Recipe Generation from Food Images using ResNet-101

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***Abstract*- Artificial Intelligence and Machine learning have shown immense potential to address problems in various fields. Convolutional Neural Networks (CNNs) and other deep learning models have revolutionized image processing in computer vision. The "FoodGenius" project simplifies the process of creating cooking recipes from images of food using AI and deep learning. The system converts food photos into readable recipes with ingredient lists and cooking directions by using a hybrid model incorporating Transformer-based architectures for text creation with ResNet101 CNN for feature extraction. The Flask-built web application allows users input photos and get recipe recommendations in real time. Scalability is guaranteed by the model's performance optimization, which supports both CPU and GPU environments. This work highlights the intersection of computer vision and natural language processing, demonstrating the potential for AI-driven solutions in the culinary domain. "FoodGenius" aims to streamline cooking processes, inspire creativity, and offer valuable assistance to both novice cooks and professionals.**

Keywords— Convolutional Neural Network (CNN), Artificial Intelligence(AI), Machine learning (ML) ,Transformer models, ResNet101.

I. INTRODUCTION

Artificial Intelligence has fundamentally changed multiple industries in recent years, including the culinary industry, particularly through deep learning. Innovation in computer vision now allows users to generate recipes from food images, making meal planning and cooking remarkably intuitive and interactive. Most recipe searching methods today are manual in nature and only permit the use of text queries which could lead to issues in situations where the user only has the picture of the dish. With the introduction of Convolutional Neural Networks (CNNs), deep learning has enabled us to shift from text based search queries to the extraction of features from food images, allowing us to input images instead. The research revolves around the use of a 101 layer deep residual neural network, ResNet-101 to analyze food images and generate recipes out of the analyzed data. ResNet-101 is proven effective for the task as a neural network based on deep architectures, given the complexity of detail needed for accurate identification of ingredients and formulation of recipes. Utilizing this model enables the system to predict not just the type of the checked dish, as well as the needed ingredients and the full recipe with step by step instructions.

In addition to the automatic generation of recipes, the customizability of the system is another enhancement to user experience. Modifications to recipes stemming from dietary restrictions or allergies can be applied by users themselves

II. LITERATURE REVIEW

[1] B. Jamalpur, "Optimizing Food Image Classification Using Black Widow Algorithm and Deep Learning Techniques", proposes the FIC-BWODL model for food image classification, which combines preprocessing using CLAHE, feature extraction with CapsNet, and classification using CAE. The Black Widow Optimization Algorithm is utilized for hyperparameter tuning, resulting in improved performance by adapting to the specific features of the dataset. [2] H. V. Hasti, "Image Processing and Machine Learning Methods for Assessing Food Quality", focuses on advanced image processing and machine learning methods for food quality assessment. The approaches include CNN-based wheat contamination detection, achieving 92.57% accuracy for apple freshness estimation and 97.33% accuracy for apple bruise classification using hyperspectral imaging. The study also highlights automated meat quality scanning and cost-effective rice classification techniques, enhancing industry efficiency and competitiveness. [3] S. P. Singh, "Food-Lens: Improving Culinary Experiences with AI-Driven Meal Analysis and Recipe Generation", introduces an AI-based system leveraging CNN and MobileNetV2 to identify food items from images and generate corresponding recipes, including ingredients and instructions. The system encourages healthier eating habits through features like personalized recipe suggestions and text-to-speech capabilities, enhancing the culinary experience. [4] R. Krutik, "Advancements in Food Recognition: A Comprehensive Review of Deep Learning-Based Automated Food Item Identification", provides an in-depth exploration of

advancements in food recognition using deep learning technologies. It highlights the role of these methods in dietary monitoring and nutritional analysis, examining motivations, state-of-the-art architectures, and publicly available datasets. Additionally, the study identifies existing research gaps and suggests future directions for progress in the field. [5] P. Chhikara, "FIRE: Food Image to Recipe Generation", introduces a multimodal methodology called FIRE for generating recipes from food images. The study employs BLIP for title generation, Vision Transformers for ingredient identification, and T5 for instruction generation. The system effectively integrates advanced deep learning models to streamline recipe creation from visual inputs, enhancing the automation of food-related AI applications. [6] E. D. Cherpanath, "Food Image Recognition and Calorie Prediction Using Faster R-CNN and Mask R-CNN", presents a deep learning-based system aimed at addressing health concerns related to obesity through food image recognition and calorie prediction. The study utilizes Faster R-CNN and Mask R-CNN to capture food images, classify them, and predict calorie content. This approach enhances dietary awareness and aids in calorie control, contributing to the prevention of obesity-related conditions. [7] E. I. Georga, "A Review of Image-Based Food Recognition and Volume Estimation Artificial Intelligence Systems", provides a comprehensive review of AI systems for food recognition and volume estimation using smartphone images. The paper explores techniques for segmentation, classification, and volume computation, offering insights into the strengths and limitations of current methods. It further discusses potential improvements and future directions for advancing dietary assessment technologies. [8] T. M. L. Rosaline, "AI-Powered Mobile Application for Image-Based Food Ingredient Detection and Recipe Generation", introduces a mobile app utilizing YOLOv8 and CNN for food ingredient detection and nutrition assessment. The model, trained on 24,583 images, demonstrates improved accuracy in ingredient identification, calorie estimation, and recipe generation. The research highlights future work, including expanding the dataset to enhance precision and reliability. [9] M. S. M. Rabby, "A Modified Transfer Learning-Based Framework for Efficient Food Image Classification", investigates food image classification using EfficientNetB7, ResNet50, and VGG19 on the Food-11 dataset. The study shows that EfficientNetB7 achieved superior performance with 87.38% validation accuracy, while augmented VGG19 variants reached up to 83% accuracy, emphasizing the importance of augmentation and regularization in improving model performance. [10] P. K. Singh, "Transfer Learning using Very Deep Pre-Trained Models for Food Image Classification", evaluates deep pre-trained CNN architectures for food image classification on the Food-101 dataset, which includes 101 food categories. The study found that Xception outperformed Inception-v3, EfficientNet-B0, DenseNet-121, and MobileNet, achieving the highest accuracy of 84.54%, highlighting the effectiveness of advanced architectures in improving food classification tasks. [11] N. V. Sai Manoj, "Enhanced Food Classification System Using YOLO Models for Object Detection Algorithm", evaluates YOLOv5 and YOLOv7 for food classification, demonstrating that YOLOv5 outperforms the other with an accuracy of 0.851, a recall of 0.836, and a 0.892 mAP at 0.5 IoU. The study highlights YOLOv5's potential in improving food categorization, nutrition assessment, and ensuring safety in the food industry. [12] J. Sultana, "A Study on Food Value Estimation From Images: Taxonomies, Datasets, and Techniques", reviews the automation of nutritional value estimation from food images using deep learning. It categorizes research efforts, evaluates performance metrics such as accuracy and precision, and discusses current trends, challenges, and opportunities. This study provides valuable insights for researchers, health practitioners, and nutritionists in the field of food value estimation. [13] S. Chaudhary, "ChefAI.IN: Generating Indian Recipes with AI Algorithm", explores the generation of Indian recipes using the Autochef algorithm, which incorporates mutation and similarity techniques. The system utilizes models like NLP and LSTM to develop and refine recipes, with the goal of improving the accuracy and efficiency of recipe creation specifically for Indian cuisine. [14] K. Srinivas, "Self-Attention Architecture for Ingredients Generation from Food Images", introduces an image-to-recipe generation system specifically for Indian cuisines. The system uses a self-attention-based architecture to predict a dish's title, ingredients, and cooking instructions from its image, enhancing the relevance and accuracy of recipe generation for Indian dishes. [15] D. P. Papadopoulos, "Learning Program Representations for Food Images and Cooking Recipes", proposes a method to generate cooking programs from food images and recipes using a Vision Transformer-based encoder for images, a Transformer-based encoder for recipes, and a program decoder. This approach aligns image and recipe embeddings in a shared space through self-supervised learning, enabling effective program generation. [16] G. A. Papakostas, "An Update on Cooking Recipe Generation with Machine Learning and Natural Language Processing", reviews recipe generation methods that use user-provided ingredient lists or suggested ingredients. By leveraging advancements in natural language processing and deep learning, the paper highlights innovative, personalized, and healthier recipe creation techniques, offering inspiration and context for culinary endeavors. [17] H. Wang, "Learning Structural Representations for Recipe Generation and Food Retrieval", introduces an unsupervised method to create level tree structures for cooking recipes, enhancing recipe generation and food cross-modal retrieval tasks. Using ON-LSTM, the model extracts paragraph structures, generates recipe trees from images, and integrates them into generation and retrieval frameworks. [18] M. Goel, "Ratatouille: A Tool for Novel Recipe Generation", introduces Ratatouille, a web application for generating unique recipes. The system employs neural network-based LSTMs and the transformer-based GPT-2 model. By including ingredient quantities, GPT-2 achieved superior performance, with a BLEU score of 0.806, surpassing LSTM-based methods in recipe generation. [19] Y. Sun, "Image-Based Food Classification and Volume Estimation for Dietary Assessment: A Review", reviews methods for image-based dietary assessment, focusing on algorithms and models for food recognition and volume estimation. It identifies challenges in improving accuracy, speed, and efficiency, emphasizing the potential of integrated systems combining deep learning and complementary approaches to enhance dietary intake assessment. [20] A. S. Metwalli, "Food Image Recognition Based on Densely Connected Convolutional

Neural Networks", presents DenseFood, a densely connected convolutional neural network for food image recognition. By utilizing softmax and center loss functions, DenseFood enhances intra-category consistency and inter-category distinction. Tested on the VIREO-172 dataset, it achieved 81.23% accuracy, outperforming fine-tuned DenseNet121 and ResNet50 models.

III. METHODOLOGY

Fig.1. Block diagram of implementation

Image Dataset: A diverse set of food images is gathered from publicly available datasets such as RecipeNLG, Food101, or custom datasets sourced from food blogs and recipes. These images should cover a wide range of cuisines, dish types, and ingredients to ensure diversity. Quality, balanced images, with clear representations of food, are critical for effective training of the model. This dataset will be used for both training and testing, and images are annotated with ingredient information**.** The **Food101** dataset is a widely used collection for food image classification tasks. It contains a total of 101,000 images, with 1,000 images per class, representing 101 different food categories. Each image in the dataset is labeled with a food class corresponding to one of the categories, such as pizza, sushi, salad, pasta, etc.

- Number of classes: 101
- Number of images: 101,000 (1,000 images per class)
- Image resolution: 512x512 pixels
- Format: JPG
- Classes include: pizza, sushi, burger, pasta, salad, sandwich, and other food items.

The **RecipeNLG** (Natural Language Generation) dataset is a collection designed for generating recipe descriptions and instructions. It contains a large number of recipe entries, each comprising multiple fields such as ingredients, cooking instructions, and recipe title. The dataset is used for the task of text generation where, given a set of ingredients, a model should generate a coherent recipe.

- Number of recipes: 2.3 Million originally
- Fields: title, ingredients, directions, NER(list of ingredients without servings), etc.
- Data format: Structured text (CSV)
- Recipe categories: The dataset includes various types of recipes such as desserts, main courses, beverages, and salads, among others, but only the ones related to the 101 food classes were taken in the end.

The Recipe NLG dataset is essential for mapping the food classification output from the Food101 dataset to actual recipe generation. Once an image is classified into one of the 101 food categories, the model uses the Recipe NLG dataset to generate a corresponding recipe based on the food class. This combination of food classification and recipe generation enables the model to provide both the food type and a detailed recipe for preparation.**Feature Extraction (ResNet-101)**: ResNet-101 is employed for feature extraction from the food images. This pre-trained deep learning model is capable of identifying important visual patterns and features within food images. The extracted features are used to classify the food type and predict relevant ingredients. The use of ResNet-101 provides a robust and efficient way to identify high-level features like textures, shapes, and color distributions within the food images.**Food Image Classification**: After the feature extraction process, a deep learning classifier (such as a CNN or ResNet-101) is used to classify the food images into predefined categories like pasta, burger, salad, etc. This classification process serves as the initial step for recipe generation, as the predicted food type is associated with a list of common ingredients. **Ingredient Prediction**: The classified food type, along with the features extracted from the image, is fed into a machine learning model trained on the RecipeNLG dataset. The model predicts the ingredients likely present in the dish. The predicted ingredients are validated using a combination of ingredient rules and known recipe patterns. The accuracy of ingredient prediction is crucial for generating precise and realistic recipes. **Recipe Generation**: Using the predicted ingredients and food type, the system generates a recipe. If a matching recipe is found in the RecipeNLG dataset, it is retrieved and formatted into a readable step-by-step procedure. If no direct match exists, an AI-based text generation model (such as an LSTM or Transformer model) is used to create a new recipe based on the available ingredients and food type. The generated recipe includes ingredients, cooking steps, and estimated cooking time.**User Interaction**: The generated recipe is displayed in a user-friendly interface. The system provides a platform for users to interact with the generated recipe by allowing them to modify ingredients (e.g., exclude certain items) and receive customized alternatives. Users can also save or share their recipes.

IV. DESIGN AND IMPLEMENTATION

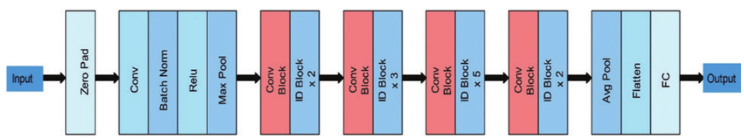

Fig. 2. Resnet-101 Architecture

ResNet-101 (Residual Network with 101 layers) is a deep convolutional neural network (CNN) crucial for food image classification and feature extraction in the recipe generation system. It enables the model to learn deep hierarchical representations of food images, distinguishing dish types and mapping them to the corresponding ingredients and recipes.

Key Components of ResNet-101 in Recipe Prediction

Convolutional Layers The first layers of ResNet-101 consist of multiple convolutional layers that extract low-level visual features from the input food images. **Function:** Detects basic patterns like edges, textures, and color variations, which help differentiate various food items. **Importance:** Identifies key visual characteristics, such as whether a dish has pasta, bread, or leafy greens. **Example:** In a pizza image, the convolutional layers detect circular edges, cheese texture, and tomato toppings, which contribute to accurate classification. **Residual Blocks** ResNet-101 uses residual blocks to solve the vanishing gradient problem in deep networks. **Function:** Allows information to flow directly across multiple layers via skip connections, ensuring stable and efficient training.

Importance: Maintains meaningful gradients, helping deeper layers focus on relevant features for better food image recognition. **Example:** With two burger images having different lighting conditions, residual blocks ensure that the model focuses on relevant features (such as a bun and patty) rather than lighting differences. **Global Average Pooling (GAP) Layer** After feature extraction, ResNet-101 uses a GAP layer to convert feature maps into a compact representation. **Function:** Reduces each feature map to a single value by averaging all activations, avoiding the need for fully connected layers. **Importance:** Helps generalize the model across diverse food images and reduces overfitting.

Example: In a spaghetti dish, GAP ensures high-level features like noodle patterns are retained, while details like the plate or background are ignored. **Fully Connected (FC) Layer** The extracted features are passed through a Fully Connected (FC) layer. **Function:** Converts extracted features into meaningful numerical representations that correspond to dish types or ingredients. **Importance:** Responsible for mapping the visual representation to a text-based output, predicting dish names and ingredients. **Example:** For a pasta image, the FC layer outputs a probability distribution for dish categories like Pasta (95%), Curry (3%), and Burger (2%). **Softmax Layer (Final Classification)** The final softmax layer assigns probabilities to the different dish categories based on the features. **Function:** Converts FC layer outputs into a probability distribution over dish categories. **Importance:** Helps identify the most probable food category, which is used to fetch ingredients and recipe steps. **Example:** For a fruit salad image, the softmax layer outputs: Fruit Salad (97%), Pasta (2%), Soup (1%).**Image Collection**: A collection of food images is gathered. These images represent various cuisines, dishes, and ingredients and are annotated accordingly. **Preprocessing**: The images are resized to 224x224 pixels and normalized to prepare them for input into the ResNet-101 model. **Classification**: The processed images are passed into a deep learning model (ResNet-101), which classifies the images into predefined categories (e.g., pasta, salad). **Ingredient Prediction**: The predicted food type is used to predict the corresponding ingredients based on the features extracted from the image. A machine learning model, trained on the RecipeNLG dataset, helps make this prediction.**Recipe Generation**: The system either retrieves a matching recipe from the RecipeNLG dataset or uses an AI-based model (e.g., LSTM or Transformer) to generate a recipe, which includes ingredients, instructions, and cooking time. **User Interface**: The generated recipe is presented in a user-friendly interface. Users can interact with the recipe, customize ingredients, and save or share their results. **Evaluation**: The system's results can be evaluated through user feedback and interactions.

Tools and Technologies Used:

Deep Learning: ResNet-101 for feature extraction, CNN for food classification, LSTM/Transformer for recipe generation. **Machine Learning**: Ingredient prediction using a model trained on the RecipeNLG dataset. **User Interface**: Interactive frontend built using HTML, CSS, and JavaScript for presenting recipes to the user. **Data**: RecipeNLG dataset, Food101, and other food image datasets for training and testing the models. This approach ensures the effective classification of food images, prediction of ingredients, and generation of accurate recipes based on user input, resulting in an intelligent recipe generation system.

V. RESULTS AND ANALYSIS

The model was trained over **10 epochs**, with both training and validation loss consistently decreasing, indicating effective learning. The **validation accuracy** steadily improved from **41%** in epoch 1 to **84%** in epoch 10, reflecting the model's increasing proficiency in classifying food items correctly. This improvement in accuracy suggests that the model successfully captured the underlying patterns in the data without overfitting.

- **Final Training Loss**: 0.12
- **Final Validation Loss**: 0.21
- **Final Validation Accuracy**: 84%

A front-end web interface was developed and hosted on a local server to allow for a more convenient user interaction with the food classification and recipe generation system. The interface allows users to upload an image of a food item, which is processed by the classification model to determine the most likely category. The design focuses on **usability and efficiency**, providing a clean and interactive experience. Backend processing ensures smooth communication between the classification model and recipe retrieval system, while features such as real-time image preview and error handling enhance the overall user experience.

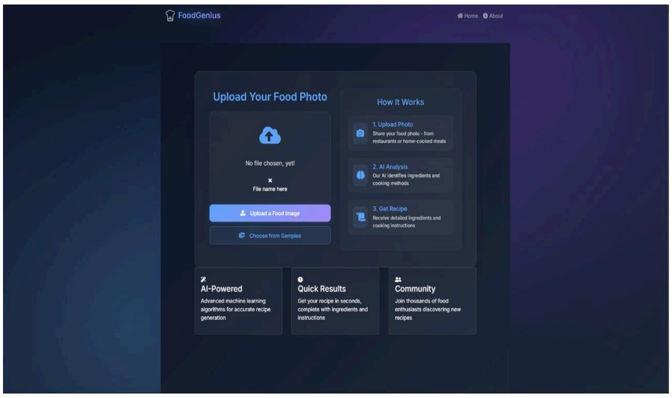

Fig. 3. UI for uploading image

Following successful classification, the system retrieves and displays a relevant recipe, including a structured list of ingredients and cooking instructions. Additionally, the system allows for customized recipe generation based on user-defined parameters, allowing them to add/remove ingredients of their choice. This dynamic approach enhances the personalization of recipe suggestions, ensuring they align with individual user needs. The output is efficiently retrieved from pre-processed pickle files, making the system responsive and capable of delivering relevant recipes quickly. Future enhancements may focus on expanding the recipe database and integrating additional user preferences for a more tailored experience

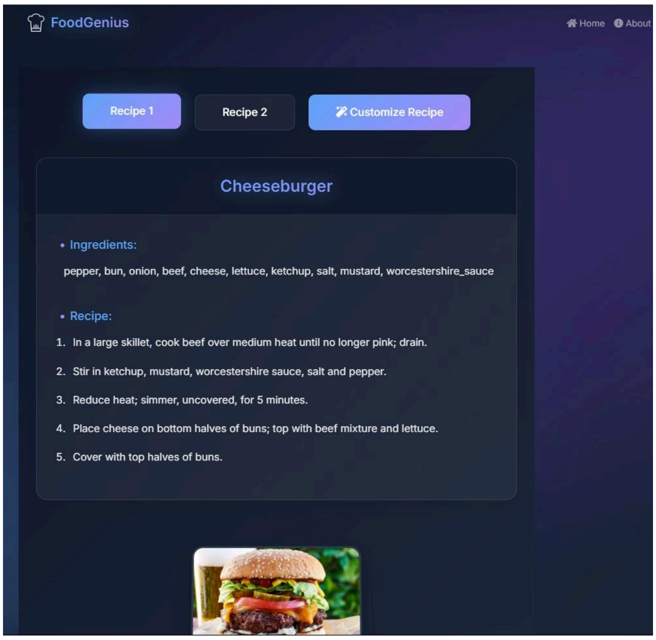

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Fig. 4. Output with classification and base recipe

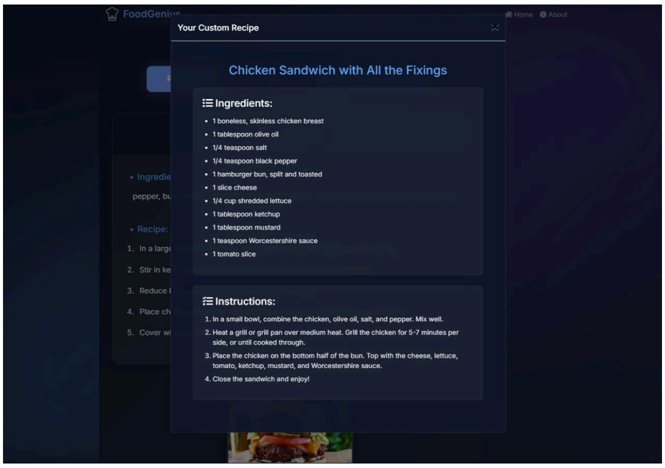

Fig. 5. Customized recipe as output

VI. CONCLUSION

The FoodGenius project showcases the merge of Computer Vision and Natural Language Processing in recipe creation. Food recognition was combined with recipe generation by using ResNet101 for image feature extraction and modeling with the Transformer architecture. The deep learning methods guarantee accurate food detection and algorithmically generated recipes, thereby demonstrating the advantages of multi-modal learning in these AI based culinary applications. Image processing pipeline, based on CNNs, makes robust features, while the Transformer decoder builds contextually relevant recipes with the help of multi-head attention. The technology is demonstrated in a user-friendly web interface, where advanced AI algorithms are available for practical aid in cooking styles. Due to a modular architecture, FoodGenius is open for further extensions such as new cuisines or dietary restrictions. This project has demonstrated that AI can generate recipes and serves as a basis for further developments in food applications.

VII. FUTURE ENHANCEMENTS

Cultural and Regional Variations: The system could offer alternate recipes that reflect regional or cultural preferences for the identified food items, catering to diverse culinary tastes. **Meal Planning:** The system can be further developed to offer daily or weekly meal plans that fit the user\s needs, diet, and ingredients on hand, making it more user friendly. **Multiple Language Support and Voice Detection:** Adding voice input and output will improve usability for non-English speakers and greatly augment the user experience. **Mobile Application Integration**: Developing a mobile application would allow users to scan or capture food items on the go, providing results conveniently from anywhere, extending the system's reach. **Interactive Recipe Steps**: The system could include step-by-step cooking instructions, potentially supplemented with video tutorials, to enhance the cooking process for users. **Dynamic Recipe Recommendations:** The system can provide recipe recommendations based on the users' feddback, likes, and cooking history, which ensures the meals are more tasty and relevant to the users, and guaranteed to be more enjoyable. **Context Aware Recommendation:** The system should be smart enough to recommend recipes based on contextual factors such as season, time of day, or even the user's mood, which would make the system more responsive to the users needs. **Health Impact Analytics**: The system could provide long-term dietary impact reports, analyzing user food choices and recipe history to help users make more informed decisions about their health and eating habits.

VIII. REFERENCES

[1] B. Jamalpur, S. P. G, S. Venkat, A. R, S. Kavitha and G. C. Babu, "Optimizing Food Image Classification Using Black Widow Algorithm and Deep Learning Techniques," 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 2024, pp. 1-6.

[2] H. V. Hasti, S. A. Jatan, T. Nahar, V. Dubey and C. Parmar, "Image Processing and Machine Learning Methods for Assessing Food Quality," 2024 International Conference on Data Science and Network Security (ICDSNS), Tiptur, India, 2024, pp. 01-06.

[3] S. P. Singh, D. Siddharth, S. Prabakeran, R. Das and A. Balaji, "Food-Lens: Improving Culinary Experiences with AI-Driven Meal Analysis and Recipe Generation," 2024 2nd International Conference on Sustainable Computing and Smart Systems (ICSCSS), Coimbatore, India, 2024, pp. 1385-1391.

[4] R. Krutik, C. Thacker and R. Adhvaryu, "Advancements in Food Recognition: A Comprehensive Review of Deep Learning-Based Automated Food Item Identification," 2024 2nd International Conference on Electrical Engineering and Automatic Control (ICEEAC), Setif, Algeria, 2024, pp. 1-6.

[5] P. Chhikara, D. Chaurasia, Y. Jiang, O. Masur and F. Ilievski, "FIRE: Food Image to Recipe generation," 2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV), Waikoloa, HI, USA, 2024, pp. 8169-8179.

[6] E. D. Cherpanath, P. R. Fathima Nasreen, K. Pradeep, M. Menon and V. S. Jayanthi, "Food Image Recognition and Calorie Prediction Using Faster R-CNN and Mask R-CNN," 2023 9th International Conference on Smart Computing and Communications (ICSCC), Kochi, Kerala, India, 2023, pp. 83-89.

[7] F. S. Konstantakopoulos, E. I. Georga and D. I. Fotiadis, "A Review of Image-Based Food Recognition and Volume Estimation Artificial Intelligence Systems," in IEEE Reviews in Biomedical Engineering, vol. 17, pp. 136-152, 2024.

[8] T. M. L. Rosaline, C. A. Suciawan, W. Ng, S. Achmad and J. V. Moniaga, "AI-Powered Mobile Application for Image-Based Food Ingredient Detection and Recipe Generation," 2024 International Conference on Information Management and Technology (ICIMTech), Bali, Indonesia, 2024, pp. 123-128, doi: 10.1109/ICIMTech63123.2024.10780810.

[9] M. S. M. Rabby, M. Uddin, E. Islam, M. Khaliluzzaman, M. N. I. Shanto and A. Islam, "A Modified Transfer Learning-Based Framework for Efficient Food Image Classification," 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS), Cox's Bazar, Bangladesh.

[10] P. K. Singh and S. Susan, "Transfer Learning using Very Deep Pre-Trained Models for Food Image Classification," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India.

[11] S. S, P. Kokil, A. R and N. V. Sai Manoj, "Enhanced Food Classification System Using YOLO Models For Object Detection Algorithm," 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), Delhi, India, 2023, pp. 1-6.

[12] J. Sultana, B. M. Ahmed, M. M. Masud, A. K. O. Huq, M. E. Ali and M. Naznin, "A Study on Food Value Estimation From Images: Taxonomies, Datasets, and Techniques," in IEEE Access, vol. 11, pp. 45910-45935, 2023.

[13] S. Chaudhary, B. Soni, A. Sindhavad, A. Mamaniya, A. Dalvi and I. Siddavatam, "ChefAI.IN: Generating Indian Recipes with AI Algorithm," 2022 International Conference on Trends in Quantum Computing and Emerging Business Technologies (TQCEBT), Pune, India, 2022, pp. 1-6.

[14] J. N. V. R. S. Kumar, C. Jyothsna, K. Srinivas, A. E. Sravanth, A. T. Kumar and D. Indira, "Self-Attention Architecture for Ingredients Generation from Food Images," 2022 Second International Conference on Next Generation Intelligent Systems (ICNGIS), Kottayam, India, 2022, pp. 1-7.

[15] D. P. Papadopoulos, E. Mora, N. Chepurko, K. W. Huang, F. Ofli and A. Torralba, "Learning Program Representations for Food Images and Cooking Recipes," 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), New Orleans, LA, USA, 2022, pp. 16538-16548.

[16] N. -I. Galanis and G. A. Papakostas, "An update on cooking recipe generation with Machine Learning and Natural Language Processing," 2022 IEEE World Conference on Applied Intelligence and Computing (AIC), Sonbhadra, India, 2022, pp. 739-744.

[17] H. Wang, G. Lin, S. C. H. Hoi and C. Miao, "Learning Structural Representations for Recipe Generation and Food Retrieval," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 3, pp. 3363-3377, 2022.

[18] M. Goel et al., "Ratatouille: A tool for Novel Recipe Generation," 2022 IEEE 38th International Conference on Data Engineering Workshops (ICDEW), Kuala Lumpur, Malaysia, 2022, pp. 107-110.

[19] F. P. W. Lo, Y. Sun, J. Qiu and B. Lo, "Image-Based Food Classification and Volume Estimation for Dietary Assessment: A Review," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 7, pp. 1926-1939, 2020.

[20] A. -S. Metwalli, W. Shen and C. Q. Wu, "Food Image Recognition Based on Densely Connected Convolutional Neural Networks," 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Fukuoka, Japan.