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EfficientNetB0-Based Food Image Recognition for a Smart Diet Tracking Application

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Abstract
Food image recognition is an important component of smart diet tracking systems. Existing approaches often rely on benchmark datasets dominated by Western cuisines and lack real-world deployment. This paper presents an EfficientNetB0-based food recognition system focused on South Indian cuisine using a custom dataset of approximately 8,000 images across 30 food categories. Data augmentation techniques are applied to improve generalization and address class imbalance during training. The proposed model achieves a validation accuracy of about 84% for single food item classification. To demonstrate practical applicability, the trained model is integrated into an Android-based diet tracking application that enables food identification and basic nutritional estimation. The results highlight the feasibility of an end-to-end, region-specific food recognition solution for real-world dietary monitoring and smart health management.

Keywords: Food Recognition, EfficientNetB0, Deep Learning, South Indian Cuisine, Diet Tracking, Calories Estimation.

I. INTRODUCTION

Diet-related health issues such as obesity, diabetes, and cardiovascular diseases have increased significantly in recent years, making diet tracking applications an essential tool for monitoring daily food intake and nutritional balance. Traditional diet tracking methods rely heavily on manual food logging, which is time- consuming, inconvenient, and prone to inaccuracies due to incorrect food identification and portion estimation. As a result, automated food recognition systems are needed to reduce user effort and improve the accuracy of dietary monitoring.

Automatic food recognition using computer vision techniques has gained significant attention in recent years. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in image classification tasks by automatically learning hierarchical visual features from images. This capability makes CNNs suitable for recognizing complex food items and enables the development of intelligent systems for dietary assessment and monitoring.

Despite these advancements, food image recognition remains a challenging task due to high intra-class variation, visual similarity between different dishes, and variations in preparation and presentation styles. In addition, most existing food recognition studies focus on Western or globally mixed cuisines, while region-specific cuisines such as South Indian food remain underrepresented in current research. This limitation reduces the effectiveness of existing models in real-world applications where regional food diversity plays a significant role.

Unlike existing studies that mainly use benchmark datasets such as Food-101, this work focuses on region- specific South Indian cuisine and demonstrates real-world deployment through an Android-based smart diet tracking application. The proposed system integrates food recognition with portion-based calorie and macronutrient estimation, providing a practical end-to-end solution that combines deep learning, computer vision, and mobile health technology for effective dietary monitoring.

The main contributions of this work are as follows:

- Development of a custom South Indian food image dataset consisting of 30 food categories to address the lack of region-specific datasets.
- Design and implementation of an EfficientNetB0-based food recognition model using transfer learning for accurate and efficient classification.
- Application of data augmentation techniques to handle dataset imbalance and improve model generalization.
- Integration of the trained model into an Android-based smart diet tracking application for real-time food recognition.
- Implementation of portion-based calorie and macronutrient estimation for practical nutritional monitoring.

II. Related Work

Early food recognition approaches relied on handcrafted features such as color histograms, texture descriptors, and shape-based representations combined with traditional machine learning classifiers. Although these methods demonstrated initial feasibility, their performance was limited due to the high visual complexity and variability of food images, which made accurate classification difficult in real-world conditions.

With the advancement of deep learning, CNN-based food recognition systems became the dominant approach. Several studies employed pretrained architectures such as VGGNet, ResNet, and Inception using transfer learning to improve classification accuracy and reduce training time [2], [4], [7]. These models automatically learn hierarchical image features and have shown significant improvements over traditional methods, establishing CNNs as effective tools for food image classification.

More recently, EfficientNet architectures introduced compound scaling strategies that balance network depth, width, and input resolution to achieve better performance with fewer parameters [12]. EfficientNet- based approaches have demonstrated high accuracy and computational efficiency, making them suitable for mobile and resource-constrained environments [5], [2]. Due to these advantages, EfficientNet models are increasingly adopted in food recognition and dietary assessment applications.

Despite these advancements, many existing studies rely on publicly available benchmark datasets that are dominated by Western cuisines and do not adequately represent region-specific food variations [3], [6]. In addition, several works focus mainly on model accuracy without considering practical deployment aspects such as mobile integration and user interaction. To address these limitations, this work focuses on South Indian food recognition and demonstrates end-to-end deployment in an Android-based smart diet tracking application.

III. Proposed System

The proposed system consists of two major components: a food image classification model and a smart diet tracking application. The system is designed to recognize a single dominant food item present in an input image and provide nutritional information to the user.

A. System Overview

The overall workflow of the proposed system includes:

- Image acquisition using the mobile application.
- Image preprocessing and resizing.
- Feature extraction and classification using EfficientNetB0.
- Food label prediction.
- User-selected portion size input.
- Calorie and macronutrient estimation.

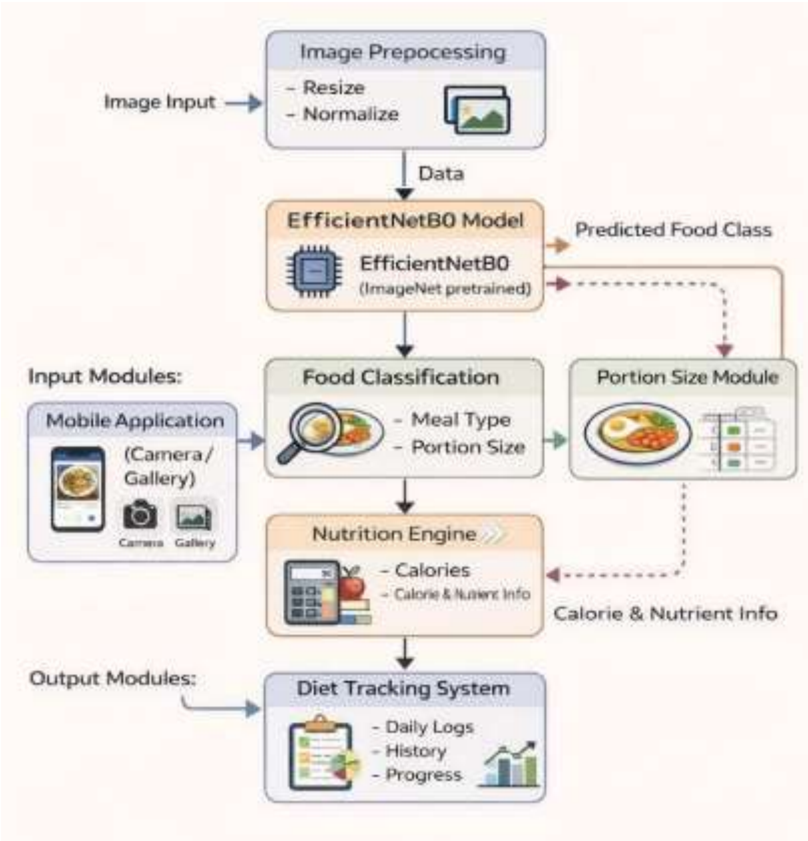


Fig. 1. Overall architecture of the proposed EfficientNetB0-based food recognition and diet tracking system.

IV. Dataset Preparation and Preprocessing

A. Dataset Collection

A custom dataset was created by collecting images of South Indian food items from publicly available online sources and for academic and research purposes. The dataset consists of approximately 8,000 images across 30 distinct food categories, representing a wide range of commonly consumed South Indian dishes such as Biryani, Dosa, Idli, Vada, Samosa, Upma, Pulihora, and several curry-based and snack items. Each image contains a single dominant **food** item, ensuring that the classification task focuses on single-food recognition rather than multi-object detection.

During the data collection process, all images were manually reviewed and curated. Images exhibiting poor visual quality, excessive background clutter, watermarks, or irrelevant content were removed to maintain dataset reliability. The final dataset includes variations in illumination, viewing angles, portion presentation, and background conditions, reflecting real-world scenarios encountered in mobile-based food image capture. Such diversity is essential for improving the robustness and generalization capability of the proposed deep learning model.

Furthermore, the number of images per class varied across food categories, resulting in a moderate level of class imbalance. To mitigate this issue, appropriate data augmentation techniques were later applied during the training phase. Table I summarizes the distribution of images across selected South Indian food categories used in this study.

Table 1. Distribution of images across South Indian food categories.

Food Category	Number of images
Dosa	481
Idli	310
Chicken_65	231
Pulihora	202
Sambhar_Rice	206
Curd_Rice	223
Egg_Curry	201
Fish_Curry	245
Brinjal_Curry	212
Biryani	289
Halwa	317
Paneer_Curry	334

The remaining food categories contain a comparable number of images, resulting in an overall dataset size of approximately 8,000 images across 30 classes.

B. Preprocessing and Data Augmentation

All images were resized to 224 × 224 pixels to match the input requirements of EfficientNetB0. Pixel values were normalized to improve training stability. To address class imbalance and improve generalization, data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness variation were applied.

C. Dataset Splitting

The dataset was divided into training and validation sets using an 80:20 ratio to evaluate model performance.

Fig. 2. Sample images from the custom South Indian food dataset.

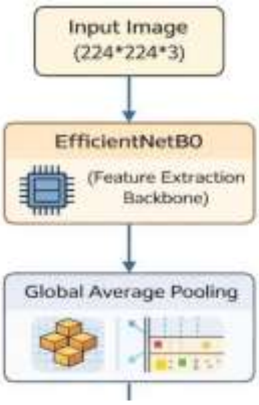
V. Model architecture and training

A. Model Architecture

The proposed model is based on EfficientNetB0 using a transfer learning approach. The architecture consists of:

- Input layer
- EfficientNetB0 base model pretrained on ImageNet
- Global Average Pooling 2D layer
- Dropout layer to reduce overfitting
- Fully connected Dense layer
- Softmax output layer for 30-class classification

Following this architecture, the pretrained EfficientNetB0 model serves as the core feature extraction network, while the subsequent layers refine the learned representations for the target task. The Global Average Pooling layer reduces feature dimensionality, and the Dropout layer enhances model generalization by minimizing overfitting. The final Dense layer, coupled with the Softmax activation, produces the prediction for a single food item among the predefined classes. The overall structure of the proposed model is illustrated in the architecture diagram below.



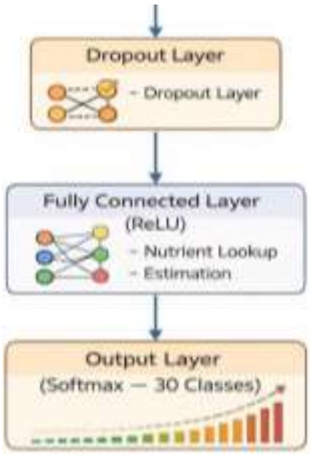


Fig. 3. Architecture of the EfficientNetB0-based food recognition model.

B. Training Configuration

The model was implemented using TensorFlow and Keras and trained using the Adam optimizer with categorical cross-entropy loss. Training was performed for 30 epochs with a batch size of 32 and a learning rate of 0.001. All experiments were conducted on Google Colab with GPU support, and model performance was evaluated using classification accuracy, precision, recall, F1-score, and a confusion matrix.

VI. Results and discussions

The trained model achieved a validation accuracy of approximately 84%, with training and validation curves indicating stable convergence and minimal overfitting. Model performance was further assessed using precision, recall, F1-score, and a confusion matrix to analyze class-wise predictions.

The results show that EfficientNetB0 effectively captures discriminative visual features across South Indian food categories while maintaining computational efficiency, making it suitable for mobile-based diet tracking applications.

The confusion matrix indicates that visually similar food categories such as dosa and uthappam occasionally produce misclassifications, while distinct items such as biryani and samosa achieve higher accuracy. These results demonstrate the robustness of EfficientNetB0 for region-specific food classification.

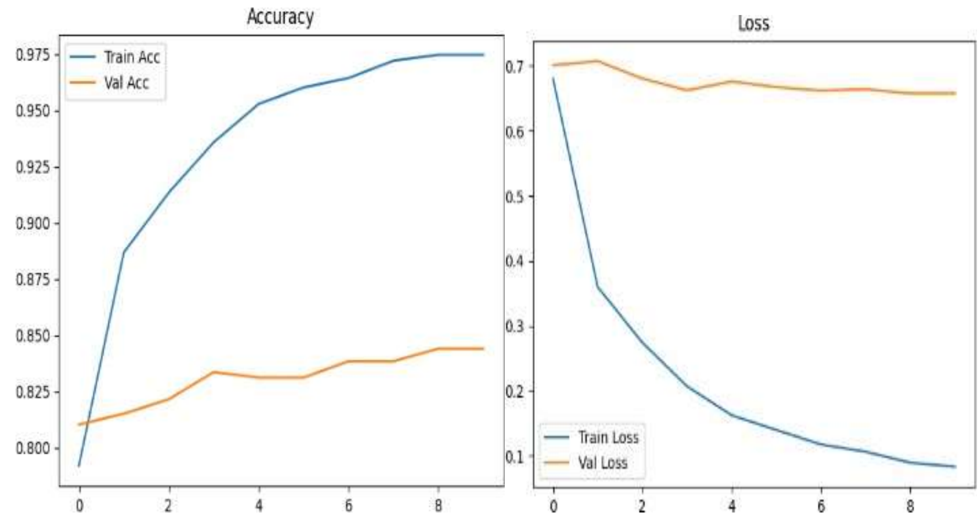


Fig. 4. Training and validation accuracy and loss curves

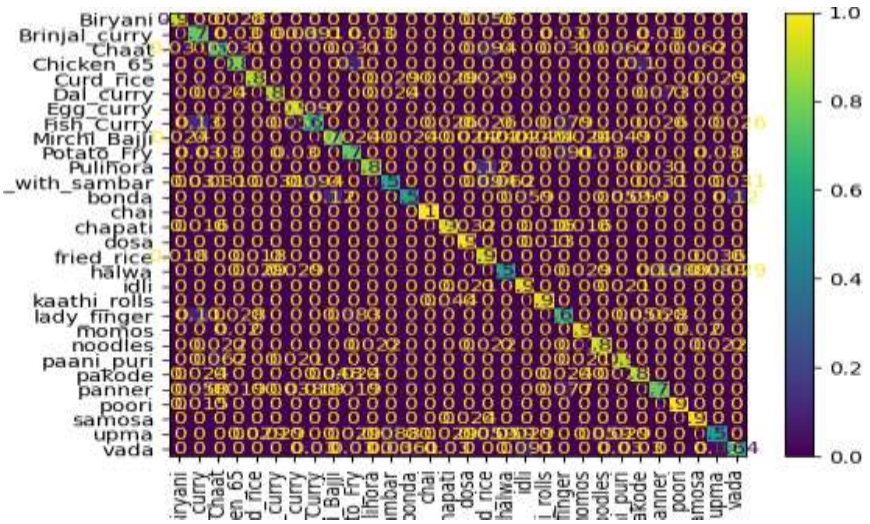


Fig. 5. Normalized Confusion matrix of the proposed food recognition model

VII. APPLICATION INTEGRATION

The trained food recognition model was integrated into a smart diet tracking Android application to enable real-time food identification and nutritional monitoring. The TensorFlow Lite version of the EfficientNetB0 model is deployed in the Android environment, allowing efficient on-device inference with low latency and reduced computational overhead. The application provides a user-friendly interface where users can capture food images using the camera or upload images from the gallery, which are then processed by the model to identify the food item accurately.

The system is designed to recognize a single dominant food item per image and display the predicted food label to the user. After recognition, portion size estimation is performed through user selection among predefined options such as ½ (50g), 1 (100g), and 1.5 (150g). Based on the selected portion size, the system calculates calorie and macronutrient values including carbohydrates, proteins, and fats using a predefined nutritional database. The application also maintains daily calorie targets, tracks food intake history, and provides personalized dietary recommendations to support healthy eating habits. This integration demonstrates the practical usability of the proposed food recognition model in a real-world mobile health monitoring system.

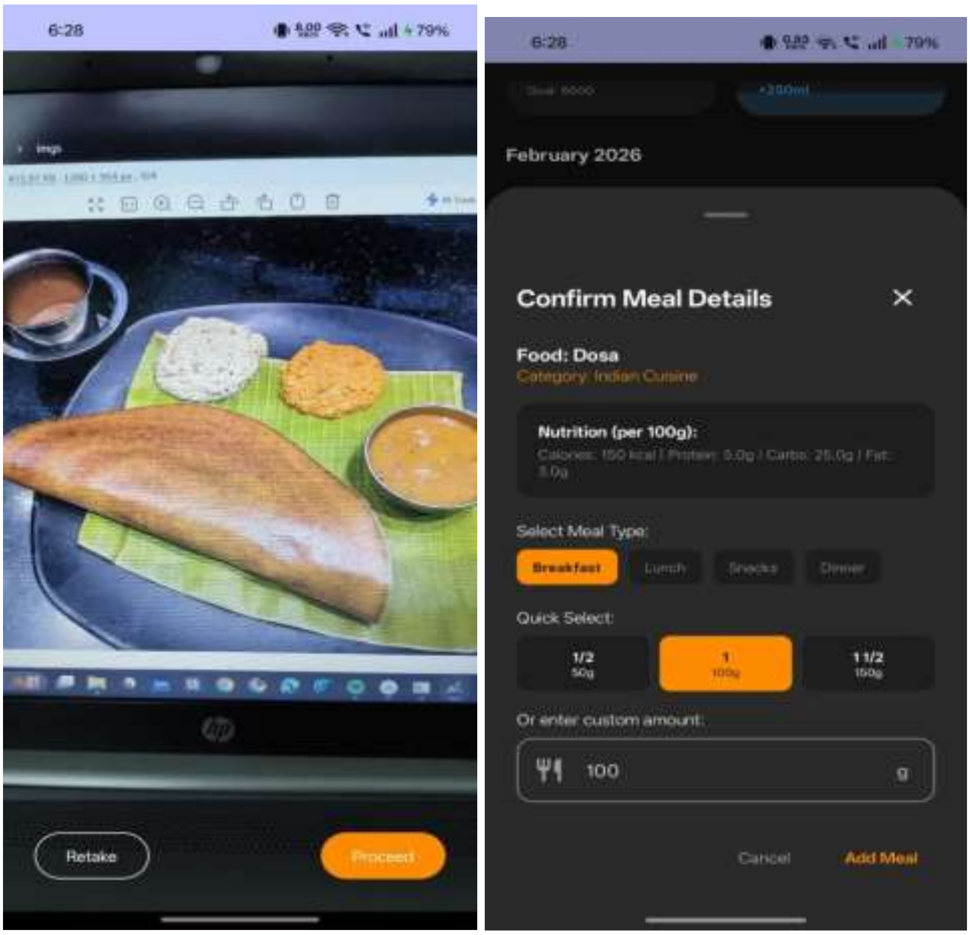


Fig. 6. Food recognition result displayed in the smart diet tracking application.

VIII. CONCLUSION

This paper presented a deep learning-based food recognition system using EfficientNetB0 for South Indian cuisine. A custom dataset of 30 food categories was created, and class imbalance was addressed using data augmentation. The proposed model achieved approximately 84% validation accuracy and was successfully integrated into a smart diet tracking application.

Future work includes expanding the dataset with additional food categories, improving recognition accuracy, and enhancing nutritional estimation and personalization features.

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