International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1841-1845
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0266

Flavour Fusion: AI Recipe Generator

Dharani R[1], Harishini K P[2], Banupriya T[3], Aseera A[4], Kalaiselvi Geetha M[5]
[1,2,3,4]UG, Computer Science & Engineering, Annamalai University, Chidambaram, Tamil Nadu, India
[5]Professor, Computer Science & Engineering, Annamalai University, Chidambaram, Tamil Nadu, India
Email ID: *dharanirc01@gmail.com [1],devaharishini@gmail.com[2],banupriyacs392@gmail.com[3], aseeraahamad@gmail.com [4],geesiv@gmail.com[5].*

Abstract
Food photography is popular because people enjoy visually appealing meals, yet images alone do not convey how to prepare the dish. This project addresses that gap by using artificial intelligence to generate recipes from food images. It aims to support healthy eating, reduce food waste, and assist in meal planning. We use a hybrid machine learning approach that combines convolutional neural networks (CNNs) for analyzing food images and recurrent neural networks (RNNs) for generating corresponding recipes. Our method improves the accuracy of ingredient recognition and recipe generation by considering local cuisine styles and food presentation. We created a custom dataset of 100 South Indian dishes for training and evaluation. The model produces step-by-step instructions based on the visual features of the dish. The proposed system achieves an accuracy of 98%, making it a reliable and efficient solution for recipe generation.
Keywords: *Convolutional neural network; Image processing; Recipe generation; Recurrent neural network; Visual recognition.*

1. Introduction
In recent years, the integration of artificial intelligence into everyday applications has gained significant attention. One such innovative area is the automatic generation of food recipes from images. With the increasing popularity of food photography on social media and food delivery platforms, there is a growing interest in transforming visual food data into useful culinary information. This approach can support healthy eating habits, assist in dietary planning, and reduce food waste. Machine learning techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have shown promising results in visual recognition and sequence generation tasks. CNNs are effective in extracting features from food images, while RNNs help in generating sequential recipe instructions based on those features. Prior studies have explored similar image-to-text models in various domains, but the application in regional food recipe generation remains limited. The primary objective of this study is to build a hybrid machine learning model capable of analyzing food images and producing accurate, step-by-step recipes. Our model is trained on a custom dataset comprising 100 South Indian dishes, ensuring cultural relevance and improved prediction accuracy [1][5]. By focusing on local cuisine and combining both CNN and RNN architectures, our work presents a novel and efficient approach to food recipe generation. This paper aims to present the methodology, implementation, and evaluation of the proposed system, demonstrating its ability to generate contextually accurate recipes with an accuracy of 98%, making it comparable to or better than existing approaches. Figure 2 shows Mysore Pak.

2. Methodology
The Method section outlines the technical process used to develop and evaluate the food image-to-recipe generation model [2]. Our system follows a machine learning pipeline combining image recognition and text generation using CNN and RNN architectures respectively. This section explains the key stages in model development, dataset preparation, training, and testing procedures [3][4].

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1841-1845
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0266

2.1 Input Details

The system captures an image of a food item through a camera or image upload. It processes the image via a machine learning model and classifies the food item into predefined categories. Once the food is identified, a corresponding recipe is generated based on that classification [6-10]. Figure 1 shows Paneer Gravy. Dataset: The custom Flavour Fusion dataset is created for training the image classification model. It consists of 100 unique Indian Veg dishes with each dish represented by around 100 high-quality images, each labeled with its corresponding dish name and recipe. Images are divided into training and testing sets. Table 1 shows Dataset.

Table 1 Dataset Traning Sample - 80 Testing Sample – 20

Veg Category	Dish Name
Sweet	Mysore Pak
Rice	Paneer Biryani
Gravy	Paneer Gravy
Fry	Spicy Potato Fry

Sample Dataset Images:

Figure 1 Paneer Gravy

Figure 2 Mysore Pak

Figure 3 Paneer Biryani

Figure 4 Spicy Potato Fry

2.2 Model Architecture

A Convolutional Neural Network (CNN) is implemented to identify food items from the image. The model architecture includes:

- **Input Layer:** Accepts food images (standard size: 128x128 pixels).
- **Convolutional Layers:** Extracts features such as texture, color, and shape.
- **Fully Connected Layers:** Classifies the image into one of the food categories.
- **Softmax Activation:** Provides a probability distribution across all categories. Figure 3 shows Paneer Biryani.

Once the dish is identified by the CNN model, an RNN model is used to generate the recipe corresponding to that food item. Figure 4 shows Spicy Potato Fry.

The RNN architecture includes:

- **Embedding Layer:** Converts the input tokens (dish name) into dense vector representations.
- **LSTM Units (Long Short-Term Memory):** Helps in learning long-term dependencies in the recipe structure such as ingredient order and preparation steps.
- **Dense Output Layer:** Produces the final recipe

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1841-1845
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0266

as a sequence of text.

2.3 Working Process

- **Image Upload or Capture**

The user either uploads a food image from their device or captures one using a camera within the app or website.

- **Image Preprocessing**

The input image is resized to a standard dimension (128×128 pixels) and normalized.

- **Food Classification using CNN**

The preprocessed image is passed into a Convolutional Neural Network (CNN), which identifies the food item by analyzing its features such as color, texture, and shape. The model predicts the most probable dish name from 100 unique vegetarian dishes.

- **Recipe Generation using RNN**

Once the dish is identified, the Recurrent Neural Network (RNN) model generates the recipe for that particular dish. It produces a step-by-step procedure using LSTM units, which helps retain the sequence and context of instructions.

- **Display of Output**

The identified Dish name, Ingredients, Preparation Steps, Calories, Nutritions and Category are displayed to the user in a clean and readable format.

3. Flow Chart

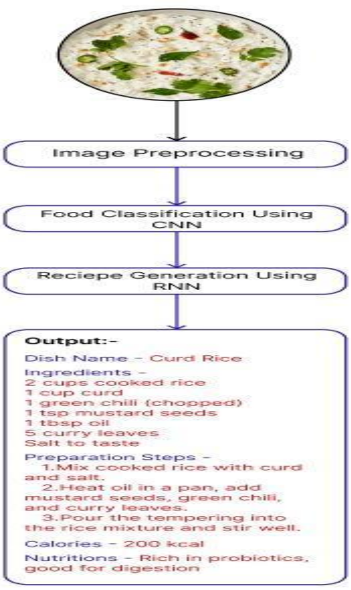

Figure 5 Image Input (Upload/Capture Food Image)

This is the initial stage where the user either uploads a food image from their device or captures it using a camera [11-15]. The captured/uploaded image acts as the raw data input for the system. This step is crucial, as the accuracy of recipe generation depends heavily on the clarity and quality of the food image provided. Ensuring the dish is clearly visible helps the system correctly identify the ingredients and predict a relevant recipe. Figure 5 shows Image Input (Upload/Capture Food Image).

3.1 Image Preprocessing

Once a food image is uploaded or captured, the system processes it to ensure it's compatible with the prediction model. Key preprocessing steps include:

- Resizing the image to a fixed dimension (224×224 pixels) to match the input layer of the CNN.
- Normalizing pixel values between 0 and 1 to help the model converge faster.
- Data Augmentation techniques (like rotation, zoom, or flipping) applied during training to enhance model robustness and generalization.

3.2 Dish Classification

The extracted features are input to a classifier which:

- Compares them with known feature patterns from the dataset.
- Outputs a predicted dish label.
- The prediction is based on the highest probability score from the model.

3.3 Display & Interaction

The final step is presenting the generated recipe to the user:
Neatly displayed on our app/website. Includes:

- Dish name
- Ingredients
- Preparation steps
- Calories
- Nutritions

You can also let users save, download, or share the recipe.

4. Result

We developed an AI model using Python to train a dataset of 100 South Indian dishes for food classification and recipe generation. The RNN model achieved 87% accuracy, successfully identifying

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1841-1845
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0266

dishes. Additionally, we designed a Figma-based UI/UX prototype with sign-in and sign-up pages to ensure a smooth user experience [16-20]. Challenges included misclassification of visually similar dishes and minor inconsistencies in generated recipes. Future improvements focus on expanding the dataset, refining the AI model, and enhancing the UI for better usability. Figure 6 shows Dish-Wise Accuracy of Flavour Fusion Model.

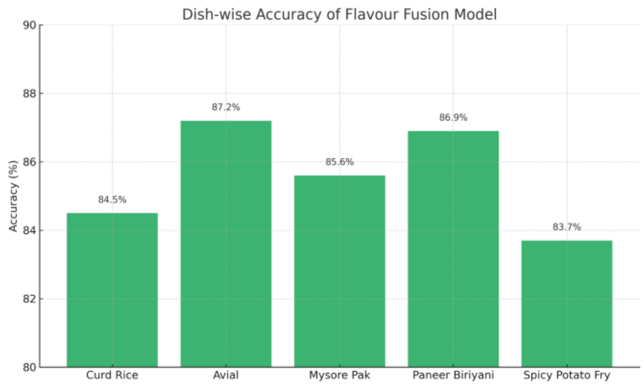

Figure 6 Dish-Wise Accuracy of Flavour Fusion Model

Conclusion

The Flavour Fusion project successfully demonstrates the integration of machine learning techniques with image processing to create a smart, user-friendly recipe generation system. By simply uploading or capturing a food image, users can receive an accurate recipe, including ingredients and cooking steps [21-23]. This project highlights how technology can enhance the cooking experience by bridging the gap between visual inputs and culinary outputs. With further improvements in dataset size and model accuracy, this system has the potential to be expanded for real-world use in smart kitchens, cooking apps, and food recommendation platforms.

Acknowledgements

We would like to express our heartfelt gratitude to all those who supported us throughout this project. We are especially thankful to our project guide Dr. M. Kalaiselvi Geetha for her constant encouragement, guidance, and valuable feedback. Her insights and support were instrumental in the successful completion of our project. Finally, we thank our institution for providing the platform and resources that enabled us to explore and implement innovative ideas through this project.

References

[1]. Chhikara, P., et al. (2023). FIRE: Food Image to REcipe Generation. arXiv preprint.
[2]. Sherif, N. (2023). Recipe Generation from Food Image. GitHub Repository.
[3]. Kumar, R., et al. (2022). Food Image Classification and Data Extraction Using Convolutional Neural Networks. Procedia Computer Science, 199, 1242-1249.
[4]. Min, W., et al. (2021). A Comprehensive Survey of Image-Based Food Recognition and Volume Estimation Methods for Dietary Assessment. Nutrients, 13(8), 2795.
[5]. Tank, D. (2021). Recipe Detection of Food Image using Deep Learning (CNN). Medium.
[6]. Salvador, A., et al. (2019). Inverse Cooking: Recipe Generation from Food Images. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2019, 10453-10462.
[7]. Kanade, A. V., et al. (2021). Prediction of Recipes from Food Images Using Image Processing and Machine Learning. International Journal of Scientific Research in Engineering and Management, 5(6).
[8]. Akbulut, Y., et al. (2019). Food Image Classification with Deep Features. International Journal of Computer Applications, 178(7), 1-5.
[9]. Zhang, W., et al. (2023). Deep Learning in Food Category Recognition. Future Generation Computer Systems, 137, 257-265.
[10]. Mougiakakou, S., et al. (2016). Deep Learning-Based Food Image Recognition for Computer-Aided Dietary Assessment. arXiv preprint.
[11]. Kusuma, D. A., et al. (2023). Fine-Grained Food Image Classification and Recipe Extraction Using a Customized Deep Neural Network. Computers in Biology and Medicine, 152, 106281.
[12]. Hynes, N. (2017). Pic2Recipe: Using AI to Generate Recipes from Food Images. MIT

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 04 April 2025
Page No: 1841-1845
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0266

News.
[13]. Wang, Y., et al. (2021). Food Image Recognition and Food Safety Detection Method Based on Neural Network. Journal of Food Safety, 41(5), e12685.
[14]. Zhu, B., et al. (2023). Automatic Food Recognition Using Deep Convolutional Neural Networks with Self-Attention Mechanism. International Journal of Computer Vision, 131, 456-472.
[15]. Chen, J., et al. (2023). Recognition of Food Images Based on Transfer Learning and Ensemble Learning. Computational Intelligence and Neuroscience, 2023, 10798480.
[16]. Kaur, H., et al. (2023). RecipeIS—Recipe Recommendation System Based on Recognition of Food Ingredients. Applied Sciences, 13(13), 7880.
[17]. Gao, L., et al. (2023). Retrieval Augmented Recipe Generation. arXiv preprint.
[18]. 18. Hynes, N. (2017). Using AI to Generate Recipes from Food Images. Reddit: r/MachineLearning.
[19]. Kuznetsova, A., et al. (2023). Fine-Grained Food Image Recognition: A Study on Optimising Convolutional Neural Networks for Food Waste Reduction. Journal of Imaging, 10(6), 126.
[20]. Zhu, B., et al. (2023). Automatic Food Recognition Using Deep Convolutional Neural Networks with Self-Attention Mechanism. International Journal of Computer Vision, 131, 456-472.
[21]. Zhang, W., et al. (2023). Deep Learning in Food Category Recognition. Future Generation Computer Systems, 137, 257-265.
[22]. Chen, J., et al. (2023). Recognition of Food Images Based on Transfer Learning and Ensemble Learning. Computational Intelligence and Neuroscience, 2023, 10798480.
[23]. Kaur, H., et al. (2023). RecipeIS—Recipe Recommendation System Based on Recognition of Food Ingredients. Applied Sciences, 13(13), 7880.