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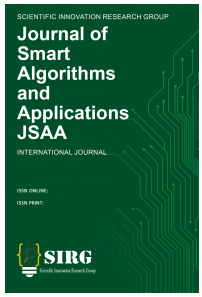

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Leveraging Transfer Learning and Fine-Tuning for Improved Skin Cancer Detection in Dermatoscopic Images

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Abstract- This study presents a deep learning-based approach to improve skin cancer detection using dermoscopic images. The proposed system employs the ResNet50 architecture with transfer learning to enhance the classification accuracy of skin lesions. Training and evaluation were conducted on the HAM10000 dataset, with specialized techniques applied to mitigate class imbalance and improve model generalization. To ensure interpretability, the study integrates SHAP (Shapley Additive explanation), which identifies key image regions influencing classification decisions. The model leverages texture and morphological features extracted by the convolutional neural network (CNN) to distinguish between benign and malignant lesions effectively. A comprehensive evaluation framework was developed, incorporating random sampling and visualization methods to rigorously assess performance. The results demonstrate consistent accuracy across diverse lesion types, highlighting the model's clinical applicability.

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-Skin detection
-Artificial intelligence

Introduction

Cancer occurs when abnormal cells grow uncontrollably and gain the ability to invade surrounding tissues and metastasize to distant sites in the body [1]. One extremely dangerous and aggressive type of cancer is skin cancer. Skin cancer can only be treated if it is discovered early on. The skin, which surrounds all of the body's structural components, including muscles and bones, is essential to human health. Every system in the body is significantly impacted by even small changes in the way the skin functions, making it a key player. The skin area that is impacted is referred to as a lesion. Skin lesions come in a wide variety. Every lesion is divided into sets based on the specific kind of skin cells that caused it. Melanocytic lesions, which resemble melanoma, are produced by melanocytes. Melanocytes produce the pigment known as melanin [1]. The difficulties of detecting skin cancer early are discussed in this study. This research investigates deep learning methodologies, with particular emphasis on data-driven approaches, including few-shot learning and convolutional neural networks (CNNs) to enhance diagnostic precision. While combining both qualitative and quantitative methods could potentially offer a more comprehensive understanding of clinical challenges and practical applications, the current work focuses exclusively on quantitative analysis due to the inherent characteristics of machine learning systems and their dependence on extensive datasets. The study specifically addresses melanoma, among the most aggressive forms of cutaneous malignancies and a significant global public health issue. The World Health Organization (WHO) has released figures showing that 132,000 melanoma skin cancers and more than 2-3 million non-melanoma skin cancers develop annually worldwide [2]. Improving survival rates requires early diagnosis, but conventional diagnostic techniques are sometimes expensive, time-consuming, and unavailable, particularly in rural locations [3]. The development of artificial intelligence (AI)-driven methods, like the ones this paper outlines, may offer a practical, accurate, and affordable way to identify skin cancer early on, possibly saving lives. The goal of this project is to create deep learning models that can tackle the difficulties associated with early skin cancer diagnosis, providing fresh possibilities for incorporation into

actual healthcare systems, such as telemedicine apps.

Related work

This section examines various recent methods for multi-classification and detection of skin cancer, emphasizing techniques that employ deep learning (DL) models, and a Summary of References and Their Contributions to Skin Cancer Detection as shown in Tab. 1.

Tab. 1: Summary of References and Their Contributions to Skin Cancer Detection Using Deep Learning Techniques.

Skin Cancer Diagnosis	Methodology	Dataset Used	Key Findings
Benign/ Malignant [5]	LightNet (Deep Learning Framework)	ISIC 2016 Dataset	Achieved accuracy of 81.6% suitable for mobile applications.
Melanoma/ Benign [4]	CNN Classifier	170 Skin Lesion Images	Reported accuracy sensitivity and a specificity of 81% each.
Melanoma/ Nonmelanoma [1]	CNN-Trained with Features	DermIS and DermQuest Datasets	Accuracy of 93.75% using a median filter and CNN.
Basal Cell Carcinoma Detection [6]	CNN	40 FF-OCT Images	Accuracy: 95.93% Sensitivity: 95.2% Specificity: 96.54%.
Depression Detection [7]	Machine Learning and Deep Learning	Social Networks Data	Surveyed techniques for detecting depression from social media data.
Malignant Melanoma/ Nevus/SK [8]	CNN Ensemble of AlexNet	VGGNet	GoogleNet ISIC 2017 Dataset Average AUC: 84.8% Average Accuracy: 83.8%.

Chaturvedi et al. developed a lightweight deep learning system for multi-class skin cancer detection using MobileNet architecture. They applied transfer learning to adapt the model for classifying dermoscopic images into seven categories, comprising both malignant types like melanoma and basal cell carcinoma, along with benign lesions such as keratosis [9]. Kausar and colleagues introduced a combined deep learning methodology for classifying multiple skin cancer types. Their approach involved optimizing five pretrained architectures - ResNet, InceptionV3, DenseNet, InceptionResNetV2, and VGG19 - through transfer learning using ISIC dataset images. The researchers implemented two ensemble techniques (majority voting and weighted voting), which showed enhanced diagnostic capability, reaching 98.6% classification accuracy and surpassing both single-model performance and existing benchmark results in the field [10]. Bedeir and colleagues developed a deep learning framework for seven-class skin cancer classification. Their methodology employed three distinct architectures: ResNet-50, VGG-16, and a hybrid model integrating both networks. The system was trained and validated using the HAM10000 dataset across various experimental trials. Results showed the combined architecture achieved superior performance with 94.14% classification accuracy, exceeding the capabilities of either standalone model [11]. Tahir and the research team introduced an innovative deep learning architecture called DSCC_Net for four-class skin cancer classification (MEL, BCC, SCC, MN). This CNN-based solution demonstrated exceptional performance with 94.17% accuracy and 99.43% AUC score, surpassing conventional convolutional neural networks, including ResNet-152, VGG-16, and EfficientNet-B0 in comparative evaluations [12]. Saleh et al. proposed a skin cancer classification model integrating convolutional neural networks (CNNs) and multicriteria decision-making (MCDM). Classification was performed using six machine learning classifiers, leading to the development of 51 different models. The ranking of the alternatives by the perimeter similarity (RAPS) method was utilized to select the optimal model, where the combination of AlexNet with a classical GWO and a wide neural network achieved the highest classification accuracy of 94.5% on the ISIC [13].

Methodology

Our proposed approach, illustrated in Fig. 1, details a seven-part methodology that leverages transfer learning integrated with a CNN architecture for enhanced detection and delineation of skin malignancies in histopathology samples. The systematic framework demonstrates how these techniques synergistically improve diagnostic accuracy.

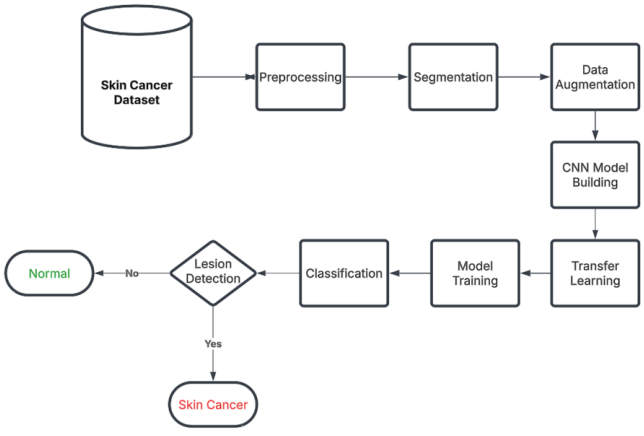

Fig. 1: Skin Cancer Classification and Segmentation Proposed Model.

A. Dataset Description

This paper used a dataset that comprises 7930 dermatoscopic images [14], which are represented as the following categories in Fig. 2.

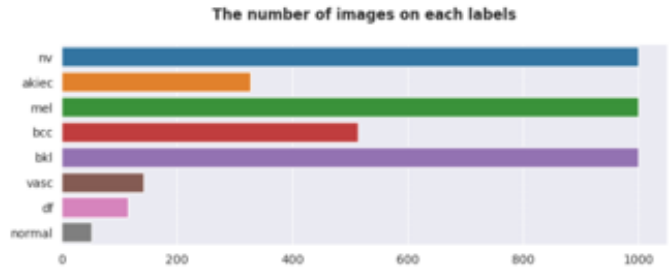

Fig. 2: The number of images in each class.

Over half of the lesions examined (50%) received histopathological confirmation, with the remaining cases being verified through clinical examinations, expert agreement, or in vivo confocal microscopy techniques.

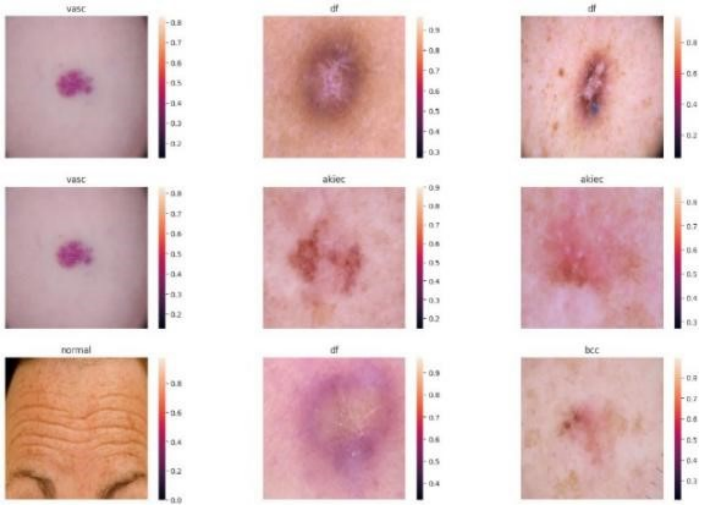

Fig. 3: Random images from the dataset.

B. Preprocessing

The dataset, as shown in Fig. 3, comprises Random images from the dataset, comprising skin lesion images and metadata, which were preprocessed to ensure consistency and balance. Images were resized to 224×224 pixels and converted from BGR to RGB format. To address class imbalance, data augmentation was performed using the MixUp technique, which linearly combines pairs of images and their labels to generate new training samples. Labels were one-hot encoded for multi-class classification. The final dataset included both original and augmented images, ensuring a balanced distribution across all classes. Errors such as missing or corrupted files were logged and excluded during preprocessing.

C. Image segmentation

Image segmentation divides digital images into separate sections, simplifying representation by grouping pixels with similar features. We applied K-means clustering to segment the images into 2 clusters (foreground and background) to determine the position of the lesion Eq. 1 is the k-means.

$$WCSS = \sum_{i=1}^{K} \sum_{x \in C_i} \|x - \mu_i\|^2 \quad (1)$$

Where:

- k: Number of clusters.
- C_i: The i-th cluster.
- x: A data point in the cluster C_i.
- μ_i: The centroid of the cluster C_i.
- $\|x - \mu_i\|^2$: The squared Euclidean distance between a data point x and the centroid μ_i.

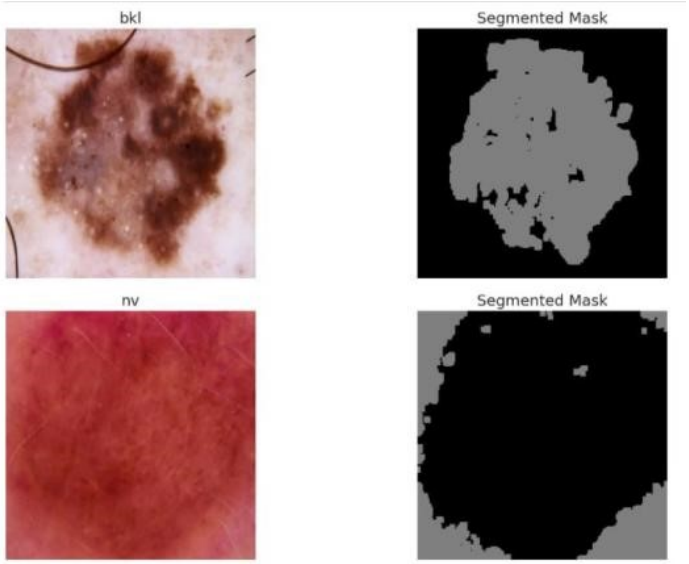

Fig. 4: K-means Segmentation.

After clustering, it creates a segmentation mask to represent the position of the disease using morphological operations, as shown in Fig. 4.

D. Data Splitting

Then we split the dataset into train, validation, and test to apply the models as shown in Tab. 2.

Tab. 2: dataset splitting.

Skin class	Total Images	Training Data	Validation Data	Testing Data
akiec	999	799	100	100
bcc	976	780	98	98
bkl	1000	800	100	100
mel	1000	800	100	100
df	997	797	100	100
normal	996	796	100	100
nv	1000	800	100	100
vasc	982	786	98	98

E. Image Augmentation

To enhance model performance on underrepresented classes and boost generalization capability, we implemented the MixUp data augmentation strategy. This technique generates synthetic training examples by linearly interpolating between both image pixel values and their corresponding label vectors. The method serves dual purposes: expanding the variability within the training dataset while simultaneously promoting the development of more resilient feature representations by the model shown in Fig. 5 and Fig. 6.

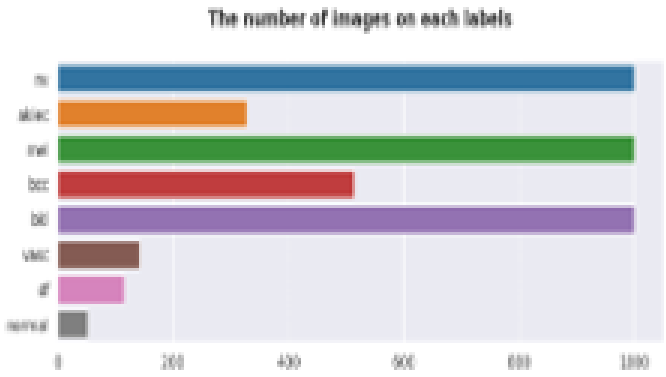

Fig. 5: Data before.

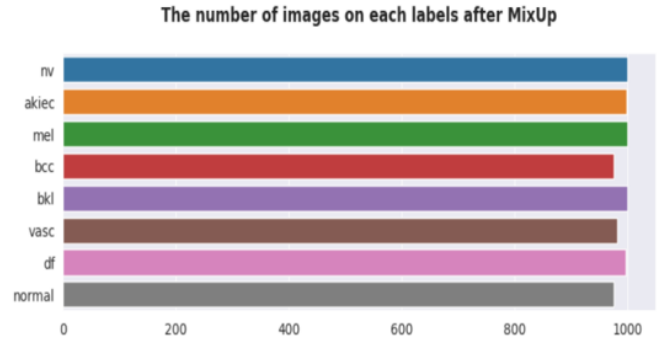

Fig. 6: Data after Augmentation.

F. Image Classification

The purpose of this research is to classify skin cancer into eight distinct categories. Transfer learning is used in conjunction with convolutional neural networks to accomplish this classification. Pre-trained convolutional neural network models were utilized to extract important features, which made the classification process easier.

G. Models: Define and Transfer Learning

We employed three deep learning models for skin lesion classification:

G..1 CNN

A custom Convolutional Neural Network with four convolutional layers, max-pooling, and fully connected layers, serving as a baseline model as shown in Fig. 7.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
max_pooling2d (MaxPooling2D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 26, 26, 128)	0
conv2d_3 (Conv2D)	(None, 24, 24, 128)	147,584
max_pooling2d_3 (MaxPooling2D)	(None, 12, 12, 128)	0
flatten (flatten)	(None, 18432)	0
dense (Dense)	(None, 512)	9,437,696
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 8)	4,104

Fig. 7: CNN Summary.

G..2 ResNet50

A deep residual network with 50 layers, leveraging pre-trained ImageNet weights and residual connections to address vanishing gradients as shown in Fig. 8.

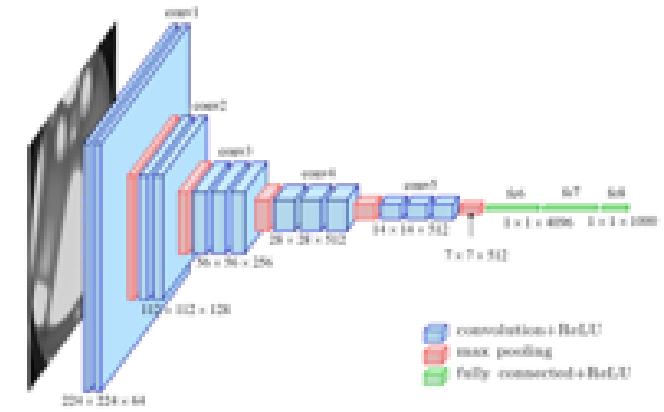

Fig. 8: ResNet50 Architicture.

G..3 Xception

An efficient architecture using depthwise separable convolutions, initialized with ImageNet weights for transfer learning Tab. 3.

Tab. 3: Performance Comparison of Models.

Model	Accuracy	Loss	Parameters
CNN	80%	0.4	9,682,632 (36.94 MB)
ResNet50	94%	0.2	23.60M
Xception	60%	1.9	20.88M

G..4 Hyperparameter Tuning

Optimization of applied techniques is possible by tuning hyperparameters. Deep learning models nearly demonstrate individual hyperparameters for memory and computation complexity. The suggested networks were optimized via hyperparameter tweaks Tab. 4.

Tab. 4: Hyper Parameters used in The Models

Configuration of hyperparameters	Value
Epochs	50
Batch size	32
Learning rate	0.001
Optimizer	Adam
Dropout	0.2 or 0.5
Training set	80%
Validation set	10%
Test set	10%

Results and discussion

In the paper, the following benchmark metrics were utilized: accuracy, sensitivity, specificity, precision, and F1-score. These metrics are visualized in Eq. 2, Eq. 3, Eq. 4, and Eq. 5.

$$\text{Precision} = \frac{T_p}{T_p + F_p} \tag{2}$$

$$\text{Recall} = \frac{T_p}{T_N + F_N} \tag{3}$$

$$\text{F-measure} = 2 \times \frac{(\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})} \tag{4}$$

$$\text{Accuracy} = \frac{T_p + T_N}{T_p + T_N + F_p + F_N} \tag{5}$$

H. Training And Validation Performance

The accuracy, progress, and loss during the training and validation phase of the proposed training network models. Fig. 9, Fig. 10, and Fig. 11 show the accuracy progress and loss for the model that achieved the best accuracy and the least loss.

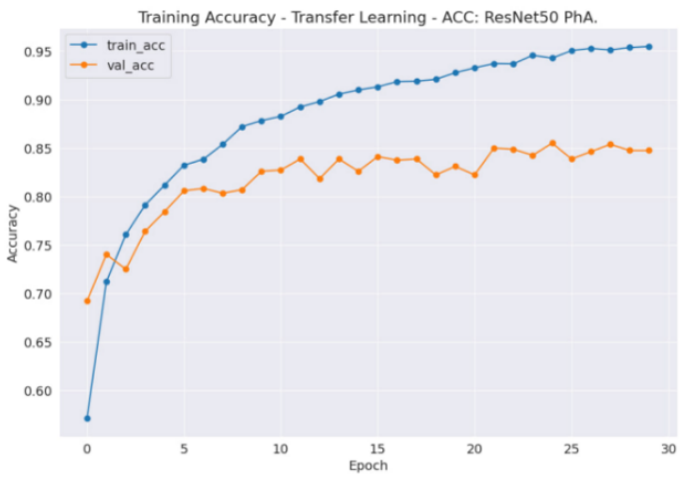

Fig. 9: Training Accuracy.

Fig. 10: Training Loss.

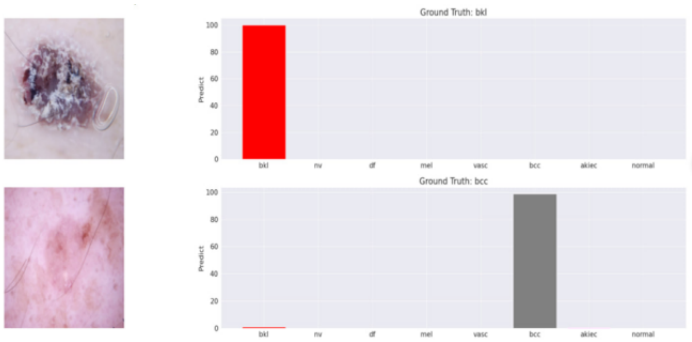

Fig. 11: Final Result (Lesion Classification.

Conclusions

This paper explores developing a deep learning model using Convolutional Neural Networks (CNNs) and transfer learning for skin cancer recognition and classification from dermoscopic images. skin cancer is a serious disease that needs early recognition. This work has seven types of skin cancer. Our technique achieved 80% accuracy with Convolutional Neural Networks and improved to 94.9% after using transfer learning. Future studies might improve the dataset with more high-quality images to enhance model generalization, find advanced deep learning techniques to enhance feature extraction, and add multi-model data to improve and increase accuracy.

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