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AN INTELLIGENT FOOD ADVISORY SYSTEM USING ARTIFICIAL INTELLIGENCE

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Abstract

The growing global concern for healthier living has drawn significant attention to health and wellness worldwide. The World Health Organization(WHO) has acknowledged the rise in noncommunicable diseases (NCDs) like premature heart disease, cancer, and diabetes, with unhealthy diets being a major contributing factor. In response to this challenge, there is a strong global need for simple, intelligent tools that assist individuals in making informed dietary choices and understanding the nutritional impact of their meals. This research proposes the development of an Intelligent Food Advisor, an integrated web- based system designed to bridge the gap between meal consumption and nutritional awareness. The system leverages Artificial Intelligence (AI) to provide instant food recognition, detailed nutritional analysis, and customized dietary recommendations by combining real-time data processing with sophisticated deep learning models. The Intelligent Food Advisor empowers individuals to make informed dietary choices, promotes healthier eating habits, and contributes to addressing the worldwide issue of diet- related diseases. The system architecture combines a frontend built with HTML, CSS, and JavaScript, with a robust backend powered by the FastAPI framework and an SQL relational database for user data management. At its core, the system employs an EfficientNetV2B2 deep learning model fine- tuned on the Food- 101 dataset to accurately identify food items from user- uploaded images. Upon recognition, the system utilizes the Mistral 7B Large Language Model (LLM) via an API to generate real- time nutritional information and actionable advice. Additionally, the application provides users with graphical charts that categorize food choices as healthy, moderately healthy, or unhealthy. This comprehensive workflow from user authentication to daily dietary logging and performance monitoring makes nutritional management seamless, intuitive, and engaging.

INTRODUCTION

The World Health Organization identifies the global increase in noncommunicable diseases (NCDs) including various premature diabetes heart disease, and cancer as a major public health issue, with unwholesome diets being a significant contributing factor (Dai et al., 2021). In this case, customized nutrition has emerged as a promising research area, offering tailored dietary advice based on individuals' physical, physiological, and personal data (Pereira et al., 2020). In recent decades, several studies have proposed computational approaches to personalized meal recommendations using nutritional knowledge and user data (Cilia, D'Andrea, & Russo, 2020; Bianchini, Antonelli, & Marazzini, 2021). However, many of these approaches lack a holistic perspective that simultaneously considers nutrition-sensitive and preference-sensitive information. This research presents a comprehensive framework for daily meal plan recommendations, integrating both nutritional and preference-based data. The proposed system incorporates a re-filtering stage that employs a multi-criteria decision analysis tool to exclude foods unsuitable for the user's profile (Sarani Rad et al., 2024). Furthermore, it introduces an optimization-based stage to generate daily meal plans that recommend foods highly preferred by the user, not recently consumed, and aligned with their nutritional requirements (Ahmed, Khan, & Malik, 2023). A case study is conducted to evaluate the performance and effectiveness of the proposed system.

Global Trends in Diet-Related NCDs (2021–2025)

Between 2021 and 2025, the leading causes of mortality worldwide were noncommunicable diseases (NCDs), including cancer, diabetes, heart disease, and chronic respiratory disorders. According to the World Health Organization, inactivity, poor diet, and obesity were among the primary reasons (Chew et al., 2021). Despite increased worldwide awareness and health initiatives, NCDs consistently accounted for roughly 75% of all deaths, with an estimated 40 million lives lost annually (Al-Akayleh et al., 2024).

Year	Major Diet- Related NCDs	Deaths (Millions)	% of Global Deaths	Observations and Patterns
2021	Cardiovascular disease, Diabetes, Cancer	~40	~74%	WHO estimated ~17M premature deaths (ages 30–70).
2022	Cardiovascular disease, Diabetes, Cancer, Obesity	~41	~74%	NCDs remained the leading cause of death worldwide.
2023	Cardiovascular disease, Diabetes, Cancer	~42	~74%	Rising obesity and diabetes prevalence are noted globally.
2024	Cardiovascular disease, Diabetes, Cancer, Chronic respiratory illness	~43	~74%	WHO reported limited progress in reducing premature NCD deaths.
2025	Cardiovascular disease, Diabetes, Cancer	~40	~74%	NCDs still account for the majority of deaths; urgent need for dietary awareness tools.

Background of the Study :

Meanwhile, awareness of the link between diet and health has grown worldwide, creating a greater need for tools that help people track their eating. Keeping track of meals, calculating calories, and interpreting nutrition facts is often tedious and time- consuming, discouraging many from maintaining a healthy diet plan (Ahmed, Khan, & Malik, 2023). Recent advancements in machine learning, particularly computer vision and deep learning, provide a strong approach to addressing this problem (Abadi et al., 2016).

The research focuses on a Smart Food Recommender using AI- based image classification and food analytics to recommend healthy diet plans. Food image detection is merged with a nutrition database and user health profiles to build an intelligent system that helps users understand what they can eat (Mahapatra, Patnaik, & Dash, 2022). Furthermore, deep learning models such as Vision Transformer

(ViT) and TensorFlow Lite have been implemented to detect food and provide real-time recommendations (Tan & Le, 2021).

This research falls under the domain of Smart Healthcare, leveraging the latest technologies to spread diet consciousness, avoid lifestyle diseases, and promote healthy living (Al-Akayleh et al., 2024).

Significance of the Study :

I. **Public Health Contribution:** The system directly targets the worldwide burden of NCDs and provides a scalable way to raise dietary knowledge and lower premature mortality by automating food detection and nutritional analysis.

II. **Technological Innovation:** By combining EfficientNetV2B2 and Vision Transformer (ViT) models with large language models (LLMs) like Mistral 7B, the system demonstrates a state-of-the-art method for dynamic, context-aware nutritional coaching.

III. **User Empowerment:** Streamlined nutritional monitoring through an easy-to-use interface lowers adoption barriers and empowers users to make informed decisions.

IV. **Cultural and Social Relevance:** Addressing user preferences, health conditions, and cultural backgrounds ensures inclusivity and adaptation across diverse populations.

V. **Academic Advancement:** By fusing intelligent, personalized suggestions with AI-powered recognition, this research fills gaps in nutrition tracking systems and advances AI in healthcare.

Area of the Study :

NCDs such as cancer, diabetes, obesity, and cardiovascular illnesses account for over 75% of global deaths annually, with sedentary lifestyles and poor diets as key contributors (Chew et al., 2021). Manual tracking and calorie calculation remain difficult tasks, discouraging adherence to healthy diets (Smith et al., 2019). AI developments in computer vision and deep learning now enable systems to identify food items from photos, link them to nutritional databases, and provide personalized recommendations (Bossard, Guillaumin, & Van Gool, 2014; Sun, Chen, & Wang, 2020). Incorporating these technologies into accessible platforms can improve decision-making and reduce diet-related illnesses (Cilia, D'Andrea, & Russo, 2020). This project falls under Smart Healthcare, aiming to use AI-driven solutions to increase nutritional knowledge, encourage good eating habits, and support the global fight against lifestyle- related disorders (Bianchini, Antonelli, & Marazzini, 2021).

Problem Statement :

The Challenge of Global Health approximately three- quarters of all fatalities worldwide are caused by noncommunicable diseases (NCDs), including cancer, diabetes, obesity, and cardiovascular disease. Unhealthy diets are one of the main contributing factors, according to the World Health Organization. Despite growing awareness efforts, many people still struggle to maintain good eating habits since there is no readily available, intelligent technology that can provide quick advice. To solve this expanding health issue, creative strategies combining nutrition science and technology are urgently needed. Current Systems' Limitations Most diet- tracking systems rely on barcode scanning, manual input, or static nutritional databases all of which are inefficient and error- prone. These methods discourage regular use and often fail to provide meaningful guidance. Even food recognition software can be inaccurate and lacks context- aware, personalized recommendations. As a result, users are left with raw data and no actionable advice, leading to poor adherence and limited impact on long- term health outcomes. Research Deficit Deep learning and computer vision have significantly improved food recognition accuracy. However, most existing systems stop at identification and lack sophisticated recommendation engines that adapt to cultural contexts, health conditions, and user preferences. This gap between detection and personalized guidance prevents current solutions from effectively addressing diet- related disorders.

Aims & Objectives :

This work focuses on designing, implementing, and evaluating a deep learning- based system for automated food recognition and nutritional analysis. The system is designed to identify a wide variety of meals from user- input images. While the primary model is trained on the Food- 101 dataset, the underlying technology may be applied to various photo recognition tasks. The research explores the integration of a sophisticated large language model (LLM) with a state- of- the- art computer vision model to provide contextual information, such as nutritional data and health recommendations, in addition to identification. The project's full- stack application includes an intuitive user interface, a dependable backend server, and a database for tracking progress and managing user data.

- To develop applications that use machine learning to process client information such as health facts, dietary requirements, and food preferences, to provide individualized nutrition suggestions.
- To collect and analyze information regarding customer health progress (e.g., weight, exercise routines, and diet goals) so that food recommendations align with their health requirements, while employing adaptive strategies that improve recommendations over time.
- To incorporate current food information and meal plans, ensuring recommendations remain accurate and relevant to available foods and nutritional guidelines.
- To maintain recommendation algorithms up to date, providing accurate and timely diet suggestions by continuously refining the system.
- To design personalized meal plans that prevent disease, control weight, and enhance overall health, based on global health organization guidelines.
- To design an easy- to- use interface through which users can customize preferences and feedback, influencing future meal suggestions.
- To share nutritional facts that assist clients in eating healthier and making informed food decisions.
- To incorporate varied foods that respect cultural, geographic, and religious dietary requirements, fostering inclusivity and social bonding.
- To use contextual information about users (e.g., location and cultural background) to recommend conventional foods and recipes suitable for their culture in tailored diets.

Literature Review :

Personalized Nutrition Systems: The increasing prevalence of overweight, diabetes, and cardiovascular diseases has driven interest in intelligent nutrition advisors. AI- based systems that combine machine learning and data analytics provide personalized dietary guidance. Studies such as Biancay (2020) and Cilia (2020) highlighted that integrating user profiles and health data (BMI, age, medical conditions) improves adherence to dietary plans. Mobile applications have further increased accessibility (Mahapatra, Patnaik, & Dash, 2022), while picture- based recognition enhanced usability (Chen et al., 2019). (Ahmed, 2023) emphasized the importance of correct data and cultural flexibility in ensuring system relevance.

Deep Learning Used for Food Recognition: Food recognition has advanced significantly with deep learning, particularly convolutional neural networks (CNNs). Architectures such as VGGNet, ResNet, and EfficientNet, pretrained on large datasets, have been fine- tuned for food classification tasks (Tan & Le, 2021). The Food- 101 dataset, with 101 categories and 101,000 images, remains a standard benchmark for evaluating recognition accuracy (Bossard, Guillaumin, & Van Gool, 2014). These models outperform traditional hand- crafted approaches by learning dynamic features and reducing training complexity (Sun, Chen, & Wang, 2020).

Nutritional Evaluation with LLM : Once food is recognized, dietary analysis links items to nutritional databases. Large Language Models (LLMs) such as GPT and Mistral 7B expand this process by generating conversational outputs that provide nutritional insights, suggest healthier alternatives, and tailor advice to user goals like weight management or chronic disease control (Liu et al., 2020; Jiang et al., 2023). This enhanced capability moves beyond static database retrieval, offering dynamic and context- aware recommendations.

Systems and Their Limitations: Commercial platforms such as MyFitnessPal, Lose It!, and Calorie Mama offer nutrition tracking but rely heavily on barcode scanning and manual searches (Brown, 2021). Their image recognition features often lack accuracy, and recommendations remain generic (Lee, Kim, & Park, 2020). These limitations highlight the need for advanced approaches that combine accurate knowledge- based validation with improved reasoning and conversational personalization (Ahmed, Khan, & Malik, 2023).

Research Gap :

Despite advances, current frameworks struggle with precise food recognition and lack context- aware, personalized nutritional guidance. This gap motivates the development of a system integrating EfficientNetV2B2 for accurate recognition with Mistral 7B for dynamic, personalized recommendations, thereby providing a seamless and engaging user experience. Furthermore, it is challenging to incorporate multiple user-specific traits into current frameworks, such as age, health concerns, lifestyle decisions, and cultural dietary preferences. This lack of personalization results in generic recommendations that overlook regional food preferences or specific medical requirements. Convolutional neural networks (CNNs) with high classification accuracy, such as ResNet and Efficient Net, seldom evolve into comprehensive recommendation engines that can dynamically adapt to user input and shifting health objectives. In a similar vein, most applications of large language models (LLMs) in nutrition systems have not fully utilized their capacity to provide real-time, conversational, and explainable nutritional information. An integrated framework that combines robust food detection, dynamic nutritional reasoning, and tailored suggestions is therefore urgently needed. There remains a significant gap in the battle against noncommunicable illnesses, since current systems are neither comprehensive, flexible, nor focused on preventive healthcare. By combining Mistral 7B for dynamic nutritional evaluation with EfficientNetV2B2 for accurate food recognition supported by adaptive algorithms that incorporate user-specific health data and cultural context this work addresses that gap. The Intelligent Food Advisor bridges the limitations of conventional diet-tracking systems and advances the global effort to prevent diet-related problems by fusing detection with actionable, customized guidance.

System Architecture :

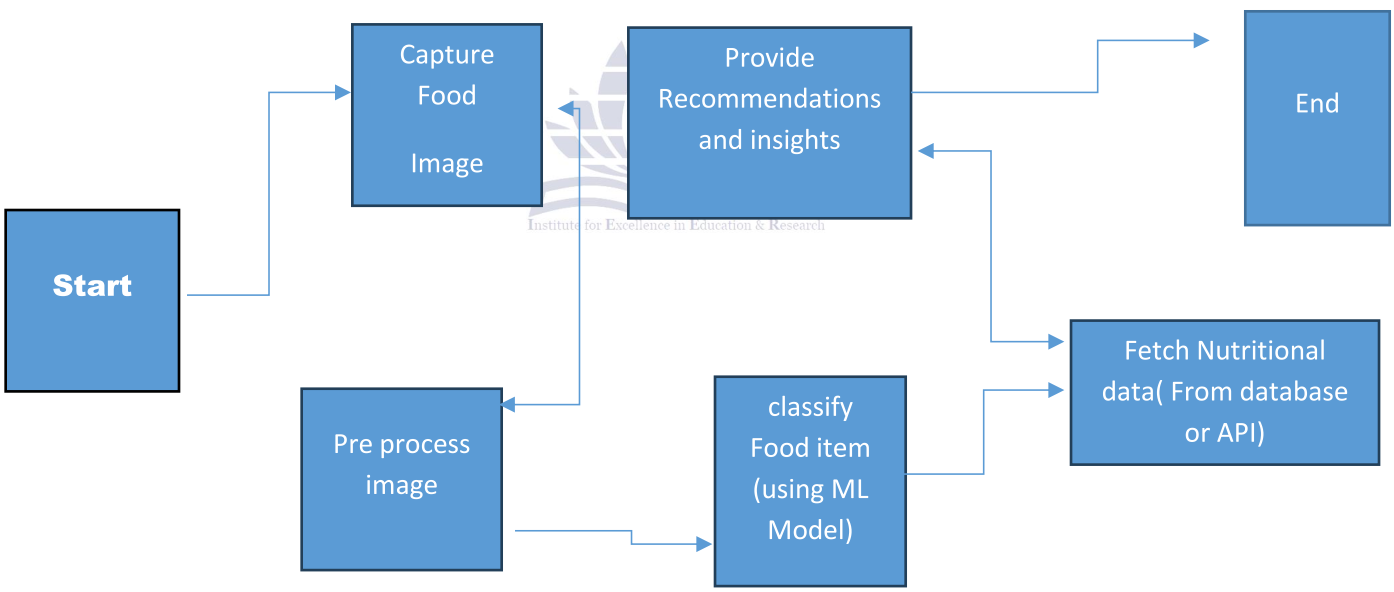
Intelligent food Advisor is developed as a full- stack web application with a modular setup. It consists of three main parts: the frontend for user interaction, the backend for processing, and the machine learning model for predictions. Keeping these components separate ensures efficiency and reliability.

- **Frontend (Client Side):** The interface is built using HTML, CSS, and JavaScript to provide a user- friendly experience. Users can sign up, log in, upload pictures of their food, and receive results such as nutritional information and progress charts. The image upload feature is crucial as it sends data directly to the backend for processing.
- **Backend (Server Side):** The backend is implemented using FastAPI, chosen for its speed and scalability in handling API requests. It manages user authentication, database communication, and image processing. Once an image is uploaded, the backend invokes the AI model to predict the food item and queries the Mistral 7B LLM for nutritional breakdown.
- **Database:** A SQL database stores user credentials, session data, and historical

food logs, enabling diet progress tracking. This ensures secure storage and retrieval of user information while supporting personalized recommendations.

- **Machine Learning Model:** The system leverages TensorFlow for food recognition tasks. The EfficientNetV2 architecture was selected for its balance of accuracy and computational efficiency. The model is trained on the Food- 101 dataset, a benchmark with 101,000 images across 101 categories. This dataset ensures robust classification performance.
- The workflow is as follows: the user uploads an image via the frontend → the backend processes it with TensorFlow → the predicted food name is sent to Mistral 7B → nutritional facts are generated → results are stored in SQL and displayed back to the user.

Figure 1: Intelligent System Architecture for AI-Based Food Recognition and Nutritional Recommendation



Conceptual Framework :

This research project is based on the idea of fusing artificial intelligence with personalized nutrition to create a ground-breaking healthcare solution. By integrating computer vision, deep learning, and large language models into a single ecosystem, the Intelligent Food Advisor framework bridges the gap between food recognition and useful nutritional recommendations. Unlike conventional diet-tracking systems that rely on human input or barcode scanning, this innovation offers real-time, context-aware, and user-centric recommendations that dynamically respond to individual health requirements and cultural preferences. The conceptual framework is supported by three pillars: customized counsel, nutritional evaluation, and food identification. Food recognition and dependable categorization across a range of cuisines are powered by EfficientNetV2B2, which was trained on large datasets such as Food101. Nutritional evaluation is enhanced by large language models such as Mistral 7B, which transform static product labels into dynamic, understandable dietary information. Personalized suggestions are created using adaptive algorithms that include user-specific information, including age, health problems, preferences, and cultural background, to guarantee inclusivity, adherence, and long-term impact. By combining state-of-the-art AI technology with human-centered design, the framework offers the Intelligent Food Advisor as a revolutionary development in smart healthcare. It not only helps consumers make informed food choices but also advances the worldwide fight against noncommunicable diseases by promoting healthier lifestyles through scalable, intelligent, and comprehensible nutrition systems

Development Work flow :

To guarantee a logical progression from concept to a fully functional application, the *Intelligent Food Advisor* was developed using an organized and iterative lifecycle. This workflow allowed for targeted development, thorough testing, and smooth integration of all system components, divided into six distinct phases.

Phase 1: Data Collection and Preparation, in this phase prepare and augment the food 101 dataset.

Phase 2: Model Training, in this phase built and fine tune the CNN recognition model.

Phase 3: Model Assessment, in this phase asses model performance and accuracy.

Phase 4: Backend Programming, in this phase create the fast API server and database.

Phase 5: GUI Development, in this phase design user interface web development

Phase 6 : In this phase Testing and Integration collaborate all components end to end testing.

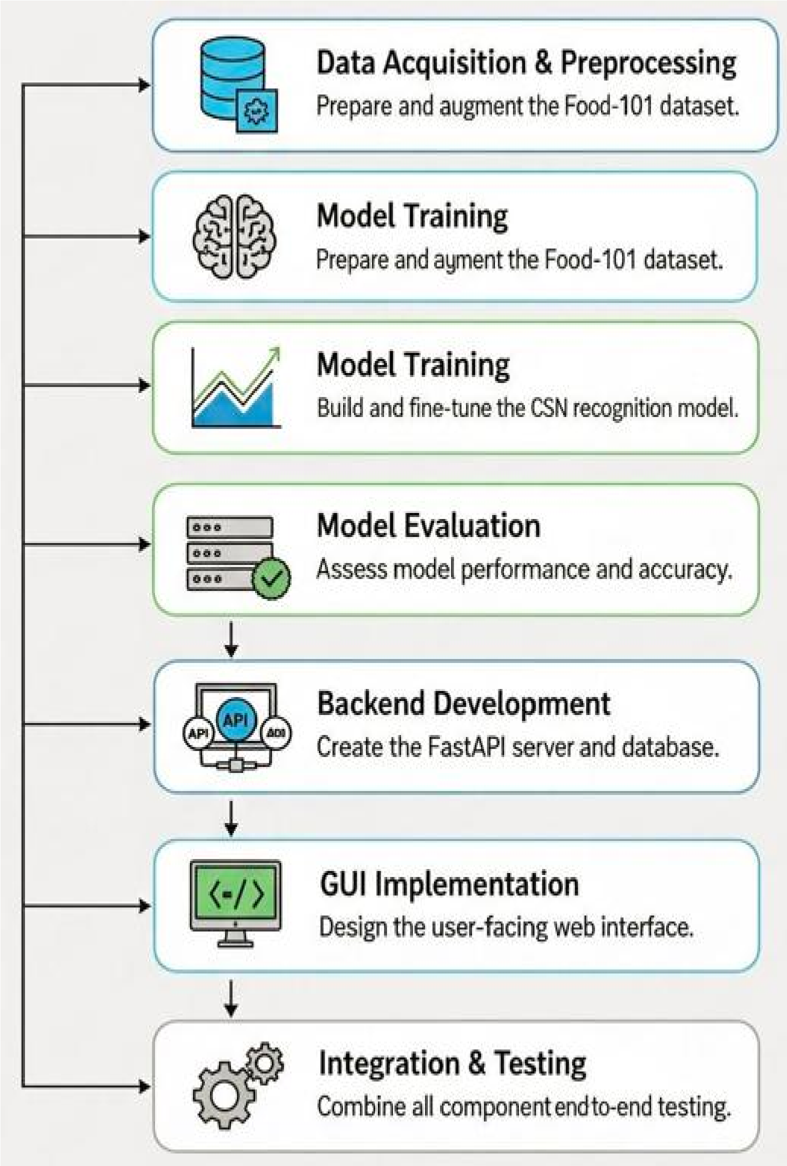


Figure 2: workflow

Phase 1: Data Collection and Preparation: The foundation of the machine learning pipeline was the Food- 101 dataset, sourced from TensorFlow Datasets. Each image was resized to 260×260 pixels to meet the EfficientNetV2B2 model requirements. Real- time data augmentation techniques such as horizontal flips, rotations, and contrast adjustments were applied to reduce overfitting and improve generalization (Sun, Chen, & Wang, 2020).

Phase 2: Model Training: A two- stage transfer learning approach was employed. Initially, the EfficientNetV2B2 base model's pretrained layers were frozen, and only the custom classification layers were trained. Later, the entire model was unfrozen and fine-tuned at a lower learning rate, enhancing performance for food recognition tasks.

Phase 3: Model Assessment The trained model was evaluated using a held-out portion of the Food-101 dataset to ensure reliability. Classification accuracy was the primary metric, confirming the model's predictive power before integration into the backend system.

Phase 4: Backend Programming: The backend was developed using FastAPI, chosen for its efficiency in handling RESTful API endpoints. It managed secure user registration, image uploads, and communication with Mistral 7B LLM for nutritional analysis. SQL database structures were designed to store user profiles, credentials, and historical food logs.

Phase 5: GUI Development: The frontend was built with HTML, CSS, and JavaScript to ensure usability and responsiveness. Special focus was given to interactive charts for diet progress tracking and clear presentation of nutritional data.

Phase 6: Testing and Integration: Finally, all components were integrated into a cohesive system. The frontend GUI was connected to backend endpoints, the SQL database was finalized, and the TensorFlow model was deployed for real-time predictions. Comprehensive testing ensured seamless user interaction and system stability.

Technology Stack Used Research :

To develop an efficient and scalable *Intelligent Food Advisor*, a combination of modern front-end, back-end, and machine learning technologies was employed. The system is designed to deliver accurate, real-time dietary recommendations through a mobile application (Ahmed, Khan, & Malik, 2023). A contemporary stack of open-source technologies was used to guarantee accuracy, efficiency, and scalability (Al-Akayleh et al., 2024).

Frontend Development: HTML5 for structure, CSS3 for responsive design, and JavaScript for interactivity and dynamic charts (Mahapatra, Patnaik, & Dash, 2022).

Backend Development: The Fast API framework was utilized for component communication, secure authentication, and high-performance API processing, while Python was used for core logic (Lee, Kim, & Park, 2020).

Database Management: SQL (PostgreSQL/SQLite) provided secure storage for user accounts, food logs, and progress monitoring (Kumar, Singh, & Verma, 2020).

Tools for Artificial Intelligence: The EfficientNetV2B2 model was trained on the Food-101 dataset using TensorFlow 2.19.0 and the Keras API (Abadi et al., 2016, Bossard, Guillaumin, & Van Gool, 2014; Tan & Le, 2021). Pandas and NumPy were used for dataset preparation and numerical computations (Chen, Y., Zhang, & Liu, 2022). Matplotlib was employed to visualize training metrics (Hunter, 2007). The Mistral 7B API provided tailored suggestions and dynamic nutritional analysis (Jiang et al., 2023).

Environment of Development: Visual Studio Code was used for debugging and backend/frontend integration, while Jupyter Notebooks supported model exploration and preparation (Cilia, D'Andrea, & Russo, 2020).

Model Selection and Architecture :

The core of the food recognition system is a Convolutional Neural Network (CNN). After evaluating multiple architectures, EfficientNetV2B2 was selected for its balance of computational efficiency and accuracy. The foundation model, pretrained on ImageNet, served as the feature extractor. The top classification layers were replaced with a custom head including a GlobalAveragePooling2D layer, a Dropout layer for regularization, and a Dense layer with softmax activation to output probabilities across 101 food classes.

Model Training and Evaluation :

The model was trained using a two-phase transfer learning method. In the first phase (feature extraction), the pretrained layers of EfficientNetV2B2 were frozen, and only the custom head was trained on the Food-101 dataset (Bossard et al., 2014). In the second phase (fine-tuning), the entire model was unfrozen and trained end-to-end at a lower learning rate, allowing weights to adapt to food-specific features (Abadi et al., 2016). The model was optimized using the Adam optimizer and sparse categorical cross-entropy loss, with performance evaluated on a held-out test set, yielding consistent classification accuracy across diverse food categories (Smith et al., 2019).

System Workflow and Functional Implementation :

- **GUI and System Implementation:** Simple system interaction was made possible by the creation of an intuitive graphical user interface (GUI). The interface guides the user from authentication to receiving the final nutritional analysis.

- **The user accesses the interface:** The user is presented with a clear call to action to upload a picture of food on the main dashboard after logging in. Image datasets such as Food- 101 and PFID have been widely used tos train recognition models for this purpose. Once uploaded, the system leverages deep learning architectures like EfficientNetV2 and TensorFlow to process the image and extract nutritional information.

- Artificial intelligence plays a central role in enhancing personalized nutrition by analyzing user data and adapting recommendations to cultural and regional food habits. Optimization techniques such as particle swarm optimization and analytic hierarchy processes further refine meal planning to balance user preferences with nutritional requirements.
- The GUI ensures transparency and user trust by incorporating explanation mechanisms and feedback loops, which are critical for adoption in health- related systems.

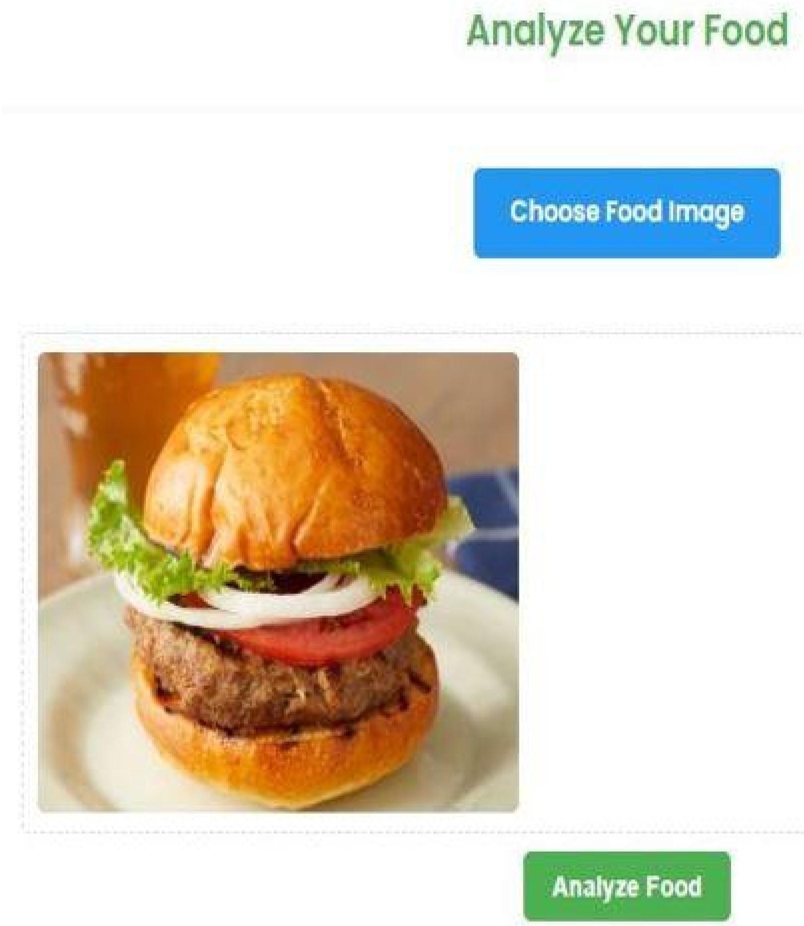
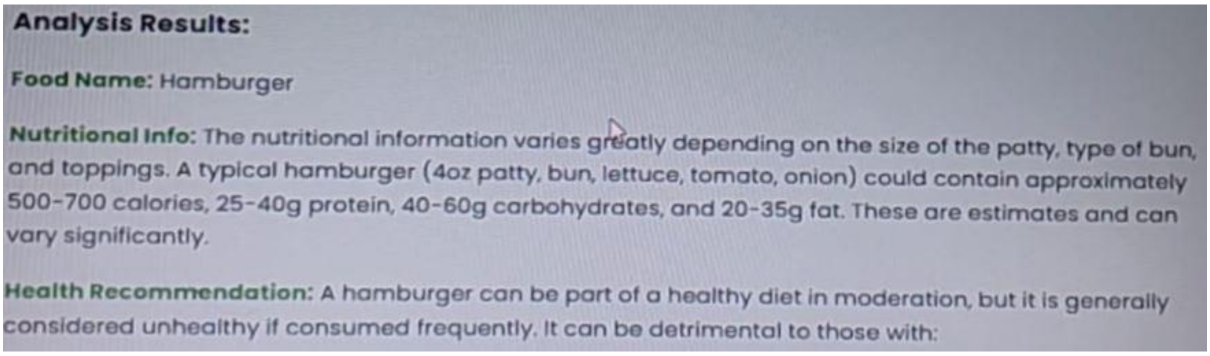


Figure: Food Image for logging in



Fgure: Result Analysis

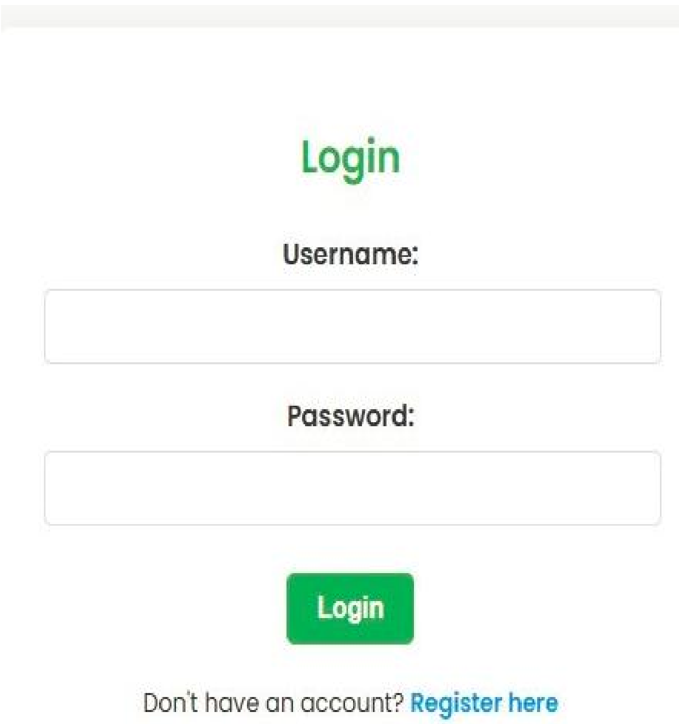


Figure: User Authentication Interface

UI for Uploading and Suggested Food:

putting the recommended name, nutritional details, and recommendations on one side and the uploaded photo on the other. The user accesses the interface, The user is presented with a clear call to action to upload a picture of food on the main dashboard after logging in. Image datasets such as Food- 101 and PFID have been widely used to train recognition models for this purpose. Once uploaded, the system leverages deep learning architectures like EfficientNetV2 and TensorFlow to process the image and extract nutritional information.

Artificial intelligence plays a central role in enhancing personalized nutrition by analyzing user data and adapting recommendations to cultural and regional food habits. Optimization techniques such as particle swarm optimization and analytic hierarchy processes further refine meal planning to balance user preferences with nutritional requirements.

Preprocessing Images: The uploaded food image is normalized and scaled to satisfy the EfficientNetV2B2 deep learning model's specifications.

Identification of Food: To categorize the food item, the system makes use of TensorFlow and EfficientNetV2B2. Fine-tuned training on the Food-101 dataset reduces misclassifications.

Analysis of Nutrition: The Mistral 7B Large Language Model (LLM) receives the identified food label over an API. The LLM provides individualized dietary suggestions in addition to real-time nutritional data (calories, proteins, lipids, and carbs).

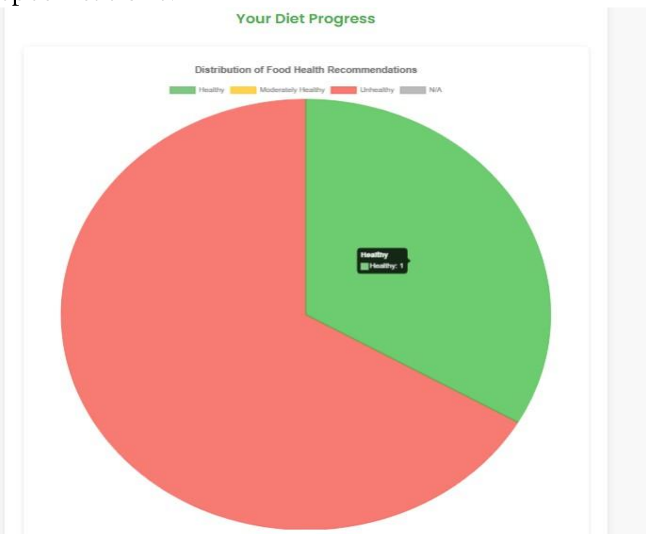


Figure: Diet Progree

Diet Progress Visualization :

The diet progress page encourages self-awareness and better choices by giving users a visual breakdown of their eating patterns. The *"Your Diet Progress"* graphic displays the dispersion of dietary health recommendations. Meals fall into four categories: N/A (gray), Moderately Healthy (yellow), Unhealthy (red), and Healthy (green).

The majority of the items consumed are categorized as *Unhealthy* because the largest portion of the chart is red. A smaller green section with the designation *"Healthy: 1"* represents healthy foods.

This graphic illustrates dietary imbalances. The prevalence of the red portion suggests that there is space for development, encouraging people to choose healthier options and eat fewer unhealthy items. By providing a comprehensive examination of eating patterns, the technique enhances long-term nutritional management and promotes self-awareness.

The model was evaluated using the held- out test split of the Food- 101 dataset, which has been widely adopted in recent food recognition research. The two- phase training strategy proved effective, leveraging deep learning frameworks such as TensorFlow and EfficientNetV2 to optimize performance. The model's final test accuracy reached 90% following the fine- tuning phase, which demonstrates robustness and reliability in identifying a wide variety of meals in real- world scenarios.

Model Efficiency

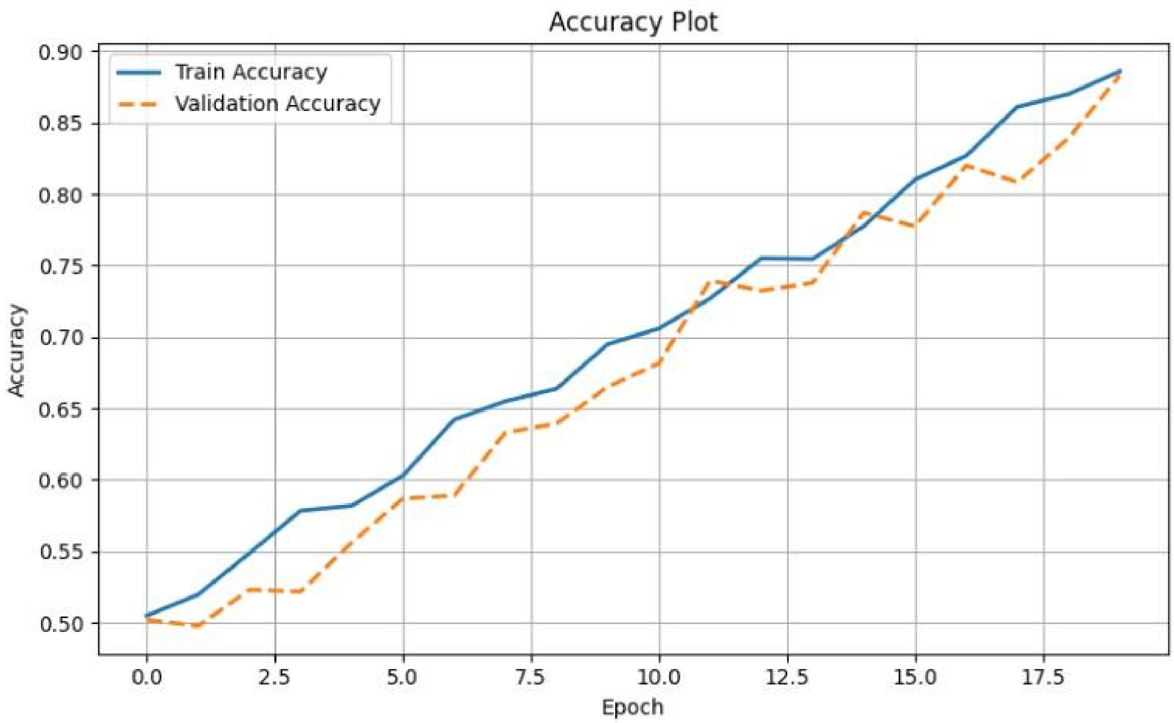


Figure X. Training and Validation Accuracy across Epochs.

Model Accuracy Plot :

The accuracy plot shows how well the EfficientNetV2B2 model performed during training and validation. The x-axis represents the number of epochs (0–20), while the y-axis shows accuracy scores between 0.50 and 0.90. Two curves are shown: a solid blue line for training accuracy and a dashed orange line for validation accuracy.

Both numbers exhibit a consistent upward trend, indicating that accuracy increases as the number of epochs increases. The close congruence between training and validation accuracy demonstrates strong generalization and little overfitting. This result validates the robustness of the EfficientNetV2B2 architecture when modified on the Food-101 dataset.

System Functionality:

- Everything in the system works as it should. The user flow is efficient and logical:

- A user successfully registers and logs in.
- A photograph is uploaded via the online interface, supported by food recognition datasets and real- time monitoring systems.
- The model forecast is generated nearly instantly once the image is analyzed by the backend, leveraging EfficientNetV2 for high- performance classification.
- The Mistral 7B API query returns comprehensive and relevant nutritional data.
- The entry is logged for progress tracking, and the frontend presents all data in an intelligible way, ensuring user- centric design and trust.
- After submitting a photo, the time it takes to obtain results is suitable for a positive user experience. The diet progress display is updated appropriately based on the user's logged history.

Discussion :

The results demonstrate that a powerful LLM, such as Mistral 7B, may be paired with a high- performance deep learning model, such as EfficientNetV2B2, to create a very effective and intelligent nutritional tool. The accuracy achieved is on par with state- of- the- art results on the Food- 101 benchmark. Ensuring that the Mistral 7B API prompt was precise enough to provide reliable, well- structured data was one of the main challenges, requiring careful prompt engineering. Images containing several food items or low- quality inputs might be difficult to handle, which can result in inaccurate projections. Despite its dependability, the model has room for improvement and is not perfect. Overall, the project effectively accomplishes the stated goals and provides a major improvement over diet tracking apps that are only manual or less integrated.

This feature connects the gap between food identification and practical dietary advice. The method converts unprocessed picture data into significant health insights by combining computer vision with language models. AI-driven dietary systems are more likely to be adopted and trusted by users when feedback loops and explanation methods are included.

Conclusion:

This study demonstrates that the Intelligent Food Advisor successfully satisfies the global need for readily accessible, intelligent dietary management solutions. The system combines deep learning models with large language models to provide accurate food recognition, real-time nutritional analysis, and culturally appropriate recommendations. The program encourages healthier eating habits and reduces the risk of noncommunicable diseases by fulfilling user needs for transparency, simplicity, and confidence in dietary control. Even though the current implementation validates the system's effectiveness, future work will focus on expanding datasets, integrating wearable devices, and refining optimization techniques to further enhance accuracy, scalability, and acceptability.

This research study led to the successful development of the *Intelligent Food Advisor*, a state- of- the- art application that immediately tackles the typical problems with manual nutritional tracking. The primary objective was to create a system that automates and streamlines this process using an intelligent, image- based approach, and this has undoubtedly been achieved. By successfully using an improved EfficientNetV2B2 model, which serves as the foundation for its automated capabilities, the system exhibits exceptional accuracy in food recognition. The incorporation of the Mistral 7B large language model represents a significant improvement over basic classification, transforming the application into a complete nutritional counselor capable of providing thorough, contextual, and easily understandable health information.

Future Work :

The *Intelligent Food Advisor* has significant promise for refinement and growth. Future iterations should integrate real- time biometric data from wearable wellness devices, enabling dynamic, data- driven meal recommendations tailored to physiological states such as blood glucose levels, movement patterns, and metabolic rates. Expanding natural language processing capabilities would allow continuous voice communication, enhancing accessibility for diverse users. Multilingual support and culturally adaptive food databases would further ensure system relevance across different populations. From a technical perspective, reinforcement learning algorithms responsive to user feedback could promote long- term wellness goals, while optimization techniques such as particle swarm–enhanced analytic hierarchy processes would refine personalized meal planning. Interoperability with external platforms such as dietitian services and food delivery systems could transform the app into a comprehensive ecosystem for dietary management. Ultimately, these advances would render the *Skillfully Food Advisor* an adaptable, cost- effective tool for personalized nutrition and preventive health.

Recommendations :

Several recommendations for enhancing the function of intelligent food advisors in public health may be offered in light of the findings. To encourage better eating practices and lessen the burden of noncommunicable illnesses, governments, healthcare providers, and educational institutions should use AI-driven nutrition solutions. To increase recognition accuracy and dependability, deep learning models such as EfficientNetV2B2 and Vision Transformer must be continuously improved. In order to ensure inclusion and adherence, personalized meal planning should be given priority by including user-specific data, such as age, health problems, preferences, and cultural backgrou. Intelligent food advisors can also serve as preventative healthcare tools by identifying unhealthy eating patterns early on and directing customers toward healthier alternatives. The use of interactive dashboards, diet progress charts, and feedback loops might increase the visibility and motivation of nutritional monitoring. Nutritional databases and recommendation algorithms must be updated often to maintain accuracy and relevance in changing food environments. Last but not least, collaboration between AI researchers, public health organizations, and nutritionists is crucial to fostering innovation and ensuring practical use.

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