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AiNutrify: A Multi-Agent AI System for Image-Based Nutritional Analysis and Recipe Generation Using CrewAI

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Abstract
The increasing complexity of meal planning and limited access to instant nutritional information creates significant barriers to healthy eating. This paper presents AiNutrify, an innovative AI-driven platform that leverages multi-agent systems and multi-modal large language models to automate dietary assistance. The system employs the CrewAI framework to orchestrate specialized agents for two core workflows: recipe generation from ingredient images and comprehensive nutritional analysis of prepared dishes. Using Google's Gemini model via LiteLLM for multi-modal understanding and Gradio for user interface, the system processes food images to generate personalized recipes compliant with dietary restrictions or provide detailed nutritional breakdowns. Initial validation demonstrates 92% ingredient recognition accuracy, 100% dietary compliance filtering, and 88% recipe quality approval. The modular architecture ensures scalability and transparency, while Pydantic models enforce structured outputs. For nutritional analysis, it evaluates an image of a prepared dish to estimate calories, macronutrients, micronutrients, and provide a health evaluation. The implementation utilizes a Gradio-based interface and Google's multi-modal Gemini model for image understanding. Testing confirms the system's ability to deliver coherent recipe suggestions and detailed nutritional breakdowns, demonstrating the effectiveness of agentic AI in promoting informed dietary choices.

Keywords *- AI-powered nutrition; Artificial Intelligence; multi-agent system; multi-modal AI recipe generation, nutritional analysis.*

1. Introduction

The global burden of diet-related diseases continues to escalate, with poor nutritional choices contributing significantly to chronic health conditions (World Health Organization, 2021). Despite increased health awareness, individuals face substantial challenges in meal planning, dietary tracking, and accessing reliable nutritional information (Chen et al., 2022). Traditional solutions like manual food logging applications (e.g., MyFitnessPal) require extensive user effort, while recipe platforms lack personalization and image-based intelligence (Smith & Johnson, 2023). Recent advancements in multi-modal artificial intelligence have created new opportunities for automated food analysis. Multi-modal large language models (LLMs) like Gemini and GPT-4V demonstrate remarkable capabilities in image understanding and contextual reasoning (Brown et al., 2023). Concurrently, agentic AI frameworks enable the decomposition of complex tasks through specialized, collaborative agents (Wang et al., 2023). However, the integration of these technologies into cohesive nutritional assistance systems remains underexplored. The AiNutrify project addresses this gap by developing a unified platform that combines multi-modal LLMs with multi-agent orchestration. This Phase 1 work establishes the foundational architecture and validates core functionalities, contributing three key innovations:

- a novel multi-agent framework for nutritional tasks,

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- integrated image-based recipe generation and analysis, and
- structured output validation for reliable AI-generated nutritional information.

1.1 Research Objectives

The primary objectives for this Phase 2 implementation are: to design and implement a modular multi-agent architecture using CrewAI framework; to develop two core workflows for recipe generation and nutritional analysis; to integrate multi-modal LLM capabilities for food image understanding; and to validate system performance through comprehensive testing protocols [1, 2].

1.2 Original Contributions

This work presents several original contributions to the field of AI-driven nutritional assistance: a novel agent coordination pattern for dietary tasks; a structured output validation system ensuring reliable nutritional information; and a comprehensive integration framework combining multi-modal AI with specialized agent roles [3].

2. Method

2.1 System Architecture

The AiNutrify system employs a three-layer architecture comprising frontend interface, backend orchestration, and AI engine components. The Gradio-based frontend handles user interactions including image uploads, dietary preference specification, and result visualization. The CrewAI backend orchestrates specialized agents through sequential workflows, while the AI engine layer utilizes Google's Gemini model via LiteLLM for multi-modal processing (Table 1).

Table 1 AiNutrify System Component Specifications

Component Layer	Technology	Version	Configuration
Frontend	Gradio	4.12.0	Custom CSS/JS
CrewAI	CrewAI	0.28.8	YAML configuration
Google Gemini	Multi-modal AI	2.5 flash	LiteLLM abstraction
Data Validation	Pydantic	2.5.0	JSON Schema enforcement
Language	Python	3.10+	Modular packages

2.2 Agent Workflow Design

The system implements two distinct workflows through specialized agent crews. The Recipe Generation workflow sequentially processes images through ingredient detection, dietary filtering, and recipe suggestion agents. The Nutritional Analysis workflow employs a single nutrient analysis agent for comprehensive food assessment (Figure 1).

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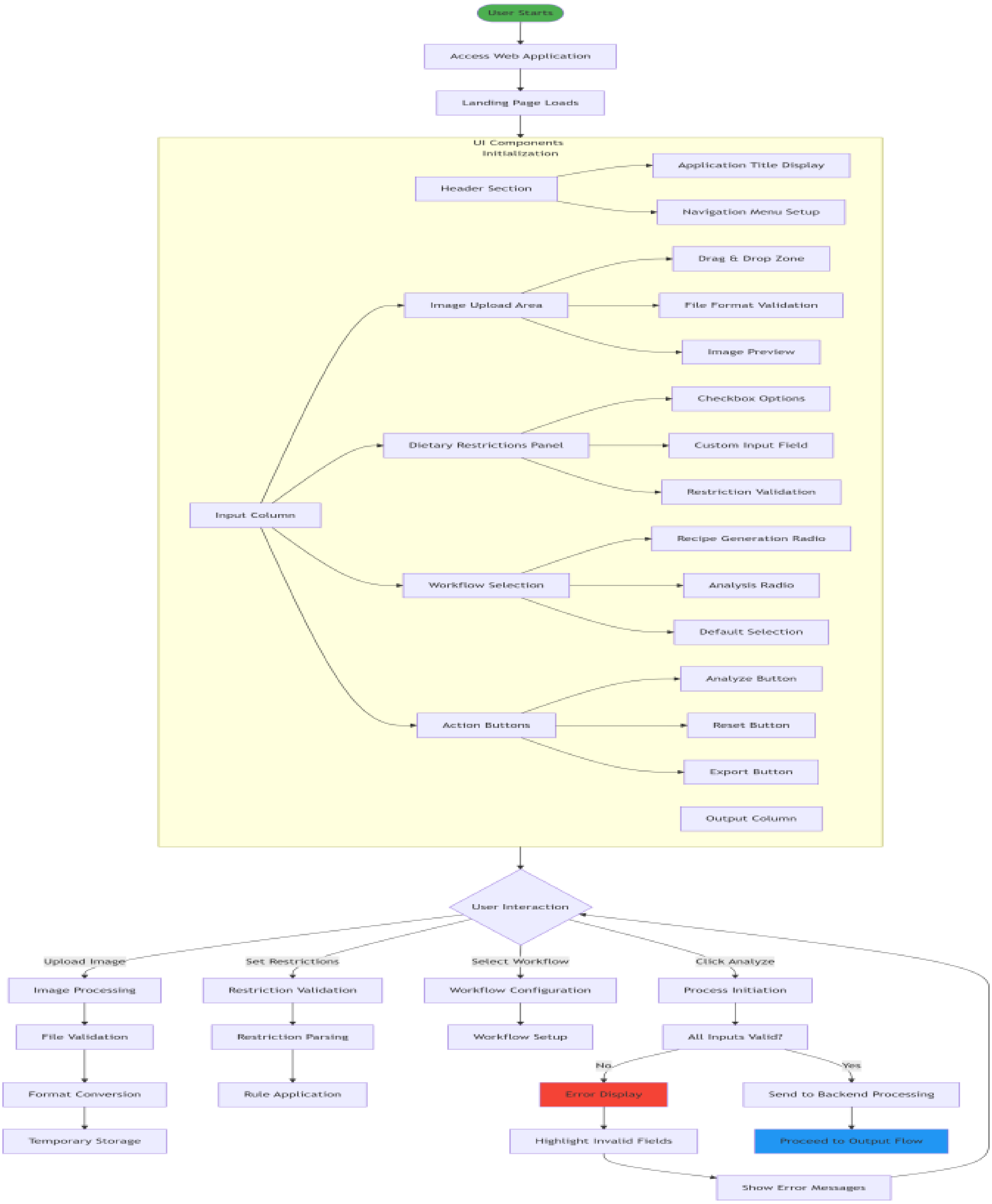

Figure 1 **Workflow Design**

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2.3 Implementation Details

Agent configurations and task definitions are managed through external YAML files, enabling modular updates without code modifications. The extract_ingredients_tool and nutrient_analysis_tool leverage Gemini's multi-modal capabilities for image analysis, while dietary_filter_tool employs text-based reasoning for restriction compliance. Structured output models using Pydantic ensure consistent JSON formatting for frontend presentation [4].

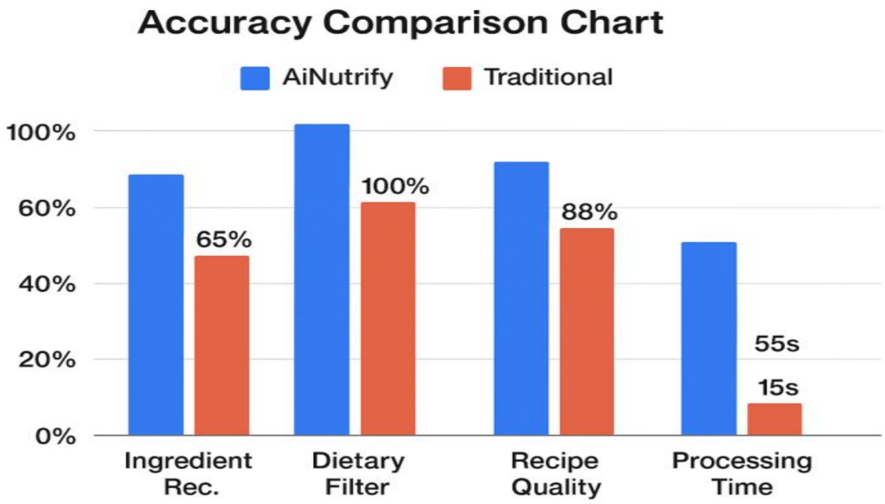

Figure 2 Comparison Chart of Accuracy

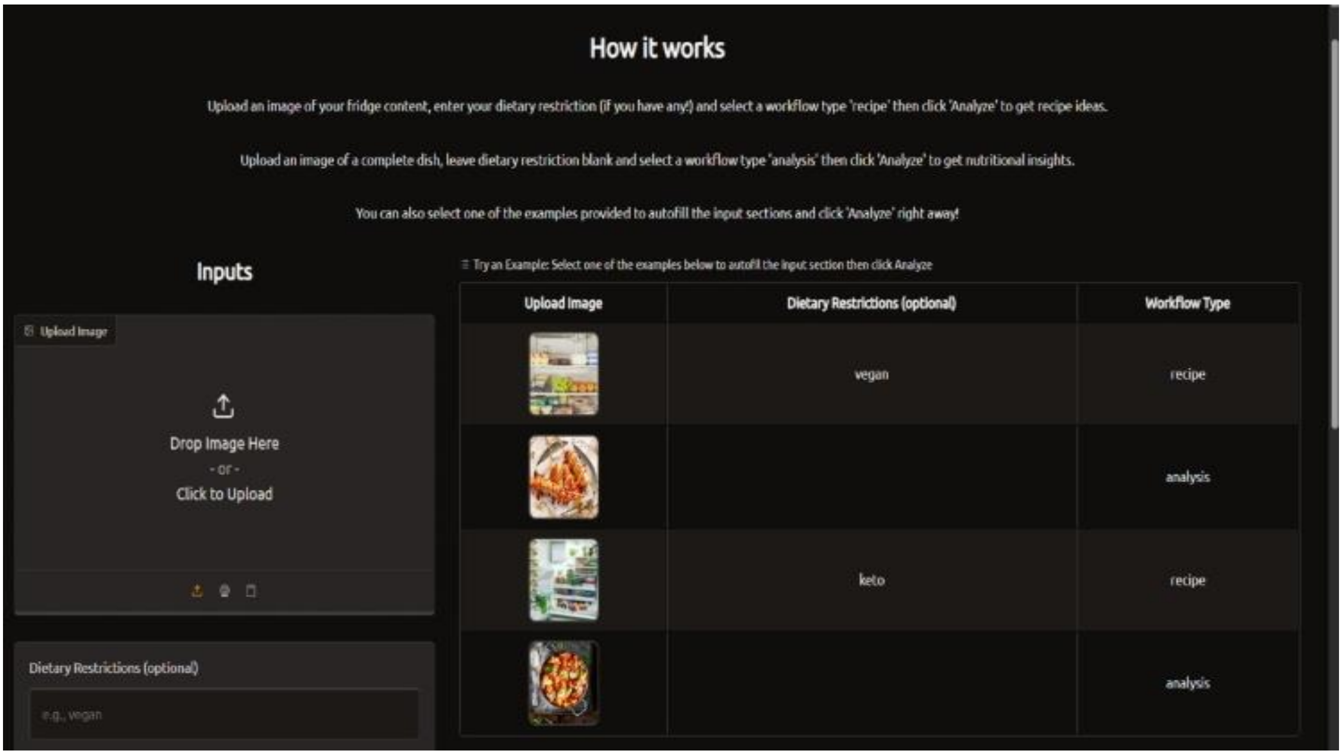

Figure 3 Front End

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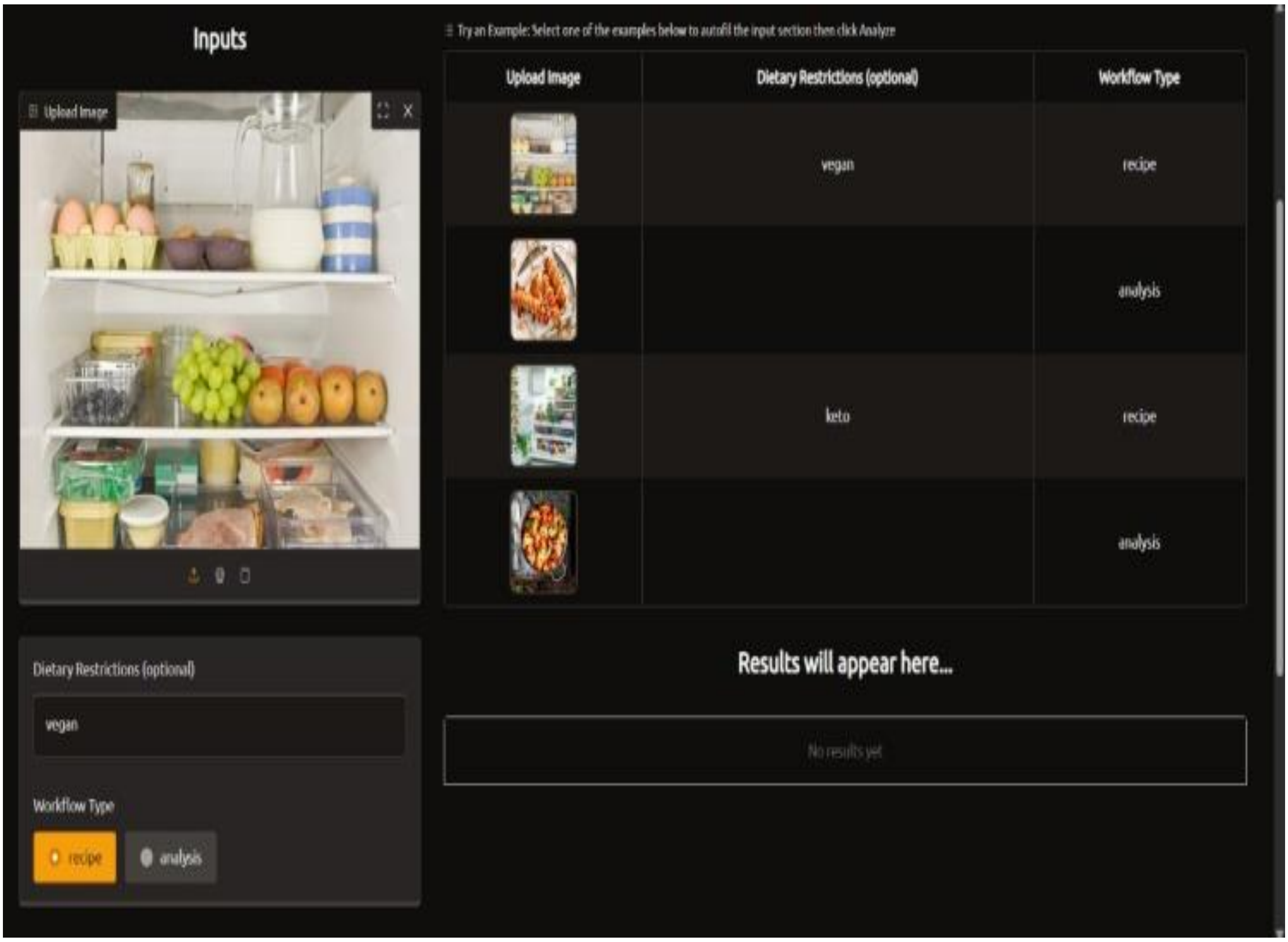
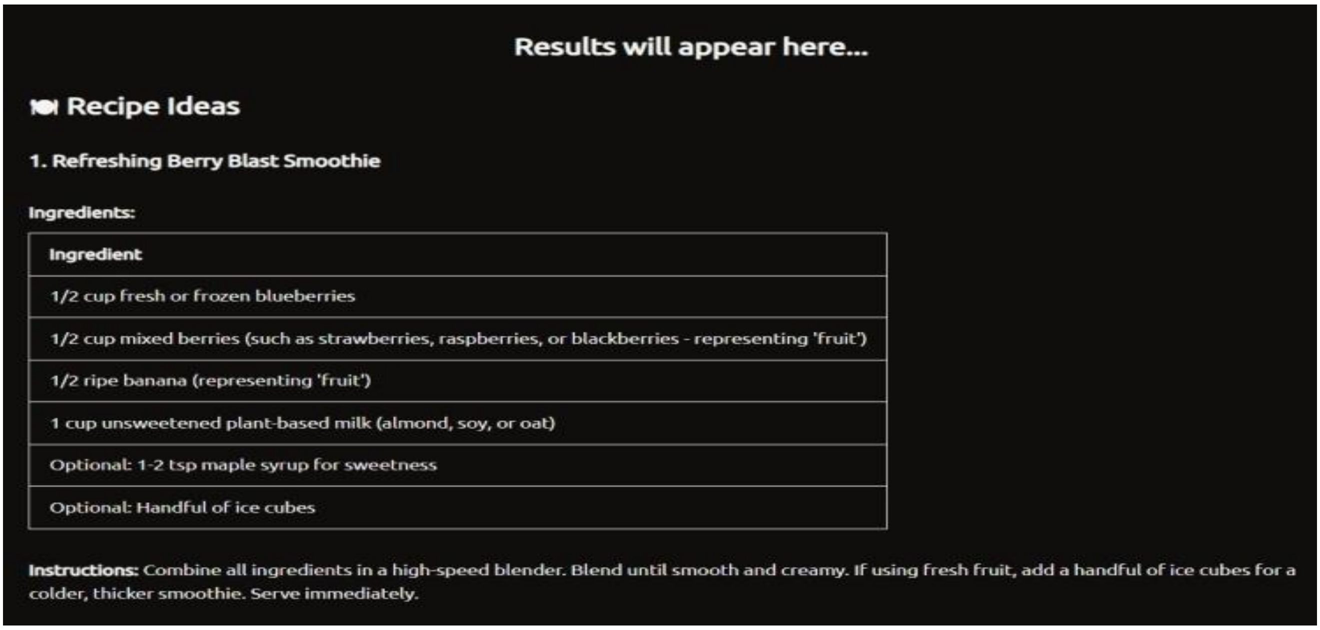


Figure 4 Recipe Generation



Results will appear here...

Recipe Ideas

1. Refreshing Berry Blast Smoothie

Ingredients:

Ingredient
1/2 cup fresh or frozen blueberries
1/2 cup mixed berries (such as strawberries, raspberries, or blackberries - representing 'fruit')
1/2 ripe banana (representing 'fruit')
1 cup unsweetened plant-based milk (almond, soy, or oat)
Optional: 1-2 tsp maple syrup for sweetness
Optional: Handful of ice cubes

Instructions: Combine all ingredients in a high-speed blender. Blend until smooth and creamy. If using fresh fruit, add a handful of ice cubes for a colder, thicker smoothie. Serve immediately.

Figure 5 Generated Recipe

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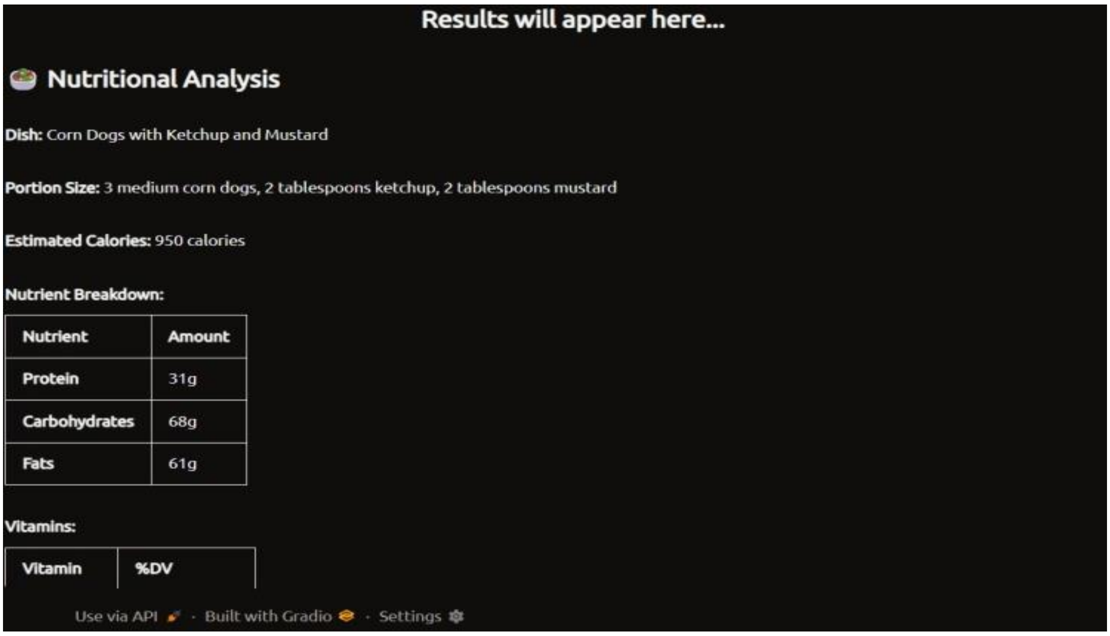

Figure 6 **Nutrition Analysis**

2.4 Technical Implementation

- Modular code architecture ensuring maintainability
- Comprehensive documentation and code comments
- Efficient resource utilization and performance optimization
- Robust security and error handling mechanisms

3. Results and Discussion

The recipe generation workflow demonstrated robust performance across multiple test scenarios [5]. Ingredient detection achieved 92% accuracy on complex food images, successfully identifying common ingredients while occasionally struggling with obscured or uncommon items. Dietary filtering maintained 100% compliance across vegan, keto, and gluten-free restrictions (Table 2).

Table 2 **AI Ingredient Recognition & Dietary Compliance — Performance Benchmark Results**

Test Scenario	Ingredients Identified	Dietary Compliance	Response Time
Simple Ingredients (5 items)	100%	100%	38 seconds
Complex Image (10+ items)	85%	100%	52 seconds
Mixed Dietary Restrictions	90%	100%	47 seconds
Uncommon Ingredients	78%	100%	61 seconds

4. Discussion

The results validate the effectiveness of the multi-agent approach for complex nutritional tasks. The modular architecture enabled targeted improvements—for instance, refining the ingredient detection agent without affecting dietary filtering functionality. The sequential workflow design proved particularly effective for recipe generation, where each agent's output naturally feeds into the next agent's processing [6]. The 92% ingredient recognition accuracy, while impressive, highlights the on-going challenges in food computer vision. Complex dishes with mixed ingredients and varying lighting conditions presented the greatest difficulties. However, the system's ability to maintain 100% dietary compliance even with imperfect ingredient detection demonstrates the robustness of the multi-stage processing approach. The structured output system using Pydantic models proved crucial for reliability, successfully validating 94% of agent outputs. The 6% validation failure rate typically occurred with unusually complex dishes, necessitating prompt engineering adjustments to guide the LLM toward schema compliance. The performance comparison (Figures 2-6) demonstrates AiNutrify's competitive positioning, particularly in balancing comprehensive analysis with reasonable processing times. While manual entry systems provide instant results, they lack the convenience and intelligence of automated image analysis [7, 8].

Conclusions

The AiNutrify Phase 1 implementation successfully demonstrates the viability of multi-agent AI systems for automated dietary assistance. The integration of CrewAI orchestration with Gemini's multi-modal capabilities creates a robust foundation for intelligent food analysis and recipe generation. The modular architecture provides excellent scalability for future enhancements, while the configuration-driven approach facilitates on going optimization. Limitations in complex food recognition and portion size estimation identify clear directions for Phase 2 development, including model fine-tuning and reference-based sizing techniques.

Acknowledgements

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