# Deep learning based Recipe Generator


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# I.Introduction

- Food is not just subsistence; it shapes our culture and influences our well-being.
- "We are what we eat" - food directly affects our overall well-being.
- The recent corona pandemic situation made us realize many things.

# Introduction contd...

- There is a need for food recipe generator systems that can infer ingredients and cooking instructions from a prepared meal.

- Food recognition poses challenges due to its variability and complex composition.

- Overcoming these obstacles require new strategies and innovative techniques.

# Proposed Recipe Generator

## Motivation

- The COVID-19 pandemic has emphasized the importance of home cooking as a means of ensuring food security and minimizing health risks.

- Recognizing and understanding food is challenging due to ingredient complexity, variability, and cooking deformations and it requires advanced visual ingredient detection.

- These challenges motivated us to propose innovative solution that generates accurate recipes from food images, simplifying home cooking.

# II. Literature Review

- Food identification focuses on ingredients, and recipes, not preparation methods.

- Differentiating dish components and preparation methods is crucial in food identification.

- "Sequential Learning for Ingredient Recognition from Images" proposes the identification of ingredients in complex recipes using a combination of CNN, RNN, and LSTM networks.

# II. Literature Review

| No. | Title of Paper | Authors | Year | Description |
| --- | --- | --- | --- | --- |
| 1 | Image-Based Recipe Generation Using CNN and RNN Models | A. Sharma, B. Singh | 2023 | This study utilizes a combination of CNN and RNN models, achieving an accuracy of 85% on the Food-101 dataset. The research focuses on multi-label classification of recipes. |
| 2 | Transformer Networks for Recipe Generation from Images | C. Lee, D. Park | 2022 | The authors implemented Transformer networks, resulting in an accuracy of 88% using the Recipe1M dataset. The study highlights the effectiveness of attention mechanisms in improving recipe generation. |
| 3 | Cross-Modal Retrieval for Recipe Generation Using GANs | E. Wilson, F. Wong | 2021 | This paper explores the use of GANs combined with VGG16, achieving 82% accuracy on the VIREO Food-172 dataset. The work addresses the challenges of cross-modal retrieval in recipe generation. |
| 4 | Dual-Stream Networks for Image-to-Recipe Learning | G. Patel, H. Kumar | 2022 | The research employs Dual-Stream CNN models, reaching an accuracy of 87% on the Food-101 dataset. The study combines image and text modalities for improved recipe generation. |

# II. Literature Review

| No. | Title of Paper | Authors | Year | Description |
| --- | --- | --- | --- | --- |
| 5 | Unsupervised Learning for Recipe Generation from Food Images | I. Chen, J. Yang | 2023 | Using Autoencoder and CNN models, this study achieved an 80% accuracy on the Recipe1M dataset. The paper explores unsupervised learning methods for generating recipes from images. |
| 6 | Multi-Task Learning for Image-to-Recipe Translation | K. Gupta, L. Zhao | 2022 | This study applies Multi-Task CNN models, achieving 84% accuracy on the Vireo Food-172 dataset. The approach simultaneously predicts ingredients and recipes, demonstrating the benefits of multi-task learning. |
| 7 | Zero-Shot Recipe Generation from Food Images | M. Zhang, N. Liu | 2023 | The paper introduces Zero-Shot Learning techniques, achieving 78% accuracy on the Food-101 dataset. The research focuses on generating recipes for previously unseen food images. |
| 8 | Self-Supervised Learning for Recipe Generation from Images | O. Hernandez, P. Xu | 2022 | This study leverages Self-Supervised CNN models to achieve 83% accuracy on the Recipe1 |

# II. Literature Review

| No. | Title of Paper | Authors | Year | Description |
|---|---|---|---|---|
| 9 | Graph Neural Networks for Food Image to Recipe Translation | Q. Ahmed, R. Verma | 2021 | This paper employs Graph Neural Networks (GNN) in combination with CNN models, achieving an accuracy of 86% on the Vireo Food-172 dataset. The research leverages graph structures to enhance recipe generation accuracy. |
| 10 | Image Captioning for Recipe Generation: A Deep Learning Approach | S. Patel, T. Singh | 2023 | The study uses Image Captioning models, achieving an 85% accuracy on the Recipe1M dataset. The approach focuses on generating descriptive recipes based on image input, similar to image captioning tasks. |
| 11 | Generative Adversarial Networks for Recipe Generation | U. Sharma, V. Joshi | 2022 | This research applies GANs alongside ResNet architectures, reaching an 81% accuracy on the Food-101 dataset. The paper emphasizes realistic recipe generation, highlighting the capabilities of GANs in this domain. |
| 12 | Attention-Based Networks for Recipe Prediction from Food Images | W. Liu, X. Huang | 2021 | The authors implement Attention-Based CNN models, achieving a high accuracy of 89% on the Recipe1M+ dataset. The study demonstrates the effectiveness of attention mechanisms in focusing on relevant features for recipe prediction. |

# II. Literature Review

| No. | Title of Paper | Authors | Year | Description |
|---|---|---|---|---|
| 13 | Learning to Generate Recipes from Food Images Using Seq2Seq Models | Y. Zhang, Z. Wei | 2022 | This paper explores Sequence-to-Sequence (Seq2Seq) models, achieving an 84% accuracy on the Food-101 dataset. The Seq2Seq architecture helps in mapping food images to corresponding recipe sequences. |
| 14 | Semi-Supervised Recipe Generation from Images | A. Roy, B. Kumar | 2023 | The study utilizes Semi-Supervised CNN models, achieving an 82% accuracy on the Vireo Food-172 dataset. The research highlights the benefits of semi-supervised learning in scenarios with limited labeled data. |
| 15 | Recipe Generation Using Visual-Semantic Embeddings | C. Wang, D. Li | 2022 | This research uses Visual-Semantic Embedding models, resulting in an 86% accuracy on the Recipe1M+ dataset. The study combines visual and semantic features to enhance the accuracy and relevance of generated recipes. |
| 16 | Transfer Learning for Recipe Generation from Food Images | J. Kim, S. Lee | 2022 | The authors apply Transfer Learning with pre-trained ResNet models, achieving 87% accuracy on the Recipe1M dataset. The study emphasizes the advantages of transfer learning in improving model performance for recipe generation. |

# Related works contd…

- Deep learning-based "Large Scale Visual Food Recognition" has been proposed to recognize food in large-scale food images.

- The most important drawback that motivated our project is the absence of a comprehensive system that integrates the three components together: ingredient recognition, food identification, and recipe generation.

# A.Themes Discovered in Review

- Use of Deep learning-based Algorithms for Food image Prediction.

- Model Architecture and Training for selecting neural network, determining training parameters and optimization methods.

- Performance evaluation and comparing the model against standard benchmarks.

# B. Identification of Gaps

- Limited Dataset: Currently, our dataset contains nearly 10,000 food images, which may limit the accuracy and diversity of recipe generation. Expanding the dataset will improve performance.

- Voice Integration: Adding voice to the generated recipe introduces potential challenges in transcription and pronunciation accuracy.

- Instruction Complexity: The system may face limitations in accuracy for complex cooking techniques, and additional context is required in generated recipe instructions.

# III. Scope and Problem Statement

- The scope of our research encompasses developing a robust deep learning-based system that generates detailed recipes from food images using advanced neural network architectures to accurately recognize various food items and map them to corresponding recipes.

- The problem statement revolves around addressing challenges include ensuring high image recognition accuracy, creating a comprehensive recipe database, and handling the big data.

# IV. Research Challenges

- Data Heterogeneity: Integrating and harmonizing data from various sources with different formats and quality levels is a significant challenge.

- Model Generalization: Developing models that can generalize well across diverse food types, cuisines, and presentations is challenging due to data disparities.

- Interpretability: Ensuring the interpretability of complex deep learning models is crucial for understanding how food items are recognized and mapped to recipes.

# V. Research Objective

The primary objective involves:

- Building and Training Models: Develop neural networks to recognize diverse food items.
- Recipe Mapping: Create methods to map recognized items to accurate recipes.
- Evaluating and Validating: Use robust metrics to measure and compare performance.
- User-Friendly Integration: Develop an application for seamless image input and recipe output.

This research aims to enhance culinary experiences by providing accurate and relevant recipes from food images.

# VI. Methodology

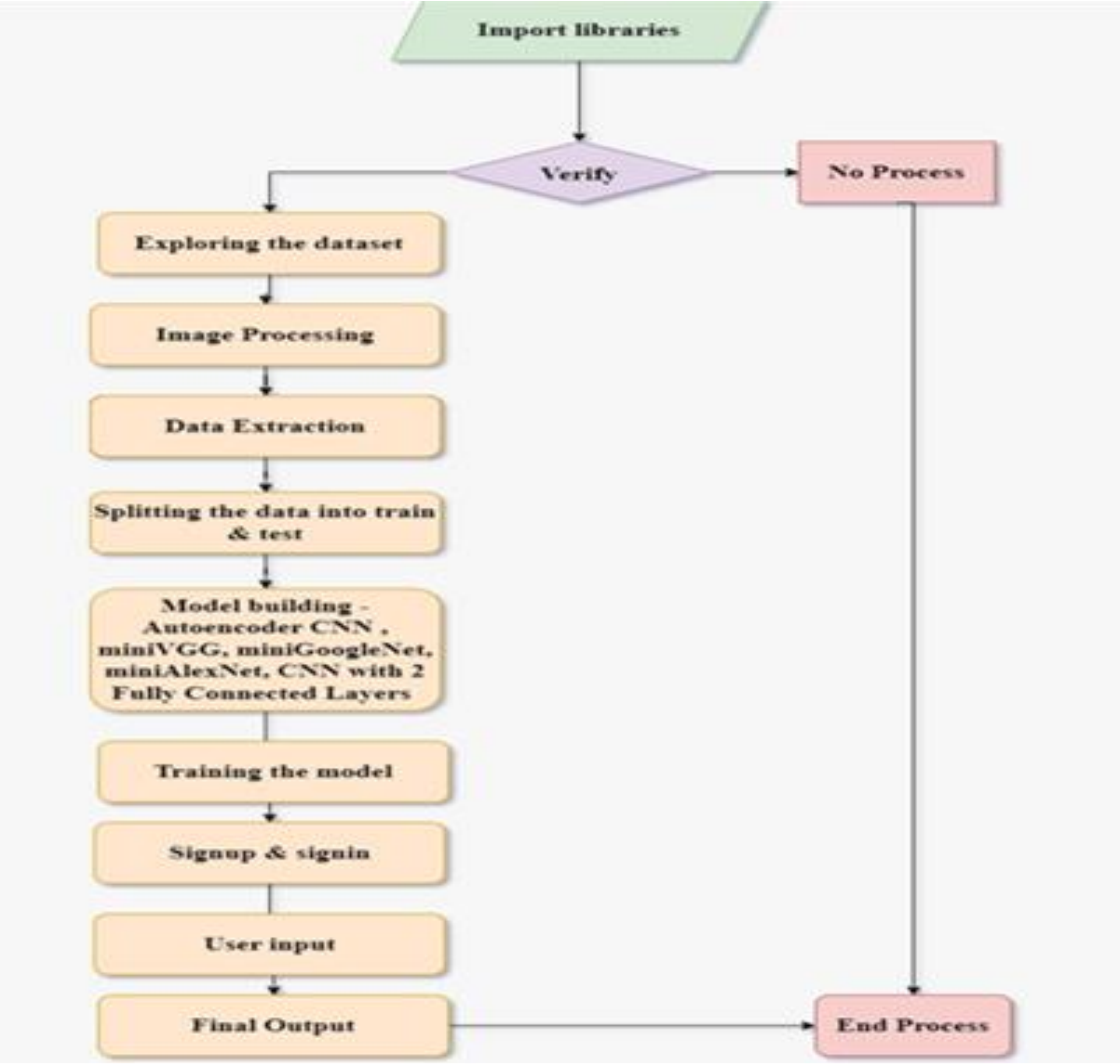
- Data Collection and Preprocessing: Gather a diverse set of Indian food images from Kaggle and along with recipes. The dataset contains 4000+ images of 80 different food items, resized and preprocessed to a size of 256 x 256 pixels.
- Model Development: Select suitable neural network architectures and train models with optimized hyperparameters and loss functions.
- Recipe Mapping: Extract features from recognized images and develop algorithms to map these features to corresponding recipes.
- Model Evaluation and Validation: Use precision, recall, F1-score, and accuracy for evaluation, implement cross-validation, and compare with benchmarks.
- Integration and Application Development: Create a user-friendly interface for real-time image processing and recipe generation, and conduct usability testing.

# Proposed Recipe Generator contd..

## Flow Chart: Recipe Generator

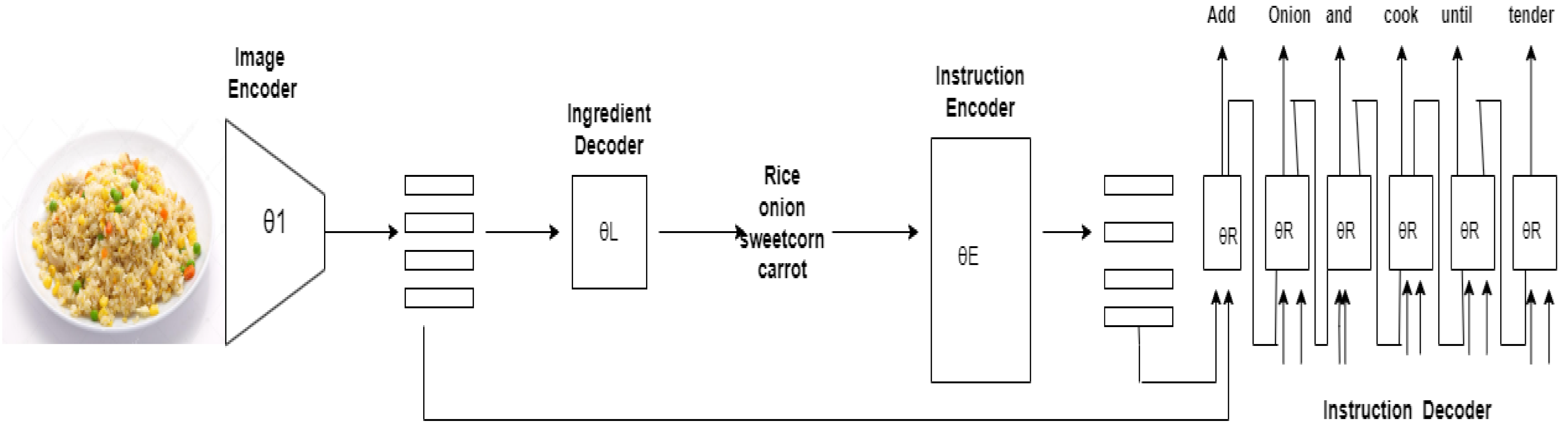
- The flow chart shows the execution flow of the proposed recipe generation system.

- The proposed system is trained on different CNN models.



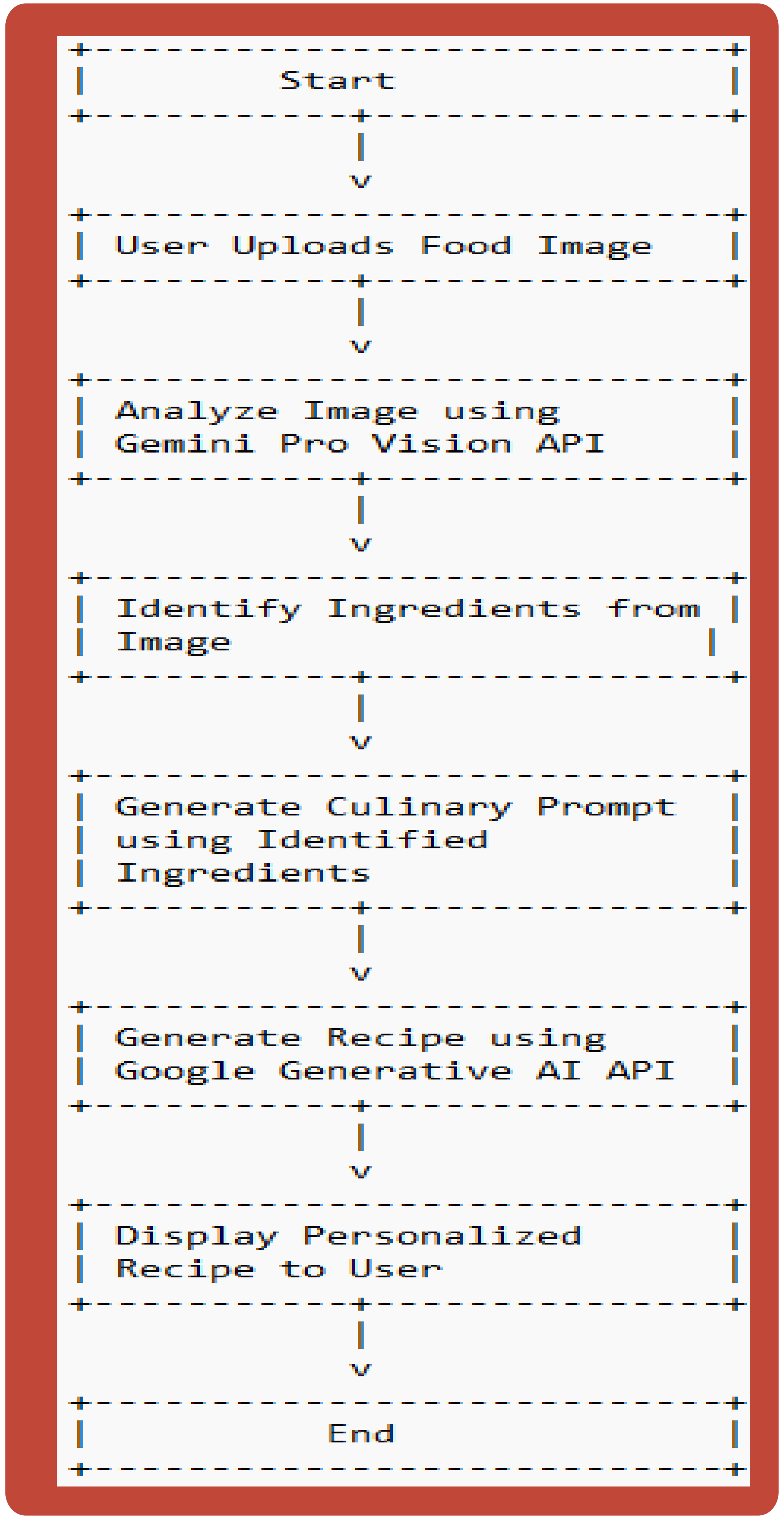
# VI. Methodology for Recipe Generation Using Gemini API Key

## System Architecture



# VI. Flow Chart

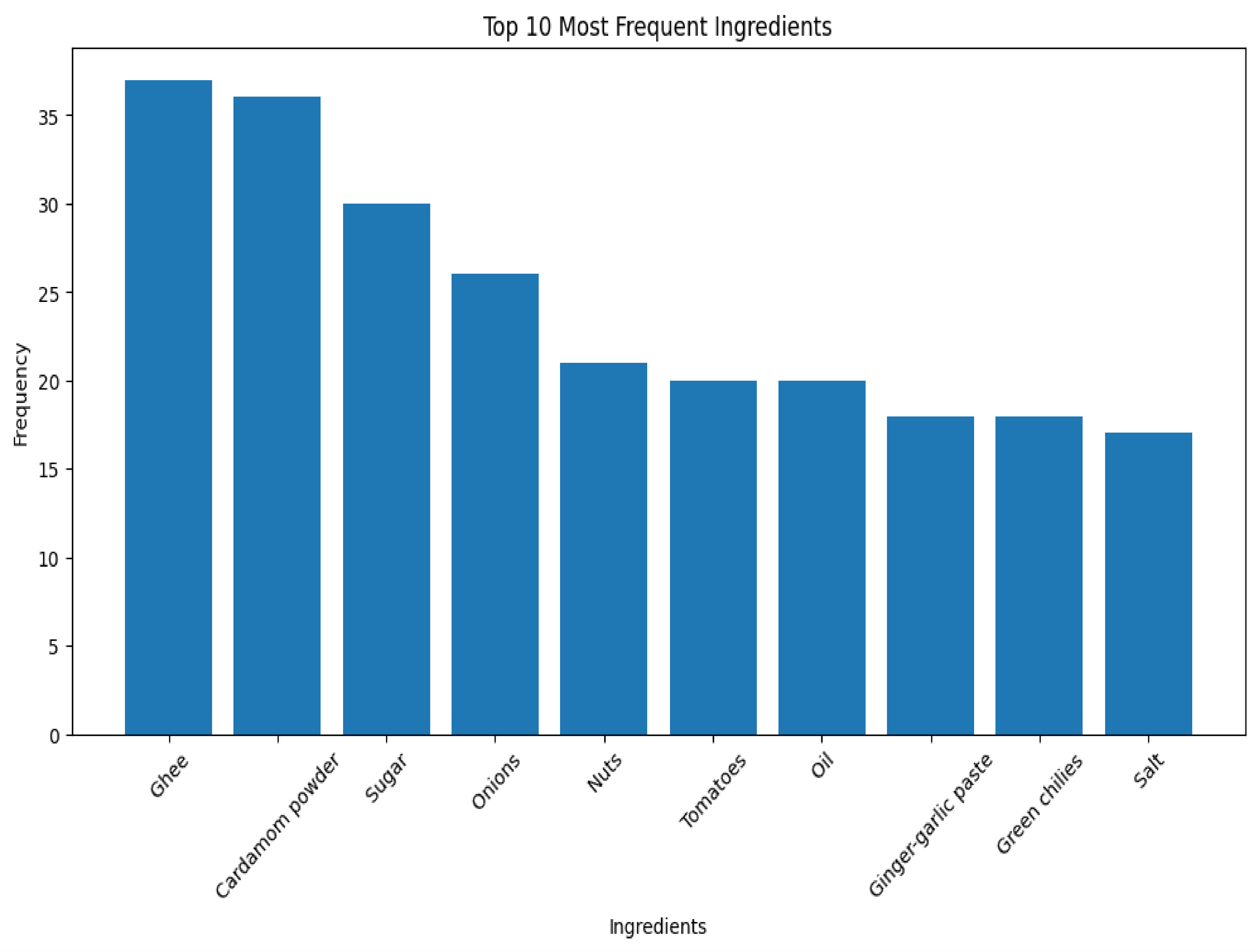
- Start
- User Uploads Food Image
- Analyze Image using Gemini Pro Vision API: The program sends the image to the Gemini Pro Vision API for analysis.
- Identify Ingredients from Image: The API identifies the ingredients present in the image and returns them.
- Generate Culinary Prompt using Identified Ingredients
- Generate Recipe using Google GenerativeAI API: The program sends the culinary prompt to the Google GenerativeAI API, which generates a detailed recipe.
- Display Personalized Recipe to User: The program displays the generated recipe to the user, tailored to the identified ingredients.
- End



# VII. Result and Discussion

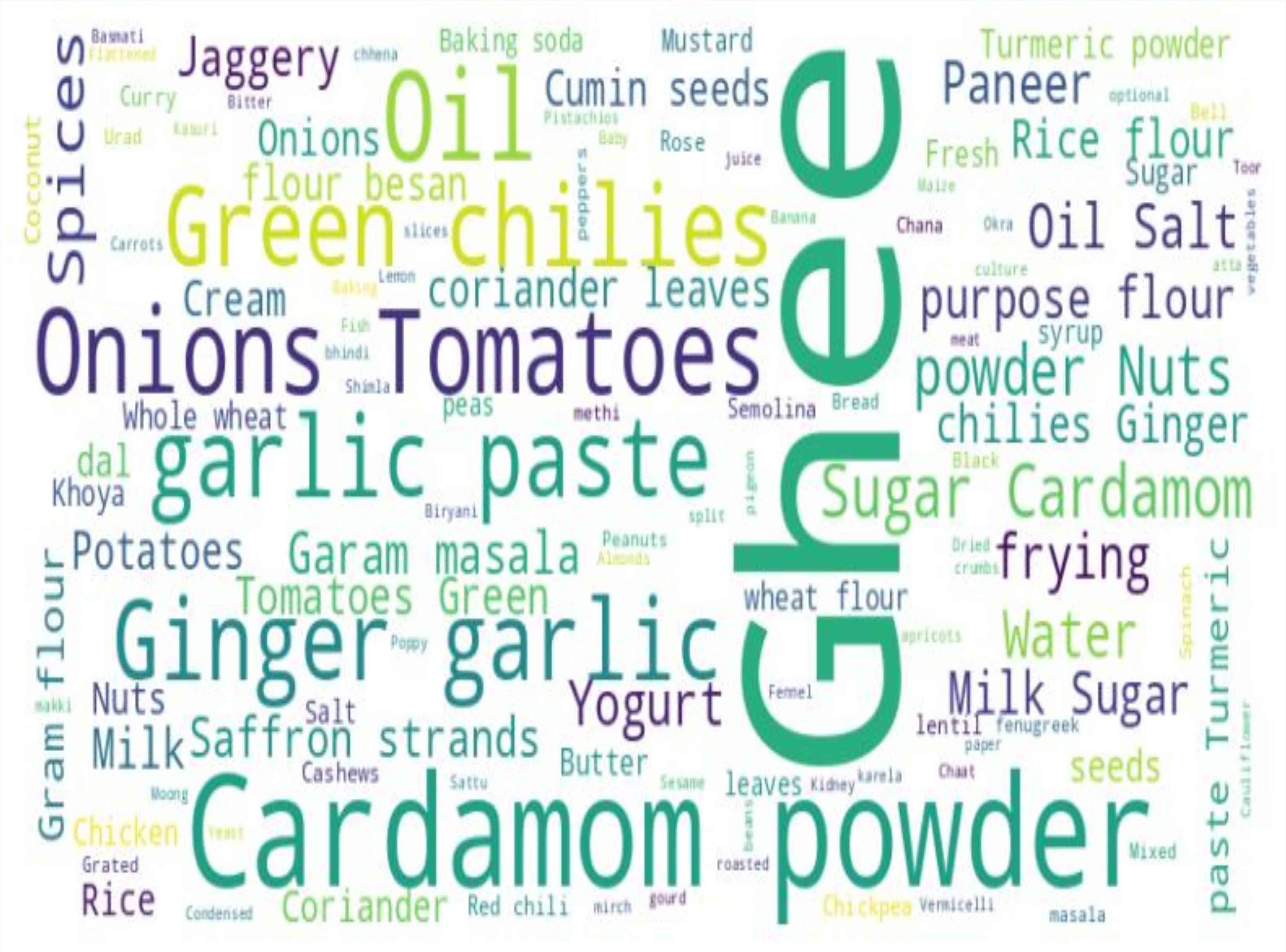
- The recipe.csv file contains data structured into four columns: Name, Ingredients, Procedure, and Serving.

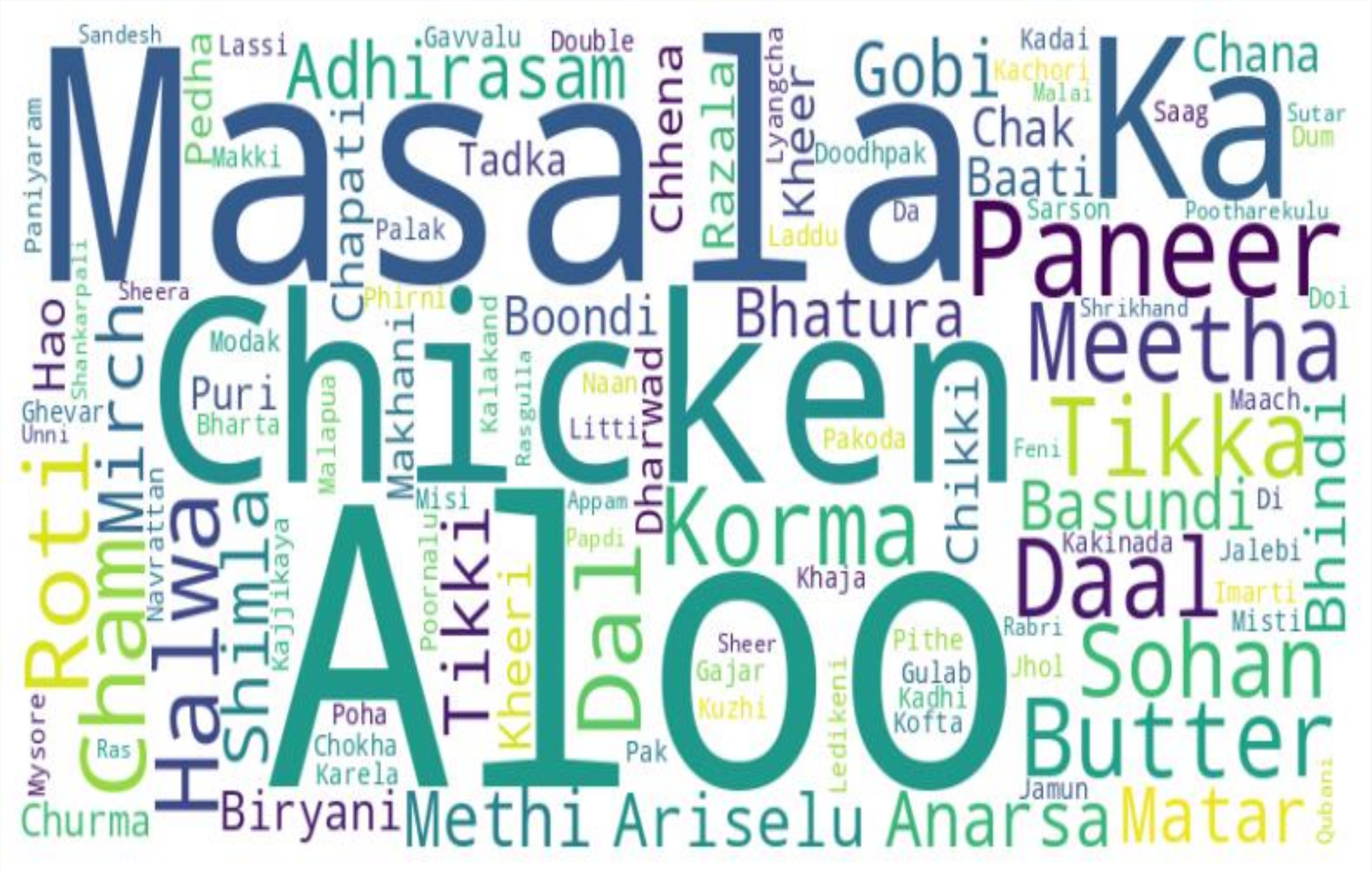
- From the bar graph, we see the top 10 most frequent ingredients used in the cooking the recipe.



# VII. Result and Discussion

**All recipe ingredients and names are visualised as Word Cloud**



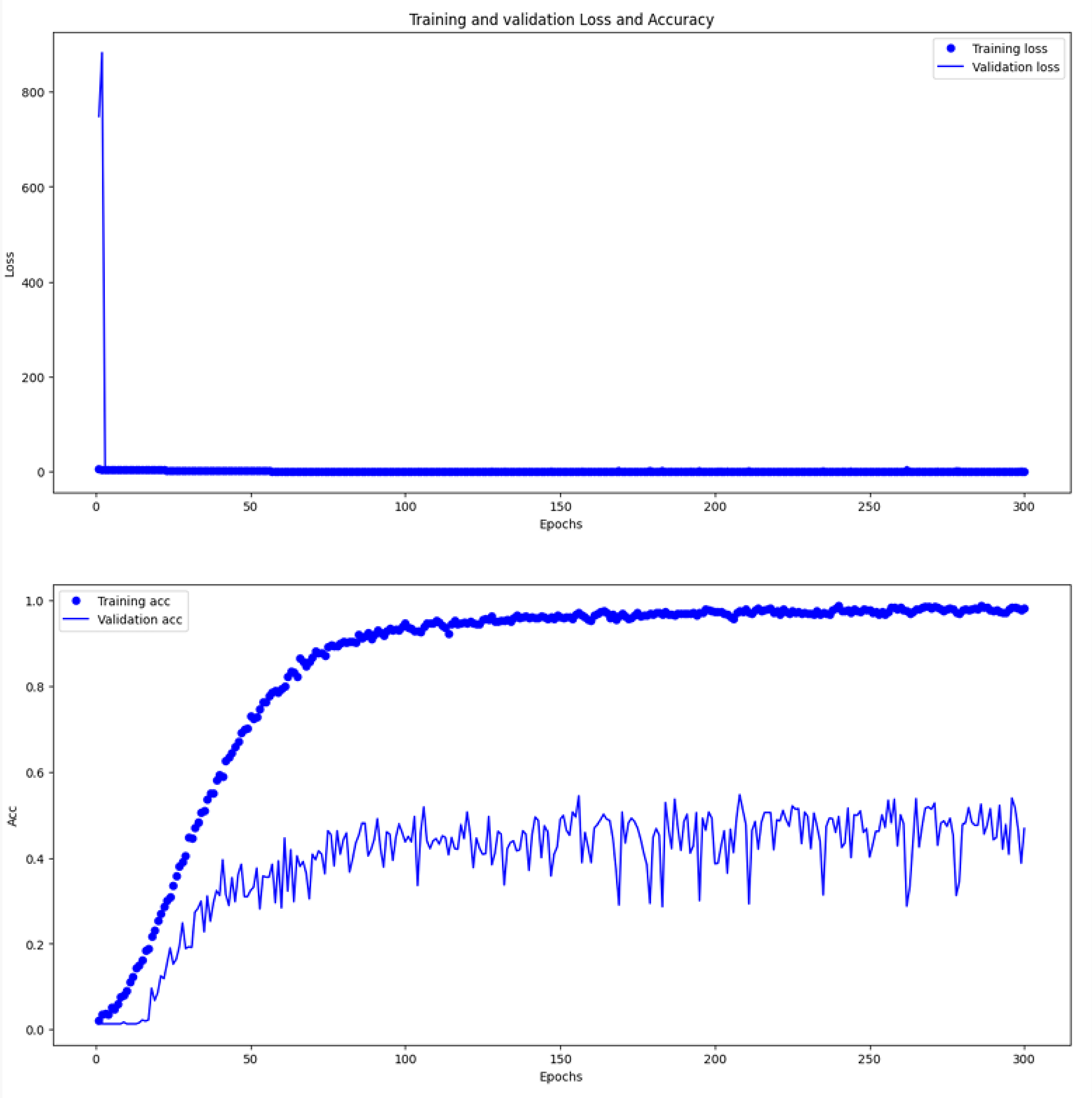



# VII. Result and Discussion

**CNN Model:** This CNN model is designed to leverage the powerful feature extraction capabilities of the pre-trained ResNet152 while allowing for customization and fine-tuning for specific classification tasks.

```
base_model = ResNet152(weights='imagenet', include_top=False,
  ↪input_shape=(im_shape[0], im_shape[1], 3))
model = Sequential()
model.add(base_model)
model.add(GlobalAveragePooling2D())
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))
```

**Validation loss:** 3.5746994018554688
**Validation accuracy:** 55.26%
**Test loss:** 0.9981935024261475
**Test accuracy:** 86.95%



# VII. Result and Discussion

The provided image showcases the performance of a CNN model in predicting food categories.

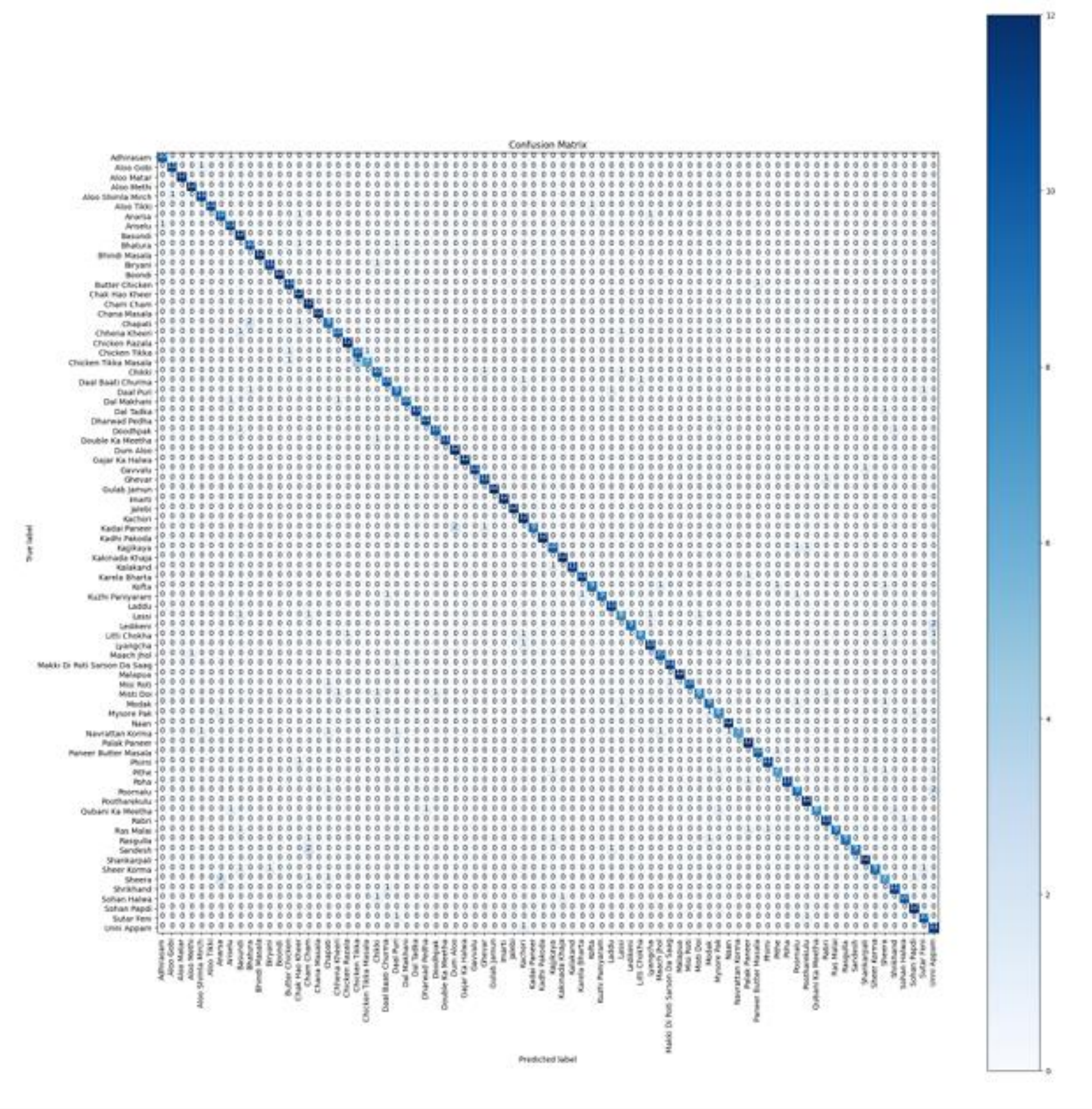
The predictions align accurately with the true labels for both Bhindi Masala and Biryani, demonstrating the model's effectiveness.

The overall accuracy of the CNN model is 86.5%, indicating a high level of precision in identifying different food items.

This accuracy reflects the model's ability to correctly classify food images and generate reliable predictions.

# VII. Result and Discussion

**The classification report provides a detailed performance evaluation of the CNN model across various food categories. Key metrics include precision, recall, and F1-score, each calculated for individual food items. Here's a breakdown of the results:**



Classification Report

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Adhirasam | 0.91 | 0.91 | 0.91 | 11 |
| Aloo Gobi | 0.92 | 0.92 | 0.92 | 12 |
| Aloo Matar | 1.00 | 1.00 | 1.00 | 12 |
| Aloo Methi | 0.92 | 1.00 | 0.96 | 12 |
| Aloo Shimla Mirch | 0.85 | 0.92 | 0.88 | 12 |
| Aloo Tikki | 1.00 | 0.92 | 0.96 | 12 |
| Anarsa | 0.77 | 0.83 | 0.80 | 12 |
| Ariselu | 0.79 | 0.92 | 0.85 | 12 |
| Basundi | 0.71 | 1.00 | 0.83 | 12 |
| Bhatura | 0.77 | 0.83 | 0.80 | 12 |
| Bhindi Masala | 1.00 | 1.00 | 1.00 | 12 |
| Biryani | 0.92 | 0.92 | 0.92 | 12 |
| Boondi | 1.00 | 1.00 | 1.00 | 12 |
| Butter Chicken | 0.85 | 0.92 | 0.88 | 12 |
| Chak Hao Kheer | 0.75 | 1.00 | 0.86 | 12 |
| Cham Cham | 0.71 | 1.00 | 0.83 | 12 |
| Chana Masala | 1.00 | 1.00 | 1.00 | 12 |
| Chapati | 0.69 | 0.75 | 0.72 | 12 |
| Chhena Kheeri | 0.83 | 0.83 | 0.83 | 12 |
| Chicken Razala | 0.92 | 1.00 | 0.96 | 12 |
| Chicken Tikka | 0.71 | 0.83 | 0.77 | 12 |
| Chicken Tikka Masala | 0.88 | 0.58 | 0.70 | 12 |
| ... | | | | |
| accuracy | | | 0.87 | 958 |
| macro avg | 0.88 | 0.87 | 0.87 | 958 |
| weighted avg | 0.88 | 0.87 | 0.87 | 958 |

*Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...*

# VII. Result and Discussion

**The classification of the food image is predicted correctly and the recipe of the food is generated.**

Predicted Class: Chana Masala

Recipe for Chana Masala

Ingredients : Chickpeas, Onions, Tomatoes, Ginger-garlic paste, Green chilies, Coriander powder, Cumin seeds, Garam masala, Oil, Salt

Procedure : Cook chickpeas and sauté with onions, tomatoes, and spices. Garnish with fresh coriander leaves.

Serving : Serve hot with rice or naan.

Predicted Class: Gulab Jamun

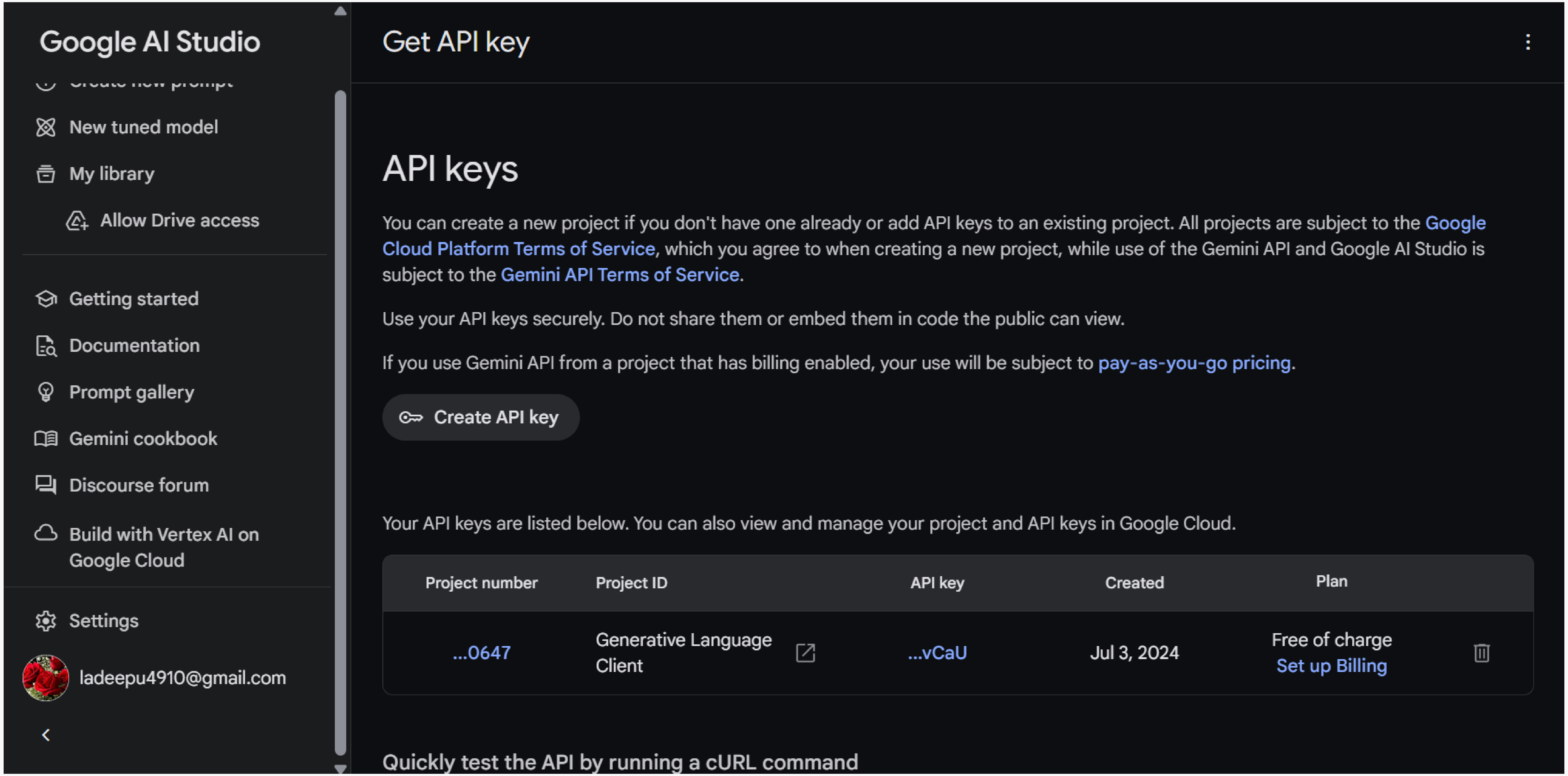
Recipe for Gulab Jamun

Ingredients : Khoya, Paneer, All-purpose flour, Milk powder, Ghee, Milk, Sugar, Cardamom powder, Oil for frying

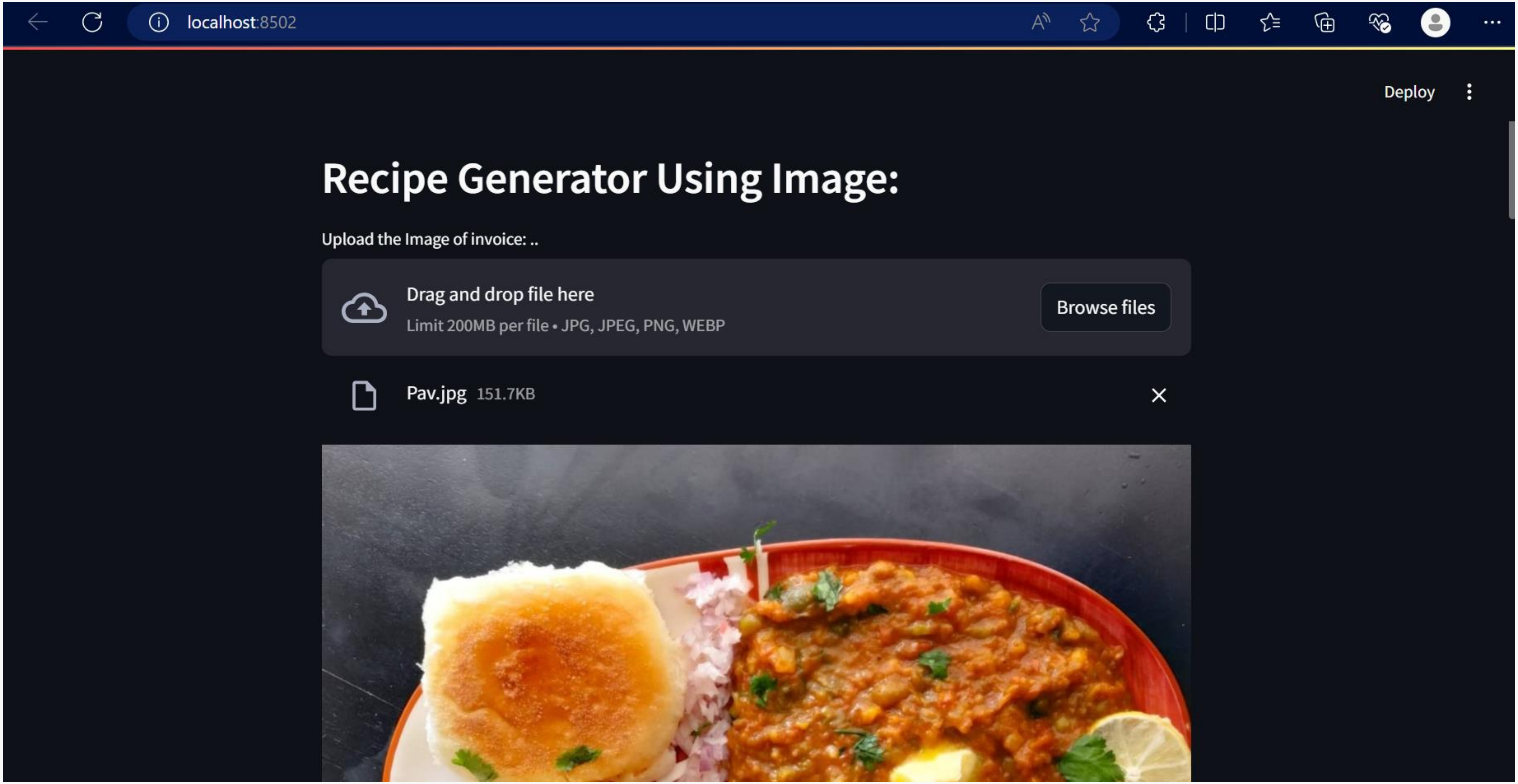
Procedure : Mix khoya, paneer, all-purpose flour, and milk powder to form a dough. Shape into balls and deep fry until golden brown. Soak in sugar syrup.

Serving : Serve as a sweet dessert.

# VII. Result and Discussion



# VII. Result and Discussion



# VII. Result and Discussion

Submit

## Response: ...

This is a popular Indian dish called Pav Bhaji. It consists of a spicy vegetable curry (bhaji) served with soft bread rolls (pav). The main ingredients of the bhaji are potatoes, onions, tomatoes, peas, and spices. The pav is usually made from white flour and is soft and fluffy. Pav Bhaji is a popular street food in India and is often served with a side of onions and lemon wedges.

To make Pav Bhaji, you will need the following ingredients:

For the Bhaji:

- 2 cups of potatoes, peeled and diced
- 1 cup of onions, diced
- 1 cup of tomatoes, diced
- 1/2 cup of peas
- 1 teaspoon of cumin seeds
- 1 teaspoon of mustard seeds
- 1 teaspoon of turmeric powder

# VIII. Conclusion

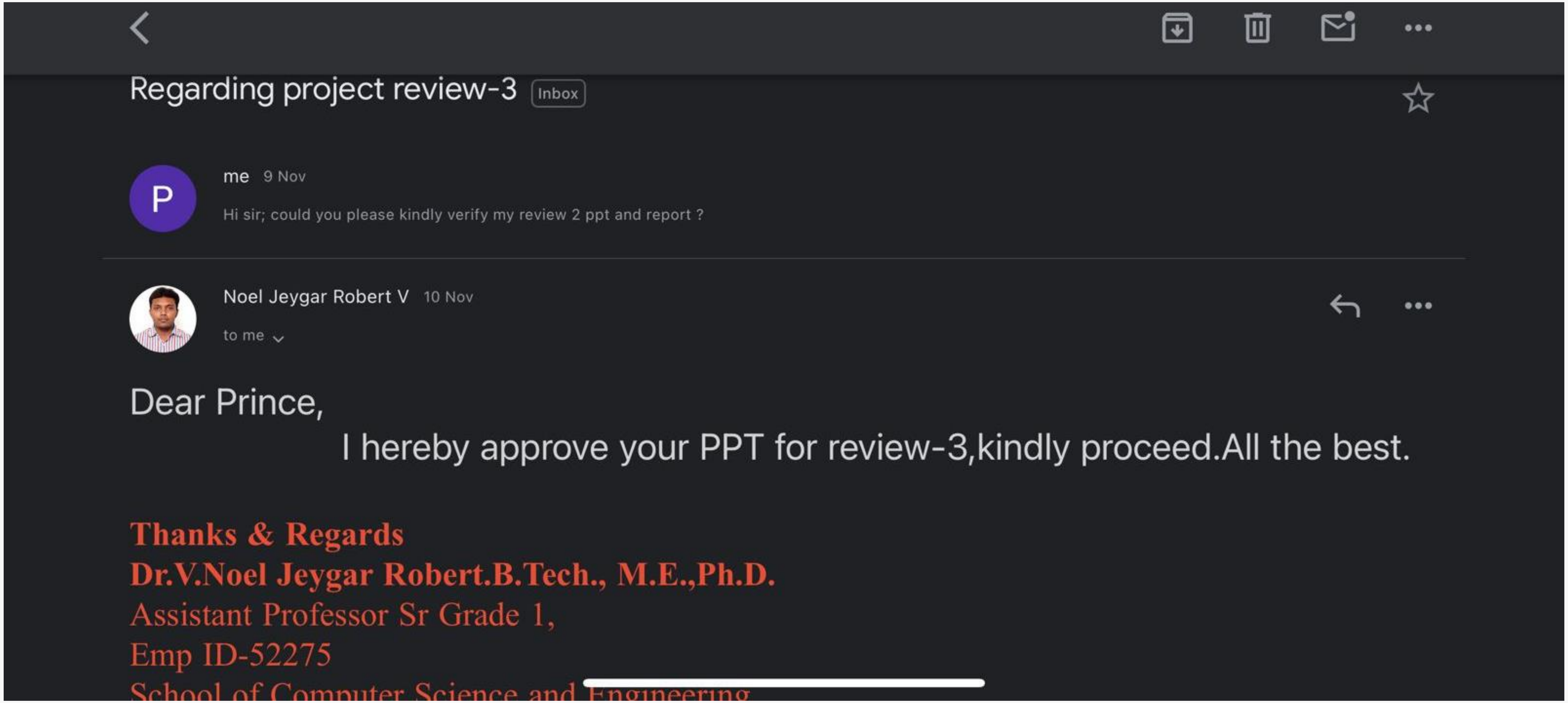
- **Proposed image-to-recipe system:** Generates recipes from food images, including title, ingredients, and cooking instructions.
- **Model comparison:** Evaluated accuracy using classification report.
- **Ingredient and instruction prediction:** Initially predicted ingredients, then generated instructions based on images and inferred ingredients.

# IX. Future work

- In the future, We plan to improve the generated recipe by adding voice functionality.

- Additionally, we will expand the dataset, explore various training models, and include reference links, such as videos, to enhance the recipe generation with additional instructions and references.

# X. Guide Approval



Regarding project review-3 Inbox

me 9 Nov

Hi sir; could you please kindly verify my review 2 ppt and report ?

Noel Jeygar Robert V 10 Nov

to me

Dear Prince,

I hereby approve your PPT for review-3,kindly proceed.All the best.

**Thanks & Regards**

**Dr.V.Noel Jeygar Robert.B.Tech., M.E.,Ph.D.**

Assistant Professor Sr Grade 1,

Emp ID-52275

School of Computer Science and Engineering

# XI. References

[1]Li, K., & Chen, Y. (2021). DeepRecipes: Exploring Massive Online Recipes and Recovering Food Ingredient Amounts.

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# XI. References contd..

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[5]M. Zhang, G. Tian, Y. Zhang and H. Liu, "Sequential Learning for Ingredient Recognition From Images," in IEEE Transactions on Circuits and Systems for Video Technology, vol. 33, no. 5, pp. 2162-2175, May 2023, doi: 10.1109/TCSVT.2022.3218790.

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# Thank You