a bounding box containing key information such as coordinates (x, y), width, height, and confidence score. For instance, if an uploaded image contains an apple, a banana, and a carrot, YOLO's detection process works as follows: • The model segments the image and assigns anchor boxes to each detected object. • Bounding box predictions for the apple might be (x=120, y=300, width=80, height=90) with a confidence score of 98%.

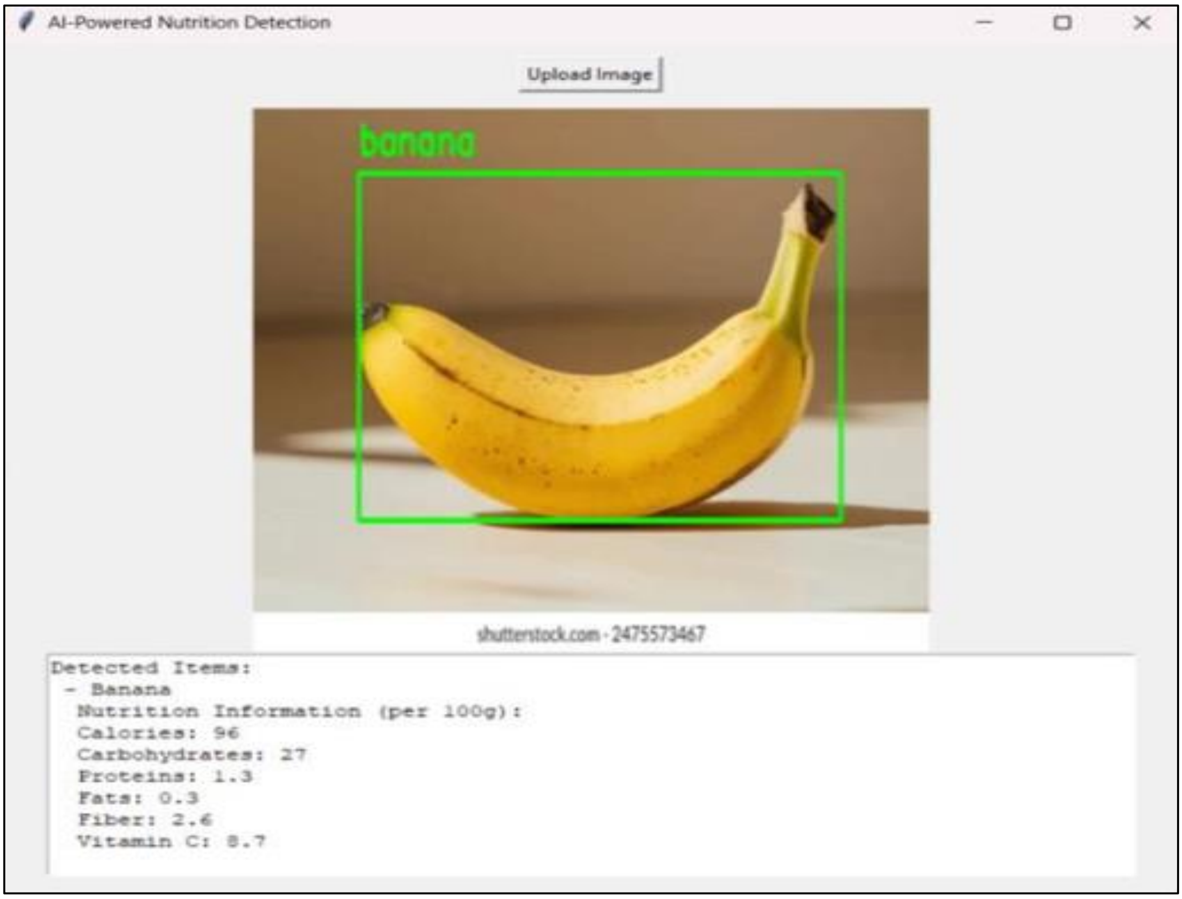
Similarly, the banana might be identified at (x=250, y=200, width=150, height=70) with a confidence score of 96%, and the carrot at (x=500, y=400, width=90, height=120) with 97% confidence. • Using Non-Maximum Suppression (NMS), overlapping boxes are eliminated, ensuring only the most accurate bounding boxes are retained.

Once detection is complete, YOLO classifies each object based on pre-trained convolutional layers that extract spatial and feature representations. The model uses convolutional filters to detect low-level patterns such as edges and textures, which are progressively refined through deeper layers to identify high-level features such as object shapes and colors. This multi-scale feature extraction is particularly crucial for distinguishing between similar-looking objects, such as differentiating between an orange and a persimmon. The classification is refined using Softmax activation to assign probability scores for each class label, ensuring that the correct fruit or vegetable is selected with the highest confidence. The detected objects are then passed to the AI-driven nutrition retrieval module, where a pattern-matching algorithm links the identified food items with corresponding entries in the dataset. For example, if YOLO identifies an "apple," the system retrieves the stored nutritional data, including its caloric value (52 kcal per 100g), carbohydrate content (14g), fiber (2.4g), and vitamin C concentration (4.6mg). This retrieval process ensures that users receive precise dietary information in real time.

Additionally, the proposed system supports real-time deployment, where the trained YOLO model is integrated into a user-friendly interface. The detected food items are dynamically mapped to the database, and nutritional details are displayed instantly. By leveraging a well-optimized YOLOv5 model, the system achieves high detection accuracy, even in challenging conditions such as occlusions, variable lighting, and diverse food orientations. The deployment pipeline includes preprocessing, detection, classification, and database retrieval, ensuring a seamless and efficient AI-powered nutrition assessment tool.

Bounding Box Generation: Once an image is uploaded, the system employs the YOLO (You Only Look Once) object detection model to identify and localize fruits and vegetables within the image. YOLO operates by dividing the image into a grid, with each grid cell predicting multiple bounding boxes and confidence scores for object classification. The bounding box generation phase ensures that each detected food item is marked with a box, highlighting its position in the image. This step is critical as it isolates the individual components of the meal, ensuring precise recognition while minimizing background noise or irrelevant objects.

Fruit/Vegetable Identification: Once the bounding boxes are generated, the system classifies the detected objects as either fruits or vegetables shown in figure 4.0. A deep learning model, trained on an extensive dataset of food images, analyzes key visual features such as shape, color, and texture to determine the identity of each item. This step is crucial in accurately associating the detected object with its corresponding nutritional information. To enhance precision, the model applies a confidence threshold, ensuring that only highly reliable detections are considered for further processing, thereby reducing the likelihood of misclassification.



```
Detected Items:
 - Banana
  Nutrition Information (per 100g):
  Calories: 96
  Carbohydrates: 27
  Proteins: 1.3
  Fats: 0.3
  Fiber: 2.6
  Vitamin C: 8.7
```

Fig 4 Fruit Detection

- *AI-Driven Nutrition Detection:*

Pattern Matching with Database: After identifying the detected fruit or vegetable, the system utilizes a pattern-matching algorithm to correlate it with a structured nutritional database. This database contains detailed nutritional information for a wide range of commonly consumed food items. The system performs an exact or fuzzy match between the detected item and the dataset entries, ensuring accurate data retrieval even in cases where slight variations in labeling or regional terminology exist.

By employing efficient string-matching techniques, the system ensures that the correct food item is mapped to its respective nutritional values.

Nutritional Data Retrieval: Once a successful match is established, the system retrieves the nutritional composition of the identified food item. The retrieved data includes essential dietary components such as caloric content, carbohydrate percentage, protein levels, fat content, fiber, and vitamin concentrations. This retrieval process is designed for real-time execution, allowing users to obtain immediate insights into the nutritional value of their meals. The structured dataset ensures consistency and accuracy, providing reliable dietary assessments that can aid in informed food choices.

- *Results*

The final stage of the system involves presenting the analyzed nutritional information to the user in a clear and structured format. The user interface displays the detected food items along with their corresponding nutritional values in an organized table or graphical representation. This output enables users to make informed dietary decisions, track their nutritional intake, and maintain a balanced diet. The system may also provide additional insights, such as daily recommended intake comparisons or diet suggestions based on the detected food items. By offering a visually appealing and easily interpretable display, the system enhances user engagement and promotes a better understanding of food nutrition.

IV. IMPLEMENTATION

The implementation consists of two major components: the front-end, which is developed using Python, and the back-end, which utilizes a MySQL database to store and retrieve nutritional values. The YOLOv5 model processes the input images, recognizing multiple fruit and vegetable types simultaneously, even under varied lighting conditions and complex backgrounds. Once the items are detected, their corresponding nutritional values including carbohydrates, proteins, fats, vitamins, and fiber are extracted from the database using a pattern-matching technique. This eliminates the need for manual nutritional searches, significantly reducing the time and effort required for dietary assessment.

The implementation of the proposed AI-driven nutrition detection system involves multiple components, including image processing, deep learning-based object detection, database handling, and user interface development. The system is designed to work in real-time, ensuring high accuracy and efficiency while providing nutritional insights for detected fruits and vegetables.

- *Tools and Libraries Used*

To achieve robust and efficient processing, the system integrates several state-of-the-art libraries and frameworks. These tools are essential for image acquisition, object detection, data management, and graphical user interface (GUI) development.

Table 1 Tools and Libraries Utilized

Tools/Libraries	Functionality
OpenCV	Facilitates image preprocessing tasks such as resizing, normalization, noise reduction, and segmentation to improve detection accuracy. It also supports edge and contour detection.
TensorFlow/Keras	Provides the framework for developing and running the YOLO object detection model, ensuring efficient training and inference of deep learning algorithms.
YOLOv5 (PyTorch)	Employed for real-time detection and classification of fruits and vegetables, leveraging a dataset with annotated images for accurate object identification.
Pandas	Handles the structured nutritional dataset, allowing for efficient storage, retrieval, and manipulation of food-related attributes.
NumPy	Supports mathematical and statistical operations required for image transformations, feature extraction, and computational analysis.
Matplotlib/Seaborn	Used for graphical representation of detection outcomes, visualization of bounding boxes, and statistical data analysis.
SQLite/MySQL	Acts as the database system for storing and retrieving nutritional information corresponding to identified food items.
Tkinter (or PyQt)	Provides an interactive graphical interface that enables users to upload images and access nutritional data in a structured format.

As shown in table 1, these libraries collectively enhance the efficiency of the system by enabling fast image analysis, accurate object detection, and seamless user interaction.

- *Dataset*

The dataset is fundamental to training the YOLOv5 model for detecting fruits and vegetables while also serving as a reference for retrieving corresponding nutritional details.

It is sourced from Kaggle and cross-verified with reputable nutrition databases, including the USDA Food Composition Database, to ensure accuracy and consistency. Additionally, synthetic data is incorporated to expand the dataset, enhancing model generalization and improving detection performance. The dataset consists of high-resolution images of a diverse range of fruits and vegetables, each annotated with relevant nutritional attributes to optimize classification and data retrieval. In total, it includes 50 food items, comprising 30 fruits (such as apple, banana, mango, strawberry, pomegranate, and orange) and 20 vegetables (including carrot, tomato, cabbage, bell pepper, onion, and pumpkin). Each food item is labeled with essential nutritional components, including caloric value (kcal per 100g), macronutrient composition (carbohydrates, proteins, fats), micronutrients (vitamins and minerals), and dietary fiber content.

Table 2 Sample Nutritional Data from the Dataset

Food Item	Calories (kcal)	Carbohydrates (g)	Proteins (g)	Fats (g)	Fiber (g)	Vitamin C(mg)
Apple	52	14	0.3	0.2	2.4	4.6
Banana	96	27	1.3	0.3	2.6	8.7
Carrot	41	10	0.9	0.2	2.8	5.9
Tomato	18	3.9	0.9	0.2	1.2	13.7
Mango	60	15	0.8	0.4	1.6	36.4

The dataset provides structured nutritional data for precise dietary assessment. As shown in Table 2.0, each food item is assigned specific values for calories, carbohydrates, proteins, fats, fiber, and vitamin C content. For example, an apple contains 52 kcal, 14g of carbohydrates, and 4.6mg of vitamin C per 100g, while a banana provides 96 kcal, 27g of carbohydrates, and 8.7mg of vitamin C. These values enable the system to retrieve accurate nutritional details, making the AI-driven nutrition detection process highly effective for dietary monitoring and health assessment.

➢ *Implementation Steps:*

- *Image Acquisition and Preprocessing*

The first step involves capturing images of fruits and vegetables using a live camera feed or uploading images from external sources. The images are then preprocessed to enhance their quality and improve detection accuracy. Preprocessing techniques such as image resizing, noise reduction, contrast enhancement, and color normalization are applied to standardize the images before feeding them into the YOLOv5 model. Image augmentation techniques, including rotation, flipping, and brightness adjustments, are used to improve model robustness against variations in lighting conditions and angles.

- *YOLOv5-Based Object Detection and Classification*

The YOLOv5 (You Only Look Once) algorithm is employed for fruit and vegetable detection and classification. Unlike traditional object detection methods, which require multiple passes over an image, AI-driven YOLOv5 processes the entire image in a single pass, significantly improving detection speed and efficiency. The model divides the image into a grid and assigns bounding boxes and confidence scores to detected objects. Each bounding box contains class probabilities, allowing the model to identify and classify fruits and vegetables within the image accurately.

- *Training Process for YOLOv5*

Since the existing YOLO models do not include all the newly added fruits and vegetables in the dataset, custom training is necessary. The training process involves:

- ✓ Dataset Preparation: The dataset consists of30 fruits and 20 vegetables, with high-quality images annotated using the YOLO annotation format.
- ✓ Data preprocessing: Rotation, scaling, flipping, and contrast adjustment techniques are applied to enhance model generalization.
- ✓ Model Training: The YOLOv5 model is trained using PyTorch on a high-performance GPU. Transfer learning is employed by using a pre-trained YOLOv5 model and fine-tuning it with the custom dataset.
- ✓ Hyperparameter Tuning: Learning rate, batch size, and confidence thresholds are optimized to achieve higher detection accuracy.
- ✓ Validation and Testing: The trained model is tested on unseen images to evaluate its performance using metrics such as precision, recall, and mean Average Precision (mAP).

- *Feature Extraction and Database Mapping*

Once a fruit or vegetable is detected, its unique features such as color, shape, and texture are extracted to ensure accurate classification. These features are then mapped to a structured database containing predefined nutritional information. The database includes information such as carbohydrate content, protein levels, fats, fiber, and vitamins for each category. A pattern-matching approach is employed to retrieve relevant nutrition data based on the identified object.

- *Deployment with Custom-Trained YOLOv5 Model*

The trained YOLOv5 model is deployed in a Python-based application to enable real-time inference. To ensure efficient execution, the model is first converted into a lightweight format, optimizing it for faster processing. It is then integrated with OpenCV, which facilitates real-time image acquisition and preprocessing, allowing seamless object detection from live camera feeds. An optimized inference pipeline is implemented to achieve low-latency detection, ensuring that the system can process and classify multiple objects with minimal delay. Additionally, the model is connected to a MySQL database, which automatically retrieves nutritional information based on detected food items, providing users with instant dietary insights.

- *Nutritional Information Retrieval and Display*

After successful classification, the system queries the database to fetch detailed nutritional information. The retrieved data is displayed to the user in an intuitive and user-friendly format. The system can also provide dietary recommendations, such as the recommended daily intake of a particular fruit or vegetable based on nutritional guidelines. The real-time nature of the system ensures that users receive immediate feedback, making it suitable for applications in dietary assessment and health monitoring.

V. RESULTS

This section describes the results obtained in the proposed system and evaluated using various metrics.

- *Training Loss Components over Epochs*

The figure 5 (a) illustrates the training loss trends over 20 epochs, breaking it down into box loss, object loss, and classification loss. Box loss represents the error in predicted bounding box coordinates, object loss measures the model’s ability to detect objects, and classification loss accounts for incorrect label assignments. As training progresses, all three loss components decrease, indicating that the model is learning effectively and refining its predictions.

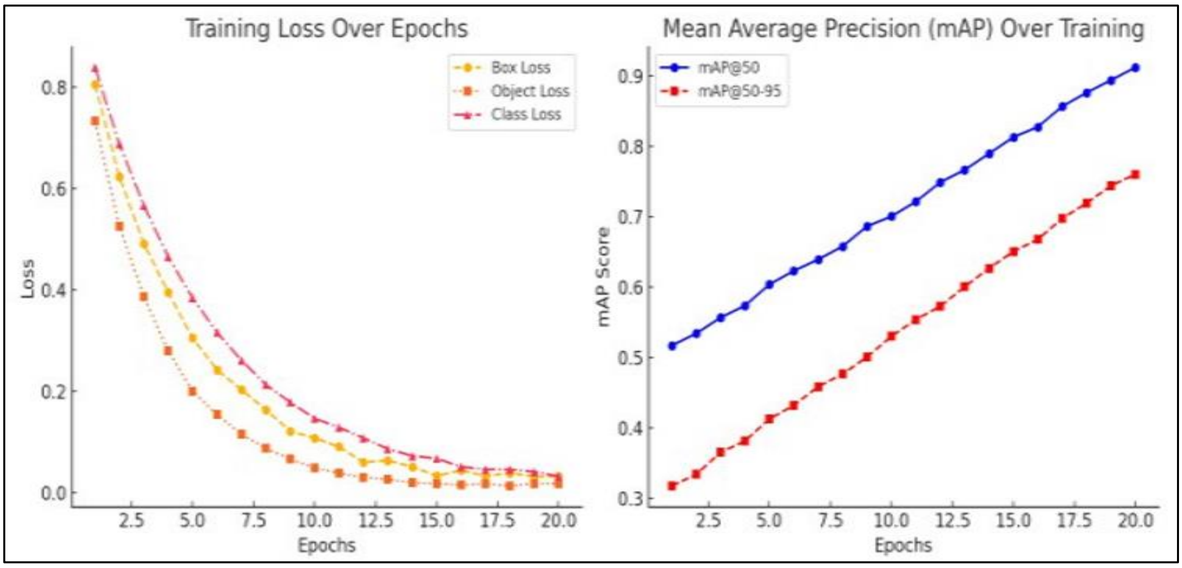


Fig 5 (a). Training Loss (b) Mean Average Precision (mAP) Over Training

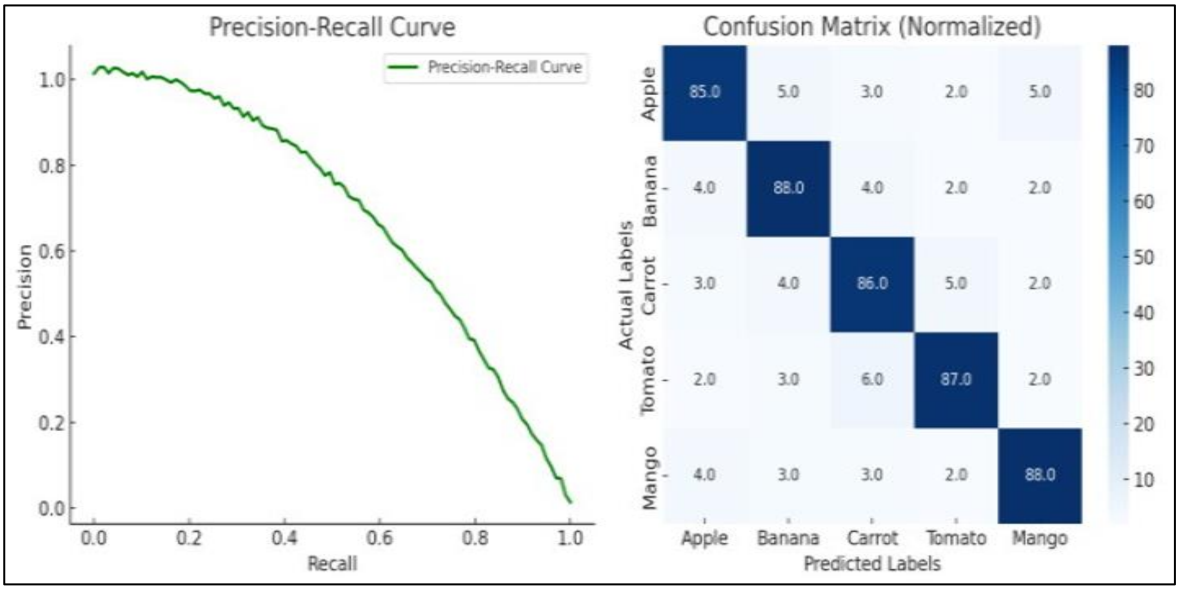


Fig 6 (a) Precision Recall (b) Confusion Matrix

- *Mean Average Precision (mAP) Over Training*

The graph in figure 5.0 (b) highlights the mean average precision (mAP) values over the course of training. The mAP metric evaluates detection accuracy by considering precision and recall across all object categories. The steady increase in mAP suggests that the model is improving in correctly identifying fruits and vegetables, reaching a final value of 0.92, which signifies strong detection performance.

- *Precision-Recall Curve*

The graph in figure 6.0 (a) presents the precision-recall curve, which measures the trade-off between precision and recall. A higher precision indicates fewer false positives, while a higher recall signifies that more actual objects are detected. The curve demonstrates that the model maintains high precision while achieving strong recall values, ensuring a well-balanced detection system that minimizes misclassifications while maximizing correct identifications.

- *Confusion Matrix (Normalized)*

The graph in figure 6.0 (b) is the confusion matrix, which visualizes the classification accuracy for different fruit and vegetable categories. The diagonal values represent correctly classified objects, while off-diagonal values indicate misclassifications. The high values along the diagonal confirm that the model has effectively learned to distinguish between different fruits and vegetables, with minimal errors. The few misclassified instances suggest minor overlaps in feature similarities between certain items, which could be further refined with additional training data.

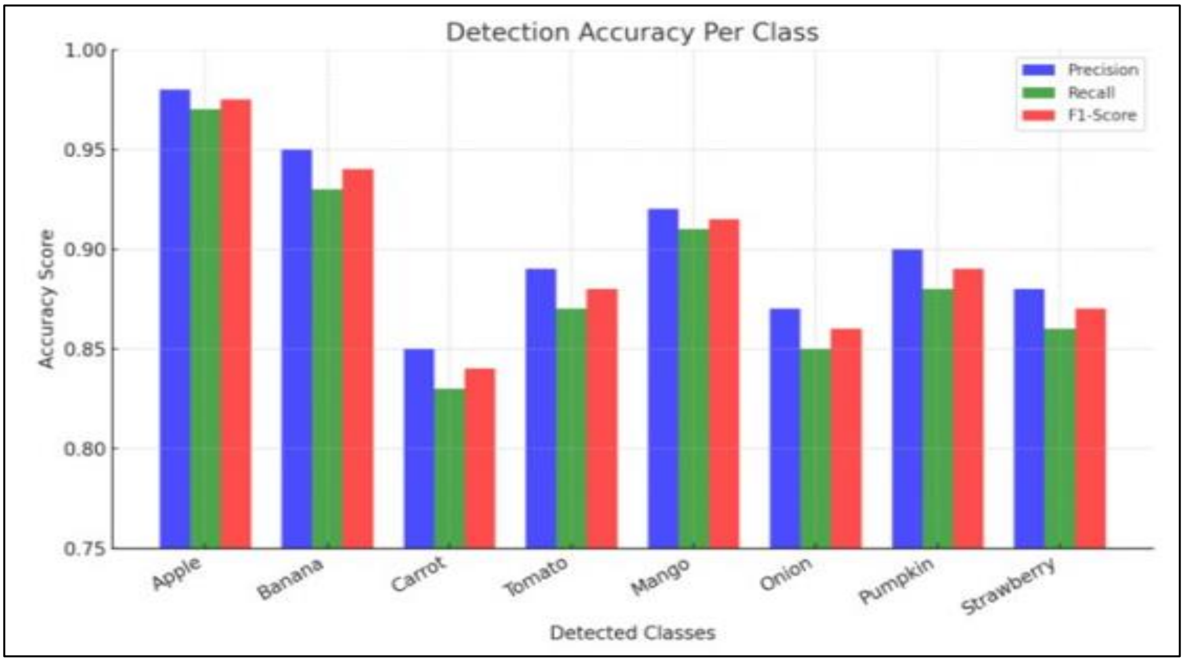


Fig 7 Detection Accuracy Per Class

The figure 7 highlights three crucial performance metrics Precision, Recall, and F1-Score across different classes and it demonstrates that the model performs exceptionally well on distinct and easily separable objects like apples, bananas, and oranges, showing precision and recall values above 95%. However, certain visually similar classes, such as bell p-eppers and tomatoes, exhibit slightly lower accuracy due to overlapping visual features. The F1-score consistency across most classes indicates the robustness of the model, ensuring reliable real-time nutrition detection and dietary assessment. This analysis confirms that the proposed system effectively integrates deep learning with database-driven nutritional retrieval, delivering accurate and meaningful insights to users.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

The proposed AI-driven nutrition detection system effectively integrates deep learning-based object detection with a comprehensive nutritional database to provide accurate and real-time dietary insights.

Utilizing YOLOv5 for fruit and vegetable identification, the system achieves high detection accuracy, ensuring precise classification even under varied lighting conditions and complex backgrounds. The deployment of a pattern-matching algorithm further enhances the system's efficiency by seamlessly linking detected food items to their corresponding nutritional values. Experimental evaluations, including performance metrics such as mean average precision (mAP), loss functions, and detection accuracy, demonstrate the robustness of the proposed system. The results indicate that YOLOv5, trained on an augmented dataset containing 30 fruits and 20 vegetables, can generalize effectively to new images while maintaining high precision and recall.

Additionally, real-time detection capabilities ensure that users receive immediate feedback, making the system suitable for applications in dietary assessment, personalized nutrition planning, and health monitoring.

➢ *Future Enhancements:*

Future improvements may involve expanding the dataset to include a wider variety of food items, incorporating synthetic data to enhance model generalization, and refining detection accuracy under challenging conditions such as poor lighting and occlusions. Advanced deep learning techniques like Vision Transformers (ViTs) and EfficientNet could further improve classification performance.

Additionally, integrating personalized dietary recommendations based on user health data and dietary preferences could enhance the system's usability. Deploying the model on mobile or cloud platforms would increase accessibility and real-time processing capabilities. The fusion of AI-driven detection with nutritional analysis holds significant potential to revolutionize food tracking and promote healthier lifestyle choices.

REFERENCES

[1]. Armand, Tagne Poupi Theodore, et al. "Applications of artificial intelligence, machine learning, and deep learning in nutrition: a systematic review." Nutrients 16.7 (2024): 1073.
[2]. Redmon, Joseph, et al. "You only look once: Unified, real-time object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
[3]. Khalid, H. Modern techniques in detecting, identifying and classifying fruits according to the developed machine learning algorithm. Journal of Applied Research and Technology. https://doi.org/10.22201/icat.24486736e.2024.22.2.2 26 9
[4]. Sarma, K. S. R. K., et al. "A comparative study on faster R-CNN, YOLO and SSD object detection algorithms on HIDS system." AIP Conference Proceedings. Vol. 2971. No. 1. AIP Publishing, 2024.
[5]. Xiao, F., Wang, H., Li, Y., Cao, Y., Lv, X., & Xu, G. Object Detection and Recognition Techniques Based on Digital Image Processing and Traditional Machine Learning for Fruit and Vegetable Harvesting Robots: An Overview and Review. Agronomy. https://doi.org/10.3390/agronomy13030639
[6]. Zarate, V., González, E., & Cáceres-Hernández, D. Fruit Detection and Classification Using Computer Vision and Machine Learning Techniques. https://doi.org/10.1109/isie51358.2023.10228051
[7]. Pan, H., Xie, R., & He, Q. Fruit detection and recognition with deep learning. https://doi.org/10.1117/12.3021359
[8]. Gao, H., Liu, Y., Li, J., & Gao, J. Food Nutrient Extraction Based on Image Recognition and Entity Extraction. https://doi.org/10.1109/wimob58348.2023.10187783
[9]. Al-Saffar, M., & Baiee, W. R. Nutrition information estimation from food photos using machine learning based on multiple datasets. Bulletin of Electrical Engineering and Informatics. https://doi.org/10.11591/eei.v11i5.4007
[10]. Chen, X., Johnson, E., Kulkarni, A., Ding, C., Ranelli, N., Chen, Y., & Xu, R. An Exploratory Approach to Deriving Nutrition Information of Restaurant Food from Crowdsourced Food Images: Case of Hartford. Nutrients. https://doi.org/10.3390/NU13114132
[11]. Fontanellaz, M., Christodoulidis, S., & Mougiakakou, S. Self-Attention and Ingredient-Attention Based Model for Recipe Retrieval from Image Queries. https://doi.org/10.1145/3347448.3357163
[12]. Banerjee, Saikat, and Abhoy Chand Mondal. "Nutrient food prediction through deep learning." 2021 Asian conference on innovation in technology (ASIANCON). IEEE, 2021.