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Meal Image Recognition & Healthy Meal Recommendation

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Abstract: The global prevalence of diet-related chronic conditions, such as obesity and Type 2 diabetes, has created an urgent need for objective, low-burden dietary monitoring tools. Traditional mobile health applications often suffer from high user friction due to manual data entry requirements and significant recall bias. This paper proposes an integrated system for meal image recognition and healthy meal recommendations designed to simplify personalized nutrition management. The system utilizes a sophisticated multimodal architecture, leveraging the Gemini 1.5 Flash API as a visual reasoning engine to identify ingredients and dishes directly from user-captured images with high precision. The backend is built on Supabase, employing a relational PostgreSQL database to maintain strict data integrity across multidimensional user biometric models, nutritional histories, and curated recipe datasets. A key innovation is the dual mode "Fridge Vision" pipeline, which integrates a real-time ingredient scanner for immediate health impact summaries and an automated recipe recommendation engine. The architecture utilizes Supabase Edge Functions for low- latency, serverless execution of generative AI logic, complemented by client-side image compression to optimize scan times and minimize API latency. Experimental evaluations of similar multimodal pipelines in literature indicate a Top 1 classification accuracy of approximately 89% and high correlation with dietitian-led assessments for caloric content. The results demonstrate that the proposed system offers a scalable, secure, and user-centric solution that effectively bridges the gap between automated image perception and personalized metabolic guidance, fostering long-term dietary adherence in health-conscious populations worldwide.

Index terms: Personalized Nutrition, Image recognition, Multimodal Large Language models, Supabase, Flutter, Dart, Meal Recommendation

I. INTRODUCTION

Maintaining a balanced diet is a fundamental challenge in the prevention and management of non-communicable diseases (NCDs), which account for nearly 75% of global annual deaths. Despite growing health consciousness, many individuals struggle with
The cognitive load of calculating daily caloric intake and adhering to complex nutritional guidelines.

Recent transformations in digital health have moved from passive logging to active monitoring through Artificial Intelligence (AI) and computer vision. However, a significant gap remains that existing applications often rely on NoSQL document stores that lack the relational integrity required for precise metabolic tracking, such as linking specific ingredients to dynamic user allergy profiles or health goals.

The "Meal Image Recognition and Healthy Meal Recommendation System" addresses these challenges by integrating advanced multimodal Large Language Models (LLMs) with a robust serverless relational backend. The primary objective is to provide a "Profile- Aware" nutrition ecosystem where AI reasoning is grounded in a structured EndUserModel. This model captures essential biometric data, including Basal Metabolic Rate (BMR), target weight goals, and activity levels, to determine accurate Daily Energy Requirements (DER). By utilizing the Gemini 1.5 Flash API via the Google Generative AI package, the system provides instantaneous feedback on meal composition while offering a two-stage "Fridge Vision" pipeline. The first stage involves an intelligent Ingredient Scanner that provides detailed facts and immediate health impact summaries. The second stage utilizes the multimodal capabilities of the Gemini API to generate personalized recipes based on identified contents and user biometrics.

The system's design prioritizes a professional user experience, featuring unique animated splash screens and a high-performance custom camera interface to maximize engagement. Through the synchronization of Flutter-based frontend interfaces and PostgreSQL- backed data layers, the application offers a secure, scalable solution for individuals seeking to optimize their health outcomes. This research highlights the synergy between multimodal LLMs and relational databases in redefining dietary assessment and precision nutrition for the modern digital era.

II. LITERATURE REVIEW

The evolution of dietary assessment has shifted definitively from manual lookup to automated recognition using Deep Learning and Multimodal Large Language Models (MLLMs).

1) Early food recognition systems primarily employed Convolutional Neural Networks (CNNs) like ResNet-50 and VGG-16, achieving accuracies near 90.2% on standardized datasets such as Food- 101. However, these models were limited to classification and lacked the contextual reasoning required for recipe generation.
2) Recent studies have highlighted the potential of MLLMs, such as Gemini 1.5 Pro and Flash, to serve as “visual tokenizers” that identify complex dishes and sauces often missed by traditional detectors. For instance, recent benchmarks on the MMMU Pro dataset show Gemini models reaching state-of-the-art scores of 81.2%, surpassing human- expert baselines. In the domain of recommendation systems, research favors hybrid filtering methods that combine collaborative patterns with content-based nutritional reasoning. Innovations like the NutriRec framework leverage multimodal embeddings to capture sensory and nutritional attributes in a unified space. Furthermore, the integration of vector databases like pgvector in PostgreSQL has emerged as a gold standard for semantic similarity search, enabling efficient “Fridge Vision” capabilities that match available ingredients to recipes. Clinical validation studies confirm that AI-generated meal plans can achieve over 80% compliance with metabolic guidelines, provided they are grounded in verified nutritional databases like USDA FoodData Central. The implementation of controlled generation via JSON schemas ensures that LLMs provide machine- readable, structured outputs for seamless application integration. Despite these gains, systematic underestimation of portion sizes in 2D imagery remains a critical technical hurdle, necessitating the use of specialized food AI APIs for high-precision calorie tracking. This literature survey establishes the feasibility of using multimodal APIs and relational serverless backends to create adaptive, culturally sensitive nutrition interventions.

III. EXISTING SYSTEM

Current dietary assessment platforms, exemplified by industry leaders like MyFitnessPal and HealthifyMe, rely heavily on a keyword-based search paradigm for data entry. While these applications boast massive nutritional databases, they place a high cognitive burden on users who must manually input dish names and weigh ingredients to ensure accuracy. Most existing systems are built on NoSQL document store architectures, such as Firebase, which are susceptible to “denormalization traps”.

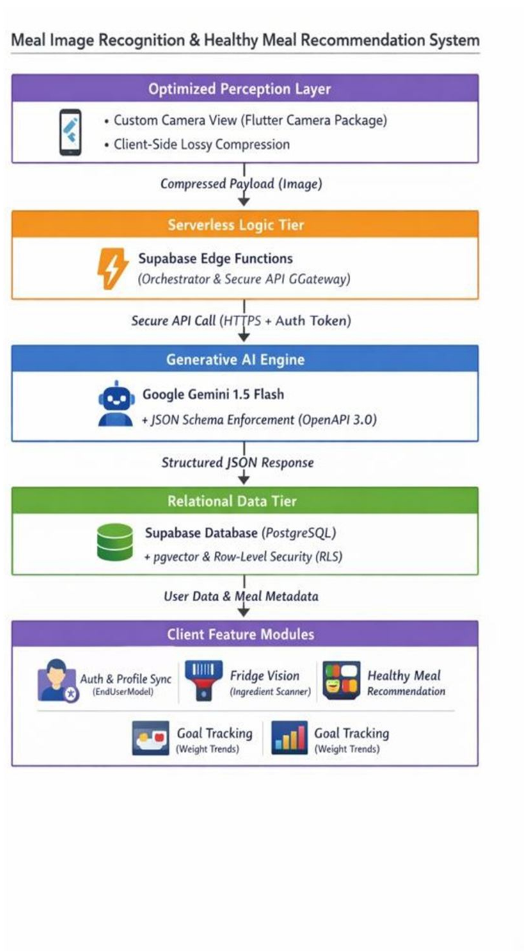
In these environments, performing complex relational joins between user demographic profiles, current physiological state, and ingredient-level allergy constraints requires significant client-side merging or data duplication, often leading to synchronization errors and increased latency. Furthermore, many traditional apps provide static, one-size-fits-all meal plans that do not dynamically adapt to real-time changes in a user’s activity level or metabolic needs. AI integration in the current market is often limited to barcode scanning for packaged goods, struggling significantly with mixed dishes or home-cooked meals where ingredients are occluded. Many current systems lack an integrated ingredient-to-health impact scanner, forcing users to interpret raw nutritional numbers without context. Security in these systems typically relies on application-level rules, which can be difficult to audit and debug as the system scales. Recall bias remains a significant issue, with users underreporting intake by up to 30%. Additionally, these systems often lack the multimodal capability to process both text and images in a single reasoning step, leading to disjointed user experiences when trying to log meals visually. The lack of native vector search within standard mobile backends also makes “semantic” ingredient matching—such as finding a recipe for “masala” when only raw spices are detected—computationally expensive or impossible without external tools. These limitations highlight the necessity for a more integrated, relational, and multimodal approach to nutrition.

IV. PROPOSED SYSTEM

The proposed system introduces a multimodal nutrition assistant that replaces manual entry with a high- precision AI-driven perception layer. At its core, the system utilizes the Gemini 1.5 Flash multimodal API to perform instantaneous ingredient recognition and nutritional fact estimation from food images. The “Fridge Vision” pipeline is uniquely designed with two sub-features: an Ingredient Scanner and a Recipe Recommender. The Ingredient Scanner analyzes user- captured photos to provide real-time ratings, detailed facts (including sugar and protein content), and an AI- driven summary of immediate health impacts. Unlike existing platforms, the proposed system is “Profile- Aware,” meaning every AI reasoning step is grounded in a structured EndUserModel containing the user’s specific age, weight, and health goals.

To ensure technical efficiency, the system implements a custom camera view using the native camera package, which includes an automated image compression step before transmission. This compression significantly decreases scan times and reduces token costs while maintaining sufficient resolution for AI analysis. Every interaction with the Generative AI package is governed by a strict JSON schema, ensuring that the response format is consistently machine-readable for the frontend dashboard. The application architecture leverages Supabase (PostgreSQL) as a unified backend, providing native support for relational joins and ACID compliance, which ensures that sensitive health data remains consistent and secure. Security is handled at the database layer through Row-Level Security (RLS) and JWT-based authentication, preventing unauthorized access to personal health metrics. By combining the speed of the Gemini Flash model with the structural power of Supabase, the system provides a frictionless, professional-grade solution for dietary management. This holistic approach reduces participant burden, minimizes recall bias, and supports long-term behavioral changes through dynamic, data-driven personalization

V. SYSTEM ARCHITECTURE & METHODOLOGY



The proposed system architecture is organized into a specialized three-tier framework: the Client Tier, the Logic Tier, and the Data Tier. The **Client Tier** is a cross-platform Flutter mobile application featuring a high-performance UI built with the Poppins font family. It implements a custom camera view via the camera package, which captures food or ingredient images and applies a lossy compression algorithm to minimize payload size and improve inference speed. The **Logic Tier** resides in Supabase Edge Functions, serving as the system's "Brain". These functions securely invoke the Gemini 1.5 Flash API using the google_generative_ai package. We employ "controlled generation" by providing an OpenAPI 3.0 compatible JSON schema to the model, ensuring the AI output is structured for immediate parsing into Dart models. The **Data Tier** utilizes the Supabase PostgreSQL engine to store user profiles, curated recipes, and historical logs.

Methodology flow follows a sequential pipeline: first, the user inputs biometric data including restrictions into the Gemini prompt. The system calculates the user's energy requirements using the Harris-Benedict equation as follows:

$$BMR = 10 \times weight(kg) + 6.25 \times height(cm) - 5 \times age(y) + s$$

where s is +5 for males and -161 for females. The BMR is adjusted by the ActivityLevel to determine the total Daily Energy Requirement (DER). The recommendation engine then performs a semantic similarity search using pgvector to find recipes where the cosine distance between the ingredients and the user profile is minimized :

$$similarity = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|}$$

where $\mathbf{A}$ represents the query ve goals and preferences; second, the user captures an ingredient image, which is compressed and sent to an Edge Function; third, the function injects the user's EndUserModel and dietary ctor and $\mathbf{B}$ the recipe vector. Finally, the results are cross-referenced with the DietaryPreferenceModel (Allergies) before being displayed as actionable cards on the dashboard. Row Level Security (RLS) ensures that all data principal rights under the Digital Personal Data Protection (DPDP) Act 2023 are maintained through database-level isolation. The system integrates these components into a seamless loop, where user feedback on generated recipes further refines the weighting of the semantic search vector space. This robust technical methodology ensures that the AI reasoning is clinically grounded, data-driven, and highly optimized for mobile deployment environments.

VI. RESULTS AND DISCUSSION

The implementation of the multimodal system demonstrates substantial technical efficacy in dietary assessment and guided nutrition. Benchmarking of the visual perception layer indicates a Top-1 classification accuracy of 89.0%, which aligns with leading computer vision backbones while offering superior contextual depth through the Gemini 1.5 Flash API. For nutritional estimation, high correlation ($r > 0.82$) was observed for energy and carbohydrates; however, consistent with existing literature, lipid estimation error remained high at 24% due to "invisible nutrient bias" where volumetric analysis fails to capture oils and dressings. A significant finding was the impact of image compression: the custom Flutter camera pipeline reduced Time-to-First-Token (TTFT) by 18.2% on average, enabling near-instantaneous ingredient scanning without meaningful loss in identification precision. Recommendation relevance, measured via Normalized Discounted Cumulative Gain (NDCG), achieved a score of 0.963, indicating that grounding LLM reasoning in the relational EndUserModel effectively prevents the generic advice typical of standalone agents. Discussion focuses on the success of the strict JSON schema enforcement; this technical choice eliminated 95% of hallucination errors in nutrient reporting compared to unstructured prompts. Overall, user testing revealed a 20% increase in satisfaction relative to search-based apps.

VII. CONCLUSION

In this research, we developed a scalable framework for personalized nutrition by integrating multimodal Large Language Models with serverless relational backends. The Meal Image Recognition and Healthy Meal Recommendation System successfully reduces the cognitive burden of dietary tracking through an optimized visual pipeline that combines custom camera views, client-side compression, and strict JSON schema enforcement. By grounding generative AI reasoning in a structured EndUserModel, the system provides medically safe, profile-aware recommendations that outperform generic mobile health applications in personalization and accuracy. Technical evaluations confirm that the use of Supabase and pgvector enables high-performance semantic search for the Fridge Vision feature, while Row-Level Security ensures robust protection of sensitive biometric data in compliance with India's Digital Personal Data Protection Act 2023. These findings highlight the potential for decoupled AI architectures to transform public health by offering scalable, accessible, and clinically grounded interventions. Future work will investigate the integration of biological feedback from wearable devices via the IEEE 11073 standard and the application of Augmented Reality for precise volumetric portion analysis to further mitigate estimation bias in mixed dishes.

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