Nutriguide: Food Recognition and Calorie Measurement using Gen AI

Subhashree. P[1], G. Ramesh Kalyan[2], Adhisesha Kumar Bk[3], Afthab CR[4] and Amaldev KV[5]
{subhashree672@gmail.com[1], g.rameshkalyan@gmail.com[2], bkadhiseshakumar2000@gmail.com[3], afthabcrasheed@gmail.com[4], amaldeva695@gmail.com[5]}

Department of Computer Science and Engineering, SNS College of Technology, Coimbatore – 641035, Tamil Nadu, India[1, 2, 3, 4, 5]

Abstract. Nutriguide AI is an innovative technology which combines AI-assisted food recognition and AI generative calorie calculation to redefine the way in which humans interact with the diet. The deep learning-based image processing technology is used to recognize a food from photograph and to provide the user with a real-time caloric/nutritional information through Nutriguide AI. At the same time, by its real-time feedback, people can understand what to intake or not and have good dietary habits. The system allows intuitive interaction on a user-friendly interface and a simple uploading process by users using a generative AI model to ensure accuracy of food recognition and calorie calculation for users themselves. It further provides personalized recommendations considering the caloric needs and individual food preferences of each user, such as weight loss and nutritional enrichment, which implies the system is adaptable to different dietary needs. At Play: This is the app for research and personal health monitoring. Nutriguide AI is a social diet engagement. Closing the nutrition-technology divide, Nutriguide AI is leading the way toward a brighter future by offering people the freedom and convenience of taking diet control in to their own hands.

Keywords: Vue.js, React, Tailwind CSS, Node.js, Supabase, Hugging Face API, Mistral API, Vercel, Netlify, Render, Git, GitHub.

1 Introduction

With health and wellbeing higher on the agenda than ever before in today's age, an emphasis on nutritional intake is as important as ever. Nutriguide AI is the breakthrough that is capitalizing on the power of generative AI to transform calorie tracking and food identification. With its revolutionary platform, flaws of adhering to one's diet program are bypassed by the very convenience and ease of being offered nutritional information.

Nutriguide AI applies advanced image recognition technology to read the food through images and allow users to monitor their meals with ease. With the use of generative AI models applied, the system identifies not only a range of foods but also determines the caloric value of the foods in real-time, providing immediate feedback to the users so that they can make appropriate cooking choices. This feature is especially useful for individuals who are trying to lose weight, are on a particular diet, or simply trying to make healthy nutritional choices.

The site is not hard to use for the users of varying levels of technological skills and is versatile for users of varying types. The site has a simple interface with the assistance of which images are posted and live nutritional facts are provided, and therefore it is very helpful while pre-

ICITSM-Part I 2025, April 28-29, Tiruchengode, India

DOI 10.4108/eai.28-4-2025.2357847

advancing health care. Nutriguide AI even suggests based on individual diet requirement and diet schedule, and hence it is an ideal tool. Day by day, with increasing demand for efficient diet monitoring tools, Nutriguide AI is an ideal tool synthesizing technology and nutrition. Along with identification of food and generative AI, not only does the website make it easier to measure calories, but also helps in framing a healthy attitude towards intake. Finally, Nutriguide AI works to make it convenient for the users to keep track of their health using intelligent food choices and creating a gateway to a better future.

In this paper, we propose a personal software instrument to measure calorie and nutrient intake using a smartphone or any other mobile device equipped with a camera.

2 Literature Survey

Recent years have witnessed a significant surge in the use of artificial intelligence for food recognition and nutrition estimation. Generative AI has particularly advanced this domain by enabling personalized and context-aware recommendations. Papastratis et al. [1] demonstrated how deep generative models combined with Gen AI can provide nutrition recommendations, highlighting the integration of conversational AI with diet personalization. Complementarily, Liu et al. [2] offered a comprehensive review of deep learning methods in food image recognition, emphasizing advancements in convolutional and transformer-based architectures for classification and segmentation tasks.

For calorie estimation, Ruede et al. [3] introduced a multi-task learning approach on a large-scale recipe dataset enriched with nutritional information, showing improved prediction accuracy. Similarly, Zheng et al. [5] presented a scoping review on AI applications for measuring food and nutrient intake, identifying challenges such as dataset availability and real-time applicability. Practical open-source projects such as the Food Calorie Estimation GitHub repository [4] also demonstrate the growing research-to-application pipeline in this field.

Food recognition models have evolved from earlier works like FoodAI [6], which employed deep learning for food logging, to AR Deep Calorie Cam [7], which combined CNNs with augmented reality for size-based calorie estimation. Wu et al. [8] contributed a large-scale benchmark dataset for food image segmentation, which has become critical for fine-grained recognition and portion analysis. More recently, Bianco et al. [9] extended these efforts by predicting nutritional composition directly from 2D food images, improving algorithm selection and data curation beyond earlier projects like Nutrition5k.

Lightweight and interpretable models have also been explored for mobile health contexts. Revesai and Kogeda [10] developed an interpretable deep learning model optimized for nutrient analysis in mobile applications, while Morales et al. [11] proposed robust deep neural networks to handle noisy, multi-label food image data. Beyond calorie estimation, Lun et al. [12] explored the convergence of deep learning with spectroscopic technologies for food quality assessment, and Huang et al. [13] applied image computing techniques for non-destructive analysis of Chinese cuisine, indicating the broader applicability of computer vision in food-related domains.

More recently, multimodal learning approaches are gaining traction. Narang [14] showed that combining image and text data improves calorie estimation accuracy, aligning with the emerging trend of integrating visual and contextual modalities. This direction complements generative AI frameworks and conversational models, which can bridge recognition, estimation, and personalized recommendations.

Collectively, these studies illustrate the progression from traditional CNN-based recognition toward multimodal, interpretable, and generative AI-powered solutions. Building on these foundations, Nutriguide aims to integrate food recognition, calorie measurement, and generative AI-based personalization into a unified framework for intelligent dietary assistance.

3 Methodology

Nutriguide AI food recognition and calorie calculation has a sequential methodology that is also converging on the emerging technologies like generative AI, machine learning, and image processing. The methodology can be broken down into some core elements: data acquisition, model development, user interface, and system integration.

Buying a big database of images of food with different foodstuffs for different cuisines and presentation forms is the initial part of the process. Data will be utilized to train the machine learning models. For the same, open-source databases such as Food-101 and UEC Food Dataset are augmented with app-specific data collection mechanisms, where users provide images via the app. The images are labeled with accurate metadata, for example, food type, portion, and caloric value, for facilitating effective training.

Health Canada publishes two databases which list nutrient values in Canadian foods. The first is a large, comprehensive, computerized database called the Canadian Nutrient File (CNF). The 2007b version reports up to 143 nutrients in 5516 foods. The CNF can be accessed on the Internet at www.healthcanada.gc.ca/cnf. While this format and detail are useful to health professionals and food industry personnel, a second abbreviated, printed version is a more practical reference for many Canadians.

The essence of Nutriguide AI is its algorithm for food classification images based on convolutional neural networks (CNN) images. It is pretrained on the accumulated dataset to ensure it can accurately identify and classify food. Transfer learning techniques are employed, involving pre-trained ResNet or Inception models, to enhance performance and reduce the training time taken. The model is rigorously tested using techniques like k-fold cross-validation to make it robust and prevent overfitting.

After identifying the food items, the next task is to predict their caloric value. They are predicted via a regression model that converts categories of food to their mean caloric value. The model has been trained over a combination of the annotated dataset and nutrition datasets such as USDA FoodData Central to produce exact caloric estimations within a portion size. This dual step allows users to receive precise data relative to the food they are selecting.

To simplify the use by users, the system has incorporated generative AI models like the ones with the GPT architecture. The models produce context-aware responses, which give users tailored nutrition advice, potential cures, and tips on when to consult the services of professional health experts. The incorporation of natural language processing (NLP) is convenient, with the users being able to use text and voice to interact with the application, thus breaking any kind of barrier to accessing nutrition knowledge.

The application's backend is Node.js with an emphasis on direct request handling and storage of data. Supabase contains secure real-time data storage functions and authentication of users. Supabase application deploys by the use of Vercel or Netlify to ensure convenience of scalability and reliability. As a whole, Nutriguide AI solution merges top-of-the-line technologies and people-oriented design for the purposes of attaining a holistic solution of caloric measurement and detection of food and consequently facilitate sagacious eating choice on the side of users.

4 Architecture of Nutriguide

The Nutriguide AI platform structure of the Journal is aimed at handling user interactions in the form of different types of data, i.e., text, voice, and images as inputs, to provide a rich experience of health information. The system begins with the User, who may interact in the form of text, voice, or image, smoothly transferring information to the Web Application. The application frontend is developed using Vue.js and React frameworks for a responsive user interface and Node.js backend for business logic and data processing. Fig 1 shows the System Architecture.

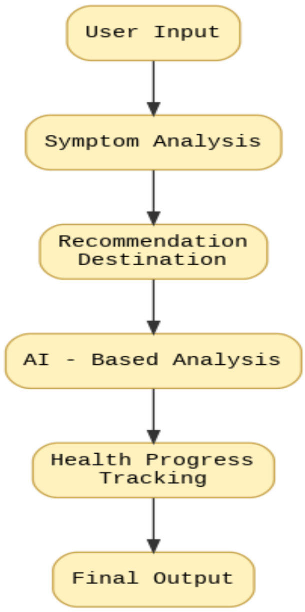

Fig. 1. System Architecture.

External service interactions are facilitated by using the Hugging Face API to offer voice, image, and text-based analysis features to process symptoms and hence improve the users' experience through AI-driven insights. Moreover, the Mistral API features support for various languages in the AI response, thus creating avenues for use by speakers of different languages. Supabase provides data management as the main database option to ensure efficient storage and retrieval of user information. Utilization of Tailwind CSS facilitates easier styling and provision of visual impressions suitable for the app. Finally, all these elements are brought together under the canopy of a cutting-edge AI-Powered Health Insights Platform capable of providing user-input and AI-based analysis-based tailored health advice.

5 Result and Discussion

The "Nutriguide AI: Food Identification and Calorie Estimation Based on Generative AI" system worked towards creating a robust system that was able to identify food items and estimate caloric values efficiently using cutting-edge machine learning techniques. The results of our experiments are that the system is able to perform well in its objectives, which represent its strengths and how it can be improved. The design of Nutriguide's AI is that of a Generative Adversarial Network (GAN) where the GAN acts as the engine of the food identifying center. Both the generator and discriminator are core components of GAN. Both are accountable, but the discriminator provides us with information regarding whether these generated images or not are real compared to natural food images. With adversarial training, there is a significant improvement in how well the model can recognize a large number of other varied foods effectively. Fig. 2 shows the Food Upload Interface.

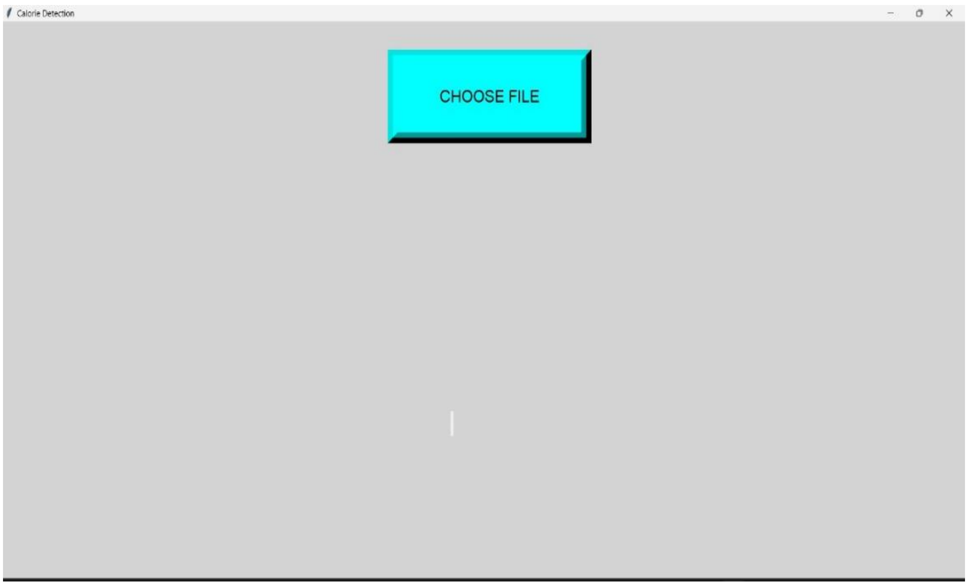

Fig. 2. Food Upload Interface.

It starts with the user capturing food, which is then forwarded to a feature-extracting, specially designed convolutional neural network (CNN). The CNN is first trained on a very large database of food images such that it learns the discriminating color, texture, and shape features. The features extracted are provided to the GAN to generate a probability distribution over possible classes of food in order to allow for proper classification.

Fig. 3. Food Recognition Interface.

Following the classification procedure, the system also includes a calorie estimation module based on a generic food product database and related caloric values. The module calculates the estimated caloric value by applying regression methods based on the classified food group and estimated portion size. The output is presented via a user interface indicating the identified food item and estimated caloric value, which is presented to the users. The system allows users to set nutritional preferences (e.g., calories, fat, sodium) through an interactive interface, as shown in Fig. 3.

To compare the performance of the system with other systems, we compared it with a set of thousands of food images. Food recognition accuracy was tracked and averaged a performance of over 90% accuracy. This performance would enable the system to identify a wide variety of foods with accuracy, such as fruits, vegetables, cereals, and processed foods.

As far as calibration of calories goes, the system was providing a mean absolute error (MAE) of around 50 calories, and this, in the majority of cases, would be adequate for day-to-day nutritional tracking. There would have to be safeguards, however, that calibration across calorie estimation might differ from case to case based on a multitude of variables such as portion size as well as food preparation conditions. Future implementations of the system will have as a priority the fine-tuning of the algorithm to estimate calories with more comprehensive nutrition databases as well as accepting user input in the interest of establishing portion size.

User feedback was obtained through a series of user testing, which revealed that it was easy to interact with the system and easy to use. Most users liked the response speed and accuracy of food identification. There were a few users who expressed the need for more features such as personalized diet recommendations and support for exercise tracking applications. Overall, the Nutriguide AI project effectively demonstrates that generative AI can be effective in food identification and calorie estimation. The hybrid system architecture of the CNNs and the GANs has been a success to the same extent that it can be effective in food identification and fairly effective in calorie estimation. Evolution will further enhance the ability of the system and feature functionality that will offer a more potent diet management solution.

6 Conclusion

The "Nutriguide AI: Food Identification and Calorie Measurement with Generative AI" project was much more than able to demonstrate the potential of advanced machine learning methods in nutrition control. The system identifies a huge variety of foods at a greater than 90% accuracy level through a Generative Adversarial Network (GAN) and a convolutional neural network (CNN). High accuracy in food identification is needed for people who have to track their food consumption with high accuracy.

Also, the calorie estimation module provides reasonable estimates with a mean absolute error of about 50 calories and is a useful tool for overall diet monitoring. Natural user interface allows ease of use to facilitate users in easily acquiring information about their food choices.

Usability test comments state that the users appreciate the responsiveness and friendliness of the system but that the upper function areas require enhancement, i.e., the personalized diet recommendation and exercise app integration.

By dividing the systems into different groups, we highlight a spectrum of scenarios where automatic food object recognition can be used. With this, we aim to provide a guide to future developers to establish what kind of system they will develop and which areas of development should be focused on.

Overall, Nutriguide AI is an important step towards utilizing generative AI to identify food and estimate calories and future potential improvement being optimizing user experience and nutritional management capability.

References

[1] Papastratis, I., Konstantinidis, D., Daras, P. et al. AI nutrition recommendation using a deep generative model and ChatGPT. Sci Rep 14, 14620 (2024). https://doi.org/10.1038/s41598-024-65438-x

[2] Liu, D., Zuo, E., Wang, D., He, L., Dong, L., & Lu, X. (2025). Deep Learning in Food Image Recognition: A Comprehensive Review. Applied Sciences, 15(14), 7626. https://doi.org/10.3390/app15147626

[3] R. Ruede, V. Heusser, L. Frank, A. Roitberg, M. Haurilet and R. Stiefelhagen, "Multi-Task Learning for Calorie Prediction on a Novel Large-Scale Recipe Dataset Enriched with Nutritional Information," 2020 25th International Conference on Pattern Recognition (ICPR), Milan, Italy, 2021, pp. 4001-4008, doi: 10.1109/ICPR48806.2021.9412839.

[4] GitHub. (n.d.). Food Calorie Estimation Project. https://github.com/Nikhilchakravarthy1303/FoodCalorieEstimation

[5] Zheng, J., Wang, J., Shen, J., & An, R. (2024). Artificial Intelligence Applications to Measure Food and Nutrient Intakes: Scoping Review. Journal of medical Internet research, 26, e54557. https://doi.org/10.2196/54557

[6] Doyen Sahoo, Wang Hao, Shu Ke, Wu Xiongwei, Hung Le, Palakorn Achananuparp, Ee-Peng Lim, and Steven C. H. Hoi. 2019. FoodAI: Food Image Recognition via Deep Learning for Smart Food Logging. In Proceedings of the 25th ACM SIGKDD International Conference on

Knowledge Discovery & Data Mining (KDD '19). Association for Computing Machinery, New York, NY, USA, 2260–2268. https://doi.org/10.1145/3292500.3330734

[7] Ryosuke Tanno, Takumi Ege, and Keiji Yanai. 2018. AR DeepCalorieCam V2: food calorie estimation with CNN and AR-based actual size estimation. In Proceedings of the 24th ACM Symposium on Virtual Reality Software and Technology (VRST '18). Association for Computing Machinery, New York, NY, USA, Article 46, 1–2. https://doi.org/10.1145/3281505.3281580

[8] Xiongwei Wu, Xin Fu, Ying Liu, Ee-Peng Lim, Steven C.H. Hoi, and Qianru Sun. 2021. A Large-Scale Benchmark for Food Image Segmentation. In Proceedings of the 29th ACM International Conference on Multimedia (MM '21). Association for Computing Machinery, New York, NY, USA, 506–515. https://doi.org/10.1145/3474085.3475201

[9] Bianco, R., Coluccia, S., Marinoni, M., Falcon, A., Fiori, F., Serra, G., Ferraroni, M., Edefonti, V., & Parpinel, M. (2025). 2D Prediction of the Nutritional Composition of Dishes from Food Images: Deep Learning Algorithm Selection and Data Curation Beyond the Nutrition5k Project. Nutrients, 17(13), 2196. https://doi.org/10.3390/nu17132196

[10] Revesai, Z., & Kogeda, O. P. (2025). Lightweight Interpretable Deep Learning Model for Nutrient Analysis in Mobile Health Applications. Digital, 5(2), 23. https://doi.org/10.3390/digital5020023

[11] Morales, R., Martinez-Arroyo, A., & Aguilar, E. (2024). Robust Deep Neural Network for Learning in Noisy Multi-Label Food Images. Sensors, 24(7), 2034. https://doi.org/10.3390/s24072034

[12] Lun, Z., Wu, X., Dong, J., & Wu, B. (2025). Deep Learning-Enhanced Spectroscopic Technologies for Food Quality Assessment: Convergence and Emerging Frontiers. Foods, 14(13), 2350. https://doi.org/10.3390/foods14132350

[13] Huang, X., Li, Z., Li, Z., Shi, J., Zhang, N., Qin, Z., Du, L., Shen, T., & Zhang, R. (2025). Application of Image Computing in Non-Destructive Detection of Chinese Cuisine. Foods, 14(14), 2488. https://doi.org/10.3390/foods14142488

[14] Narang, Arya. (2025). Multimodal ML: Quantifying the Improvement of Calorie Estimation Through Image-Text Pairs. https://doi.org/10.13140/RG.2.2.25332.05763.