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Advancing Skin Cancer Diagnosis: A Deep Learning Approach with EfficientNetB3

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Abstract.

The paper provides a well-tuned EfficientNetB3 deep learning framework to classify skin cancer. Importantly to detect skin cancer in the early stages, the instrument should be fast and precise in distinguishing between benign and malignant skin lesions. The collection includes 6600 photos, 3600 normal and 3000 cancerous cases. Results of the benign cases and the malignant cases, where the accuracy is more likely to be 91% , with a last layer of the Dense model of the binary classification. The F1-scores of 0.92 and 0.90 respectively showed that benign and malignant lesions had equal performance in each group. There is minimal misclassification depicted in the confusion matrix; the loss and accuracy graphs demonstrate how well the model trains without overfitting. The findings suggest that the EfficientNetB3 model with fine-tuning is a high-quality and valid approach to skin cancer classification.

Keywords. Artificial Intelligence, Deep Learning, Skin Cancer Detection, Model Training, Fine-Tuned EfficientNetB3 Model.

1. INTRODUCTION

Skin cancer is the most common and potentially deadly disease in existence as evidenced by millions of cases being documented across the globe. It is typically a consequence of prolonged UV exposure or other environmental and genetic factors, caused by unchecked and undisciplined growth of skin cells. Are not to be diagnosed and treated late, there are

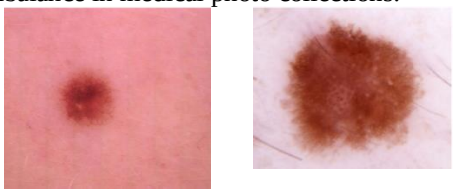
two basic types of skin cancer benign, non-cancerous and reasonably benign, and malignant, cancerous and capable of spreading to other body parts. The most dangerous type of skin cancer, malignant melanoma, requires early diagnosis particularly to enhance patient survival rates. The importance of early detection in preventing skin cancer is indisputable.

2. LITERATURE

The latest developments in deep learning and machine learning have made blood cancer detection highly accurate and reliable. Selvakumaran et al. [1] suggested a hybrid method of deep learning, which proved to be highly accurate in the classification of blood cancer by an effective feature extractor and integrator method. Likewise, Aazad et al. [2] dwelled on the analysis of microscopic images to classify blood cells, which is a powerful way to detect structural deviations among cells, which is critical in the diagnosis of cancer. Another area where machine learning methods have been extensively used is to detect cancer. San Chris and Beauty Smart [3] emphasized the promises associated with machine learning in improving diagnostic accuracy and supporting clinicians with automated processes.

3. INPUT DATASET

The input data used in this study is a massive pool of images of skin lesions as illustrated in Fig 1 and was selected carefully to make it diverse and representative. The collection consists of 6,600 good images, which can be divided into benign and malignant. This equal-selected data gives each classification the equal number of images, thus maintaining fairness in both the training and testing phases even when it addresses the issues posed by class imbalance in medical photo collections.



(a) (b)

Fig. 1 Dataset image for (a) Benign (b) Malignant

4. FINE-TUNED EFFICIENTNETB3 MODEL ARCHITECTURE

The current convolutional neural network EfficientNet B3 can be distinguished by its compound scaling method, which further maximises depth, width, and resolution of the model to achieve impressive performance with low computing cost.

5. PROPOSED METHODOLOGY

The proposed approach consists of four steps using the fine-tuned EfficientNetB3 model to diagnose the skin cancer: collecting the data, preprocessing the data, building the model and fine-tuning and evaluation and validation.

PHASE 1. DATASET COLLECTION

Training and validating the model first involves assembling a large database of skin lesion images. The dataset utilized in this work found high-quality photos of benign and malignant skin lesions on Kaggle and other available websites.

PHASE 2. DATSET PREPROCESSING

The data obtained had to be preprocessed before the next cycle of model development. The input dimensions required by EfficientNetB3 compel photographers to shrink photographs, thus maintaining the same information across the dataset.

PHASE 3. MODEL TRAINING AND VALIDATION

Third phase involved on development and improvement of EfficientNetB3 model. The model was originally trained with ImageNet database, modified specifically to classify skin cancer by dropping an output layer and replacing it with a dense layer more befitting binary classification.

PHASE 4. MODEL EVALUATION AND PERFORMANCE MATRIX

The model identified benign and malignant tumours with accuracy and precision coupled with recall and F1-score analysis and found that it performed well. By taking a separate data segment as the test set, it was possible to analyse the generalising capability of the uninformed data.

6. RESULTS

Following training and validation accuracy stabilizing at 91%, respectively, the finely tuned EfficientNetB3 model achieved good performance in skin cancer classification displaying effective generalization. The constant improvement shown by the loss curves helps to lower errors all during training.

A. Classification Report Analysis

A classification report as shown in Fig. 2 shows that the main performance measures are precision, recall, F1-score, and support of benign and malignant classes. In benign cases, the model had 0.93 precision and 0.91 recall with 91 percent of the benign samples being correctly classified. In malignant cases it came at 0.89 precision and 0.91 recall.

	Precision	Recall	F1-Score	Support
Benign	0.93	0.91	0.92	360
Malignant	0.89	0.91	0.90	300
Accuracy			0.91	660
Macro Avg	0.91	0.91	0.91	660
Weighted Avg	0.91	0.91	0.91	660

Fig. 2 Classification Report Analysis

B. Training and Validation loss Analysis

As Fig. 3 demonstrates, the model minimizes training and validation errors. First, the loss-to-training is large due to random parameters of weights though decreases drastically in the first five epochs with a rapid learning. Epoch 20 has the minimum training loss, and the same pattern can be observed with validation loss, which reaches its peak at epoch 9.

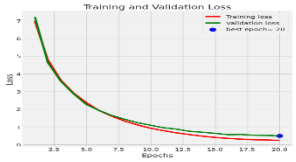


Fig. 3 Training and Validation loss Analysis

C. Training and Validation Accuracy Analysis

The Fig. 4 shows the accuracy graph of the model performance in training and validation. During the early epochs, the model learns image patterns fast and within the fifth epoch, the training accuracy reaches 91%. The accuracy of validation is steadily increasing, with the ninth epoch being the most balanced at approximately 91%.

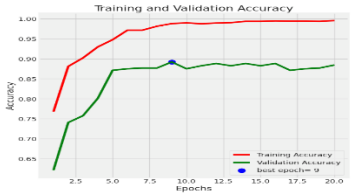


Fig. 4 Training and Validation Accuracy Analysis

D. Confusion Matrix Analysis

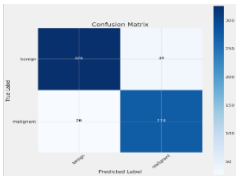


Fig. 5 Confusion Matrix Analysis

An overview of the model performance in separating benign and malignant cases can be seen in the confusion matrix in Fig. 6. It accurately categorizes 2,740 cancerous and 3,260 benign samples, and thus has high true positives on both sets.

7. CONCLUSION

The fine-tuned EfficientNetB3 model offers an amazing 91% success rate in skin cancer classification. This model distinguishes between benign and malignant cases, using specific measurements of 0.93 and 0.91 in the benign case and 0.89 and 0.91 in the malignant case. This model shows adequate identification of benign and malignant cases with F1-scores up to 0.92 and 0.90 respectively. The model exhibits good learning characteristics devoid of overfitting problems since training and evaluation curves show a small difference as indicated by both the accuracy and loss graphs. The model exhibits resistance as it fits the new information accurately.

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