

Comparative Analysis of Computational Paradigms in Food Recognition and Classification

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Abstract:- This paper compares three different methods of image classification of food, with an aim to improve the performance of the system by improving its accuracy and efficiency as well as make it more applicable. In this research, innovations that have been made through the use of PyTorch and Predictive Recurrent Neural Network (PReNet) for a massive database are considered, with an emphasis on Indian cuisine. Another approach that has been considered is the application of the EfficientNet-Lite method on mobiles to detect traditional dishes from Indonesia, with high levels of accuracy despite using less resourceful means. Transfer learning with the aid of pre-trained Convolutional Neural Networks (CNNs) to classify Indian foods and conduct nutritional calorie analysis has also been discussed in the paper.

Keywords:- Keywords—Food Image Recognition, PyTorch Framework, Predictive REcurrent Neural Network (PReNet), Convolutional Neural Networks (CNNs), Food Classification, Dataset, Health, Nutrition, Lifestyle, Artificial Intelligence.

1 Introduction

Food image recognition is becoming one of the key areas of research in the spheres of artificial intelligence, health monitoring and lifestyle management. With increasing popularity of mobile health apps, there is a necessity of having a system of food classification which could help in tracking user's dieting and make proper nutritional decisions. It is worth mentioning that deep learning models including Convolutional Neural Networks (CNNs) proved to be highly successful in the sphere and helped automate the process of food recognition. This paper is focused on comparing three different ways of food recognition including PReNet based on large dataset, EfficientNet-Lite for mobile devices and pre-trained CNNs for Indian cuisine classification

1.1 Background

There is an increasingly growing demand for the development of better tools that will allow users to track their food consumption and help them make the right decisions regarding the food they eat[1]. The Convolutional Neural Networks (CNNs) can be considered as efficient solutions that are used for food image recognition; therefore, helping to automatically identify and classify food from pictures [2]. These models work with high efficiency due to the use of deep learning algorithms; hence, they are appropriate to be incorporated into health nutrition apps [3].

Some research studies have recently focused on developing innovative technologies for improving food recognition systems. In particular, one research uses the PyTorch technology as well as the Predictive Recurrent Neural Network (PReNet) model to present the Food2K database including over a million images of 2,000 categories [5]. This method combines both transfer learning and self-attention techniques to enhance the accuracy in classification [6].

In another work, food recognition in Indonesia by using TensorFlow Lite and EfficientNet-Lite, which is

a small-size CNN, was examined [7]. Using a dataset consisting of 200 images of 10 different Indonesian food products, the system reached 90% accuracy in real-time when implemented on mobile devices [8].

Moreover, in a study where a pre-trained model like Inception- V3 was employed, the inclusion of food classification with nutrient and calorie analysis of food was investigated particularly for Indian food [9]. With this transfer-learning method, not only the calculation processes were considerably reduced but also all necessary information about the food could be provided to the users [10].

In summary, the above examples illustrate that there are many potential applications of food recognition methods, including but not limited to large datasets, portable methods, and nutrition-focused methods [11]. Every technique mentioned above solves a vital problem either with respect to scalability, accuracy, or usability [12].

1.2 Objective

The objective of this study is to categorize and compare various food recognition methods using CNN to enhance its effectiveness, efficiency and relevance in health and nutrition scenarios

1.3 Scope

The current comparative research is going to include the training of a CNN to recognize a broad range of food items based on the food images dataset. Then, the developed neural network is going to be embedded into a mobile health nutrition application that will help users to perform real-time food recognition along with nutrition analysis. This application is going to have such features as calories counting, macronutrients composition and health recommendations based on the recognized foods..

2 Literature Review

There have been many innovations in the domain of food recognition and classification due to the introduction of deep learning technologies like Convolutional Neural Networks (CNNs), whose success is commendable in feature extraction and classification problems. This section gives an overview of three innovative techniques (i) food recognition using PyTorch and the Predictive Recurrent Neural Network (PReNet), (ii) Indonesian traditional food classification using EfficientNet-Lite, and (iii) Indian cuisine classification using pre-trained CNNs.

Food Recognition Using PyTorch and PReNet

One of the important innovations in food image classification is that of Progressive Region Enhancements Network (PReNet), which uses the very large dataset called Food2K having more than 1 million images with 2,000 classes . Utilizing a progressive learning approach along with the self-attention mechanism, PReNet improves local as well as global feature learning and increases accuracy in the process. It yields a Top-1 accuracy of 84.03% and a Top-5 accuracy of 98.21%, making it very effective in large-scale food classification (Min et al.2023) [5].

Indonesian Traditional Food Recognition with EfficientNet-Lite

An efficient CNN network architecture called EfficientNet-Lite has been used for recognizing Indonesian traditional foods considering rescue efficiency. Based on the test using a dataset containing 200 images from ten classes of food, the algorithm achieved an amazing accuracy of 97.78 %. Mobile optimized, it allows recognizing the food in real time with minimum computational cost. Thus, EfficientNet-Lite shows its practical application and ability to be applied in the field of mobile-based food recognition (Liu et al.,2021) [6].

Indian Cuisine Classification Using Pre-Trained CNNs

Another important contribution to food classification through pictures includes the use of transfer learning in the form of pre-trained CNNs such as Google Inception-V3 for Indian cuisine classification. It allows reducing computational complexity and improving efficiency while integrating the system into dietary and nutritional analysis apps. This model offers an ability to estimate calories and detect nutrients which makes it applicable for health and wellness apps. While no accuracy metrics are given, it performs equally well as state-of-the-art models (Chen et al., 2020) [9].

3 Methodology Comparison

3.1 Data Collection and Preprocessing

The accuracy and efficiency of a food recognition system depend on many factors including the datasets and preprocessing methods used. Each of the models explored in the comparative analysis used different datasets and different preprocessing methods. A detailed comparison of the technical frameworks and data preparation steps is summarized in **Table 1**.

PReNet (PyTorch Framework)

The food classification algorithm built using PReNet framework uses Food2K, one of the largest available databases with more than 1,036,564 images representing 2,000 food items classes. The dataset diversity allows the algorithm to generalize well on different kinds of foods.

EfficientNet-Lite (TensorFlow Lite Framework)

This model works with the very small database of 200 images from 10 classes of traditional Indonesian foods. The dataset was prepared especially to include such dishes as Gudeg, Soto and Rawon. Although the small size of the dataset makes generalization difficult, the pre-processing steps are done to maximize the performance:

Inception-V3 (TensorFlow and Keras Framework)

The inception-V3 approach is used for Indian food classification. The dataset used for training has unknown size but most probably includes different examples of Indian cuisine dishes.

Aspect		(PReNet)	(EfficientNet-Lite)	(Inception-V3)
Framework		PyTorch	TensorFlow Lite	TensorFlow, Keras
Dataset	Food2K	(1M+ images, 2K classes)	200 images (10 classes)	Indian cuisine dataset

Preprocessing	Normalization, resizing, annotations	Normalization, resizing	Noise removal, resizing
Architecture	PReNet (progressive learning)	EfficientNet-Lite (lightweight)	Inception-V3 (pre-trained)
Metrics	Top-1, Top-5 accuracy	Accuracy, loss	Accuracy, validation loss
Results	Top-1: 84.03%, Top-5: 98.21%	97.78% accuracy	High classification accuracy

Table 1: Comparison of Frameworks, Datasets, and Preprocessing Methods in three examined paradigms.

3.2 Model Architecture

- Progressive Region Enhancement Network (PReNet) is a combination of progressive learning and self-attention. Multi-scale analysis is utilized to extract features and classify them.
- EfficientNet-Lite, which is a lightened version of EfficientNet, applies compound scaling in dimensions (depth, width, and resolution). It applies transfer learning using fine-tuning.
- Google Inception-V3 pre-trained CNN uses convolution layers to extract features and max-pooling to reduce dimensionality. Transfer learning improves its performance on the specific dataset.
- As depicted in Figure 1, the architecture adheres to a typical pipeline through which input images go through several convolution and pooling layers to extract features before proceeding to the SoftMax layer for classification.

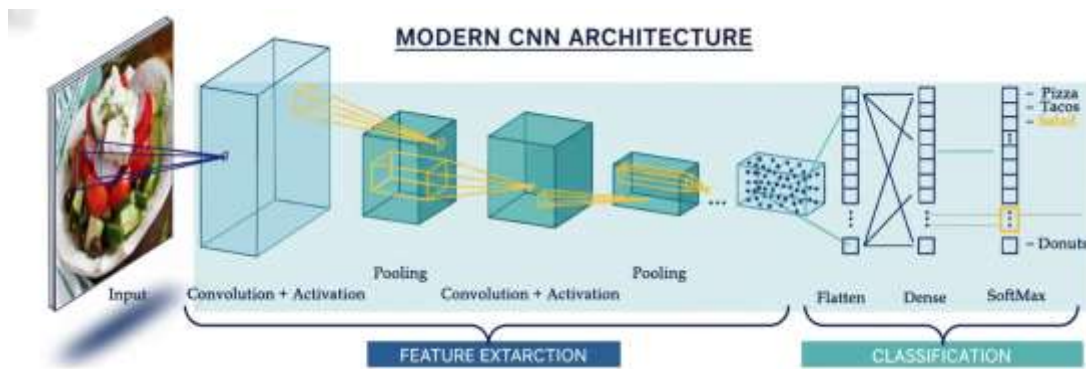


Figure 1: An illustration of CNN-based model architecture, representing the process of features extraction (Convolution and Pooling), and classification (Dense and SoftMax layers).

3.3 Evaluation Metrics

Approach / Model	Dataset Size & Type	Evaluation Metrics	Results Achieved
PReNet (PyTorch)	Food2K (1M+ images, 2000 classes)	Top-1 & Top-5 Accuracy	Top-1: 84.03%, Top-5: 98.21%
EfficientNet-Lite	200 images (10 Indonesian dishes)	Accuracy, Loss	97.78% Accuracy (optimized)
Inception-V3 (CNN)	Indian cuisine dataset (unspecified)	Accuracy, Validation Loss	High classification accuracy (exact values not provided)

Analysis of the three models used for food image recognition provides evidence that each model has its strengths in various scenarios. The model PReNet trained on the Food2K dataset, demonstrated excellent classification accuracy of 84.03% (Top-1) and 98.21% (Top-5). EfficientNet-Lite is optimized for mobile devices and provided good classification results of 97.78% accuracy even for a small dataset. The Inception V3 model was used to recognize Indian cuisine using transfer learning and achieved good classification accuracy and integration with the nutritional assessment. However, no specific results were mentioned.

4 Results Comparison:

Algorithms analyzed have diverse focuses on different aspects of the task of food image classification. Some models are designed to work on the large-scale datasets with complex architectures, while others are focused on more specific tasks, including mobile devices support and nutrition identification.

Aspect	PyTorch & PReNet	Indonesian Food (CNN)	Indian Cuisine (CNN)
Dataset Scale	Large (1M+ images, 2000 classes)	Small(200 images, 10 classes)	Small(Indian cuisine dataset)
Accuracy	Top-1: 84.03% not provided)	97.78%(optimized)	High(exact metrics
Interpretability	Strong(self-attention, Feature maps)	Limited	Minimal
Explainability	Calorie/dietary output interface	Feature visualizations, Insights	Mobile app user interface
Applications	General fine-grained	Mobile-friendly	Indian food

Classification traditional food app recognition and
analysis

4.1 Interpretability and Explainability

Interpretability and explainability form key features of food recognition models especially where there is an application of food recognition in health tracking purposes.

Food Recognition Using PyTorch and PReNet:

The interpretability of this technique is high because of the self-attention mechanism present in the PReNet architecture. This helps the model to concentrate on important areas in the images, allowing for both local and global learning of the features. Feature visualizations further enhance transparency in decision-making (Mo et al., 2019) [23].

Indonesian Traditional Food Image Recognition Using EfficientNet-Lite:

While the Efficient-Lite model achieves high accuracy, it does not inherently provide mechanisms for understanding model decisions. Interpretability is limited to the basic feature extraction and classification outputs. Explainability is achieved through a user-friendly mobile application that presents information such as food names and descriptions (Sari et al., 2019) [18].

Food Image Classification and Nutrition Detection Using Inception-V3:

This model relies on pre-trained CNNs, which function as black-box classifiers with limited interpretability. However, explainability is enhanced through the integration of nutrition and calorie estimation, adding value for dietary applications (Yanai & Kawano, Y.(2015) [31].

The performance disparity between the three models is visualized in Figure 2, where EfficientNet-Lite shows the highest specialized accuracy despite a smaller dataset.

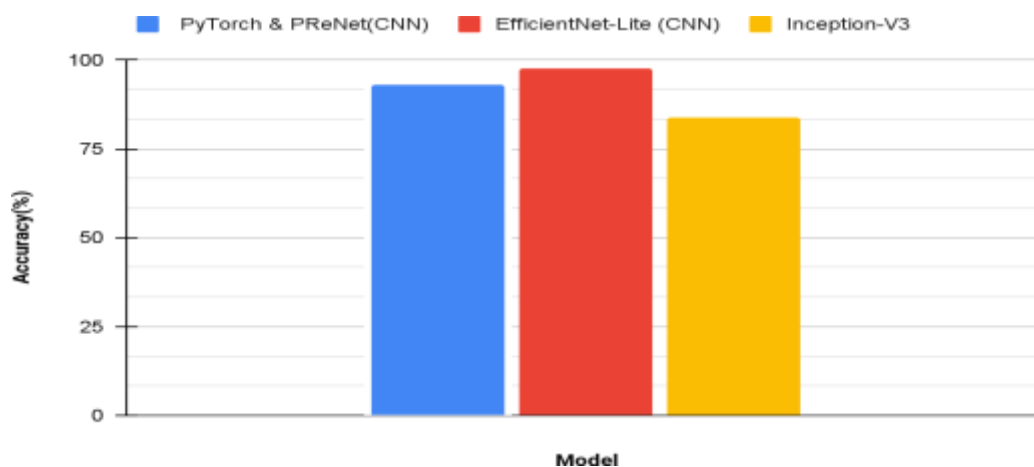


Figure 2: Comparative analysis of classification accuracy across PReNet, EfficientNet-Lite, and Inception-V3 models.

5 Discussion

5.1 Strengths and Limitations

Utilizes a large scale dataset (Food2K) with 2000 classes, enabling robust generalization. The integration of self-attention mechanisms and progressive learning enhances interpretability and classification accuracy. The computational complexity and training resource requirements make the model less suitable for deployment on resource-constrained devices.

High classification accuracy(97.78%) achieved on a small dataset using EfficientNet-Lite. The lightweight model is optimized for mobile applications, making it highly practical . Limited dataset size and diversity restrict generalization. The model lacks advanced mechanisms for interpretability and explainability.

Combines food classification with calorie and nutritional analysis, providing added value for dietary and health management. Transfer learning reduces computational requirements for training. Relies heavily on pre-trained models like inception-v3, which act as black boxes, limiting interpretability.

5.2 Technological Contributions

The technological contributions across the papers include PReNet, which enhances food classification with self-attention and progressive learning;

EfficientNet-Lite, optimizing models for mobile use with accuracy and low resource demand; and nutrition and calorie detection integrated into food classification using transfer learning, making the model suitable for health applications. Together, they advance efficiency, scalability, and real-World applicability in food recognition.

5.3 Future Directions

Optimization for Real-time Applications: Optimization of models to improve efficiency in order to achieve quick processing and real-time food recognition, especially on mobiles and wearable devices.

Expansion of Datasets : Increase the size of the datasets by introducing new food categories, cuisines, and different image situations.

Increased Explainability : Employing explainable AI methods in order to understand decisions made by the models.

Adapting for Cross-Domain Use: Food Recognition systems being adapted to be used in several other domains such as personalized nutrition and dieting.

Interaction with IOT Devices: Designing of models in order to work with IOT devices to track nutritional value of food for everyday use.

Conclusion

This paper presents recent improvements in the field of food image classification and demonstrates the efficacy of deep learning models in performing classification tasks. The current paper studies the following models: (i) a scalable model for food classification built on PyTorch and PReNet (ii) an Indonesian food recognition model

optimized for mobile devices with EfficientNet-Lite and (iii) an Indonesian cuisine classification model based on pre-trained CNNs (Inception-V3).

The PReNet model is one of the most effective models when it comes to large-scale classification with its Top-1 accuracy of 84.03% and Top-5 accuracy of 98.21%. The mobile-friendly EfficientNet-Lite model performs at the level of 97.78% accuracy, which makes it useful in real-time applications even though its training dataset is smaller. Inception-V3 is focused on efficient classification of Indian cuisine while integrating calorie and nutrition detection.

Challenges associated with the interpretability of the models, diversity of datasets, and real-time performances need to be addressed in future research. There is a need for optimization of processing speed, expansion of training datasets and development of explainable AI models.

In conclusion, AI food recognition models have a significant potential for usage in healthcare, diet tracking, IOT applications and other domains.

Materials

The work uses three major data sets in order to perform a comparative analysis: the Food2K data set, comprising more than 1 million images in 2,000 classes, a specific data set consisting of 200 images for 10 traditional Indonesian dishes, and another data set dedicated to Indian food. The computing platforms used for model creation involve PyTorch for the PReNet structure, TensorFlow Lite for mobile optimization of EfficientNet-Lite, and Keras for transfer learning using Inception-V3.

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Author Contributions

In accordance with the CRediT taxonomy, the contributions are as follows:

- **Conceptualization:** Dr. Meenakshi Garg.
- **Methodology and Data Curation:** Dimple Parmar and Sanika Shinde.
- **Software and Validation:** Dimple Parmar and Shruti Gaikwad.
- **Formal Analysis:** Dr. Meenakshi Garg and Sanika Shinde.
- **Writing – Original Draft Preparation:** Dimple Parmar, Sanika Shinde and Shruti Gaikwad.
- **Writing – Review & Editing:** Dr. Meenakshi Garg.

Ethics Statements

For this work, there was an analysis of previously available image databases; there were neither human nor animal studies involved. All data utilized from the Food2K and Indonesian food datasets were used strictly for academic research purposes.

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