Computers and Electrical Engineering 103 (2022) 108298

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Food Image-based diet recommendation framework to overcome PCOS problem in women using deep convolutional neural network☆

Rajdeep Kaur, Rakesh Kumar, Meenu Gupta *

Department of Computer Science & Engineering, Chandigarh University, Punjab, India

ARTICLE INFO

Keywords:
PCOS
CNN
RF
EfficientNet (B0-B7)
Food image analysis
Nutritional management systems
Deep learning (DL)
K-means

ABSTRACT

Polycystic Ovary Syndrome (PCOS) is a disorder that affects the reproductive, metabolic, and hormonal systems in women. The main cause behind PCOS is not exactly known by the practitioners but deficiency of the nutrients in diet may cause PCOS or its related disorders. A healthy diet with proper nutrient intake plays an important role to overcome the issue of PCOS. A novel framework is designed for managing weight with proper nutrient intake using Artificial Intelligence (AI). Pre-trained Convolutional Neural Networks (CNN) architecture (i.e., EfficientNet model variants B0-B7) is enhanced and fine-tuned to classify the food images by adding additional four layers (i.e., Augmentation layer, Dense layer, Dropout layer with dropout 0.3, and Final output classifier dense layer) on datasets derived from FOOD-101. The performance of the model is compared with the other pre-trained models such as VGG16, VGG19, ResNet50, and ResNet101 using performance evaluation metrics. After execution, 95.5% accuracy is achieved to classify the sample six food classes and 90.7% accuracy is achieved for twelve food image classes respectively. Further, K-means and Random Forest (RF) algorithms are applied to create clusters and recommend the list of foods to the PCOS patient with 97% accuracy.

1. Introduction

In the current era, women spend more time managing the responsibilities of family and their careers. To handle all such responsibilities during day-to-day activities, the women are overloaded and not able to take care of themselves, even not taking proper meals on time. Unhealthy eating habits increase the risk of various chronic diseases in women such as PCOS, insulin resistance, cancer, diabetes, etc. PCOS is the most prevalent endocrine condition in women, with a frequency of 5% to 20% worldwide [1]. PCOS is a growing non-communicable disease caused by imbalanced hormone levels in women due to an unhealthy diet and lifestyle at reproductive age [2]. PCOS is related to insulin resistance and metabolic function which increase the risk of other chronic diseases. Insulin resistance and metabolic syndrome can be managed by lifestyle modifications. Further, up to 80% of PCOS-affected women are overweight or obese because women with PCOS are more prone to weight gain [3]. Weight management or weight reduction (even 5–10% percent of body weight) by taking proper nutrients in diet may help PCOS or PCOS-related disorders in women [4]. Weight loss and lifestyle modifications required systematic and regular efforts. There are many nutrient diets type to reduce weight such as a low

☆ This paper is for special section VSI-bioml. Reviews were processed by Guest Editor Dr. Gaurav Garg and recommended for publication.

* Corresponding author.
E-mail address: gupta.meenu5@gmail.com (M. Gupta).

https://doi.org/10.1016/j.compeleceng.2022.108298
Received 9 February 2022; Received in revised form 29 July 2022; Accepted 1 August 2022
Available online 15 August 2022
0045-7906/

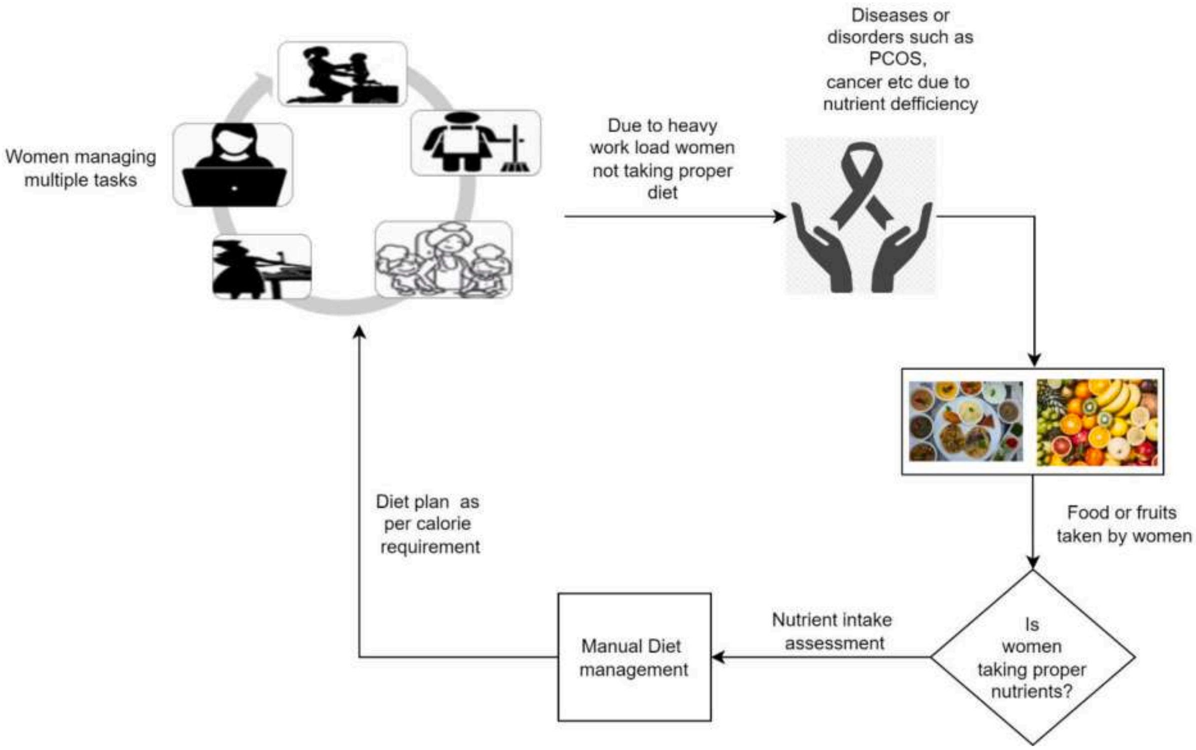


Fig. 1. Overview of health management system for PCOS patients.

carbohydrate diet, normal protein diet, high protein diet, etc. In traditional systems, macronutrient calculations are performed according to the patient physical characteristics (i.e., age, height, and weight) and diet is recommended manually according to the diet type suitable to the patient as shown in Fig. 1. Traditional diet recommendation and monitoring systems relied on food frequency surveys and questionnaires to obtain the required information about the patient the error was high, and the process is also time-consuming. To improve this, an automated smart healthcare system is required to provide awareness and guide women about the nutritional intake in their diet. In the present era, AI advancements such as DL and computer vision have made it possible to develop applications that automate processes that require intelligent human behavior, learning, and adaptation, to provide solutions for real-world problems [5].

A food image or text information can be passed to the DL model to identify the nutrients consumed by the user. Recently, it is observed that Deep Convolutional Neural Network (DCCN) has shown remarkable progress in image classification. However, a large dataset with numerous images is required to train these models [6]. Transfer learning provides a solution for systems where a large amount of data is required to train the model. Pre-trained CNN models such as EfficientNet (B0-B7) variants, VGG-16, VGG-19, ResNet-50, and ResNet-101 can be used as feature extractors, fine-tuned, or enhanced as per the problem statement. The accuracy of the DL model can be improved by increasing the width and depth of the network, or by enhancing the resolution of the images [7]. Tan et al. [8] introduced the EfficientNet model variants, which change the network's depth, breadth, and resolution uniformly using a fixed scaling coefficient to improve the model performance. Enhanced EfficientNet variants with other pre-trained models are used for food image classification in the proposed work. Further, K means algorithm is used for clustering the nutritional dataset, in which the number of clusters is identified using the elbow method. The K-means technique is an effective algorithm that aims to partition the unlabelled dataset into pre-defined distinct non-overlapping clusters [9]. Next, the RF approach is used to identify the cluster according to the user's nutrient requirement. In this approach, many classifiers are created from different smaller input data subsets and then their results are combined based on the voting mechanism to get the desired output [10].

In contribution to the proposed work, the pre-trained Convolutional Neural Networks (CNN) architecture (i.e., EfficientNet model variants B0-B7) is enhanced and fine-tuned to classify the food images by adding additional four layers (i.e., Augmentation layer, Dense layer, Dropout layer with dropout 0.3, and final output classifier dense layer) on datasets (FOOD-6, FOOD-12, FOOD-20, and FOOD-40) derived from FOOD-101. Additionally, the proposed model is used for PCOS patients to predict the list of foods as per the nutrient composition recommended (i.e., Nutrition pattern or macronutrient distribution of 40% fat, 41% carbohydrate, and 19% protein). It recognizes the class of food consumed by the user and identifies the nutrients available in the food. A list of food items will be suggested to the user as per the balanced calorie and macronutrient requirements of the individual. The proposed work is automatically recommended a list of foods to PCOS patients as per their nutritional requirements using DL algorithms.

This paper is further organized as follows: Section 2 puts forward the related work on diet recommender systems, food image analysis, and diet types for PCOS patients. Section 3 discussed the improved and fine-tuned EfficientNet (B0-B7) model architecture for image classification. Section 4 presents the framework implementation. It also includes the K means method for clustering the nutritional information data and the same clustered dataset passed to the RF algorithm that identifies clusters according to the user's nutritional requirement and recommends the list of foods. Section 5 presents the result analysis of the food image analysis model and food prediction framework. Finally, the research work has been concluded based on achieved outcomes and suggestions for future enhancement of the present work.

2. Related work

In this section, the different researcher's analyses of diet prediction for PCOS patients are discussed in detail. The existing literature has been divided into three different phases: food image analysis using deep DL, a diet recommender system for a healthy lifestyle, and manual diet recommendations for PCOS patients.

2.1. Food image analysis using DL

In [6], R. Hafiz et al. worked on a deep CNN model to classify soft drinks using transfer learning. Images were acquired from the ImageNet dataset, Internet sources, and self-capturing to create a dataset that comprises the ten most popular soft drinks in Bangladesh with varying bottle sizes. To obtain the nutritional information, a feature bag and distance ratio technique was utilized in the proposed work to estimate the soft drink bottle size. In [11], C. Kiourt et al. proposed three solutions for food image recognition using DL. In the first solution, the model was designed from the scratch, the second model was designed using transfer learning, and the last model was designed by using APIs. Further, large food image datasets were used to compare the above three solutions for food image analysis. In [12], Raikar et al. designed a DL model based on pre-trained CNN models to classify the Okra- ladies' fingers in four classes, where each class consists of 800 samples. The image classification task was performed using three pre-trained networks AlexNet, GoogleNet, and ResNet with an accuracy of 63.45%, 68.99%, and 99.17% respectively. In [13], Shen et al. proposed an approach to food image classification and nutrition estimation using pre-trained models. Inception V-3 and Inception-V4 models are fine-tuned to recognize the food images and achieved 85% accuracy.

This section summarizes the pre-trained models (CNNs) used for nutrient identification from food images that helps in diet prediction. CNN for the classification can be designed using transfer learning, in which pre-trained models are trained on ImageNet and can be used for the food image analysis (no need to design the model from the scratch). The major challenge to designing such models is the scaling of the model which needs to be performed to improve the accuracy varying with the datasets. The next subsection includes a detailed description of the different researchers' views about diet recommendation systems for a healthy lifestyle.

2.2. Diet recommender system for a healthy lifestyle

In [5], Sowah et al. designed a diabetes management system that handles the various factors that affect diabetic patients. The framework combines multiple artificial intelligence algorithms to monitor and control diabetes. A neural network is developed using TensorFlow for the food image classification to identify the nutrients of the food. Further, the authors designed a chatbot to answer the user queries related to diabetes and meal recommendations. In [14], Salloum et al. developed a novel framework named Personalized Intelligent Nutrient recommendation (PIN) which used a fuzzy logic paradigm. PIN has the capabilities to assess the caloric intake, activity, or exercise recommendation and progress evaluation to make the final adjustments. In [15], Ghosh et al. proposed a system to generate the diet chart according to the user's food preference, BMI, and the number of calories spent by the body. A hardware system was used to identify the walking activity or running activity from feet pressure and a dynamic diet chart was generated according to the physical activities. In [16], Mustafa et al. proposed an architecture named iDietScore™ for meal planning based on the profiles of athletes or individuals with high activity. This architecture comprises a mobile app for athletes and an expert system for the recommendations of a meal plan.

Based on the above study, the researchers focused only on calories as a major component of diet recommendation and did not focus on the macronutrient (carbohydrate, fat, and protein) distribution pattern. The next subsection summarizes the manual diet recommendation with a nutrient distribution pattern that is suitable for PCOS patients.

2.3. Manual diet recommendation for PCOS patients

In [17], Zhang et al. presented the effect of a Low Carbohydrate Diet (LCD) in women suffering from PCOS. Long-term LCD diets and low-fat low-CHO diets were recommended to reduce the BMI and used to treat PCOS. In [18], Mehrabani et al. explored the impacts of various diet compositions on insulin levels in women with PCOS. A group of 60 women with PCOS and overweight were recruited and assigned different diet groups hypocaloric diet (15% protein of daily energy) and modified hypocaloric diet (30% protein of daily energy with low GI foods from the list) for a clinical trial. A high protein and low GI diet have shown a significant increase in insulin sensitivity as compared to other high protein diets. In [19], Perelman et al. presented a study related to obese women suffering from PCOS for 3 weeks and compare the two diets (CHO 60%, Fat 25%) with (CHO 40%, Fat 45%) where the protein was 15% in both diets. In this research, CHO was replaced with mono/polyunsaturated fats and observed reductions in daylong concentrations which may be used as a treatment for PCOS women. In [20], Gower et al. discussed a study on standard energy diets 55:18:27% CHO/-Protein/Fat/ and low carbohydrate diets 41:19:40% CHO/Protein/Fat/ for 8 weeks which shows significant improvement in carbohydrate metabolism. It also has been revealed that minimizing carbohydrates in diet has beneficial effects on the health of women with

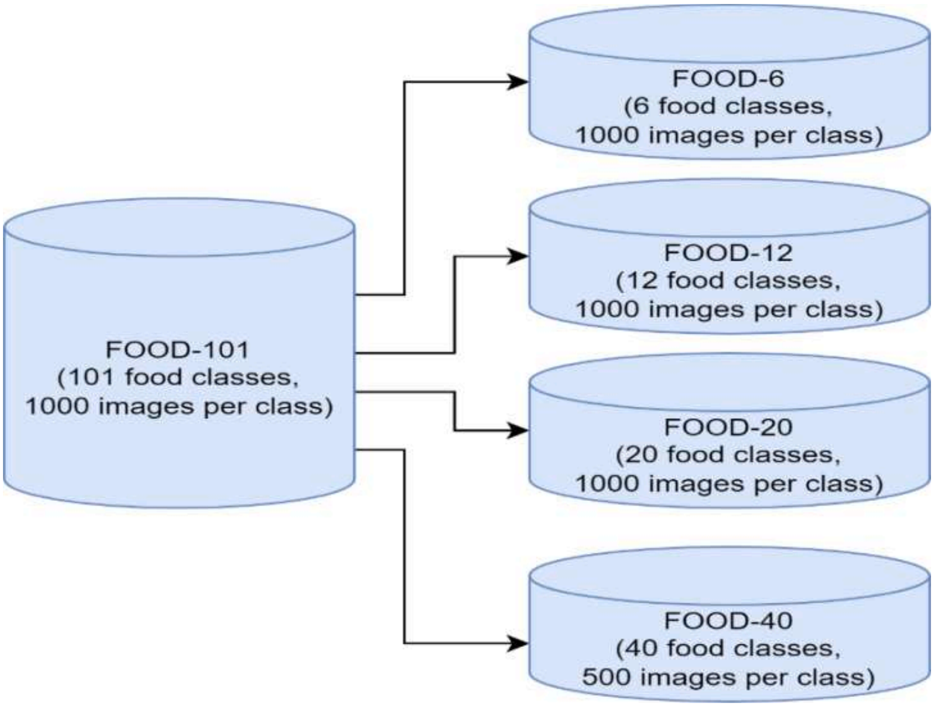


Fig. 2. Different food image datasets created from FOOD-101.

PCOS even in the absence of weight loss. In [21], Mavropoulos et al. presented low carbohydrate keto diets (LCKD) to reduce weight, improve insulin, and reduce PCOS symptoms. The number of carbohydrates reduced in the LCKD diet is less than 20 g per day.

As per the above analysis, the diet recommended for PCOS patients is managed on a manual basis. The exact requirement of nutritional intake or the calorie taken by the patient is not measured accurately. Further, many researchers had applied DL techniques to food datasets to identify the nutrients from a food image. No DL-based automatic diet prediction framework is designed for PCOS patients. In this work, the proposed model applied a deep CNN model for automatic identification of nutrients from the food image which helps in diet prediction for PCOS patients.

3. Methodology used

Women suffering from PCOS (or diseases associated with PCOS) may benefit from weight management or weight loss if they consume the proper nutrients. The proposed framework recognizes the consumed food by classifying the food image provided by the individual using enhanced EfficientNet model variants and suggested a list of food items as per the macronutrient requirement of women suffering from PCOS. This section further discusses the dataset used for the proposed work along with its framework architecture and proposed algorithm. The framework includes the estimation of the total caloric requirement of women using the Harries-Benedict equation for BMR, macronutrients consumed by a patient from the food image by using a neural network model, and a list of food that can be taken by the women to meet the daily macronutrient requirement.

3.1. Dataset description

In this research work, two different datasets (i.e., the Food image dataset and the Nutritional information dataset) have been considered. Firstly, the food image dataset is used to train the proposed model for classifying the food image. The second dataset (i.e., nutritional information) is used for providing the detail of the macronutrients of the food. The nutrients consumed by an individual are recorded using an image classification algorithm and this model is trained using these two datasets.

3.1.1. Food image dataset

A food image dataset named FOOD-101collected from Kaggle [22]. It contains 101 food classes where each class consists of 1000 images (101* 1000 = 101,000 images). The collected data set is further classified into four different subcategories for analysis. The first category named FOOD-6 dataset contains 6 food classes (6 × 1000 = 6000 images). The second category is named the FOOD-12 dataset which contains 12 food classes (12 × 1000=12,000). The third category named FOOD-20 dataset contains 20 food classes (20 × 1000=20,000). The fourth category name FOOD-40 dataset contains 40 food classes (40 × 500=20,000). Fig. 2 shows the detailed description of food data categorization

Fig. 3. Sample food images.

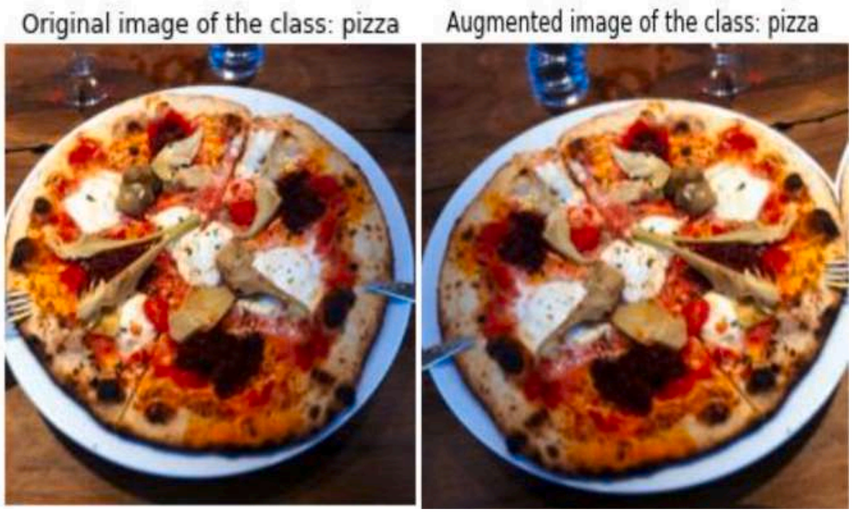


Fig. 4. Food images before and after the augmentation.

After the categorization of a dataset, the dataset images are resized to 224 × 224 pixels in RGB channels from image size 512 × 384. Further, the augmentation is applied over the resized images to avoid overfitting. Different augmentation techniques such as zoom at scale 0.2, rotation at a scale of 0.2, random height and width at 0.2, and flip set as horizontal are applied to resized images before training. Sample images of the dataset are shown in Fig. 3 and a sample of augmented images is shown in Fig. 4.

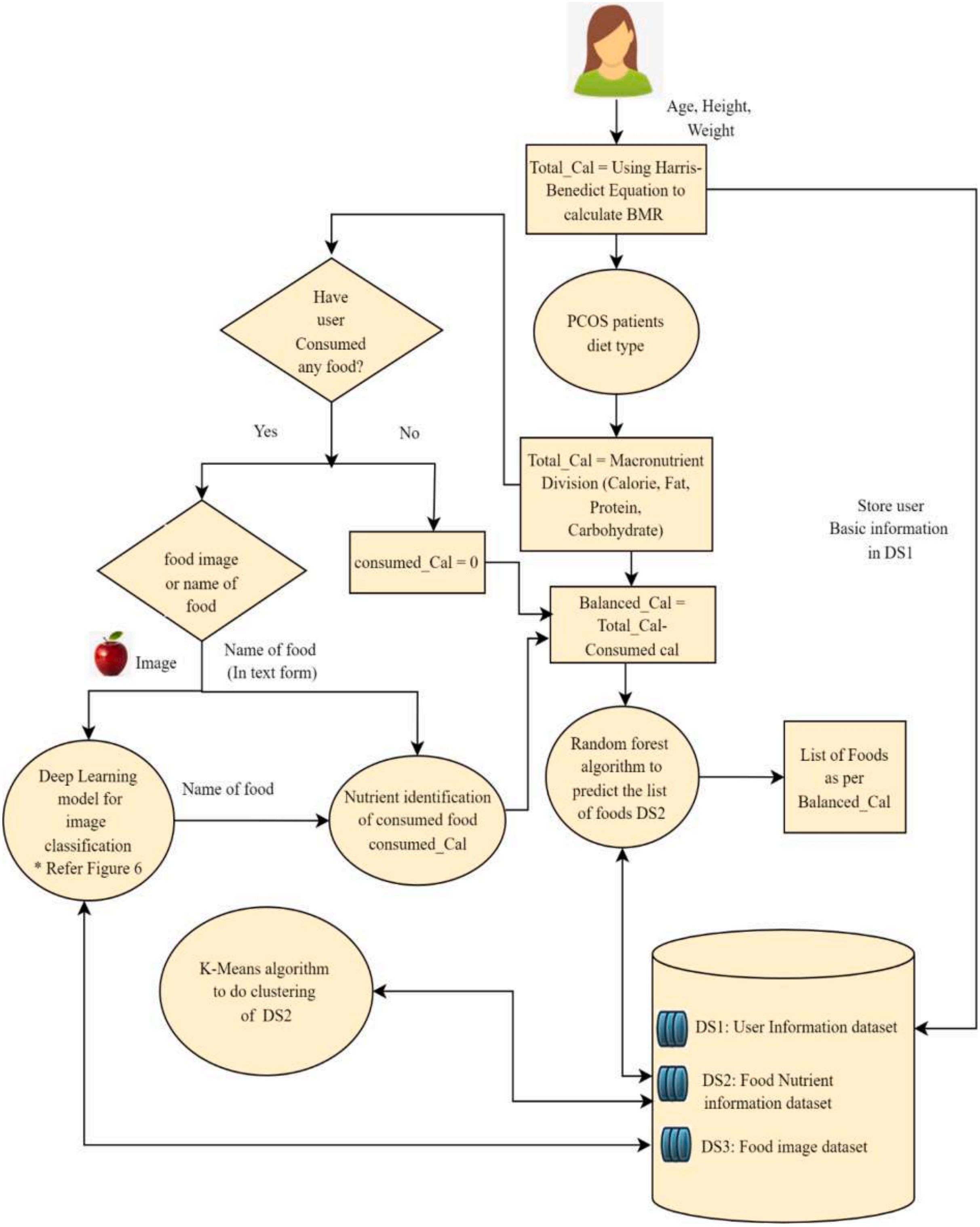


Fig. 5. HDMS framework with all sub modules for PCOS patients.
* Further DL model for image classification architecture is discussed in Fig. 6.

Table 1
Food items with macronutrient nutrient values.

Food items	Calories	Fats	Proteins	Carbohydrates
Asparagus Cooked	22	0.2	2.4	4.1
Avocados	160	15	2	8.5
Bananas	89	0.3	1.1	23
Bagels made in wheat	250	1.5	10	49
Berries	349	0.4	14	77

Table 2
Caloric requirement of a person based on weight, height, and age.

Weight (Kg)	Height(cm)	Age(years)	Energy requirement (Calories) /Day
70	164	35	1754.5
50	150	30	1504.4
66	170	33	1727.4
80	150	40	1825.2
85	160	42	1911.1

Table 3
Sample macronutrient distribution for 2000 calories.

Calories	Fat(gm)	Protein(gm)	Carbohydrate(gm)
2000	88.8	95	205

3.1.2. Nutritional information dataset

A nutritional information dataset that contains the list of food is collected from USDA [23]. This dataset consists of different parameter values of macronutrients such as calories, fat, protein, and carbohydrates as shown in Table 1. All macronutrients generate different amounts of calories, 1 g of fat provides 9 Kcal/g, and 1 g of protein and carbohydrate generates 4 Kcal/g.

3.2. Model formulation for HDMS

The HDMS model is a combination of three AI algorithms i.e., Deep CNN, K-means, and RF. First, the Deep CNN model is used to identify the class of the food from the food image. Next, K means algorithm is applied to do the clustering of the food nutritional dataset which is passed as input to the RF algorithm to identify the closest cluster as per the patient nutritional requirement to recommend the list of the foods.

3.2.1. Calorie intake requirement computation using Harris-Benedict equation

Lifestyle management with proper food nutrient intake is considered a first-line treatment for PCOS patients in the presence of overweight or obesity. To compute the user's daily calorie need, an initial list of features such as height, weight, and age, are derived from the user's input. BMI is used to calculate for a person that is obsessed or overweight whereas BMR is used to calculate the total caloric requirement as shown in Eqs. (1) and (2). The daily calorie intake for a woman can be calculated by using the Harries-Benedict equation [24].

$$BMI = \frac{Weight(Kg)}{Height(m^2)} \tag{1}$$

$$Total_{Cal}(BMR) = 655 + 9.563 \times w + 1.8496 \times h - 4.6756 \times a \tag{2}$$

According to Eq. (2), w represents the weight in Kg, h represents the height in cm and a represents the age in years. The energy requirement for a female is calculated as shown in Table 2.

3.2.2. Proposed framework for HDMS

Weight loss improves insulin levels which can be achieved by diet management. Further, total calories are subdivided into the macronutrients (Fat, CHO, Protein) as per the diet type (low carbohydrate diet, high protein diet, etc.) recommended to the women suffering from PCOS. Nutrition pattern or macronutrient distribution of 40% fat, 41% carbohydrate, and 19% protein is implemented in the HDMS to predict the list of foods that can be taken by PCOS patients. Dieticians can set different diet compositions or macronutrient distribution patterns while using HDMS. If the total energy requirement of a person is 2000 calories, then according to the above diet type the macronutrient distribution for that person's fat, carbohydrate, and protein are 800, 820, and 380 calories respectively as shown in Table 3. As 1 g fat generates 9 calories then the total fat requirement as per the diet type is 88.8 g. Similarly, the number of other macronutrients is calculated in HDMS.

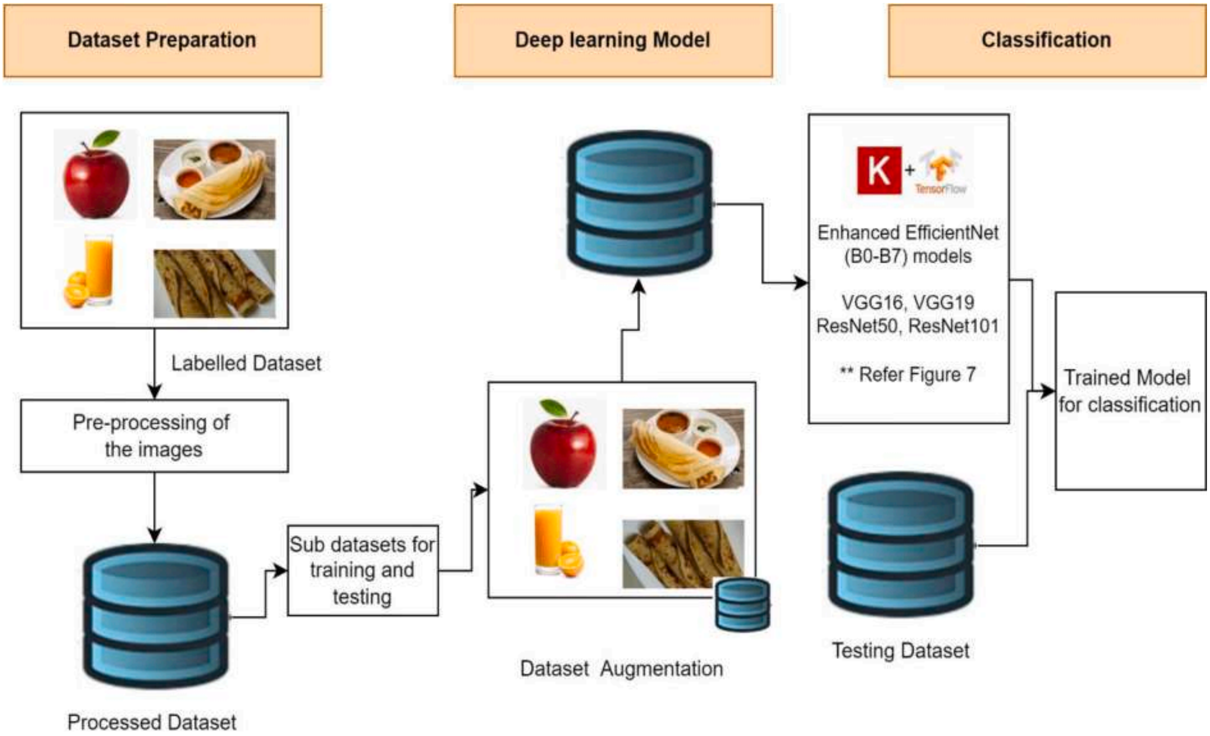


Fig. 6. Food images classification architecture.
** Further block diagram with additional layers presented in Fig. 7.

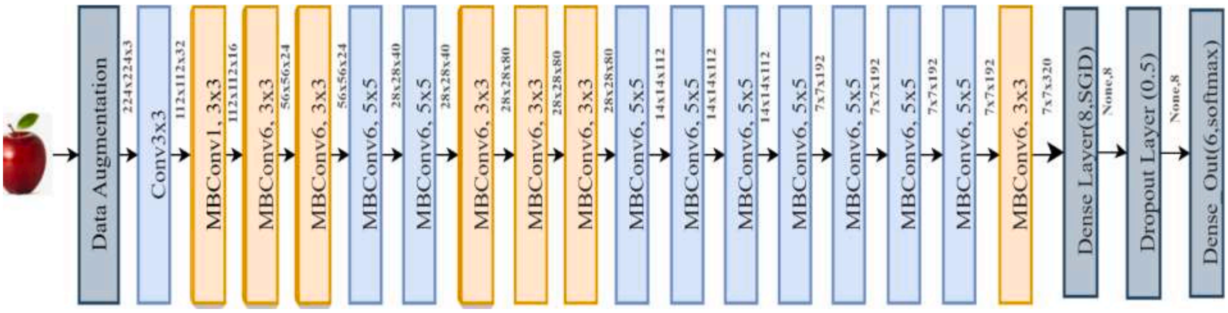


Fig. 7. Enhanced EfficientNetB0 block diagram with additional layers.

HDMS allows a user to enter the consumed food (if any) either in the form of text (name of the food) or upload a food image. If a user is consumed any food, then the calories and number of macronutrients will be subtracted from the total calorie requirement and the list of foods will be recommended according to the balanced calories. The proposed image classification model is used to recognize the name or class of food from the food image if the user uploaded a food image. Further, nutrients consumed by the user will be extracted from the nutritional dataset. Then the calculations will be made to check the number of macronutrients required to meet the calorie and nutrient need of the user.

3.2.3. Enhanced EfficientNet(B0-b7) model variants for food image classification: Food DeepNet

CNN has emerged as the image classification algorithm as it uses multiple layers to automatically learn key features from training data. CNN models can be designed from the scratch by using multiple layers or can be designed by using transfer learning. In the proposed work, transfer learning is used to design the FOOD DeepNet in which EfficientNet model variants are enhanced by adding additional four layers (i.e., Augmentation layer, Dense layer, Dropout layer with dropout 0.3, and Final output classifier layer) and fine-tuned. Food image classification architecture is shown in Fig. 6.

Pre-processed and augmented images are given as input to the FOOD DeepNet for classification. The input size of the image is resized the same as the default size accepted by the EfficientNet model variants (i.e., for EfficientNetB0 224 × 224). The model uses the EfficientNet variants in which the top classifier gives the output of 1000 classes which are replaced with a new dense layer that gives

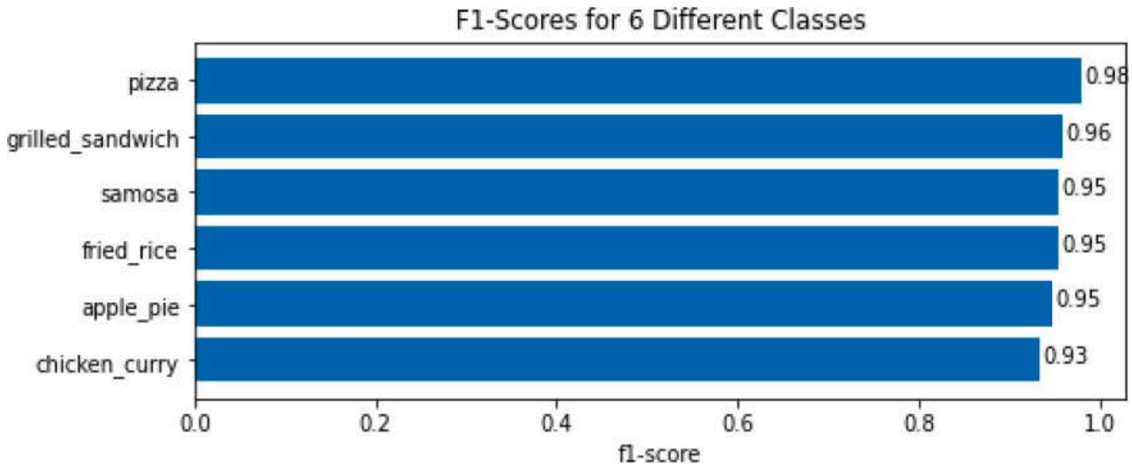


Fig. 8. Food classes F1- Score for 6 food classes using EfficientNetB4 (Best model).

Table 4
FOOD DeepNet fine-tuning strategy.

epochs	No of the layers (unfrozen)s
1–30	0
31–45	10
46–60	20
61–75	30
76–90	40
91–105	50
106–120	150
121–135	200
136–150	220

the output of 6 as per the food classes in dataset FOOD-6. In addition to the augmentation layer and final classifier dense layer, one more dense layer with 8 neurons and a dropout layer with a dropout of 0.3 are added to the proposed model as shown in Fig. 7. Then the model is compiled using an SGD optimizer and the learning rate changes with time using the learning rate schedule. The initial learning rate was set as 0.01. The dataset is a multilabel class, so the Categorical cross-entropy loss function is used to compute the loss between the labels and predictions. In the final layer, Softmax is chosen as the activation function. Early stopping call back is used to stop the training early if the model gets overfitted.

All the images have generic features and specific features (more specific to the dataset). Weights of the earlier layers are frozen to extract the low-level features from the images as start layers learn the very generic features which are generalized for all types of images. A move to the upper layers of the model, the features are more specific to the problem dataset. So, the model is fine-tuned for higher layers to adapt specialized features of food images. We gradually unfreeze the layer weights while keeping all other parameters constant. The model is fine-tuned with the increase of epochs. For the first 30 epochs, all layers of the pre-trained model are frozen. In the next 15 epochs, the top −10 layers of the proposed model are unfrozen. Next, the top 20 layers are unfrozen for the next 15 epochs. This process is repeated for further execution and the number of layers unfrozen concerning the epochs is shown in Table 4.

FOOD DeepNet model is trained on FOOD-6, FOOD-12, FOOD-20, and FOOD-40 to evaluate the performance and the output of the proposed work which is further compared with other models such as VGG-16, VGG-19, Resnet-50, ResNet-101.

3.3. Proposed algorithm

This section describes the proposed algorithm for calculating the nutrient intake requirement for PCOS patients with the help of BMR. This algorithm also identifies the total food consumption of the user (or PCOS patient) and prediction about the list of food required to meet the nutritional requirement.

Algorithm 1

In our proposed framework, the k means algorithm is used to perform the clustering on a nutritional dataset. RF algorithm identifies the cluster which is closest as per the patient's nutritional requirement. Next, list food items are selected from the closest cluster and recommended to the patient.

Table 5
EfficientNet model variants (B0-B7) performance analysis (accuracy, f1 score, mean precision, mean recall).

EfficientNet	Accuracy	weighted avg {precision, recall, F1 score)
B0	93.3%	{93%, 93%, 93%}
B1	93.5%	{94%, 94%, 94%}
B2	94.92%	{95%, 95%, 95%}
B3	93.8%	{94%, 94%, 94%}
B4	**95.5%**	**{96%, 95%, 96%}**
B5	95.3%	{95%, 95%, 95%}
B6	94.1%	{94%, 94%, 94%}
B7	94.3%	{94%, 94%, 94%}

Table 6
EfficientNetB4 model performance analysis for different datasets (accuracy, F1 score, mean precision, mean recall).

Dataset	Number of images	Dataset split Training: Validation	Accuracy	weighted avg {precision, recall, f1 score)
FOOD-6	6000	80:20	95.5%	{96%, 95%, 96%}
FOOD-6	6000	90:10	95.83%	{96%, 96%, 96%}
FOOD-12	12,000	80:20	90.71%	{91%, 90%, 91%}
FOOD-20	20,000	80:20	86.5%	{86%, 87%,87%}
FOOD-40	20,000	80:20	81.6%	{81%, 81%,81%}

Table 7
EfficientNetB4 model class-wise performance analysis for dataset FOOD-6.

Food Class	Precision	Recall	F1- Score	Support
apple_pie	95%	95%	95%	200
chicken_curry	91%	95%	93%	200
fried_rice	97%	94%	95%	200
grilled_cheese_sandwich	96%	95%	96%	200
pizza	**97%**	**99%**	**98%**	**200**
samosa	96%	94%	95%	200

4. Experiment result analysis

4.1. Food Image-based nutrient identification using the proposed model

All models are developed in Keras which is a high-level DL API written in Python and compiled on Pro-collab with GPU (NVIDIA Tesla). EfficientNet (B0-B7), VGG16, VGG19, ResNet50, and ResNet100 are trained on a different number of epochs. The datasets used to train the models with a different number of food classes are summarized in Table 6.

4.1.1. EfficientNet(B0-B7) performance analysis

The models are evaluated using the performance matrices such as precision, recall, F1 score, and accuracy. Different evaluation metrics are calculated by using the values obtained from the confusion matrix. The confusion matrix is a table of $M \times M$where M represents the prediction of food classes as True Positive (TP) represents the number of correctly identified food classes in each category, True Negative (TN) represents the sum of correctly identified food images in all other categories except the relevant class, False Positive (FP) represents the number of misclassified food images in other categories except the relevant category, and False Negative (FN) represents the number of misclassified food images from the relevant category [25]. Eqs. (10) to (12) # represents the number of food classes.

$$Accuracy(j) = \frac{\#TP(j) \ + \ \#TN(j)}{\#TP(j) \ + \ \#FN(j) \ + \ \#TN(j\ ) + \ \#FP(j)} \tag{10}$$

$$Percision(j) = \frac{\#TP(j)}{\#TP(j) \ + \ \#FP(j)} \tag{11}$$

$$Recall(j) = \frac{\#TP(j)}{\#TP(j) \ + \ \#FN(j)} \tag{12}$$

4.3. Comparison of EfficientNet model variants (B0-B7)

EfficientNet (B0-B7) models are enhanced by adding four layers and evaluated using FOOD-6 with 6 food classes dataset. All

Table 8
Model-wise Input image size, Optimizer, and number of parameters for different DL models.

VGG-16		224 × 224	Adam	84.77%	77.75%
VGG-19		224 × 224	Adam	83.03%	78.83%
ResNet50		224 × 224	Adam	85.35%	79.92%
ResNet101		224 × 224	Adam	87.31%	80.92%
Proposed Framework					
	B0	224 × 224	SGD	90.1%	93.3%
	B1	240 × 240	SGD	95%	93.50%
	B2	260 × 260	SGD	94.06%	94.92%
	B3	300 × 300	SGD	94.60%	93.83%
	B4	380 × 380	**SGD**	**94.5%**	**95.5%**
	B5	456 × 456	SGD	93.77%	95.33%
	B6	528 × 528	SGD	93.6%	94.1%
	B7	600 × 600	SGD	93.5%	94.3%

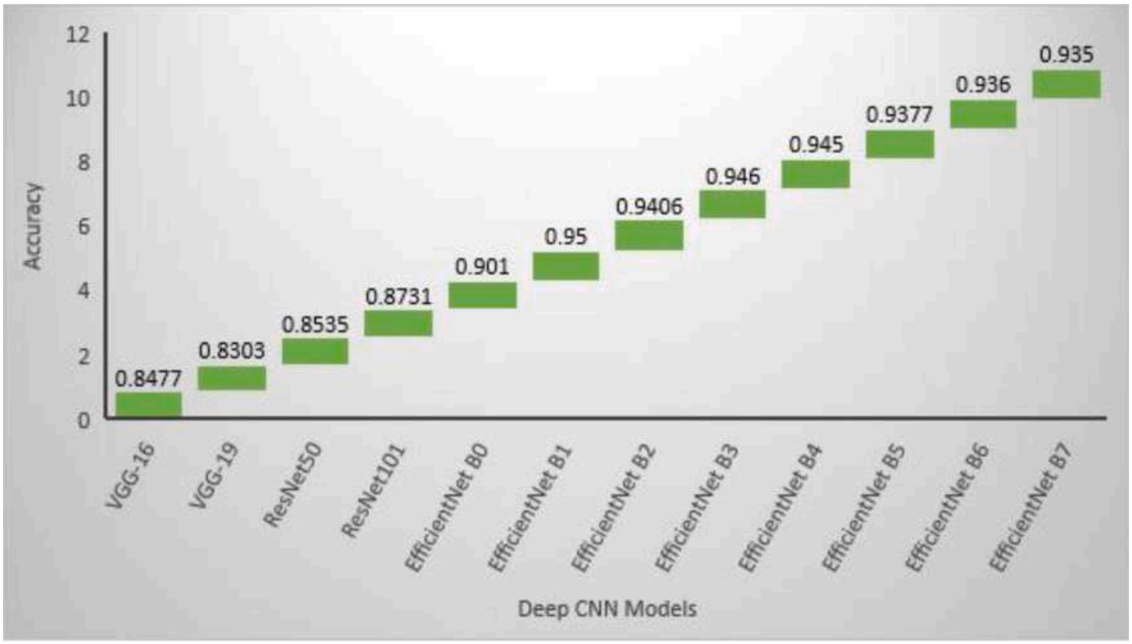


Fig. 9. Training Accuracy Comparison of enhanced EfficientNet(B0-B7) with other CNN models.

models achieved accuracy very close to each other, but the EfficientNetB4 model perform better than other models. All the model's accuracy, precision, recall, and f1 score are shown in Table 5 and the best-performed model accuracy and other performance metrics are bolded. The order of ranking of the models in terms of accuracy is $B4 \sim B5 > B2 \sim\ B7 \sim B6 > B3 \sim B1 \sim B0$. The difference between the best model of EfficientNet variants (i.e., EfficientNetB4) and the worst model (EfficientNetB0) is approximately 2.5%. The observed different order in terms of precision and recall is the same accuracy.

As discussed above, the B4 variant in the EfficientNet family performs better, so different datasets created from Food-101 are also used to evaluate this model as shown in Table 6.

The class-wise performance analysis of EfficientNetB4 using dataset FOOD-6 is shown in Table 7. The accuracy and performance metrics of the class pizza are greater than the other classes bolded and are shown. Fig. 8 depicted the F1 score of all the food classes in FOOD-6 food class pizza obtained the highest F1 score.

4.4. Comparison of EfficientNet model variants (B0-B7) with other pre-trained CNN models

Pre-trained convolutional neural networks are designed for the classification tasks and then model depth, width, or resolution is increased to improve the model performance (i.e., the number of layers can be added in ResetNet-18 to improve the accuracy). The performance of the model may be improved by following this process, but this is a manual fine-tuning task. In the proposed work, Enhanced EfficientNet model variants are used to classify the food images and achieve better accuracy as compared to the other CNN models. It uses a basic extremely effective compound coefficient to scale up CNNs in a more organized way. Due to this, the proposed model achieved the highest accuracy improvements on the food image dataset after fine-tuning as compared to other models. It scales

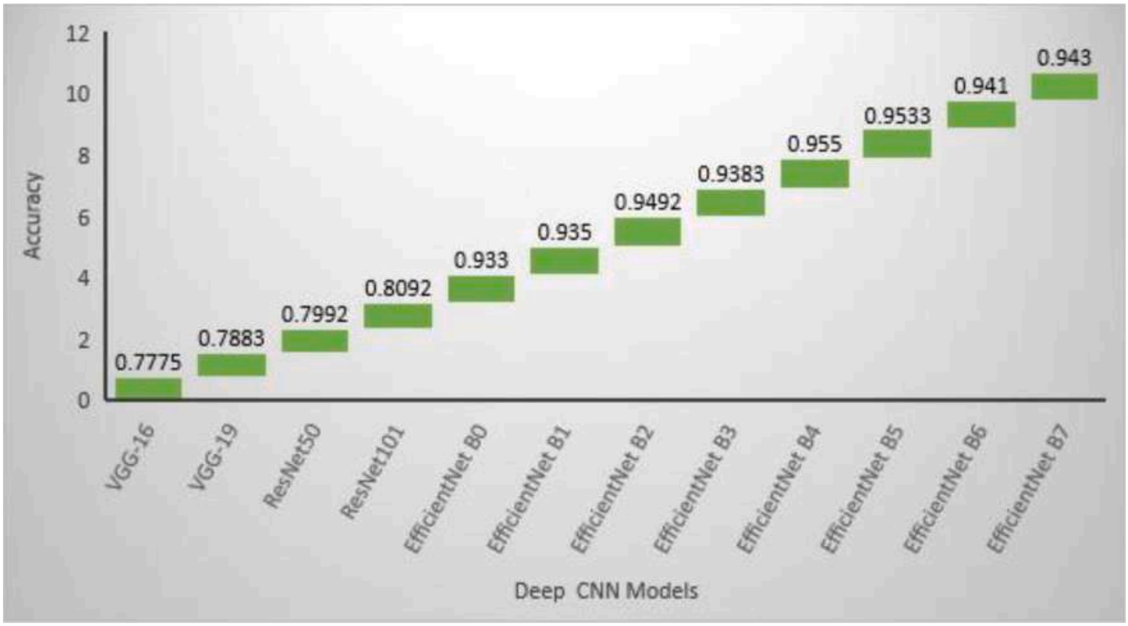


Fig. 10. Validation Accuracy Comparison of enhanced EfficientNet(B0-B7) with other CNN models.

each dimension of depth/width/resolution uniformly using a predetermined set of scaling factors which improves accuracy at a faster speed as compared to other CNNs. The training and validation accuracy of different CNNs are compared with enhanced EfficientNet model variants (B0-B7) shown in Table 8.

EfficientNet (B0-B7) models are trained using fine-tuned strategy in which all the layers are frozen for the first 30 epochs and then the model is fine-tuned with an increase in epochs. All other pre-trained models are trained for 250 epochs with Adam as the optimizer. The EfficientNetB4 achieved the highest accuracy 95.5% as compared to the EfficientNet variants and pre-trained models. The difference between EfficientNetB4 and other pre-trained models with the lowest accuracy (without fine-tuning) is approximately 17.8%. The models' training and validation accuracy are visualized in Fig. 9 and Fig. 10, respectively. The accuracy and loss curves of all the models are shown in Fig. 11. Fig. 12 show the confusion matrices for all the models.

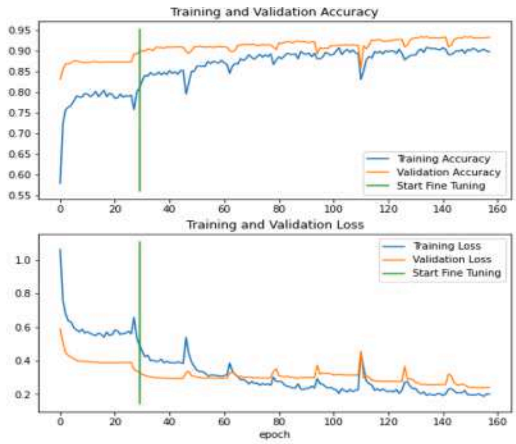
4.4. Discussion

The nutritional dataset is prepared by considering the macronutrients like calories, fat, protein, and carbohydrate as shown in Table 1. The values of different macronutrients are not in the same range and are normalized. So, the MinMax scalar is used to transform the values of macronutrients into the same range of [0,1]. Then the K-means algorithm is applied to group the foods with similar macronutrients into one group as shown in Table 9 (i.e. Asparagus Cooked belongs to cluster 0 and Berries belong to cluster (1). This algorithm is trained and validated by using the nutritional dataset to do the clustering and group the food into the k clusters where the number of clusters for the dataset is selected by using the elbow technique.

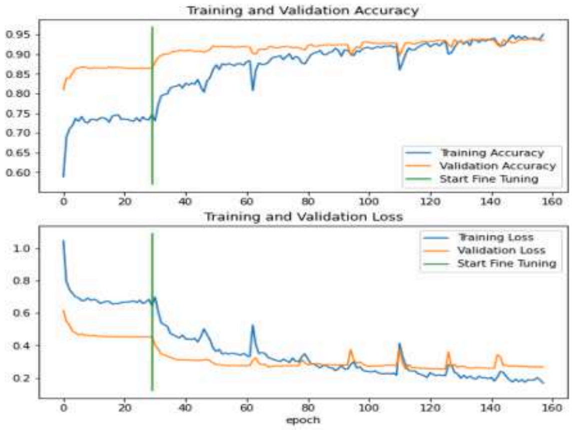
The nutritional information dataset is analyzed to select the number of clusters ($K = 5$) as shown in Fig. 13. Further, the RF algorithm identifies the group of foods (cluster) as per the user nutritional requirement of the user with 97% accuracy. A list of foods selected from the same group for the recommendation.

5. Conclusion and future scope

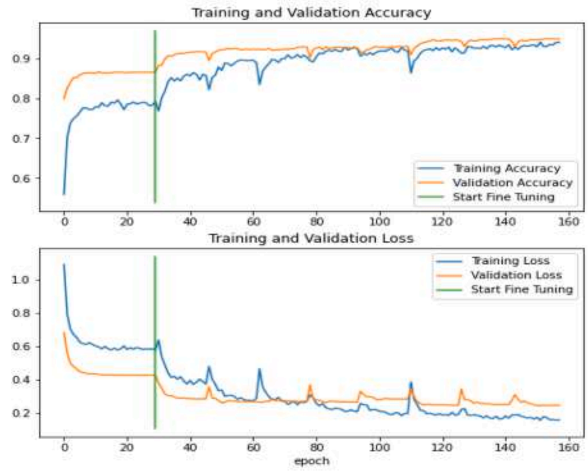
Women with PCOS disorder require a healthy diet and weight management that may help to improve insulin and obesity levels. Nutritional management systems have emerged as one of the solutions for tracking nutrient intake and recommending foods to meet the daily nutritional need of the patient. In this work, a model is proposed for the identification of the nutrient intake from food images, clustering of the nutritional dataset using the K means algorithm and RF algorithm to identify the cluster according to the nutritional requirement of the user to predict the sublist of the foods. For the nutrient identification from the food image, EfficientNet(B0-B7) models are improved and fine-tuned. EffieicientNet(B0-B7) models are enhanced by adding four different layers and fine-tuned which are further evaluated using the FOOD-6 dataset created from the FOOD-101 food image dataset. EfficientNetB4 performs better than the other variants and achieved 95.5% accuracy. Next, the EfficientNetB4 model is also trained on different categories of food image datasets FOOD-12, FOOD-20, and FOOD-40 achieving the accuracy of 90.7%, 86%, and 81% accuracy respectively. A low carbohydrate diet type is selected in the implementation of the HDMS system to recommend a list of foods to the user. Further, K means, and RF algorithms are applied to do the clustering and to predict the list of foods as per the user's nutritional requirement with



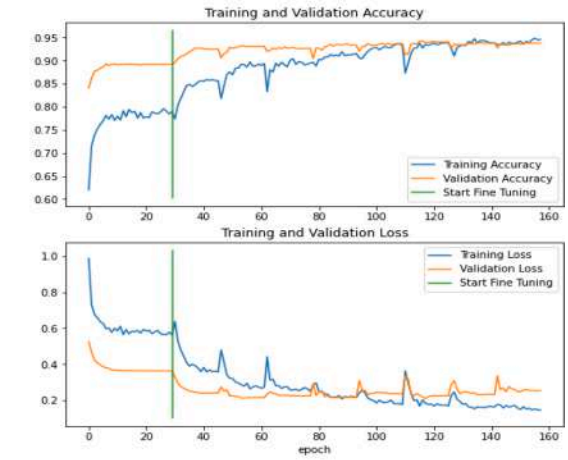
(a)



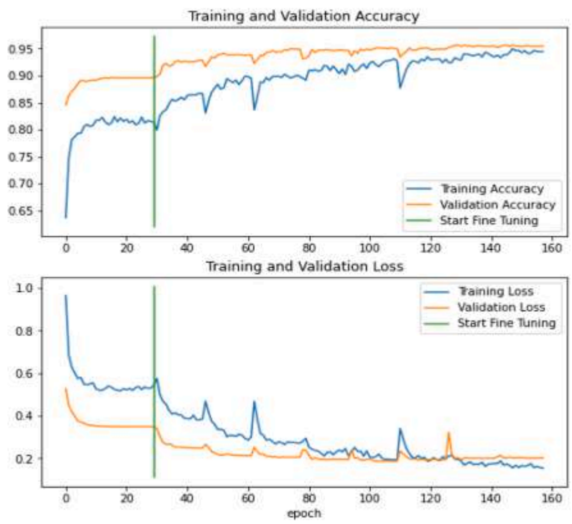
(b)



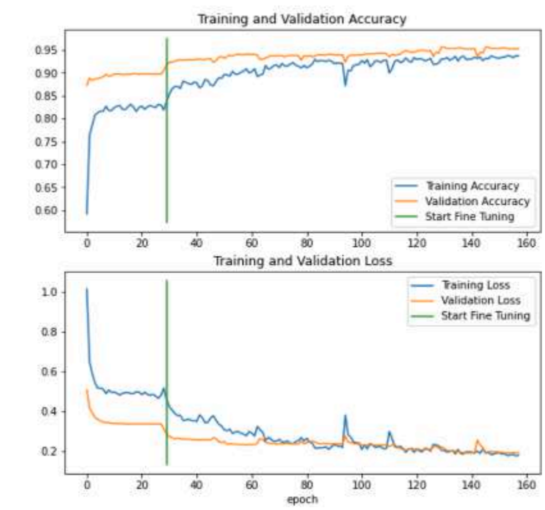
(c)



(d)

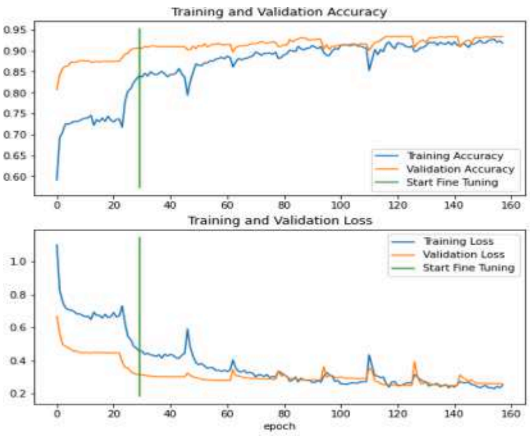


(e)

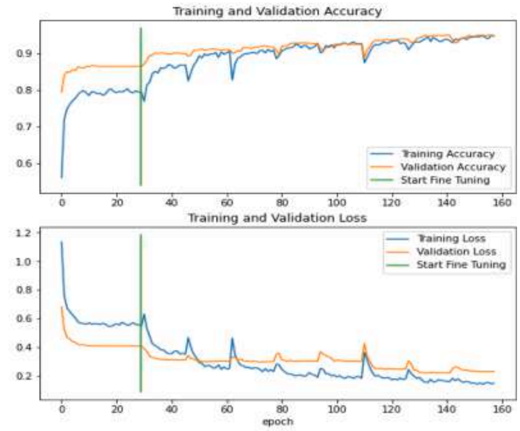


(f)

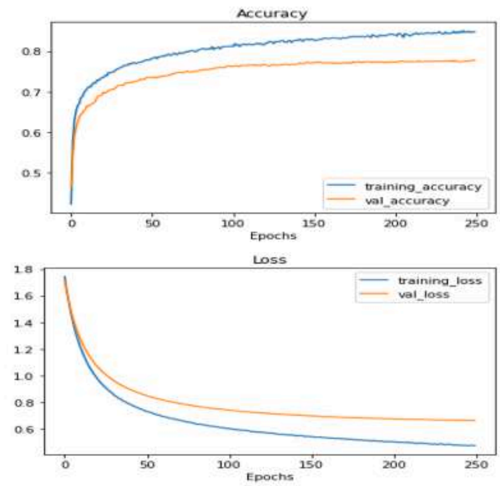
Fig. 11. Accuracy and loss curve for DL models for food image classification. (a-h) EfficientNet (B0-B7) (i) VGG16 (j) VGG19 (k) ResNet50 (l) ResNet101.



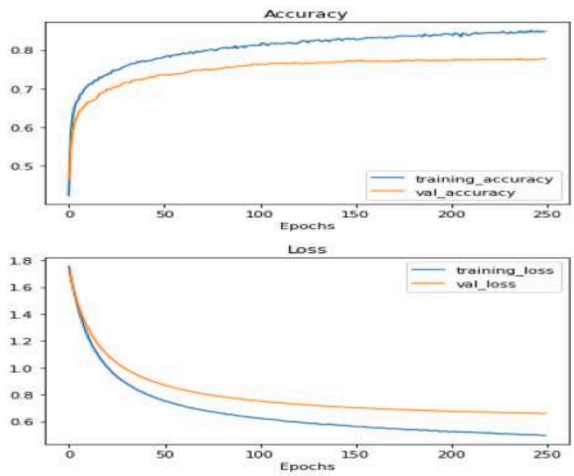
(g)



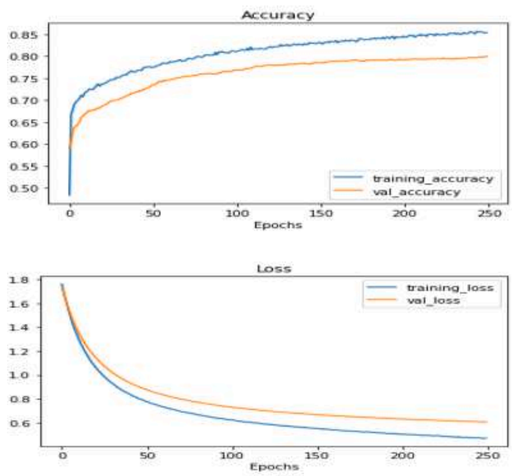
(h)



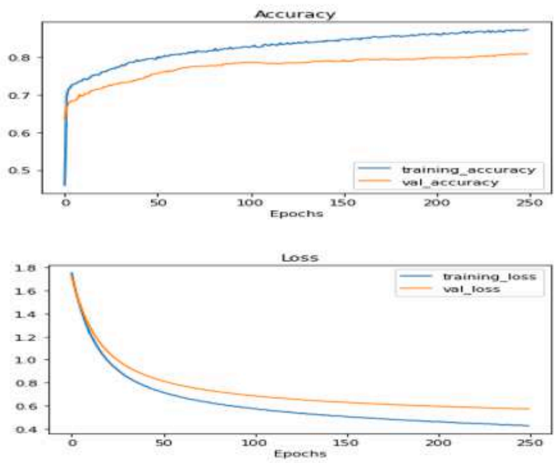
(i)



(j)



(k)



(l)

Fig. 11. (*continued*).

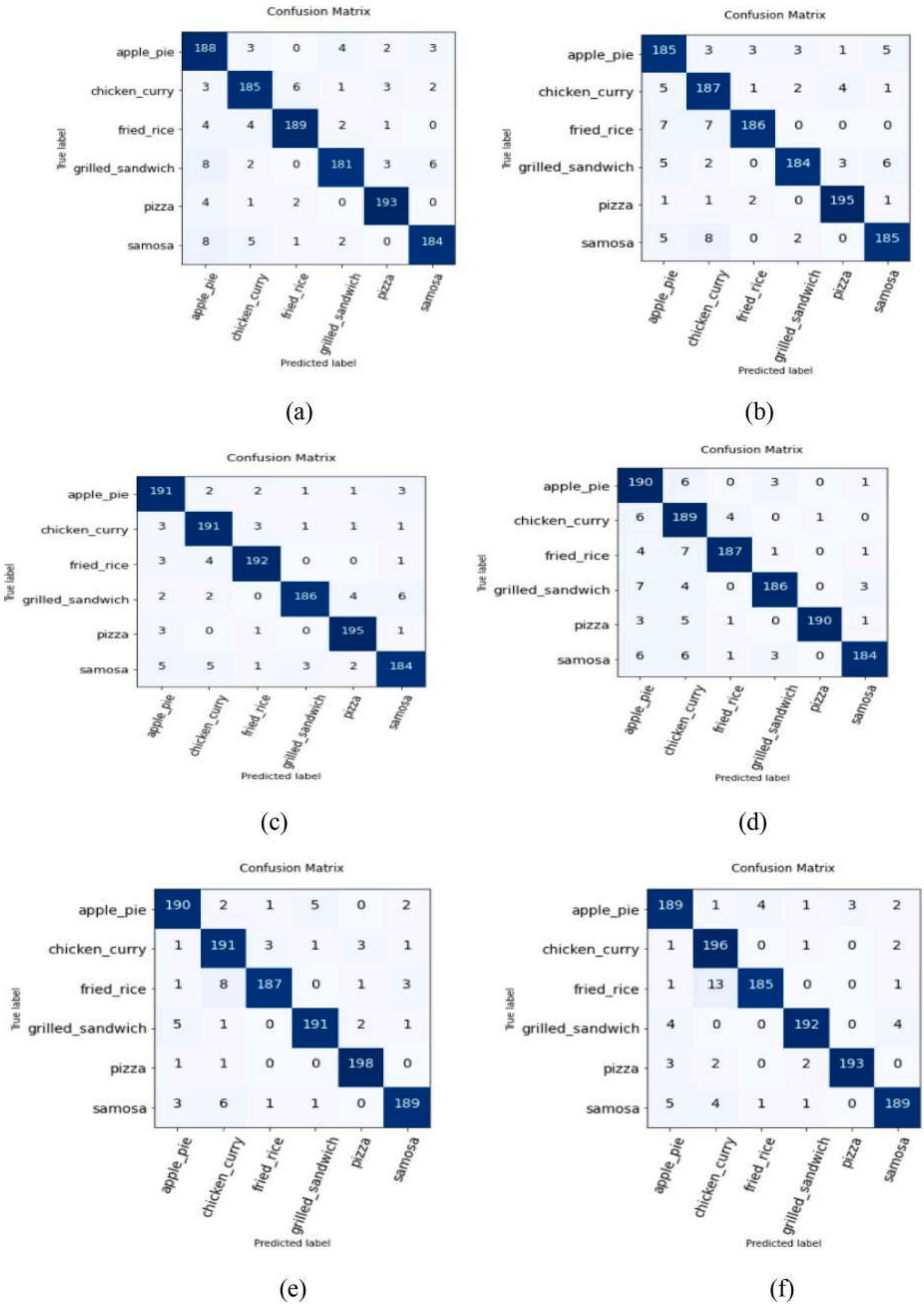


Fig. 12. Confusion matrices of DL models for food image classification (a–h) EfficientNet (B0-B7) (i) VGG16 (j) VGG19 (k) ResNet50 (l) ResNet101.

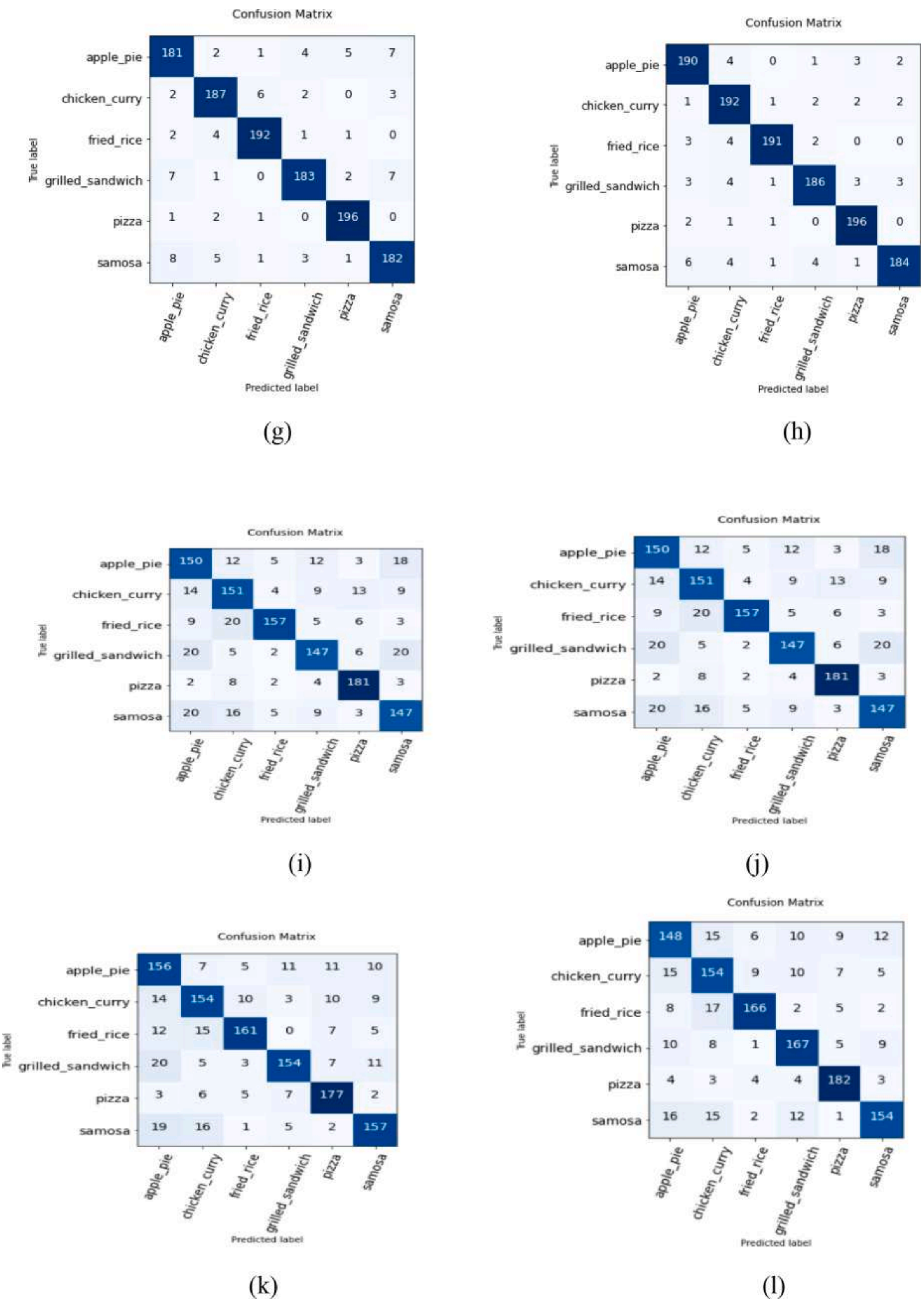


Fig. 12. (*continued*).

Table 9
Food nutritional information with clustering.

Food_items	Calories	Fats	Proteins	Carbohydrates	cluster
Asparagus Cooked	22	0.2	2.4	4.1	0
Avocados	160	15	2	8.5	0
Bananas	89	0.3	1.1	23	0
Bagels made in wheat	250	1.5	10	49	4
Berries	349	0.4	14	77	1

Algorithm 1
HDMS Algorithm.

Input: $a(ageinyears)$, $w(weightinKg)andh(heightincm)$
$Nameorimageoftheconsumedfood(ifany)$.
Output: *Predictionofnextfoodw.r.tmacronutrientdistributionandnutritional requirementofpatient.*
Data: *Foodimagedatasetandnutritionalinformationdataset*
1.*CalculateBMRtodeterminethetotalenergyrequirementforthedayusingequation*(2)
2.*MacronutrientdistributionrecommendedforPCOSpatients*41%: 19%: 40%
CHO: Protein: Fat.
$Total_{CHO} = \frac{Total_{cal} \times 41}{4}$ $Carbohydrate1gm = 4Kcal/g$ Eq. (3)
$Total_{PRO} = \frac{Total_{cal} \times 19}{4}$ $Protein\ 1gm = 4Kcal/g$ Eq. (4)
$Total_{FAT} = \frac{Total_{cal} \times 40}{9}$ $Fat1gm = 9Kcal/g$ Eq. (5)
$Total_{Cal} \rightarrow (Total_{CHO}, Total_{PRO}, Total_{FAT})$ Eq. (6)
3.*Repeatstep4andstep5toenterthemultiplefoodsconsumed.*
4.*Collectinformationfromuserifanyfoodconsumed.*
5.*Ifuserenterednameoffood, then*:
Extractthenutrientsfromthenutritionaldataset
$Consumed_{Cal} \rightarrow (Consumed_{CHO}, Consumed_{PRO}, Consumed_{FAT})$ Eq. (7)
elseIfuseruploadedthefoodimage, then:
CallFOODDeepNetmodeltoclassifythefoodimage
Extractthenutrientsfromthenutritionaldatase
$Consumed_{Cal} \rightarrow (Consumed_{CHO}, Consumed_{PRO}, Consumed_{FAT})$ Eq. (8)
$Balanced_{Cal} = Total_{Cal} \rightarrow (Total_{CHO}, Total_{PRO}, Total_{FAT}) -$
$Consumed_{Cal} \rightarrow (Consumed_{CHO}, Consumed_{PRO}, Consumed_{FAT})$ Eq. (9)
6.*CallK − meansalgorithmtoperformclusteringonnutritionaldataset.*
7.*CallRFalogirthmtodetermindeclusterwhichisclosesttothenutritionalrequirement ofthepatientasperBalanced*$_{Cal}$*requirements.*

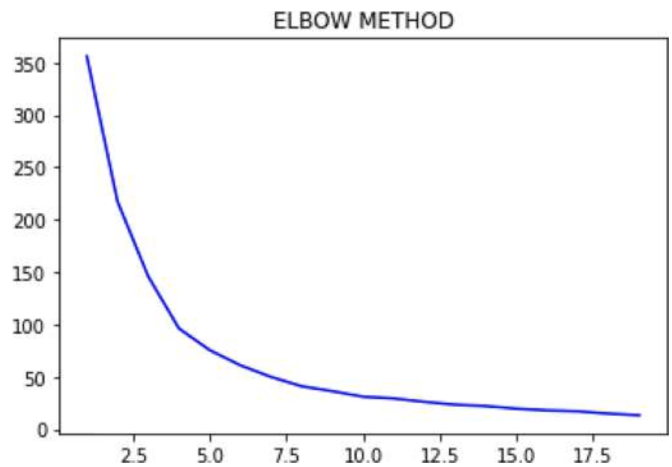


Fig. 13. Elbow method to select the number of clusters.

97% accuracy.

The proposed diet management system predicts the list of foods as per the nutritional requirement of the PCOS patient. Further, in future work, the proposed model can be improved by providing the diet recommendation with meal planning such as macronutrient distribution for breakfast, lunch, snacks, dinner, etc. Future work will also implement diet recommendations as per the age, seasonal food, and user preference. The system will be implemented in the form of a mobile application.

Data availability

Source mentioned.

Funding

This research received no external funding.

Code availability

We can upload as per requirement.

Declaration of Competing Interest

The authors declare that they have no conflicts of interest regarding the present study.

Data Availability

Data will be made available on request.

References

[1] Lie Fong S, Douma A, Verhaeghe J. Implementing the international evidence-based guideline of assessment and management of polycystic ovary syndrome (PCOS): how to achieve weight loss in overweight and obese women with PCOS? J Gynecol Obstet Hum Reprod 2021;50(6):101894. https://doi.org/10.1016/j.jogoh.2020.101894.

[2] R.S. Legro et al., “Diagnosis and treatment of polycystic ovary syndrome: an endocrine society clinical practice guideline,” C, pp. 1–29, 2013, doi:10.1210/jc.2013-2350.

[3] Lin AW, et al. Dietary and physical activity behaviors in women with polycystic ovary syndrome per the new international evidence-based guideline. Nutrients 2019;11(11):1–15. https://doi.org/10.3390/nu11112711.

[4] Faghfoori Z, Fazelian S, Shadnoush M, Goodarzi R. Nutritional management in women with polycystic ovary syndrome: a review study. Diabetes Metab Syndr Clin Res Rev 2017;11(September):S429–32. https://doi.org/10.1016/j.dsx.2017.03.030.

[5] Sowah RA, Bampoe-Addo AA, Armoo SK, Saalia FK, Gatsi F, Sarkodie-Mensah B. Design and development of diabetes management system using machine learning. Int J Telemed Appl 2020;2020. https://doi.org/10.1155/2020/8870141.

[6] Hafiz R, Haque MR, Rakshit A, Uddin MS. Image-based soft drink type classification and dietary assessment system using deep convolutional neural network with transfer learning. J King Saud Univ Comput Inf Sci 2020. https://doi.org/10.1016/j.jksuci.2020.08.015. xxxx.

[7] Zhang P, Yang L, Li D. EfficientNet-B4-Ranger: a novel method for greenhouse cucumber disease recognition under natural complex environment. Comput Electron Agric 2020;176(January):105652. https://doi.org/10.1016/j.compag.2020.105652.

[8] Tan M, Le QV. EfficientNet: rethinking model scaling for convolutional neural networks. In: Proceedings of the 36th International Conference on Machine Learning. 2019-June; 2019. p. 10691–700.

[9] WiraBuana P, Jannet DRM S, Ketut Gede Darma Putra I. Combination of K-nearest neighbor and K-means based on term re-weighting for classify Indonesian news. Int J Comput Appl 2012;50(11):37–42. https://doi.org/10.5120/7817-1105.

[10] Al Amrani Y, Lazaar M, El Kadirp KE. Random Forest and support vector machine based hybrid approach to sentiment analysis. Procedia Comput Sci. 2018;127 (March):511–20. https://doi.org/10.1016/j.procs.2018.01.150.

[11] Kiourt C, Pavlidis G, Markantonatou S. Deep Learning Approaches in Food Recognition. In: Tsihrintzis G, Jain L, editors. Machine Learning Paradigms. Learning and Analytics in Intelligent Systems, 18. Cham: Springer; 2020. https://doi.org/10.1007/978-3-030-49724-8_4.

[12] Raikar MM, Meena SM, Kuchanur C, Girraddi S, Benagi P. Classification and grading of Okra-ladies finger using deep learning. Procedia Comput Sci 2020;171 (2019):2380–9. https://doi.org/10.1016/j.procs.2020.04.258.

[13] Shen Z, Shehzad A, Chen S, Sun H, Liu J. Machine learning based approach on food recognition and nutrition estimation. Procedia Comput Sci 2020;174: 448–53. https://doi.org/10.1016/j.procs.2020.06.113.

[14] Salloum G, Tekli J. Automated and personalized nutrition health assessment, recommendation, and progress evaluation using fuzzy reasoning. Int J Hum Comput Stud. 2021;151(December 2020):102610. https://doi.org/10.1016/j.ijhcs.2021.102610.

[15] Ghosh P, Bhattacharjee D, Nasipuri M. Dynamic diet planner: a personal diet recommender system based on daily activity and physical condition. Innov Res BioMed eng 2021;42(6):442–56. https://doi.org/10.1016/j.irbm.2021.03.001.

[16] Mustafa N, Abd Rahman HA, Sani NS, Mohamad MI, Zakaria AZ, Ahmad A, Safii NS. iDietScore™: Meal Recommender System for Athletes and Active Individuals. Int. J. Adv. Comput. Sci. Appl. 2020;11(12).

[17] Zhang X, Zheng Y, Guo Y, Lai Z. The effect of low carbohydrate diet on polycystic ovary syndrome: a meta-analysis of randomized controlled trials. Int J Endocrinol 2019;2019(Lcd). https://doi.org/10.1155/2019/4386401.

[18] Mehrabani HH, Salehpour S, Meyer BJ, Tahbaz F. Beneficial effects of a high-protein, low-glycemic-load hypocaloric diet in overweight and obese women with polycystic ovary syndrome: a randomized controlled intervention study. J Am Coll Nutr 2012;31(2):117–25. https://doi.org/10.1080/07315724.2012.10720017.

[19] Perelman D, Coghlan N, Lamendola C, Carter S, Abbasi F, McLaughlin T. Substituting poly- and mono-unsaturated fat for dietary carbohydrate reduces hyperinsulinemia in women with polycystic ovary syndrome. Gynecol Endocrinol 2017;33(4):324–7. https://doi.org/10.1080/09513590.2016.1259407.

[20] Gower BA, et al. Favourable metabolic effects of a eucaloric lower-carbohydrate diet in women with PCOS. Clin Endocrinol 2013;79(4):550–7. https://doi.org/10.1111/cen.12175 (Oxf).

[21] Mavropoulos JC, Yancy WS, Hepburn J, Westman EC. The effects of a low-carbohydrate, ketogenic diet on the polycystic ovary syndrome: a pilot study. Nutr Metab 2005;2:1–5. https://doi.org/10.1186/1743-7075-2-35.

[22] Bossard L, Guillaumin M, Van Gool L. Food-101 - mining discriminative components with random forests. Lect Notes Comput Sci 2014;8694(PART 6):446–61. https://doi.org/10.1007/978-3-319-10599-4_29 (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)LNCS.
[23] U.S. Department of Agriculture, Agricultural Research Service, USDA. Food and Nutrient Database for Dietary Studies 2017-2018. Food Surveys Research Group Home Page; 2020. http://www.ars.usda.gov/nea/bhnrc/fsrg.
[24] Frankenfield DC, Muth ER, Rowe WA. The Harris-Benedict studies of human basal metabolism: history and limitations. J Am Diet Assoc 1998;98(4):439–45. https://doi.org/10.1016/S0002-8223(98)00100-X.
[25] Atila Ü, Uçar M, Akyol K, Uçar E. Plant leaf disease classification using EfficientNet deep learning model. Ecol Inform 2021;61(June 2020):101182. https://doi.org/10.1016/j.ecoinf.2020.101182.

Rajdeep Kaur received her B. Tech degree from Guru Nanak Dev University Amritsar, in 2007 and M. Tech from NIT Jalandhar, in 2015. She is pursuing PhD from Chandigarh University in Artificial Intelligence. She is author of over 15 technical publications in national and international conferences and national and international journals.

Dr. **Rakesh Kumar** is a Professor in the Department of Computer Science Engineering at Chandigarh University, Punjab, India. He has more than 17 years of teaching experience. His-research interests are IoT, Machine Learning and Natural Language Processing. He has authored or co-authored more than 50 publications various National, International Conferences and International Journals.

Dr. **Meenu Gupta** is an Associate Professor in the Department of Computer Science Engineering at Chandigarh University, India. She has more than 14 years of teaching experience. Her areas of research cover the fields of Machine Learning. She has authored or co-authored more than 20 book chapters and over 50 papers in refereed international journals and conferences.