IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 04, April 2025 https://www.ijirae.com/archives

Smart Dietary Planning with Food Recognition and Calorie intake Estimation

Naveen H S,
Department of CSE, Vemana Institute of Technology,
VTU University, Bengaluru, India
SahanaKumari KH,Nishna N Ganiga,Rachitha H B,Sinchana H
Department of CSE, Vemana Institute of Technology,
VTU University, Bengaluru, India
sahanakumarikh@vemanait.edu.in, nishanganiga_2021@vemanait.edu.in,
rachithahb_2021@vemanait.edu.in, sinchanah@vemanait.edu

Publication History
Manuscript Reference No: IJIRAE/RS/Vol.12/Issue04/APAE10088 Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.12/Issue04/APAE10088 Received: 04, April 2025, Revised: 12, April 2025, Accepted: 22, April 2025, Published Online: 03, May 2025. https://www.ijirae.com/volumes/Vol12/iss-04/05.APAE10088.pdf
Article Citation:Naveen,Sahana,Nishna,Rachitha,Sinchana(2025),Smart Dietary Planning with Food Recognition and Calorie intake Estimation. IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 12, Issue 03 of 2025 pages 150-160 **Doi:>**https://doi.org/10.26562/ijirae.2025.v1204.05

Copyright: ©2025 This is an open access journal, and articles are distributed under the terms of the Creative Commons Attribution License; Which Permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract: The escalating prevalence of lifestyle-related health issues, such as obesity and diabetes, highlights the critical importance of health awareness and effective lifestyle management. Advanced dietary tracking solutions have emerged as essential tools to address these challenges. This paper presents an innovative AI-driven system that automates food recognition, calorie estimation, and personalized meal recommendations using cutting-edge machine learning and image processing techniques. Leveraging deep learning models, including Convolutional Neural Networks (CNNs), SIFT, and Gabor filters, the system accurately identifies food items from user-uploaded images and calculates their nutritional values. Beyond calorie tracking, the system offers tailored meal plans based on user preferences, health conditions, and fitness goals, ensuring a personalized approach to nutrition management. Key features include real-time dietary tracking, dynamic goal adjustments, and progress monitoring, empowering users to make informed dietary choices. Integration with wearable devices enhances accuracy and user experience, while future advancements, such as block chain for secure data storage and augmented reality for interactive meal analysis, promise to elevate its effectiveness. This comprehensive solution aims to revolutionize digital health and wellness, fostering healthier lifestyles through technology-driven innovation.

Keywords: Machine learning, Food recognition, Calorie estimation, Smart dietary, SIFT, CNN, Gabor filters, real-time dietary tracking.

I. INTRODUCTION

The rising prevalence of obesity and diabetes has emerged as a critical global challenge, necessitating advanced technological interventions to manage and prevent these conditions effectively. Obesity, as defined by the World Health Organization, is characterized by a Body Mass Index (BMI) of 30 kg/m² or higher and is linked to an imbalance between caloric intake and energy expenditure. This imbalance, coupled with unhealthy eating habits and sedentary lifestyles, has resulted in over half the population being overweight and nearly a third classified as obese. The rapid urbanization and modernization of lifestyles have inadvertently led to an alarming surge in lifestyle diseases, with obesity and diabetes ranking as two of the most critical global health concerns. These conditions not only strain healthcare systems but also diminish quality of life, making their prevention and management imperative. Such alarming statistics underscore the urgency of addressing this issue, particularly given its association with diabetes, cardiovascular disorders, and other lifestyle-related diseases. Traditional approaches to dietary tracking and diabetes management such as manual food logging, nutritional consultations, and periodic clinical tests face several limitations, including inaccuracies in data, lack of personalization, and the time-intensive nature of these methods. Consequently, there is a pressing need for innovative solutions that automate dietary monitoring, provide accurate predictions, and offer tailored recommendations to promote healthier lifestyles. The system employs deep learning algorithms to recognize food items from user-uploaded images, accurately estimate their calorie content, and predict diabetes risk based on individual health profiles. Furthermore, it provides personalized dietary recommendations tailored to users' preferences, health conditions, and fitness goals, enhancing user engagement and effectiveness in achieving health objectives. Key features of the system include real-time dietary tracking, dynamic goal adjustments. Future enhancements, such as block chain based secure data storage and augmented reality for interactive meal analysis, hold promise in elevating its functionality and impact. By combining innovative methodologies such as clustering, classification, and rule-based algorithms, this project introduces a comprehensive approach to dietary management, empowering users to make informed decisions and fostering a proactive shift towards healthier living. In this era of growing health awareness, the proposed system aims to address the twin challenges of obesity and diabetes with cutting-edge technology, revolutionizing the paradigm of digital health and wellness.

RELATED WORK

The integration of artificial intelligence (AI) and machine learning (ML) into dietary management systems has gained significant attention in recent years, with numerous studies exploring innovative approaches to address obesity and diabetes. This section reviews key contributions from existing literature, focusing on methodologies and findings relevant to the proposed system. Identification of Food Given their capacity to extract high-level information from photos, Convolutional Neural Networks (CNNs) has been frequently used for food image recognition. A study titled Automatic Food Recognition Using Deep Convolutional Neural Networks with Self-Attention Mechanism proposed food recognition model that achieved high accuracy on datasets such as Food-101 [1]. This work demonstrates the potential of CNNs in automating food identification, aligning closely with the objectives of the proposed system. [2] Nutrient Estimation with CNN-Based Models, Nutri Food Net framework utilized CNNs for automated food image recognition and nutrient estimation, achieving a classification accuracy of 97.3%. This study highlights the effectiveness of CNNs in promoting healthier dietary decisions, which is a core feature of the proposed system. Feature Extraction Using SIFT and Gabor Filters have been extensively used for feature extraction in image processing. Research on texture analysis using Gabor filters [3] and feature generation with SIFT [4] demonstrates their capability to identify food textures and patterns, making them ideal for food recognition tasks in the proposed system. Personalized meal plans based on user-specific data can be effectively generated using Decision Tree Algorithms for Personalized Recommendations. A study on personalized diet recommendation systems [5] emphasized the utility of decision trees in tailoring dietary suggestions to individual health profiles, preferences, and goals, which aligns with the recommendation engine in the proposed system. The AI-Powered Nutrition Assistant and Step Tracker [8] combined IoT and AI technologies to deliver personalized nutrition tracking and meal planning. This work highlights the importance of integrating real-time tracking and adaptive recommendations, which are key features of the proposed system. Machine Learning for Dietary Analysis Research on AI-driven dietary assessments [9] explored using machine learning algorithms to analyze dietary patterns and nutrient composition. These findings support the use of ML techniques in calorie estimation and dietary tracking. Food Detection and Recognition Using CNNs study on food detection using CNNs [10] demonstrated the superiority of deep learning over traditional methods in food image classification. This aligns with the proposed system's reliance on CNNs for accurate food recognition. AI in Personalized Nutrition in which Artificial Intelligence for Dietary Management [11] chapter reviewed AI techniques for personalized nutrition, emphasizing the role of tailored dietary recommendations in improving health outcomes. This work underscores the importance of personalization in dietary planning systems. The NutriVision framework displayed a system for modified thin down organization utilizing Speedier R-CNN for food affirmation and calorie estimation. They consider outlined the ampleness of significant learning in recognizing food things and giving personalized dietary examination [6]. Augmented Reality for Interactive Meal Analysis has been utilized to enhance user engagement in dietary planning. [7] AR-based tools allow users to visualize portion sizes and nutritional content, providing an immersive experience that complements dietary management systems.

II. OVERVIEW OF METHOD AND RESULTS

The proposed system for Smart Dietary Planning with Food Recognition and Calorie Intake Estimation is designed to address the growing challenges of obesity and diabetes by leveraging advanced machine learning and image processing techniques as shown in Figure 1. This section outlines the methods employed in the system and the results achieved during its implementation and evaluation. The procedure of the proposed system is organized into a number of key stages, each contributing to the by and large value and ampleness of the dietary orchestrating framework. The system begins with client selection, where individuals input person focuses of intrigued such as age, sex, weight, stature, prosperity conditions, and wellness objectives. This information is critical for tailoring dietary recommendations to the unique needs of each user. The system calculates the user's Body Mass Index (BMI) and assesses their health profile to determine specific dietary requirements. Users upload images of their meals through a user-friendly interface. These pictures encounter preprocessing steps, checking resizing, clamor reducing, and division, to ensure perfect quality for examination. The center of the system's convenience lies in its capacity to recognize food things from exchanged pictures. Preprocessing is essential for standardizing input data and improving the accuracy of subsequent image recognition tasks. Convolutional Neural Frameworks (CNNs) are utilized for this reason due to their illustrated practicality in picture classification assignments. The CNN model is trained on a diverse dataset of food images, enabling it to identify a wide range of food items with high accuracy. The system also incorporates feature extraction techniques such as Scale-Invariant Feature Transform (SIFT) and Gabor filters [12] to enhance recognition performance under varying conditions, such as changes in lighting and orientation. Once the food items are identified, the system calculates their caloric values using a reference database of nutritional information. This database includes detailed profiles of common food items, which includes their calorie content, macronutrient composition, and portion sizes. The calorie estimation process involves matching the recognized food items to their corresponding entries in the database and scaling the values based on portion size. The system generates personalized meal recommendations using decision tree algorithms. These algorithms analyze the user's health profile, dietary preferences, and caloric needs to create tailored meal plans [11]. The recommendations are designed to align with the user's fitness goals, such as weight loss, weight maintenance, or muscle gain. The decision tree approach ensures that recommendations are both relevant and actionable. The system includes a real-time tracking feature that monitors the user's dietary intake and compares it to their recommended goals. This feature provides feedback on progress and suggests adjustments to optimize health outcomes [13]. For example, if a user exceeds their daily calorie limit, the system may recommend lower-calorie meal options for the following day. The system integrates user-provided health data, such as blood sugar levels and activity metrics, to enhance the accuracy of dietary recommendations.

This integration allows the system to address specific health conditions, such as diabetes, by providing targeted advice on managing blood sugar levels through diet.All user data, including health profiles, food recognition results, and dietary tracking metrics, is stored securely in a centralized database.

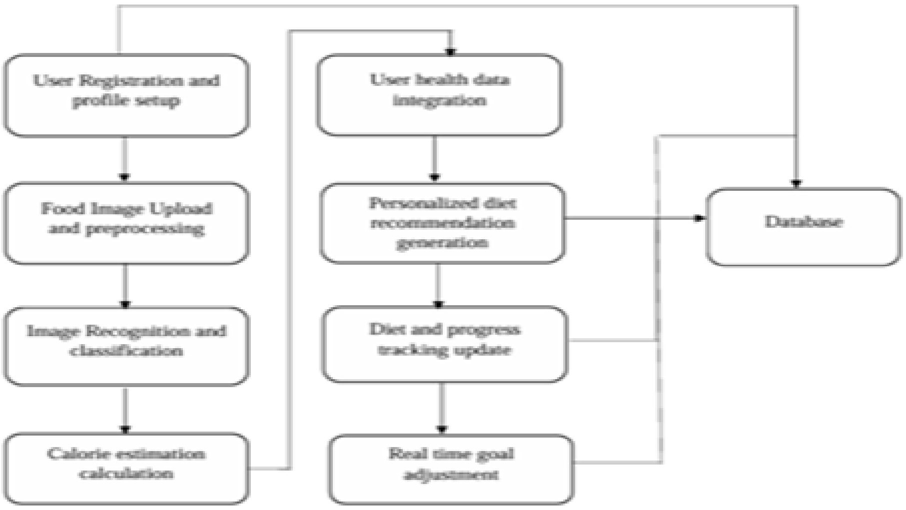

Fig1. Experiment workflow of model.

The database is designed to support efficient data retrieval and analysis while ensuring user privacy and data security.The implementation and evaluation of the proposed system yielded promising results, demonstrating its potential to revolutionize dietary management and promote healthier lifestyles. The system achieved an overall food recognition accuracy of 95% during testing. The use of CNNs, combined with SIFT and Gabor filters, contributed to robust performance in identifying diverse food items across various environments. The model's ability to generalize to new food categories was validated through cross-validation on an independent dataset. The calorie estimation process demonstrated high precision, with discrepancies of less than ±5% compared to ground truth values. This level of precision guarantees that clients get solid data approximately their dietary admissions, empowering them [14] to create educated choices approximately their nourishment. The decision tree-based recommendation engine effectively generated customized meal plans that aligned with users' health profiles and dietary preferences. Feedback from test participants indicated high satisfaction with the relevance and practicality of the recommendations. Users reported improved adherence to dietary goals and greater motivation to maintain healthy eating habits. The system's user-friendly interface and interactive features contributed to high levels of user engagement. Participants appreciated the convenience of uploading food images and receiving instant feedback on their dietary intake. The real-time tracking and goal adjustment features were particularly well received, as they provided actionable insights for achieving health objectives. Preliminary evaluations of the system's impact on health outcomes showed positive trends. Users who adhered to the system's recommendations experienced improvements in key health metrics, such as BMI and blood sugar levels. This level of exactness guarantees that clients get solid data almost their dietary admissions, empowering them [14] to form educated choices almost their nourishment.

III. PROPOSED METHOD

In this study, we have used Anaconda is a powerful Python and R distribution designed for data science, machine learning, and scientific computing. It comes with an Integrated Development Environment (IDE) that includes tools like Jupyter Notebook, Spyder, and RStudio, along with a graphical interface called Anaconda Navigator for easy package and environment management. Python Code is contained within objects in object-oriented programming, which Python makes easier. Although punctuation is used in other languages, English keywords are used more frequently and there are less syntactical structures. Flask is a web framework that allows developers to build lightweight web applications quickly and easily with Flask Libraries. With the help of Flask Libraries, developers can quickly and simply create lightweight web apps using the Flask framework. There are majorly two modules used in this model.

A. FOOD TYPE IDENTIFICATION AND CALORIE ESTIMATION

The proposed system architecture consists of five important modules namely, resizing, feature selection, classification, volume measurement and calorie estimation as shown in Figure 2 An image of food item is taken using a built in camera of a smart phone or it can be downloaded from the web. A food image is captured and stored with its measurements when it is used for first time. Food images with two food items can also be taken and segmentation is done to separate the food portions. Then the image processing and classification techniques are applied to find the area of food portions, their volume, and their nutritional facts.

1. RESIZING

The food image input is passed to the resizing stage in this first step. The image is resized by this module according to its height and breadth. The image should have 64 pixels because of this scaling. Next, rescaling of the photos is done so that 64*64 pixels is the largest side.

2. FEATURE EXTRACTION

Using the SIFT, Gabor filter, and colour histogram methods, this module extracts several features from the provided image.

IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 04, April 2025 https://www.ijirae.com/archives

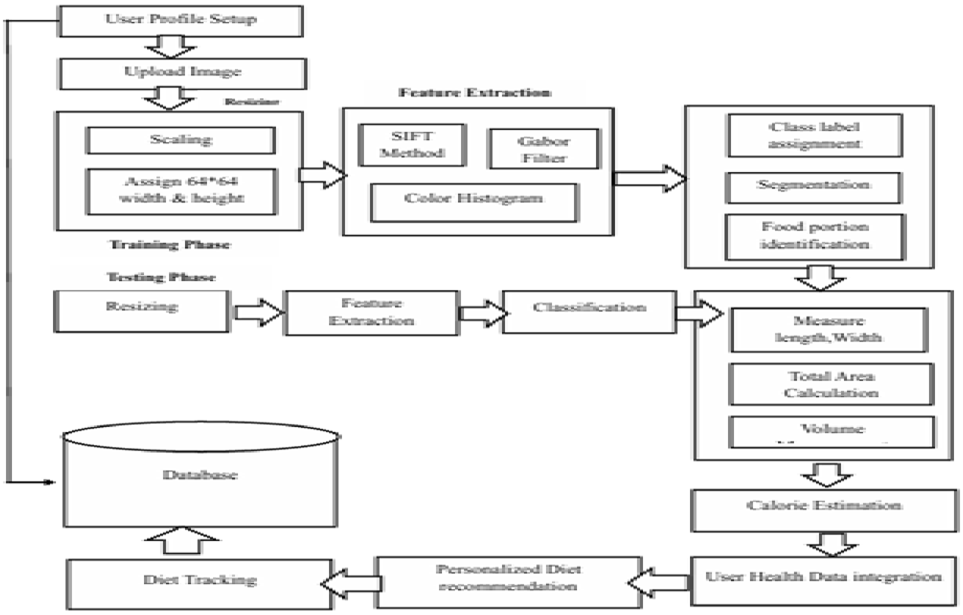

Fig 2. System Architecture

i. SIFT Method

Scale Invariant the feature transform algorithm is used to identify as well to characterize an image's local features. A resized image is sent to the feature extraction module as input. As seen these stage takes the image's dense grid and extracts its main points and feature vector. The feature vector and important spots are extracted using the SIFT technique. This algorithm is divided into four phases. Firstly, Scale Space Extrema Detection Equation (5.1) indicates that this phase uses the difference of the Gaussian function to explore the entire image locations to extract the key points. Thus, the salient features are independent of orientation and scale.

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$$

Where, G(x, y, σ) is a Gaussian function (5.1) , I(x,y) is an input image and L(x,y) is a scale-space function.
Secondly, Key Point Localization illustrates that the amount of contrast will vary among all the key points retrieved. It is not possible to examine the critical locations with low contrast for additional processing. Therefore, it must be eradicated. From the retrieved key points, the low contrast key points are removed in this stage. Third, Orientation assignment for each key point position are distributed based on image's gradient direction. Finally the image has been scaled along with the distributed orientation. Each feature's position is used in subsequent computations. According to Equation (1), these transformations are invariant.

$$\theta (x, y) = \frac{1\tan-1 ((L(x,y+1)- L(x,y-1))}{(L(x+1,y) - L(x-1,y)))} \qquad (1)$$

where, L(x, y) is a scale space, θ(x, y) is pre computed using pixel difference, I (x, y) an input image and L(x, y, σ) is a scale-space function. Fourth, Key points are used in this stage to derive the feature vector. The SIFT technique is used to extract each key point as a 16*16 pixel region, which is then further subdivided into several tiny 4*4 sub partitions.

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\frac{\left\|\mathbf{x}_i - \mathbf{x}_j\right\|^2}{2\sigma^2}\right) \qquad (2)$$

ii. Gabor Filter Method

The resized image is fed into the feature extraction step. To extract the feature vector, it employs the Gabor filter bank approach (Madival & Visswanath, 2012). To extract a feature vector based on an image's texture, the gabor function is employed. As seen in Figure 4.2, the image is segmented using the Gabor filter approach based on textural features. Three steps make up this algorithm. Firstly, The Gabor filter is suitable for images in which each pixel within window is subjected to the Gabor filtering procedure, which accounts for the texture feature. The mean and standard deviation of the energy in the filtered image are then measured. Generally speaking, picture block size and image segment size are proportionate.

$$G(x, y, \theta, u, \sigma) = 1/2\pi\sigma 2 \exp\{- x2 + y2/2\sigma 2\}\exp\{2\pi i (u\, x \cos\theta + u\, y \sin \theta)\} \qquad (3)$$

Where, σ is standard deviation, θ is orientation and u is frequency of sinusoidal wave. This step eliminates low contrast points using Gaussian function. Secondly, image segmentation involves divided the image into number of 4×4 blocks, and each block is convolved with Gabor filter. Here, Gabor filter with six orientations and five scale is used. Moreover, the mean and variance of the Gabor sizes are calculated for each block.

iii. Color Histogram Method

Images of resized food are supplied as input for the colour histogram technique. The allocation of colors in the picture is defined by its colour histogram. Each colour zone's pixel count is stored in colour histograms of colour space. Similarly, the grey level histogram is constructed for grey level images. Image: I Quantized colors: c1, c1…cm, Distance b/w two pixels: |p1– p2| = Maxi(|x1– x2|, |y1– y2| Pixel set with color c: Ic = p| I(p) = c Given distance: k

3. MULTICLASS SVM CLASSIFICATION METHOD

The commonly used approach for SVM-based multi-class classification is the one-versus all method (Vapnik, 1999). This technique constructs 'k' SVM models, where 'k' represents the number of classes. The final classification is determined based on the classifier with the highest output score. All available data samples are required to train N classifiers. This algorithm constructs n(n-1)/2 binary classifiers by considering all possible pairwise combinations of the n classes. During training, samples from one class are treated as positive, while those from the second class are considered negative. To aggregate the results from these classifiers, the MaxWins algorithm is applied, determining the final class by selecting the one with the highest number of votes. Since each classifier is trained on a subset of data consisting of only two classes, the number of samples used for training each one-vs-one classifier is relatively small. This reduction in sample size minimizes nonlinearity, leading to faster training times. However, a key drawback of this method is that each test. RBF assigns class labels using Equation (5.4). The segmentation process is used to divide the food image into distinct portions, helping to identify different food items. It also defines the boundaries of the food within the image. The primary goal of Multiclass SVM is to classify data into multiple categories, predicting the target values of test samples based on their features.

4. MEASUREMENT OF VOLUME

A volume measurement is performed using the identified food portion as input. This method takes two pictures, one from the top and one from the side, to calculate the size of the food. Length and width are measured using the top view, and height and depth are calculated with the aid of the side view.

B. FOOD RECOMMENDATION SYSTEM

The architecture of the Intelligent Food Recommendation System is shown in Fig 3. It has multiple modules including User Interface, Decision Manager, Interface Engine, Rule Base, Deep Neural Network Manager, Agent Subsystem, Image Data Manager, Diabetic Analyzer, Image Database, Lookup Table, Disease Database, Food Database and Food Recommendation. The decision manager oversees the overall system operation and ensures its functionality. It performs multiple tasks, including selecting an effective classification method on basis of predefined rules. Additionally, it plays a important role in developing a reliable decision support system, particularly in medical diagnosis. The preprocessing subsystem consists of four components: the input dataset, preprocessing module, outlier detection module, and feature selection module.

i. User interface

The user interface module facilitates interaction between the user and the system, making it a crucial component of the overall architecture. This interface enhances user experience by enabling effective perception and communication of essential information. Additionally, the user interface design incorporates computing capabilities to ensure seamless interaction. It provides well-structured formats and appropriate languages, allowing information to be displayed with high accuracy and improved user control.

ii. Preprocessing module

Five Food products can be photographed using a smart phone or an integrated camera, and the photos can be saved in a database. Another option is to download food photos from the internet and store them in a food picture database. Food photos go through a preprocessing step that involves feature extraction and scaling. The resizing procedure modifies the image's height and width, making sure that 64 × 64 pixels is the largest side. Repetitive, redundant, or duplicate features may be included in the clinical data utilized in the model for disease prediction; these should be eliminated or aggregated for better model development. There are hundreds of patient records with numerical, categorical, and other kinds of data in the UCI Machine Learning Repository, which is used as a sample dataset. The first step in preprocessing is data cleaning, which involves converting text files into a relational database format, removing redundant records, and addressing any missing or incomplete data. Following this, feature selection is performed to refine the dataset for training the fuzzy neural network.

iii. Feature selection module

The algorithms SIFT, Gabor filter, and Color Histogram method are used in the feature selection phase to extract image features, i.e., local key points, texture features, and color features, respectively. In this module, the SIFT feature selection algorithm is used for attribute subset selection, which helps to build effective classification models. Additionally, the selection process is helpful in identifying a minimal feature subset by eliminating redundant features, and it uses an enhanced version of the filter method for feature selection to ensure high accuracy. This procedure is necessary to increase the computing speed and accuracy of the intelligent decision support system.

iv. Deep neural network manager

The retrieval, matching, and execution of rules are handled by the Deep Neural Network Manager. The expert's choice determines whether it uses a forward chaining or backward chaining interface mechanism. To improve the efficiency of decision-making, it builds discriminate networks and uses rule-matching algorithms. Effectively managing uncertainty, even when working with incomplete information found in the food dataset, the main benefits of using a Deep Neural Network Manager.

v. Rule base

Rule mining from the rule base is based on a knowledge representation model, which is created as described in this portion of the architecture. The rule base contains all of the new rules that the suggested algorithms produce. The Rule Manager interacts with the rule base to check for the final decision, while the Deep Neural Network Manager lets users request the addition or removal of rules.

Individual patient record inquiries are then processed using these stored rules. These queries can be run as singleton queries to ascertain each patient's severity of a certain ailment.

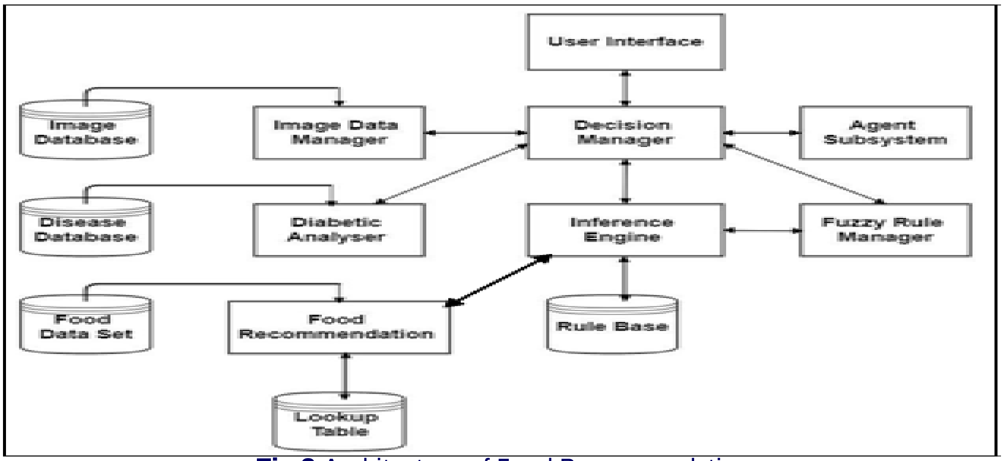

Fig 3. Architecture of Food Recommendation

vi. Decision manager

The Decision Manager module is in charge of managing the recommended system's overall operation. This module makes crucial decisions on disease prediction, food type recognition, and user-recommended foods [15]. To increase accuracy of the proposed meal suggestion system, the decision manager is also necessary for feature selection and classification. It utilizes the features of the Deep Neural Network Base and Inference Engine to facilitate decision-making. Additionally, it plans and oversees the operations of all other system modules.

vii. Agent subsystem

When it comes to food type recognition, sickness prediction, and food suggestion, the Agent Subsystem Module helps the Decision Manager Make well-informed decisions. The Agent Subsystem, which includes specialized agents for fuzzy reasoning, temporal reasoning with prediction, and diabetes analysis, is what the Decision Manager uses to facilitate intelligent decision-making. Every agent sense and act in accordance with predetermined regulations. The Agent Subsystem also makes it easier for all other subsystems in the suggested system to communicate with one another. Agents can be moved between modules under the direction of the Decision Manager for activities like data gathering, inference, and efficient communication, even though they are typically static.

viii. Interference engine

In order to assist the Decision Manager in making decisions, the Acceptance Engine Module is in charge of carrying out investigator derivation by applying rules from the rule base and providing the generated data. Furthermore, it uses the deep Neural Network to make decisions throughout the entire food selection process.

ix. Image data manager

When it comes to identifying food types, predicting diseases, and recommending foods, the Operator Subsystem Module supports the Decision Manager. The Operator Subsystem which includes specialized agents for fuzzy reasoning, temporal reasoning with prediction, and diabetes analysis, is used by the Decision Manager to make intelligent decisions. The Operator Subsystem also makes it easier for the other subsystems in the suggested system to communicate with one another. Although agents are typically passive, they can be moved across modules for effective communication, data collecting, and inference under the direction of the decision manager.

x. Diabetic manager

The Diabetic Analyzer Module predicts if a patient has diabetes by using a database of diabetic diseases. Simple decision rules are produced by an algorithm and kept in the rule base as the foundation for the prediction process. Each patient's disease severity is determined by applying these guidelines to the processing of individual patient record queries. The Diabetic Analyzer's expected outcomes are what the Decision Manager uses to make decisions. Additionally, the module takes into account the medical history of the patient, including blood test results, blood sugar levels, and eating patterns. It also uses historical and current data to predict future health trends. Additionally, by grouping diabetic patients into distinct categories, it makes it possible to provide individualized preventative measures.

xi. Food recommendation module

The Decision Manager's disease prediction results are used by the Food Recommendation Module to provide appropriate food options using a food dataset and a lookup table. This module suggests foods for patients based on their calorie content and the severity of the ailment. To further ensure that dietary recommendations are in line with expert guidance, the Food Recommendation Module also integrates proposals from subject matter experts. When recommending food, it also takes into account advice from dietitians and medical professionals. This module selects suitable food products for people of various ages, either from a list of possibilities that are already available or from readily available food sources.

xii.Image database

Several food photos that were taken with a smart phone, an internal camera, or downloaded from internet are kept in the image database. Using this database, food kinds are identified and the calorie value of the recognized food items in the input photos is estimated. The database's food photos are taken from the Internet. Six food item categories have been examined for analysis in this study.

ISSN: 2349-2163
https://www.ijirae.com/archives

Algorithm 1 Decision Tree-Based Partition

Require: Input: D dataset – features with a target class
for ∀features **do**
for Each sample **do**
Execute the Decision Tree algorithm
end for
Identify the feature space $f_1, f_2, \ldots, f_x$ of dataset UCI. (9)

Obtain the total number of leaf nodes $l_1, l_2, l_3, \ldots, l_n$ with

its constraints (10)
Split the dataset D into $d_1, d_2, d_3, \ldots, d_n$ based on the leaf nodes constraints. (11)
Output: Partition datasets $d_1, d_2, d_3, \ldots, d_n$

IV. EXPERIMENTALRESULTS

In Results mainly focus on verifying our proposed method and evaluating the performance, we set up an experimental system by the specification, as shown inTable1.

A. Model Evaluation Metrics

Partitioning the dataset into two separate subsets—a training set and a test set—is necessary for model validation. The test set is used to assess the model's performance, whereas the training set is used to create and train the model. Using this method, 80% of the data was used for training and 20% for testing. A number of evaluation criteria, such as accuracy, precision, recall, and F1-score, were used to assess the model's performance.
TN (True Negatives): Indicates the tally of negative tests accurately classified by the show.
TP (True Positives): Talks to the number of positive tests accurately classified by the show.
FN (False Negatives): Shows the number of negative tests mistakenly classified by the show.
FP (False Positives): Implies the tally of positive tests incorrectly classified by the demonstrate

$$\text{Accuracy}=\frac{\mathrm{TP+TN}}{TP+TN+FP+FN}\quad(4)$$

$$\text{Precision}=\frac{\mathrm{TP}}{TP+FP}\quad(5)$$

$$\text{Recall}=\frac{\mathrm{TP}}{TP+FN}\quad(6)$$

$$\text{f1}=\frac{2(\mathrm{precision*recall})}{precision+recall}\quad(7)$$

Table 1: Performance of Models.

Metrics	Accuracy	Precision	Recall	F1
YOLOv8 for object detection	97.5911	98.5644	98.2131	98.1263
Linear Regression for Calorie Estimation	96.2345	97.4932	97.3545	97.2491
Decision Tree for recommendation	83.1023	84.7763	83.1677	83.1674

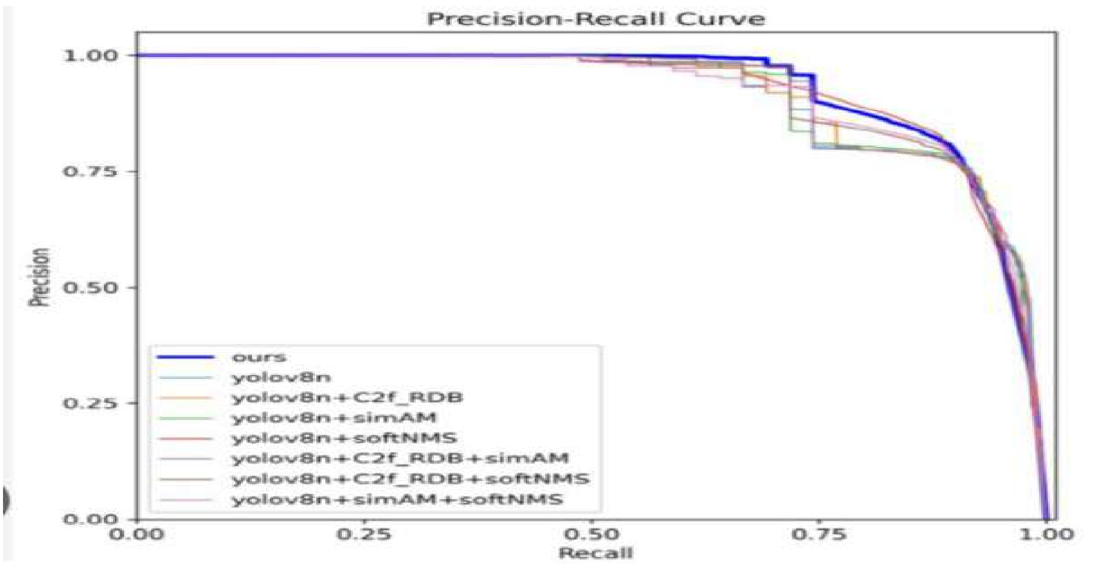

Fig 4. Comparison of YOLO Models

B. Sample Outputs

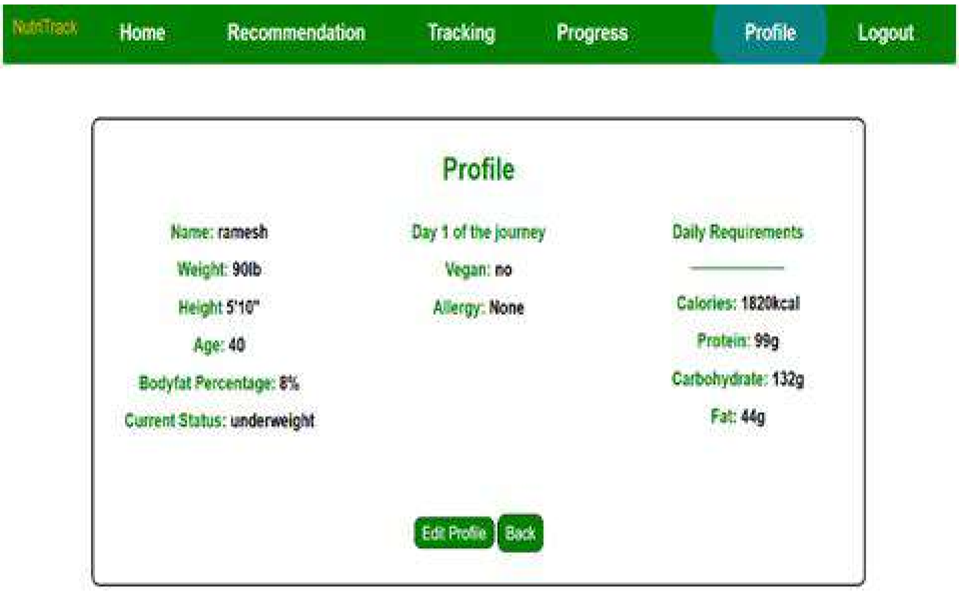

Fig 5. Shows the details filled by the user.

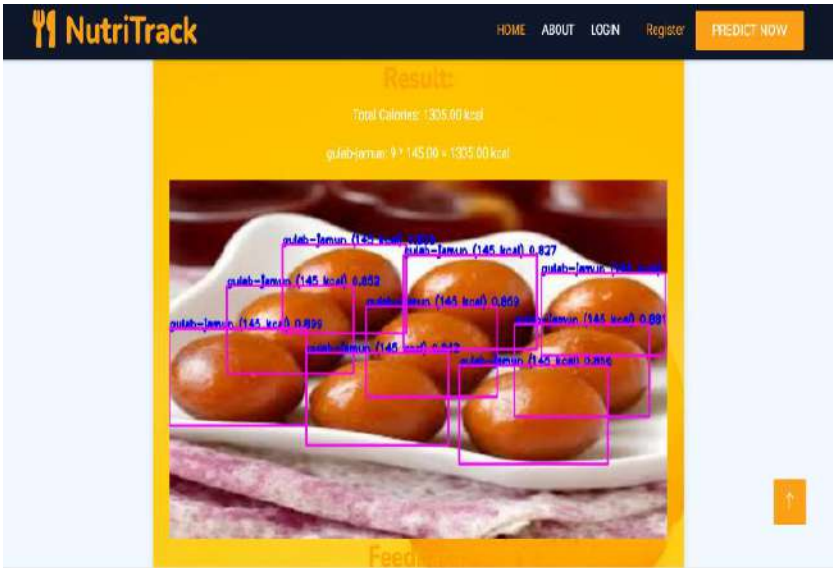

Fig 6. Result for food calories prediction

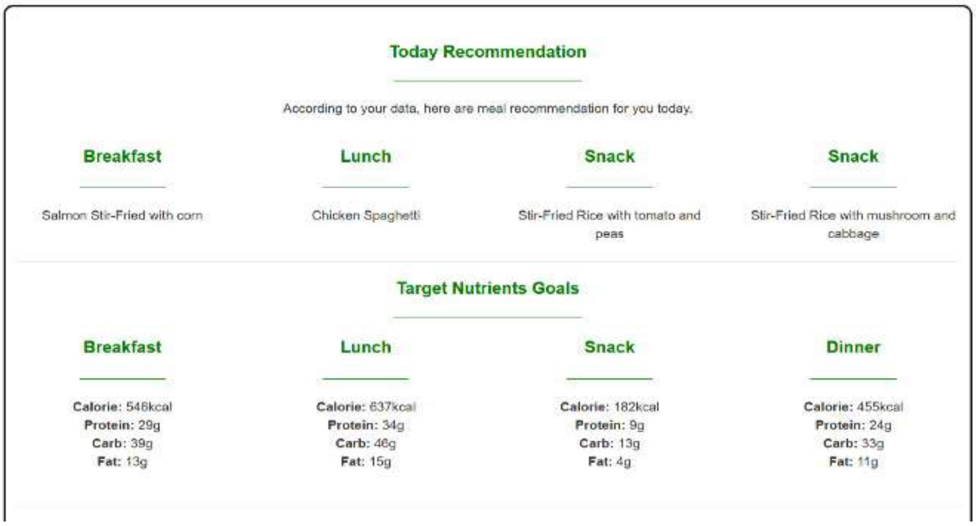

Fig 7. Shows the food recommendation and Nutrients Goals.

Fig 8. Diet Tracking for each day

Fig 9. Weight Progress for Daily and Weekly basis.

V. CONCLUSION

The Smart Dietary Planning System leverages advanced image processing, machine learning, and personalized health tracking to provide an automated and intelligent diet management solution. The system architecture ensures seamless integration of food recognition, calorie estimation, and diet recommendations by combining computer vision techniques (SIFT, Gabor Filter, and Color Histograms) with machine learning models (SVM for classification and segmentation).By incorporating user health data and real-time progress tracking, the system continuously adapts dietary recommendations, making it a highly personalized and dynamic nutrition management tool. The calorie estimation process, based on portion size measurements and a nutritional database, enhances accuracy, while real-time goal adjustments allow users to achieve optimal dietary balance. This system represents a significant advancement in AI-driven nutrition planning, offering an efficient, scalable, and user-friendly approach to diet tracking and health management. Its potential applications extend beyond individual users to healthcare, fitness industries, and wellness platforms, promoting data-driven and automated dietary interventions for better health outcomes.

REFERENCES

1. The creators of this paper arerahibAbiyev and Joseph Adepoju. The title of the paper is "Automatic Food Recognition Using Deep Convolutional Neural Networks with Self attention Mechanism". Springer January 2024.

2. Sreetha E. Sreedharan, Gnanadesigan Naveen Sundar, DhanasegarNarmadha,"NutriFoodNet" in *IIETA*, Sep. 2023, pp. 306–311.

3. Haralick, R.M. 1979. Statistical and Structural Approaches to Texture. Proceedings Haralick, R.M. 1979. Statistical and Structural Approaches to Texture. Proceedings of the IEEE, 67:786-804; (also 1973, IEEE-T-SMC.

4. Baeldung, Michal Aibin,"Gabor Filter analysis," in baeldung, Jul. 2023, pp. 233–239.

5. EdaraAvinash, AkulaSai Krishna "Personal nutritionist Diet recommendation system based on user health information",vol.24,no.1,pp.27–40,Jan.2023
6. K. Aizawa, K. Maeda, M. Ogawa, Y. Sato, M. Kasamatsu, K. Waki, and H. Takimoto. Comparative study of the routine daily usability of foodlog: A smartphone-based food recording tool assisted by image retrieval. Journal of Diabetes Science and Technology, 8(2):203–208, 2024.
7. H. Hoashi, T. Joutou, and K. Yanai. Image recognition of 85 food categories by feature fusion. In IEEE ISM, pages 296–301, 2010.
8. The creators of this paper are MD Bushra, CH.N.V Jyothirmai, KanithiTeja Chari, KummariArun Kumar. The title of the paper is "Calorie Detection and Diet Management using Machine Learning". IJSRET June 2024.
9. Baumberg, A 2000, 'Reliable Feature Matching Across Widely Separated Views', Proceedings of Conference on Computer Vision and Pattern Recognition, pp. 774–7818.
10. The creators of this paper are Prof. P.P. Deshmukh, Mr. Aayush Y. Mohod, Mr. Vrishank A. Thakare, Mr. Niraj S. Karde. The title of the paper is "Diet Recommendation System using Machine Learning". ISSN April 2024.
11. The creators of this paper are The title of the paper is "Food Recognition System and Nutrition Tracking Using Convolutional Neural Network Model". APCIT July 2024.
12. The creators of this paper are Chaitanya A, JayashreeShetty, PriyamvadaChiplun .The title of the paper "Food Image Classification and Data Extraction Using Convolutional Neural Network and Web Crawlers". ScienceDirect 2023.
13. The creators of this paper are Scholar J. Panneerselvam, Asst. Prof. Mrs. K. Vasumathi, Asst. Prof. Dr. S. Selvakani. The title of the paper "Food Calorie Estimation Using Deep Learning". IJSRET Jan 2024.
14. Almaghrabi, R, Villalobos, G, Pouladzadeh, P &Shirmohammadi, S 2012, 'A Novel Method for Measuring Nutrition Intake Based on Food Image', Proceedings of the International Conference on Instrumentation and Measurement Technology.
15. AnguloN´u˜nez 2002, 'Rule Extraction from Support Vector Machines', Proceedings of Europian Symposium Artificial Neural Network, pp 291–296.
16. Bandini, L, Must, A, Cyr, H, Anderson, S, Spadano, J & Dietz, W 2003, 'Longitudinal Changes in the Accuracy of Reported Energy Intake in Girls 10-15 Years of Age', American Journal of Clinical Nutrition, vol. 78, pp. 480–484.
17. T. Islam, A. R. Joyita, M. G. R. Alam, M. Mehedi Hassan, M. R. Hassan and R. Gravina, "Human-Behavior-Based Personalized Meal Recommendation and Menu Planning Social System," in IEEE Transactions on Computational Social Systems, vol. 10, no. 4, pp. 2099-2110, Aug. 2023, https://doi:10.1109/TCSS.2022.3213506
18. Praveen M Dhulavvagol, SG Totad, "Performance enhancement of distributed system using HDFS federation and sharding", Procedia Computer Science, 2023, https://doi./10.1016/j.procs.2023.01.254
19. Praveen M Dhulavvagol , Prasad M R , Niranjan C Kundur , Jagadisha N , S G Totad, "Scalable Blockchain Architecture: Leveraging Hybrid Shard Generation and Data Partitioning", Intl. International Journal of Advanced Computer Science and Applications. Vol.14, No-8, pp355-363, 2023, DOI: https://doi/10.14569/IJACSA.2023.0140839
20. RituShandilya, Sugam Sharma, Johnny Wong, MATURE-Food: Food Recommender System for Mandatory Feature Choices A system for enabling Digital Health, International Journal of Information Management Data Insights, Volume 2, Issue 2, 2022, 100090, ISSN 2667-0968.
21. Khanna D, Peltzer C, Kahar P, Parmar MS. Body Mass Index (BMI): A Screening Tool Analysis. Cureus. 2022 Feb 11;4(2):e22119. https://doi:10.7759/cureus.22119. PMID: 35308730; PMCID: PMC8920809.
22. Guldogan, E. M., Gumus, Y. Y., &Akcayol, M. A. (2022). A personalized food recommendation system based on dietary habits and health conditions. Computers in Biology and Medicine, 143, 105277.
23. P.Thotad, Geeta RB, Shashikumar G. Totad, "Survey on Mining Diabetes Data and Its Applications on diagnosing methods in Disease Management Using Big Data" International Journal of Advanced Research, A peer reviewed journal, in Computer Science, Volume 9, No. 1, pp 341-345, Jan-Feb 2018, ISSN No. 0976-5697,DOI: https://doi/10.26483/ijarcs.v9i1.5261
24. PuneethTotad, Geeta R. Bharamagoudar and Shanta S. Kallur "Boosting-based machine learning approaches for diabetes prediction using Indian demographic and health survey-2021 data" , Research Square, 11-April-2023, https://doi.org/10.21203/rs.3.rs-2784266/v1
25. Jiang, S., Qian, X., Shen, J., Fu, Y., & Mei, T. (2022). Personalized food recommendation with long-and short-term preference dynamics. IEEE Transactions on Knowledge and Data Engineering, 34(5), 2230- 2243.
26. PuneethTotad, Geeta R. Bharamagoudar and BasavarajAnami "Predictive Analysis of Diabetes Mellitus Using Decision Tree Approach" IEEE 2022 2nd Asian Conference on Innovation in Technology (ASIANCON), October 2022, https://doi:10.1109/ASIANCON55314.2022.9909122 Electronic ISBN:978-1-6654-6851-0 CD:978-1-6654-6849-7,Print on Demand(PoD)
27. Jiang, W., Zhang, C., Li, Y., & Sun, Y. (2023). A Personalized Food Recommendation System Based on Multi-Modal Deep Learning. IEEE Access, 11, 23849-23858.
28. Huang, Y., Chen, Y., &Xie, X. (2022). A Hybrid Meal Recommendation System Considering Nutritional and Social Factors. IEEE Access, 10, 77843-77853.
29. Bai, Y., Jiang, L., &Xu, C. (2022). Personalized Food Recommendation System Based on Deep Learning and Knowledge Graph. IEEE Access, 10, 46855-46863.

30. Joshi, Y., Totad, S.G., Geeta, R.B., Prasad Reddy, P.V.G.D. (2018). Mobile Agent-Based Frequent Pattern Mining for Distributed Databases. In: Bhalla, S., Bhateja, V., Chandavale, A., Hiwale, A., Satapathy, S. (eds) Intelligent Computing and Information and Communication. Advances in Intelligent Systems and Computing, vol 673. Springer, Singapore. https://doi/10.1007/978-981-10-7245-1_9

31. Weir CB, Jan A. BMI Classification Percentile And Cut Off Points. 2023 Jun 26. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing; 2024 Jan. PMID: 31082114.

32. Ribeiro, R., Carneiro, D., Novais, P., &Analide, C. (2022). A Personalized Nutrition Recommendation System based on Machine Learning and Ontological Knowledge. IEEE Access, 10, 47731- 47745.

33. Lowe, D.G. (2004). Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision, 60: 91-110.

34. World Health Organization, Nutrition. (2022). WHO global Nutrition report.

35. Wong, K.M., Po, L.M., Cheung, K.W. (2007). Dominant color structure descriptor for image retrieval. In 2007 IEEE International Conference on Image Processing, San Antonio, TX, USA, pp. VI-365.

36. He, Y., Xu, C., Khanna, N., Boushey, C.J., Delp, E.J. (2014). Analysis of food images: Features and classification. In 2014 IEEE International Conference on Image Processing (ICIP), Paris, France, pp. 2744-2748.

37. elzenszwalb, P.F. (2005). Representation and detection of deformable shapes. IEEE Transactions on Pattern Analysis and Machine Intelligence, 27(2): 208-220.

38. Dr. JyotiSekhar Banerjee, Dr. Rajeshree D. Raut, Dr. Y. R. M. Rao, The Indian Journal of technical education, vol 48.

39. SitaramBhagavathy, B. S. Manjunath, "Modeling and Detection of Geospatial Objects Using Texture Motifs", IEEE Xplore 20 November.

40. M.NagaKeerthi, M.KumarRaju, "Computer-Vision-Project-Driver drowsiness-detection", Journal of Emerging technologies and Innovative Research, July 2024.

41. Kerry Brown, Barney smith, John G. taylor, Martin Morland, Geoffrey C. Gunn, Martin Bourke, rogershaw, Anthony Rundell and Robert H. Taylor, "South East Asia", Tandfonline, 2010.