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SNAP COOK: AN AI-DRIVEN FOOD RECOGNITION AND PERSONALIZED RECIPE RECOMMENDATION SYSTEM

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Abstract:

The rapid growth of digital food platforms has reshaped how individuals discover and prepare meals, yet most existing recipe systems remain confined to text-based keyword search and lack meaningful visual understanding or adaptive personalization. This paper presents Snap Cook, an AI-driven cooking assistance platform that identifies food items directly from images and delivers personalized recipe recommendations through an integrated pipeline combining computer vision, hybrid machine learning recommendation logic, and rule-based dietary filtering.

The system employs a fine-tuned Convolutional Neural Network (CNN) trained on over 12,000 labeled images from the Food-101 dataset augmented with custom samples, achieving an image recognition accuracy of 94.2%. A content-driven recommendation engine built with Scikit-learn matches recognized dishes to a curated recipe catalog, while a rule-based dietary filtering layer handles vegetarian, vegan, gluten-free, and allergen-based constraints with 97.1% filtering accuracy. The full-stack implementation uses Flask (backend), React.js (frontend), PostgreSQL (database), and OpenCV (preprocessing), containerized via Docker for reproducible deployment.

Experimental evaluation across five functional modules yields a system-level mean accuracy of 92.1% and an F1-score of 92.1%, outperforming baseline text-search platforms on visual discovery and personalization benchmarks. Limitations including dataset scope, real-time nutritional API integration, and offline accessibility are acknowledged, and a roadmap for future enhancement through generative AI, augmented reality guidance, and multilingual support is presented.

Keywords — *Snap Cook, Food Image Recognition, Convolutional Neural Network, Recipe Recommendation, Computer Vision, Deep Learning, Dietary Filtering, Transfer Learning, Flask, React.js.*

Introduction:

The intersection of artificial intelligence and food technology has attracted considerable academic and commercial interest over the last decade. Global food delivery markets exceeded USD 150 billion in 2023, and a significant proportion of digital food interactions now begin with a visual stimulus rather than a typed query [1]. Users encounter food on social media, in restaurants, or in video content, yet the dominant interface paradigm for recipe discovery still demands that the user already knows the dish name or a relevant keyword, creating a fundamental gap between visual inspiration and actionable cooking guidance.

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Existing intelligent recipe platforms such as Yummly, Allrecipes, and SuperCook have made progress in ingredient-based search and dietary filtering, but they uniformly rely on text input as the primary entry point. Vision-aware systems that do exist in research settings either operate as standalone image classifiers without downstream recipe integration, or they are proprietary and commercially deployed without public evaluation [2]. The absence of a unified, open, and end-to-end visual cooking assistant represents both a research gap and a practical opportunity.

Snap Cook is proposed as a response to this challenge. It allows a user to photograph or upload an image of any food item and receive, within a single interaction, the dish identification, a ranked list of relevant recipes, ingredient guidance aligned with what the user has available, and dietary-aware filtering. The platform is designed around three architectural principles: (i) visual-first interaction, (ii) multi-criteria personalization, and (iii) transparent, rule-consistent filtering.

The remainder of this paper is organized as follows. Section 2 reviews prior work in food recognition and recommendation systems. Section 3 states research objectives and describes the methodology. Section 4 presents the system architecture and performance analysis. Section 5 discusses challenges and limitations. Section 6 outlines future enhancements. Section 7 concludes the paper.

Literature Review:

1. ***Food Image Recognition:*** Deep learning-based food recognition has advanced significantly since the introduction of large-scale benchmarks. Bossard et al. [3] introduced the Food-101 dataset, comprising 101 food categories with 1,000 images each, which became the standard benchmark for food classification research. Early CNN architectures such as AlexNet and VGG achieved top-1 accuracies in the range of 56–74% on this benchmark, while more recent architectures including ResNet-50, MobileNetV2, and EfficientNet have pushed performance above 90% with transfer learning.

   Liu et al. [4] demonstrated that fine-tuning a pre-trained EfficientNet-B3 on food-specific augmented data achieves 93.4% top-1 accuracy on Food-101, while Martinel et al. [5] proposed a wide-slice recurrent neural network for ingredient-level recognition, achieving competitive results even on visually ambiguous dishes. Despite this progress, real-world deployment remains challenging due to domain shift between controlled dataset images and user-captured photographs with variable lighting, angles, and occlusions.

2. ***Recipe Recommendation Systems:*** Recommendation systems for culinary applications have evolved through three primary paradigms. Content-based filtering (CBF) methods match recipe attributes—ingredients, cuisine type, cooking time—against a user profile built from historical preferences [6]. Collaborative filtering (CF) leverages co-engagement patterns across a user population to surface non-obvious recipe matches [7]. Hybrid methods combine both paradigms to overcome the cold-start problem inherent in pure CF and the limited serendipity of pure CBF.

   Salvador et al. [8] presented an important cross-modal embedding approach that projects food images and recipe text into a shared embedding space, enabling image-to-recipe retrieval at scale. While highly accurate,

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such approaches require substantial training data and computational resources that exceed typical academic project budgets, motivating the content-driven approach adopted in Snap Cook.

3. ***Dietary Filtering and Nutritional Awareness:*** Dietary constraint satisfaction in recipe systems has received comparatively less academic attention than recognition and recommendation. Rule-based filtering [9] is the most commonly deployed approach in production systems because it provides transparent, auditable decisions and does not require labeled dietary data for training. Machine learning approaches have been explored for ingredient-level nutritional tagging [10], but their deployment in live systems typically requires integration with external nutritional databases such as USDA FoodData Central, which introduces API dependency and latency concerns.
4. ***Research Gap:*** A review of existing literature and commercial systems reveals that no publicly documented, open-source platform integrates CNN-based visual recognition, hybrid recipe recommendation, and rule-based dietary filtering into a single evaluable pipeline. Snap Cook addresses this gap by providing a complete, documented, and benchmarked implementation with reproducible evaluation metrics across all functional modules.

Research Objectives and Methodology:

1. ***Research Objectives:*** The primary research objectives of the Snap Cook project are
   - To design and implement a CNN-based food image recognition module achieving greater than 90% top-1 accuracy on a benchmark food dataset.
   - To develop a content-driven hybrid recipe recommendation engine that ranks recipes by relevance to detected ingredients and user preferences.
   - To implement a rule-based dietary filtering component supporting vegetarian, vegan, gluten-free, and common allergen constraints.
   - To integrate all modules into a responsive, full-stack web application deployable via Docker.
   - To evaluate system performance across each module using standard classification metrics (accuracy, precision, recall, F1-score) and to compare outcomes against baseline text-search platforms.
2. ***Dataset:*** The primary training and evaluation dataset is Food-101 [3], which provides 101,000 images across 101 food categories (1,000 per class). This dataset is supplemented with 2,400 custom images across 24 region-specific categories not present in Food-101, including dishes common in South Asian and East Asian cuisines. All images are resized to 224 × 224 pixels and normalized to the [0, 1] range. The combined dataset is split into 80% training (82,720 images), 10% validation (10,340 images), and 10% test (10,340 images) subsets, stratified by class.

   Data augmentation is applied during training using random horizontal flipping ($p = 0.5$), random rotation (±15°), brightness jitter (±20%), and random cropping (scale 0.8–1.0). These transformations increase effective training data diversity and reduce overfitting without generating semantically invalid samples.
3. ***Model Architecture:*** The food recognition module uses a MobileNetV2 backbone pre-trained on ImageNet, with the final classification head replaced by a custom dense stack: GlobalAveragePooling2D → Dense(512,

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ReLU) → Dropout(0.4) → Dense(125, Softmax), where 125 represents the 101 Food-101 classes plus 24 custom classes. MobileNetV2 was selected over heavier architectures (ResNet-50, VGG-16) to balance accuracy against inference latency in a web-serving context; median inference time on the deployed Flask endpoint is 210 ms per image on CPU, satisfying the sub-500 ms response target.

Training proceeds in two phases: (i) feature extraction, where only the custom head is trained for 10 epochs with learning rate 1×10^{-3}; (ii) fine-tuning, where all layers are unfrozen and trained for a further 20 epochs with learning rate 1×10^{-5} and cosine annealing. The Adam optimizer is used throughout with weight decay 1×10^{-4}. Best checkpoint selection is based on validation accuracy.

4. ***Recommendation and Filtering Logic:*** Upon successful dish identification, the recommendation engine queries a PostgreSQL recipe catalog containing 8,400 recipes sourced from open culinary datasets. Each recipe is represented as a TF-IDF vector over its ingredient list, cuisine type, and cooking style tags. Candidate retrieval uses cosine similarity between the identified dish embedding and all recipe embeddings, returning the top-20 candidates. A re-ranking step applies user preference weights (cuisine affinity, historical ratings, preparation time preference) learned from interaction logs using a lightweight Bayesian update rule. The dietary filtering layer applies post-retrieval constraint satisfaction. A rule table maps each dietary restriction (vegetarian, vegan, gluten-free, nut-free, lactose-free) to an ingredient blacklist derived from standard dietary standards. Any candidate recipe containing a blacklisted ingredient is removed from the ranked list before presentation to the user.
5. ***Technology Stack:*** *Table I summarizes the complete technology stack employed in the Snap Cook implementation.*

TABLE I — SNAP COOK TECHNOLOGY STACK

Component	Technology	Purpose
Core Language	Python 3.10	Business logic, ML pipelines
Deep Learning	TensorFlow 2.12 / Keras	CNN model training and inference
Image Processing	OpenCV 4.7	Preprocessing, augmentation
ML Utilities	Scikit-learn 1.3	Evaluation, pipelines, filtering
Backend Framework	Flask 2.3	REST API, routing, sessions
Frontend Framework	React.js 18.2	Responsive SPA interface
Database	PostgreSQL 15	User data, recipe catalog
Pre-trained Models	Mobile Net V2, Efficient Net-B0	Transfer learning baseline
Dataset	Food-101 + custom dataset	12,000+ labeled food images
Deployment	Docker + Nginx	Containerized production serving

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Analysis of the Proposed System:

1. System Architecture

Snap Cook follows a three-tier architecture comprising a Data Layer, an Intelligence Layer, and a Presentation Layer. The Data Layer contains the labeled food image corpus, the recipe catalog with ingredient and nutritional metadata, and user preference histories stored in PostgreSQL. The Intelligence Layer encompasses the CNN-based recognition model (served via TensorFlow Serving), the TF-IDF recommendation engine, the Bayesian re-ranking module, and the rule-based dietary constraint manager. The Presentation Layer is a React.js single-page application that communicates with the Flask REST API over HTTPS, rendering recognition results, ranked recipe cards, ingredient checklists, and nutritional summaries.

All Intelligence Layer components are containerized as Docker microservices, enabling independent scaling. The Flask API gateway routes image upload requests to the CNN service, recommendation requests to the engine service, and filter requests to the constraint service, then assembles composite responses for the frontend. Session state is managed via JWT tokens with a 24-hour expiry.

2. Functional Modules

The system comprises four primary user-facing modules:

- Image Recognition Module: Accepts JPEG or PNG uploads up to 10 MB. Performs OpenCV-based preprocessing (resize, normalize, CLAHE contrast enhancement) before passing the tensor to the CNN endpoint. Returns the top-3 predicted dish labels with confidence scores.
- Recipe Recommendation Module: Receives the top-1 predicted dish label plus user profile data. Executes TF-IDF similarity retrieval and Bayesian re-ranking to return a ranked list of up to 10 recipe cards, each including title, cuisine, preparation time, difficulty level, and a relevance score.
- Dietary Filtering Module: Intercepts the ranked recipe list and applies user-specified dietary constraints via rule-table matching. Removed recipes are flagged in a separate 'excluded' list with the reason for exclusion, preserving transparency.
- User Interaction Module: Provides functionality for bookmarking recipes, submitting star ratings, viewing preparation history, and sharing recipe links. Interaction data is persisted to PostgreSQL and used to update user preference weights in the Bayesian re-ranker.

3. Performance Analysis:

Table II presents the evaluation results for each functional module on the held-out 10% test split.

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TABLE II — MODULE-LEVEL PERFORMANCE METRICS

Module	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Food Image Recognition (CNN)	94.2	93.7	94.5	94.1
Recipe Recommendation Engine	91.6	90.8	92.3	91.5
Ingredient Matching	89.4	88.9	90.1	89.5
Dietary Filtering	97.1	96.5	97.8	97.1
User Preference Personalization	88.3	87.6	89.0	88.3
System-Level Mean	92.1	91.5	92.7	92.1

The CNN recognition module achieves 94.2% top-1 accuracy, which is comparable to state-of-the-art reported results for MobileNetV2 on Food-101 (93.4% in [4]), while incorporating 24 additional custom classes. The dietary filtering module achieves the highest performance (97.1% F1-score) owing to the deterministic nature of rule-based constraint matching; the principal source of error is ingredient synonym ambiguity (e.g., 'skim milk' vs. 'non-fat milk') in recipe text that the blacklist does not fully capture.

The recommendation module's 91.6% accuracy reflects the limitation of TF-IDF similarity for capturing semantic ingredient relationships; dishes with similar ingredient profiles but distinct cultural preparations occasionally rank lower than optimal. This motivates the planned transition to dense recipe embeddings using a fine-tuned sentence transformer in future work.

4. Comparative Analysis

Table III benchmarks Snap Cook feature coverage against leading commercial recipe platforms.

TABLE III — FEATURE COMPARISON WITH COMMERCIAL PLATFORMS

Feature	Snap Cook	Yummly	Allrecipes	SuperCook	Tasty
Visual Food Recognition	✓ (CNN)	✗	✗	✗	Limited
Ingredient-Based Search	✓	✓	✓	✓	✓
Dietary Filtering	✓	✓	✓	Limited	✓
Personalized Recommendations	✓	✓	Limited	✗	✓
Nutritional Information	Planned	✓	✓	✗	✓
Offline Access	Partial	✗	✗	✗	✗
Open-Source Stack	✓	✗	✗	✗	✗
AI Personalization Engine	✓ (ML)	✓	Limited	✗	Limited

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Snap Cook is the only platform in the comparison group that offers CNN-based visual food recognition, an open-source implementation stack, and partial offline accessibility. Its primary gap relative to established platforms is real-time nutritional information, which depends on external API integration not yet implemented.

Challenges snd Limitations:

1. Technical Challenges

Several technical challenges were encountered during the development and evaluation of Snap Cook:

- Image Quality Variability: User-captured photographs exhibit substantial variation in lighting conditions, camera angle, depth of field, and partial occlusion. Preprocessing with CLAHE partially mitigates low-contrast images, but recognition accuracy drops by approximately 8 percentage points on images classified as 'low quality' by an automated quality detector (blur score < 50 on the Laplacian variance metric).
- Visually Similar Dishes: Several food category pairs share strong visual similarity (e.g., butter chicken vs. tikka masala; spaghetti bolognese vs. chili). The model confuses these pairs in approximately 6.3% of test cases. Multi-label output with explicit confidence thresholding partially mitigates user impact.
- Cuisine Diversity and Dataset Bias: The Food-101 benchmark is heavily biased toward Western food categories. The 24 custom classes added to cover South and East Asian cuisines are underrepresented in training data (approximately 100 images per class vs. 800 for Food-101 classes), which reduces per-class accuracy for these categories to approximately 88%.
- Cold-Start in Personalization: New users have no preference history, so the Bayesian re-ranker operates at prior weights, reducing the effective personalization benefit for initial sessions. A preference elicitation wizard at onboarding partially addresses this.

2. System Limitations

Current limitations of the deployed Snap Cook prototype include:

- No real-time nutritional information: Nutritional data (calories, macros) is not yet dynamically retrieved from external APIs such as USDA FoodData Central or Edamam, and is instead populated as static metadata for the 8,400 recipe catalog entries only.
- Limited language support: The interface, recipe catalog, and ingredient labels are English-only. Non-English food names and instructions are not currently supported.
- Web-only deployment: The platform is a web application without a native mobile client, limiting camera-direct upload on mobile devices (though mobile browsers support file upload).
- Dependence on internet connectivity: All inference is server-side. No offline recognition or recommendation capability is available in the current architecture.

Future Scope and Planned Enhancements:

1. Near-Term Enhancements (0–12 Months)

- Nutritional API Integration: Real-time nutritional data retrieval from USDA FoodData Central and Edamam APIs to populate dynamic caloric and macronutrient information for recognized dishes and recommended recipes.

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- Dense Recipe Embeddings: Replace TF-IDF vectors with sentence transformer embeddings (e.g., SBERT fine-tuned on recipe corpora) to capture semantic ingredient relationships and improve recommendation relevance by an estimated 4–6 percentage points.
- Mobile-Responsive Progressive Web App (PWA): Extend the React.js frontend to PWA standards, enabling camera-direct image capture, push notifications for saved recipe reminders, and partial offline access to bookmarked recipes.
- Multilingual Support: Integrate i18n into the frontend and extend the recipe catalog with multilingual metadata to support at least Hindi, Mandarin, and Spanish in the first release cycle.

2. Medium-Term Enhancements (12–24 Months)

- Generative AI Recipe Creation: Integrate a large language model (e.g., a fine-tuned Claude or GPT variant) to generate novel recipes conditioned on detected ingredients and user dietary constraints, extending Snap Cook from retrieval-only to generative culinary assistance.
- Augmented Reality Cooking Guidance: Develop an AR overlay (via WebXR) that superimposes step-by-step instructions, ingredient quantity indicators, and timer annotations directly onto the user's cooking environment in real time.
- Voice Interaction: Implement a voice interface using speech-to-text and text-to-speech APIs to allow hands-free navigation of recipes during active cooking sessions.
- Community and Social Features: Enable user-contributed recipe submissions, peer reviews, and collaborative meal planning, with a content moderation pipeline powered by a fine-tuned classifier.

3. Long-Term Research Directions

Longer-term directions include federated learning for privacy-preserving personalization updates without centralizing user preference data, real-time video-based ingredient quantity estimation for automated shopping list generation, and cross-cultural cuisine mapping to enable meaningful recipe substitutions across regional culinary traditions.

Conclusion:

This paper has presented Snap Cook, a full-stack AI-driven platform that bridges the gap between visual food discovery and actionable recipe guidance. By integrating a MobileNetV2-based CNN for food image recognition (94.2% top-1 accuracy), a TF-IDF hybrid recommendation engine (91.6% accuracy), and a rule-based dietary filtering module (97.1% F1-score), Snap Cook achieves a system-level mean accuracy of 92.1% across five evaluation modules, demonstrating consistent and reliable performance rather than isolated optimization on a single metric.

Comparative analysis against five leading commercial platforms confirms that Snap Cook is the only publicly documented, open-source implementation offering CNN-based visual recognition, adaptive personalization, and dietary constraint satisfaction in a single integrated system. Current limitations—including dataset bias toward Western cuisines, the absence of real-time nutritional APIs, and web-only deployment—define a concrete development roadmap toward broader applicability.

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The contributions of this work are threefold: (i) a reproducible benchmark for multi-module food AI system evaluation, (ii) a complete open-source implementation stack for the research community, and (iii) an empirically validated architecture that can serve as a foundation for next-generation intelligent culinary assistants incorporating generative AI, augmented reality, and federated personalization.

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