MUKESH PATEL SCHOOL OF TECHNOLOGY MANAGEMENT & ENGINEERING

B.Tech.
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Project Title: Culinary Curator- An AI Powered Recipe Assistant

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Roadmap

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- Problem definition
- Literature Review & Market Survey
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Introduction

- Welcome to Culinary Curator, a revolutionary culinary assistant that seamlessly combines cutting-edge AI, NLP and computer vision to redefine your kitchen experience.
- Our groundbreaking Recipe Recommendation System offers a diverse range of functionalities, revolutionizing your culinary journey.
- Seek culinary inspiration with customized recipe suggestions, identify ingredients through image recognition, craft recipes through advanced language models and gain insights into meal nutrition, elevating technology's role in the culinary realm.
- The project's focus lies at the intersection of AI and culinary arts, as it aims to leverage advanced technologies to provide ingredient specific and relevant recipe recommendations to users.

Problem Definition

The culinary landscape lacks a streamlined solution for individuals seeking efficient and diverse recipe recommendations that consider their ingredient availability, dietary preferences and nutritional needs.

Traditional recipe search methods do not harness the capabilities of ingredient recognition and AI-driven personalization, resulting in a gap between user expectations and the culinary resources available.

The aim is to design and develop an AI-powered recipe recommendation system that generates personalized and diverse Indian recipe suggestions based on user input of available ingredients by leveraging AI, NLP and Computer Vision techniques to process user input, analyse a comprehensive dataset of Indian recipes and employ advanced recommendation algorithms as well as a large language model to offer users a curated list of recipes based on the ingredients they have at hand.

Literature Survey

Paper Title	Methodology
RecipeGPT: Generative Pre-training Based Cooking Recipe Generation and Evaluation System (2020)	• GPT-2 fine-tuned on Recipe1M dataset. • Pre-processing involved filtering out non-ingredients, non-instructional sentences and lemmatizing nouns of ingredients
RecipeIS—Recipe Recommendation System Based on Recognition of Food Ingredients (2023)	• Uses ResNet-50 for ingredient recognition. • Use Edamam API for recipe recommendation.
Machine Learning Based Food Recipe Recommendation System (2023)	• Uses collaborative filtering to recommend recipes based on user preferences
Image to Recipe and Nutritional Value Generator Using Deep Learning (2022)	• Uses KNN and DenseNet-121 to for image processing to get recipe for user-provided food dish image. • Uses API for nutrition value retrieval
Recipe Recommendation With HierarchicalGraph Attention Network (2022)	• Uses Hierarchical Graph Attention Network to generate recommendation scores using both user and recipe embeddings. These scores are used to rank and recommend recipes to users.

Table 1: Literature Survey

Market Research

Feature	Supercook	Yummly	SideChef	Cooked	RecipeGPT
Personalization	Limited	Moderate	Moderate	Moderate	Limited
Ingredient Utilization	Limited	Moderate	Moderate	Limited	Limited
Dietary Preferences	Limited	Moderate	Moderate	Limited	Limited
Recipe Diversity	Moderate	Moderate	Moderate	Limited	Moderate
Ingredient Matching	Limited	Moderate	Moderate	Limited	Limited
NLP Techniques	Limited	Moderate	Moderate	Limited	Limited
Nutritional Information	Limited	Limited	Limited	Limited	Limited
Sustainability Focus	Limited	Limited	Limited	Limited	Limited
User Reviews and Ratings	Yes	Yes	Yes	Yes	Limited
User-Friendly	Yes	Yes	Yes	Limited	Limited
Comprehensive Dataset	No	No	No	Limited	Limited

Table 2: Market Research

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Research Gaps

Our project aims to fill the following research gaps:

1. Ingredient Availability: Current recipe recommendation systems do not take into account the ingredients the user currently has access to. This can be frustrating for users who want to cook with the ingredients they already have.

2. Indian Food: Most existing recipe recommendation systems are not specifically focused on Indian cuisine, renowned for its complexity and diversity, with a wide variety of regional recipes.

3. Nutritional Analysis: Few recipe recommendation apps include a nutritional analysis feature. This can be a barrier for users who want to make informed choices about their dietary needs and preferences.

4. Comparative Analysis: There is a lack of comparative analysis of different recipe recommendation models. Our Culinary Curator system contributes to this research gap by comparing and contrasting different models.

Proposed System

Our culinary assistant is built on a robust and flexible architecture that seamlessly integrates the following components:

1. Recipe Recommendation System: An AI-powered engine that suggests recipes based on the ingredients the user has, by implementing a BERT model.

2. Ingredient Recognition System: It identifies ingredients at hand from uploaded images by using Transfer Learning, for tailored recipe recommendations.

3. GPT-Powered Recipe Generation: Simply enter your ingredients and our NLP-driven system crafts recipes on the fly, making cooking an effortless and enjoyable experience.

4. Nutritional Analysis: Gain insight into your meal's nutritional profile by inputting ingredients and their quantities, all facilitated by seamless API integration.

Ingredient Recognition

Our ingredient recognition system uses a **MobileNetV2** architecture to identify ingredients in images and provide the corresponding ingredient name.

MobileNetV2 is a neural network architecture meticulously crafted for the efficient execution of computer vision tasks.

- **Data Augmentation:** Data augmentation techniques include rescaling, rotation, shifting, shearing, zooming, etc. to reduce overfitting and increase the size of the dataset
- **Efficient Feature Extraction:** It processes input images & extracts meaningful features from them by utilizing depthwise separable convolutions and linear bottlenecks.
- **Transfer Learning:** A pre-trained model therefore has a robust understanding of general visual features that serve as an excellent starting point. Fine-tuning the model on our dataset allows it to specialize in recognizing the ingredients.
- **Model Training:** The model has been trained for 10 epochs on the training data.

Ingredient Recognition

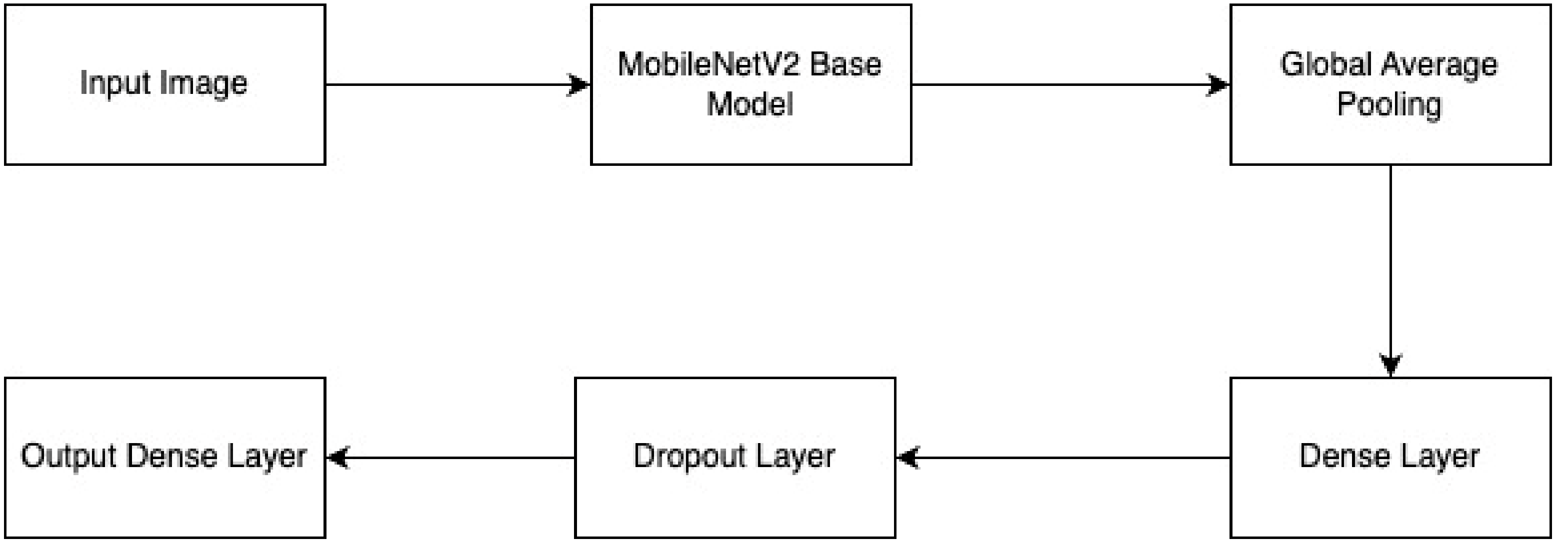

Figure 1: Model Architecture of MobileNetV2

Recipe Recommendation

Our system employs the **BERT-based SentenceTransformer model**, cosine similarity and the numpy library to offer personalized recipe suggestions.

- **Tokenization & Lemmatization**: Tokenization is used to split paragraph or sentence into individual units or tokens. Lemmatization allows to break a word down to its root form, enabling comparison and processing of ingredients.
- **Contextual Embeddings:** Capture the meaning of words based on their context in the input sentences by creating representations of both the user's input and the recipe ingredients
- **NLI (Natural Language Inference) Mean Tokens:** Used to convert words into contextual embeddings and encoding them using BERT models, enabling the capture of contextual meaning and relationships within sentences.
- **Cosine Similarity Scores:** The function calculates cosine similarity scores between the user's input embedding and the embeddings of all recipes in the dataset, which measures how closely the user's ingredient preferences align with each recipe.

Recipe Recommendation

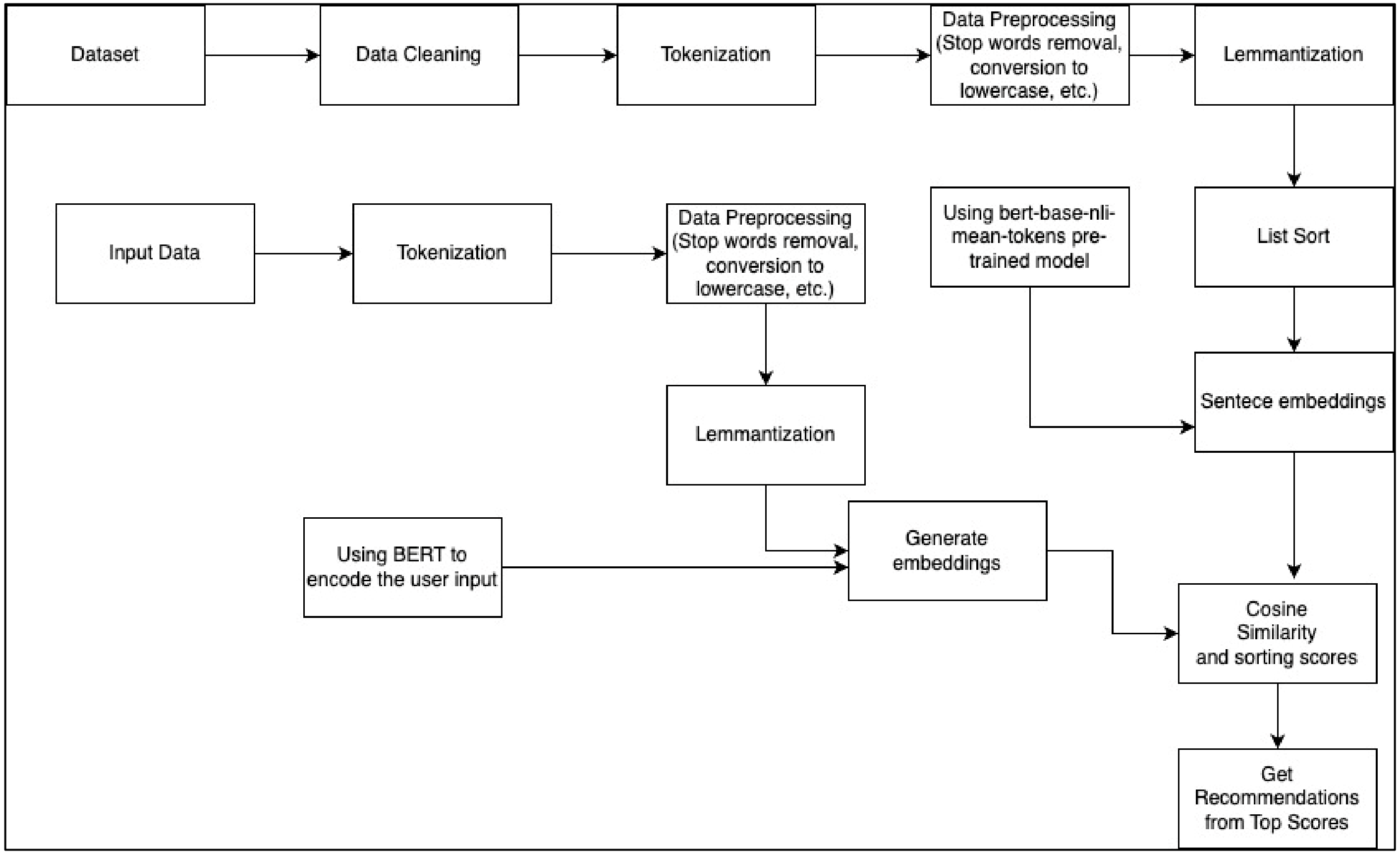

Figure 2: Model Architecture for BERT Model using Sentence Transformer

GPT-powered Recipe Generator

Our GPT-powered recipe generator makes use of the GPT-2 model to generate real time recipes based on the user's input of ingredients at hand.

Architecture:

GPT-2 model is a natural language processing model developed by OpenAI. It is a variant of the Transformer architecture.

- Deep autoregressive language model: Generates text one token at a time while considering the context of the previously generated tokens.
- Multiple layers of multi-head self-attention & feedforward neural networks: Making it highly expressive for natural language generation tasks.
- Fine Tuning: Updates the model's parameters to adapt it to the specific recipe generation task, allowing it to generate contextually relevant recipes based on the provided ingredients.

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GPT-powered Recipe Generator

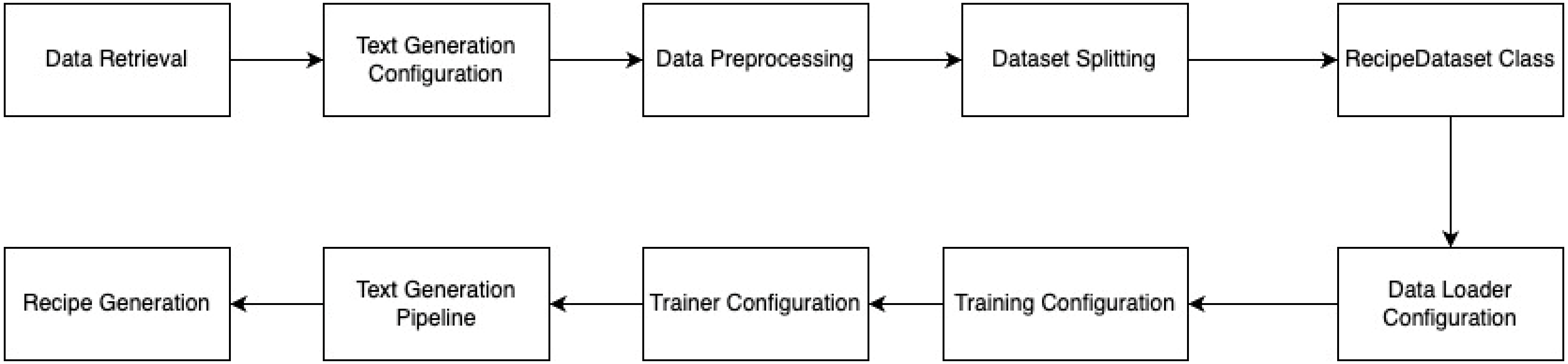

Figure 3: Model Architecture for GPT-2

Nutritional Analysis

This functionality empowers users to perform detailed nutritional analysis of recipes, facilitating informed and health-conscious dietary decisions.

Implementation:

- Imports: Necessary libraries for web app creation and API interactions.
- Read API Credentials: Fetch Edamam API credentials from config.ini.
- get_nutritional_info Function: Retrieve nutritional information for provided ingredients.
- Streamlit App: Create the "Nutritional Analysis App" using Streamlit.
- User Interaction: Users input ingredients, and a button triggers the analysis.
- Fetching Nutritional Information: Check for user input, fetch nutritional data from Edamam API.
- Displaying Nutritional Data: Show calorie, weight, labels, and nutrients for each ingredient.
- Error Handling: Gracefully handles API errors and missing input.

Streamlit Frontend

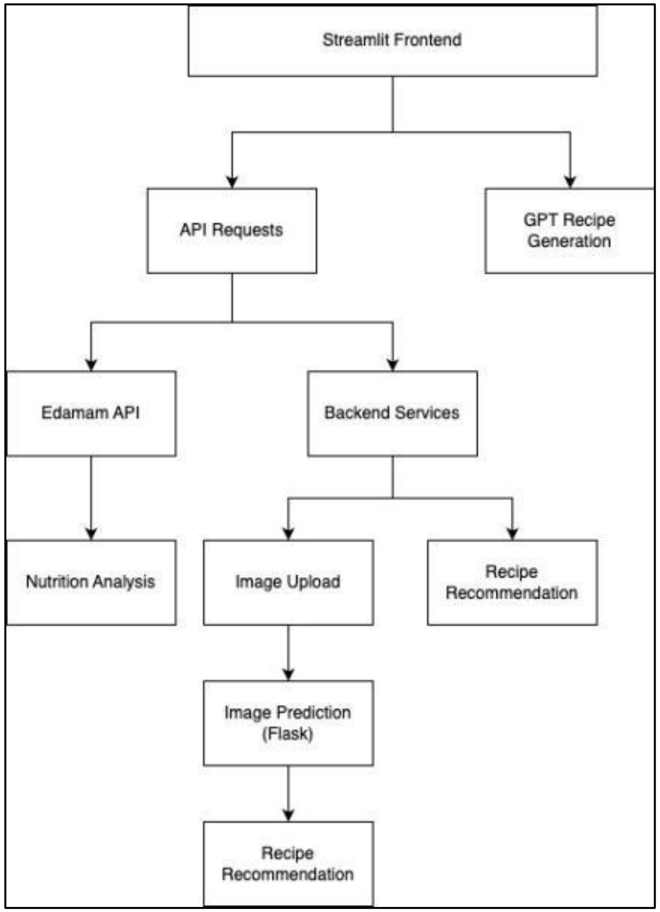

Figure 4: Model Architecture for Streamlit

Implementation

Video Demonstration

Code Folder

Results: Ingredient Recognition

	precision	recall	f1-score	support
apple	0.88	0.70	0.78	10
banana	1.00	0.67	0.80	9
beetroot	1.00	1.00	1.00	10
bell pepper	0.90	1.00	0.95	9
cabbage	1.00	1.00	1.00	10
capsicum	1.00	0.90	0.95	10
carrot	1.00	0.89	0.94	9
cauliflower	0.91	1.00	0.95	10
chilli pepper	1.00	0.89	0.94	9
corn	0.80	0.80	0.80	10
cucumber	1.00	1.00	1.00	10
eggplant	0.83	1.00	0.91	10
garlic	1.00	1.00	1.00	10
ginger	1.00	1.00	1.00	10
grapes	0.90	1.00	0.95	9
jalepeno	1.00	1.00	1.00	9
kiwi	0.91	1.00	0.95	10
lemon	0.71	1.00	0.83	10
lettuce	1.00	1.00	1.00	9
mango	1.00	1.00	1.00	10
onion	1.00	1.00	1.00	10
orange	1.00	0.89	0.94	9
paprika	1.00	1.00	1.00	10
pear	0.91	1.00	0.95	10
peas	0.91	1.00	0.95	10
pineapple	0.91	1.00	0.95	10
pomegranate	1.00	1.00	1.00	10
potato	0.89	0.80	0.84	10
raddish	1.00	1.00	1.00	9
soy beans	1.00	1.00	1.00	10
spinach	1.00	1.00	1.00	10
sweetcorn	0.89	0.80	0.84	10
sweetpotato	1.00	0.70	0.82	10
tomato	1.00	1.00	1.00	10
turnip	0.91	1.00	0.95	10
watermelon	1.00	1.00	1.00	10
accuracy			0.95	351
macro avg	0.95	0.95	0.94	351
weighted avg	0.95	0.95	0.94	351

Figure 5: Results for MobileNetV2

MobileNetV2 model emerged as the standout performer, surpassing the CNN model with an impressive accuracy of 95%.

This model not only excels in recognizing a diverse range of fruits and vegetables but maintains consistently high precision, recall and F1-score values.

The model's ability to generalize across different ingredients and maintain high accuracy is a testament to its robustness.

Results: Ingredient Recognition

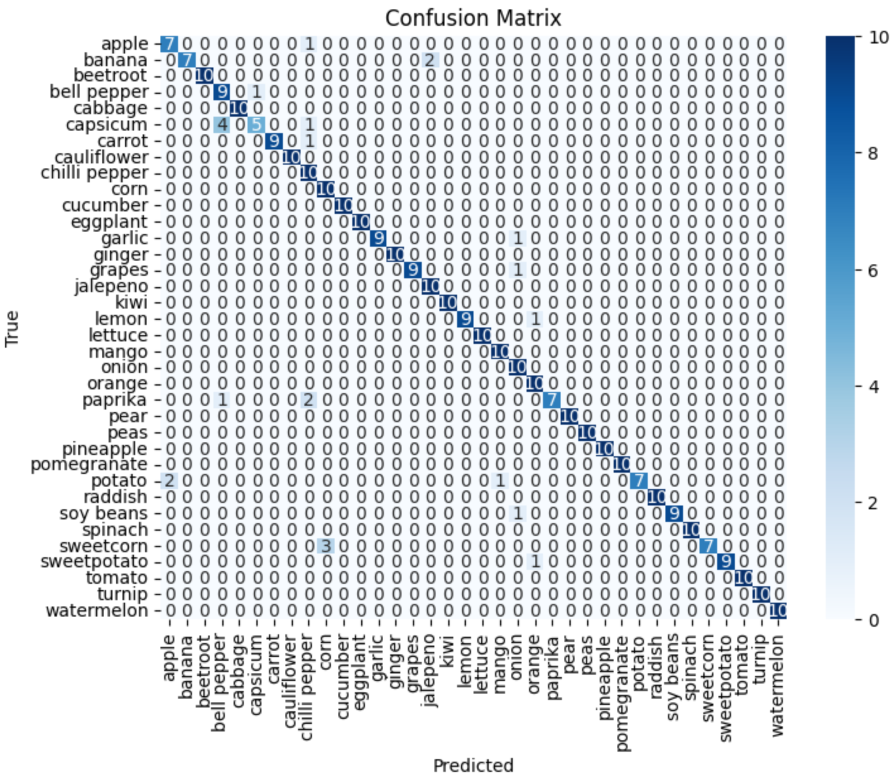

Figure 6: Confusion Matrix for CNN

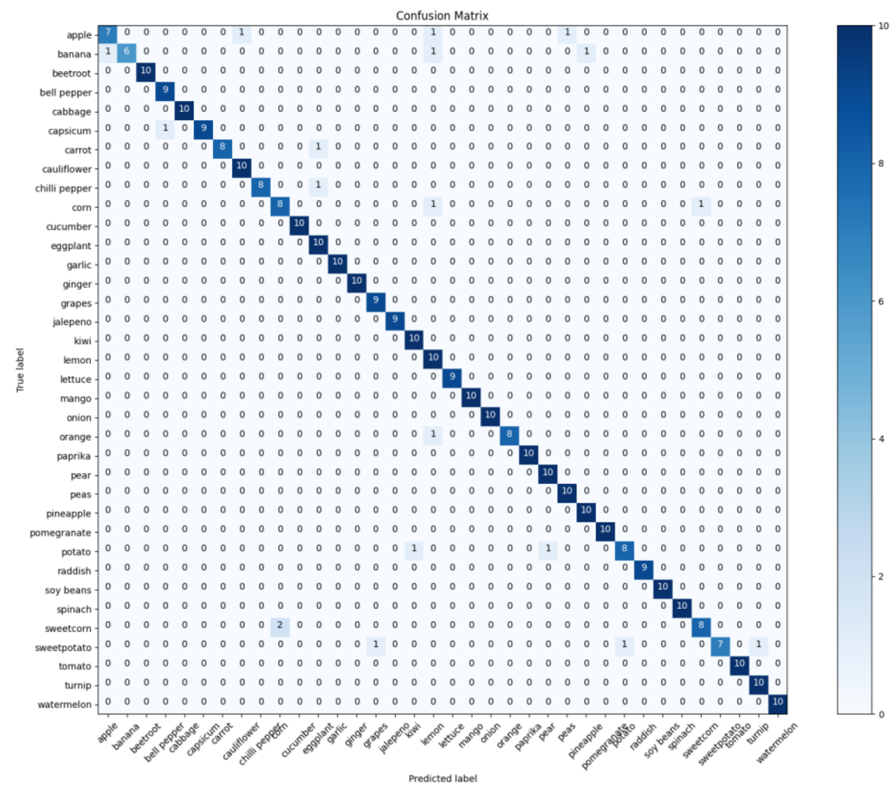

Figure 7: Confusion Matrix for MobileNetV2

Results: Recipe Recognition

Model for Recipe Recommendation	Precision at k (k=10)
BERT Model using Sentence Transformer (NLI Mean Tokens)	0.5
Word2Vec and TF-IDF	0.2
GENSIM (FastText)	0.1
BERT Model using BERT Embeddings (BERT Base Uncased)	0.1
LSTM	0.0
Logistic Regression	0.0

Table 3: Results of the various recipe recommendation models

BERT Model using Sentence Transformer emerged as the top-performing recommendation system, this model achieves an impressive precision at k of 0.5.

It excelled in capturing the semantic meaning of ingredients and consistently provided recommendations that closely matched user preferences, making it the standout choice.

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