Pix2Plate: Transforming Food Images into Comprehensive Cooking Guides

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***Abstract* - Food computing is an emerging field that utilizes artificial intelligence (AI) to interpret and generate meaningful food-related information. This paper presents a multimodal approach that integrates computer vision (CV) and natural language processing (NLP) to automatically generate structured cooking guides from food images. The proposed system employs deep learning models, Vision Transformer (ViT) for ingredient identification, Bootstrapping Language-Image Pretraining (BLIP) for recipe title generation, and the T5 transformer model for step-by-step cooking instructions. Unlike conventional text-based recipe recommendation systems, our approach allows users to generate a complete cooking guide solely from food images, enhancing accessibility. Our evaluation demonstrates high ingredient recognition accuracy and contextually relevant recipe generation, providing a scalable solution for AI-driven cooking assistance. In such a scenario, text-to-speech guided technology is used to enable the user to repeat the process only as required rather than reading it repeatedly and language translation for the user's convenience.**

Keywords - Food Computing, Computer Vision, Natural Language Processing, Deep Learning, Recipe Generation, Vision Transformer (ViT), Bootstrapping Language-Image Pretraining (BLIP), Text-to-Text Transfer Transformer (T5).

I. INTRODUCTION

In the modern world, Machine learning and Artificial intelligence are revolutionizing by making complex processes automatic and increasing the efficiency of operations. Food computing is one among those fields that have witnessed remarkable growth using AI models for meal planning, recipe suggestion, and food recognition. The traditional methods of recipe search are text-based, which limit users not knowing the dish name or ingredient. Deep learning architectures, particularly computer vision and natural language processing (NLP) models, can be a solution by enabling the generation of recipes from food images directly.

Vision-based food recognition has traditionally been the preserve of Convolutional Neural Networks (CNNs) [1], which can perform high-quality image classification, object detection, and feature learning. CNN-based models don't perform so well at handling long-range dependencies and require gigantic-scale datasets to generalize. To mitigate these shortcomings, Vision Transformers (ViT) have been introduced, employing self-attention to capture more global context within an image. ViT outperforms CNNs on challenging, multi-ingredient food classification tasks in ingredient detection. This paper proposes an artificial intelligence-driven recipe suggestion module that employs a multimodal [14] deep learning approach to transform food images into formal recipes.

By the integration of deep learning models [3] and NLP models, this work is expected to bridge the gap between automatic recipe generation and food images [6], providing a scalable and effective solution to intelligent cooking applications, personalized meal suggestion, and nutrition counseling. The experimental result confirms that the developed system achieves high accuracy in ingredient detection, recipe title generation, and step-by-step instruction generation, and therefore is an effective solution for modern AI-based cooking applications. It also provides a language translation feature along with a text-to-speech (TTS) feature greatly enhances accessibility since the users can hear cooking instructions read out and change the language.

II. LITERATURE SURVEY

In one of the recent works, Recipe Recommendation Using Image Classification, a new paradigm of recipe recommendation based on user-uploaded food image was introduced [1]. The paradigm employs Convolutional Neural Networks (CNNs) for ingredient image classification and recommending corresponding recipes based on feature learning during training. Personalized recipe recommendation is achieved with the combination of image recognition and content-based filtering. The novelty of the approach lies mainly in the use of a text-to-speech module, which facilitates accessibility with audio support for listening to cooking recipes. The limitation of the paradigm is the requirement of high-quality image data for effective classification, which may not be practical in real applications in case of varying lighting and image conditions.

In a recent paper, a recipe generation system called Inverse Cooking was proposed, which takes food images [2] as input. The system uses cross-modal embeddings to combine image features with step and ingredient textual descriptions. Although it shows excellence in generating high-quality recipes, one of its main limitations is that it fails to work well with complicated or new food compositions.

Another research [3] suggested FoodAI, a deep learning-enabled automatic food image recognition system. It uses CNNs for the classification of foods and the identification of ingredients. The model is effective with general food items but not with foods that are heterogeneous or culturally distinct because of the unavailability of datasets.

Deep-based ingredient recognition was investigated [7], extracting cooking recipes by recognizing ingredients using deep neural networks. While the technique is effective, it relies on having high-quality food image data and is additionally impacted by occluded and overlapping ingredients.

A work suggested a food recommendation system with Generative Adversarial Networks (GANs) [6], in which a vision-based model recognizes ingredients and makes personalized food recommendations. GANs are utilized for improving data diversity and augmentation; however, a significant amount of labeled data is needed for the system to perform optimally.

Additionally, a comparative analysis was performed on multimodal deep learning methods [15] used in food image analysis, e.g., using Vision Transformer (ViT) models for ingredient enhancement and T5 (Text-To-Text Transfer Transformer) [12] for recipe generation. While multimodal learning is shown to have higher accuracy, issues of generalization across diverse food representations arise.

These investigations, in general, provide vital information on food computing, thus our proposed system becomes a better-balanced recipe generation system.

III. PROPOSED SYSTEM

The proposed system aims to convert food recipe image to step-by-step cooking recipe based on advances in deep learning algorithm and natural language processing (NLP). Compared to common text-based recipe recommendation systems, the proposed architecture enables users to construct structured recipes from food images with accurate ingredient extraction and cooking direction creation.

To realize this goal, the system combines three state-of-the-art deep learning models:

- Vision Transformer (ViT) – for food image ingredient recognition.
- Bootstrapping Language-Image Pretraining (BLIP) [13] – for ingredient feature-based image and recipe title generation.
- Text-to-Text Transfer Transformer (T5) [16] – for step-by-step cooking instruction generation based on ingredients identified.

The proposed system overcomes the limitations of traditional recipe recommendation systems through the implementation of a fully automatic, image-based recipe generation system, thus increasing its ease of use, accessibility, and user-friendliness.

IV. METHODOLOGY

The proposed system in this work is based on an organized framework incorporating deep learning models, natural language processing (NLP), text-to-speech (TTS), and language translation methods to generate ingredient identification, recipe generation, instruction generation, and support for multilingual access.

Every module is essential in making food pictures get properly processed, ingredients recognized, recipes created, and instructions being translated into multiple languages.

A. Data Acquisition

The data acquisition module is responsible for collecting, organizing, and preprocessing food image datasets to train and test the model. The dataset is made up of labeled images and the associated ingredients and recipe metadata.

The main dataset employed in this study is Food-101 [9], with labeled images of different dishes. To increase the diversity of food images and the overall ability of the system to generalize, additional recipe information (ingredients, cooking instructions, and nutritional values) is collected from the web.

The data is split into training (70%), validation (15%), and testing (15%) sets for model evaluation. High-resolution images are selected to obtain accurate feature extraction and recognition.

The module gives the system excellent, high-quality input training data for deep learning models.

B. Image Preprocessing

Image preprocessing is an important process that enhances image quality and normalizes input images prior to being fed into the Vision Transformer (ViT) model for feature extraction. The preprocessing steps are:

- Rescaling: Images are resized to a standard size of 224×224 pixels for uniformity.
- Normalization: Pixel intensity values are normalized to between 0 and 1 for better model convergence.
- Data augmentation methods like rotation, flipping, brightness adjustment, and contrast change are used to enhance model robustness and reduce overfitting.

The preprocessing of images is performed using TensorFlow and OpenCV to enhance the images for classification and feature extraction.

C. Feature Extraction

Feature extraction is the core process in the system, wherein deep learning models identify useful features from the pre-processed food images. Unlike traditional Convolutional Neural Networks (CNNs) that are founded on local feature extraction, the research utilizes Vision Transformers (ViT), which leverage the use of self-attention mechanisms in identifying global dependencies in an image.

- The ViT model divides the input image into segments and converts them into feature vectors.
- Self-attention mechanisms inspect the spatial context between various image elements, refining ingredient recognition accuracy.

These generated feature vectors are then used as input by the recipe recommendation and generation modules. The use of the ViT model replaces that of typical CNNs based on its enhanced classification accuracy on substances that are hard to identify in foods containing more than one element.

D. Image Recognition & Recipe Recommendation

After feature extraction, the image recognition and recommendation module matches detected ingredients with a recipe database to suggest relevant cooking guides. This is achieved through:

1. Ingredient Identification with ViT
   - These feature vectors that are extracted are processed to classify the top ingredients present in the image.
   - The approach utilizes a pre-trained ViT model, a food categorization dataset that is fine-tuned, to identify multiple substances at once.

2. BLIP (Bootstrapping Language-Image Pretraining) Recipe Title Generation
   - The BLIP method [15] generates a contextually appropriate recipe title as a function of the elements present.
   - The model combines visual and textual embeddings to ensure precise recipe labeling.

3. Generation of Cooking Instructions Utilizing the T5 Transformer
   - Upon identifying the components and title, the T5 transformer model [16] produces sequential cooking directions.
   - The T5 model processes ingredient lists and transforms them into meaningful, structured cooking instructions.
   - The outcome is a coherent and comprehensible, systematically arranged recipe that enhances the user experience.
   - The amalgamation of ViT, BLIP, and T5 guarantees the generation of very precise and formalized culinary recipes.

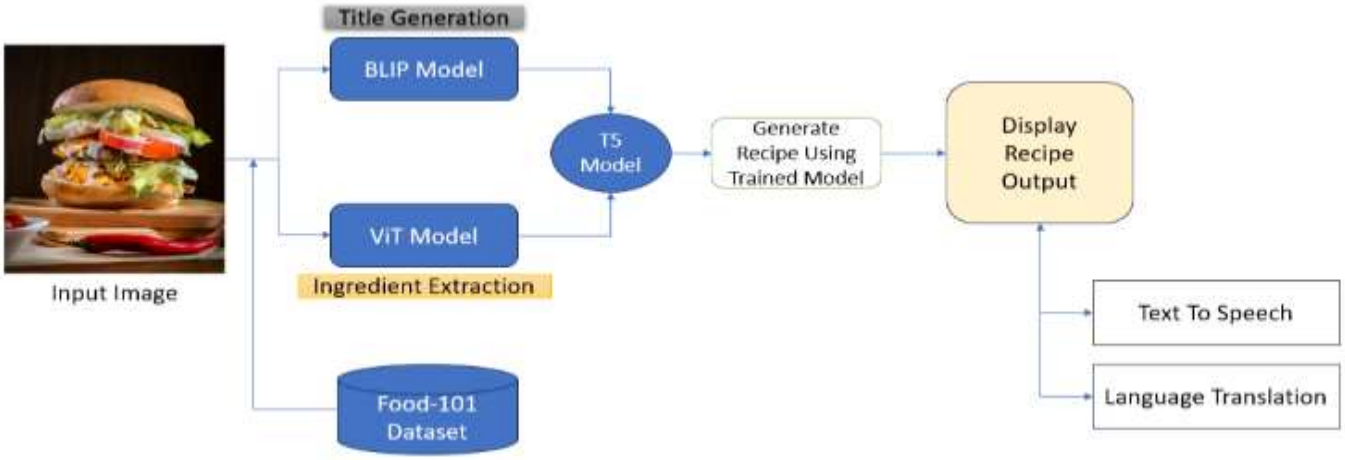

Fig. 1. System Architecture

E. Text-to-Speech (TTS) Module

The system has a text-to-speech (TTS) module to be more accessible and convenient for the users. It enables users to hear the recipe's instructions rather than reading them.

- The TTS or Text-to-Speech API is used for the transformation of the text generated into speech that can be heard.
- Users can personalize volume, speed, and language to their comfort.
- The TTS module increases accessibility for users with visual impairments and offers an enhanced interactive cooking experience.

F. Language Translation Module

A language translation module, where users can translate recipe instructions into various languages, is incorporated into the system to enable it to be used by a global audience.

- Real-time translation is done using the Language Translate API.
- The system will enable the user to manually choose the user's preferred language.
- Users can switch between different languages in the interface to view recipes in their native language.
- The translated content is synchronized with the TTS module, and users can listen to instructions in the language of their choice.

The feature provides greater accessibility for non-English speaking users, increasing the system's inclusivity and global adaptability.

V. RESULTS

Fig. 2. User Interface (Home Page)

Fig. 3. Registration Interface

Fig. 4. Login Interface

Fig. 5. Main Page Interface

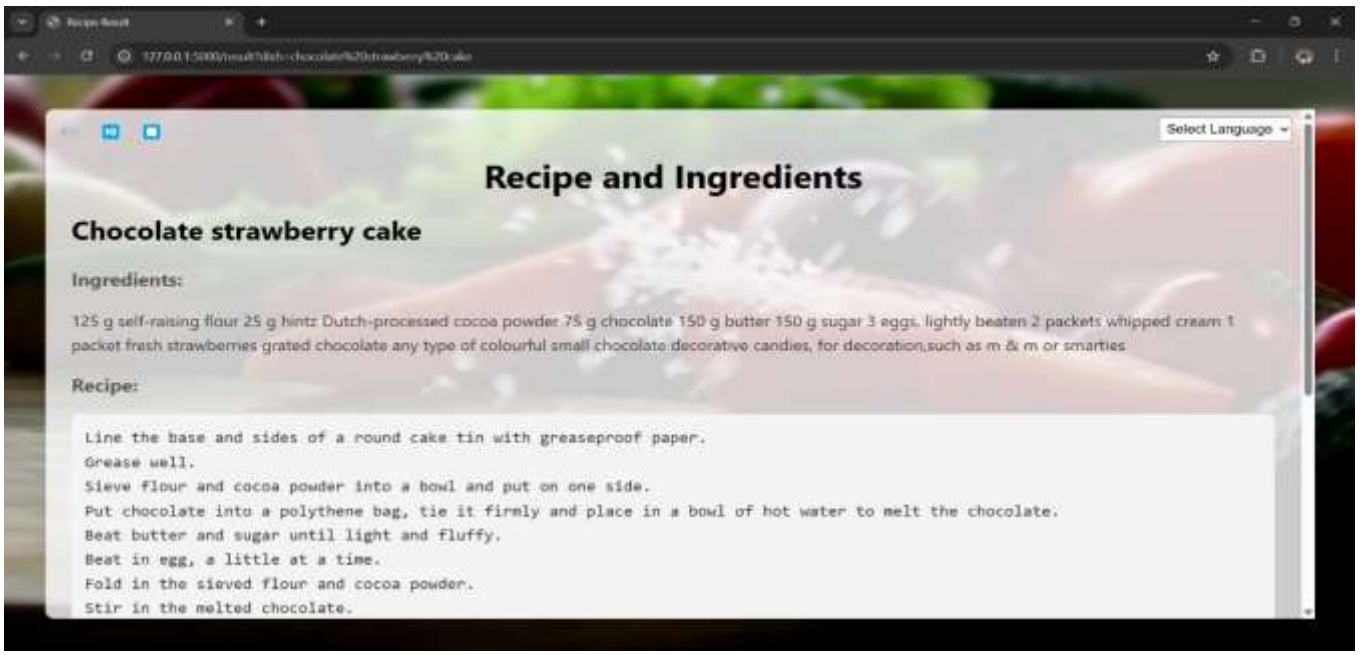

Fig. 6. Result Page Interface - I

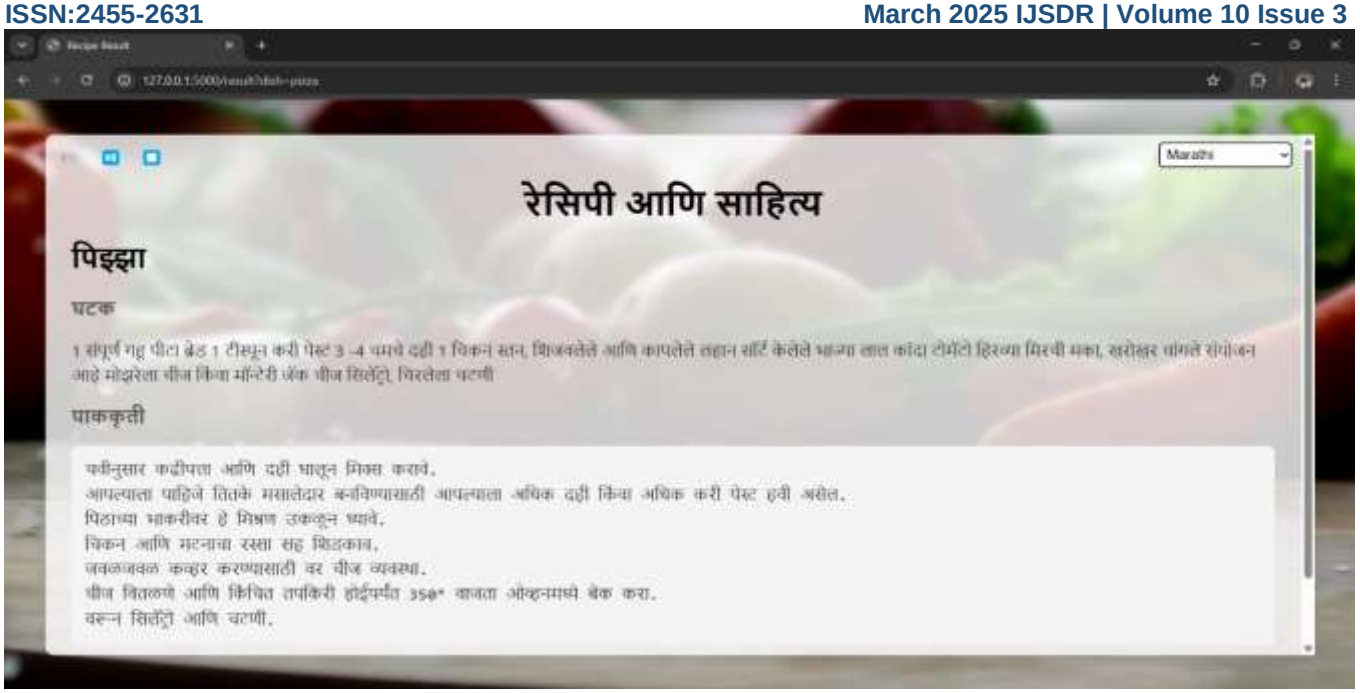

Fig. 7. Result Page Interface - II

VI. CONCLUSION

This method prescribes a multimodal deep learning model for automatic recipe generation from food images. With the application of Vision Transformer (ViT) for ingredient detection, BLIP for recipe title generation, and T5 for formal cooking directions, the proposed system overcomes the shortcomings of current recipe recommendation models.

Addition of content-based filtering for substitute ingredients and the incorporation of a Text-to-Speech module guarantee the system is usable, easy to use, and flexible. The experimental findings corroborate the system's very high accuracy and usability, indicating a promising AI solution for intelligent cooking and personal recommendation of meals.

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VIII. REFERENCES

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