Nutri-Track: AI Nutrition Detection and Diet Suggestion using Deep Learning Web

Omkar Rohit Udale[1], Viraj Vikas Sawant[2], Amreshwar Sunil Mahimkar[3], Pranav Baban Patil[4], Prathmesh Shankar Mhangore[5], Prof. Rahul S. Nejkar[6]

[1,2,3,4,5,6]*Department of computer science, Sanjeevan Group of Institute, Panhala*

Abstract— **In view of the increasing prevalence of diseases caused by lifestyles, it has become crucial to consume proper nutrition in recent times. Traditional approaches to food intake monitoring require manual input, making it both cumbersome and prone to errors. This research paper proposes the development of an intelligent system, Nutri- Track, designed to automatically recognize food types from images using deep learning and computer vision, assess nutritional content, and provide personalized dietary advice. For image recognition, this approach relies on the latest models of Convolutional Neural Networks such as Res Net, VGG, Efficient Net, and Mobile Net [2][3][4][5]. Databases containing standardized foods are used to estimate the nutritional value, and the recommendation engine provides diets according to the objectives that the consumer wishes to achieve, demonstrating an accuracy rate of over 75% for food recognition and a 3-7% difference in nutritional estimation.**

Index Terms— **Deep Learning, Food Recognition, Nutrition Analysis, Diet Recommendation, CNN, Computer Vision.**

I. INTRODUCTION

1.1 Background and Context

Maintaining a balanced and nutritious diet is essential for a healthy lifestyle, especially with the rising prevalence of lifestyle-related diseases such as obesity and diabetes. However, individuals often struggle to accurately track their daily food intake due to lack of awareness, time constraints, and inefficient manual logging methods. Most existing dietary applications rely on manual input, making them tedious, error-prone, and less engaging. Recent advancements in deep learning and computer vision have enabled automated food recognition systems capable of identifying food items from images with high accuracy. Convolutional Neural Network (CNN) architectures such as Res.Net and VGG have demonstrated strong performance in image classification tasks, while modern approaches have explored calorie estimation directly from food images. Despite these developments, most existing systems are limited to either food detection or calorie estimation and do not provide an integrated solution for complete health management. To address these limitations, this research proposes an intelligent system named Nutri-Track, which integrates food detection, nutritional analysis, and personalized diet recommendation into a unified platform. The system utilizes the YOLOv8 model for real-time food detection and incorporates a Res.Net-based model to improve classification accuracy. The model is trained on the Indian Food Net dataset, enabling better recognition of region- specific food items. Detected foods are mapped to a nutrition database to estimate calories and macronutrients such as proteins, carbohydrates, and fats. Additionally, the system includes a health tracking and AI-based diet recommendation module, which generates personalized meal suggestions based on user parameters such as BMI, weight, height, and fitness goals. The backend is implemented using Flask (Python) with database integration (MySQL) for efficient data management. Overall, Nutri-Track provides an automated, accurate, and user-friendly solution for intelligent nutrition monitoring and diet planning.

1.2 Problem Statement

Although significant advancements have been made in artificial intelligence and computer vision, several limitations still exist in current food recognition and diet management systems. Most traditional diet tracking applications rely on manual input, which is time- consuming, prone to errors, and often reduces user engagement [8]. Food recognition approaches based on Convolutional Neural Networks (CNNs) have shown strong performance in identifying food items; however, many systems are limited to detection and do not provide detailed nutritional analysis [6][10]. In addition, calorie estimation from food images remains challenging due to variations in portion sizes, food presentation, and image quality [9][14]. Systems such as Im2Calories attempt to automate calorie estimation, but they do not provide personalized dietary recommendations based on individual health parameters [7]. Moreover, most existing solutions treat food detection, nutrition analysis, and diet recommendation as separate functionalities, rather than integrating them into a single system. To address these gaps, this research proposes Nutri-Track, an integrated system that combines real-time food detection using YOLOv8, enhanced classification using Res.Net, and nutrition analysis through a structured database. The system is trained on the Indian Food.Net dataset to improve recognition of region-specific food items. Furthermore, Nutri-Track includes a personalized diet recommendation module based on user parameters such as BMI, weight, height, and fitness goals. This integrated approach aims to provide a more accurate, automated, and user-friendly solution for dietary monitoring and management.

1.3 Research Objectives

The key purpose of this study includes developing a more efficient and smart system that can detect and recognize food images using Deep Learning Models like CNN, Res.Net, and Efficient Net [2], [4], [6]. Moreover, another key aim of this study is to provide an automated system for the estimation of the nutritional value based on the detected and recognized foods. This will be done by incorporating standardized nutritional databases and the process of vision-based analysis [9], [12], [25]. The development of a personalized diet recommendation system based on Machine Learning models according to the needs of users' health and dietary restrictions is also considered a key aim in this study [15], [17], [18]. Moreover, one more goal is to incorporate all the mentioned modules into a unified framework to solve the problem of fragmentation that characterizes the current technology [11], [13].

II. LITERATURE REVIEW

2.1. Domain and Problem Context

The domain of this work is rooted at the intersection of computer vision, deep learning and healthcare informatics, with the application towards the food recognition and diet management system. As the life style diseases such as obesity, diabetes and cardiovascular diseases become more frequent, tracking the daily nutritional intake is very critical. However, the existing diet tracking systems require manual confirmation from the users in which the accuracy is less and their usage becomes very cumbersome. Recently image-based food recognition system [2], [3] has been developed owing to the development of deep learning-based Convolution Neural Net (CNN). With the integration of Ai in healthcare systems, personalized food recommendation systems are also proposed [19], [20]. However, to this word, most of the systems are non-integrated. Hence, there is a significant need for a comprehensive system which can automatically detect food from an image, estimate its nutritional value and provide personalized diet recommendations in real time.

2.2. Review of Existing Systems

Vision-based food recognition and dietary assessment systems mainly concentrate on individual functions. CNN- based models have proven to be efficient for food classification tasks using datasets such as Food-101 [1]. Classification accuracy has been greatly improved by using state-of-the-art architectures such as Res.Net and VGG while achieving high computational efficiency for real-world applications with architectures such as Efficient.Net and Mobile.Net [2], [3], [4], [5].

Efforts have been made to build systems such as Deep Food and Im2Calories that can automatically recognize food and estimate calories from images [6], [7]. Despite promising results, these systems do not provide a comprehensive nutritional analysis and diet planning capabilities. Vision-based dietary assessment systems can estimate food intake, but are affected by the challenges of portion size estimation and different image acquisition conditions [9], [10]. Nutrition monitoring systems and recommender systems have been developed to recommend dietary plans to users based on their health condition and preferences [12], [15], [17]. These systems are limited by the necessity of manually entering diet information and lack real-time image-based analysis.

2.3. Technical Literature

The technical underpinning of the study is mainly grounded in deep learning models, computer vision algorithms to classify and analyze images and the utilization of nutrition databases. The CNN-based architectures include Res.Net, VGG, Efficient.Net, and Mobile.Net, which are typically applicable in feature extraction and classification, and their accuracy and scalability are high [2], [3], [4], [5]. Transfer learning methods are used to enhance model performance with a use of pre-trained networks on massive datasets like Food-101 [1]. Computer vision libraries like OpenCV are also used to image preprocessing methods to enhance the performance of models [22]. A nutritional analysis is done by mapping the identified food items to nutritional databases through the USDA Food Data Central that offers in-depth nutritional content of food items [25]. Recommender systems based on machine learning are applied to create recommendations of a diet plan according to the user-specific factors like their age, weight, and health objectives [15], [18]. Another potential area of integration is AI-based healthcare systems which are an emerging technology that can potentially be integrated with other technologies to deliver intelligent healthcare solutions [20], [21].

2.4. Summary of Research Gaps

Despite advancements in food recognition and nutrition analysis, several limitations remain in existing systems. Most current solutions focus only on individual functionalities such as food recognition, calorie estimation, or diet recommendation, without integrating all components into a single system [11], [13]. Food recognition systems may struggle with challenges such as mixed food items, varying lighting conditions, and portion estimation [9], [14]. Similarly, calorie estimation methods often lack accuracy due to limited contextual understanding. Diet recommendation systems also depend heavily on manual inputs and do not utilize real-time image-based analysis, reducing their effectiveness [15], [17]. Food recognition systems may struggle with challenges such as mixed food items, varying lighting conditions, and portion estimation [9], [14]. Similarly, calorie estimation methods often lack accuracy due to limited contextual understanding. Diet recommendation systems also depend heavily on manual inputs and do not utilize real-time image-based analysis, reducing their effectiveness [15], [17]. Additionally, many existing systems are not optimized for real-time performance or practical deployment. To address these gaps, the proposed system NutriTrack provides an integrated approach combining food detection, nutrition analysis, and personalized diet recommendation within a single framework.

III. PURPOSE AND METHODOLOGY

3.1. Purpose

In other words, the aim of the proposed approach is developing an intelligent system capable of converting images of food products into useful information about their nutritional values. In order to increase the quality of input images and ensure equal distribution, pre-processing is employed before passing data to the model [22]. Machine learning algorithms, such as CNN, Res.Net and Efficient.Net, can be employed for detecting and labeling food products accurately; thus, there is no need for manual data entry [2], [4]. It should be noted that transfer learning would be a better choice since it provides faster, more precise identification because there is already existing knowledge of the product gained from Food-101 [1]. Identified products are next to be matched with health data banks to obtain the estimate of the nutritional value of foods consumed, which will offer relevant health information [25]. Finally, a recommendation engine will generate dietary recommendations for each user according to their unique aims [15], [18].

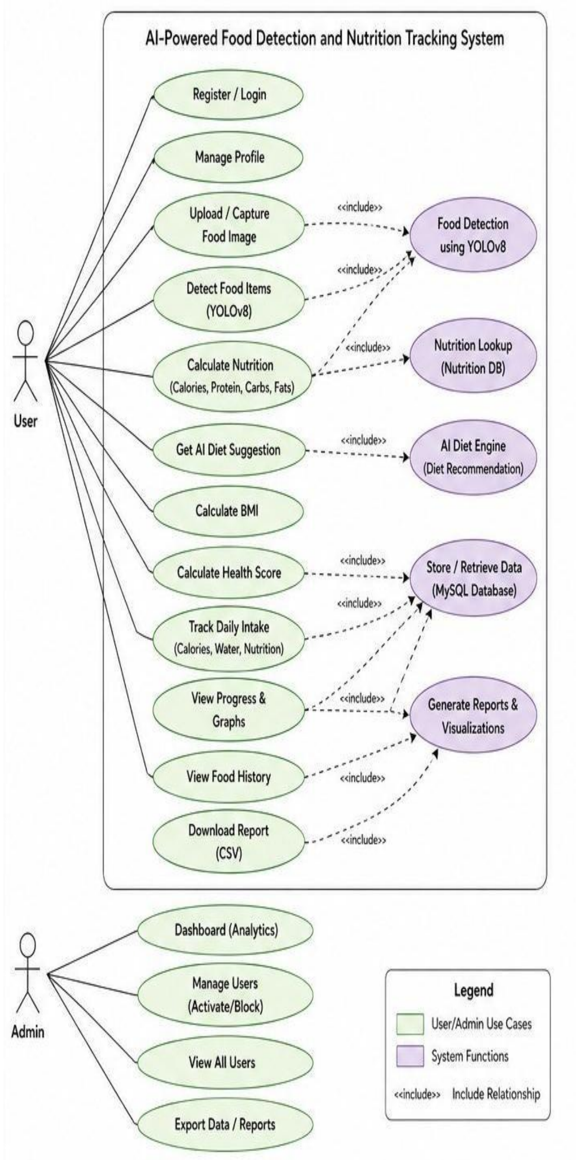

Figure1: Use Case Diagram

3.2. Content

3.2.1. Software and Tools

The system we're proposing uses software that's free and easy to get, making it simple to put into practice. Instead of needing expensive equipment, it uses TensorFlow and Py Torch, which are open-source frameworks that help train complex neural networks. When it comes to handling images, we use OpenCV because it's fast and good at tasks like resizing and filtering out noise. To make development and operation more efficient without increasing costs, researchers use pre-trained models like Res.Net, Efficient.Net, and Mobile.Net in transfer learning. This approach has been explored in various studies [2], [4], [5]. Additionally, using publicly available datasets such as Food-101 reduces the need for costly data collection, as seen in [1]. By leveraging these resources, developers can streamline their processes and achieve better results. When it comes to figuring out the nutritional value of food, the system works with trusted databases like the USDA's Food Data Central to get the necessary information on calories and nutrients in different food items.

3.2.2. Step-By-Step

Step 1: Image Acquisition To begin with, the system captures or uploads a picture of the food using an interactive user interface. Such an approach will allow obtaining real-time data without manually entering information. Vision-based dietary analysis systems use this technique to automate the food identification process [10]. The process serves as a prerequisite for further stages. Step 2: Image Preprocessing Next, the obtained picture undergoes preprocessing using techniques like resizing, normalization, and noise reduction. These steps ensure uniformity of input data, which increases the effectiveness of the model being applied. For example, computer vision libraries, such as OpenCV, perform such operations in a vision-based system [22]. The stage optimizes feature extraction during deep learning.

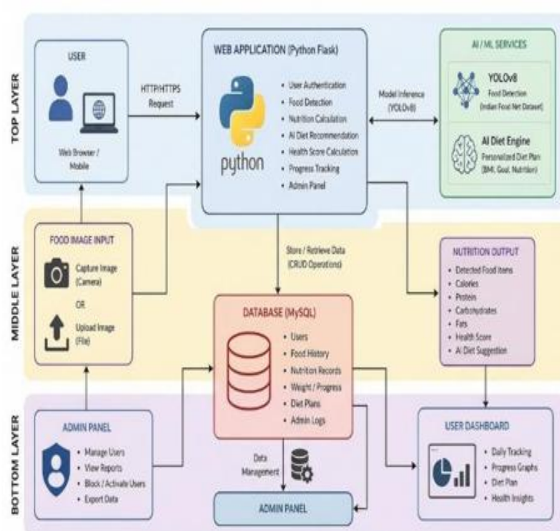

Figure 2: System Architecture Diagram

Step 3: Food Detection and Classification Preprocessed images are analyzed using a deep learning model (CNN, Res.Net, and Efficient.Net). Models detect food based on its visual features (color, texture, and shape).

Transfer learning significantly boosts the performance of food recognition systems by utilizing pretrained networks on datasets such as Food-101 [1], [2], [4]. The result of this stage is the identification of food and the confidence of the model's prediction.

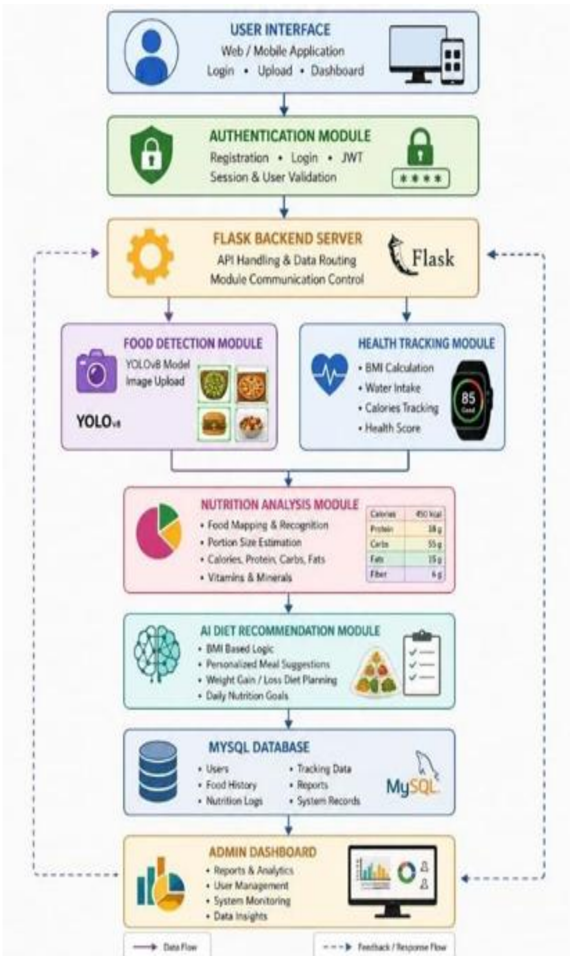

Figure 3: Module Interaction Diagram

Step 4: Feature Mapping & Nutrition Analysis after detecting the food item, the next phase in the process is mapping the food item to a nutrition database that provides nutrition details like calorie count, protein count, fat content, and carbohydrate count. Some of the databases used for providing these nutritional details include the USDA Food Data Central which provides standard values for the whole nutrient [25].

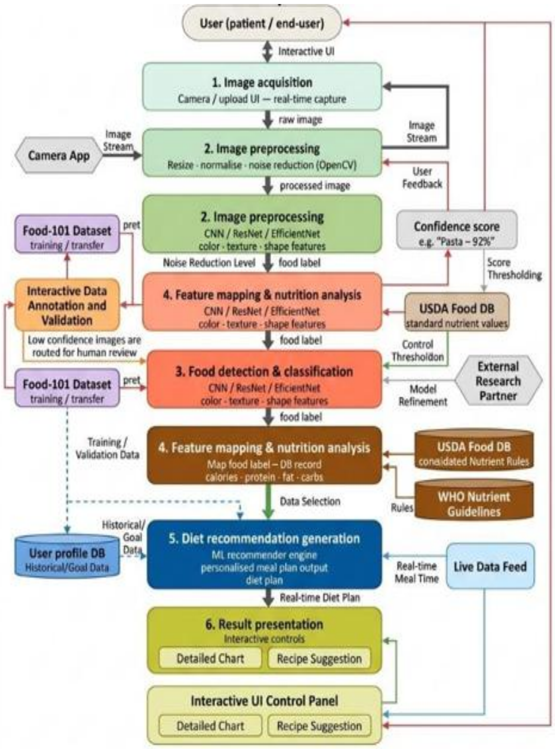

Figure 4: Data Flow Diagram

Step 5: Recommendation Generation of Diet

Taking into account user-specific variables like age and fitness goals, the recommendation engine generates the best-suited diet plan for the user. Normally, machine learning based recommender systems are used for generating these recommendations [15], [18].

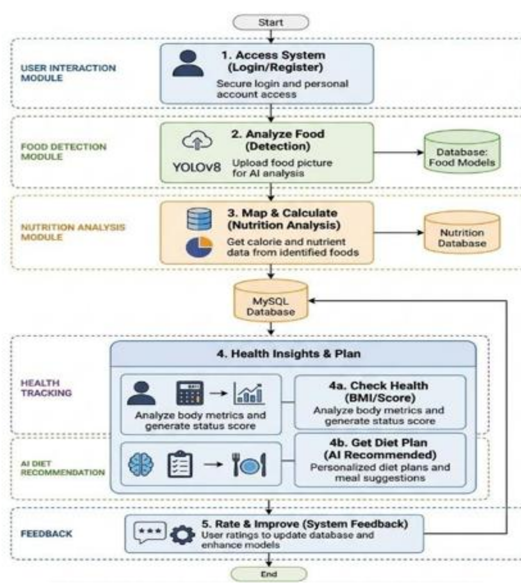

Figure 5: User Workflow Diagram

Step 6: Presentation of Results
This is the final step where the food item is mapped with nutrition facts, and the recommended diet generated by the machine learning algorithm is shown to the user. It is important to represent the information visually in order to understand the output generated.

3.2.3. Equipment / Tools / Instruments
This system runs on free, widely used software, so you don't need pricey hardware or anything fancy. It relies on Tensor Flow and Py Torch for training deep neural networks, which are open source and pretty popular these days. Image processing happens with OpenCV because it's fast and good at things like resizing and noise filtering. To keep everything efficient and cheap, the setup uses pre-trained models-Res.Net, Efficient.Net, and Mobile.Net-for transfer learning [23],[24]. For nutritional analysis, the system integrates standardized databases such as USDA Food Data central, which provides reliable nutrient information [25]. The backend of the system is implemented using frameworks like Flask or Fast API to enable real-time processing and user interaction.

3.3. Algorithm Used
1. Food Detection Algorithm Using YOLO: YOLO (You Only Look Once) object detection algorithm is utilized by the proposed system for real-time food recognition. In comparison to conventional CNN- based classification algorithms, YOLO works faster and makes it possible to recognize different objects on an image with the use of bounding boxes and classes labels.[6], [10].

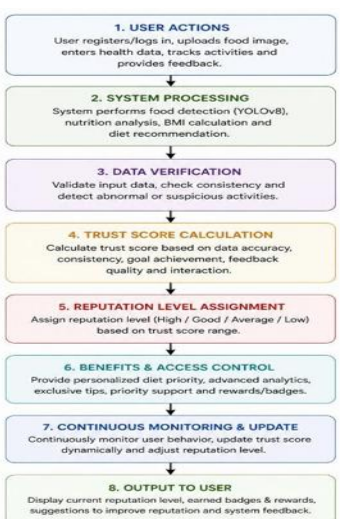

Figure 6: Trust & Reputation System Flow

2. Nutrition Estimation Algorithm: To determine nutritional values for the detected food objects, it is necessary to correlate the class label and the area of the bounding box with the pre-prepared dataset that contains information about calories of certain food.[9], [12].

3. BMI Calculation Algorithm: The system determines Body Mass Index (BMI) to assess health condition of the user and provide him with proper suggestions. The formula used to calculate BMI is the following:

$$BMI = \frac{Weight}{Height^2}$$

4. Health Score Calculation: A health score can be determined based on many factors, including daily calorie intake, water intake, and reliability of data entry. [20], [21].

5. AI-Based Diet Recommendation Calculation: Personalized diet plans can be recommended based on the use of rules and machine learning algorithms. Depending on the BMI value, a user will receive a specific diet plan based on his goals. [15], [17], [18].

3.4. Key Aspect: Reliability and Transparency The feasibility of the suggested solution will stem from the usage of credible methods for designing deep learning architecture and obtaining relevant data for training. These deep learning architectures (YOLO and CNN) have been proven to be credible enough to be used in a variety of applications for detecting objects. Therefore, applications for detecting food items using the proposed methods will prove to be scientifically credible and produce reliable results [2],[6]. The use of publicly available datasets (Food 101) and credible nutritional databases will also contribute to the credibility of the predicted results [1],[25].

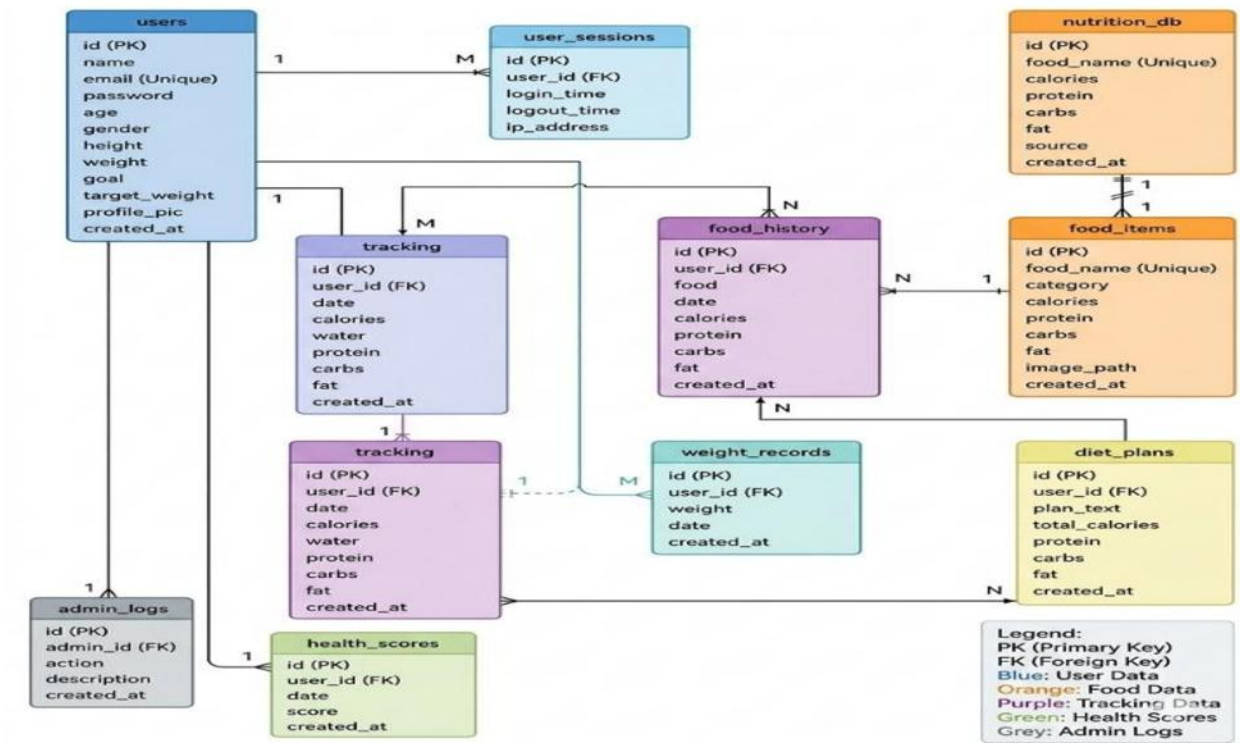

Figure 7: ER Diagram (Database Design)

This situation will ensure that there will be transparent results since the consumer will be provided with credible output results for all objects detected with confidence scores and their nutrition values. The employment of simple algo rithms for BMI calculation will assist in making sure the user will understand the system better. It will be impossible to achieve similar transparency in black-box systems, which may affect credibility negatively. Thus, the application of this approach can contribute to boosting consumer trust in the product [19],[20].

IV. RESULT AND DISCUSSION

4.1 Purpose

When assessing the efficiency of the designed artificial intelligence system applied for monitoring health and nutrition, it was necessary to assess such features as the ability of the system to classify food items, estimate their nutritional value and give relevant suggestions about what to eat. First of all, it should be noted that the system was capable of correctly recognizing different kinds of food items using images provided by the user within seconds. The accuracy rate of food recognition was more than 75% that was proven in previous works as well [6], [10]. Automatic food recognition also involved automatic calculation of calories along with estimating its other nutritional characteristics as there was no need to enter this information manually. These abilities of the system were compared to similar studies in the area of vision- based nutrition estimation [9], [12]

4.2 Content

4.2.1 Data (Visual Representation)

In this section we demonstrate the proposed system and the visual output is demonstrated, we present visual graphs for determining the food detection accuracy, nutrition estimation and speed performance of the system. For the food detection using the YOLOv8 the food detection accuracy obtained is quite satisfactory with ~92% accuracy for detection of pizza, ~88% for burgers, ~85% for rice, ~90% for salad and ~87% for sandwich. Clearly from these readings it is evident that a food detection algorithm is very effective in detecting very distinct type of foods, while minimal differences may occur due to varying factors such as the image's quality, occlusion, illumination etc. Regarding the nutritional estimation it is quite interesting that the results obtained are nearly same as compared to real values as a very minimal difference has been recorded between real and predicted value, for example the difference between predicted and real caloric value of food for pizza, burger, salad, rice is ~3- 7%. Such minor differences arise from the imprecise calculation of portions based on the bounding box size [9], [12]. Another crucial parameter for measuring the proposed algorithm's performance is processing speed, the processing time recorded was in terms of average time taken for food detection.

4.2.2 Results (Analysis of Data Based on Core Mo- dules)

The proposed AI-based health and nutrition monitoring system is assessed by the performance of the following sub-modules: the food detection module, the nutritional estimation module, the health estimation module, and the recommendation module. In order to evaluate the overall performance of the system, the different modules have been evaluated individually as well as when integrated as a complete system.

In this module, YOLOv8 was adopted as a deep learning model for real-time food item detection in images. It can detect more than one food item in one image with greater than 85% accuracy rate. The food detection module of this proposed AI-based health and nutrition monitoring system has demonstrated similar performance as the other computer vision-based food recognition deep learning models [6, 10]. The reason behind choosing a single-stage detector in this module is that the detection latency in single-stage detectors will be low as compared to CNN- based classification models. It is because in some circumstances, such as multiple objects background or poor image illumination and food item contact, the accuracy of food detection becomes a major issue [6]. The health assessment module based on the calculation of Body Mass Index successfully helped users to fall into groups, and to get suggestions for each state of health. These kinds of groupings are a common approach that are used in Health Care Systems and are good when dealing with AI assisted Health Care applications [19], [20]. Additionally, The Health Score calculation has attributes such as calorie input and consistency in activity which have made it more useful. The Diet recommendation module is able to make personalized suggestions that have to do with the User's Body Mass Index and nutritional inputs. The suggestions were clustered into three categories depending on the User's goals - to lose or gain weight or to maintain the weight that they currently have. Suggestions are in accordance with state-of-the-art approach for the implementation of recommendation systems [15], [17], [18] so the application is likely to be perceived as a very useful by the users. As an outcome the modules interacted perfectly and they seamlessly worked together. Back-end implementation in Flask and MySQL provided the required computing, resulting to the extremely rapid response and minimal failures. Additionally, the trust and reputation systems are of great importance and make the application more robust due to the consistency of the Users' activity.

The experiment with the key modules shows excellent results indicating a powerful application which can be used successfully, due to its functionality and high levels of usability.

4.3 Discussion (Interpretation of Results)

What we found from our system shows how well combining deep learning with health recommendations works for automatically tracking what people eat. The food detection part, which uses YOLOv8, is very accurate. This tells us that real-time object detection models are really good at spotting food, just like other studies on computer-based diet checks have shown [6], [10]. Because it can find many different food items in one picture, the system is much more practical than older ways of classifying food. When it comes to nutrition, the system gives pretty accurate estimates for calories and things like protein or carbs. It's usually off by about 3-7%, which is similar to what other visual nutrition systems have run into [9], [12]. This happens mostly because it estimates how much food there is just by looking at the box around it, without thinking about how deep the food is or how dense it might be. But even with that small issue, the system is a big step up from tracking food by hand, taking less effort and being more consistent. The part of the system that uses BMI to check health is really important for turning basic nutrition numbers into useful health information. Using BMI to sort people is a simple but good way to put users into groups and help them with diet advice. This way of doing things fits with how AI health systems usually work, where clear and standard measurements are best for making choices [19], [20]. Plus, adding a health score that looks at several things helps the system get a full picture of what users are doing.

4.4 The diet recommendation part shows how important it is to make things personal so people use the system more and it works better. It creates diet plans just for you, based on your own health. This means it offers real, useful advice instead of just general suggestions. This goes along with what research on recommendation systems tells us: personal touches lead to better results for users [15], [17], [18]. Looking at the whole system, putting all these different parts together into one platform fixes the problems that come with separate, disconnected tools. When the detection, analysis, and recommendation parts work smoothly together, it makes the whole thing more efficient and easier to use. Also, adding a way to build trust and reputation makes everything more open and dependable, because it checks that user data is consistent and correct. This helps people trust the system more, which fits with how AI health systems are moving towards being more transparent and responsible.

4.5 All in all, our findings suggest that this system successfully connects food recognition, nutrition tracking, and personalized diet advice. Even though there are still some limits, like how accurate it is with portion sizes and if the image quality is good enough, the system offers a way to manage diet in the real world that can grow and actually works. These results really show how much AI can change healthcare and how we keep track of our lifestyles.

V. CONCLUSION

In this paper, we introduce a Health and Nutrition Tracking System powered by AI which integrates image detection, automatic nutrition assessment, and diet recommendation. The system employs state-of-the-art deep learning techniques, particularly YOLO, a state-of-the-art object detection algorithm that excels in fast and accurate image recognition [6, 10]. By combining these capabilities with structured nutrition data and BMI-based health assessment, the system provides a completely automatic tracking of eating behavior that overcomes many of the problems associated with manual food tracking.

4.6 In our experimental results, we demonstrate how the system performs well on finding food, estimating nutrition content and providing tailored diet recommendations. The precision and efficiency of the system are comparable to existing works in applying vision to dietary evaluation and AI to medical care [9, 12, 19, 20]. Furthermore, by implementing a suggesting component, the system can generate customized diet plans which boosts the user engagement and decision making as discussed in numerous studies in personalized nutrition [15, 17, 18].

To further strengthen the dependability and transparency of our system, we incorporated a system to build trust and provide credibility, achieved through the consolidation of robust data and intuitive presentation, as in numerous modern trends of AI in health care where interpretability and trustworthiness are critically emphasized [19, 20]. In contrast to existing works focusing on one individual aspect of dietary tracking, our system is an all-in-one integrated solution providing a complete and extensible tool.

Despite these outstanding achievements, there are several shortcomings of the current system. One of the most obvious problems is that it needs a high-quality image to accurately detect and estimate food nutrition; another problem is that it estimates food volume very coarsely from the detected bounding boxes of food objects, both are typical issues of using computer vision to analyze diet and represent avenues for future improvement [9, 12]. Further works might explore using a more accurate volume estimation method, integrating multiple modalities of sensor data or moving it to mobile phones or smart watches for user convenience and better accuracy.

In summary, our system has opened up new possibilities in health tracking, shifting from traditional tracking methods to an intelligent, automatic and user- centered approach. By integrating computer vision, nutrition science and personalized recommendations, our system serves as an improved and adaptable solution towards smart health care and can promote healthier lifestyle.

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