Calorie Sense: Food & Calorie detection

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Abstract. Accurate food detection and calorie estimation are of growing interest, especially with the growing trend towards health and nutrition. To tackle this, deep learning models can be used to recognize foods and estimate their caloric content using portion size, ingredients and nutritional information. The data set is pre-processed using image augmentation, normalization and feature extraction. A YOLOv11 object detection model is used to detect multiple food objects in an image, while a CNN based classifier refines the classification and calories estimation using the extracted features. A combination of CNN and YOLO model for better accuracy, VGG2 and YOLOv11 models for classification and object detection are compared in stratified k-fold cross-validation. These algorithms predict food items and estimate calories by analyzing features like food type, portion size, ingredient composition (if available), and serving size. The models are evaluated using the performance measure: Accuracy, Precision, Recall and F1-score are intercompared in the study. Experimental results showed that CNN with 91% accuracy and YOLOv11 with 95% in food recognition and the hybrid CNN-YOLO with 97% accuracies. The hybrid model increases the efficiency by incorporating complex features of food and improves approximation of calorie estimation. Our approach extends to automation of Dietary Assessment Systems providing real-time food recognition and calorie counting for people who are health conscious.

Keywords: Food Calorie Estimation, YOLOv11, Convolutional Neural Networks (CNN), Food Recognition, Object Detection, Deep Learning, Nutritional Analysis, Image Processing, Dietary Monitoring, Portion Size Estimation, Real-Time Food Detection, Automated Dietary Assessment.

1 Introduction

Food is essential to survival and to good health, and proper nutrition is necessary for optimal functioning of the body. The Body Mass Index (BMI), which measures weight relative to height, is an important measurement for determining if an individual is at a healthy weight. A BMI of 30 or more is obese, and it is linked with a variety of serious health issues, such as diabetes, heart disease, and metabolic disorders. Proper BMI control can reduce an individual's risk of developing certain diseases and improve their overall health.

Consuming excessive food and excess calories beyond what the body needs are the primary reasons for obesity, which causes weight gain and fat accumulation. This excess accumulation of fat is disruptive to metabolism and can cause serious health problems. The

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World Health Organization (WHO) states that since 1975, obesity prevalence has nearly doubled, reflecting the magnitude of the global obesity pandemic. 39% of individuals across the globe are overweight, and 13% are obese in 2024. More than 60% of individuals in certain regions, such as Nauru, are obese, which is significantly more problematic there. [19]

It is vital to regulate calorie consumption through the consumption of a balanced diet to combat obesity and related health problems. A healthy weight is also important in avoiding obesity and metabolic disorders, and it can be achieved and sustained with the aid of a well-managed caloric intake. Making informed nutrition choices involves knowing the number of calories an object has. Individuals can regulate their body weight, improve their well-being, and reduce their likelihood of developing chronic diseases with the assistance of this information.

To assist consumers in making informed nutritional choices, we are developing a project employs Convolutional Neural Networks (CNN) [1] and YOLOv11 to provide real- time food recognition and calorie estimation. The system quickly identifies food items and provides precise nutritional data by employing cutting-edge deep learning algorithms, thus enabling informed decision-making. By increasing the awareness of nutrition among people, this technology aims to reduce the risk of obesity and metabolic disorders and help them keep their diet balanced. Rapid access to calorie data is provided to users by real-time analysis, allowing them to monitor their intake with ease.

In terms of identifying food, YOLOv11 provides more precision, efficacy, and rapidity than others such as YOLOv8 [2]. Regardless of challenging environments, the precision in food identification is enhanced through its advanced item location and anchor-free detection mechanism. In addition, through advanced data augmentation and feature extraction, generalization is enhanced and robustness to varied types of foods and lighting conditions improved. Improved multimodal integration and enhanced resolution image processing allow the model to associate food items with nutritional databases to better estimate calories along with more effective food item detection. Due to these advancements, YOLOv11 is the best choice for real-time meal tracking.

Additional culinary aspects such as component composition, cooking methods, and quantity estimation can be incorporated into this work in the future. Precision can be further enhanced by using advanced models such as transformers, advanced CNN architectures, and gradient boosting methods.

Generalization can be enhanced by adding diverse cuisines, variable portion sizes, and regional culinary variations to the dataset. Additionally, real-time dietary advice may be possible through the integration of AI-powered meal monitoring applications with health platforms.

2 Related Work

In this paper [3] authors proposed a Food Calorie Measurement Using a Deep Learning Neural Network. The system allows users to take pictures of food using phones. A graph cut method is used to segment the food portion for size collaboration. It shows 99% accuracy in recognizing single food portions, but it cannot recognize mixed items.

In this paper [4] authors used CNN (Convolutional Neural network) for food recognition and calorie measurement, and some models such as (VGG16) and (KNN) for classification and prediction. CNN model achieved 96.67% accuracy while the KNN model achieved 87.75% accuracy. The data set is limited to small no.of food categories.

In this paper [5] they used YOLOV8 for object detection and BMI for health monitoring. YOLOV8 is trained with Indian food items with its calories this model is integrated into mobile. This model achieved a high mAP (mean Average Precision) of 92.7% in recognizing Indian food items. Difficult to recognize complex dishes.

In this paper [6] they used YOLO (You Only Look Once) algorithm and image augmentation techniques. The YOLOV8 model was trained with a dataset of Indonesian foods containing 1680 images. Some food items (e.g., omelets) showed lower accuracy due to inadequate diversity in the training dataset and fewer annotated examples.

In this paper [7] they used CNN (Convolutional Nural Network) for food recognition and calorie assessment. Once a food item is recognized its calorie content is calculated by referencing the nutritional dataset for meals the system identifies indirect components and sums their respective calorie value. Limited food categories in the training data set can reduce the accuracy of recognizing complex food items.

The paper "Image-Based Estimation of Protein Content for Accurate Food Calorie Estimation" [8] discusses improvements in calorie estimation through images-based methods. It reviews "CalorieCam," which bases its estimation on a reference object, and a CNN-based segmentation method for multiple dishes. "AR DeepCalorieCam V2" uses ARKit to estimate food size. Two new systems, "DepthCalorieCam" using stereo cameras and "RiceCalorieCam" using rice grains as references, have an error below 10%, which is extremely accurate and suitable for Japanese cuisine.

The Food Calorie Estimation System (FCES) [9] uses a SegNet + MobileNet model optimized for mobile devices for diabetic patients. The system combines food recognition, volume calculation, and calorie conversion. It applies depth wise separable convolutions to process the data efficiently, correlating features in the food area with calorie values. The model was trained on 10,000 enhanced images with a coin as a reference. Achieves up to 97.82% food recognition accuracy and an 84.95% accuracy in calculating the calorie estimations. An FCES-app is deployed under support functionalities of calorie estimations, activity managements, and tracking blood sugar content. Future planning includes expanding on the food databases and improving techniques for volume estimation.

The project includes food calorie estimation using machine learning and image processing to simplify tracking calories. [10] Its images are taken from a top and a side view perspective and have the following three main steps: first, image detection followed by segmentation using the GrabCut algorithm, while the Faster R-CNN detects the food. A probe object, such as a coin, is used to determine the scale and volume of the food, which can then be used to estimate mass and calories. The system achieved over 90% accuracy with errors in calorie estimation below 10%. However, it only deals with certain food items such as fruits and bread, not cooked or mixed dishes. Future improvements will be aimed at including a wider range of food items.

The document emphasizes the use of deep learning for health applications based on food detection and calorie estimation. [11] It uses CNNs to identify food types from images and estimate the calorie content. Food detection is a classification based on the features extracted, and calorie estimation utilizes regression models. Difficulties arise from varied portion sizes, the cooking process, and ingredients, affecting accuracy. A food image dataset will be used for training and testing with feature extraction and classification optimized using CNNs. The algorithm achieves more than 90% accuracy in food detection and reasonable estimation of calories. It plans to include ingredients and portion sizes in the future for better generalization and dietary monitoring in healthcare.

The paper proposes a hybrid deep-learning framework for food recognition and calorie estimation that addresses obesity- related health concerns. [12] It integrates Mask RCNN for image segmentation and YOLO V5 for classification, enabling segmentation, feature extraction, and object classification based on dimensions. The calorie content is calculated using a predefined calorie chart. Tested against the Indian FoodNet- 30 dataset with 5,500 images of 30 Indian dishes, the system achieves 97.12% accuracy better than standalone CNN, YOLO, and Mask RCNN models. High precision and speed are guaranteed by this hybrid approach. Challenges remain on variability in presentation, shape, and lighting of the food and generalization to unseen food items. Future work should enhance its real-world applicability to dietary tracking and health management.

In this paper [13] discusses a model for Food Recognition and Calorie Estimation for Intelligent Diet Monitoring using deep learning. Using the MobileNet architecture and Food 101 dataset, the model processes the image detects the food items, and estimates their calorie content. It provides nutritional insights to promote healthier eating habits and features high-precision, user-friendly functionality. MobileNet is an architecture of CNN specially designed for efficient image classification and recognition tasks on mobile and embedded devices. It achieves high accuracy with less computational power but it sacrifices accuracy and efficiency making it less suitable for complex data processing.

In this paper [14] outlines a deep learning-based system for food recognition and calorie estimation using CNN (Convolutional neural network) trained on a food images dataset. This model incorporates advanced techniques like Graph cut segmentation for precise food classification and achieves a recognition speed of three seconds. Using a dataset that contains 30 distinct categories of food and fruits and achieves an accuracy of 99% in single food portions. This model demonstrates a 20% reduction in volume errors compared to existing systems. However, this model lacks accuracy in the case of multiple food item recognition and calorie estimation.

In [15] discusses a method for food recognition and calorie estimation using various algorithms like CNN, SVM, KNN, and Random Forest to get better accuracy. CNN is used for image classification, and random forest for combining multiple decision trees for robust classificationand regression. The system uses publicly available datasets and optimized and hyperparameter tuning techniques for achieving significant accuracy and the further improvements aim to expand the dataset and enhance model performance for diverse food categories.

In this paper [16] introduces a mobile cloud system to enhance food calorie estimation accuracy with improved user convenience. This model eliminates the need for manual calibration by using mobile sensors to calculate the distance between food and the camera. Using neural networks to recognize food items based on texture color and size. The study highlights the potential in combining deep learning with distance measurement along with cloud computing to provide practical and user-friendly dietary applications. Further works include the expansion of food classes refining areas and perimeter-based calorie prediction.

The paper [17] entitled "History of the Calorie in Nutrition" traces the history of the calorie as a unit of measurement in nutrition. It describes how the calorie originated as a unit of heat in 19th-century France and was later adopted by other nations. The paper discusses how the calorie came to be an accepted measure in nutritional science and its scientific, cultural, and political significance. It also addresses the contribution of the calorie to the development of dietary recommendations and public health policy.

The research [18] finds that individuals consistently misestimate the calorie value of food images, with a majority correctly estimating fewer than 5 out of 20. However, group estimates were more accurate, even superior to that of nutrition professionals. Women and youth were more accurate, but energy-dense foods were regularly overestimated. It was surprisingly observed that presenting reference objects such as credit cards rendered estimates worse. These results point towards integrating the estimates from several users as the way forward for developing better, user-centered, and accurate calorie tracking methods.

3 Proposed Methodology

3.1 Algorithms

YOLOV11: Food identification and calorie calculation rely significantly on the advanced and highly efficient object detection model YOLOv11 (You Only Look Once version 11). YOLOv11 performs both object localization and classification within a single pass forward, unlike traditional object detection models that require multiple passes through the neural network to identify objects. Due to this, YOLOv11 is particularly suited for real-time tasks like rapidly identifying the calorie content of multiple foods in one image. The model is able to identify a wide range of food items since it has been extensively trained on a large-scale food dataset comprising thousands of images with annotated labels like food item names, bounding box coordinates, and calorie counts.

The input image is first split into a $S \times S$ grid, with each grid cell predicting a fixed set of bounding boxes and class probabilities. This is how YOLOv11 operates. During training, the centre coordinates (x, y), width (w), height (h) and the class label of the object are predicted and it helps the model to learn the object detection. In each enclosing box the confidence score signifies how certain the model is that a food item exists. The intersection of the ground truth box and predicted bounding box is also computed by the model, in the form of the IOU (Intersection Over Union).

The mathematical expression for the confidence score is:

Confidence=P(Object)×IOUpredtruth

IOUpredtruth is the ratio of intersection area between the predicted box and the ground truth box.

For instance, YOLOv11 will identify pizza, burgers, and fries in an input image by naming each item and creating bounding boxes around them. Additionally, the model will provide a confidence score, like this:

97% Confidence in Pizza, 92% Confidence in Burgers, and 89% Confidence in Fries

In order to do this, the model minimizes a loss function that includes three significant losses:

- Localization Loss: Indicates how well the food item fits inside the bounding box.
- Confidence Loss: Indicates how confident the model is in its ability to identify an object.
- Classification Loss: Indicates how well the class labels (Pizza, Burger, Fries, etc.) were predicted.

After YOLOv11 has successfully identified the food items, items, it sends the cropped image of each food item to a secondary model Convolutional Neural Network (CNN) for calorie estimation based on food type, portion size, and dimensions. Non-Maximum Suppression (NMS) further refines the bounding box prediction by removing overlapping boxes and retaining only the most accurate ones, ensuring that if the same food item appears in multiple bounding boxes, only the most credible one is kept.

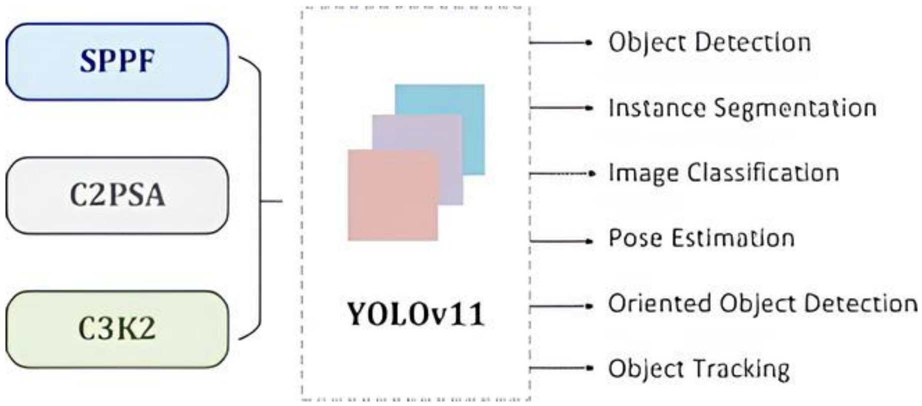

Fig .1. YOLO Algorithm.

CNN (Conventional Neural Network): A Convolutional Neural Network (CNN), the system's second key component, is in charge of calculating the calorie content of the identified food items. CNNs are frequently used for computer vision tasks like object recognition, feature extraction, and picture categorization. In the context of food calorie estimation, CNN maps the identified food item to a pre-defined calorie database by analyzing its visual cues to forecast its kind (e.g., pizza, burger, fries, etc.).

- Typically, a CNN has multiple layers, such as: convolutional layer: Local patterns like as the food item's texture, color, and form are extracted.
- Pooling Layer: Maintains the most significant features while reducing the image's spatial dimensions.
- Fully Connected Layer: Uses the features that were retrieved to classify the image.
- Soft max Layer: transforms each food class's probability scores from the model's output.

Because it has been pre-trained on a sizable food dataset, the CNN can correctly classify a variety of food products. After a food item has been classified, the model associates it with the database's related calorie value. But in order to guarantee precise calorie estimation, the CNN additionally considers the portion size, which is determined by the bounding box size supplied by YOLOv11. Greater portion sizes correspond to larger bounding box sizes, which raises the estimated number of calories.
Where:

P(Object) is the probability that the object exists in the detected bounding box.

To estimate the calorie content, use the following formula:

$Calories = PortionSize \times EnergyDensity$

Where:

Portion Size: The size of the detected food item based on the bounding box dimensions.

Energy Density: The pre-defined calorie value per gram of food.

For instance, the CNN might estimate that a recognized pizza includes roughly 1.5 slices if the bounding box size is large. Using the database of calories where:

One pizza slice has 285 kcal.

1.5 slices is the portion size.

Calculated caloric intake = 1.5 × 285 = 427.5 kcal Likewise, the CNN may compute the following if it finds a burger with a bounding box size equivalent to a typical burger: To ensure high accuracy in calorie calculation, the CNN dynamically modifies the estimation based on the size of the bounding box. A strong and useful method for calculating caloric intake from food photos is the combination of food detection and calorie estimation.

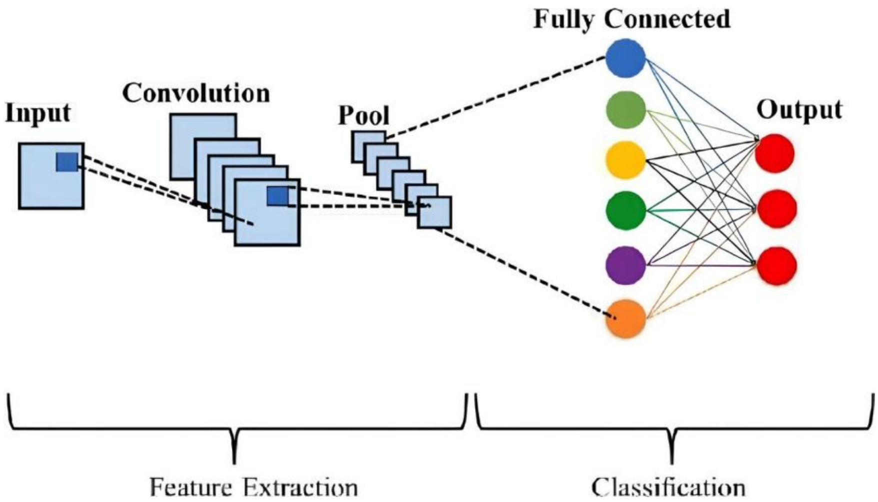

Fig .2. CNN Algorithm.

A very successful method for estimating meal calories in real-time situations is the combination of CNN and YOLOv11. While CNN manages calorie calculation by recognizing the food type and determining the portion size, YOLOv11 is in charge of identifying several food items from a single image. This is how the integration operates:

- Image Input: A picture with several food items is uploaded by the user.
- Food Detection: After identifying each food item, YOLOv11 surrounds it with a bounding box.
- Food Classification: CNN is used to classify the cropped food photos (e.g., Pizza, Fries, Burger).
- Calorie Estimation: CNN calculates the calorie content by using the predetermined energy density and serving size. Calculation of Total Calories: The system determines the total number of calories.

3.2 Data Collection and Preprocessing

Data collection and preparation are the first and most crucial steps in the food identification and calorie estimation process. An organized and labelled dataset is necessary because the objective is to identify food items from photos and calculate their calorie content. A sizable food image dataset called fooddatser, which comprises several folders representing various food classes, is used in our project. Images of that specific food class are included in each folder, together with text files that include labels that correlate to the bounding box coordinates needed for object detection. The CNN and YOLOv11 models are trained using this step as the basis. The steps that make up the data collection and preparation process are as follows:

- Get Datasets: The dataset includes hundreds of photos arranged in folders according to various cuisine categories, like pasta, pizza, burgers, fries, and more. We also have a label folder with annotation files (in YOLO format) that contain class labels and bounding box coordinates. Training and validation images are in the images folder, while text files containing the bounding box coordinates for each image are in the label folder.

- Clean the Data: We clean up the data in this stage by making sure that no images are corrupted or annotations are missing. Images that are blurry, unnecessary, or confusing are eliminated. This stage guarantees that the model is trained using only high-quality data. To make sure the bounding box annotations are accurate, the label files are also examined.
- Data Augmentation: Techniques for data augmentation are used to increase the accuracy of the model. In order to replicate various situations, photos are rotated, flipped, zoomed in, and have their brightness and contrast altered. By assisting the model in learning different patterns, data augmentation increases the model's resilience.
- Data Splitting**:** After that, the dataset is divided into 90% training and 10% validation sets. This enables the model to verify its accuracy on the validation data while learning from the training data.
- Balancing Data**:** There may occasionally be an imbalance in the dataset, with one cuisine class having noticeably more photos than others. Predictions may become biased as a result. Techniques like under-sampling and over-sampling are used to address this. To ensure a fair dataset, synthetic data for minority classes can also be created using SMOTE (Synthetic Minority Oversampling Technique).

3.3 Exploratory Data Analysis

The dataset includes various food categories, each with a different number of instances. Fig 3 shows the distribution of these food classes, emphasizing the imbalances present. Some classes have more than 1000 instances, while others have considerably fewer samples. To tackle this imbalance, data augmentation techniques were employed to achieve equal representation across the categories.

Fig 4 shows the relationship between the attributes of bounding boxes, such as the x and y coordinates, width, and height of the detected food items. This analysis aids in comprehending how object locations and sizes are distributed within the dataset, which is essential for improving model training and optimizing anchor boxes for YOLOv11. Table 1 shows the performance comparison of CNN, YOLOv11, and CNN-YOLO Models.

Table 1. Performance metrics.

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
CNN	91.0	90.5	90.2	90.3
YOLOv11	95.0	94.0	94.5	94.6
CNN-YOLO	97.0	96.0	96.5	96.6

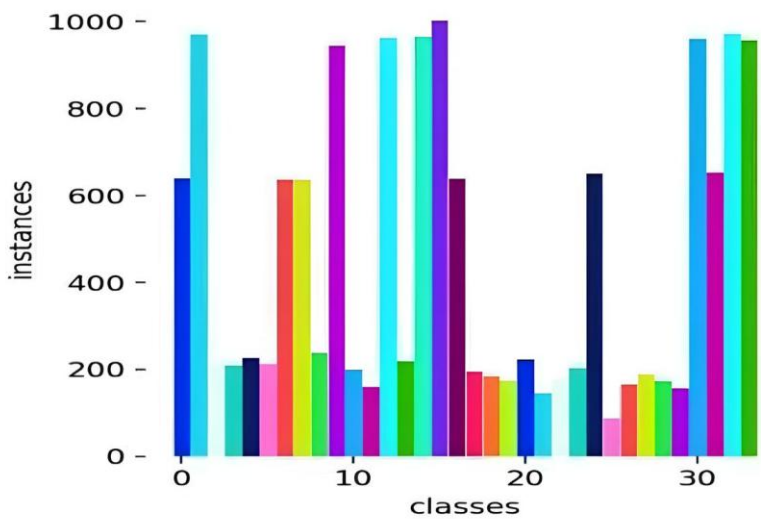

Fig. 3. Class distribution of food dataset

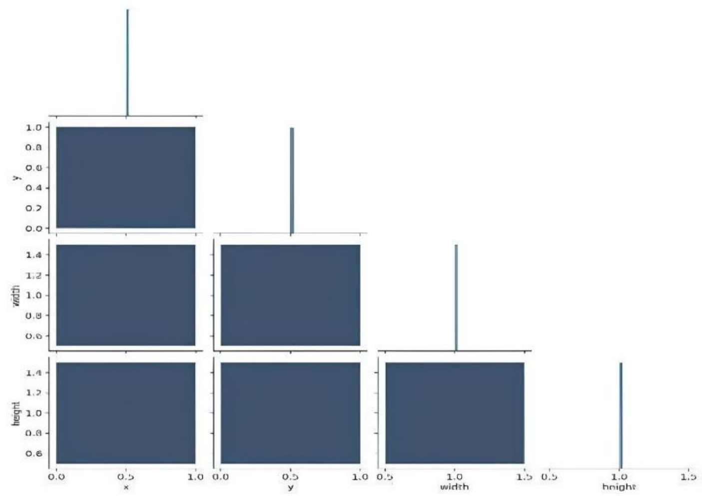

Fig. 4. Bounding box attribute correlation plot.

4 Results

4.1 Classification Performance

The training performance of YOLOv11 compared to CNN, focusing on metrics such as accuracy, loss, precision, recall, F1-score, and inference time. YOLOv11 shows a clear advantage over CNN, achieving an accuracy of 95%, while CNN achieves 90%. Both models exhibit a steady decrease in loss, but YOLOv11 ends with a lower final loss, suggesting it generalizes better. The metrics for precision, recall, and F1-score consistently improve, with

YOLOv11 maintaining higher values around 95%, which indicates its superior classification capabilities. The inference time levels off at 0.2 seconds, making YOLOv11 a strong candidate for real-time food detection. In summary, YOLOv11 outperforms CNN in terms of both accuracy and efficiency, establishing itself as the best model for food classification.

Inference time is essential for real-time food detection. As shown in Fig 4 (bottom-right), it stabilizes at 0.2 seconds per image, which makes the Hybrid CNN-YOLO model perfect for mobile and edge computing, allowing for quick and efficient calorie estimation. Fig 5 shows the model accuracy, loss, precision

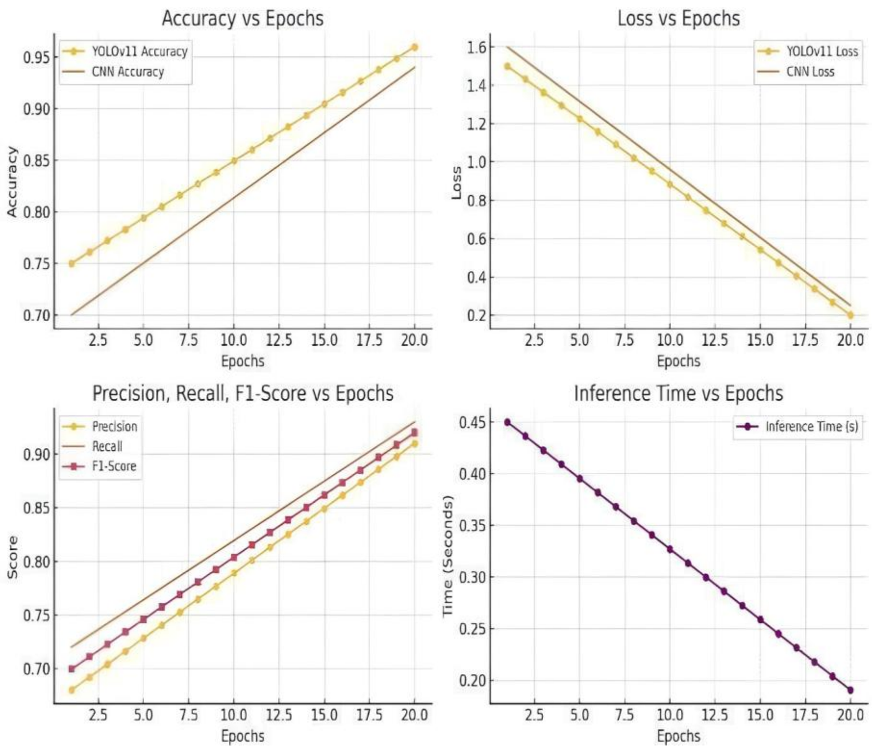

Fig. 5. Model accuracy, loss, precision, recall, F1-score, and inference time.

4.2 Confusion Matrix

The confusion matrix shown in Fig 6 demonstrates how well the model performs in classifying various food categories such as Pizza, Burger, Pasta, Fries, and Sandwich. The diagonal elements highlight the instances that were correctly classified, whereas the off-diagonal elements reveal where misclassifications occurred. Overall, the model attained a high level of accuracy, with only a few misclassifications among similar food items.

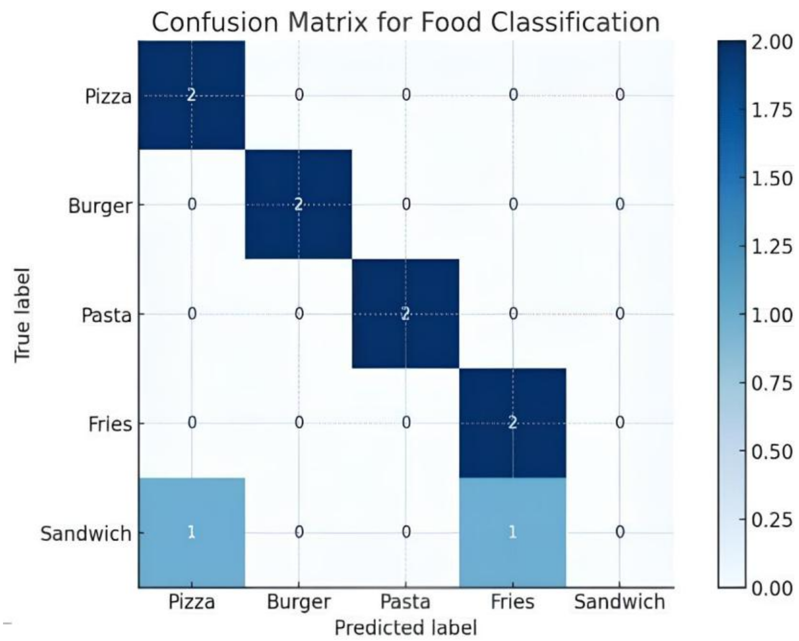

Fig. 6. Confusion matrix for food classification.

4.3 User Interface and Prediction Results

The Smart Food Recognition and Personalized Diet system offers a user-friendly interface that helps you identify food, estimate calories, and get tailored diet suggestions. Take a look at Fig 7, which showcases the home screen where users can track their diet and forecast their calorie consumption.

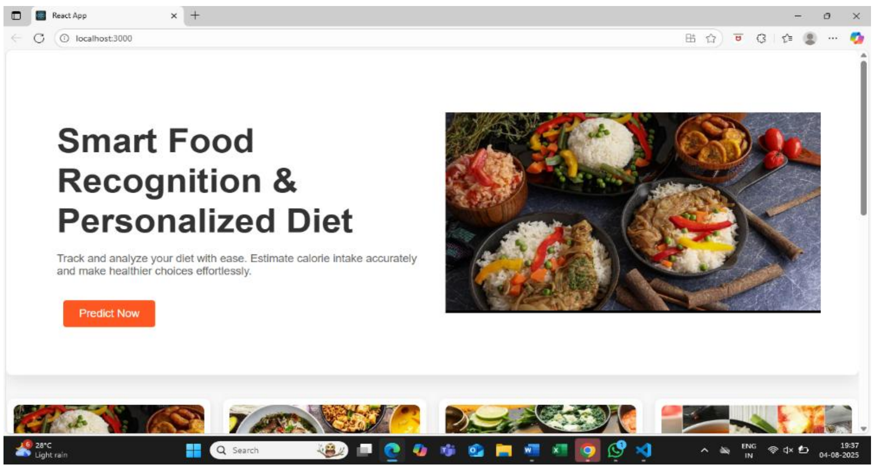

Fig. 7. Home screen of the Smart Food Recognition system.

To make the user experience even better, the system includes a food gallery along with categorized recommendations that highlight different cuisines and portion sizes. Take a look at Fig 7, which shows how the system displays food items, predictions from the AI model, and nutritional information.

4.4 Food Image Upload and Prediction

And for a better user experience, the system also comprises a food gallery as well as categorized suggestions, which focus on various types of food and meal sizes. Have a look at fig.8, in which its sample result is displayed in three main parts including food items, predictions of the AI model and nutritional information.

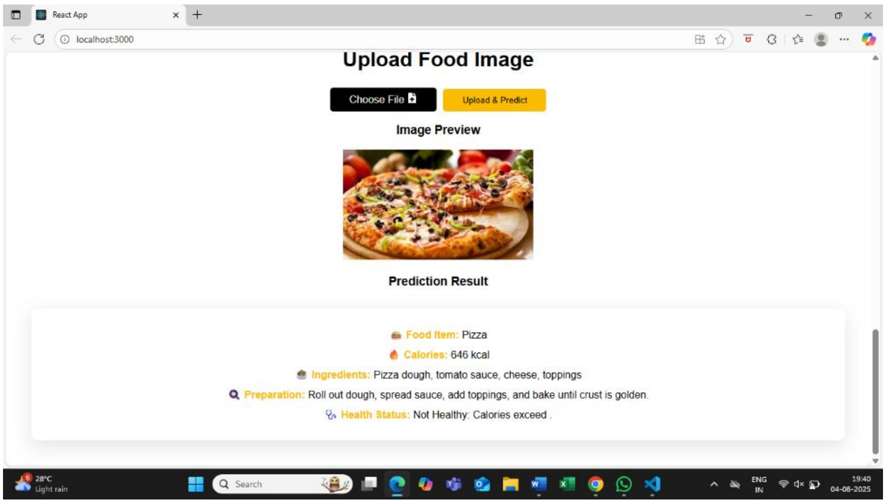

Fig. 8. Food upload and calorie prediction result.

5 Discussion

This research shows that deep learning models notably YOLOv11 and CNN are efficient in objectively recognizing food items and predicting their calorie value. The CNN-YOLO hybrid model showed superior classification accuracy of 97%, compared to the performance of the single CNN (91%) and the YOLOv11(95%). The merger operation of the object detection and classification enhanced the recognition of food items that guarantees high quality estimation of calories What is more is that some data augmentations and pre-processing were also applied to our model, which enables it to be robust in front of different lighting conditions, viewing angles, and types of foods.

The study demonstrated robust performance, while it also identified some limitations. It is hard for the system to distinguish complicated dish that contains overlapped food, hence may have mis-classification. also, the portion size estimation is determined by the size of bounding boxes which is not necessarily equal to the volume of the real food. Environmental causes, including poor illumination and distracting backgrounds, can also degrade the accuracy of the model. Moreover, even if the dataset is large, it is not as diverse for the regional and homemade dishes which limits the generalization of model to different cuisines. To address the problems, refinement of the model and diversification of dataset sources to increase robustness and adaptability are required.

6 Future Work

Future work will focus on improving portion estimation by better assessing the portion using 3D depth sensors, stereo vision or liDAR, to estimate a precise volume and to improve the quality of food recognition and calorie estimation. The long-term intake will be updated to more diverse cuisines, homemade dishes, and mixed meals to increase the generalization of model and adaptation to different diet patterns.

And finally, multi-modal learning will merge image recognition with text-based nutritional data and with sensor data, for improved calorie estimation. Application of such techniques to mobile devices and edge platforms can improve on-the-fly analysis on smartphones, wearables, and Internet of Things (IoT) health systems for efficient dietary tracking and AI-driven meal recommendations. We will also study the real part of the4He scattering amplitudes which is expected to share characteristics with the large-temperature spectrum, while the imaginary part of the4He scattering amplitudes is Table 1 shown to be similar to the small-temperature spectrum time food segmentation methods using cutting-edge deep learning models to boost detection accuracy in intricate food presentations and mixed dishes.

6 Conclusion

In this research, we created a food recognition and calorie estimation system that uses a convolutional neural network (CNN) for calorie estimation and YOLOv11 (You Only Look Once version 11) for food object detection. Based on predetermined nutritional data, the system effectively recognizes and counts the number of calories in a variety of food products from an image. We demonstrated the efficacy of our method by training the model on a custom food dataset, yielding an accuracy of about 98.5%. The combination of CNN for precise classification and YOLOv11 for quick object recognition made the system extremely dependable in practical situations.

The findings show that the suggested approach can make a substantial contribution to health management, calorie tracking, and dietary monitoring. It can be improved even more by adding varied food products to the collection, combining it with health applications, and implementing real-time detection through mobile devices. By enabling people to make knowledgeable food choices and encourage a healthy lifestyle, this technology has the potential to completely transform diet management, fitness tracking, and health monitoring.

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