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Nutritional Optimization: Recipe Creation for Dietary Restrictions

Shobha K[1] and Rajashekhara S[2]
[1]Amity University/Amity School of Engineering & Technology, Bengaluru, India
Email: shobhak@blr.amity.edu
[2]Siddaganga Institute of Technology /Department of Chemical Engineering, Tumakuru, India
Email: rs@sit.ac.in

***Abstract*— The prevailing systems exhibit flaws in accurately generating Indian food recipes and there calories and nutritional facts, indicating a notable limitation. To mitigate these flaws, a sophisticated machine learning-powered cooking recipe generator and nutritional fact checker is proposed. This generator prioritizes users diverse dietary preferences and food choices, with a specific focus on Indian cuisine. The primary objectives entail developing a robust machine learning model capable of comprehensively analyzing food images to generate detailed and customized recipes. The goal is to transform culinary experiences to visually impaired by automating recipe creation through the analysis of provided food images. The model assimilate essential additional features to become a comprehensive culinary tool by including nutritional facts alongside recipes. Furthermore, proposed method aims to seamlessly integrate with online video sharing platform YouTube, offering personalized video recommendations to magnify user experiences. Moreover, emphasis is placed on cultural sensitivity by accurately identifying and classifying vegetarian and non-vegetarian dishes. This empowers users to plan their meals ahead. Proposed model has demonstrated an accuracy of nearly 75% compared to existing models ResNet (43%) and Inception v3 (52%), emphasizing its superiority in predicting Indian food recipes.**

***Index Terms*— Cooking Recipe Generator, Deep Learning, Dietary Preferences, Cultural Inclinations, Personalized Diet Plans, Culinary Experience, Nutritional Balance, Vegetarian Dishes.**

I. INTRODUCTION

India has the largest population of vegetarians globally, with 40% of Asian Indians following a vegetarian diet. There is a notable ”nutrition transition” occurring among vegetarians in India, with a shift towards lower consumption of whole plant foods and an increase in refined carbohydrates, fried foods, and processed foods. This transition highlights the significance of comprehending the relationship between diet and health, especially within the framework of vegetarian diets.
Health is a significant factor driving the adoption of vegetarian food among non-vegetarians. The contemporary culinary landscape is evolving, with an increasing emphasis on personalized and diverse gastronomic experiences. In response to the rising need for personalized culinary solutions, by harnessing the capabilities of artificial intelligence, this endeavor seeks to redefine how individuals engage with cooking [4].

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Food computing utilizes technology for food-related studies, including the acquisition and analysis of Indian food datasets. This analysis involves computer vision, machine learning, data mining, and other modern technologies to bridge the gap between technology and food, supporting human-centric services such as understanding human culture, guiding human behavior, and improving human health. In this context, frequently utilised data for the classification and prediction of Indian food diets are introduced, providing an overview and comparison of datasets used in existing food studies [5].

Through the amalgamation of technology as well as gastronomy, food computing aims to open doors for a fresh era in culinary innovation, offering users a personalized and nutritionally informed culinary expedition[7].

Considering the importance of technology in food computing the objective of this work is to develop an intelligent system capable of interpreting food images, and understanding dietary preferences to curate personalized and engaging recipes. At its core, our design posits individual tastes and dietary requirements. Utilizing machine learning techniques like VGG16 (Visual Geometry Group16) and sophisticated image analysis techniques like feature extraction, object detection, texture analysis, the system places paramount importance on ensuring the nutritional balance of the resultant dishes, fostering not just delightful but also health-conscious culinary experiences by giving the approximate calories for the recipe [13].

Beyond merely generating recipes, the envisioned system integrates seamlessly with YouTube, providing users with personalized video recommendations to augment their culinary journey. Moreover, it highlights the significance of cultural sensitivity by adeptly discerning between vegetarian and non-vegetarian dishes, empowering users, particularly vegetarians, to make informed dietary choices. The motivation springs from a desire to empower individuals to embark on culinary adventures with confidence and ease, simultaneously encouraging better ways of living through nutritional awareness. Driven by the belief that by enhancing the cooking experience and incorporating calorie counting, one can contribute to the well-being of users holistically.

A. Background Study

In recent years, the food recipe generation field has made great progress, thanks to the incorporation of natural language processing and machine learning techniques. An extensive review of literature was carried out using articles from well-known publishers like IEEE, HDSR, Springer, and more, to investigate the most recent advancements and trends in this field. Automated generation of cooking recipes from natural language texts and food images has been a major area of focus in these studies. Scientists have investigated different methods, like employing CNNs and Transformers, to create correct recipes and resonate with users' dietary choices and cultural heritage.

Teodor Stoev et al. have worked on automatically generating special models from written texts which is fascinating, especially in its similarity to recipe generation. Just as recipes combine different ingredients and steps to create a dish, this tool combines different types of information to create models. This approach could be particularly useful in the context of recipe generation, where creating models manually can be time consuming. By automating the process, researchers and developers can save time and focus on other aspects of their projects [1].

Yifan Salvador et al. have explored learning structural representations for lengthy recipes. The study involved unsupervised learning of sentence-level tree structures for lengthy cooking recipes. It addresses challenges in food cross-modal retrieval with mixed ingredient images. The novel approach includes unsupervised learning of tree structure labels, generating trees from images, and integration into recipe generation and food cross-modal retrieval in [2].

G. N. R. Prasad et al. have presented Swasth, creating recipes by starting with food images rather than traditional ingredients and directions. This utilizes CNN and deep learning, which have been thoroughly tested on the extensive Recipe 1 million dataset. The unique layout foresees components as sets, show casing their relationships without needing a specific order [3].

Cooking recipe generation based on ingredients using ViT5 is proposed by Minh Duc Nguyen et al. This study aims to make cooking easier and more convenient by recommending classic recipes from the database or generating new recipes using the ViT5 model. The model is fine-tuned on the CookyVN-recipe dataset, achieving competitive ROUGE-1, ROUGE-2, and ROUGE-L scores [4].

Sequential learning with cooking logic for identifying ingredients in food photos is explored by Mengyang Zhang et al [5]. The article presents techniques including visual feature maximization, Bi-LSTM for sequential ingredient generation, and reinforcement learning for guided generation inspired by cooking logic.

A mixture of loss used for optimizing ingredients. Reinforcement learning for creating logic-based recipes is discussed by Meng Xia, Reshika Palaniyappan Velumani, Yong Wang, Huamin Qu [6]. The article presents a hierarchical attention mechanism to efficiently extract features in ingredient production and recipe generation.

The idea of creating ingredients is suggested as an intermediary step in assisting recipe generation within a reinforcement learning framework.

Data engineering challenges in intelligent food and cooking recipes are the focus of Frederic Andres [7] .The article discusses difficulties with gathering, purifying, combining, and managing data, highlighting the importance of utilizing machine learning techniques and big data analysis for creating meal plans and finding recipes.

The advanced mobile application Cheer Up is introduced by Ahfuzulhoq Chowdhury et al [8]. This app offers chef-picked dishes, a recipe finder, and chef support services for the people of Bangladesh. It involves choosing a chef based on factors like cost, reputation, and skills, as well as functions such as applying for a chef job, confirming the selected chef, reporting misbehavior, leaving a review, and rating the chef.

A framework for creating cooking recipes using reinforcement learning techniques is presented by Jumpei Fujita et al. The paper introduces a cooking recipe generation model using reinforcement learning, with an emphasis on the application of reinforcement learning techniques in the encoder-decoder framework [9].

Ratatouille, a web-based application for novel recipe generation, is discussed by Mansi Goel et al. The article discusses the issue of creating new recipes through the use of advanced deep learning models such as LSTMs and GPT-2. It also introduces Ratatouille as a web application for generating fresh recipes [10].

The text introduces an examination of Japanese cooking recipes and the development of motion planning for a cooking robot is presented by Masahiro Inagawa et al. The paper introduces a method enabling cooking robots to operate autonomously, analyzing recipes without the need for recipe-specific programming. It addresses challenges posed by varied expressions in recipes and implements a word-classification system for standardized information extraction [11].

Visualization of texture expressions for recipes using reviews is the focus of Kento Shigyo et al [12]. The paper discusses the extraction and aggregation of texture terms from a large number of reviews for recipe representation, aiming to propose a visualization method allowing users to intuitively imagine the result of their cooking by following the recipes.

Existing recipe generation systems, despite of their advancements, often overlook specific cuisines, calorie tracking, and the popularity of video-based recipe learning on platforms like YouTube. To tackle these limitations this work proposes a novel approach by focusing on Indian cuisine, integrating calorie tracking functionalities, and exploring potential connections with YouTube recommendations.

III. Proposed Method

The proposed model works in numerous stages to recognize, generate and to pick out the nutritional facts of the chosen dish. The sequence of steps are detailed below:

A. Data Collection and Preprocessing:

This is the first stage of the proposed model, which focus on collection of diverse culinary datasets to train the proposed model, to ensure that the model apprehend the diversity of recipes, the large datasets are included. This makes the model to learn the necessary information and to learn the complexities of different cuisines and their cooking styles.

As a part of preprocessing phase the images are preprocessed by resizing, normalizing, and applying augmentation techniques. Additionally, the textual recipes are converted into a structured format for easier and faster processing. To make the model learn diversity of recipes, it is trained with numerous large datasets like Food101 dataset, (https://www.kaggle.com/datasets/dansecker/food-101), the Indian food image dataset (https://www.kaggle.com/datasets/iamouravbaerjee/), and the Food20 dataset (https://www.kaggle.com/datasets/cdart99/food20dataset).

B. Model Architecture and Training

This is the second phase in the proposed work, in this phase encoding and decoding of images are done to identify and to generate cooking recipes. The Proposed method exploits VGG-16 Convolutional Neural Network (CNN) architecture for image encoding to ensure higher accuracy. The Instruction Decoder components of the model have been designed accordingly and it has been fine-tuned to enhance the performance. To effectively leverage both image and textual data multimodal training strategies have been administered. The trained VGG-16 Image Encoder will be utilized to process food images, followed by the generation of cooking instructions using the Instruction Decoder.

C. Evaluation

This work aims to assess the model's performance by measuring instruction accuracy and coherence. The model's effectiveness are analyzed against ground truth data and empirical results of the proposed method. Additionally, the model's training time and resource requirements are considered for model evaluation.

Fine-tuning and Iteration: User studies are conducted to assess the system's practicality and usability in real-world cooking scenarios. The model is continuously well propagated based on user feedback and evaluation results, with a focus on improving overall performance iteratively.

Testing and Validation: Meticulous testing of the recipe generation model is conducted using a separate validation dataset. The model's performance is evaluated based on predefined metrics, and necessary adjustments are made to improve its performance.

Fig.1. shows the data flow diagram of the proposed model. The proposed model takes food images as input and that images are further preprocessed and sent to the neural network model VGG-16.

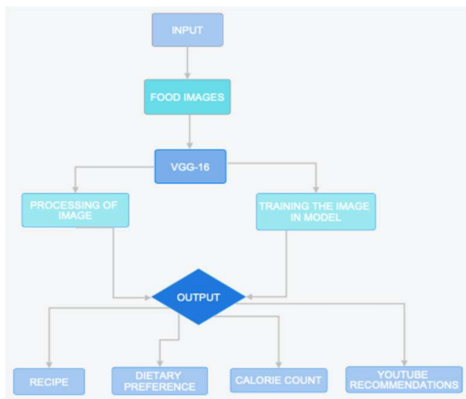

Fig. 1: Data Flow of the proposed system

In the model, the processing of images and the training of images takes place. The work aims for the output as steps of the recipe, the dietary preference which is vegetarian and non-vegetarian, the calorific value of the recipe, and YouTube recommendation for the recipe generated.

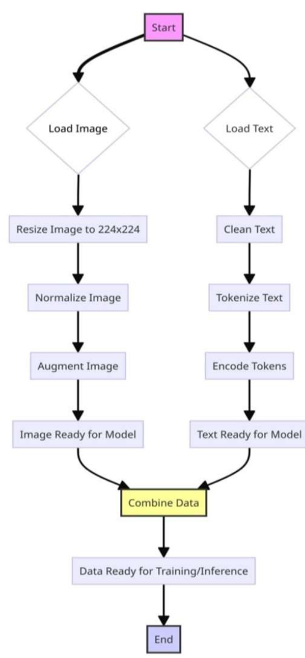

Fig. 2: Design of Data Pre-processing

Fig. 2 delineates the successive stages involved in data pre-processing for the cooking recipe generation system. Commencing with both image and text data, the diagram elucidates a series of transformations. Image data is subjected to resizing, standardizing it to dimensions of 224x224 pixels, followed by normalization to ensure uniform pixel values across the dataset. Additionally, an optional augmentation step is depicted, offering a means to diversify the dataset. Concurrently, text data undergoes cleansing to eliminate superfluous characters and formatting irregularities, succeeded by tokenization, segmenting the text into discrete units such as words or phrases. These tokens are subsequently encoded into numerical representations conducive to model comprehension.

Upon completion of these preparatory steps, the image and text data are combined to form an integrated dataset primed for training tasks.

IV. EXPERIMENTAL RESULTS

The proposed technique focuses on both Indian and foreign culinary tastes, in contrast to previous efforts that mostly focused on international food. This gives consumers a wide range of recipe generating choices.

The system is designed to adapt to changing circumstances in order to provide a smooth user experience. It prioritizes responsiveness and speed in order to provide recipes quickly.

To create recipes for the Indian food dataset, the VGG-16 model is fine tuned. The suggested method works better than previous models like ResNet- 50 and InceptionV3, with a greater accuracy and a shorter training time. The recommended approach has accomplished the aim with a target response time of less than three seconds.

The suggested system automatically modifies resources as needed to meet different user demand levels.

To provide seamless and intuitive experience for users the UI of this work is designed to search and explore culinary content. An overview of the key components are explained in below section.

A. Interactive Image Upload Feature

Fig.3. shows an interactive landing page of a website where Users can easily upload images, presumably related to food. The landing page serves as the entry point for users to interact with the websites content. On this page users can upload images related to food to get the details of recipe and its nutritional facts.

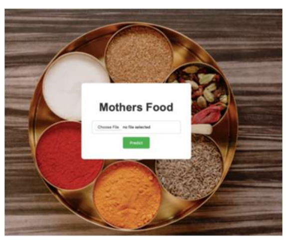

Fig. 3: User Interface for Image upload

Fig. 4: Name of the Recipe Predicted by the Model

B. Recipe Display and Calorie Information:

Fig. 4. displays the name of the recipe that has been predicted by the model based on the uploaded image. This page will be the results page after uploading an image. The content of this page will be the name of the recipe and Fig. 5. shows the information about the calorie content of the dish. This page outcome helps users to make informed decisions about their dietary choices.

Fig. 5: Detailed Steps of How to Make Recipe

C. YouTube Video Recommendations

The proposed work also aims at recommending the YouTube videos related to the uploaded food image. Fig. 6. Presents a snapshot of top five videos in connection to the predicted recipe. These recommended videos provides a value added service by providing add on visual and auditory content to complement the recipe instructions.

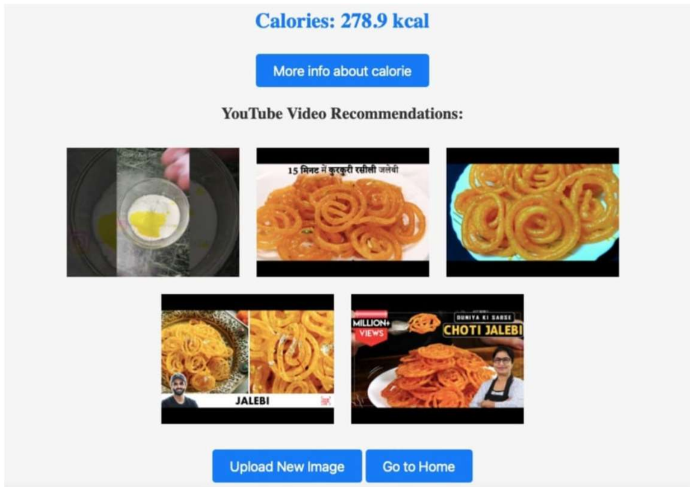

Fig. 6: YouTube Video Recommendations

Users are given comprehensive instructions on how to produce the recipe that the model has predicted in Fig. 5. It ensures that consumers have clear directions to follow by providing a thorough list of components and a step-by-step approach. Even for inexperienced cooks, this feature aims to make it simpler for consumers to replicate the recipe at home. A comprehensive and user-friendly guide improves the user experience and encourages users to experiment with different recipes and culinary creations.

Fig.7. provides users with detailed nutritional values of the food item predicted by the model, including information such as calories, protein, carbohydrates, fats, vitamins, and minerals. Additionally, it offers a guide on the steps needed to burn off the calories consumed from the food item. This information is crucial for users who are conscious about their diet and health, as it allows them to make informed decisions about their food choices and understand the impact of their dietary intake on their overall health and fitness goals.

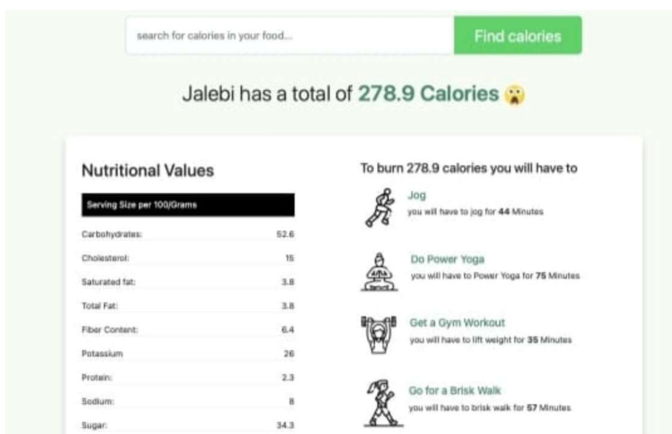

Fig. 7: Detailed Nutritional Values

Fig.8 depicts the comparison of accuracy and loss over epochs. This visualization provides insights into how the models accuracy and loss evolve during the training process. The accuracy over epochs curve shows the models performance in correctly predicting outcomes, while the loss over epochs curve indicates the models convergence and the extent of its errors. Analyzing these curves helps in understanding the models learning behavior and optimizing its training process for better performance.

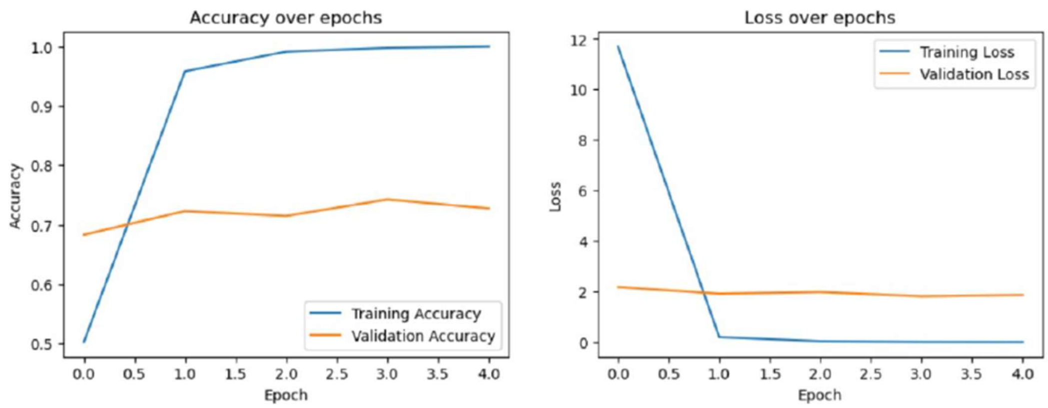

Fig. 8: Comparison of accuracy over epochs and loss over epochs

As the number of epochs increases, the training time also tends to increase. This is because each epoch involves iterating over the entire dataset to update the models parameters. With more epochs, the model undergoes more iterations, leading to longer training times. However, it's essential to balance the number of epochs to avoid overfitting, where the model learns the training data too well and performs poorly on unseen data. Training time is a critical factor in model development, as it impacts the time and resources required to train the model effectively.

Fig.9. provides a comparison of the training times for different models, including VGG16, ResNet50, Xception, MobileNet, and DenseNet121. By comparing the training times of these models, researchers and practitioners can gain insights into their efficiency and suitability for various tasks. This comparison will help in selecting the most appropriate model based on the available resources and the specific requirements of the work.

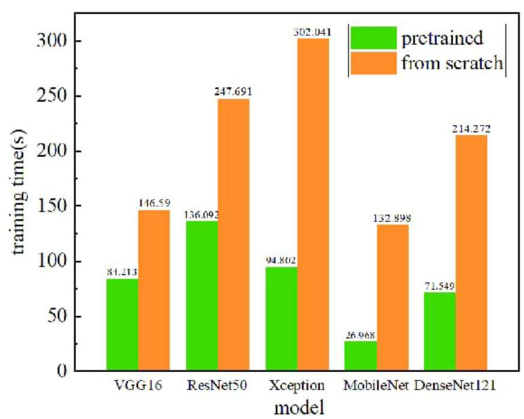

Fig. 9: Comparison of accuracy over epochs and loss over epochs

V. CONCLUSION AND FUTURE SCOPE

This study introduces an advanced machine learning system for generating recipes, focusing on Indian and international cuisines. By addressing limitations like lack of personalization and ingredient diversity in existing systems, this model enhances user experience through personalized recipes, tailored to dietary needs.

The system employs convolutional neural networks (CNNs) for food image analysis, offering features such as calorie counts and YouTube integration for personalized video tutorials. It promotes healthier eating habits by providing nutritional information and empowering users, especially vegetarians, to make informed dietary choices.

With an accuracy rate of nearly 75%, outperforming existing models, this system revolutionizes culinary experiences. It not only generates recipes but also highlights the potential for expanding to more cuisines and incorporating real-time feedback for future improvements.

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