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Use of Xception Architecture for the Classification of Skin Lesions

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ABSTRACT

This study investigates the application of the Xception architecture for accurate classification of skin lesions, focusing on the early detection of melanoma and other malignant skin conditions. Utilizing deep learning techniques, the research aims to enhance the precision and efficiency of skin lesions diagnosis. The study utilizes the TensorFlow framework and the HAM10000 dataset, comprising a vast collection of benign and malignant skin lesion images, for training and evaluating the Xception model. Preprocessing steps, including data splitting, augmentation, and image resizing, are applied to the dataset. The Xception architecture, a deep convolutional neural network, serves as the foundational model, supplemented with customized classification layers for specialized features and predictions. The model's performance is evaluated using diverse metrics. The experimental outcomes reveal the Xception architecture's potential in accurately classifying skin lesions. Moreover, the study underscores the significance of extensive and diverse datasets, as well as rigorous clinical validation, in the development of deep learning models for skin cancer detection. The findings contribute to the advancement of early melanoma detection, thereby improving patient outcomes and alleviating the burden of the disease.

Keywords: skin lesions, CNN architecture, skin cancer, deep learning

1. INTRODUCTION

Globally, skin cancer ranks among the most prevalent diseases [1], with its occurrence steadily increasing because of factors such as extended sun exposure and genetics. Detecting skin cancer early and accurately is vital for enhancing survival rates [2] and minimizing treatment expenses [3]. It is crucial to categorize various skin cancer types to facilitate effective early detection and provide suitable treatment for patients [4]. In this regard, the implementation of deep learning methodologies for classifying skin cancer images has demonstrated promising results concerning efficiency and precision [5].

This study, entitled "Use of Xception architecture for classification of skin lesion types," has it focus on the classification of skin lesions to facilitate the early detection of melanoma and other types of malignant skin lesions using a technique based on the Xception architecture. This architecture is a prominent convolutional neural network (CNN) in computer vision. The research suggests the development and deployment of a model with the aid of the mentioned architecture to automatically classify images of skin lesions, with the goal of identifying distinct skin cancer types as melanoma.

For this purpose, we used the HAM10000 dataset, comprising over 10,000 images of benign and malignant skin lesions captured through dermatoscopy. We employed these images to train and assess our model within the TensorFlow framework, a leading platform for creating deep learning models.
By addressing the challenge of accurately classifying skin lesions, we aim to contribute to the early detection and intervention of melanoma, ultimately improving patient outcomes and reducing the burden of this devastating disease [5].
The structure of this paper is as follows: in Section 2, we examine the existing literature on skin lesions detection and classification using deep learning methods and CNN architectures; in Section 4, we outline the suggested approach, encompassing data preprocessing, model training, and evaluation; finally, in Section 5, we explore the results obtained, study limitations, and potential enhancements for future work.

2. RELATED WORKS

Here, we present a thorough overview of the latest research advancements in the field of AI for skin lesions recognition, shining a spotlight on the methodologies employed, and the outcomes achieved.

A significant aspect of several studies has been the adoption of convolutional neural networks (CNNs), credited with its exceptional abilities in image recognition. For example, a study pitted the diagnostic accuracy of a deep learning CNN against 58 dermatologists in differentiating dermoscopic images of melanocytic lesions [6]. Their custom CNN surpassed most dermatologists at matching sensitivity levels, a success attributed to the robustness of the CNN trained to classify dermoscopic images of melanocytic lesions. On similar lines, another research group capitalized on the strength of CNNs, achieving an AUC of 0.96 for melanoma diagnosis through the categorization of skin lesions into disease categories [7]. This notable result underscores the promise of deep learning in elevating the accuracy and efficiency of diagnosing skin diseases, especially in geographies with restricted access to dermatological services. It was

recommended that more clinical images be included, particularly from diverse patient populations, to bolster the performance of the diagnostic system [6,7].

Progress in the field of deep learning also extends to skin lesion segmentation, an important aspect of skin cancer treatment. Two groundbreaking studies offered new deep learning-based methodologies for this task. One suggested a pipeline model which combined the YOLO deep convolutional neural network and the GrabCut algorithm [9], while the other proposed an ensemble method amalgamating Mask R-CNN and DeeplabV3+ [10]. Both techniques demonstrated superior performance compared to current state-of-theart techniques for skin lesion segmentation, indicating potential for further enhancements through hyperparameter fine-tuning and additional pre-processing techniques [9,10].

The idea of synthesizing human and AI decision-making was also explored, showing potential for enhancing skin cancer diagnosis accuracy. A hybrid approach that combined the decisions of a CNN with those of 112 dermatologists using the XGBoost algorithm, a flexible machine learning system, exhibited superior performance [8]. This indicates the potential of AI to augment human expertise rather than replacing it. A study introduced Deep Learning Studio (DLS), a tool allowing nonprogrammers to create complex deep learning models. Models created on this platform achieved an area under the curve of 99.77 percent, illustrating the potential of cloud-based deep learning models in skin cancer detection [11]. Optimization algorithms have played a crucial role as well. A research team put forth an innovative method combining an optimized CNN and an enhanced version of the whale optimization algorithm (WOA) [12]. The WOA algorithm was used to optimize the CNN, leading to superior performance in skin cancer diagnosis as compared to other methods.

Delving into two additional researches, we come across two more methodologies. The first one presents a multi-modal deep learning system that leverages both patient metadata and skin lesion images to diagnose melanoma [13]. This model emphasizes the importance of context and demonstrates a comprehensive approach to melanoma diagnosis, integrating both image-based and patient demographic data. The second paper presents a transfer learning approach, utilizing a pre-trained InceptionV3 model with an attention mechanism for classifying skin cancer images [14]. This method demonstrates the promise of transfer learning and the value of model interpretability in improving diagnostic accuracy.

Each of these studies brings to light the remarkable potential of deep learning and AI in skin cancer detection and diagnosis, notwithstanding the inherent challenges.

3. GENERAL CONTEXT

TensorFlow

TensorFlow is a potent open-source software library and a comprehensive platform for machine learning and artificial intelligence. It enables model creation across various platforms, including desktops, mobile devices, the web, and the cloud, offering deployment flexibility for AI solutions. Whether you prefer pre-trained models or custom training, TensorFlow provides essential tools. Additionally, it includes multiple data tools for preprocessing, consolidating, and debugging substantial data volumes. In summary, TensorFlow is a versatile platform driving the development and deployment of machine learning models, streamlining the construction of effective and scalable AI solutions. [17]

Keras

Keras is a Python-based open-source library for Neural Networks, compatible with TensorFlow, Microsoft Cognitive Toolkit, or Theano. It emphasizes user-friendliness, modularity, and extensibility to facilitate rapid experimentation with deep learning networks. Keras offers diverse implementations of neural network components like layers, objective functions, activation functions, and optimizers. It stands out as a versatile and widely used tool in the field of artificial intelligence. [18]

Xception's Architecture

Xception is a deep convolutional neural network architecture incorporating Depthwise Separable Convolutions, considered an "extreme" version of an Inception module. It consists of a linear stack of layers with depthwise separable convolutions and residual connections. Developed by Francois Chollet, creator of Keras at Google, Xception offers a distinctive approach to CNNs, particularly notable for its effectiveness in image classification tasks.[19]

4. METHOD

Dataset

In this study, the HAM10000 dataset was utilized to address the issue of limited dermatoscopy datasets in early skin cancer classification studies [15]. The HAM10000 dataset, published in 2018, consists of 10,015 skin lesion images. These categories include actinic keratoses and intraepithelial carcinoma/Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines/seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).The labels of the images were confirmed through various means, such as histopathology, reflectance confocal microscopy, follow-up, or expert consensus [16]. Figure 1 provides a visualization of the class distribution, where the largest class (nv) contains 6,705 images, while the smallest class (df) has only 115 images.

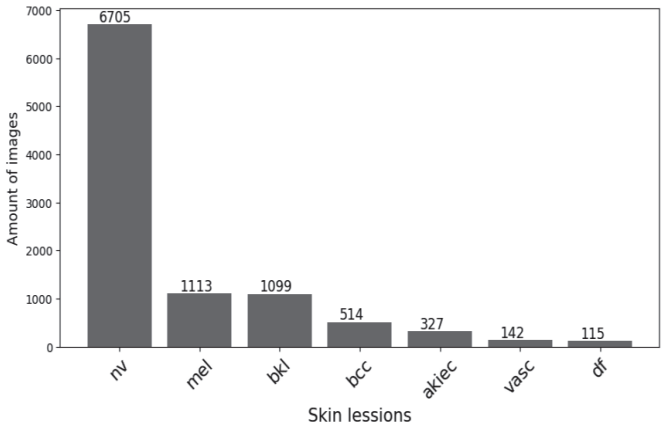

Fig. 1. Amount of images per skin lesion type after duplicate drop.

To execute our experiments, we need to prepare this data Although the dataset consists of 10,015 images, an examination of the metadata reveals that there are only 7,470 distinct skin lesions. The remaining images are duplicates captured at different magnifications or angles of view. The presence of duplications is illustrated in Figure 2.

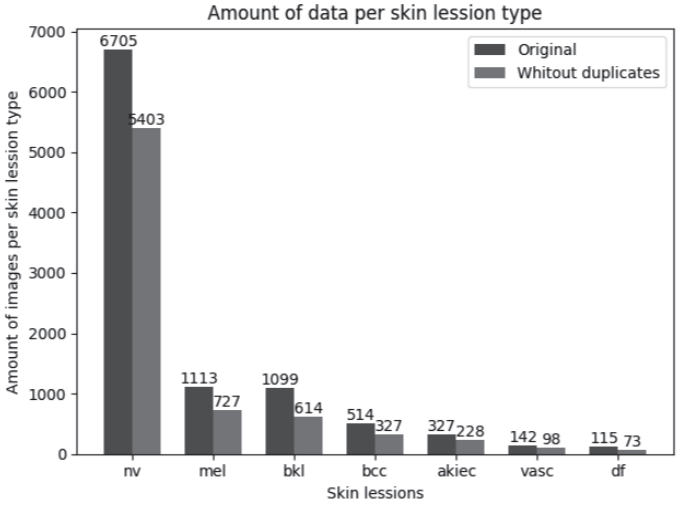

Fig. 2. Example of a figure caption.

Based on this information, we have preprocessed the dataset to ensure data quality and compatibility with the Xception architecture. This includes data splitting, augmentation, and resizing of images to a standardized resolution. It is important to note that the dataset does not have information on the race associated with each image.

Data Splitting

Prior to training and testing the AI models, a duplicate removal step was performed on the dataset, resulting in a dataset with 7,470 distinct lesion images. The non-duplicate dataset was then divided into the following subsets:

- Training set: Comprising 60 percent of the non-duplicate dataset (4482 images).
- Validation set: Composed of 20 percent of the nonduplicate dataset (1494images).
- Test set: Consisting of 20 percent of the non-duplicate dataset (1,494 images).

The validation data serves as an unbiased evaluation of the model that has been trained on the training data, while also tuning the hyperparameters. The testing data is used for an unbiased evaluation of the final model that was trained using the training data.

Data Augmentation

The training set underwent data augmentation, including operations such as rotation, flipping, cut out, and cropping. A python code was written to define the parameters that were going to be applied to the training images. Table 1 shows the parameters used with the class *ImageDataGenerator* of TensorFlow to accomplish this task.

TABLE I
PARAMETERS USED FOR DATA AUGMENTATION

Parameters	Value	Brief Description
rescale	1 / 255	Scale the pixel values of the images to a range of 0 to 1 by dividing by 255. This is important to normalize the input data and facilitate model training.
rotation range	10	The images will be randomly rotated up to 10 degrees.
zoom range	0.1	Random zoom range to apply to images during training
width _shift range	0.0	In this case, the images will not be shifted horizontally
height shift range	0.0	In this case, the images will not be shifted vertically

Image Resizing

Additionally, all samples were resized to a resolution from 650x450 to 256x256 pixels during the preprocessing stage to reduce training time and save resources.

In summary, data augmentation and resizing were applied to improve the performance and generalization capability of deep learning models, this is especially useful when working with small or large data sets.

Model Architecture

For the skin lesion classification task, the Xception architecture was chosen as the deep learning model.

Transfer learning was employed to utilize the knowledge and feature representations learned from pre-trained models on large-scale datasets. The pre-trained model, which was pre-trained on the ImageNet dataset, consisting of 14,197,122 images, which served as the base model for our skin lesion classification task.

To incorporate this architecture into our model design, the following steps were followed:

- Pre-trained Model Initialization: The pre-trained Xception model was loaded without the top classification layers. This model has learned rich and general image features from the vast ImageNet dataset.
- Custom Classification Layers: On top of the pre-trained base model, custom classification layers were added. These layers allow the network to learn task-specific features and make predictions based on the skin lesion images.

The resulting model architecture consists of the pre-trained base model followed by the custom classification layers which include: (1) A convolutional layer is added with 64 filters, each of size 3x3, and ReLU activation function. This layer helps extract additional features from the representations learned by Xception. (2) A max pooling layer with a window size of 2x2 is added to reduce the dimensionality of the extracted features. (3). A dropout layer is added with a rate of 0.40, which helps prevent overfitting by randomly deactivating 40 percent of the neurons during training. (4) A flattening layer is added to convert the output from the previous layer into a one-dimensional vector, preparing it for fully connected layers. (5) A densely connected

layer with 128 neurons and ReLU activation function is added. Additionally, an L2 regularization with a penalty of 0.001 is applied to avoid overfitting. (6) Another dropout layer is added with a rate of 0.4 to continue preventing overfitting. (7) Finally, the output layer with 7 neurons and softmax activation function is added, which produces the probability output for each of the 7 classes of skin lesions.

5. EXPERIMENTS

Experiment Protocol

This work was developed on a laptop with a Ryzen 5800H CPU, an NVIDIA GeForce RTX 3060 GPU of 6GB and 16 GB of RAM at 3200Mhz. To train and test the models we used VS Code with Jupyter Notebooks and, to run the cells of code, it needs and environment with "TensorFlow 2.10.1", "Keras 2.10.0 and "Python 3.10.11". The source code for this project is available at https://github.com/cledmir/DCPModel.

Validation Metrics

To evaluate the performance of the model a set of baseline metrics where employed. These baseline metrics are developed from True positive (TP), True negative (TN), False positive (FP) and False negative (FN) predictions. Those baseline metrics are:

- Accuracy: The percentage of correctly classified skin lesions.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

- Precision: The proportion of true positive predictions out of the total predicted positive instances.

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

- Recall: The proportion of true positive predictions out of the actual positive instances.

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

- F1-Score: The harmonic mean of precision and recall, providing a balanced measure between the two.

$$F1 - Score = \frac{2TP}{2TP + FP + FN} \quad (4)$$

These baseline metrics will be used as a starting point for further validation of our proposed model, which will include a model comparison between other 2 ImageNet base models and a confusion matrix with a classification report for the proposed model.

Results

After performing the experiments using the preprocessed dataset presented in Section IV, we evaluate their performance using the evaluation metrics mentioned above:

Comparison Model*:* Table 2 presents a comparative analysis of the performance of the models using the baseline metrics. The evaluation was performed on the test set, which was previously unseen by the models.

TABLE II
MODEL COMPARISON USING VALIDATION METRICS

Model	Accuracy	Precision	Recall	F1-Score
Xception	0.81	0.89	0.74	0.40
Resnet50V2	0.80	0.85	0.75	0.39
Inception V3	0.77	0.90	0.70	0.21

The Xception model achieved the highest accuracy with 81% and a F1-score of 40% among the three models. Followed by the Resnet50V2 and Inception V3 models with an accuracy of 0.80% and 0.77% respectively.

Confusion Matrix*:* We generate the confusion matrix for each model, which shows the number of correct and incorrect predictions for each class. Figure 3 shows the confusion Matrix for the proposed model, followed by Figure 4 and 5 for the Resnet50V2 and Inception V3 models.

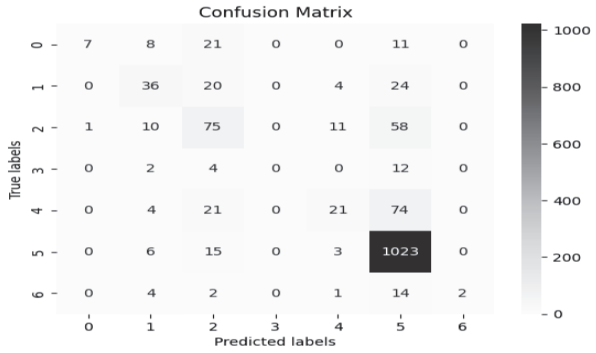

Fig. 3. Confusion Matrix of the Xception model

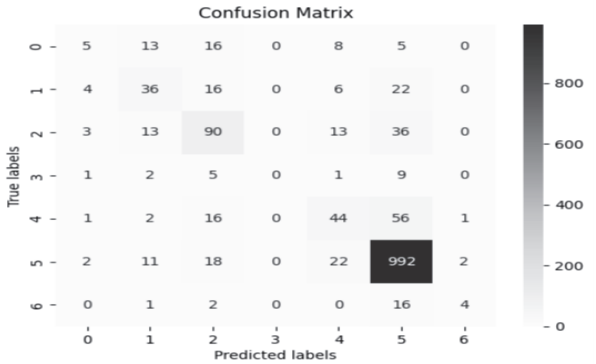

Fig. 4. Confusion Matrix of the ResnetV2 model

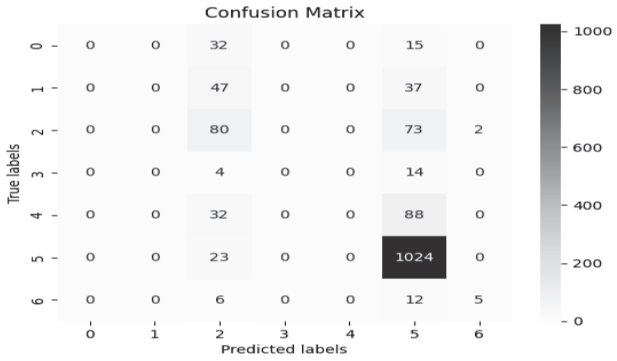

Fig. 5. Confusion Matrix of the Inception V3 model

These confusion matrix results support the accuracy, recall and F1-score metrics presented in the model comparison table. The Xception and ResNet50V2 models perform similarly in terms of the confusion matrix, although Xception shows a slight advantage in most classes. On the other hand, Inception V3 shows inferior performance compared to the other two models, which is reflected in the confusion matrix.

Classification Report: We calculate accuracy, precision, recall, F1-score and support of each model for each class using the classification report. These metrics provide us with detailed information about the model's performance in classifying each skin lesion type. Bellow, we have the classification reports for the proposed model and the compared models.

	precision	recall	f1-score	support
0	0.61	0.30	0.40	47
1	0.55	0.44	0.49	84
2	0.55	0.53	0.54	155
3	0.00	0.00	0.00	18
4	0.43	0.39	0.41	120
5	0.88	0.95	0.91	1047
6	1.00	0.43	0.61	23
accuracy			0.79	1494
macro avg	0.57	0.44	0.48	1494
weighted avg	0.77	0.79	0.78	1494

Fig. 6. Classification Report of the Xception model

	precision	recall	f1-score	support
0	0.41	0.15	0.22	47
1	0.53	0.40	0.46	84
2	0.49	0.58	0.53	155
3	0.00	0.00	0.00	18
4	0.44	0.31	0.36	120
5	0.87	0.95	0.91	1047
6	0.62	0.22	0.32	23
accuracy			0.78	1494
macro avg	0.48	0.37	0.40	1494
weighted avg	0.75	0.78	0.76	1494

Fig. 7. Classification Report of the Resnet50V2 model

	precision	recall	f1-score	support
0	0.00	0.00	0.00	47
1	0.00	0.40	0.46	84
2	0.35	0.58	0.53	155
3	0.00	0.00	0.00	18
4	0.27	0.31	0.36	120
5	0.87	0.95	0.91	1047
6	0.62	0.22	0.32	23
accuracy			0.74	1494
macro avg	0.30	0.30	0.27	1494
weighted avg	0.68	0.75	0.69	1494

Fig. 8. Classification Report of the Inception V3 model

Based on the information provide in every classification report, we can observe that.

For the Xception model:

- Accuracy varies between the different classes, being highest in classes 5 and 6.
- Recall also shows significant variations between classes, being high for classes 5 and 2, and very low for class 3.
- The f1-score is relatively low for most classes, especially for classes 0, 3 and 4.

For the Resnet50V2 model:

- Accuracy is lower overall compared to the Xception model, especially for classes 0 and 6.
- The recall shows similar performance to the Xception model, being higher for classes 5 and 2.
- The f1-score remains relatively low for classes 0, 3 and 4.

For the Inception V3 model:

- Accuracy and recall are very low overall, especially for classes 0, 1 and 4.
- The f1-score is low for most classes, with slightly better performance in classes 2, 5 and 6.

Discussion

In this subsection, we proceed to discuss the results obtained above for each validation metric.

Model Comparison: Table 2 shows the comparison results obtained by the Xception, Resnet50V2 and Inception V3 models using validation metrics. Although the Xception model shows the highest overall accuracy (0.81) and F1-Score (0.40), it is also important to consider the imbalance of the data. In particular, the performance of the models in detecting minority classes may be affected due to the unequal distribution of instances in the dataset. Therefore, caution is needed when interpreting these results and consider that additional approaches, such as class balancing techniques, may be required to improve the ability of the models to adequately classify all skin lesion classes.

Confusion Matrix: By analyzing the confusion matrices for the three models (Xception, ResNet50V2 and Inception V3), some trends can be observed:

- Xception: The Xception model shows a confusion matrix that reflects reasonably good performance for most classes. However, some confusion can be observed in classes 1, 4 and 5, where some samples were misclassified into other classes. Class 6 shows a high hit rate, as most samples were correctly classified as belonging to that class.
- ResNet50V2: The confusion matrix of ResNet50V2 also shows acceptable overall performance. As with Xception, there is some confusion in classes 1, 4 and 5. However, compared to Xception, ResNet50V2 shows a tendency to classify more samples in class 1 as class 2. Class 6 also has a high hit rate.
- Inception V3: The confusion matrix of Inception V3 shows a lower overall performance compared to the other two models. High confusion can be observed in classes 1, 2 and 5, where samples were misclassified into other classes. Class 6 again shows a high hit rate.

Classification Report

In general, the three models show difficulties in correctly classifying certain classes, especially those with a smaller number of samples or imbalance in the data. This may be due to the models' failure to capture the distinguishing features of those classes or the lack of sufficient examples to learn correctly.

Furthermore, the results highlight the superiority of the Xception model in terms of accuracy, recall and f1-score compared to the

Resnet50V2 and Inception V3 models. Therefore, the Xception model could be considered as the most suitable model for skin lesion classification in this dataset, due to its overall better performance. However, it is important to keep in mind the need to address class imbalance and explore additional approaches to improve performance across classes.

6. CONCLUSIONS

In this paper, we proposed the utilization of the Xception model for skin lesion classification using the HAM10000 dataset for training. Through our experiments and analysis, we have gained several important insights.

Firstly, our results indicate that the Xception model outperformed the baseline models, Resnet50V2 and Inception V3, in terms of accuracy, precision, recall, and F1-score. This suggests that the model is well-suited for the task of skin lesion classification and can potentially aid in accurate diagnosis and treatment.

Moving forward, there are several avenues for future exploration and improvement. One potential direction is to investigate the application of transfer learning and fine-tuning techniques. By leveraging pre-trained models on large-scale datasets, we can enhance the generalization and efficiency of our model, potentially achieving even higher accuracy and robustness.

Lastly, an interesting prospect for future research is the exploration of transformer-based models in skin lesion classification. This avenue can offer new insights and advancements in the field of skin lesion classification.

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