Meal And Recipe Generator (MARG)

AI-Powered Meal Generation System Proposal

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1. Problem Statement

Many people face the daily challenge of deciding what to cook with the available ingredients in their kitchen. This challenge leads to:

- Food waste occurs when ingredients aren't used before spoiling
- Unnecessary grocery purchases when existing ingredients could be combined effectively
- Missed opportunities for creative meal preparation
- Time wasted searching through recipe websites with incomplete ingredient matches

This problem is ideal for a generative AI solution because:

- Recipe creation follows patterns that can be learned from existing recipes
- Ingredient combinations and cooking techniques have underlying rules and relationships
- The solution requires both understanding ingredient compatibility and generating coherent, detailed instructions
- Traditional rule-based systems cannot capture the nuanced relationships between ingredients and cooking methods

2. Proposed Solution

We propose developing an AI-powered recipe generation system that creates detailed, customized recipes based on available ingredients.

Primary Components:

- 1. Ingredient Analysis Module
 - o Processes user input of available ingredients and quantities
 - o Identifies potential ingredient combinations
 - o Suggests additional ingredients if needed
 - Optionally accepts tags such as dietary restrictions or themes (e.g., "gluten-free," "spicy")
- 2. Recipe Generation Module
 - o Uses the Ashikan/dut-recipe-generator model
 - o Creates complete recipes using available ingredients
 - Generates step-by-step cooking instructions
 - o Provides cooking times, temperatures, and serving suggestions
 - o Can reroll new recipes using the same input.

Model Selection:

- Primary: Ashikan/dut-recipe-generator
 - A BLOOM560 m-based model fine-tuned on the DUT Diabetic-Friendly Recipes and a cleaned version of RecipeNLG. It generates structured, coherent recipes with metric units and health-conscious guidelines.
- Optional: Stable Diffusion for recipe image generation

The generative aspect enables:

- Dynamic recipe creation based on specific ingredient combinations
- Adaptation of cooking instructions to available equipment
- Scaling recipes based on ingredient quantities
- Generation of coherent, detailed cooking procedures

3. Dataset(s)

We do not train our own model, so we rely on the datasets used to fine-tune the Ashikan model:

- RecipeNLG: A large dataset of structured recipes used in the initial training
- DUT Diabetic-Friendly Recipes: Custom-curated recipes reviewed by food science experts for nutritional value and clarity

We may optionally reference:

- USDA FoodData Central: For basic nutritional estimates
- Public recipe datasets (e.g., Food.com) for UI examples or tag matching logic

Preprocessing Requirements:

- Standardization of ingredient names and measurements
- Extraction of cooking techniques and times
- · Classification of cuisine types and dietary restrictions (rule-based)
- Standardize user input (e.g., lowercase, remove typos)
- Format the prompt as a JSON object for the model

Ethical Considerations:

- Cultural sensitivity in recipe modifications
- Dietary restriction accuracy
- Attribution of recipe sources
- Bias monitoring in ingredient combinations
- Privacy protection for user data

4. System Design Overview

Architecture Components:

- 1. Input Processing Layer
 - o Ingredient parser and normalizer
 - Quantity converter
 - o Equipment availability checker
- 2. Recipe Generation Engine
 - Ingredient compatibility analyzer
 - o Recipe structure generator
 - Instruction sequence creator
 - o Scaling calculator
- 3. Output Generation Layer
 - Recipe formatter
 - Nutritional calculator
 - o Alternative suggestion generator
 - Safety check system

Implementation Approach:

- Python-based development using modern NLP libraries
- API-first design for easy integration

- Open Source LLMs
- StreamLit for UI

Evaluation Metrics:

- Recipe success rate
- Ingredient utilization efficiency
- User satisfaction ratings
- Nutritional balance
- Instruction clarity
- Safety compliance

5. Challenges and Limitations

Technical Challenges:

- 1. Recipe Scaling
 - o Solution: Create robust quantity adjustment algorithms
 - o Validate scaling logic with expert chefs
- 2. Safety Considerations
 - o Solution: Implement multiple validation layers
 - o Include warning systems for potentially unsafe combinations

Timeline (6-Week Project):

| Timing | Task Descriptions |
|--------|--|
| Week 1 | Dataset collection and preprocessing |
| | Initial system architecture setup |
| | Basic ingredient parsing implementation |
| Week 2 | Build prompt formatting and testing with the model |
| | Add dietary tag parsing and validation |
| | Polish UI and reroll logic |
| | Optional: nutritional info estimation |
| Week 3 | Instruction generation system development |
| | Safety validation implementation |
| | Initial user interface development |
| Week 4 | Recipe scaling system implementation |
| | Integration testing |
| | User feedback collection |
| Week 5 | System optimization |
| | Error handling improvement |
| | Documentation development |
| Week 6 | Final testing and validation |
| | Performance optimization |
| | Deployment preparation |

6. References

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