Performance Evaluation of EfficientNet Variants for Image Retrieval Tasks

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Abstract

Content-Based Image Retrieval (CBIR) is a computational technique focused on retrieving images from a database based on their visual content. In CBIR systems, the primary focus is analysing visual features within images, enabling the matching and retrieval of relevant images. Nevertheless, deploying deep learning models for CBIR feature extraction, issues of trade-off between computational time and space complexity are of great concern. This paper explores EfficientNet, a relatively recent deep learning model famous for its computational cost efficiency and accuracy to improve the efficiency of CBIR systems. Further, the various EfficientNet model variants are investigated and analysed to assess their performance in CBIR tasks. The evaluation encompasses eight architectures within the EfficientNet family, namely EfficientNet-B0 through EfficientNet-B7, leveraging the CorelDB80 dataset as a benchmark for CBIR. The experimental results underscore the suitability of the EfficientNet family for CBIR applications, achieving a mean precision of up to 89.03%. Notably, the EfficientNet-B7 architecture consistently outperforms other variants regarding precision across different categories within the dataset. These findings provide valuable insights into the performance nuances of various EfficientNet architectures for CBIR developers, emphasizing the crucial consideration of precision in the model selection process.

Keywords: Content-Based Image Retrieval, EfficientNet, Feature Extraction, Similarity Measure, CorelDB80

1 Introduction

Image retrieval based on visual content is the focus of solving Content-Based Image Retrieval (CBIR) systems (Martey et al., 2021). Numerous applications in the domain include image recognition in surveillance, image retrieval in databases, and recommendation systems. Most applications retrieve images using the various phases in the CBIR pipeline. CBIR methods have a two-stage structure: feature extraction and similarity measurement (Wang et al., 2022). A critical phase in the CBIR pipeline is the feature extraction and representation. CBIR methods use feature extraction and representation to describe the image's content. Although many solutions have been proposed, the semantic gap remains one of the most challenging problems in the domain (Yang and Zhu 2012; Jagtap and Bhosle 2021; Barz and Denzler 2021). The Semantic Gap discusses the differences between how humans perceive images and how computers perceive pixels in an image (Alzubaidi, 2017; Martey et al., 2021). In recent years, deep learning methods, particularly CNNs, have made significant progress in solving this problem, but the trade-off between accuracy and computational cost remains a challenge for small datasets (Popescu et al., 2017).

EfficientNet is a family of CNN architectures known for its excellent performance in image classification applications (Hoang and Jo, 2021). The architecture was initially presented by Tan and Lee (2019) and is famous for its computational cost efficiency and accuracy. EfficientNet is based on a scalable approach that balances the model's depth, width, and resolution to optimise performance. Additionally, the architecture's ability to recognise complex features in images and its efficiency in terms of parameters and FLOPS make it an excellent choice for processing datasets in image retrieval applications.

Several domains use the EfficientNet architecture, but the medical field is the most prominent. Its widespread use in the medical field for diagnosing COVID-19 (Müftüoğlu et al., 2020), identifying malaria in blood cells (Aggarwal et al., 2022), detecting brain tumours (Nayak et al., 2022), and kidney tumour segmentation (Abdelrahman and Viriri, 2023) attests to the model's effectiveness. Consequently, the architecture can be leveraged to address the challenges in the various phases of CBIR pipelines that contribute to narrowing the semantic gap challenge in the CBIR domain. Specifically, the EfficientNet architecture can be utilised in the CBIR task to extract discriminative and compact feature representations from images, aiding in accurate image retrieval. The EfficientNet architecture family comprises eight variants ranging from EfficientNet-B0 to EfficientNet-B7. The neural

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network grows deeper as the family number increases, enabling it to capture more complex image features. A higher B number usually guarantees better performance; however, a trade-off exists between model complexity and computational efficiency.

In this study, we mainly evaluate the performance of EfficientNet variants and compare their performance on image retrieval tasks. The novelty is to provide CBIR developers with a comprehensive overview of the effectiveness and efficiency of EfficientNet for feature generation for CBIR tasks and to inform future studies.

2 Methodology

The conceptual framework of the proposed method used in this study is presented in Fig. 1. Images are initially preprocessed, followed by a deep feature extractor (EfficientNet). The EfficientNet analyse the images, identifies patterns, and generates a feature vector. A detailed description of the EfficientNet architecture is presented in Section 2.3. Finally, similarity matching is performed to retrieve relevant images to the query image. Experimental settings and results are detailed in Section 3. The logical steps of CBIR are shown in Algorithm 1.

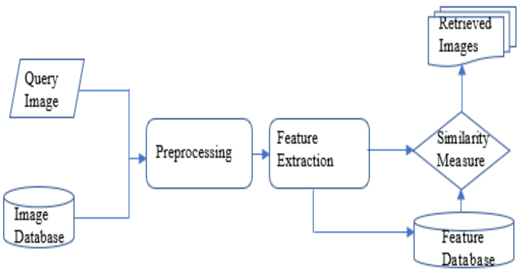

Fig. 1 Conceptual Framework of Proposed Method

Algorithm 1 CBIR algorithm

Input: Image

Output: Retrieved Results

1 Use pretrained EfficientNet to extract features from all database images

2 Save the features in the feature database

3 Select a query image as input.

4 Use EfficientNet to obtain features from the query image

5 Retrieve images closest to the query image using the similarity measure

6 Get the top N images from the database. Repeat the above process, varying the number of images received for each query image.

2.1 Description of Dataset

This study used the CorelDB80 benchmark dataset (Li et al., 2006). This collection consists of 80 semantic groups of 100 images each, totaling 8000 images. The images are in JPEG format and range in average size from 256x256 to 512x512 pixels. This dataset is suitable for evaluating CBIR systems because it represents various image types, including natural environments, objects, animals, and abstract concepts.

2.2 Preprocessing

The input images of the CorelDB80 dataset have been preprocessed to meet the input specifications of the EfficientNet model. All images were resized to n×n pixels to utilise the EfficientNet model. For example, the value of n is 224 for EfficientNet-B0, 240 for EfficientNetB1, 260 for EfficientNet-B2, 300 for EfficientNetB3, 380 for EfficientNetB4, 456 for EfficientNet-B5, 528 for EfficientNet-B6 and 600 for EfficientNet-B7.

2.3 EfficientNet

EfficientNet-B0 to EfficientNet-B7 architectures were analysed in this study. First, load the pretrained EfficientNet model weights and architecture using PyTorch's deep learning framework. The feature extraction part of the pre-trained EfficientNet model is then obtained by removing the top layers of the model (including the fully connected layers). The remaining layers of the pre-trained EfficientNet model form the backbone of the feature extraction process, they are frozen to stop further training and preserve the learned features throughout the feature extraction process. To prevent layers' weights from being modified during subsequent training, their weights are specified as non-trainable. To get the output from the last layer, the input image of the CorelDB80 dataset is routed through the feature extraction backbone of the pre-trained EfficientNet model. These learned features from images are represented in this output and then used as feature vectors for queries and dataset images. The obtained features are saved in the form of feature vectors.

2.4 Similarity Matching

The image features extracted from the query image are compared with those in the feature database to complete retrieval and obtain the relevant images

(Mensah et al., 2019; Martey et al., 2021). The similarity between two images is estimated using the Euclidean distance metric specified in Equation 1, and images with the shortest distance are considered the most similar.

$$d_{ED} = \sqrt{\sum_{k=1}^{n} |x_k - y_k|^2} \quad (1)$$

where

x_k = target image

y_k = query image

A top-N strategy was employed for image retrieval. The system returns a ranked list of N database images that are most like a query image according to a similarity measure.

3 Results and Discussion

3.1 Experimental Settings

Experiments were conducted to evaluate the accuracy and computational efficiency of EfficientNet-based image retrieval using a system equipped with an AMD Ryzen 7-3700X CPU, Nvidia GeForce RTX 3060, VRAM of 12 GB, 64 GB of RAM, and an NVMe.2 SSD of 1 TB. The experiments were implemented using the PyTorch deep learning framework and the Python 3.7 programming language.

3.2 Evaluation of Performance

Precision and Average Precision (AP) are fundamental criteria for judging the effectiveness of a CBIR system. Both are based on relevance. Precision measures the ratio of relevant images retrieved among the total number of images displayed in the top-ranked results. Equation 2 provides the mathematical definition.

$$Precision = \frac{R_I}{R_J} \quad (2)$$

Where,

R_I = number of relevant retrieved images

R_J = total number of retrieved images

The average of all precisions determines the system's overall retrieval precision. Equation 3 illustrates how to calculate average precision.

$$AP = \frac{1}{N} \sum_{N-1}^{N} Precision(i) \quad (3)$$

where

Precision(i)= precision of each query

N = total number of images used as queries

3.2 Results and Analysis

This section presents the retrieval results and the precision of the EfficientNet family architecture across different categories and retrieval sizes. Furthermore, precision among the various EfficientNet Models is compared for the CBIR task.

3.2.1 Image Retrieval of Sample Query Images

EfficientNet architecture was applied to the top 10 values of the CorelDB80 dataset for a query image as shown in Fig. 2. The 10 retrieved images are all related to the query image, which belongs to the obj_door category. Hence, the precision score of the search image is 1. On the other hand, Fig. 3 shows the retrieval results obtained for a different search image from the Corel dataset, which belongs to the bld_sculpt category. Out of the 10 retrieved images, 7 are similar to the search image, resulting in a precision score of 0.70 for this image.

Fig. 2 Retrieval Results for the Door Query when Top = 10

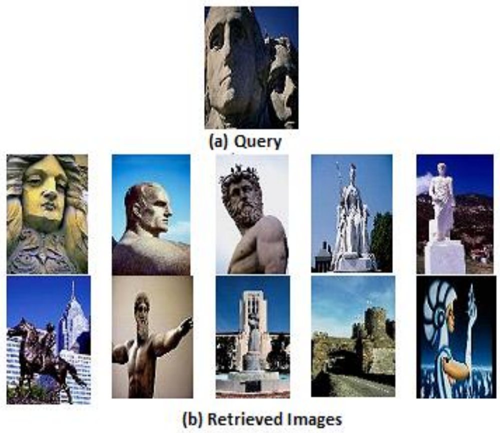

Fig. 3 Retrieval Results for the bld sculpt Query when Top = 10

3.2.1 Retrieval Performance on CorelDB80

Figs. 4 to 11 show the detailed results of the respective EfficientNet family on the CorelDB80.

Fig. 4 demonstrates the precision scores of the EfficientNet-B0 model across the different classes. The scores range from 38 to 100, implying that the precision values of the CBIR system vary by category. Classes such as fitness had a precision of 100. The high precision value indicates that EfficientNet-B0 is effective in retrieving images that are relevant to that class. On the other hand, the wl_cougr recorded the least precision of 38 due to a messy background and other distractions.

Fig. 5 shows precision scores for different categories using EfficientNet-B1. It can be observed that most categories improved in terms of precision scores. Significant improvements are identified with categories such as art_antiques, bld_castle, and eat_drinks which had the precision of 75, 80 and 78, respectively, compared to 70, 79 and 70 in Fig. 4. The highest precision value of 100% is registered by fitness, texture_6, obj_door, obj_eastregg, wl_horse, obj_decoys, wl_elephant, and obj_mineral categories. Nevertheless, some classes, such as art_cybr, bld_lighthse, bld_sculpt, obj_aviation, obj_balloon, obj_ship, and wl_wolf had relatively low precision values below 50%.

Fig. 6 shows a precision score of each category on the CorelDB80 using EfficientNetB2. According to Fig. 6, precision values for many of the classes, such as art_antiques, bld_castle, eat_drinks, obj_bonsai, obj_decoys, and woman have seen increased precision values compared with the results generated by B0 and B1, indicating that the depth of the model has contributed to retrieving images from these categories accurately. In addition, classes such as fitness, obj_door, obj_eastregg, and texture_6 had a precision value 100, indicating that the model can retrieve all images from these categories accurately. Conversely, two classes recorded low precision values of 41 and 40 for sc_forests and wl_cougrn, respectively.

Fig. 7 presents precision scores ranging from 40 to 100 for using EfficientNet- B3. The fitness, art_dino, obj_decoys, woman, and obj_door were the five categories with the highest scores of 100, 99, 99, 96, and 100, respectively. These classes are well-defined and relatively easy to distinguish from others in the dataset. On the other hand, the classes with the lowest precision scores are wl_cougr, sc_forests, wl_fox, sc_iceburg, and wl_cat, with scores between 40 and 45. These classes are more challenging to distinguish from others and may share similar features to those in the dataset. The results suggest that the EfficientNet B3 model performs well on the CorelDB80 dataset, achieving an average precision score of 85.27% across all classes.

Fig. 8 presents precision scores using EfficientNet-B4 on the CorelDB80 dataset. The results demonstrate improved precision scores for most classes compared with EfficientNet-B3. For example, the precision score for the ”art_1” class improved from 54 to 56, ”art_antiques” improved from 82 to 86, ”eat_drinks” improved from 81 to 83, and ”pl_flower” improved from 83 to 85. In addition, the precision score for the” woman" class increased to a perfect score (100). However, it is worth noting that some cases did not see an improvement in precision scores, such as wl_fox and pl_foliage. These results suggest the model may be more accurate overall but needs improvement in identified classes such as wl_fox and pl_foliage.

From Fig. 9, the precision of many classes improved using EfficientNet-B5. For instance, results when compared with EfficientNet-B4, the precision for "art_mural" increased from 72 to 78, eat_drinks from 83 to 89, obj_mineral from 87 to 93, sc_sunset from 76 to 82, and wl_wolf from 58 to 58. In fact, out of the 80 classes, 66 classes had improved precision using the B5 variant. Categories such as fitness, obj_decoys, and sc_indoor had a precision score of 100, indicating that the model performs exceptionally well in these categories and has made no false retrievals. However, there were also some classes where the precision decreased slightly or stayed the same. For example, the precision for art_1 dropped slightly from 56 to 55 and obj_car remained the same with 90. Nevertheless, model EfficientNet-B5 positively impacted the precision of the CorelDB80 datasets, with the majority of classes showing improved accuracy.

Fig. 10 illustrates the precision scores for each class for the EfficientNet-B6 model. In general, the model EfficientNet-B6 scored highly for precision over a wide range of classes, with an average precision of approximately 88%. In addition, the model achieved a perfect score for classes such as art_dino, obj_decoys, obj_decoys, sc_indoor and texture_6 and correctly retrieved relevant images. On the other hand, there were some classes such as wl_cougr, wl_fox, and pl_foliage in which the model performed relatively poorer compared to the B5.

Fig. 11 shows that the EfficientNet-B7 performed excellently, with several classes obtaining 90% or higher precision scores. The model achieved perfect precision scores for classes such as art_dino, obj_door, obj_eastregg, obj_mineral, obj_steameng, and texture_6. Additionally, the model achieved high precision scores for other classes, such as woman, obj_bonsai, obj_bus, and obj_train.

However, it is also worth noting that there were some classes for which the model could have performed better, with precision scores below 70%. These classes include wl_cougr, wl_fox, and pl_foliage. These classes had complex backgrounds and other distractions. The findings imply that EfficientNet-B7 is a potent and effective model as indicated in the literature (Tan and Lee, 2019; Rengel et al., 2022).

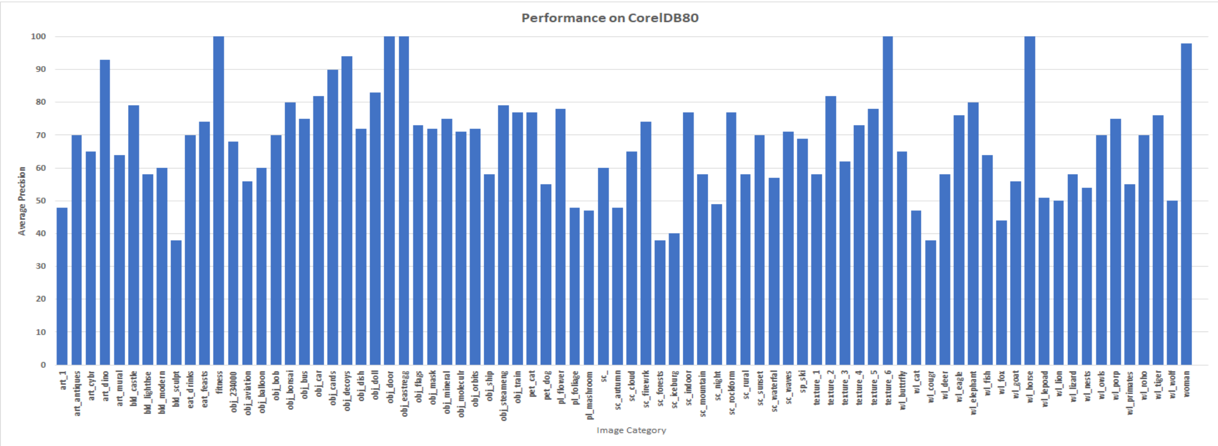

Fig. 4 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B0

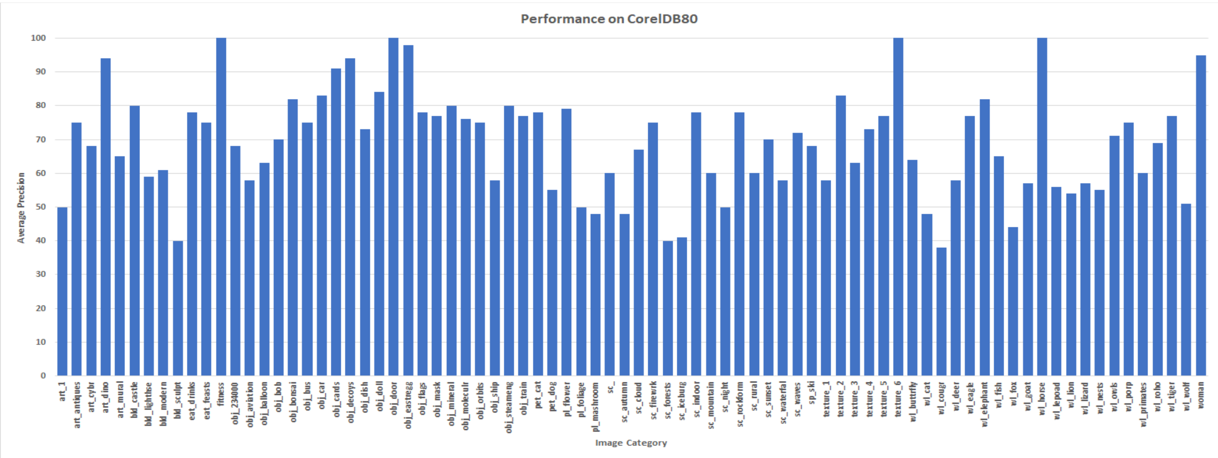

Fig. 5 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B1

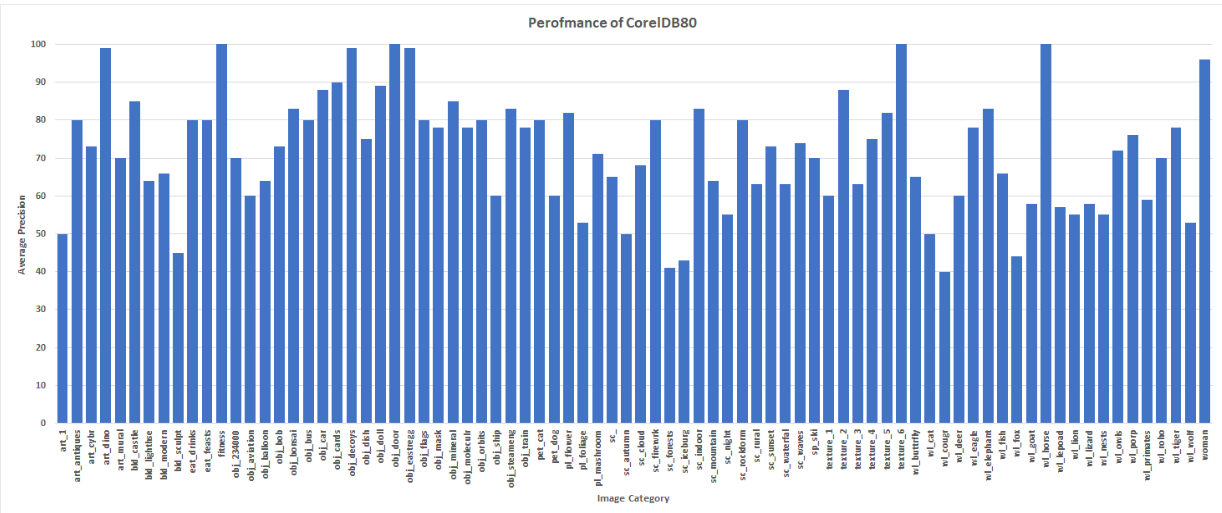

Fig. 6 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B2

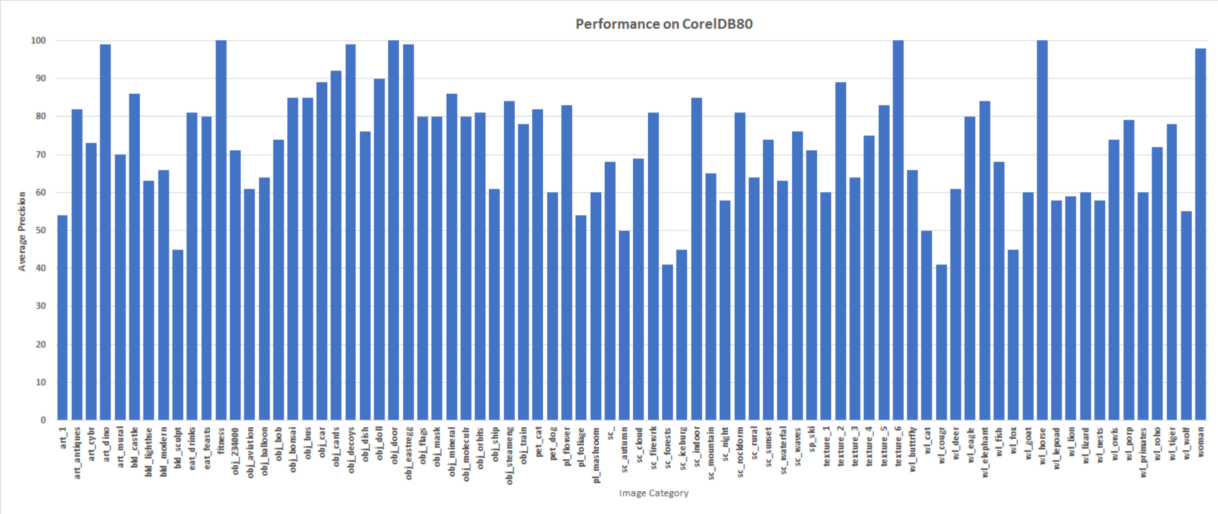

Fig. 7 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B3

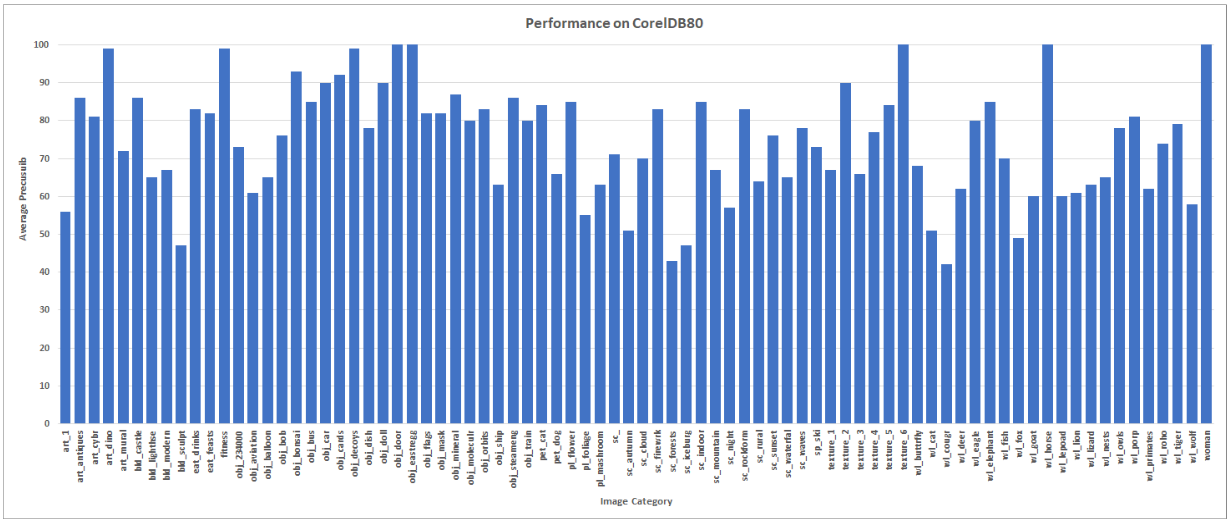

Fig. 8 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B3

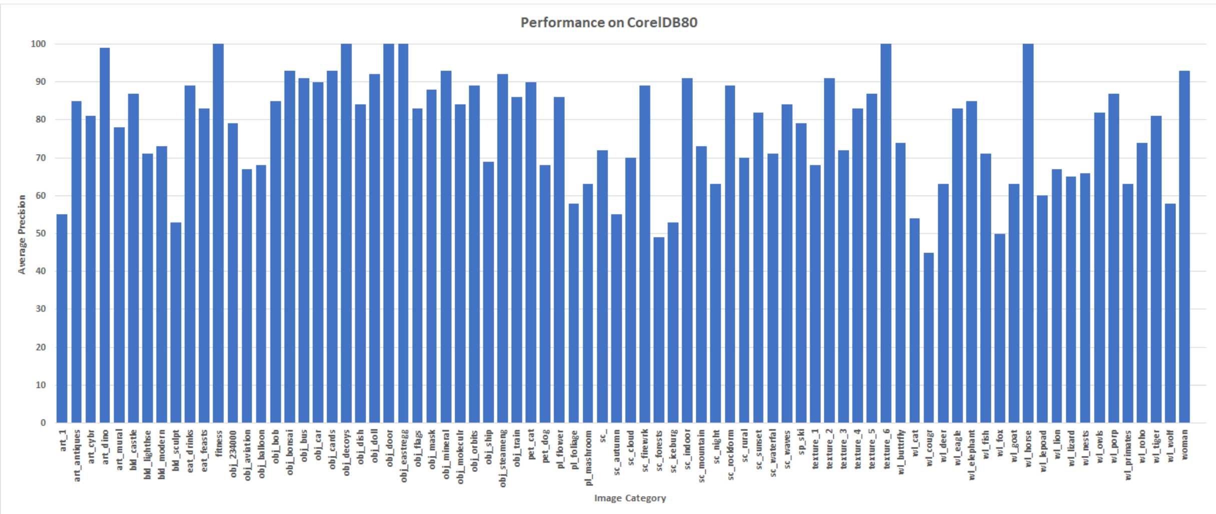

Fig. 9 Average Precision of each category on the CorelDB80 dataset using EfficientNetB5

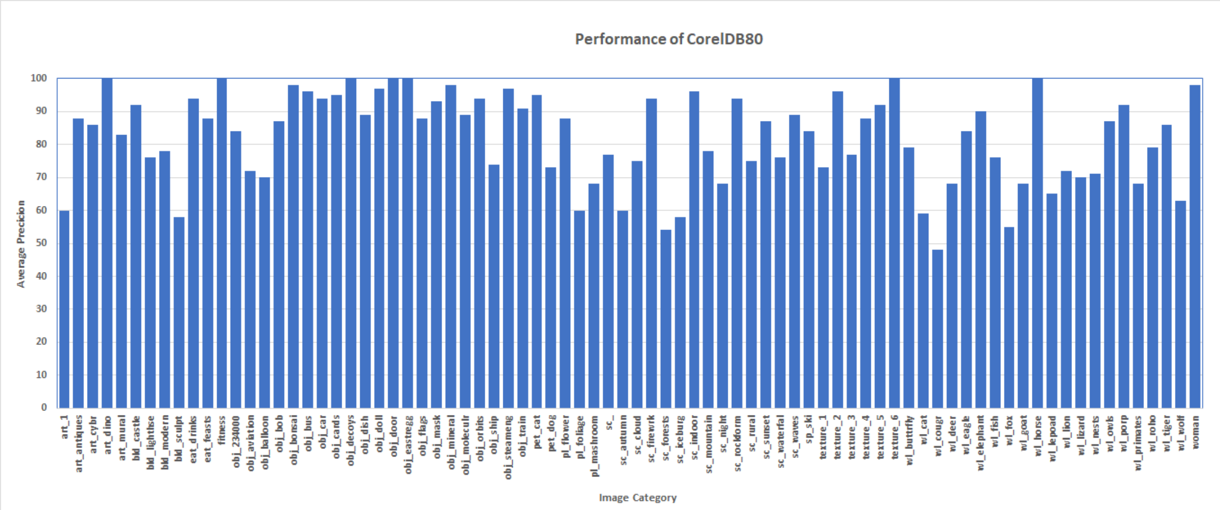

Fig. 10 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B6

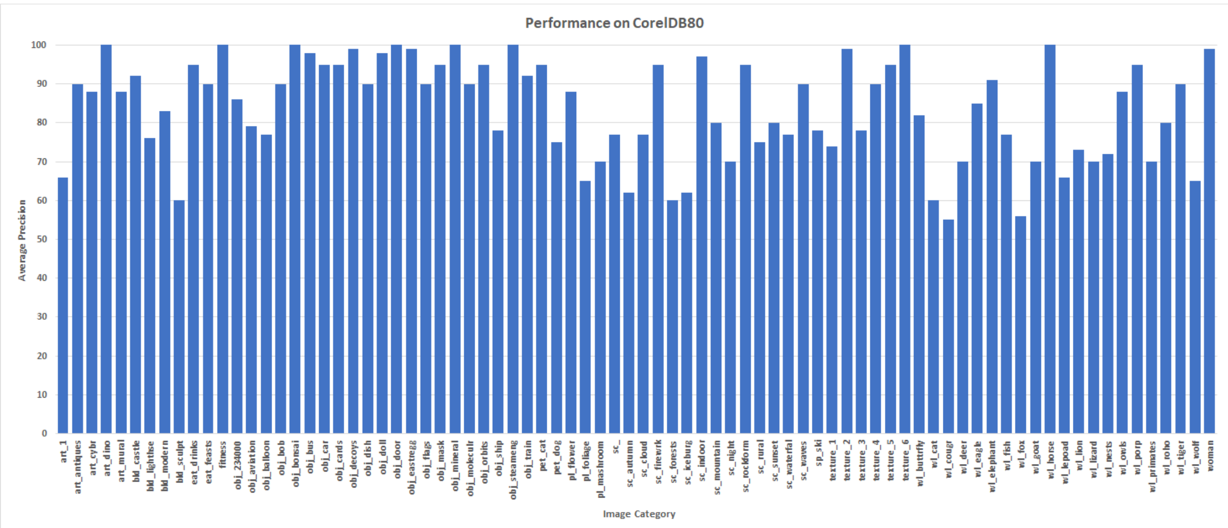

Fig. 11 Average Precision of each category on the CorelDB80 dataset using EfficientNet-B7

Table 1 Performance Comparison of EfficientNet Family Architectures

Variants Top images considered for retrieval										
	10	20	30	40	50	60	70	80	90	100
B0	82.16	80.62	79.31	78.12	77.02	76.06	75.04	74.62	73.29	71.67
B1	83.09	81.32	80.07	79.08	77.93	76.85	76.19	75.33	74.76	72.39
B2	84.93	82.15	81.86	80.42	78.99	77.42	76.83	76.56	75.49	73.44
B3	85.27	83.94	82.71	81.02	79.84	78.07	77.98	77.09	76.47	74.81
B4	86.16	85.01	83.12	81.99	81.03	80.08	78.19	77.99	77.68	75.98
B5	87.08	85.98	84.93	82.89	82.67	81.27	79.76	78.84	78.19	76.78
B6	88.45	86.48	85.48	84.73	83.29	82.44	71.83	80.53	79.11	77.15
B7	89.03	88.77	87.62	85.84	84.75	83.41	82.11	81.84	80.61	78.63

Table 1 demonstrates a performance comparison of EfficientNet family architectures regarding average precision (AP) on the CorelDB80 dataset. Generally, the EfficientNet variants generate high precisions ranging from 71.67 to 89.03. The EfficientNet-B7 model achieved the highest scores among all the variants, ranging from 78.63% to 89.03%. This suggests that the model had the highest retrieval of relevant images from the database. The highest precision score of EfficientNet-B7 was recorded with the Top 10 Results. This performance demonstrates the EfficientNet-B7 with the most depth learnt highly complex patterns in the data and the representation that distinguished the heterogeneous images well. The efficientNet-B0 model variant achieved the lowest average precision scores compared to the other variants. This is expected since EfficientNet-B0 is the simplest and shallowest model in the series and may need more capacity to learn complex patterns in the data. Generally, there is an increase in precision scores with increasing depth of the model. Therefore, adding depth and complexity to the model architecture can help improve performance on the CBIR task.

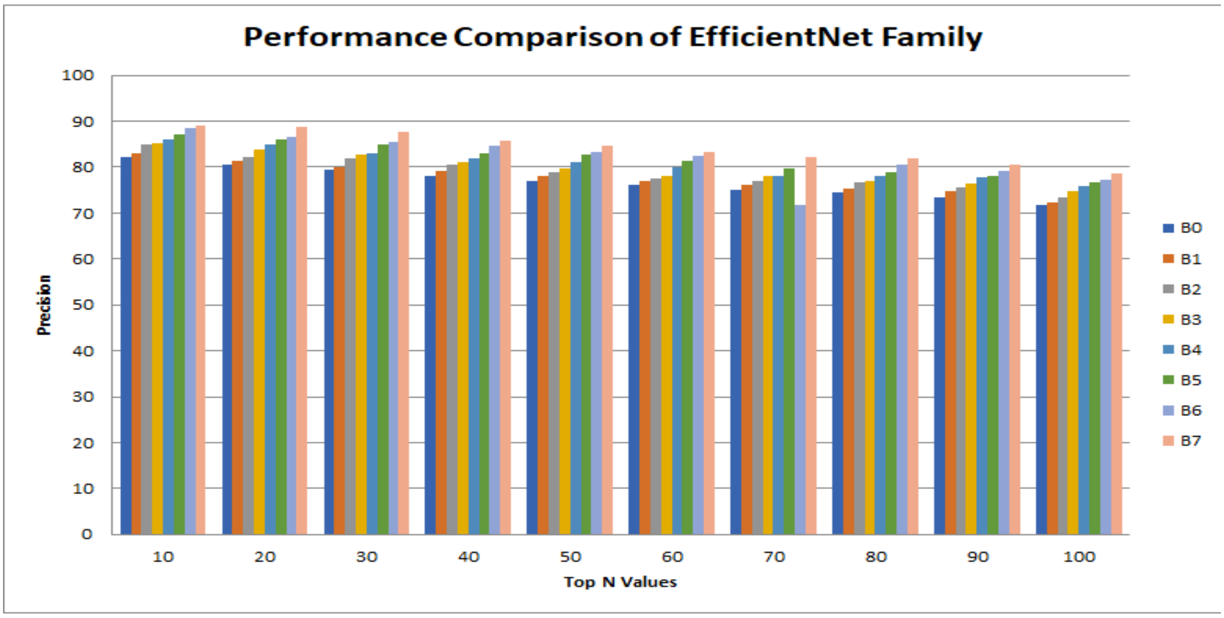

Fig. 12 Performance Comparison of EfficientNet Variants

4 Conclusions

This paper evaluated various EfficientNet architectures for content-based image retrieval (CBIR) using the CorelDB80 dataset. The results affirm the applicability of the EfficientNet family in CBIR tasks, demonstrating a mean precision of up to 89.03%. EfficientNet-B7 consistently outperforms other variants across diverse dataset categories, highlighting its effectiveness in precision-sensitive CBIR tasks. The detailed analysis of EfficientNet variants elucidates nuanced performance disparities, yielding valuable insights for CBIR developers. The study advocates for a conclusion centered on precision, recognising its pivotal role in achieving high accuracy in retrieval tasks. This precision-oriented perspective aligns with the pragmatic needs of CBIR systems, where precise and relevant image retrieval is paramount.

Despite EfficientNet's commendable performance, certain limitations were observed. The different image resolutions and depth of model variants significantly impacted retrieval time. Further, the model variants encountered challenges in some categories exhibiting background complexities. These limitations underscore the need for further research to enhance the models' ability to handle diverse and complex backgrounds. To this end, future works will explore advanced feature extraction techniques and attention mechanisms in CBIR.

Additionally, we will investigate methods to optimise the computational efficiency of EfficientNet architectures for CBIR tasks without compromising retrieval precision. Lastly, we will extend EfficientNet architectures to large-scale and domain-specific datasets beyond the CorelDB80 dataset to assess their generalizability and effectiveness across diverse application domains.

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