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Optimized Skin Cancer Detection through Dermoscopic Imaging Using EfficientNetB4 Architecture

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Abstract: Background: Skin cancer classification is a challenging task due to the fine-grained diversity in the appearance of various diagnostic categories. Detecting skin cancer at an early stage is vital for enhancing patient outcomes, as the prognosis for this condition greatly improves when diagnosed early. Convolutional neural networks have been found to be more effective than dermatologists in classifying multiclass skin cancer. Problem: The identification of skin cancer is frequently impeded by the subjective analysis of dermoscopic images, resulting in misdiagnoses and delayed treatments. The objective of this study is to create a reliable and effective classification system using the efficientnetb4 model, which will aid in early detection and ultimately enhance patient outcomes. Objective: The main goal of this study is to create a highly efficient and accurate classification system for skin cancer using the efficientnetb4 model. The goal of this system is to improve the accuracy of diagnoses, minimize misdiagnoses, and enable early detection of skin lesions, leading to better patient outcomes and a more efficient diagnostic process in dermatology. Methods: The EfficientNetB4 model is trained on the HAM10000 dataset using transfer learning and fine-tuning techniques on rotated images, zoomed in and out, and even flipped over to make variations. Then, it adjusted the hyperparameters in the fine-tuning step to fine-tune its weights so that the model could fit the classification task for skin lesions more precisely. Results: The leading model, EfficientNetB4, achieved a Top-1 Accuracy of 89.22%, a Top-2 accuracy of 88.82%, and a top-3 accuracy of 88.62%. Precision, recall, and F1 scores are computed for each class. This model has demonstrated excellent performance in melanoma (MEL) and benign kurtosis-like lesions (BKL). Criteria considering high-class imbalance were used in the assessment of Efficient Net classifiers. Models with an intermediate level of complexity, such as EfficientNetB4, demonstrated the most optimal performance. Confusion matrices were also discovered to be useful in identifying skin cancer varieties with the greatest capacity for generalization. Conclusion: Overall, EfficientNetB4 demonstrated superior performance in classifying multi-class skin cancer. Further development would be oversampling or synthetic data generation for even more class-balancing techniques to improve performance over underrepresented classes. More medical data, including images and clinical data, will probably increase the overall diagnostic accuracy.

Keywords: Skin Cancer; Classification; EfficientNetB4; Optimization; Image-Based System.

1. Introduction

The epidermis is the largest organ that an individual possesses. Skin cancer is one of the most severe and fatal manifestations of the illness[1]. Every day, a significant number of people pass away from skin cancer [2]. If detected early enough, treating cancer can be effective, even though it can spread swiftly. Early detection is crucial since it can raise the likelihood that a treatment will be successful [3]. New data shows that 20% of skin cancer cases became so advanced that survival was no longer an option [4]. Doctors detect skin cancer in a variety of ways. They examine your skin, take images, and occasionally do a biopsy [5].To aid in the identification of melanoma, the American Centre for the Study of Dermatology created a handbook. The acronym ABCD rule refers to the set of guidelines and stands for asymmetry, border, color, and diameter. When a mole is asymmetrical, it indicates that one half does not match the other half. The term "border" describes a mole's ragged or ill-defined boundaries. Because moles are present in a spectrum of hues, the term "color" is an accurate description. A mole is considered to be of greater size when its diameter exceeds 6 millimeters, an amount comparable in size to that of a pencil eraser [6]. Dermoscopy utilizes a handheld instrument to magnify and illuminate skin lesions, providing a non-invasive method[7]. When diagnosing melanoma, dermoscopy is a more precise method than visual inspection [8].

Deep Neural Networks ′(DNNs) increasing use in picture categorization has been a significant advancement in machine learning in recent years. Directed Neural Networks (DiNNs) have demonstrated exceptional performance across a range of image classification tasks, such as segmenting images, identifying faces, and detecting objects [9]. Medical photos can have their features automatically extracted by deep learning, which can subsequently be used to categorize the images or pinpoint particular features within the images[10]. This study employed the region-based convolutional neural network technique. Faster R-CNN, also known as FRCNN. This is what was made when the Fast R-CNN and region proposal network (RPN) algorithms were combined into one network [11]. Melanoma, basal cell carcinoma, actinic keratoses, and squamous cell carcinoma are the four primary forms of skin cancer that can result from Ultra Violet (UV) radiation exposure. Actinic keratoses, which are precancerous lesions, have the potential to progress into malignant skin cancer. Pre-cancerous lesions called actinic keratoses have the potential to progress to skin cancer. Bassal cell carcinoma is the most commonly occurring form of skin malignancy. Squamous cell carcinoma ranks second in frequency among all skin cancers. Without exception, melanoma is the most perilous type of skin malignancy [12]. Experts estimate that the United States will identify approximately 5.4 million new cases of skin cancer annually.

Better chances of survival can result from early identification of skin cancer [13]. Melanoma skin cancer affects 1 in 52 women and 1 in 33 men in the US at some point in their lives. About 9,320 Americans lost their lives to melanoma skin cancer in 2018. The good news is that, if detected early, melanoma skin cancer is very curable. This is the reason it's critical to have routine skin examinations performed by a physician and to be aware of the warning signs and symptoms of melanoma skin cancer [14]. The variable characteristics of melanoma skin cancer lesions—color, texture, shape, size, contrast, and location make automatic detection difficult. Differentiating between melanoma and non-melanoma lesions may prove challenging due to their striking resemblance in appearance. Because early-stage melanoma lesions are frequently tiny and have little contrast with the surrounding skin, they might be challenging to find. Lastly, melanoma lesions might become even more obscured and challenging to detect due to artifacts such as hairs, veins, ruler markings, and color calibration[15]. Some people might not be able to receive a diagnosis in a timely manner. A novel approach to diagnosing skin conditions is data-driven diagnostics. This analyses skin images using machine learning to identify patterns connected to various skin conditions. This is a costly and relatively new technology [16]. When it comes to data and image classification, deep learning models outperform conventional techniques. More accurate ease of classification and abnormality detection are becoming increasingly necessary in healthcare diagnostics.

To detect anomalies and categories of illnesses, deep learning models can be applied to the analysis of X-ray, MRI, CT, PET, ECG, and EEG pictures and data [17]. Among the potential uses for deep learning systems is the identification of cutaneous cancer. In terms of both speed and accuracy, deep learning systems surpass human physicians in the domain of skin cancer screening. Algorithms capable of machine learning may detect characteristics and patterns in skin images that humans fail to notice. This could increase the precision of skin cancer diagnosis, resulting in earlier intervention and better results for patients. Here, we provide a more comprehensive analysis of each [18]. For the classification of cutaneous lesions, researchers have also dabbled in hybrid schemes that integrate deep learning with additional machine learning techniques. The utilization of deep learning models to accurately classify skin diseases possesses the capacity to fundamentally transform the fields of early detection and treatment [19]. Many mobile phone applications have been developed to detect skin cancers. As an alternative to the dermoscopy images utilized by dermatology specialists, these applications utilize smartphone camera images. Instead of dermoscopy images, clinical images were utilized to develop a technique for categorization based on neural networks [20].

The objective of our research is to develop an optimized dermoscopy-image-based classification system for skin cancer. EfficientNetB4 is the most advanced model in the analysis of skin pigment lesions, making it the principal choice for this research. This model classifies in detail those lesions with the publicly available dataset by using different methods of classification. The model was tested on the HAM10000 dataset, and for seven classes of skin lesions, the classification accuracy achieved was 89.22%. Thus, the performance of this proposed model was superior. The findings indicate that the model exhibits a commendable performance in classifying skin malignancies.

Over contribution of this study is that it applied the efficient model EfficientNetB4 and the HAM10000 dataset to improve efficiency and accuracy in the classification of skin lesions. The research transfers learning from a pre-trained Image Net model to make it suitable for a medical imaging application and fine-tunes it for its particular domain of interest like pigmented skin lesions. It further employs intricate image preparation operations like hair removal and resizing in order to enhance the quality of datasets, and further applies techniques of image augmentation to boost the size of a given dataset for smoother model training. To open up further research on the perception of skin lesions, the study concludes with a comprehensive evaluation of the EfficientNetB4 model performance and benchmarking on the HAM10000 dataset.

This paper is organized as follows: Section 1 provides an overview of the skin cancer class prediction system; Section 2 summarizes the literature review of previous studies related to skin cancer; In Section 3, the data set utilized, procedures of classification, complexities in the skin cancer problem, and methodology are explained. In Section 4, we detail the implementation; the performance evaluations of the methods are elaborated along with our evaluation criteria in Section 5, while the results and discussions are presented in Section 6. Conclusions for further research are given in Section 7.

2. Related Works

Artificial intelligence has advanced significantly over the last decade, particularly in the areas of deep learning and CNNs. Reliable image-based medical surveillance and detection systems are now attainable as a result of these developments [21]. Using deep learning, Liu et al. [22] created a novel technique for segmenting lesion images. Their technique collects information from the photos at a level that is less abstract than the object level but more abstract than the pixel level since it employs a mid-level feature representation. They distinguish the various areas of interest (ROIs) in the picture by creating a segmentation mask with this information. Pour and Seker [23] segmented lesions and dermoscopic features in pictures using a convolutional neural network. They did not, however, employ a pre-trained model or heavy augmentation. Rather, they combined the RGB colour channels with the CIELAB colour system. Dash et al. [24] presented a novel approach to segmentation using a deep, fully convolutional network with 29 layers. Xie et al. [25] proposed a technique for segmenting dermoscopy photos utilizing a convolutional neural network that incorporates an attention mechanism. This can aid in increasing segmentation accuracy, particularly for pictures with intricate edges. Manzo and a team published a method for melanoma detection consisting of three stages [26]. The photographs are resized, and the dataset is balanced in the initial phase. Step two involves the application of deep transfer learning to extract features. In the third phase, we employ a combination of classification algorithms to generate predictions. Table 1 provides a comparison of a variety of machine learning and deep learning methods for the classification and detection of skin lesions, with a focus on models, datasets, performance, and key limitations.

Table 1. Summary of Tasks, Methodology, Dataset, Performance and Limitations

References	Objective	Model Tested	Dataset	Model Performance	Limitations/Comments
Liu et al. [22]	Goal to create a new mid-level Feature learning approach that enhances	SVM classifier trained CNN models ResNet and	ISIC2017 dataset, consisting of 2000 photos.	Model execution attains cutting-edge results in the	Restrictions include reliance on pre-trained models, which

	robustness and discrimination in the identification of melanoma and other skin lesions.	DenseNet for feature extraction.		Classification of skin lesions as compared to current CNN-based techniques.	might not capture local information, and susceptibility to complex skin conditions.
Pour and Seker [23]	To create a CNN-based model that is effective at segmenting skin lesions and dermoscopic features without heavily depending on preprocessing or data augmentation.	CNN uses multiscale, multi-direction picture representations from the transform domain and 15 convolutional layers in the encoder section.	ISIC2016 and ISIC 2017 datasets.	6% higher Jaccard index, 7% better segmentation metrics, 17% better dermoscopic feature Segmentation.	Absence of a pre-trained Model on relevant medical data; lack of a large dataset and data augmentation.
Dash et al. [24]	Objective to create a modified U-Net architecture (PsLSNet) based automated psoriasis lesion segmentation technique for Effective lesion detection And segmentation from RGB pictures.	PsLSNet(29 layers deep fully convolutional network).	Dermatologists collected a dataset of 5241 photos of psoriasis lesions from 1026 patients.	Dice coefficient: 93.03%, Accuracy: 94.80%, Sensitivity: 89.60%, Specificity: 97.60%	Overfitting to training data could occur from relying too much on deep learning.
Xie et al. [25]	To present a skin lesion segmentation approach using CNN with an attention mechanism that maintains edge details and accurately recovers skin lesion borders in dermoscopy images.	CNNs with spatial attention, channel-wise attention branches, and high-resolution feature blocks(HRFBs)	PH2, ISBI2016, and ISBI2017 datasets.	Jaccard index:0.783 on the ISBI 2016 dataset,0.858 on the ISBI 2017 dataset, 0.857on the PH2 dataset.	The complexity of the model is due to several branches.
Manzo & Pellino [26]	The aim of the melanoma detection model framework is to	SVM, LLP &KNN	PH2 dataset.	Competitive or superior state-of-the-art methods in	The difficulty of computation during the

	enhance classification through deep learning and ensemble learning.			melanoma detection.	feature extraction stage.
Carolin Flosdorf [27]	Goal to increase Precision and automate skin cancer detection with Vision Transformer(ViT) models, Especially for melanoma, theworst type of skin cancer.	Pre-trained Vision Transformers (ViT-L32, ViT-L16) evaluated against less sophisticated ViT models, CNNs, KNN classifiers, and decision tree classifiers.	Not mentioned	ViT-L32: Accuracy of 91.57%, Recall Of melanoma: 58.54%, ViT-L16: Melanoma Recall: 56.10%, Accuracy: 92.79%.	Low recall(sensitivity) of melanoma cases(58.54% and 56.10%).
MA Rahman [28]	Create an accurate, autonomous model using DCNNs to classify skin cancer (melanoma vs non-melanoma).	Optimized NASNet Mobile and NASNet Large.	2637 skin images.	NASNet Large: 83.98% accuracy, NASNet Mobile: 85.62% accuracy.	Few images of aggressive tumors; reduce classification accuracy.
AVP Rajesh [29]	To optimize Deep Convolutional Neural Networks (DCNNs) for the Classification of Seven different kinds of skin lesions	Inception V3 and DenseNet201.	HAM10000dataset.	Inception V3: Accuracy of 85.94%, DenseNet 201: Accuracy of 87.42%, Ensemble: accuracy of 85.94%	Inception V3's Accuracy is matched by the Ensemble model's performance, DenseNet 201Outperforms it in the test set
Hritwik Ghosh [30]	Improve accuracy and correct class imbalance in a dataset of skin disorders by utilizing Deep Learning (DL) capabilities.	Hybrid model pre-trained on the Image net dataset that combines VGG16 andResNet50.	3,000 photos Covering9 different Skin disorders, such as melanomas and carcinomas.	Accuracy:98.75%, Precision: 97.60%,Recall: 97.55%,F1 Score:97.58%	Imbalance in Model performance
Owida, H.A [31]	The creation of a deep learning model to categorize images of multiple skin	Convolutional Neural Network (CNN)	HAM10000 dataset.	Accuracy of the model:95.23%, Sensitivity: 95.30%,Specificity:95.91%	Not mentioned.

	diseases in order to aid in the diagnosis of skin cancer.	

Almansi et al. [32] created a novel technique called FrCN for picture segmentation. Being a full-resolution convolutional network, FrCN does not require down sampling and can process the entire image at once. FrCN is easier to use and faster because it doesn't require any pre- or post-processing. Serte and Demirel [33] introduced a novel deep-learning model specifically designed for the classification of seborrhoeic keratosis and melanoma. They developed the model on the basis of a collection of seven convolutional neural network (CNN) models incorporating Gabor wavelets. Additionally, the model combines an image-based CNN model with a Gabor wavelet-based model. The ensemble model outperformed the individual models constructed using Gabor wavelets and images.

Li et al. [1] proposed a technique referred to as digital hair removal (DHS) to eliminate hair from images of skin lesions. A deep learning model is employed by DHS to recognize and eliminate hair from pictures. The authors found out what effect DHS had by using intra-structural similarity (Intra SSIM) to figure out how similar images taken before and after hair removal were. A deep learning system was developed based on the Inception V4 architecture [34]. Level II included clinical information, a dermoscopy image, and a close-up of the patient's visage. Level I show cased images exclusively pertaining to dermoscopy. Comparing the deep learning system to that of Level I dermatologists, its sensitivity and specificity were 95%. Level II data shows no change in average specificity but an increase in average sensitivity to 94.1% [32]. Among the participants were 16.2% family physicians, 23.1% dermatology residents, and 55.4% board-certified dermatologists. The researchers discovered that, on average, AI algorithms out performed humans in diagnostic tasks by 2.01 points. Researchers have put for a novel approach to identifying skin cancer using photos taken with regular cameras. Using a dataset of 463 pictures, the technique produced an overall classification accuracy of 76.9% [35]. It has been demonstrated that CNNs are useful for categorizing skin conditions. CNNs all performed better than dermatologists, improving by an average of 11%. The top-performing CNN was Dense Net 201, which had an overall classification AUC of 98.16%.10,135 dermoscopy skin pictures were included in the dataset utilized for the study [36]. The classification of skin lesions on the HAM 10000 dataset was suggested utilizing an individual Inception-v4 model. The model achieved a precision rate of 94.7%on the verified ISIC 2018 benchmark test. By utilizing lengthy residual connections for feature reuse, the model was improved [37].

A novel deep-learning algorithm is capable of automatically classifying seven distinct types of cutaneous lesions. The system demonstrated an accuracy of 93%, 97%, and 91%, respectively, in the highest-1, highest-2, and highest-3 rankings. We utilized the HAM 10000 dataset, which comprised over 10,000 images of skin lesions, to train the algorithm [38]. Zhang et al. [39] came up with attention-based residual learning as a way to sort skin lesions into groups, especially nevus, seborrhoeic keratosis, and melanoma. The attention-based layers in this strategy are modeled after the last levels of the ResNet deep learning model. Researchers implemented a deep learning system to facilitate the classification and segmentation of lesions. Three datasets (PH2, ISBI2016, and ISIC2017) were utilized to evaluate the proposed method by the researchers. Khan et al.[21] claim that the proposed framework has the potential to attain the following metrics: F1-score of 86.28%, accuracy of 86.5%, sensitivity of 85.57%, and precision of 87.01%. Skin Trans was trained utilizing a clinical dataset and the HAM10000 dataset, which is associated with skin cancer. Xin et al. [40] reported that the model demonstrated an accuracy of 94.1% on the clinical dataset and 94.3% on the HAM10000 dataset. Four distinct skin cancer imaging datasets were utilized to assess the ACO-KSELM model: ISIC 2016, ACS, HAM10000, and PAD-UFES-20. The accuracy of predictions made by the ACO-KSELM model on the datasets citeliu 2023 aco was 98.5%, 98.6%, 97-9.9%, and 98.5%, respectively [41]. Six publicly accessible databases of skin lesions were utilized by Menegola et al. [42] to train two deep learning models: Google Inception-v4 and Deep ResNet-101.They set out to determine whether integrating these databases could enhance the accuracy of lesion categorization. Deep learning techniques employ a variety of deep neural network architectures to categorize skin cancer as malignant or benign. Numerous datasets have been used to assess these techniques, including HAM10000, ISIC 2019, and ISIC 2020. The techniques have produced results with great accuracy [43], with some reaching up to 94.00% accuracy.

In this study, we use EfficientNetB4 to outperform models like Inception-v4 and DenseNet-201 in terms of accuracy and computing efficiency. Lesion visibility and noise reduction are both improved by our improved preprocessing methods, which include optimized hair removal and picture augmentation. Furthermore, we apply a fine-tuned transfer learning technique and the Adamax optimizer to achieve improved accuracy and sensitivity on larger datasets than in earlier studies.

3. Methodology

This section covers the methodology and distribution of the HAM10000 dataset for testing, validation, and training.

3.1. HAM10000Dataset

We evaluated the technique by utilizing the standard HAM10000 collection. The HAM10000dataset is used to teach neural networks to automatically detect skin lesions with pigment in the absence of sufficient dermatoscopic images. The dataset contains 10015 pictures show casing all types of pigmented lesions suitable for diagnosis as shown in Table 2. Vascular lesions, actinic keratoses, basal cell carcinoma, dermatofibroma, melanoma, melanocytic nevi, benign keratosis-like lesions, and intraepithelial carcinoma are all in this group. Histopathological examination validates more than 50% of the cases. In order to validate the remaining instances, subsequent examinations or in vivo confocal microscopy is required. A variety of lesion images are included in the dataset. You may record them in the lesion ID column of the HAM10000 metadata file [44].

3.2. Dataset distribution

Dermatoscopic images of skin lesions make up a sizable portion of the HAM10000 dataset. Ten thousand fifteen images hailing from seven different categories (AKIEC, BCC, BKL, DF, MEL, NV, and VASC) make up the collection. Testing, validation, and training are the three parts of the dataset that we divided. We checked the validation and testing collections for duplicate photos. It uses 8012 training photographs, 1001 validation images, and 1002 testing photos.

Table 2. Classes of the HAM10000 dataset's distribution

Classification of Diagnostics	Number of Pictures	Percentage
AKIEC	327	3.27%
BCC	514	5.13%
BKL	1099	10.97%
DF	115	1.15%
MEL	1113	11.11%
NV	6705	66.95%
VASC	142	1.42%

The HAM10000 dataset was divided into three sections: 80% training, 10% validation, and 10% testing. It uses 1001 validation photos, 8012 training images, and 1002 test images. The testing set facilitated evaluating the performance of our trained models. We ensured that each image contained a variety of testing and validation sets. Table 3 displays three sets of class-wise distributions from the HAM10000 dataset.

Table 3. Dataset distribution in Training, Validation, and Testing Set

Class Name	Train Set	Validation Set	Testing Set	Total
NV	5364	670	671	6705
MEL	890	111	112	1113
BKL	879	110	110	1099
BCC	411	51	52	514
AKIEC	262	33	32	327
VASC	114	14	14	142
DF	92	12	11	115

3.3. Image Preprocessing

The HAM10000 dataset resized the images, originally measuring 600×450 pixels, to meet the input specifications of the EfficientNet [45] model used for training as shown in Figure 1. Hair is irrelevant to our objective of categorizing skin cancer classes because the HAM10000 dataset only includes photos of pigmented skin lesions. CNN will have to learn to ignore the random fur strands since they are unrelated to our mission. To make accurate forecasts, CNN will need to learn to differentiate between the skin lesion and the fur. Inaccurate predictions may result from the CNN model learning to correlate the image's noise with the intended class. CNN will have to learn to ignore the noise if it is not eliminated from the images, which can be a laborious and costly operation in terms of processing. CNN might not be able to learn to ignore the noise in some situations, which could result in subpar performance.

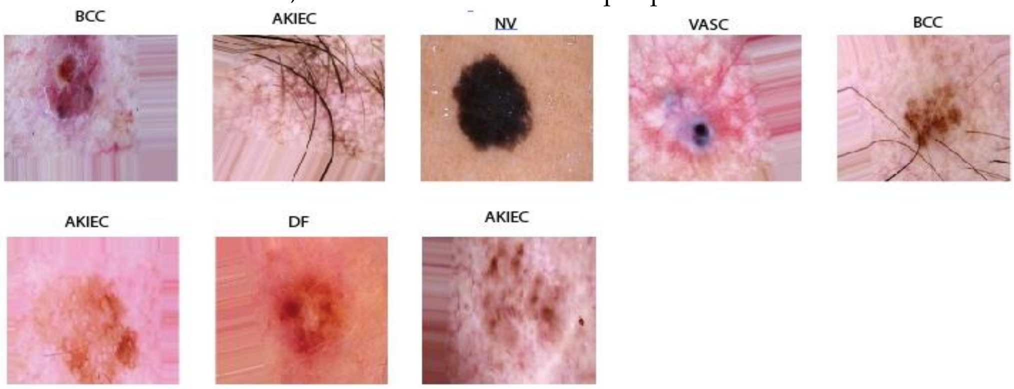

Figure 1. Skin Cancer Lesions Images after Preprocessing [44]

By using picture augmentation, the size of the dataset was expanded, overcoming the difficulty of obtaining large-scale labeled data for neural net training in the medical field a costly and skilled endeavor requiring a medical practitioner. As previously demonstrated, this procedure is significant in the evaluation of cutaneous lesions. Rotating, zooming, and flipping the dataset both horizontally and vertically allowed us to adjust its size. We describe the preparation picture pipeline that was created in this section, which improves the dataset, eliminates hairs from images, and resizes images in compliance with EfficientNetB4's specifications.

3.4. Framework for EfficientNet Model

Scaled-up convolutional neural networks (CNNs) enhance precision. However, researchers had not comprehensively examined the scaling procedure. Some ways that the iterative human modification needed for the scaling technique was done by randomly increasing the CNN's depth or breadth, using a higher input image resolution, or doing both. At the moment, the founder of the EfficientNet architecture family is looking into a good way to scale convolutional neural networks (CNNs) in order to improve the parameters of the systems and the models' effectiveness, precision, and efficiency.

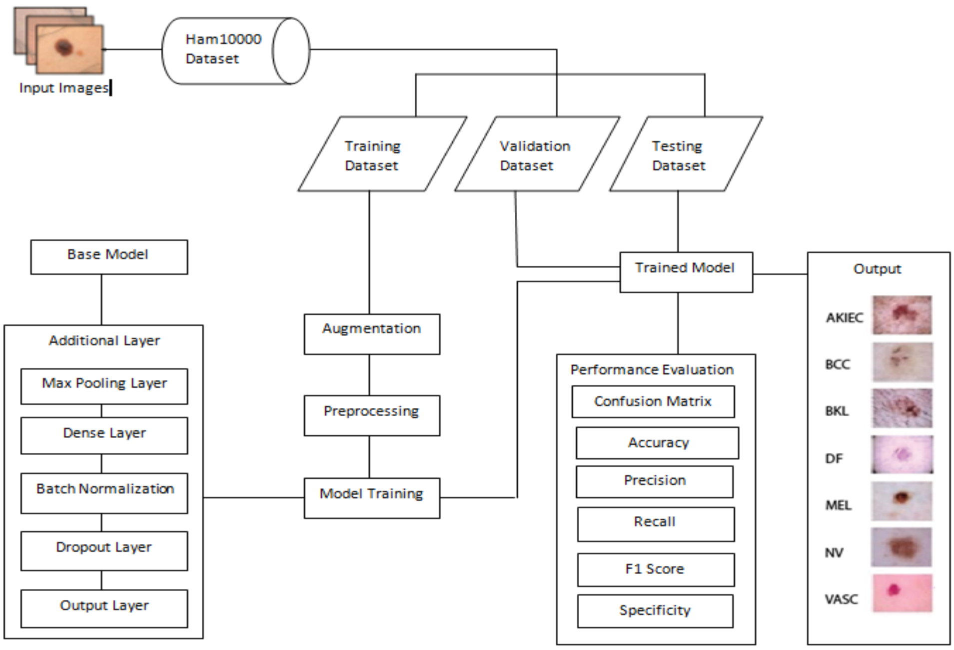

Figure 2. High level architecture diagram of a deep learning model [45]

EfficientNetB4 takes a 380×380 image as input and consists of 19 million parameters. By adjusting the network depth, CNNs are capable of capturing more intricate and varied attributes. On the contrary, the issue of vanishing gradients introduces increased complexity into the process of training networks. The network can gather a greater number of fine-grained attributes by adjusting its breadth. Likewise, training is a pleasure. Conversely, broad and sparse networks lack the capability to capture features at a higher level. Lastly, higher-resolution images facilitate the ability of CNNs to discern more subtle patterns. Processing larger images necessitates increased processing capacity and memory. We utilized the HAM10000 dataset to assess the EfficientNetB4 model in our research. Figure 2 shows the high level architecture diagram of a deep learning model.

3.5. Transfer Learning

Domain adaptability and transfer learning are interchangeable terms, that leverages knowledge acquired in one field to accomplish related tasks. We utilized the knowledge gained from training models using the Image Net dataset to accomplish our objective. In contrast, by employing a medical image dataset that comprises darkened lesions of the skin, our approach evaluates EfficientNet models. Because the pictures in the dataset include such a wide range of topics, we can't assume top performance when we immediately use pre-trained weights for inference.

`Consequently, we adjusted the method. At this stage, we modify the trained model parameters precisely to account for the novel domain of the images. There are an abundance of methods for fine-tuning. You can improve the features that specialized classifiers (like support vector machines for classification) use in two ways: by optimizing the parameters in the last few layers of the pre-trained model or by using the models themselves to pull out fixed features.

4. Implementation

This section provides implementation and training details for EfficientNetB4 to ensure reproducibility.

4.1. Range of Learning Rate

The learning rate is a critical hyperparameter that significantly influences the dependability and efficacy of neural network training. By implementing these techniques, we were capable of ascertaining the optimal learning rate limitations (specifically for a given dataset and model).

In order to accomplish this, we raised the rate of learning of each network linearly within a specified range of values following a few training epochs. The range of values 0.0001 to 0.01 is where the model trains most effectively; beyond this range, there is a significant validation loss. Successful model training takes place between values 0.0001 and 0.01; outside of this range, there is a significant validation loss. For the model, we used early stopping. We implemented the model on Kaggle using Keras, which has a 16 GB GPU P100, and TensorFlow as the backend.

4.2. Fine Tuning B4

Researchers designed the HAM10000 dataset specifically for medical imaging. Due to the substantial disparity in distributions between the two datasets, it was necessary to make adjustments to each convolutional layer. To optimize this model, we employed a stochastic gradient descent (SGD) that incorporates learning rate decay. A learning rate of 0.0005 was employed by the Adamax optimizer instead of SGD as shown in Table 4. There was a significant performance and stability gap between the SGD method and the Adamax optimizer during training.

Table 4. Model Specific Modification

Model	Image Size	Batch Size	Learning Rate	Optimizer
EfficientNetB4	380×380	8	0.00050	Adamax

5. Performance Evaluation Metrics

These tests are used to rate how well each model works. These tests include confusion matrices, F1 scores, specificity, and accuracy. Measuring how well a classification model works does not rely on set rules. A common set of speed metrics has been written about, which are based on what the userwants. The following metrics precision, recall, accuracy, F1 score, specificity, and confusion matricesbecome extremely useful when there is no ambiguity between the classes.

5.1. Confusion Matrix

We constructed an NxN table to summarize the accuracy of predictions generated by a classification model, where N represents the number of classes. The matrix illustrates the correlation between the expected label of the model and the actual label. The confusion matrices generate four distinct categories. When the model predicts the positive category of an image with precision, it generates a true positive (TP). A false positive (FP) occurs when the model erroneously classifies an image as positive. A model accurately classifying the negative aspect of an image is referred to as a ”true negative” (TN). A false negative (FN) occurs when a model erroneously predicts a negative class. When confronted with a problem involving multiple classes, the model will designate the positive class using the computation label and the negative class using the remaining label [46].

5.2. Accuracy

To assess performance, we utilize the proportion of accurately predicted picture classes in relation to the total number of photographs. No simpler method exists for assessing performance than this. The class distribution is symmetrical when the number of photographs (or observations) in each class is nearly equivalent; this is the sole circumstance under which this statement remains valid. EfficientNetB4 demonstrates its accuracy in the Top-1, Top-2, and Top-3 categories [47]. The model meets the top-1 accuracy condition when its predicted class precisely matches the actual or expected class. A model is considered accurate in terms of top-k accuracy when each of its initial k probabilistic predictions matches the true picture class [46]. Table 6 shows the Class wise Precision, Recall, F1Score, Specificity and Support.

Accuracy = True predictions / Total predictions (1)

5.3. Precision

To determine precision, the model divides the total number of positively categorized photographs by the number of correctly identified photos in the positive class [48].The ratio of true positives to the sum of true positives and false positives represents the formula for precision [46].

Precision = True Positives/ (True Positives + False Positives) (2)

5.4. Recall

The model computes recall statistics by accurately identifying the proportion of true positives. Divide the total count of positive photographs by the count of authentic positives in order to obtain theoutcome [49].

Recall = True Positives/ (True Positives +False Negative) (3)

5.5. F1 Score

Based on what we know about recall and precision, it appears that the two metrics are compromised in some way. Precision decreases when recall is increased, and vice versa [50]. Our need to prioritizeone over the other may vary depending on the application domain and user requirements. However, if you assign varying weights to each parameter, the F Beta Score can be utilized to achieve a compromise. Zhong [51] explains that the F Beta Score computes the arithmetic mean of the weightedharmonic means of recall and precision. The beta factor assigns greater weight to recall compared to precision. In this context, recall and precision hold equivalent significance. Consequently, the F1 scoreequals beta = 1. The F1 grade is calculated by averaging precision and recall. An increase in the F1 score indicates an improvement in predictive capability [52]. In order to comprehensively evaluate themodel’s performance in a multiclass categorization task, the F1 score was computed for each class, asillustrated in the subsequent statement. Remember that F1 Score results do not fall under the category of recall or precision [46].

F1= (2*Precision*Recall)/ (Precision + Recall) (4)

5.6. Specificity

Researchers quantify the accuracy of the model’s classification of authentic negative situations using its specificity [53]. Specificity is defined as the ratio of total TN to specificity (FP) posits that anincrease in TN value and a decrease in FP value are indicative of enhanced specificity [46].

Specificity = (True Negative/False Positive+ True Negative) (5)

6. Results and Discussion

Table 5 presents the accuracy results of EfficientNetB4 on the HAM10000 dataset, including its Top-1, Top-2, and Top-3 rankings.

Table 5. Conclusions drawn from the accuracy evaluations of EfficientNetB4

Model	Top-1Accuracy	Top-2Accuracy	Top-3Accuracy
EfficientNetB4	89.22%	88.82%	88.62%

Figure 3. Training and validation loss and accuracy

The best epoch is the one with the lowest validation loss. In Figure 3, the optimal epoch is 21. This means that the model scored best on the validation set at the end of the 21st epoch of training. The training and validation accuracy curves follow a similar pattern as the training and validation losscurves. The training accuracy measures how well the model predicts the proper labels for the trainingdata. The validation accuracy indicates how effectively the model predicts the correct labels for the validation data. In summary, the graphs illustrate that the model is training properly and not overfitting the training data.

Table 6. Class wise Precision, Recall, F1Score, Specificity and Support

Classes	Precision	Recall	F1-Score	Support
AKIEC	0.88	0.66	0.75	32
BCC	0.80	0.94	0.87	52
BKL	0.79	0.88	0.83	110
DF	0.62	0.91	0.74	11
MEL	0.76	0.75	0.75	112
NV	0.96	0.93	0.94	671
VASC	0.67	0.71	0.69	14
Accuracy	NULL	NULL	0.89	1002
Macro Avg	0.78	0.83	0.80	1002
Weighted Avg	0.90	0.89	0.89	1002

As described in the Dataset Section, the HAM10000 dataset exhibits a significant class imbalance, also known as a highly asymmetric class distribution. Both the magnitude of the dataset and the intricacy of the model provide support for the observed pattern in performance. More advanced models have a higher chance of producing superior performance metrics. On the other hand, they are also more likely to overfit the dataset. Both the magnitude of the dataset and the intricacy of the model provide support for the observed pattern in performance. More advanced models have a higher chance of producing superior performance metrics. On the other hand, they are also more likely to overfit the dataset. At the same time, they have a higher tendency to overfit the dataset. The predictability of the observed middle-level complexity model's (EfficientNetB4) impressive performance is not unexpected. Reduced-complexity models, such as EfficientNet B0-B3, exhibit diminished discriminatory capability. Not with standing, the more complex models of EfficientNet B6-B7 overfit our dataset.

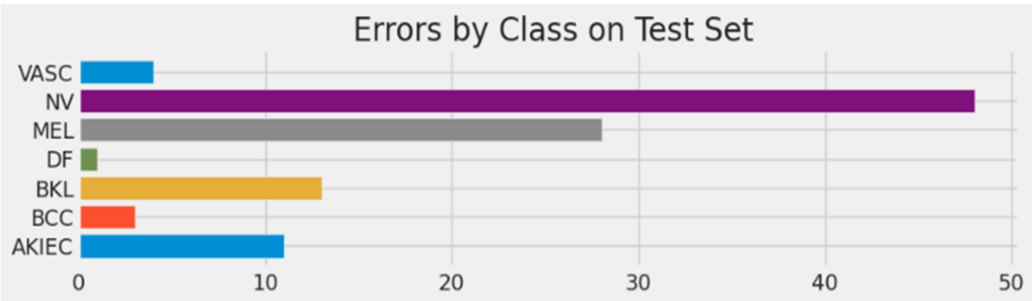

Figure 4. Class wise errors on test dataset

Figure 4 shows that model produced the fewest errors in VASC class. Our model made the most errors in NV class, indicating a major challenge in correctly classifying data from this category. MEL, DF, BKL, BCC, and AKIEC: The frequency of errors in these classes ranges from VASC to NV, with varying degrees of accuracy. Overall, the graph shows that the model is performing well in certain classes but not in others.

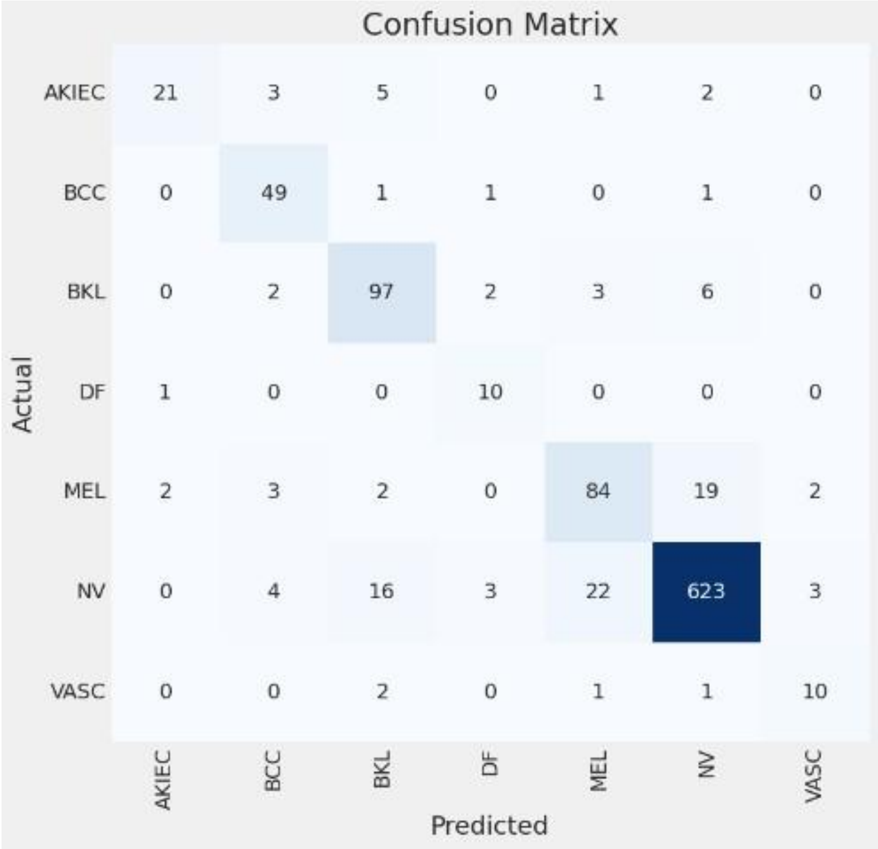

Figure 5. ConfusionmatrixofEfficientNetB4

The confusion matrix as shown in Figure 5 illustrates the effectiveness of a skin disease predictor on an image dataset. The matrix presents the expected picture classes in the columns and the actual picture classes in the rows. By displaying the number of accurately classified photographs along the diagonal of the matrix. For instance, the matrix's first row and first column's cell display that 21 pictures of actinic keratoses, or AKIECs, were correctly identified as such. In the cell located in the first column and second row, the classifier mistakenly identified three BCC (basal cell carcinoma) photos as AKIEC. The confusion matrix helps determine the advantages and disadvantages of a classifier. For instance, the classifier in this case does exceptionally well in recognizing melanoma and AKIEC but struggles a little bit in classifying BCC and BKL (Benign Keratosis-like Lesions).

Table 7. Comparative study of the HAM10000 dataset

Reference	Preprocessing	Image type	Number of Classes	Methods	Accuracy
Nugroho et al. [54]	YES	RGB	7	CNN	78%
Bassi et al. [55]	YES	RGB	7	CNN-transfer learning	82.8%
Moldovan et al. [56]	YES	RGB	7	CNN-transfer learning	85%
C¸eviket al. [57]	YES	RGB	7	CNN	85.62%
Karar et al. [58]	YES	RGB	7	CNN-transfer learning	87.9%
Our Proposed EfficientNetB4	YES	RGB	7	CNN-transfer learning	89.22%

Each individual utilized the HAM10000 dataset. Nugroho et al.[54] achieved an accuracy level of 82.8%, while Bassi et al. [55] achieved 78 percent accuracy. In contrast, the accuracy of C¸ evik et al. [57] and Moldovan et al. [56] was 87.9%, 85.62%, and 85.5%, respectively. This comparison shown in Table 7 indicates that our suggested approach performs better than the multiclass skin cancer classification methods currently in use.

7. Conclusion

When considering both the incidence and severity of cancers, skin cancer ranks highly. Generally, an examination of the eyes is required for dermatologists to diagnose this condition. The task of multi- class skin cancer categorization presents a significant challenge, as evidenced by the minor distinctions that exist among the different diagnostic categories. Recent trials, however, demonstrated that CNNs outperformed humans in several skin cancer classification categories. The dataset was optimized by removing undesired hairs, resizing the photographs to ensure compatibility with all models, and cropping out undesirable hairs. Following that, EfficientNetB4 was trained on the HAM10000 dataset utilizing a pre-treatment picture system and pre-trained Image Net weights. We used precision, recall, accuracy, F1 score, and confusion matrices to compare how well all versions of EfficientNet did on this unbalanced multiclass classification problem. This was done to see what effect transfer learning and fine-tuning had. The paper provides confusion matrices that exhibit the classification scores for each class for all eight models. The accuracy rate of our most dependable model, EfficientNetB4, was 89.22%. We evaluated the performance of EfficientNetB4 using the HAM10000 dataset and the skin cancer classification task. The parameters accounted for the margin of error in our evaluation criteria for EfficientNet classifiers. The most favourable outcomes were achieved by employing models of moderate complexity, such as EfficientNetB4. In conclusion, confusion matrices illustrated the variable degrees of generalizability among distinct skin cancers. Utilizing models that were originally designed for specific forms of cancer may still yield improved outcomes. Further development would be oversampling or synthetic data generation for even more class-balancing techniques to improve performance over underrepresented classes. More medical data, including images and clinical data, will probably increase the overall diagnostic accuracy.

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Data Availability: Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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Ethical Statement: The authors hereby consciously assure that for the manuscript, the following conditions are fulfilled: (1) The material presented is the authors' own original work and has not been previously published elsewhere. (2) The paper is not currently under consideration for publication in any other venue. (3) It truthfully and comprehensively reflects the authors' own research and analysis. (4) The manuscript duly acknowledges the significant contributions of co-authors and co-researchers. (5) The results are appropriately contextualized within the framework of prior and existing research. (6) All sources utilized in the paper are properly cited, with any literal copying of text clearly indicated through the use of quotation marks and appropriate references. (7) Finally, all authors have actively participated in substantial work leading to the manuscript and accept public responsibility for its content.

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