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The Effect of Applying Transfer Learning Approach on Different Domains: Medical and Non-Medical Imaging (Skin Cancer and Flower Types)

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Abstract Transfer Learning is an important technique used to transfer knowledge from one pre-trained model (called source domain) to another (called destination domain), this technique improves good evaluation especially when the dataset of destination is small, transfer learning may achieve a good valuation and may not, this is depending on the common features between source and destination domain. In this work, an investigation is proposed to show the effects of using Transfer learning on medical and non-medical images. In this work, three datasets are used (International Skin Imaging Collaboration (ISIC), Human Against Machine with 10000 training images (HAM10000), and Flowers), two for skin cancer lesions as medical images and the third is flowers types, In addition, four pre-trained models are used (InceptionVersion3, Residual neural Network with 50 layers (ResNet50), Mobile network (MobileNetV2) and Extreme version of Inception (Xception). The results show that transfer learning does better using nonmedical images than medical images, and the best pre-model metrics are got from Xception model, with an accuracy of approximately 89% in non-medical images and 68% in medical images, this is because the pre-trained model is fruitful when the features are common between the source and destination domain, these common features are more available in nonmedical than medical (especially in skin lesions).

Keywords Transfer learning, Skin Cancer, Deep learning, Hashing perceptual, Artificial Intelligence

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1. Introduction

Despite the rapid multiplication of data last decade, still there are some applications need for data but unfortunately this data is small especially in medical field, small data may lead to make the decision is difficult or even wrong [1], Transfer learning is one of the strategies of deep learning. It achieves good performance when the data to be trained is small. The attitude of TL is to reuse the pre trained knowledge get out from a model trained on a huge dataset, (like Imagenet which contains millions of images categorized in 1000 classes) [2]. This approach is measured better than establishing new model from the scratch, hence, this approach eliminates the time and computational process [3]. The core goal behind transfer learning is sharing features learned from one domain called to another domain. This approach approved achievement in different applications such as image classification, natural language dealing, and speech recognition [4], object detection, and others. It has proven to be a powerful tool for improving the accuracy of deep learning models while reducing the amount of training data and time required [5]. Medical area becomes one of the popular applications that be used in deep learning, many researches are focused on using deep learning in disease classification, lesions detection, drug discovery, cancer, Alzheimer's disease, and heart disease [6, 7]. Deep learning plays a vital role in medical Image classification [8], prediction [9], recognition [10] and detection [11], this benefits in pre-diagnostic and self treatment. Deep learning models can be trained on medical datasets such as Magnetic Resonance Imaging (MRI) [11, 12, 13], CT scans [14],

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and X-rays to accurately detect and classify abnormalities [15, 16]. Skin cancer is by far the most common type of cancer. it is the abnormal growth of skin cells; it can become deadly. The good news though is when caught early, the dermatologist can treat it and eliminate it entirely, there are many types of skin cancer, each of which can look different on the skin. Ultraviolet radiation from the sun causes 1.8 million skin cancers every year according to a WHO report in June 2022 [17] Deep learning has shown great promise in improving the accuracy and efficiency of skin cancer detection. Convolutional neural networks (CNNs) are commonly used for this purpose, as they are able to automatically learn and extract meaningful features from skin lesion images. use a CNN to segment skin lesions in images, allowing for more precise analysis of the lesion's features. This can be particularly useful for identifying areas of irregularity or asymmetry in the lesion, which are often indicative of malignancy [18]. In this work, we show a comparison analysis between using medical and non medical based transfer learning, our case study in non medical is flowers type, and in medical skin cancer, also in our investigation we used four different pre trained models for representation to judge the best model for this purpose, this work studies:

- The evaluation of pre-trained models for medical and non medical tasks, through the evaluation of popular model like (ResNet, Inception,. . .) and show their strength and limitation by using medical and non medical datasets.
- Comprehensive analysis of transfer learning by providing a systematic analysis of the effectiveness of transfer learning in vastly different domains: non-medical (flower classification) and medical (skin cancer).

2. Skin Cancer Medical Knowledge

The major factor that causes the skin lesions is the exposition to the sun, these lesions are founding as unregular growth on skin, some of them are malignant and the other benign. Malignant skin cancer may causes death, because it dives deep the body and reaches to internal body organs and damage them, the skin lesions can be noticed by vision, and it can be examined by ultraviolet light and polarized light photography [19], Three main types of common skin diseases:

- Basal Cell Carcinoma: This kind of disease can be seen in the form of a slightly transparent bump on the surface of the skin, and it can be of different shapes. Basal cell carcinoma most often occurs in areas of the skin exposed to direct sunlight, such as the head and neck.
- Squamous Cell Carcinoma: This disease changes in the squamous cells which is being in the middle and surface layers of the skin. It may rarely spread all over the other area of the skin and is generally more aggressive than Basal Cell Carcinoma. But it doesn't threaten life.
- Melanoma: This kind of skin lesion is the least common, but it is the most dangerous and poses a threat to life and sometimes causes death, due to its ability to spread to other parts of the body without the patient noticing it. It is considered more dangerous than the previous two types.

In general exposure to ultraviolet radiation (UV) is one of the most important factors that cause skin diseases, so it is advised to avoid exposure to direct rays or reduce exposure. One can search for any changes that can be observed on the surface of the skin to ensure that there are no skin cancers at an early stage. Detection of the disease in the early stages can ensure treatment and the preservation of life [20]. As same as other cancers, skin cancers initial as normal skin lesion. this lesion develops by time to be a skin cancer, Figure 1 below denotes the three types of skin diseases:

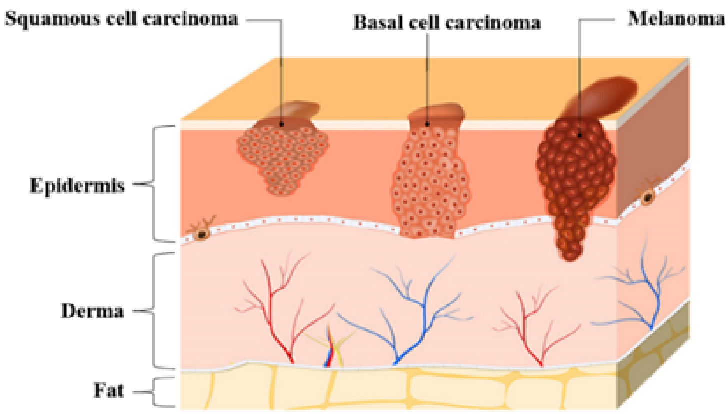


Figure 1. The depths of the three types of skin cancer [18]

3. Transfer Learning

The principle of TL education is inspired by one's own education, whereby one does not learn from scratch to solve any new problem but takes advantage of similar previous experiences in order to solve the new. TL also aims to transfer the knowledge gained by a source model and pass them to a new one, this is done by passing weights that get out from the source model to the destination model, Figure 2 below shows the general TL diagram:

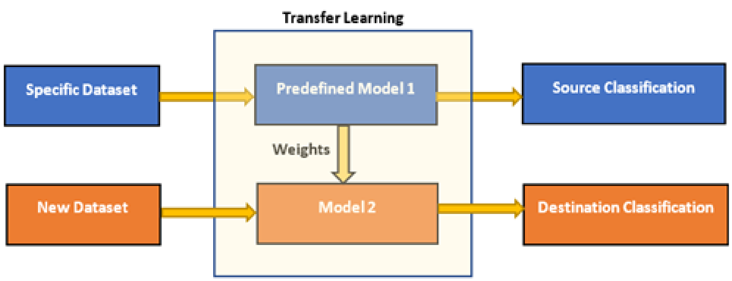


Figure 2. General transfer learning diagram

Firstly the model is pretrained on huge dataset like ImageNet or COCO dataset, this model is called "Source" then freeze the layers and fine-tune to feed in the new dataset which may be small, and the by using the acknowledgement of the source model, the second model is called "Destination" [5, 21].

4. Inception V3

InceptionV3 is a deep convolutional neural network model that is considered to classify images. It was founded by investigators at Google in 2015. The principle idea behind InceptionV3 is using a mixture of many different filters for convolutions with various kernel sizes (1x1, 3x3, 5x5) parallelly, allowing the model to capture features at different spatial scales efficiently. This architecture is known for its depth and computational efficiency, making it suitable for various computer vision applications [22]. Inception-v3 is trained for the ImageNet Large which is a familiar huge dataset consists of 1000 labeled data for different objects.

5. ResNet50

Residual network ResNet50 is a deeper neural network, presented by Kaiming He et al. in 2015. ResNet is, in this model, residual blocks are used that are based on skip connection to decrease vanishing degradation and the final parameters, this model involves 50 layers, and it achieves extraordinary outcomes in classification and computer vision tasks that it is intelligent to handle with actual deep model [23]. This model is trained on ImageNet.

6. MobileNetV2

It is a convolutional neural network consists, designed for mobile and image classification, it consists of 53 deep layers, in addition, the model customs inverted residual blocks. It was developed by Google researchers in 2018. The vital aim of MobileNetV2 is to offer good accuracy for image classification tasks with few computational resources, by consuming deep convolution layers, that mainly decrease the features and computations [24], this model is trained on COCO dataset with 91 labeled classes.

7. Xception

Xception or Extreme Inception, is an advance form of the Inception model, it produced by François Chollet in 2016. Xception based on the same structure of InceptionV3, with additional swapping the typical Inception structures with depth wise divisible convolutions. This variation decreases the computational rate. Xception is particularly known for its effectiveness in tasks such as object recognition and detection [25]. This model is pretrained on the ImageNet dataset.

8. Methodology

This work proposes using the Transfer learning approach to investigate the effect of using it on medical imaging and nonmedical imaging, the medical case study in this work is skin cancer lesions and nonmedical imaging is Flowers, and then discuss the results using three datasets (two for skin cancer lesions and the third Flowers types), in this work, four types of pretrained models (InceptionV3, ResNet50, MobileNetV2, Xception), Figure 3 below shows the process diagram of the methodology:

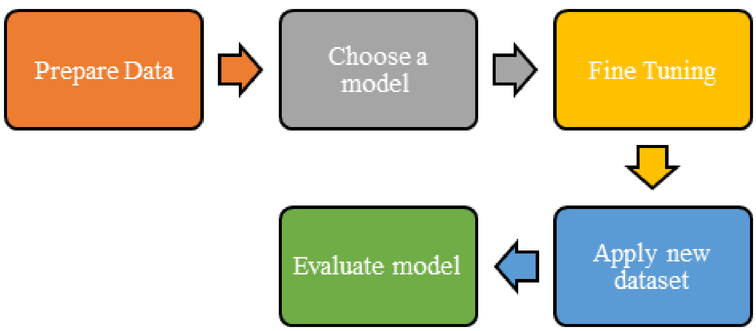


Figure 3. The process diagram of the methodology

Where the steps of the proposed methodology are:

- prepare data: Fix data, detect and delete duplicates, then split it into training, validation, and test groups.
- Select a model: select the appropriate pretrained model to be a source for the new model.

- Fine Tuning: Alter the network to fit destination model problem, by using fine tuning to train the latter limited layers. Naturally, this work, depends on ImageNet and pretrained weights.
- Apply new dataset: using the knowledge of the source model, then passing the new dataset and training it on the pretrained model.
- Evaluate model: using some evaluation metrics to understand the performance of the model.

9. Dataset

9.1. ISIC Dataset

The International Skin Imaging Collaboration (ISIC) dataset, ISIC involves 2750 images of three classes of skin cancer lesions: (Melanoma, Nevus, and Seborrheic keratosis), Tabel 1 shows the statistics of this dataset classes [26]:

Table 1. ISIC Dataset Classes

Disease	**Total**	**Percentage**
Melanoma	521	19%
Nevus	1843	67%
Seborrheic keratosis	386	14%
Total	2750	100%

where:

- Melanoma: It is a really aggressive kind of skin cancer, that grows in the melanocytes cells which are responsible for generating melanin. Melanoma may be formed in the eyes and, seldom in the other parts of the body, melanoma formed in an irregular shape and variation color.
- Nevus: Benign skin tumor, it looks like a big size of mole, it sounds flat on the surface with different colors with irregular boundaries. It may be found in any part of the body person who has nevi typically as well has many public moles.
- Seborrheic keratosis: It benign skin tumor, it is a harmless-spot that generates during an adult lifetime, it is a clear sign of skin aging. Figure 4 below shows ISIC samples:

Melanoma Nevus Seborrheic keratosis

Figure 4. ISIC Dataset samples

9.2. HAM10000 Dataset

Human Against Machine dataset which contains ten thousand images (HAM10000). The real overall number of images in HAM10000 are 10015 images. The whole images are gathered from many inhabitants for skin lesions and categorized into 7 classes. The classes are skin lesions: Actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), keratoses and lichen-planus like keratoses (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and Vascular lesions (vasc) [27], Table 2 shows the HAM10000 dataset details:

Table 2. HAM1000 Dataset Classes

Disease	**Total**	**Percentage**
Actinic keratoses	327	3%
Basal cell carcinoma	514	5%
Benign keratosis	1099	11%
Dermatofibroma	115	1%
Melanoma	1113	11%
Melanocytic nevi	6705	67%
Vascular lesions	142	2%
Total	10015	100%

Figure 5 denotes HAM10000 Dataset samples:

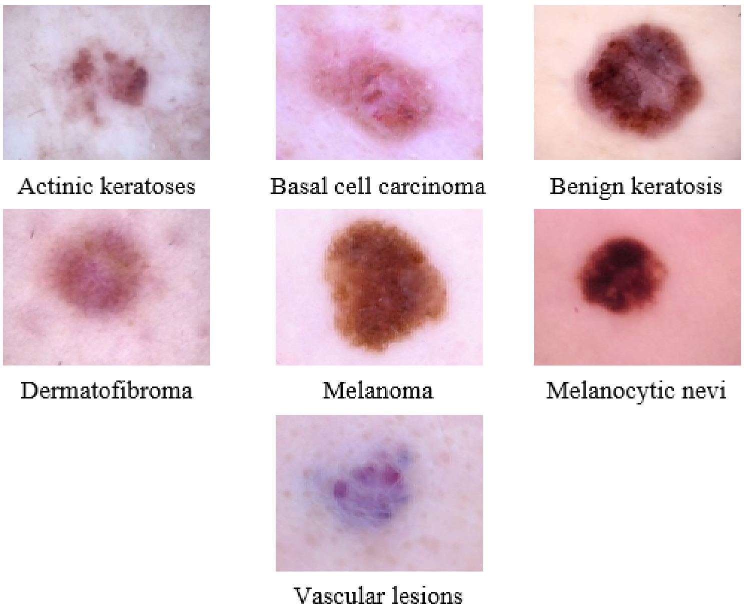


Figure 5. HAM10000 Dataset Samples

9.3. Flowers Dataset

The dataset is available on Kaggle web site, it consists of more than 3600 jpg images, classified into five classes as shown in Table 3 below:

Table 3. Flowers type Dataset Classes

Flower Type	**Total**	**Percentage**
daisy	633	17%
dandelion	898	25%
rose	641	17%
sunflower	699	19%
tulip	799	22%
Total	3670	100%

Figure 6 below shows Flowers Dataset samples:

Figure 6. Flowers Types samples

10. Delete Duplicates image

Duplicates in the training group may cause biased learning. While duplicates in the test group may generate an improper performance evaluation of the model results, because unseen images are important to create real evaluation and ensure the model is trained well. Therefore, in this work, an algorithm for detecting and deleting duplicate images is proposed, by using perceptual hashing to calculate the similarity among images, Figure 7 below shows the steps of the proposed detecting and deleting duplicate images:

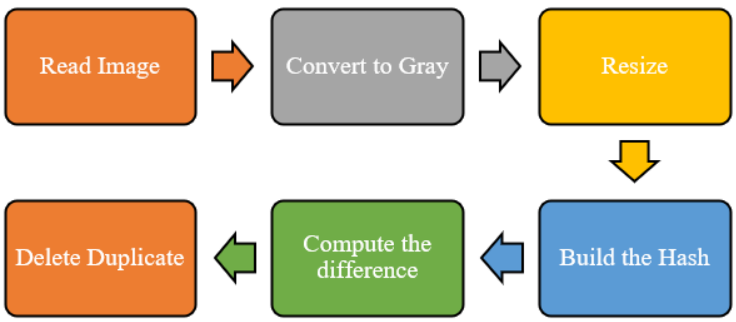


Figure 7. Process diagram of detecting and deleting duplicate images algorithm

10.1. Image Perceptual Hashing

Image hashing means creating a unique hash parameter to image, Identical copies of images with rare simple variance may have the same hash parameter, or close to [28]. The algorithm of perceptual hashing depends on perceptual factors of images in order to create the hashes features. The aim of this algorithm is to generate hashes that keep on unaffected after applying changes on image, let assume couple images X and $X^{'}$, hX = H(X) and h$X^{'}$= H($X^{'}$) their equivalent perceptual hashes, and D(hX,h$X^{'}$) is a likeness system of measurement, and τ is the threshold that calculated experimentally, D(hX,h$X^{'}$) less than τ refers to that X and X' are duplicated images with minor modifications [29]. Perceptual is an image extraction, it uses in many applications like neural networks and deep learning [30, 31] encryption [32, 33, 34, 35], watermarking medical images [36, 37].

10.2. Hamming Distance

Hamming distance (HD) is a factor that is used to compare the similarity between two strings, this factor usually used as evaluation metric in perceptual hashing approach to calculate the similarity between two images, HD uses XOR relation to calculate the distance. Let the first string H_1 and the second H_2 each consists of h(i) bits, then:

$$H_1 = \{h_1(0),\ h_1(1),\ \ldots,\ h_1(nn-1)\},$$
$$H_2 = \{h_2(0),\ h_2(1),\ \ldots,\ h_2(nn-1)\}$$

is calculated as in Equation 1 below [29]:

$$HD(H_1, H_2) = \sum_{i=0}^{n-1} h_1(i) \oplus h_2(i) \tag{1}$$

Algorithm 1 below shows the process diagram for it:

Algorithm 1: Detecting and Delete Duplicate images Algorithm
Step1: Start
Step2: Import important library.
Step3: Specify the dataset directory.
Step4: For each image:
Convert to gray scale.
Resize image to image+1.
Calculate the hash Factor.
Compare with all.
Delete the duplicate.
Step5: Stop

Table 4 below shows the statistics of the three datasets after applying the perceptual hashing algorithm on the ISIC dataset, and as denotes in the Table 4:

Table 4. dataset Statistics after applying To Detect and Delete Algorithm

Dataset	Classes	All	Duplicate	Remained
ISIC	Melanoma	521	0	521
	Nevus	1843	6	1837
	Seborrheic_Keratosis	386	0	386
	Total	2750	6	2744
HAM10000	Actinic keratoses	327	0	327
	Basal cell carcinoma	514	0	514
	Benign keratosis	1099	0	1099
	Dermatofibroma	115	0	115
	Melanoma	1113	0	1113
	Melanocytic nevi	6705	2	6703
	Vascular lesions	142	0	142
	Total	10015	2	10013
Flower	daisy	633	0	633
	dandelion	898	0	898
	rose	641	0	641
	sunflower	699	2	697
	tulip	799	0	799
	Total	3670	2	3668

11. Proposed Transfer Learning Model

This work uses the Transfer learning approach to detect and classify skin cancer and hen flowers. Hence, four types of pretrained training models are used in this investigation (InceptionV3, ResNet50, MobileNetV2, Xception). Algorithm 2 below describes the process of the proposed method for each X and Y:

Algorithm 2: The Proposed Method
Step1: Start Step2: Import important library. Step3: resize the input image as neede by model. Step4: Define epochs=10, classes=C, image size=S, optimizer=adam Step5: Load X Step6: Freeze layers Step6: Fine Tuning Step7: Train the new Y Dataset data set Step8: Evaluate the model Step9: Stop

Where: C is the classes of dataset (ISIC=3, Ham1000=7, Flower=5), S is the image size it differs by the model (InceptionV3=299x299, ResNet50=224x224, MobileNetV2=224x22, Xception=299x299), X is one of the four pretrained models (InceptionV3, ResNet50, MobileNetV2, Xception), and Y is the one of the three datasets (ISIC, HAM10000, and Flowers).

12. Results

The model is run by python's language using Jupyter Notebook, the four models (InceptionV3, ResNet50, MobileNetV2, Xception) are used respectively, and the Table 5 denotes the metrics of accuracy and loss functions for each Model:

Table 5. The metrics of Precison, Recall and F1 score for each model

Database	Model	Accuracy	Loss
ISIC	InceptionV3	0.6884	0.8352
	ResNet50	0.6884	0.8334
	MobileNetV2	0.6884	0.7602
	Xception	0.6884	0.8081
HAM10000	InceptionV3	0.7075	0.9287
	ResNet50	0.6705	1.1294
	MobileNetV2	0.7075	0.8963
	Xception	0.7200	0.8485
Flower	InceptionV3	0.8769	0.7006
	ResNet50	0.3844	1.4875
	MobileNetV2	0.8824	0.6837
	Xception	0.8878	0.6963

Where these parameters are computed using the following equations [5]:

$$Accracy = (TP + TN)/(TP + TN + FP + FN) \tag{2}$$

$$Precision = TP/(TP + FP) \tag{3}$$

$$Recall = TP/(TP + FN) \tag{4}$$

$$F1Score = (Precision.Recall)/(Precision + Recall) \tag{5}$$

where TP, TN, FP, and FN denote the true positives, true negatives, false positives, and false negatives, respectively. Tabel 6 below summarizes the metrics comparison among the four models

Table 6. The metrics of precision, Recall, and F1 score for each model

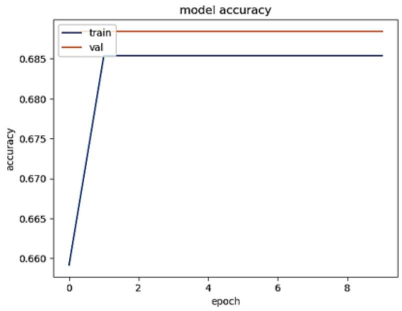
Database	Model	Precision	Recall	F1 Score
ISIC	InceptionV3	0.6884	0.6884	0.3442
	ResNet50	0.6884	0.6884	0.3442
	MobileNetV2	0.7645	0.6608	0.354439
	Xception	0.7187	0.6482	0.340816
HAM10000	InceptionV3	0.8546	0.6085	0.355426
	ResNet50	0.6705	0.6705	0.33525
	MobileNetV2	0.8483	0.6265	0.360361
	Xception	0.8614	0.6275	0.363039
Flower	InceptionV3	0.9387	0.8167	0.43673
	ResNet50	0	0	0
	MobileNetV2	0.9213	0.8167	0.432926
	Xception	0.9340	0.8126	0.43454

As noticed from Table VI, According to ISIC and HAM10000 dataset, for the four models, the accuracy metrics are alike and not high, in other world, the transfer learning doesn't achieve the metrics (Accuracy as well as the loss function), this is because the medical imaging is visually different from the images fed the pretrained models that used in this paper, this is called "Domain Shift", this may cause dropping in performance between these two different databases, On the other hand, the results of the model using flowers dataset, however, the flowers are objects which are trained in the pretrained model, so the accuracy and loss function are better than the two previous datasets. Table 7 below shows the hyperparameter of the proposed model:

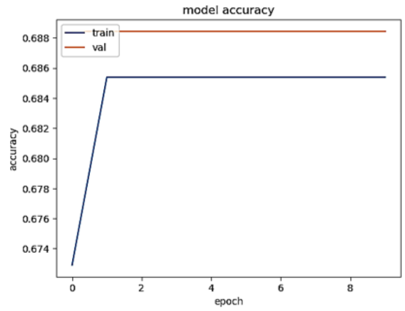
Table 7. Hyperparameter of the proposed model

Parameter	**Value / Description**
Model Architecture	InceptionV3, ResNet50, MobileNetV2, Xception (pretrained on ImageNet)
Trainable Layers	Last 4 layers fine-tuned, rest frozen
Input Image Size	$224 \times 224 \times 3$
Number of Classes	3 for ISIC, 5 for types of flowers, 7 for HAM10000
Batch Size	32
Number of Epochs	10
Optimizer	Adam (default parameters)
Loss Function	Categorical Crossentropy
Metrics	Categorical Accuracy, Precision, Recall
Data Augmentation	No explicit augmentation, only rescaling (rescale=1/255)
Validation Split	20% (via ImageDataGenerator subset argument)
Learning Rate	0.001
Framework	TensorFlow / Keras

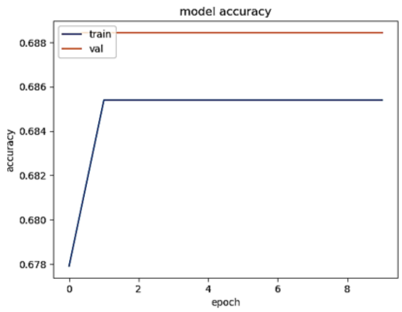
The figures denote in Figures 8, 9, 10, 11, 12, 13 below show the Accuracy and Loss function across the epochs =10, of the model for ISIC, HAM10000, and Flowers dataset. The investigation results proved that the two different applications (medical and non-medical) belong to two different domains. For the medical image, we used two different datasets concerned with skin cancer classification, and for non-medical we used one dataset for flower type classification, as denoted by results, the accuracy in nonmedical images is higher than the accuracy in medical images, this is reasonable, because, transfer learning is using predefined knowledge that got from the predefined model (in this work we used three models InceptionV3, ResNet50, MobileNetV2), so, if the features of the predefined model are close to the features of the new model, then the metrics of the new model will be satisfied, while, if the features of the new model are not like the predefined mode, then the new model metrics' will be not satisfied. It is like a kid who is starting to learn about animals, he will be able to recognize their features like (eyes, nose, mouth, tails,...) but he will not be able to recognize the types of cars (Mercedes, BMW, Nissan,...) because the features of animals are not common with cars.



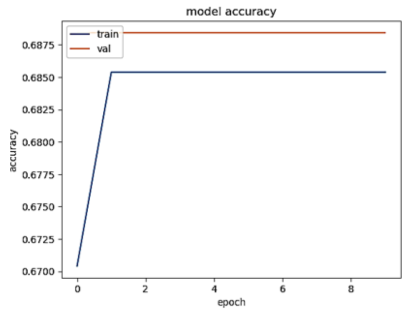
a: InceptionV3 Model



b: ResNet50 Model

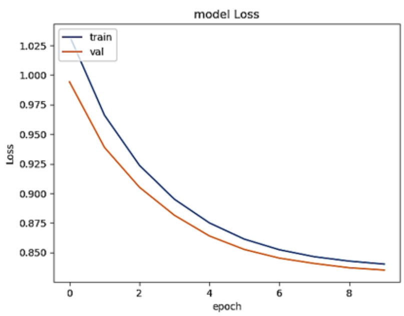


c: MobileNetV2 Model

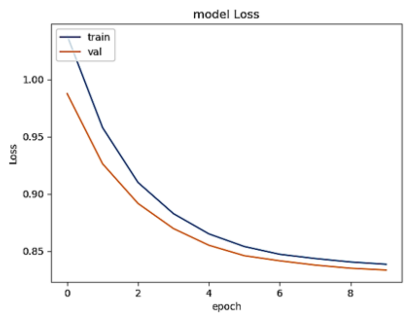


d: Xception Model

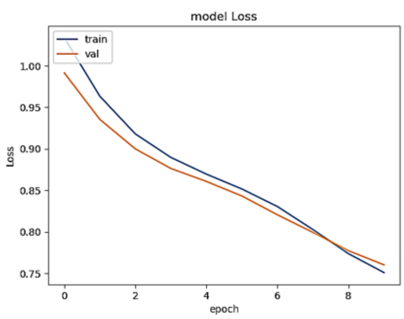
Figure 8. Accuracy function of trainig and validation for ISIC dataset



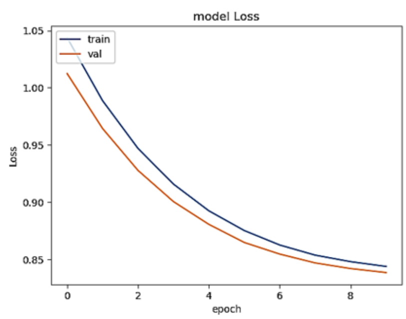
a: InceptionV3 Model



b: ResNet50 Model

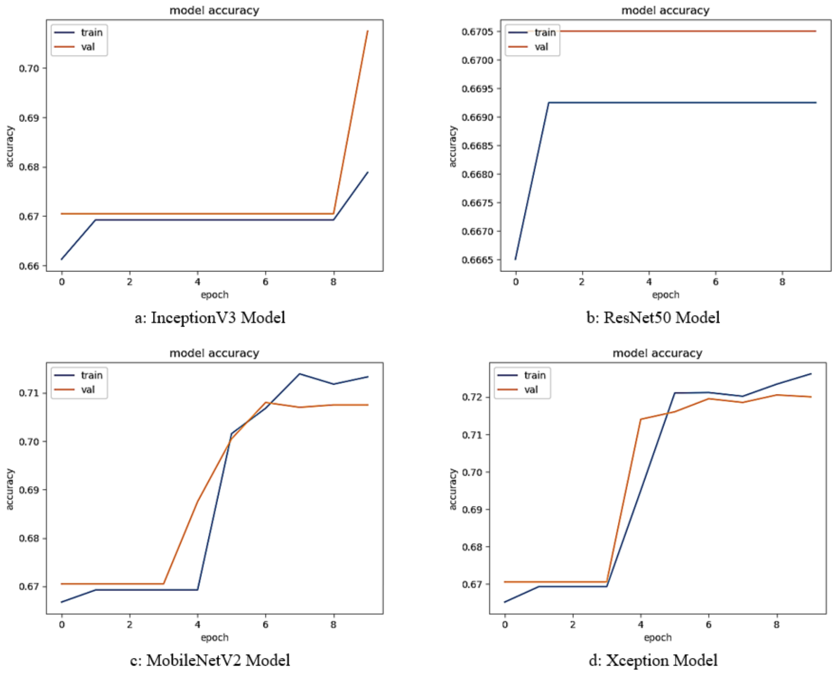


c: MobileNetV2 Model



d: Xception Model

Figure 9. Loss function of training and validation for ISIC dataset



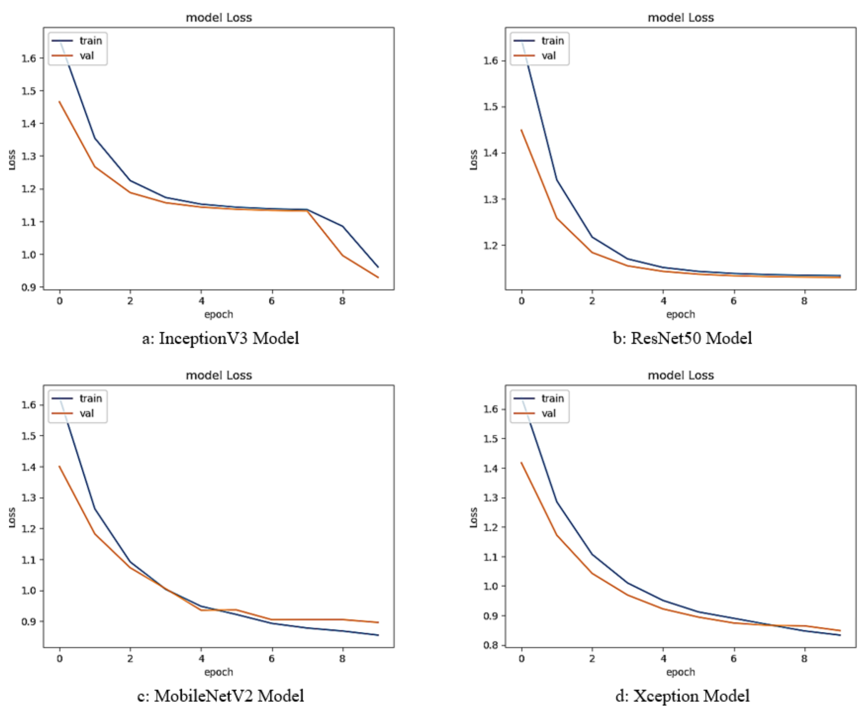
a: InceptionV3 Model

b: ResNet50 Model

c: MobileNetV2 Model

d: Xception Model

Figure 10. Accuracy function of training and validation for HAM10000 dataset



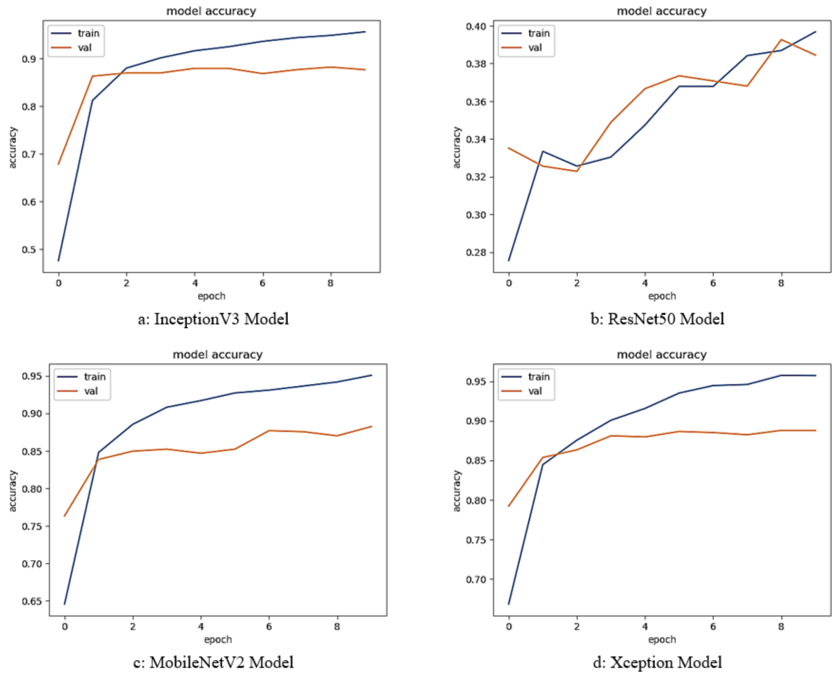
a: InceptionV3 Model

b: ResNet50 Model

c: MobileNetV2 Model

d: Xception Model

Figure 11. Loss function of training and validation for HAM10000 dataset



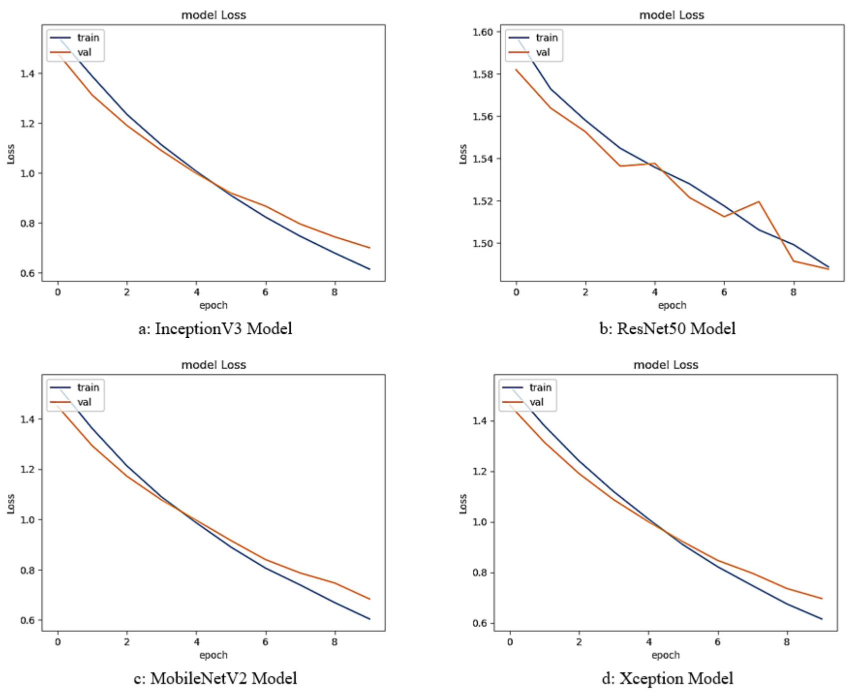
a: InceptionV3 Model

b: ResNet50 Model

c: MobileNetV2 Model

d: Xception Model

Figure 12. Accuracy function of training and validation for Flower dataset



a: InceptionV3 Model

b: ResNet50 Model

c: MobileNetV2 Model

d: Xception Model

Figure 13. Loss function of training and validation for Flower dataset

Figure 14 shows the confusion matrix for the fourth model applied on Flower dataset:

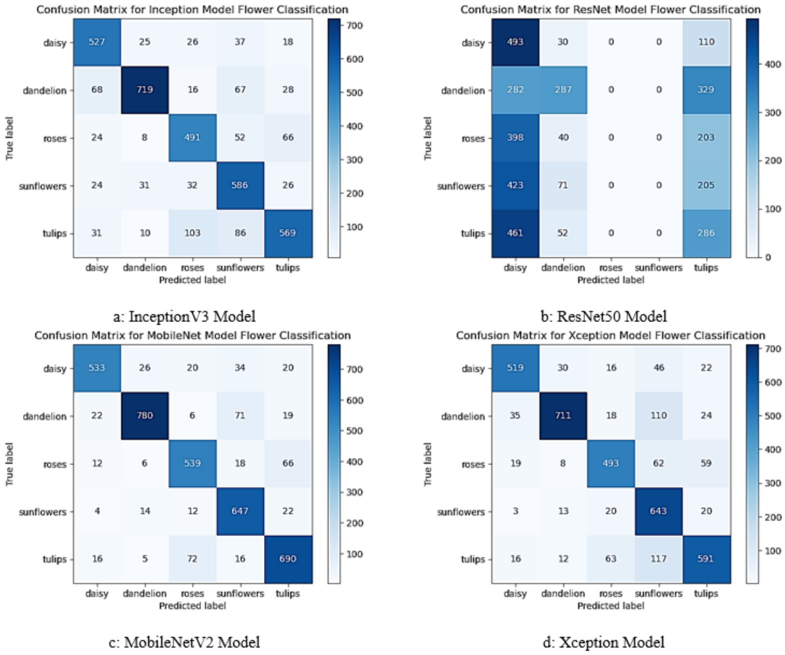


Figure 14. Confusion Matrix for Flower dataset

Figure 15 shows the confusion matrix for the HAM dataset:

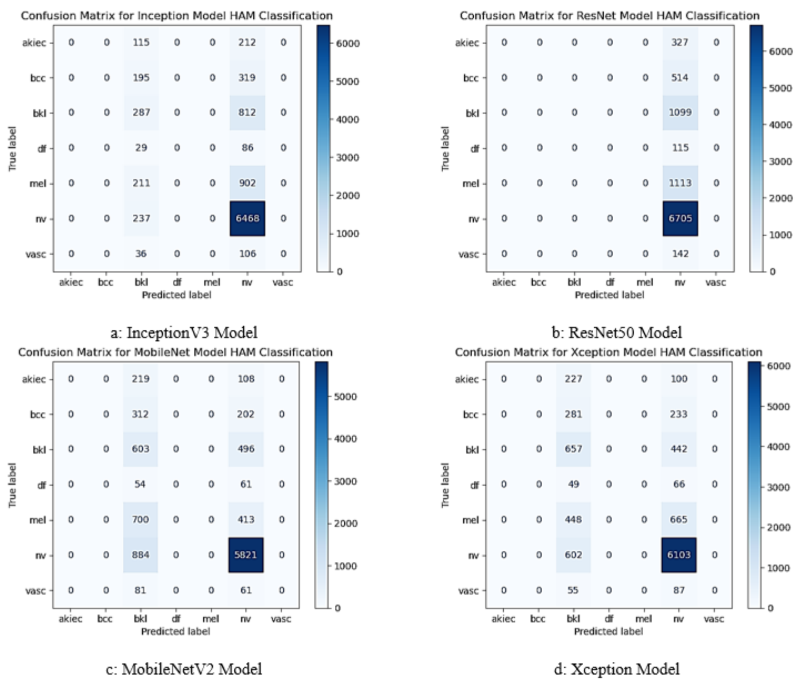


Figure 15. Confusion Matrix for HAM dataset

Figure 16 denotes the confusion matrix after applying the fourth model on ISIC dataset:

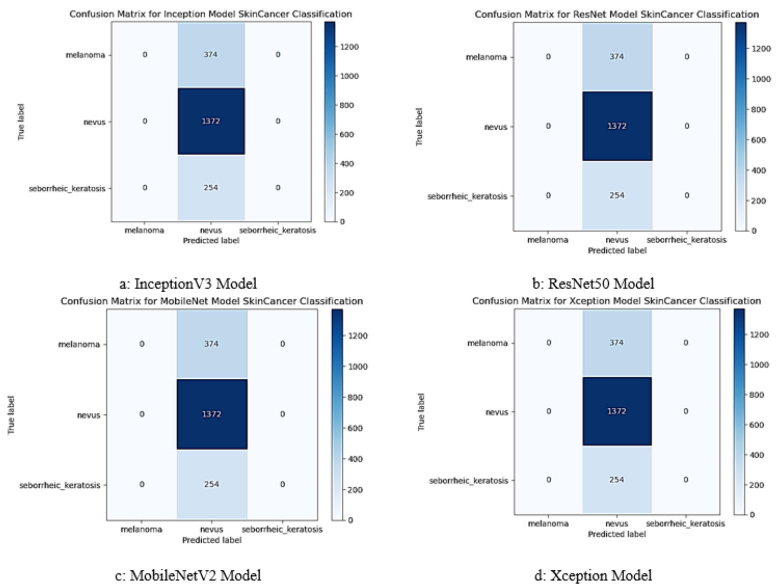


Figure 16. Confusion Matrix for ISIC dataset

By looking at figures 14, 15, 16 one can observe, the confusion matrix presents well metrics when using flower dataset, while the HAM and ISIC dataset the metrics are very poor.

13. Discussion

By referring to figures 8, 9, 10, 11, 12 and 13 above.

- Scenario1: The figures 8 and 9 shows the validation accuracy and loss function using ISIC dataset, the curves of the metrics are fixed from the first epoch and along the rest epochs, which means no previous useful knowledge are used, this is because skin lesions are not seen before in ImageNet dataset, also the best accuracy (0.6884) achieved by Xception model, which is not satisfying by comparing to other dataset (HAM, Flower types).
- Scenario2: The figures 10 and 11, shows the accuracy and loss function for HAM1000 dataset, the best accuracy achieved by Xception (0.7200), However this dataset has not common features with the previous knowledge, but it valued better accuracy than the ISIC dataset, because HAM dataset is fourfold ISIC dataset, which make the better accuracy.
- Scenario3: In figures 12 and 13 above, the flower type dataset is used, this dataset achieved better accuracy than the others, because of the flower is a class in the source dataset, so pre-knowledge is useful, and the second because the dataset is bigger than HAM 1000 three times.

Returning to the same figures and Table 5, the best accuracy and metrics are gained by Xception model, this is because of the model has very deep layers comparing by other models. (the reason behind using two types of skin cancer dataset is to show that the small dataset didn't achieve good metrics using transfer learning as known). Overall, each model has its weakness and strengthen as summarized below:

- InceptionV3:

- Strengths: Good for image classification and work better with huge datasets.
- Weakness: Expensive computational process and it causes overfitting for small dataset

- ResNet50:
  - Strengths: Overcome vanishing in gradient and it achieves good accuracy even with small features.
  - Weakness: Expensive computational process and Degradation problem.
- MobileNetV2
  - Strengths:For Mobile applications and it good has good computational process.
  - Weakness: The architecher is simpler than others therefore cannot extract deep features and it needs good grained recognition.
- Xception:
  - Strengths: uses deep convolutions to reduce the number of parameters and computational and it effective in image training.
  - Weakness: more effected by hyperparameters.

14. Conclusion

The proposed model is implemented using Python language in Jupyter Notebook, and by referring to the table and figures, the best accuracy obtained by the model trained on flowers than the two datasets of skin lesions (89%, 72%, and 68%), it can be concluded that the transfer learning is not absolutely achieving satisfactory results, simply because the domain of the source model must be compatible with the domain of the destination model. In most, the medical images dataset may not succeed in obtaining well outputs, in this case, using a new model from scratch can be a good choice. Skin cancer lesions may be created with random shapes, in other words, there aren't common features with any other predefined object in this paper we investigate using three datasets (two for skin cancer classification, and the third for flower classification). the transfer learning improves better results when using the Flowers dataset then the two other skin cancer lesions dataset, this is because the features of skin cancer lesions are not close to any of objects in the pretrained model, while the features flowers are defined in the pretrained models, in other words, the transfer learning approach may not serve all cases, in addition, the models used inside transfer learning approach also present variant metrics. We recommend the next studies using medical images that have common features with the pre-extracted features using transfer learning. Finally, this work is a study of comparison between two kinds of images (Medical and non-medical), regardless of whether the metric is as high as possible, however, there are many ways to rise the metrics (like segmentation), but this study is to compare between two types of raw datasets. We recommend expanding this work in future by depend many different types of medical dataset and make a comparison among these datasets. In the future, this work can be improved to offer a robust solution by using a domain adaption like Correlation Alignment (CORAL), Maximum Mean Discrepancy (MMD), DomainAdversarial Neural Networks (DANN), or CycleGAN. These techniques eliminate the numerical variances between the feature supplies of the domains.

Competing Interests

The authors declare that they have no competing interests

Ethical and informed consent for data used

All data that are used in this manuscript are granted and they are referred in references.

Data availability and access

Data will be available on request

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