MARG: Meal And Recipe Generator

AI-Powered Meal Generation System Final Project Report

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1. Introduction

The Meal And Recipe Generator (MARG) is an AI-powered system designed to solve the common challenge of deciding what to cook with available ingredients. The implemented solution uses a generative AI model to create customized recipes based on user-provided ingredients, dietary restrictions, meal types, and serving requirements.

MARG addresses several key problems:

- Reduces food waste by suggesting recipes for ingredients already available
- Eliminates unnecessary grocery purchases
- Provides creative meal preparation options
- Saves time that would otherwise be spent searching through recipe websites

While the current implementation successfully generates recipes, there are some limitations:

- The recipe generation occasionally produces inconsistencies in measurements or instructions
- Some generated recipes contain minor spelling errors (e.g., "dilsilled" instead of "dill")
- The system currently lacks image generation for recipes
- Nutritional information is not yet implemented

2. Dataset Description

The implementation leverages pre-trained models rather than training from scratch. The primary model used is based on the lax-community/t5-recipe-generation, which was fine-tuned on:

- RecipeNLG: A large dataset of structured recipes
- Chef Transformer (T5): Custom-curated recipes language model trained on novel dataset of cooking recipes.

The system performs several preprocessing steps:

- Standardization of ingredient names (lowercase, removal of typos)
- Formatting user input as structured prompts for the model
- Parsing comma-separated ingredient lists
- Validation of dietary restrictions and meal types
- Conversion of user inputs into appropriate prompt format for the model

3. Methodology

The implemented solution consists of a Streamlit web application that interfaces with a generative AI model. The core components include:

Input Processing Layer	Recipe Generation Engine	Output Generation Layer
Ingredient parser and normalizer	Prompt formatting for the AI model	Recipe formatting with title, ingredients, and instructions
Meal type selector	Recipe structure generation	Presentation in a user-friendly interface
Dietary restriction input	Instruction sequence creation	
Serving size specification		

Tools Used

- Streamlit: For creating the web interface
- Hugging Face Transformers: For accessing and using the recipe generation model
- Python: Core programming language
- PyTorch: Backend for the transformer models

4. Results

The implemented system was evaluated based on the metrics outlined in the proposal:

Recipe Success Rate

The system successfully generates complete recipes with titles, ingredient lists, and step-by-step instructions for all tested ingredient combinations. Examples include:

- Baked salmon with dill (lunch, pescatarian)
- Cheesy spinach baked eggs (breakfast, vegetarian)
- Greek chicken orzo salad (dinner)

Ingredient Utilization Efficiency

The system effectively incorporates all provided ingredients into the generated recipes. For example, in the "Baked salmon with dill" recipe, all five ingredients (salmon, dill, lemon, greek yogurt, cucumber) are utilized in the recipe.

Instruction Clarity

The generated instructions are clear, sequential, and include specific details like cooking temperatures and times. For example, the baked salmon recipe includes precise instructions like "Preheat oven to 350 F" and "Bake for 20 minutes until the top is browned and the salmon flakes easily."

Safety Compliance

The system generates recipes with appropriate cooking instructions, including proper cooking temperatures for different types of food (e.g., 350°F for baking salmon).

5. Discussion

The MARG system successfully demonstrates the potential of generative AI in recipe creation. The system shows particular strength in:

- Creating diverse recipes from limited ingredient lists

- Adapting to dietary restrictions (e.g., vegetarian, pescatarian)
- Generating coherent cooking instructions
- Scaling recipes for different serving sizes

Several challenges were encountered during implementation:

1. **Prompt Engineering**: Finding the right prompt format to generate well-structured recipes required experimentation.
   - Solution: Developed a standardized prompt template that includes ingredients, dietary restrictions, meal type, and servings.
2. **Output Consistency**: The model occasionally produced inconsistent formatting or minor errors.
   - Solution: Implemented post-processing to standardize output format and correct common errors.
3. **Ingredient Parsing**: Handling various ways users might input ingredients.
   - Solution: Created a robust ingredient parser that normalizes inputs.

Based on the current implementation, several enhancements could be made:

1. Recipe Images: Integrate Stable Diffusion to generate images of the completed dishes.
2. Nutritional Information: Add calculation of nutritional values using USDA FoodData.
3. User Profiles: Allow users to save favorite recipes and ingredient preferences.
4. Alternative Suggestions: Provide alternative ingredients when certain items are unavailable.
5. Feedback Loop: Implement a rating system to improve recipe generation over time.

The MARG system successfully demonstrates the application of generative AI to solve the everyday challenge of meal planning and recipe creation. By leveraging pre-trained models and creating an intuitive user interface, the system provides immediate value to users while minimizing development time and resource requirements. It can be used to reduce food waste and enhance culinary creativity.

6. References

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