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NutriSenseAI: An Intelligent System for Automated Nutrition Tracking

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***Abstract*— Diet intake monitoring is an important aspect in the management of healthy life that is unaffected of obesity, diabetes, and other diet related conditions. Most applications and websites require manual meal entry by users, which can be time-consuming and prone to errors, leading eventually to user despondency due to interest attrition over time. This paper proposes an AI-based system responsible for tracking food as a possible solution toward overcoming such challenges. The proposed system applies advanced artificial intelligence capable of automatically and accurately recognizing what people are eating from different multimodal inputs that include images and textual descriptions. We hereby used Google's Gemini pro model for real-time recognizing the food item as being integrated with USDA data for nutritious content validation is done as much accurate as possible. We implemented a JSON-based approach which ensures standard data handling and effective integration with other systems. Through our app user will be able to resize portion, set custom diets, keep an eye on its diet in real- time environment. It supports voice input, making it easier and more fun to record food consumption. The effectiveness of the system was evaluated by using 50 different food images. The model reaches a mean absolute error of 9.8% in the calorie estimate and an accuracy of 92% in food recognition beating quite a few existing methods both in terms of accuracy as well as ease of use.**

***Keywords*— AI-Based Nutrition Tracking, Food Recognition System, Multimodal AI Models, Automated Dietary Monitoring, Nutrient Estimation, Portion Size Detection, USDA Food Data Central.**

I. Introduction

Exact monitoring of the food you consume is necessary to stay healthy and prevent diseases such as obesity, diabetes, cardiovascular issues, and metabolic disorders [1]. Knowing the calories eaten, the correct nutrient ratio, and the vitamins and minerals acquired from the food allow people to make healthier food choices, which in turn, leads to better health over time [2]. Unfortunately, the majority of dietary apps require that the user input data manually. This means that the users have to search for food, estimate how much they have have consumed.
With growing artificial intelligence technologies empowered with computer vision have created a way for more efficient and accurate methods of diet-tracking [3]. The solutions take in image recognition with other machine learning method to not only identify diet content but also to estimate portion sizes and calculate the nutrients in the given meals [4].

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A model like Google Gemini can better understand both the picture and text provided, thereby facilitating the recognition of complex Food items, memorizing the context, and differentiating even between those foods that have similar appearance [5]. This makes the diet monitoring less tedious and much more efficient; thus, people feel relieved from their manual input's method. Such an AI solutions offer immediate contract-based feedback and nutrition tracking. hence, our user will be able to control his diet better.

However, AI-powered nutrition applications can also have problems like data corruption, model biasing, and errors in calorie estimation [6]. Therefore, it is important to use reliable and standardized nutrition databases to back up these paced AI results. The USDA Food Data act as Central database that offers detailed information about nutrients, macronutrients, and food constituents of the diet [7]. When such efficient AI results are backed up with highly reliable data, the system gives the most accurate and scientifically worthy nutrition guidance to user that is both feasible for people and medical practitioner.

Our experiment presents an AI-guided tool that utilizes Google Gemini's ability to compute images as well as text and the USDA Food Data's Central database. The system, which is developed with Streamlit, features an easy-to-use interface with the listed functionalities: JSON outputs, varying portion sizes, user-defined diet targets, progress tracking, and voice command enabled for enhanced accessibility [8]. With this, users are allowed to download their Diet history and receive the balance diet comments so that it becomes easier to keep their health goals over time.

To assess the performance of the system, 50 different food images were used. The model achieved an average error rate of 9.8% in calorie prediction and had an accuracy of 92% in food identification, which is a result better than most other methods. These results are a clear indication of the promise of AI when used in conjunction with accurate nutritional data to transform digital food tracking into a more accurate, automatic, and convenient process for users [10]. The system described here is the core future devices can rely on to adapt diet plans, support public health programs, and improve the general digital health sector

II. Literature Review

- World Health Organization (WHO Global Health Estimates 2021) Ng, M., Fleming, T., Robinson, M., et al. (2014). "Global Nutrition and Health Challenge": Malnutrition and malnourishment, whether by under or overnutrition, remain leading health issues worldwide. According to the World Health Organization (WHO) in 2021, unhealthy diet consumption and lack of physical activity were major contributors to the increasing number of obese people as well as cases of diabetes, cardiovascular diseases, and other non-communicable diseases. Close to 70% of all deaths throughout the world are caused by these non-communicable diseases. Traditionally used nutrition assessment methods such as dietary interviews, food diaries, and manual calorie counting were common but inefficient and hard to sustain for extended periods. All the available methods depend on user compliance and accurate self-reporting which makes them less useful practically when applied in real-life health management (Ng et al., 2014). Hence there is a growing need for automated systems that would be easy to use continuously for monitoring dietary intake as well as maintaining long-term health. Recent innovations in digital health technologies placed nutrition at the problems' core.
- A. Afshin, P. J. Sur, K. A. Fay, et al., "Health effects of dietary risks in 195 countries, 1990–2017: A systematic analysis for the Global Burden of Disease Study 2017," The Lancet, 2019, doi 10.1016/S0140-6736(19)30041-8:
  Dietary risks continue to be the main contributors to illness and death worldwide. Malnutrition includes both undernutrition and overnutrition, continuing to place a great burden on the health of populations in all parts of the world. Improper eating habits strongly correlate with deaths caused by obesity, diabetes, or heart diseases as per the reports from WHO. The traditional methods of diet assessment which include questionnaires, food recalls, and manual calorie counting are time-consuming, suffer heavily from reporting errors, and cannot be sustained over long periods effectively; hence they lose their effectiveness when applied for real health monitoring. Thus ,there is an increased appetite for technological systems that could automatically measure dietary intake and provide true health insight with little effort required from users.
- GBD 2017 Diet Collaborators. "Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017." The Lancet (2019): Global comparative risk assessment indicates that poor diet is the largest modifiable driver of NCD outcomes, with 11 million deaths and 255 million DALYs attributable to dietary risks in 2017. Results indicate that high intake of sodium, low intakes of whole grains, and fruits were the leading dietary risks for the burden attributable to diet globally. This is most important for digital nutrition systems because high uncertainty challenges emanate

from mixed dietary data sources with incomplete country coverage which underscores the urgent need for better measurement and monitoring methodology.

- Boushey, C. J., Spoden, M., Zhu, F. M., Delp, E. J., Kerr, D. A. “New mobile methods for dietary assessment: review of image-assisted and image-based dietary assessment methods.” Proceedings of the Nutrition Society (2017): This review describes the way image-assisted and image-based dietary assessment methods try to overcome the limitations of traditional self-report by using pictures taken at eating occasions to recall more details and to estimate portion size better. In studies reviewed here, underreporting was reduced when pictures were added compared with using the traditional method alone, indicating that picture use might improve data quality in typical field conditions where underreporting is a problem. However, as emphasized in this review, usable picture-based systems for real-world deployment must still be carefully designed regarding understandability and different sources of error and validated across different user groups and settings.
- Timon, C. M., Astell, A. J., Hwang, F., et al. “Mobile ecological momentary diet assessment methods for behavioral research: systematic review.” JMIR mHealth and uHealth (2018): It briefly describes the mobile ecological momentary diet assessment (mEMDA) methods, targeting the measurement of food behaviors nearer the meal, through event-contingent (conducted while the person is eating) and signal-contingent methods (prompted reporting). The argument posed is how mEMDA can provide more accurate results through the reduction or complete avoidance of recall periods, improving ecological validity through the conduct of dietary assessments in everyday life. Yet, the article continues to state how real-world limitations, based on study periods, methods of collection, and considered food categories, can work against the accurate measurement of total dietary energy.
- Vasiloglou, M. F., Marcano, I., Lizama, S., et al. “Multimedia Data-Based Mobile Applications for Dietary Assessment: Systematic Review.” (Published review available via PubMed Central, 2022): The review describes and compares smartphone-based dietary assessment systems supporting the estimation of nutrient composition based on multimedia data (photos and videos), which is based on the ongoing trend of AI-driven mobile health applications for nutritional support. The researchers describe 22 different systems according to the assessment environment (laboratory, preclinical, and clinical) and conclude that many of those are insufficiently assessed in real-life settings. Also, greater emphasis is given to the involvement of end users (patients and healthcare practitioners) in the design of these systems and comparisons to traditional assessment methods in evaluating the accuracy.

III. SYSTEM DESIGN AND ARCHITECTURE

The AI-Powered Nutritionist System has an aim to be very accurate, personalized, and trustworthy for the user. These goals eradicate the types of errors that are possible in current day food recognition systems such as the inability to count calories accurately, adapt to different diet formats, or use real time standard nutrition data. To accomplish all these goals, the system features a flexible, multi-layered type of structure that fuses AI for food recognition with verified nutrition data sources in order to be accurate, precise and trustworthy. At the core of our system is an efficient and smart AI unit that uses both type of data like images and text to recognize food, to figure out how much is eaten, and to calculate the nutritional content on the basis of portion analysis. Using powerful models such as Google Gemini, the system is able to understand complex structured meals, mixed dishes, and even challenging ingredients with a high accuracy.

This component works closely with trustworthy standard sources such as USDA Food Data Central that helps in automatically chaining the food to the right calorie value and nutritional contents. Thanks to this advance setup, the system is efficiently able to offer reliable, scientifically grounded guidance which are free from the shortcomings that are usually faced by stand-alone AI systems. Besides the recognition and data matching parts, a personalized and user- friendly interface component is also an important component of the system. It gives the users an opportunity to set their own best suited dietary goals, and allows to change the portion sizes, track their progress and get recommendations based on their specified health and dietary habits. Advance features like voice activation, meal history tracking and exporting, interactive dashboards make the system more accessible and friendly for different type of user groups. By fusing advance AI analysis with verified standard data and user-friendly design, the system builds a strong, dependable, and convenient environment for nutrition tracking. Therefore, it is beneficial not just for individual health but also for large- scale public health initiatives throughout the society.

A. Architectural Overview

The proposed system works on a three-tier client–server database architecture, consisting of:
Front-End Client – Users get in touch with the system through a Streamlit web application interface. By means of an interactive dashboard, users are capable of uploading their food images, entering desired prompts, and viewing or analyzing nutrition data output. Moreover, the system is designed in a manner that it is both user-friendly and enjoyable, includes voice input features, meal history export facility, as well as portion size adjustment features.
Back-End Server – The system's main pillar that handles image interpretation and processing, user authentication for personalized usage, and coordinating between AI and databases. Besides ensuring that the data is transferred precisely and securely, the server also takes care for user sessions and is capable of handling any number of requests concurrently. In addition, the server uses caching for speedier operations and has provisions for errors to ensure system stability.
AI Core – It's the place where intelligent computation occurs. The multimodal model of Google Gemini is used to get the most accurate and precise food recognition and the AI unit is connected with the high standard USDA Food Data Central database to verify from the trusted nutrition data. These components are involved in estimating users' food consumption, performing nutrient- based calculations, and understands meal context to offer precise, accurate, user oriented and dependable diet-based suggestions.
This setup gives several advantages. In fact, it allows each part of the system to be built, improved, or extended singly. Besides that, it makes it possible for the system to become larger and to work efficiently on different types of devices and with a great number of users. Plus, the manner in which goods are kept apart in the back-end and AI core is a move towards the safety of sensitive data. The design also doesn't limit itself to only those features it currently has but rather new features can be easily added later on such as tailored diet recommendations, predicting nutrition intake, or integration with health wearables. Figure 1 demonstrates how the different parts - front-end, back-end, and AI core - work together smoothly to provide output that is user friendly, dependable, and in real-time.

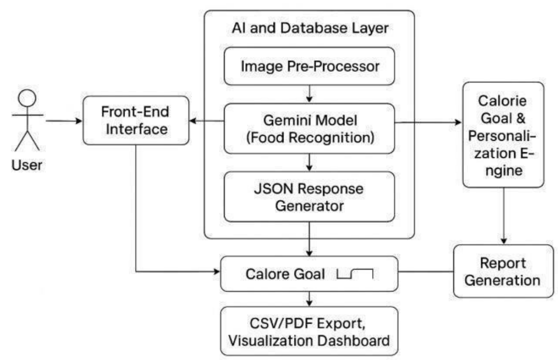

Fig 1:Architecture for Automated Food Recognition and Calorie Estimation

The system consists of three main parts: the Front-End Client, the Back-End Server, and the AI Core. The FrontEnd Client offers users an attractive, safe, and easy to navigate interface by which they can write a journal and talk to a chatbot. Back- End server handles the incoming requests, performs the users' validation and hence decides whether they should be given the access or not, and finally it keeps users data in a safe encrypted form. The AI Core is the most significant component, which basically works the most in therapy situations. It includes the Input Preprocessor that is capable of detecting crisis traces, a Retrieval-Augmented Generation system, which utilizes both the fixed and dynamic information sources, and a Response Post-processor, which ensures that the responses are polite and acceptable for returning them to the user. The main principles on which the system operates are protection of the users, giving them personalized care, and cultural sensitivity. In case of an announcement of an emergency, the system will immediately link the user with a reliable human help line.
The components of the system may individually be altered or extended to bring in new features such as more sophisticated analysis, using alternative input like pictures or sound, or connecting with wearable medical devices. With this modular configuration, the system is also capable of checking its performance, handling any problems that may arise and learning from new data, thereby always keeping the AI Core up to date, helpful, and aware of the situation. The integration of an intuitive design, behind the scenes robust security, and clever AI

make the system an all-in, dependable, and a socially responsible way of digital health that is suitable for different people and can easily be scaled up to meet the needs that arise in the future.

B. System Components

Front-End Client: Streamlit being the core framework, the front-end is straightforward, user-friendly, and mobile ready. It is possible for users to upload one or more food images, get instant nutritional data, track calorie and nutrient goals for the day, and save in-depth progress reports. Moreover, the interface comes with voice input support for food logging in a hands-free manner and visually appealing charts to understand nutrient intake trends. In fact, all communication with the back-end is done via encrypted HTTPS links, thus user information is kept safe and confidential. Back-End Server: This part, which is created with Python, is the main idea of the application, it includes the functions of the app like food recognition, database access, and user experience.

Back-End Server: This part, which is created with Python, is the main idea of the application, it includes the functions of the app like food recognition, database access, and user experience. It stores in a secure way user-related data such as age, weight, food liking, and health goals in order to provide personalized calorie, nutrient, and micronutrient guidance. Moreover, the back end is responsible for converting AI results into a structured JSON format which is easy for other systems to use, as well as user sessions management, error handling, and multi-user functionality at the same time to guarantee the smooth and efficient flow of the system.

AI and Database Layer: This layer combines two intelligence modules:

- Multimodal AI Engine: It uses Google Gemini 2.0 Flash, which can process both text and images to identify complex food items, determine portion sizes, and calculate nutritional values. The text and image features help the model understand mixed dishes and ambiguous ingredients more effectively.
- Nutrition Database Module: It is the USDA Food Data Central Application Programmer Interface that provides standardized nutritional information for all food items, such as calories, macronutrients, and micronutrients. The system notes AI-generated results and compare against this database to confirm the accuracy and reduce the probability of fake data which is a very common problem associated AI models.

Combining AI logic with standardized database verification builds the system more trustworthy and providing nutrition analysis that is consistent with science. The modular architecture allows for future upgrades such as the inclusion of personalized eating plans, prediction of nutritional trends, or connecting with wearable health devices such as smartwatch for real-time health monitoring. By balancing responsive user interfaces, solid back-end infrastructure, and AI- driven guidance that are verified with standard real data, the system offers better scalable, dependable, and practical solution for digital nutrition tracking.

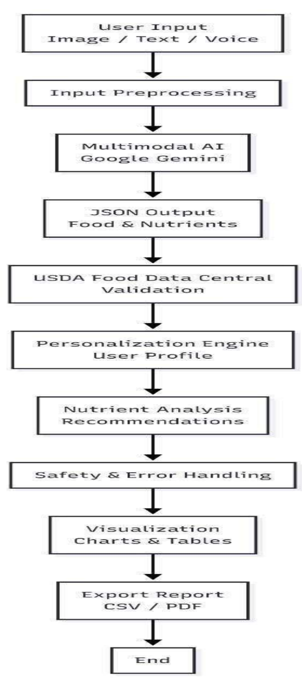

Fig 2: Flowchart of Implementation

C. Data Flow and Processing Pipeline

The system has a series of steps to process food images and give correct nutrition facts:

- Firstly, the users can do one of the following: upload a food picture or describe the food. The system supports multiple image uploads, voice recording of food, and adding comments so that different categories of users can easily put in their data.
- Secondly, the photos that have been uploaded are of various qualities and are thus processed to standardize their quality. The processing includes resolution, color, and orientation adjustments and also changing these into a format that can be used by Google Gemini API. Preprocessing ensures that the pictures are bright and consistent and thus allow AI to accurately recognize food items and lower the number of mistakes.
- Once the images are prepared, the Gemini AI model takes them up for processing. It identifies the food, measures the quantity, and predicts the nutritional value. The model gives a precise output in JSON format, with the description of calories, proteins, carbohydrates, fats, vitamins, and minerals, together with the confidence rates for each of the identified items.
- After AI has made the predictions, the system verifies the food items from the USDA Food Data Central database. It helps in adjusting the nutritional values, correcting the AI that might have committed errors, and making the results scientifically valid. This process helps therefore in the reduction of the risk of false and fabricated information from the AI model.
- After that, the system goes on to use personal data about the user such as their age, weight, activity level, and eating goals to calculate how much of each nutrient they have taken. It compares this data with their individual goals and makes recommendations to them in order that they may meet their nutritional needs. The machine also keeps an eye on the balance of macronutrients, calorie intake, and the levels of important vitamins and minerals, so that the advice given is tailored to the individual.
- The final step is the demonstration of the results in the easiest manner to the user. They are able to see graphics, progress bars, and tables that condense the nutritional and food intake data of the user. Also, they can view the trends within a specified time, identify any missing nutrients, and have the option of saving CSV or PDF reports for record keeping, sharing with doctors, or long-term reference.

The scheme is also equipped with functions to handle errors, store data efficiently, and manage user sessions to make the service usage quick and smooth.

D. Personalization And Safety Mechanisms

The system emphasizes ethical data handling and user safety:

Personalization Engine: The device uses the Harris Benedict equation to calculate the daily caloric requirement of each individual. According to the person's need, e.g. weight loss, weight maintenance, or muscle gaining, the program changes its advice. In addition, the application takes into account the person's activity frequency, sedentary lifestyle, age, and gender so that the food recommendations are compatible with the individual's body type and level of physical activity.

Error Handling: The system, in cases of doubt, incomplete information, or low confidence in its conclusions, it significantly highlights the output as "Estimated values – verification recommended". This makes the users recognize the results more and avoids them being deceived. Along with nutritional data, the platform also displays confidence levels thereby giving users the necessary information to decide wisely.

Data Privacy: Without obtaining consent from the user, the system is not allowed to keep any health data. Any temporary images or words that are entered are instantly removed after the processing is done. The personal data of users are protected with encryption while at rest and in transit, following the established standards for personal data protection.

Safety and Compliance Checks: Besides, the system has built-in safety checks to uncover mis portions, misleading calorie figures, and unbalanced nutrients. In addition, the system aligns the dietary advice given with the official nutrition guidelines so that it is safe and beneficial, especially for people suffering from chronic diseases such as diabetes or hypertension.

User Empowerment: Our system gives clear notices for user input, and giving instructions to guide the user so he can get a better understanding of the nutrition values as well as about their limitation. Thus, user become more confident in making a suitable dietary decision, and the trust in AI nutritional guidance systems is built stronger gradually over the time.

By adding safety, support features and visible disclaimers, the system preserves and proves its reliability and ethical compliance while providing user with precise, user-centered dietary suggestions. Without obtaining consent from the user, the system is not allowed to keep any health data. Besides, the system has built-in safety checks to uncover mis portions, misleading calorie figures, and unbalanced nutrients. Thus, user become more confident in making a suitable dietary decision, and the trust in AI nutritional guidance systems is built stronger gradually over the time.

IV. RESULT AND VALIDATION

A. Experimental Setup and Ground Work

To assess the proposed NutriSense pipeline, the experiments were carried out on the test set, which comprised 50 images of foods commonly eaten as meals and as munchies, captured as realistic images using smartphones with varying lighting, viewpoints, and background images. The basis for the groundtruth data was the systematic mapping of the foods to a standard food entry, based on the USDA FoodData Central, with the data accessed using the API endpoints for searching for foods and for the details for each food. The labelling approach, using the USDA FoodData central, ensures best practices and fits well with the need for systematic calculations for nutrient analysis, as opposed to unverifiable or inconsistent values for nutrient data.

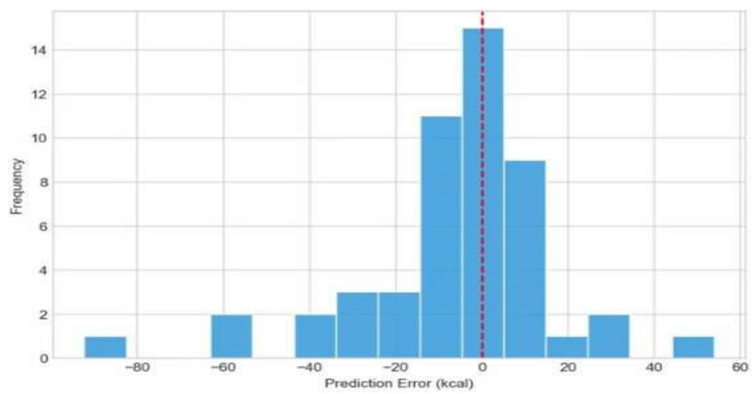

Fig 3. Distribution of Prediction Error in Calorie Estimation

To further check how accurate the NutriSense pipeline is, we found the prediction error in kilocalories (kcal) by taking the difference between the predicted calorie values and the ground-truth calorie values from USDA FoodData Central. The histogram of prediction errors shows that most of the predictions are close to zero. This means that the system gives fairly accurate calorie estimates with only small errors in most cases.

B. Quantitative Results

On the 50-image evaluation set, NutriSense achieved high recognition reliability and comparatively low calorie estimation deviation for an automated workflow.
The Table Below shows the results after testing the model we created:

TABLE I: RESULTS

METRIC	RESULT
FOOD RECOGNITION (TOP-1 ACCURACY)	92%
CALORIE ESTIMATION ERROR (MEAN ABSOLUTE % ERROR)	9.8%

These results support the feasibility of using multimodal AI for reducing manual logging burden, which is a known barrier in mobile dietary assessment workflows. They also align with the broader research direction showing that image-based approaches can reduce underreporting and improve practicality compared with purely text-based diaries, although careful validation remains essential.

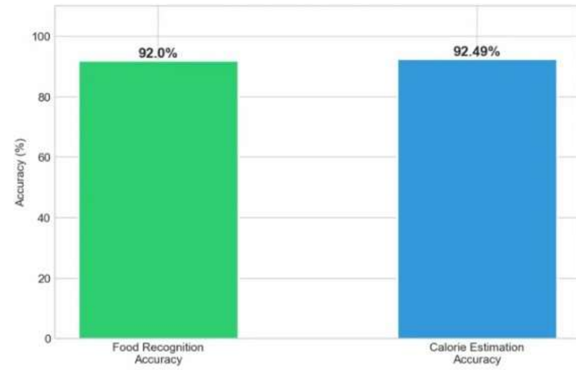

Fig 4. Performance Evaluation Metrics of the Proposed System

C. Validation and Error Analysis

The errors that are identified are mainly due to the existing challenging cases of image-based dietary analysis: mixed dishes, occlusions, and portion size uncertainties. From the existing literature on image-based dietary analysis applications, it has also been seen that the system often needs correction from the user itself on certain parameters (like serving size modifications) or even involves the concept of auditing or verification stages while achieving the goal of a correct group or individual level output of nutrients. In the NutriSense system, the integration of the USDA FoodData Central serves the purpose of the verification step where the output of the nutrients has been limited to a standard value that is traceable using the API. This allows a positioning of NutriSense as a pragmatic link between (i) time-consuming and high-burden manual entry and (ii) image-based systems where high levels of edits are still a requirement. This is in line with the direction found in the reviews related to mobile diet assessment, where there is a need to minimize user burden without sacrificing scientific interpretability.

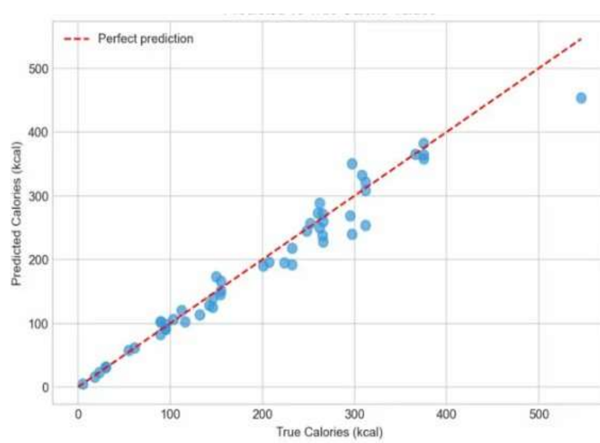

Fig 5. Predicted vs. True Calorie Values of the Proposed Model

Figure X shows how the predicted calorie values and the actual calorie values are linked. The scatter plot shows that most of the guesses are close to the perfect prediction line, which is the ideal diagonal line. This means that the NutriSense pipeline usually gives calorie estimates that are close to the real values, even though it's hard to use pictures to figure out what someone eats. To be honest, this is in line with what the reviews say about mobile diet assessment, which is that we need to make it easier for users without losing scientific accuracy.

V. Conclusion and Future Scope

NutriSense really shows what happens when you mix AI with top-notch nutrition databases enabling you to get a smarter, faster way to track what you eat. Thanks to some serious computer vision, smart multimodal AI, and reliable sources like the USDA Food Data Central, NutriSense can spot what’s on your plate, guess the portion size, break down the nutrients, and dish out advice that actually fits your needs. Let’s be honest, most old school methods like food diaries, calorie counting and filling out endless surveys are a pain and are pretty unreliable. People forget, guess, or just give up. NutriSense changes that. It takes all the hassle out of the process, so tracking your diet becomes easy and actually accurate. You get the info you need, right when you need it, to make better choices and stay healthy without getting bogged down in the details.

Even with all the progress so far, AI-driven nutrition monitoring still hits a few roadblocks. Figuring out portion sizes in everyday life That's tricky. People eat differently, dishes get mixed together, and how food looks on the plate varies wildly from one culture to another. On top of that, these AI systems have to keep up with all kinds of diets from different places and backgrounds if they want to give advice that actually works for real people. And none of this matters if folks stop using the app after a few weeks. Keeping people interested and engaged is just as important as getting the science right.

NutriSense has a lot of room to grow. Imagine if it connected with wearables and IoT sensors tracking what you eat would feel almost effortless. Throw in some predictive analytics, and suddenly you're not just logging meals, you're getting real warnings about health risks before they show up. That's real preventive care. But it's not just about data. Make the interface more interactive, add a bit of gamification, let people use their voice, and give instant feedback now you're making the experience actually enjoyable.

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