Enhanced Skin Cancer Classification using Pre-Trained CNN Models and Transfer Learning: A Clinical Decision Support System for Dermatologists

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***Abstract*— Skin cancer is one of the fatal illnesses that cause a high percentage of deaths worldwide. The treatment of skin cancer depends critically on early detection of the disease. Dermatologists face several difficulties in the diagnostic process to address this issue. This study aims to improve the classification accuracy of seven types of skin tumors by using transfer learning on pre-trained Convolutional Neural Network models. The modified models, including EfficientNetB3, EfficientNetB0, and ResNet50, were trained on a dataset of 10,015 dermatoscopic images. The dataset was augmented using data augmentation techniques, and the class imbalance problem was addressed. This study offers a promising approach for clinicians to make informed judgments about patient diagnoses. Our results showed the superiority of the modified models over the official models. Our best model, the modified EfficientNetB3, achieved an accuracy of 91.6%, Precision of 83%, F1-Score of 88 %, and Recall of 94% on the HAM10000 dataset.**

Keywords— Skin cancer, Transfer Learning, EfficientNet, Deep Learning, HAM10000 dataset

I. INTRODUCTION

The World Health Organization estimates that one-third of all cancer diagnoses globally are for skin cancer [1]. Skin cancer has one of the world's highest rates of growth. It is prevalent cancer whose prevalence is rising globally every year and poses a severe threat to human health [2]. Smoking, genetics, environmental changes, exposure to ultraviolet (UV) radiation, and other factors are the major causes of this disease [3].

Estimated 5-year survival rates for diagnosed patients range from 15% if the cancer is identified at its most advanced stages to over 97% at its earliest stages. This is why finding cancer early drastically lowers the probability of mortality if it is recognized in the earliest stages [4]. Melanoma develops from the cells (melanocytes) that produce melanin. Furthermore, melanoma can form in the nose, throat, and other internal organs of the body [5].

Correct diagnosis is necessary to prevent problems because several lesion types are similar to each other. The accuracy percentage of a dermatologist used to be between 65% and 80% based just on eye examination, The doctor's training and experience are relevant to this inspection [6]. Dermoscopy is used to detect skin lesions that may not be visible to the naked eye. When dermatologists have high efficiency in training with dermoscopy, diagnostic accuracy is increased [7]. There are some challenges for Dermatologists to distinguish between different types of skin cancers, One of the most popular methods used to detect melanomas is the ABCDE rule [8]. Measurement mistakes and inaccuracies in this methodology could occur, This encourages using of an automated system to aid in the diagnostic process to get the maximum levels of accuracy and efficiency, in addition to saving time and effort.

Deep learning and machine learning have recently been used extensively. Convolution neural network (CNN) is one of these models, and it has proven to be superior to all others in tasks requiring object detection, it acquires highly discriminative features while undergoing supervised end-to-end training, which eliminates the need for manually handcrafting features [9]. The only issue with convolutional neural networks is that they require a lot of data to train and perform well for feature extraction, Transfer learning is an effective way to deal with this issue [10].

Deep learning techniques have shown significant promise in several medical fields, as a result of their capacity to automatically identify features from vast volumes of data and generate precise predictions. A Kronecker product-based convolution technique is used to extract more effective and in-depth features from input CT images for identifying kidney stones [11]. A customized skip-connection-based network with a feature union approach, called "SCovNet," is introduced for detecting COVID-19 in chest X-ray images. Furthermore, an innovative hierarchical classification strategy is provided for both balanced and unbalanced datasets [12]. To further computer-aided cancer identification methods for brain tumor segmentation, a modified U-Net structure based on residual networks is presented. This structure uses sub-pixel convolution at the decoder portion and periodic shuffling at the encoder part of the original U-Net [13]. The utilization of deep learning techniques can enhance the precision and effectiveness of ECG-based applications, including ECG beat classification, biometric authentication, and early detection of cardiac abnormalities, as demonstrated by research studies [14,15,16,17,18,19].

In this research, The classification performance of the pre-trained models was examined, and these models were modified and employed to achieve more accurate results.

Using ImageNet's pre-trained weights and the HAM10000 benchmark dataset, all experiments were performed. The modified models outperformed the original models regarding classification ability. With an accuracy of 91.6%, a precision of 83%, an F1-Score of 88%, and a recall of 94%, the EfficientNetB3 was our best model. Our results show that the modified models perform better for multiclass skin cancer classification on our dataset.

The related work is covered in Section II of this paper, which is structured as follows. The suggested methodology is described in Section III. Section IV explains the results and discussion, and the paper is concluded in Section V.

II. RELATED WORK

In previous works, As we'll briefly describe in this part, many studies show that there are numerous technologies have been created over time to identify skin lesions. These studies use the manual evaluation techniques that are frequently employed and are based on the ABCD rule to detect skin malignancies [20][21]. Preprocessing, segmentation with thresholding, and statistical feature extraction were applied, achieving a classification accuracy of 92.1% using a Support Vector Machine based on the ABCD rule [22].

The first comprehensive analysis using CNNs to classify skin lesions was presented. Additionally, the difficulties that must be overcome in this field moving forward are demonstrated [23]. Transfer learning and a pre-trained model with GoogleNet were successfully used to categorize eight distinct types of skin lesions. The achieved classification accuracy was 94.92%, and precision, specificity, and sensitivity were 80.36%, 97%, and 79.8% respectively [24].

A Convolutional Neural Network (CNN) was used on the dermoscopy images of the HAM10000 dataset for skin cancer, achieving training and testing accuracies of 80% and 78%, respectively [25]. Deep learning techniques, such as parallel networks, CNNs with segmentation, transfer learning, and fine-tuning, were applied to the HAM10000 dataset, which contains labeled images. The study achieved an average F-score of 0.7% and an accuracy rate of 82.8%. [26].

An ensemble method was applied to use Inception V3 and ResNet-50 architectures to identify various types of skin lesions, achieving an accuracy of up to 0.899 [27]. A method for the classification of skin lesions based on transfer learning and deep learning on the HAM10000 dataset was presented, which contains two steps. In the first step, the test accuracy was 85%, while in the second step, the test accuracy was 75% [28]. The original dermoscopic images were pre-processed using the decorrelation formulation method then the generated images were passed to the MASK-RCNN for lesion segmentation and pre-trained DenseNet for classification [29].

The HAM10000 dataset was used with VGGNET-16 architecture with the K-Fold Cross Validation technique to classify the images into seven lesion classes with an accuracy of 85.62% [30]. All EfficientNet variants were trained to determine the efficiency on the HAM10000 dataset, the EfficientNet B4 achieved high accuracy of 87.91 percent and an F1 Score of 87 percent [31]. The proposed Medical Vision Transformer (MVT) was evaluated on the HAM10000 dataset and achieved 96% accuracy, outperforming existing methods for skin cancer detection. The input image is split into image patches and then fed to the transformer in a sequence structure by this MVT [32].

In this study, A benchmark dataset that had more difficulties was employed, issues with class imbalance were addressed, and a developed methodology was provided to enhance the diagnosis process.

III. PROPOSED APPROACH

This section explains the preprocessing image pipeline to understand better our proposed skin tumors classification, Figure. 1 shows the general stages in our methodology: First, collecting dermoscopic images, Then data resizing, balanced sampling, and augmentation can deal with the problem of imbalanced data. After that, the pre-trained models such as EfficientNetB3, EfficientNetB0, and ResNet50 with modifications in model architectures, using transfer learning to train the HAM10000 dataset using ImageNet's pre-trained weights and fine-tuning, Finally Validation, and testing of results.

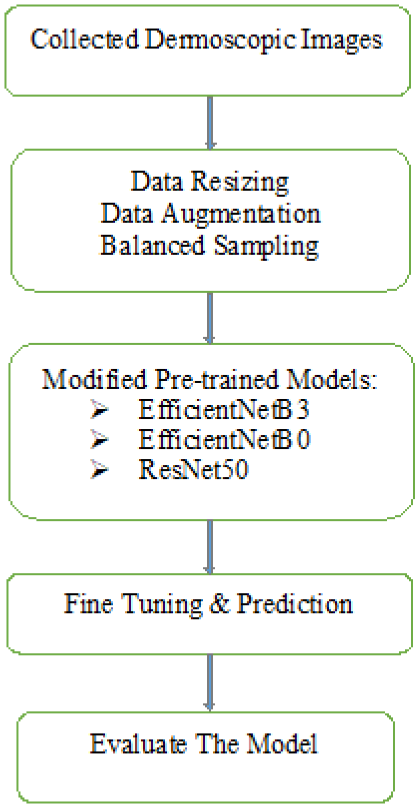

Fig. 1. The general stages of our proposed approach.

A. Dataset

The used dataset is called Human Against Machine with 10000 training images (HAM10000), It was gathered over 20 years from Cliff Rosendahl's skin cancer clinic in Australia, and the Department of Dermatology at the Medical University in Austria [33].

It consists of 10015 dermatoscopic images of seven skin cancer types with a 600 x 450 pixel resolution. The seven classes of the HAM10000 training dataset are: Although benign, actinic keratosis (AKIEC) can develop into a malignant tumor. Malignant tumors include melanoma (MEL) and basal cell carcinoma (BCC). Vascular lesions, Dermatofibroma, Benign Keratosis, and Melanocytic Nevi are all benign lesions. This dataset was split into three parts: 70% as a training set with 7010 images, 10% as a validation set with 1001 images, and 20% as a testing set with 2004 images. Figure. 2 illustrates the distribution of images in each class. The dataset shows a high-class imbalance, with the largest class, NV, having 6705 images and the smallest class, DF, having only 115.

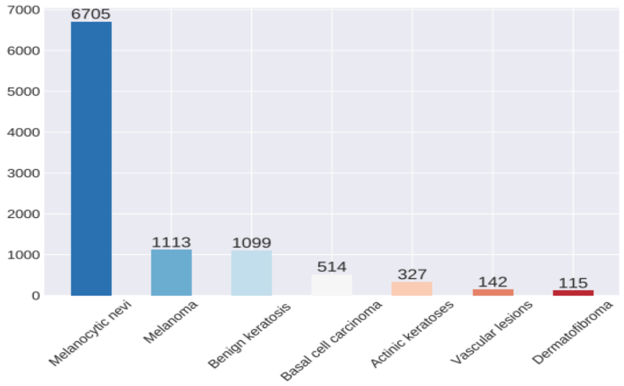

Fig. 2. The distribution of images in each class.

B. Data Preprocessing

B.1 Data Resizing

The HAM10000 dataset includes the images in 600 × 450 dimensions. The dataset has been scaled down to 224 × 224. The complexity of the model will be drastically reduced, as also the processing time.

B.2 Data Augmentation

The process of adding slightly changed copies of existing data without actually gathering new data from training sets is known as data augmentation. perhaps it aids in shielding the model from over-fitting by removing the cause of the issue [34]. To overcome this overfitting, with the aid of the image data generator function of the Keras library in Python, we applied different augmentation techniques, including rotation with a range of 0 to 90 degrees, zooming, and horizontal and vertical flipping.

B.3 Imbalance Handling

In the HAM10000 dataset, The class distribution is highly imbalanced, and if left unaddressed, the model may be biased towards the majority class and perform poorly on the minority classes. Deep learning frequently encounters imbalanced data problems. A weighted loss function was used as an effective method to minimize the impact of this issue during training to give more importance to the minority classes.

Class weights can be calculated based on the number of samples in each class, and these weights can be used to adjust the loss function in the model. The whole purpose is to punish the minority class's misclassification by increasing the class weight, which effectively makes the model pay more attention to these classes while reducing the weight for the majority class. This helps the model to improve its performance in all classes.

C. Transfer Learning

Transfer learning is the process of enhancing learning in a new task by transferring knowledge already acquired from the models that were trained using the ImageNet dataset [35]. The utilization of transfer learning is chiefly aimed at reducing the need to train multiple models from scratch for similar tasks, thereby conserving time and resources. Additionally, transfer learning can help overcome the challenge of limited labeled training data by utilizing pre-trained models [36].

In this study, three pre-trained models, namely EfficientNetB3, EfficientNetB0, and ResNet50, were used on the HAM10000 dataset to classify skin tumors between seven classes. Both fine-tuning and transfer learning were employed to achieve high performance.

C.1 EfficientNetB3

EfficientNetB3 is part of a family of models designed through a principled approach to model scaling. The authors found that simply increasing the size of the network by adding more layers and filters led to diminishing returns in terms of accuracy and computational efficiency. Instead, they proposed a compound scaling method that balances the network's number of layers, width, and resolution. In particular, EfficientNetB3 has 25.2 million parameters, achieved by scaling up the baseline network architecture with a compound scaling factor of 1.2. It has a width multiplier of 1.2 and a depth multiplier of 1.1 [37].

C.2 EfficientNetB0

EfficientNetB0 was designed to achieve accuracy on image classification tasks while minimizing the number of parameters and computational resources. It employs a compound scaling method to consistently scale the width, depth, and resolution of the network. This enables the network to enhance performance without increasing the number of parameters [37].

C.3 ResNet50

ResNet50 refers to a convolutional neural network that has 50 layers. One of the well-known models that perform in solving various computer vision issues [38]. Additionally, ResNet50 has been built with varying numbers of layers, including 18, 34, and 152. It has a fully connected layer and 49 convolution layers. It consists of five convolutional layer blocks, designated Blocks 1 through 5, a 1000 node fully connected layer with a softmax function at the end [39].

D. Modifications in network architecture

The three pre-trained models were modified and used to increase the performance. The Modifications to the EfficientNetB3, EfficientNetB0, and ResNet50 were made by trial and error to obtain high-level features. After various experiments, It was observed that the modified models with better classification performance than the original models were obtained using transfer learning and then fine-tuning.

The top three layers of the original pre-trained models were appropriate for the ImageNet dataset. Our dataset substituted the three top layers of Global Average Pooling2D, dropout, and an output layer of each model with new layers. Two convolution layers consist of a 3x3 kernel size with 128 filters, followed by a batch normalization layer. The output of these layers is used as input into a global average pooling layer, followed by a dense layer with 256 units and ReLU activation, then a dropout layer with a rate of 0.2 to prevent overfitting. Finally, The dense layer with softmax activation is added as the output layer with seven units to produce a probability distribution over the possible classes. The categorical cross-entropy is used as a loss function in the model with the Adam optimizer, which has a learning rate of 0.0001. Like EfficientNetB3, all other official models, including EfficientNetB0 and ResNet50 had the same modifications. The block diagram of the modified EfficientNetB3 is shown in Figure. 3 The layers on the left of the figure show the original EfficientNetB3 architecture, while the modifications added to the model are highlighted with a red color on the right.

Fig. 3. Modified EfficientNetB3 block diagram.

E. Evaluation Metrics

In this section, to classify skin lesions between seven different types, The pre-trained models such as EfficientNetB3, EfficientNetB0, and ResNet50 with modifications in model architectures were tested with 2004 dermoscopic images, as the best results were obtained with EfficientNetB3. Several metrics are recommended by the HAM10000 dataset to assess the performance, taking into account accuracy, precision, recall, and f1-score [40]. According to these mathematical equations, the efficiency of the system is determined:

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

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

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

$$F1\text{ - }score = 2 * \frac{Precision * Recall}{Precision+Recall} \tag{4}$$

Where TP stands for true positive, FN indicates false negative, TN indicates true negative, and FP stands for false positive.

IV. Experimental Results and Discussion

EfficientNetB3, EfficientNetB0, and ResNet50 were fine-tuned as transfer learning models on the HAM10000 dataset. The HAM10000 dataset was then split into 70% for training, 10% for validation, and 20% for testing. All models were fine-tuned for 50 epochs with a batch size of 64, and the Adam optimizer with a learning rate of 0.0001 was applied. The models were evaluated using accuracy, recall, precision, and f1-score measures. The proposed models were trained and tested in Python using Keras and Tensorflow libraries. The performance results of the models are displayed in Table 1 and Table 2.

Table 1. Performance results of the original proposed models.

Original Pre-trained model	Accuracy	Precision	Recall	F1 score
Original EfficientNetB3	88.8%	80%	93%	85%
Original EfficientNetB0	87.4%	78%	90%	83%
Original ResNet50	86.6%	78%	92%	84%

Table 2. Performance results of the modified proposed models.

Modified Pre-trained model	Accuracy	Precision	Recall	F1 score
Modified EfficientNetB3	91.6%	83%	94%	88%
Modified EfficientNetB0	90.4%	82%	95%	88%
Modified ResNet50	87.8%	81%	93%	86%

From the previous results, it can be observed that the modified pre-trained models outperformed the original models in terms of accuracy, precision, recall, and F1-score. The modified EfficientNetB3 model achieved the highest performance with an accuracy of 91.6%. Compared to the original EfficientNetB3 model, the modified model improved by 2.8% in accuracy, 3% in precision, 1% in the recall, and 3% in F1-score. Similarly, the modified EfficientNetB0 and ResNet50 models performed better than their original counterparts. These results indicate that the modifications made to the pre-trained models have significantly improved their performance on the given task. Overall, the modified pre-trained models appear to be more effective than the original pre-trained models in this study.

Table 3. Final performance results for each class in our Modified models.

Model		AKIEC	BCC	BKL	DF	MEL	NV	VASC
Modified EfficientNetB3	**Accuracy**	1.00	0.95	0.92	1.00	0.87	0.90	0.96
	Precision	0.80	0.89	0.83	0.73	0.68	0.98	0.86
	Recall	1.00	0.95	0.92	1.00	0.87	0.90	0.96
	F1-score	0.89	0.92	0.87	0.85	0.76	0.94	0.91
Modified EfficientNetB0	**Accuracy**	0.98	1.00	0.90	1.00	0.88	0.90	1.00
	Precision	0.78	0.87	0.80	0.76	0.69	0.99	0.87
	Recall	0.98	1.00	0.90	1.00	0.88	0.90	1.00
	F1-score	0.87	0.93	0.85	0.86	0.77	0.94	0.93
Modified ResNet50	**Accuracy**	1.00	0.96	0.86	1.00	0.83	0.88	1.00
	Precision	0.76	0.88	0.76	0.79	0.63	0.98	0.87
	Recall	1.00	0.96	0.86	1.00	0.83	0.88	1.00
	F1-score	0.86	0.92	0.81	0.88	0.72	0.93	0.93

Table 3 represents the final performance results for each class in the three modified models, which are used for skin lesion classification. The evaluation metrics used are precision, recall, and F1-score for each of the seven classes: BCC, BKL, DF, MEL, NV, AKIEC, and VASC in the HAM10000 dataset. The results show that the modified EfficientNetB3 model achieved the highest average precision score among all models with scores ranging from 0.68 to 0.98. The modified EfficientNetB0 model demonstrated a moderate performance with an average precision score while achieving higher average recall score. The average F1-score for all models was relatively high.

Overall, the modified EfficientNetB3 model outperformed the other two models in terms of precision, and overall performance to effectively classify skin lesions.

As shown in Figure. 4 The best outcomes were obtained with the modified EfficientNetB3 model on the HAM10000 dataset. The model has a good learning rate as the training accuracy improves with the number of epochs and the performance of validation accuracy reached 92.5% through 50 epochs. In contrast, the model obtained a validation loss of about 0.24. It demonstrates the model's ability to generalize to new images.

Fig. 4. Modified EfficientNetB3 in terms of loss vs epochs, and accuracy vs epochs.

As shown in Figure. 5 The provided ROC AUC values for the modified EfficientNetB3 model in the prediction of different types of skin lesions have demonstrated exceptional performance. With an average ROC AUC of 0.99, indicating accurate differentiation between the various types of skin lesions.

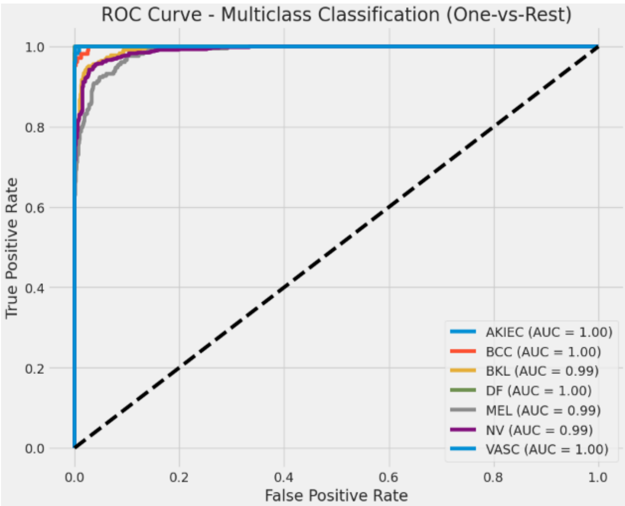

Fig. 5. ROC curve for Modified EfficientNetB3

Table 4. The effective of Imbalance Handling & data augmentation on results.

Modified Pre-trained model	**ACC With applying Imbalance Handling & data augmentation**	**ACC Without Imbalance Handling & data augmentation**
Modified EfficientNetB3	91.6%	87.8%
Modified EfficientNetB0	90.4%	87%
Modified ResNet50	87.8%	85.5%

In Table 5, the performance of our best EfficientNetB3 model is compared with previous works on the HAM10000 dataset to classify seven types of classes. This comparison demonstrates that our proposed method has outperformed other classification methods.

Table 4 shows that applying imbalance handling and data augmentation techniques increased the classification accuracy for all three models. The Modified EfficientNetB3 model achieved the highest accuracy of 91.6% with applying the techniques, compared to 87.8% without applying them. Likewise, we find a noticeable increase in the accuracy after applying the techniques of Imbalance Handling and data augmentation to the other models.

Table 5. Comparison between our model and other previous works on the HAM10000 dataset.

Ref	**Classifier**	**Accuracy**
[25]	CNN	ACC = 78%
[26]	CNN with transfer learning	ACC = 82.8%
[28]	CNN with transfer learning	ACC = 85%
[30]	CNN	ACC = 85.6%
[31]	CNN with transfer learning	ACC = 87.9%
Our proposed EfficientNetB3	**CNN with transfer learning**	**ACC = 91.6%**

V- Conclusion

The different pre-trained models were developed with modifications to the top three layers to improve the classification accuracy of seven types of skin cancer by performing transfer learning on ImageNet's pre-trained weights then fine-tuning. The performance of all modified models was assessed on this unbalanced classification issue using metrics such as F1-Score, Precision, Recall, and Accuracy using the HAM10000 dataset which has more challenges with applying the preprocessing steps on it. Our results showed the superiority of the modified models over the original models such as EfficientNetB3, EfficientNetB0, and ResNet50. We trained all models and EfficientNetB3 had the highest accuracy. In the future work, we'll work on a sizable dataset with more labelled skin lesions to make greater advancement with fine-tuned models for most specific types of cancer including pre-processing steps to get the highest prediction and classification accuracy.

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