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DishGenie - Recipe Recommendation System using Deep Learning

Mrs. K.Lakshmi Viveka [1], Mrs. T.Tejasvi [2], Tejaswini Koppada [3], Kadipina Neelima [4], Rejeti Kaushik [5], J. Jyothi Sri [6]

[1] Associate Professor, [2] Assistant Professor, [3, 4, 5,6] B.Tech Students,
Department of CSE (Artificial Intelligence),
Pragati Engineering College, ADB Road, Surampalem, Near Kakinada, East Godavari District, Andhra Pradesh, India 533437.

ABSTRACT:

Artificial intelligence together with deep learning technology has enabled the development of intelligent systems which reduce complexities in different daily life processes. The process of identifying suitable recipes for existing ingredients remains difficult for most people within the culinary domain. Users can benefit from this solution named "DishGenie - Recipe Recommendation System using Deep Learning" because it generates recipe recommendations from their provided ingredients. Having Convolutional Neural Networks (CNNs) and Natural Language Processing (NLP) as deep learning models allows the system to process textual data and recognize ingredients through images. Flask enables a user-friendly interface which allows people to enter ingredients to receive customized recipe recommendations and handle their personal recipe lists. The system combines structured database storage which verifies ingredients and maintains recipes alongside its operational functions. DishGenie implements artificial intelligence image identification with data-based recipe structuring coupled to an adaptive recommendation system that transforms eating experiences while reducing culinary waste through stimulated kitchen innovation. This document offers complete details about project development alongside its goals and actual influence on outcomes.The software system allows customization based on individual user food needs and recipes because it automatically adjusts to specific dietary rules and cooking abilities. The recommendation engine uses intelligence to evaluate ingredients for creating multiple recipes including standard daily meals together with sophisticated restaurant-style dishes. Supplementing features through external API integration allows users to access YouTube recipe videos along with nutritional details and substitute ingredients
on the platform. The features at DishGenie enable users to select meals with knowledge while saving food and trying innovative cooking approaches.

KEYWORDS:

Artificial Intelligence, Deep Learning, DishGenie, Convolutional Neural Networks (CNNs).

1. INTRODUCTION

People commonly face difficulties in deciding suitable recipes for their daily cooking sessions based on their available ingredients. People now use artificial intelligence (AI) in the food industry to streamline their meal planning activities because it provides personalized solutions based on individual requirements. Deep learning technology which belongs to the broader category of artificial intelligence has excelled in processing images and text to make it the key technology for building smart recipe recommendation platforms.

Deep learning powers DishGenie to make cooking simpler through its function of delivering customized meal recommendations. The system uses two methods for operation: it accepts text-based ingredient entries and identifies ingredients through images taken via Convolutional Neural Networks (CNNs). Users can choose their preferred method of interaction because the system adopts an innovative design that offers flexibility. The training process relies on an extensive variety of food ingredients and recipes from diverse sources which enables better performance when matching ingredients with recommendations.

A Flask-based web application receives implementation alongside a powerful backend system which regulates user authentication and data management and model computation operations. Users have access to pantry management via the system which enables them to monitor and track their food ingredients and stock levels. DishGenie intends to merge deep learning capabilities with user-friendly web development methods in order to establish a connection between artificial intelligence programming and practical meal solution competencies while offering users a seamless and pleasurable meal preparation experience.

2. OBJECTIVES OF STUDY

DishGenie's main purpose is to produce an AI-generated virtual assistant able to generate custom recipe suggestions that match users' ingredients. Deep learning techniques which combine CNNs for image recognition and NLP processing of textual inputs enable the system to offer users an easy to use interface for their cooking experience. The feature of DishGenie also seeks to minimize food waste through its recipe suggestion service which helps users discover innovative ways to maximize their ingredients. User accessibility improves within the system through three features: voice-based inputs, smart pantry tracking and dietary preference customization implemented with current AI methodologies. The research tackles culinary industry meal planning and ingredient utilization through its objective to show how AI works in real-world catering practices. The system works as an educational resource by presenting users to different recipes together with cooking methods aside from offering a user-friendly interface. An effective implementation of this project will prove that artificial intelligence can revolutionize everyday activities including cooking through improved efficiency and enjoyment and sustainable practices.

Key Objectives

1. The platform should contain an AI system that generates relevant recipes according to user ingredients for efficient use.
2. CNNs will identify ingredients from images combined with NLP techniques that will process text-based input data.
3. A system will recommend innovative recipes for using food items that are approaching their expiration dates as part of kitchen sustainability measurements.
4. The system should have a friendly interface which accepts voice commands and offers simple navigation to improve ease of access.
5. The system creates customized recommendations whose ingredients offer adaptability according to food restrictions and method of preparation together with dietary requirements.
6. A pantry management system should enable users to keep track of ingredient availability which improves the accuracy of recommended recipes.
7. Deep learning models within this system would automate the process of deciding meals.
8. Cross-Platform Accessibility – Ensure compatibility with mobile and web applications for wider user reach.
9. Through diverse educational cooking insights the platform stimulates users to develop interest in discovering new recipes.
10. The system should include modular structure and future-readiness by supporting new components such as IoT technologies together with enhanced NLP functionality.

3. BACKGROUND WORK

The most crucial phase in software development is the background work. Numerous writers conducted preliminary studies on this relevant topic, and we will consider key papers to expand our work.Below is a literature survey table summarizing key studies on the application of deep learning in the food industry, focusing on ingredient detection, food classification, and personalized recipe recommendations.

Author(s) and Year	Paper Title	Findings and Problem Gap
Abdul Kareem et al., 2024	Fine-grained food image classification and recipe extraction using a customized deep neural network and NLP [1]	Proposed a framework integrating a customized lightweight CNN model (MResNet-50) for food image classification and NLP techniques for automated recipe extraction. Achieved improved accuracy on Food-101 and UECFOOD256 datasets. However, the study primarily focuses on classification and extraction, lacking emphasis on personalized recipe recommendations.
Nijhawan et al., 2024	VTnet+Handcrafted based approach for food cuisines classification [2]	Introduced a method combining Vision Transformer network (VTnet) with handcrafted features for classifying food cuisines. Demonstrated enhanced classification accuracy, but did not address ingredient detection or personalized recipe recommendations.
Wu et al., 2022	Visual-aware food analysis (VAFA) [3]	Employed deep learning models (ATNet and PiNet) to classify food items from multimedia inputs, achieving state-of-the-art performance in food classification and recipe recommendation precision. The study

		focuses on visual analysis but lacks integration with user-specific preferences for personalized recommendations.
Buzcu et al., 2022	Virtual Coaching System (NVS) [4]	Developed a system integrating user-specific factors like allergies and preferences to offer personalized recipe recommendations via an ontology-based approach. Validated through user surveys showing a preference for interactive explanation-based interactions over conventional recommendation systems. However, the system's reliance on user input for preferences may limit its adaptability to dynamic user behavior.
Wang et al., 2022	Intelligent recipe recommendation model [5]	Proposed a model optimizing weekly meal plans to accommodate user restrictions and nutritional needs using the Hungarian algorithm and integer programming, ensuring personalized balanced diets. While effective in meal planning, the model does not incorporate real-time ingredient recognition from images.
Tran et al., 2018	An overview of recommender systems in the healthy food domain [6]	Provided a comprehensive review of recommender systems tailored for healthy food choices, highlighting the integration of user preferences and nutritional information. Identified the need for incorporating advanced AI techniques for improved recommendation accuracy.
Freyne & Berkovsky, 2010	Intelligent food planning: personalized recipe recommendation [7]	Explored methods for personalized recipe recommendations based on user preferences and dietary restrictions. Emphasized the importance of user modeling in enhancing recommendation relevance. However, the study predates recent advancements in deep learning methodologies.
Teng et al., 2012	Recipe recommendation using ingredient networks [8]	Introduced a network-based approach to recommend recipes by analyzing ingredient compatibility. While innovative, the approach lacks integration with image-based ingredient recognition, limiting its applicability in real-world scenarios.
Lin et al., 2014	A content-based matrix factorization model for recipe recommendation [9]	Proposed a matrix factorization model incorporating content-based features for recipe recommendation. Achieved improved recommendation accuracy but did not address the use of deep learning techniques or image-based inputs.
Ge et al., 2015	Using tags and latent factors in a food recommender system [10]	Investigated the use of tags and latent factors to enhance food recommendation systems. Highlighted the potential of combining multiple data sources for improved recommendations but did not incorporate deep learning methodologies.

This survey highlights the evolution of AI-driven solutions in the food industry, emphasizing the progression from traditional recommendation systems to

more advanced deep learning approaches. However, a comprehensive system that seamlessly integrates image-based ingredient recognition with personalized recipe recommendations remains an area for further exploration.

4. EXISTING SYSTEM

The typical operation of recipe recommendation systems depends on manual search functionality and user preference input and predefined ingredient list options. These systems offer a search function to find recipes through ingredients yet they do not automatically identify accessible ingredients dynamically. The accessibility of users with automated preferences in meal planning is reduced because only a limited number of systems use image-based ingredient recognition. Existing recipe solutions work in a static way because users need to input information manually while they lack AI automation to optimize their recipe selection systems.

Limitations

1. The majority of systems fail to use AI for individual user preference-based recommendation generation.
2. Modern deep learning models that detect ingredients through images do not get sufficient use in current systems.
3. The current system gives users the responsibility of keeping track of ingredient availability through manual processes which introduces potential errors to inventory records.
4. Food wastage occurs when users cannot match recipes effectively because they lack intelligent planning support for ingredient optimization.

5. PROPOSED SYSTEM

DishGenie introduces an AI-driven approach combining deep learning for ingredient recognition, Natural Language Processing (NLP) for textual input, and intelligent recipe recommendations. The system uses Convolutional Neural Networks (CNNs) to identify ingredients from images and NLP models to match textual inputs to recipes. DishGenie also features pantry tracking, allowing users to maintain an updated inventory of ingredients. The system leverages Flask for the backend, providing an easy-to-use web interface that enhances user interaction by enabling ingredient-based recipe selection and meal planning.

Advantages of the Proposed System

1. **AI-powered ingredient recognition**: CNN models accurately identify ingredients from user-uploaded images, eliminating manual entry.
2. **Personalized recipe recommendations**: The system generates recipe suggestions based on available ingredients and individual user preferences.
3. **Integrated pantry tracking**: Users can keep track of their ingredients, making meal planning more efficient.
4. **User-friendly web interface**: The interface, built with Flask, provides a smooth and intuitive experience for recipe searching and ingredient management.
5. **Reduction in food wastage**: The system recommends recipes based on current pantry items, promoting efficient ingredient use and reducing food waste.

6. PROPOSED MODEL

1. CNN for Image Recognition:

Step 1: Pre-processing the Image

- Convert the uploaded image into a standardized format.
- Apply techniques such as resizing, normalization, and color adjustments to standardize the input for the model.

Step 2: Feature Extraction using Pre-Trained Models

- Use pre-trained models like MobileNet, ResNet, or EfficientNet to extract features from the image.
- These models are optimized for lightweight yet accurate image recognition.

Step 3: Data Augmentation

- Enhance the training dataset using techniques like rotation, flipping, and brightness adjustments to improve generalization.

Step 4: Classification of Ingredients

- Pass the pre-processed image through the CNN to classify the ingredients into specific categories.
- The system recognizes the food items and maps them to predefined classes (e.g., tomatoes, onions, chicken).

Step 5: Confidence Score Integration

- For each predicted ingredient, the model assigns a confidence score that reflects the certainty of the classification.
- If the confidence score is low, users are prompted to manually verify the ingredient.

2. NLP for Text Processing:

Step 1: Tokenization

- Use tools like spaCy, NLTK, or Transformer-based models to tokenize the text input (ingredient list).
- Break down the sentence into smaller components, such as words or phrases, to understand context.

Step 2: Entity Recognition

- Identify key ingredients, quantities, and descriptors in the text (e.g., “chopped onions” or “2 tomatoes”).
- Leverage Named Entity Recognition (NER) models to accurately recognize ingredient names, quantities, and preparation methods.

Step 3: Synonym Mapping

- Map common ingredient synonyms (e.g., "bell pepper" to "capsicum") to ensure broad ingredient matching.

Step 4: Context-Based Matching

- Use context cues (e.g., "sliced," "boiled") to refine ingredient identification.
- This helps in matching ingredients with more accuracy and can inform the preparation method.

3. Recipe Matching Algorithm:

Step 1: Ingredient Matching

- Compare the user's available ingredients with the list of ingredients required for each recipe.

Step 2: Weighted Scoring System

- Assign a score to each recipe based on the percentage of matched ingredients.
- Recipes with a higher number of matching ingredients are scored higher.

Step 3: Partial Match Handling

- If some ingredients are missing, suggest recipes that still partially match, with alternatives or substitutions where possible.

Step 4: Customizable Filters

- Allow users to apply filters such as cuisine type, cooking time, and dietary preferences to refine the recipe suggestions.

Step 5: Dynamic Ranking

- Display recipes with higher ingredient matches at the top of the list.
- Recipes with fewer matches appear lower, along with recommended ingredient substitutions.

4. Inventory Update Mechanism:

Step 1: Automated Deduction

- When a user selects a recipe, the ingredients required are automatically deducted from the user's pantry inventory.

Step 2: Manual Adjustment

- Users can manually mark ingredients as "available" or "unavailable" based on their stock.

Step 3: Alert System

- The system sends notifications to users when certain key ingredients are low or need to be replenished.

Step 4: Integration with Recipe Suggestions

- The system proactively suggests recipes that make use of soon-to-expire ingredients, encouraging users to utilize them before they go to waste.

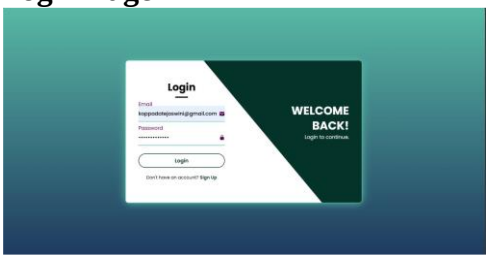
7. EXPERIMENTAL RESULTS

In this project, we utilized Python as the programming language to develop the proposed application, which is executed on Uses Flask to serve dynamic HTML templates for user interaction.

Home Page

Explanation: This interface defines the registration page.

Login Page

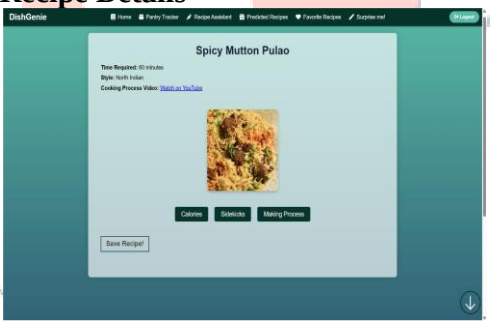


Explanation: This interface defines the login page.

Pantry Tracker Page with Text input.

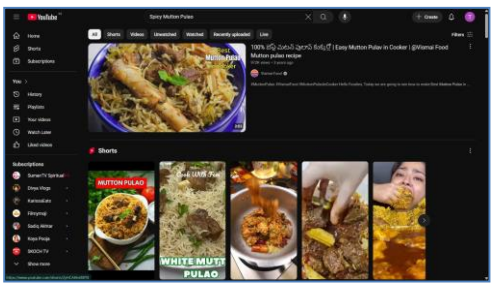
Explanation: The above window clearly defines the pantry tracker page.

Recipe Details



Explanation: The above window clearly tells Recipe details page of chosen recipe.

YouTube Recipe Process



Explanation: This screenshot shows Watch on you tube in Recipe details page of chosen recipe.

8. CONCLUSION & FUTURE WORK

The smart efficient recipe recommendation system operates through DishGenie which applies deep learning approaches successfully. The system uses

Convolutional Neural Networks (CNNs) to analyze ingredient images while using Natural Language Processing (NLP) to process text queries so it generates specific recipe suggestions that match user contexts. Accessibility through the Flask-based web interface streamlines the process of entering ingredients and managing pantries and recording recipes. The system underwent extensive testing which validated its reliability along with its security features and total performance outcomes. Through its food waste reduction features and meal planning assistance DishGenie delivers people a sustainable and convenient service which proves to be an essential daily tool for culinary activities.

FUTURE SCOPE

Future progress of DishGenie includes the feature of AI-based personalization to recommend customized recipes adapted to specific user preferences and nutrition requirements. The system's worth will increase through better voice command performance together with live nutritional data updates that will aid users in making better dietary choices. Data will be accessible across multiple devices because the cloud synchronization feature provides seamless access to information. The system can serve more users from diverse backgrounds through improved language diversity and visual step-by-step instructions for cooking recipes. The system will experience major functional improvements through the implemented updates.

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