# A Computer Vision Based Food Recognition Approach for Controlling Inflammation to Enhance Quality of Life of Psoriasis Patients

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***Abstract*—Deep learning becomes the spotlight in computer vision based recognition approaches in recent years. Psoriasis affects people of all ages around the world and causes inflammation on the skin with significant systemic disability and illness. Inflammatory foods increase inflammation rapidly, patients can easily control inflammation to enhance the quality of life by eliminating these foods from their everyday diet. This paper addresses a rapid food recognition approach to assist psoriasis patients to recognize fifteen highly inflammatory foods. Using image augmentation techniques, a dataset of 41250 images of different inflammatory foods have generated from 10000 images. AlexNet, VGG16, and EfficientNet-B0 have used in this study using the transfer learning approach, and EfficientNet-B0 has achieved the highest accuracy of 98.63% under the test set of 5250 images. AlexNet and VGG16 have achieved 87.22% and 93.79% accuracy, respectively. EfficientNet-B0 has consumed the lowest time in recognizing unseen images compared to others.**

***Keywords*—Deep Learning, Computer Vision, Transfer Learning, Food Recognition, Psoriasis**

## I. INTRODUCTION

Psoriasis is a chronic, noncontagious autoimmune skin disease that causes inflammation in the body and has a significant negative impact on a patient's quality of life. Psoriasis affects the ability to perform activities of everyday life, causes social discrimination and embarrassment, and leads to a terrible emotional impact on patients. 125 million people have psoriasis all over the world, treatment of psoriasis is not so effective but highly expensive [1]. Patients living with inflammation on the body may feel embarrassed when they want to reveal their bodies during using public showers, swimming, social activities, or anyway living in situations that do not provide suitable privacy. Inflammatory foods have a remarkably negative impact on the severity of inflammation in the body, taking highly inflammatory foods regularly increases inflammation rapidly. Living with psoriasis increases the risk of high blood pressure, diabetes, arthritis, Crohn's disease, cancer, and other major diseases [2]. Avoiding highly inflammatory foods in the everyday diet decreases the symptoms of inflammation which is very crucial to control the severity of psoriasis and enhance the quality of a patient's life.

In this study, fifteen highly inflammatory foods such as red meat, sausage, bacon, egg, eggplant, bread, burger, pizza, sandwich, pasta, cookies, pastry, doughnut, french fry, and ice cream have selected to establish a dataset for the purpose of the study. Red meat and egg contain polyunsaturated fat known as arachidonic acid, on the other hand, sausage and bacon are the variants of processed meats, and these foods can worsen the symptoms of inflammation [3]. Eggplant contains solanine which is a chemical compound that exacerbates psoriasis and increases itching of psoriasis affected area of skin. Consuming gluten, refined carbohydrates, sugar, and high fructose corn syrup in the everyday diet increases inflammation on the body, and these are found in bread, burger, pizza, sandwich, pasta, cookies, pastry, and doughnut. French fry is produced from potato that also contains solanine, on the other hand, casein and lactose are found in ice cream that increases the amount of inflammatory cytokines in the body [4].

This inflammatory food recognition approach will be highly beneficial to psoriasis patients while taking food from restaurants, hotels, airlines, hospitals, retirement homes, and care centres of the disabled. People can easily recognize inflammatory foods using this rapid recognition approach, it will be kept far away from them the panic of inflammation. During traveling to new places, this food recognition system will be helpful in reducing anxiety for inflammatory foods. Moreover, a remarkable number of peoples in developing countries less know about inflammatory foods, this approach can play a vital role for them in reducing inflammation and enhancing the quality of life.

Recently, computer vision approaches have obtained remarkable success in recognizing skin disorders [5], leaf diseases [6], and many other fields. In this paper, a rapid and accurate computer vision based recognition approach for recognizing inflammatory foods has been introduced to assist psoriasis patients using state-of-the-art convolutional neural network (CNN) models. An inflammatory food dataset has been established and lays a crucial base for the generalization of the CNN models such as AlexNet, VGG16, and EfficientNet-B0. Image augmentation techniques have been utilized to control the overfitting of the CNN models by generating enough images for training. The inflammatory food dataset contains 30000 training images, 6000 validation images, and 5250 testing images. Using the transfer learning approach, all models have used in this study. During the training, the early stopping technique has used, EfficientNet-B0 has taken more time than others, on the other hand, AlexNet has achieved the lowest training time per epoch but taken more time in recognizing unseen new images. According to the experimental results, EfficientNet-B0 has reached 98.63% accuracy which is better than other models. Finally, based on the recognition time of unseen new images of different foods and the test accuracy of models, EfficientNet-B0 has been proposed in this study for inflammatory food recognition.

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The rest of this paper is arranged as follows. Section 2 introduces and summarizes related work. Section 3 describes the inflammatory food dataset, and state-of-the-art CNN architectures used in this study. Experimental studies are presented in Section 4. The results acquired in the study are given and discussed in Section 5. The study is concluded with Section 6.

## II. Related Work

With the continuous growth and success of deep learning algorithms, many researchers have made tremendous efforts in several studies to recognize different types of foods.

Safak Kayikci et al. have used CNN to classify Turkish foods using three different datasets and also have compared the performance of different optimization algorithms such as stochastic gradient descent (SGD), Adam and Adadelta, and activation functions such as rectified linear unit (ReLU), Tanh, and Softmax [7]. Utilizing the SGD optimization algorithm with Softmax activation function, they have achieved 93% accuracy. Renaldi Primaswara Prasetya et al. have used Inception V3 for Indonesian food items labelling and achieved 70% accuracy after 500 iteration process [8]. Mohammed A. Subhi et al. have used CNN with 24 weight layers to classify eleven foods using a dataset of 5800 images [9]. Punnarumol Temdee et al. have achieved 75.2% accuracy using Inception V3 for classifying 40 categories of foods and have compared the performance of different training steps, after both 8000 and 10000 training steps, accuracy has reached 73.4% [10]. Three different types of distortions have been used in their study such as random brightness, random scale, and random crop, and among these random brightness has achieved the highest accuracy. Weishan Zhang et al. have used CNN for food image recognition and have achieved 80.8% and 60.9% accuracy for the fruit image dataset and UEC-FOOD100 dataset, respectively [11]. Guoxiang Zeng has achieved 95.6% accuracy in classifying 26 categories of fruit and vegetable images using 12,173 images with the image saliency and VGG model [12]. Woo Chaw Seng et al. have used k-Nearest Neighbours (KNN) to classify seven different fruits and have achieved 90% accuracy. Color, shape, and size features of 50 fruit images have been used in their study [13]. Md Tohidul Islam et al. have achieved 74.70% accuracy using their proposed CNN architecture and 92.86% accuracy using Inception V3 in classifying 11 different foods [14]. 100 and 32 epochs have been used with a dataset of 16643 images to train proposed CNN architecture and Inception V3, respectively. Rajayogi J R et al. have used Inception V3, VGG16, VGG19, and ResNet to classify 20 different Indian food images and achieved 87.9% accuracy with a loss rate of 0.5893 using Inception V3 [15]. Hokuto Kagaya et al. have used support vector machine (SVM) and CNN to classify 10 food items and have achieved 89.7% and 93.8% accuracy, respectively [16]. Siyuan Lu et al. have used a six-layer CNN to classify nine different fruits and have achieved 91.44% accuracy [17]. Both training and test set have been used in their study contains 900 images. Rajesh Yamparala et al. have used CNN to classify four different fruits, and have achieved 90% accuracy with a dataset of 200 images [18].

According to these related studies, CNNs have acquired surprising outcomes in several computer vision based food recognition approaches. However, no recognition approach has been introduced for inflammatory food classification still now. In addition, state-of-the-art CNN models have been used using transfer learning techniques in a remarkable number of studies. Hence, an image recognition model for inflammatory food that is based on pre-trained CNNs is proposed in this paper.

## III. Materials and Methods

### A. Dataset

In this study, an inflammatory food dataset has established containing 41250 images of 15 different highly inflammatory foods. Fig. 1 shows 15 representative images belonging to each class of the used dataset. Image augmentation has been utilized to overcome the overfitting problem of the training phase of CNNs. Using image augmentation techniques such as rotation transformations (including 90 and 270 degrees), horizontal and vertical shift, and horizontal and vertical flip 41250 images have generated from 10000 original images. All images have been reshaped into 227×227, 224×224 dimensions using Pillow, a library of Python 3. The inflammatory food dataset has been randomly divided into training, validation, and test set, where each class contains 2000 training images, 400 validation images, and 350 testing images.


Fig. 1. Sample from the inflammatory dataset: 1) red meat 2) sausage 3) bacon 4) egg 5) eggplant 6) bread 7) burger 8) pizza 9) sandwich 10) pasta 11) cookies 12) pastry 13) doughnut 14) french fry 15) ice cream

Fig. 2 represents an example that illustrates the image generation process using image augmentation.

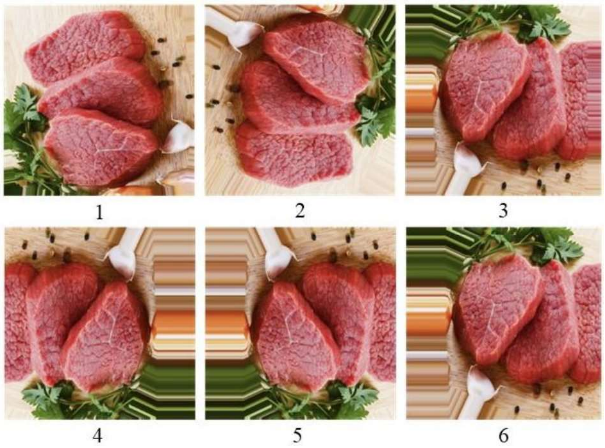


Fig. 2. Image augmentation of a read meat image: 1) 90 degree rotation 2) 270 degree rotation 3) horizontal shift 4) vertical shift 5) horizontal flip 6) vertical flip

### B. State of the art CNN based models

In this study, state-of-the-art CNN architectures such as AlexNet, VGG16, and EfficientNet-B0 have been used to recognize highly inflammatory foods using the transfer learning approach, and different experimental studies have been introduced to evaluate the performance of these models. Transfer learning is very superior in terms of saving time with obtaining better performance and computational efficiency compared to train a new CNN model from scratch. The knowledge obtained during the training of a CNN model is used to train another CNN model in transfer learning. During the training of a CNN model in deep learning, the first few layers are trained for explaining the characteristics of the problem. On the other hand, the last few layers of the trained architecture of a CNN can be dropped and retrained with new layers for the target task in transfer learning.

The AlexNet is an 8 layer deep CNN architecture that contains approximately 61 million parameters, takes 227×227 pixels images as input, and was introduced in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition which was held in 2012 [19]. The architecture of AlexNet contains five convolution layers and three fully connected layers, uses ReLU as an activation function in both convolution and fully connected layers. The last fully connected layer of AlexNet architecture is connected to the Softmax layer with 15 neurons for the purpose of the study.

VGG16 is a 16 layer deep CNN architecture, won the ILSVR-2014 which contains approximately 138 million parameters and takes 224×224 pixels images as input [20]. VGG16 always has the same convolution layers instead of having a large number of hyper-parameters that use 3×3 filters with stride 1, the same padding, and maximum pooling layers that use 2×2 filters with stride 2. Finally, it contains three fully connected layers and the first two fully connected layers use ReLU as an activation function. To train VGG16 with our inflammatory food dataset, the last fully connected layer of VGG16 architecture is connected to the Softmax layer with 15 neurons.

The EfficientNet group consists of eight models, and EfficientNet-B0 is the base model of this group that takes 224×224 pixels images as input [21]. This architecture uses mobile inverted bottleneck convolution (MBConv) which is similar to MobileNetV2 but is slightly larger due to an increased floating point operation per second (FLOP) budget. In general, the EfficientNet models obtain both higher accuracy and better efficiency over existing state-of-the-art CNN models, reducing parameter size and FLOPS by an order of magnitude. While other CNN models use ReLU as an activation function, models of EfficientNet use Swish that is a multiplication of a linear and a sigmoid activation. EfficientNet-B0 uses the inverted residual block that decreases trainable parameters by a large number. The schematic representation of the EfficientNet-B0 architecture is presented below in Fig. 3.

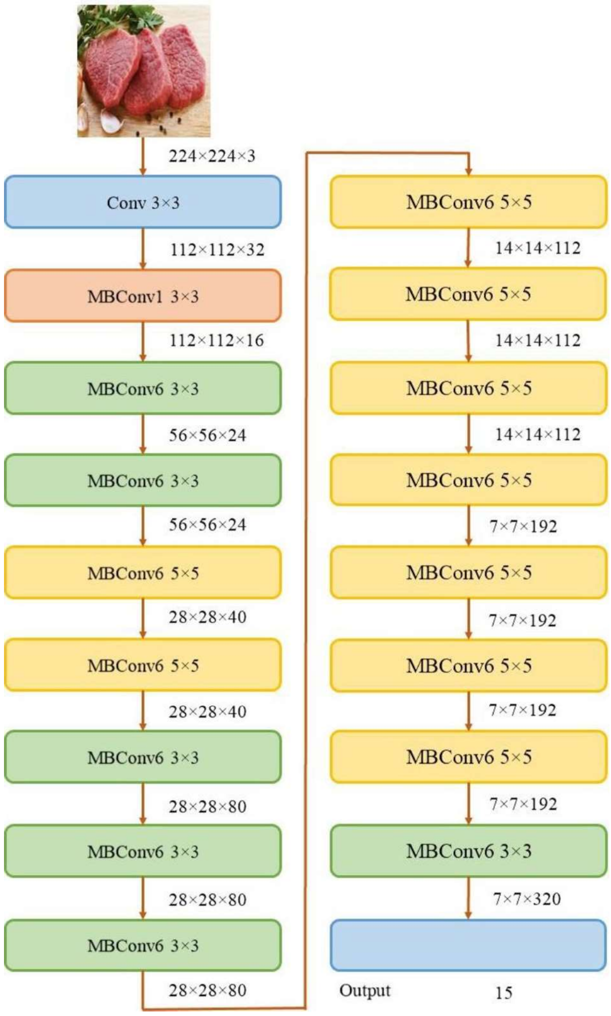


Fig. 3. Schematic representation of EfficientNet-B0 architecture.

## IV. Experiments

### A. Training

Training and validation set of inflammatory food dataset have used to train and fit pre-trained CNN models and to compare the performance of these models test set have used. During the training phase, all layers of AlexNet, VGG16, and EfficientNet-B0 have been set as trainable, and the last fully connected layers of these with 1000 outputs have been replaced with 15 outputs in order to classify images of 15 different highly inflammatory foods. In the last layer of these models, Softmax has been selected as an activation function, and categorical cross entropy has been chosen as a loss function to estimate the loss of CNN models so that the weights can be updated to decrease the loss on the next evaluation. Adam optimization has used during the training phase of AlexNet and EfficientNet-B0, SGD has used for VGG16, and the early stopping technique has used to avoid overfitting which is one of the most widely used and oldest forms of neural network regularization. All CNN models have been trained with GPU support, and experimental studies have introduced using Google Colab. Table 1 summarizes the default input size, learning rate, number of epochs, and number of parameters defined for each CNN model.

TABLE I. THE DEFAULT INPUT SIZE, LEARNING RATE, NUMBER OF EPOCHS, AND NUMBER OF PARAMETERS OF MODELS

| Model Name | Input Size | Learning Rate | Number of Epochs | Number of Parameters |
|---|---|---|---|---|
| AlexNet | 227×227 | 0.001 | 31 | 25,735,531 |
| VGG16 | 224×224 | 0.01 | 26 | 134,321,999 |
| EfficientNet-B0 | 224×224 | 0.001 | 42 | 66,673,702 |

## B. *Performance Metrics*

Different performance metrics such as sensitivity, specificity, accuracy, and precision have been used in this study to evaluate the performance of AlexNet, VGG16, and EfficientNet-B0. Using True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), the metrics have presented below in between (1) to (4) have calculated considering the values in the confusion matrix acquired after multi-class classifications as inflammatory food dataset contains 15 classes. Sensitivity (sen) is the proportion of accurately categorized positives out of all true positives. Specificity (spe) is the proportion of correctly categorized negatives out of all true negatives. Accuracy (acc) specifies the rate of accurately categorized images out of all images. On the other hand, Precision (pre) is the ratio of accurately categorized positives out of all positive recognitions.

For a class $g$,

$$Sen(g) = \frac{TP(g)}{TP(g) + FN(g)} \tag{1}$$

$$Spe(g) = \frac{TN(g)}{TN(g) + FP(g)} \tag{2}$$

$$Acc(g) = \frac{TP(g) + TN(g)}{TP(g) + TN(g) + FP(g) + FN(g)} \tag{3}$$

$$Pre(g) = \frac{TP(g)}{TP(g) + FP(g)} \tag{4}$$

# V. RESULTS AND DISCUSSIONS

Establish accurate and rapid food recognition approach for highly inflammatory foods with state-of-the-art CNN models is the principal purpose of this study. Several experimental studies have been conducted with the dataset of inflammatory food to evaluate the performance of AlexNet, VGG16, and EfficientNet-B0. In this context, the training and test accuracies have been obtained by used pre-trained CNN models using the transfer learning approach on inflammatory food dataset that contains 30000 training images, and 5250 testing images are presented below in Fig 4.

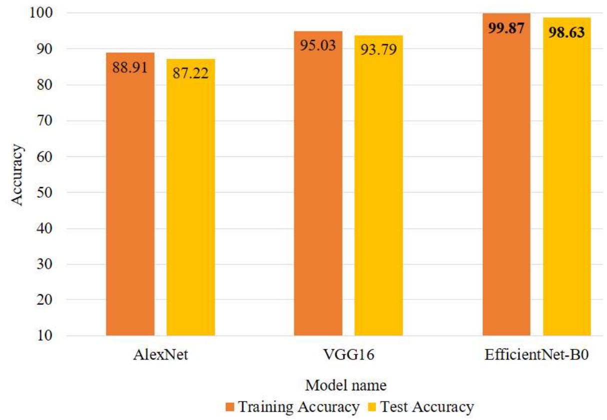


Fig. 4. Training and Test accuracies of CNN models.

In this study, EfficientNet-B0 has shown better performance than other CNN models, achieved 99.87% training accuracy and 98.63% test accuracy. AlexNet has achieved the lowest training and test accuracy. On the other hand, EfficientNet-B0 has misclassified 72 images while AlexNet and VGG16 have wrongly predicted 671 and 326 images, respectively. The confusion matrix of EfficientNet-B0 is presented below in Fig. 5.

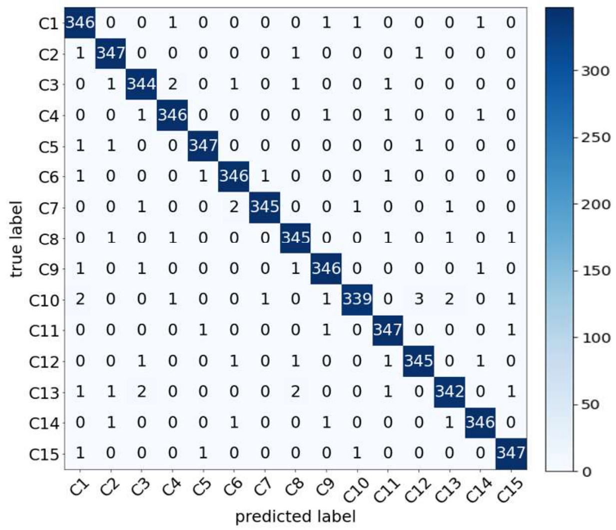


Fig. 5. Confusion matrix of EfficientNet-B0: C1) red meat C2) sausage C3) bacon C4) egg C5) eggplant C6) bread C7) burger C8) pizza C9) sandwich C10) pasta C11) cookies C12) pastry C13) doughnut C14) french fry C15) ice cream

To examine the recognition time of CNN models used in this study, an experimental study has conducted with 10 new images of different highly inflammatory foods which were not in the inflammatory food dataset. EfficientNet-B0 has taken 11.27 seconds to classify 10 images accurately, while AlexNet and VGG16 have taken 17.03 and 15.58 seconds, respectively. But, in this experiment, AlexNet and VGG16 have wrongly predicted 3 and 2 images, respectively. In order to more perceptibly demonstrate the performance of the EfficientNet-B0 architecture discussed in this study, class-wise classification performance has been analyzed. Sensitivity, specificity, accuracy, and precision values of the EfficientNet-B0 model for each class of inflammatory food dataset have calculated using TP, TN, FP, FN which have been obtained from the confusion matrix presented in Fig. 5, and class-wise classification performance is presented below in Table 2.

TABLE II. CLASSIFICATION PERFORMANCE OF EFFICIENTNET-B0 FOR EACH CLASS

| Class Name | Sen (%) | Spe (%) | Acc (%) | Pre (%) |
|---|---|---|---|---|
| Red meat | 97.74 | 99.92 | 99.77 | 98.86 |
| Sausage | 98.58 | **99.94** | 99.85 | **99.14** |
| Bacon | 98.29 | 99.88 | 99.77 | 98.29 |
| Egg | 98.58 | 99.92 | 99.83 | 98.86 |
| Eggplant | 99.14 | **99.94** | **99.89** | **99.14** |
| Bread | 98.58 | 99.92 | 99.83 | 98.86 |
| Burger | **99.42** | 99.90 | 99.87 | 98.57 |
| Pizza | 98.29 | 99.90 | 99.79 | 98.57 |
| Sandwich | 98.58 | 99.92 | 99.83 | 98.86 |
| Pasta | 99.12 | 99.78 | 99.73 | 96.86 |
| Cookies | 98.30 | **99.94** | 99.83 | **99.14** |
| Pastry | 98.57 | 99.90 | 99.81 | 98.57 |
| Doughnut | 98.56 | 99.84 | 99.75 | 97.71 |
| French fry | 98.86 | 99.92 | 99.85 | 98.86 |
| Ice cream | 98.86 | **99.94** | 99.87 | **99.14** |

In the burger class, EfficientNet-B0 has achieved the highest sensitivity of 99.42%. On the other hand, EfficientNet-B0 has achieved the highest specificity and precision in the sausage, eggplant, cookies, and ice cream classes, 99.94%, and 99.14%, respectively. In eggplant class, EfficientNet-B0 has achieved the highest accuracy of 99.89%. The misclassification number of EfficientNet-B0 on the test set for each class is presented below in Fig. 6.

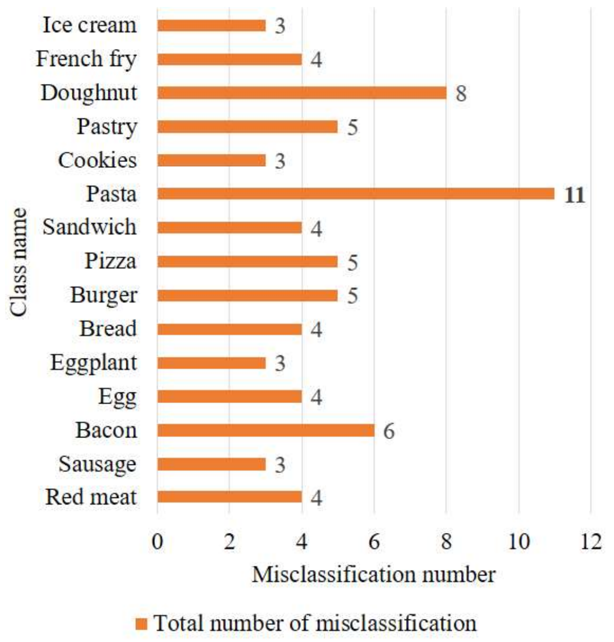


Fig. 6. False prediction numbers of EfficientNet-B0 for each class.

Based on the false prediction numbers of each class, in sausage, eggplant, cookies, and ice cream classes, EfficientNet-B0 has shown significant performance, but in pasta class, it has misclassified 11 images which was the highest number of misclassification. The accuracy and loss curve of both training and validation of EfficientNet-B0 architecture is shown below in Fig. 7 and Fig. 8.

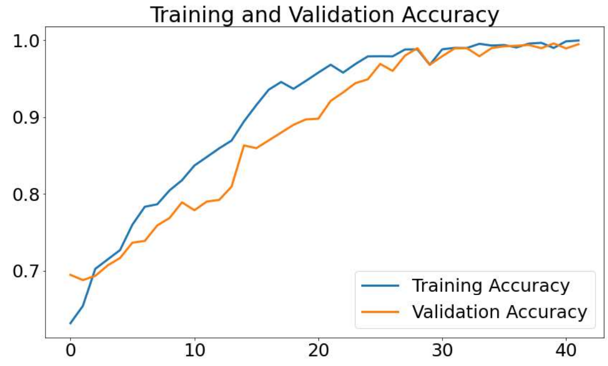


Fig. 7. Training and validation accuracy curve of EfficientNet-B0.

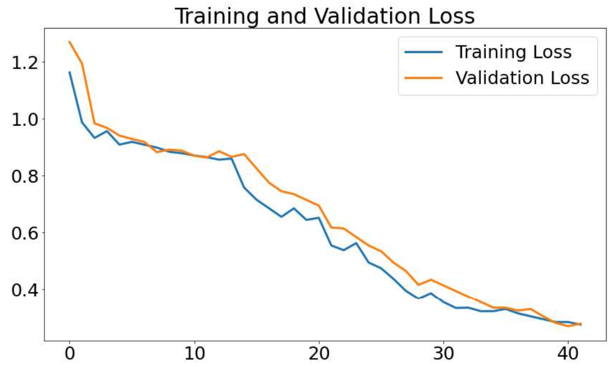


Fig. 8. Training and validation loss curve of EfficientNet-B0.

The outcome of this study has compared with several studies have conducted in the literature for recognizing various types of foods, shown below in Table 3, and this study is the first attempt to recognize inflammatory foods to assist psoriasis patients using deep learning techniques.

TABLE III. COMPARISON OF DEEP LEARNING METHODS FOR FOOD RECOGNITION.

| Study | Method | Number of Classes | Accuracy |
|---|---|---|---|
| Safak Kayikci et al. [7] | Inception-V3 | 15 | 93.00% |
| Renaldi Primaswara Prasetya et al. [8] | Inception-V3 | 6 | 70.00% |
| Punnarumol Temdee et al. [10] | Inception-V3 | 40 | 75.20% |
| Weishan Zhang et al. [11] | CNN | 30 | 60.90% |
| Woo Chaw Seng et al. [14] | Inception-V3 | 11 | 92.86% |
| Rajayogi J R et al. [15] | Inception-V3 | 20 | 87.90% |
| Hokuto Kagaya et al. [16] | CNN | 10 | 93.80% |
| Siyuan Lu et al. [17] | CNN | 9 | 91.44% |
| Rajesh Yamparala et al. [18] | CNN | 4 | 90.00% |
| Our study | EfficientNet-B0 | 15 | **98.63%** |

## VI. CONCLUSIONS

Computer vision approaches have become popular nowadays for image processing and pattern recognition tasks. Inflammation of psoriasis patients is a great threat to their quality of life, avoiding inflammatory foods can play a crucial role to control inflammation. An improved computer vision based recognition approach is proposed for recognizing inflammatory foods accurately using EfficientNet-B0 which has achieved a recognition accuracy of 98.63%. Performance of Efficient-B0 has compared with two other state-of-the-art CNN architectures such as AlexNet and VGG16, achieved 87.22% and 93.79% accuracy, respectively. A dataset of fifteen different highly inflammatory foods contains 41250 images have generated from 10000 original images using image augmentation techniques. AlexNet, VGG16, and EfficientNet-B0 have used in this study using the transfer learning approach, and AlexNet has consumed less training time than others. EfficientNet-B0 has achieved the highest accuracy of 99.89% in the eggplant class, misclassified 11 images of pasta which was the highest number of false predictions. Compared to others, EfficientNet-B0 has taken less time to recognize unseen images, in 11.27 seconds it has classified 10 images with 100% accuracy. Experimental studies showed that EfficientNet-B0 which offers a remarkable recognition performance in this study, could be successfully used in other types of food recognition.

In the future work, it is planned to establish a more efficient food recognition approach that will be able to recognize both inflammatory and non-inflammatory foods with less recognition time to assist psoriasis patients.

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