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A DSegNet Model for the Classification and Detection of Skin Cancer Diseases Using Transfer Learning

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Abstract: ***Detecting and categorizing diseases in skin, particularly skin cancer, involves applying techniques such as Computer Vision (CV) and Machine Learning (ML) to identify and classify skin ailments. The integration of these methodologies has the potential to assist healthcare professionals in promptly identifying and managing skin conditions, contributing to early diagnosis and effective treatment. The classification and detection of skin cancer using Deep Learning (DL) have proven to be a successful approach for automated disease detection. As a subset of Artificial Intelligence (AI), DL focuses on training neural networks with intricate layers to learn complex representations and patterns from data autonomously. In this research, the Deep-SegNet model is employed to develop the DSegNet method for the Automatic Recognition and Classification of Skin Cancer. The DSegNet approach incorporates multiple stages to enhance accuracy and diagnostic performance. Initially, a pre-processing stage is implemented, involving image resizing and the application of a Bilateral Filter (BF) to improve image quality. Subsequently, SegNet-based segmentation is utilized to identify the disease-affected areas, and feature extraction is performed using the MobileNetV3 architecture. Finally, the extracted features are input into a VGG-19 classification model to differentiate between various types of skin cancer. A thorough analysis of experimental results demonstrates that the DSegNet technique outperforms other recent approaches in terms of performance.***

Keywords: Deep Learning, Segmentation, Skin Disease, Machine Learning, Transfer Learning, Computer Vision

1. Introduction

Skin cancer holds the status of being the most prevalent form of cancer globally. Dermatologists face challenges in the diagnosis of skin cancer through dermoscopy images [1]. In many instances, pathology and biopsy analyses are essential for cancer diagnosis. Earlier studies introduced computer-based systems to identify skin cancers from images of skin lesions [2]. Prior to 2016, these methods relied on traditional machine learning (ML) approaches that required the segmentation of cancer from the surrounding skin in an image. Subsequently, valuable features were extracted from the cancerous region, including the color, texture, and shape of the lesion. Finally, these features were fed into a classifier for cancer diagnosis [3, 4]. This methodology was complex due to the difficulty in determining and extracting features beneficial for cancer identification [5].

Several techniques have been developed to automatically diagnose melanoma-affected areas of the skin [6]. Initially, a method based on handcrafted features was introduced for melanoma identification. The integration of machine learning (ML) and artificial intelligence (AI) technologies has paved the way for novel possibilities in assistive diagnosis within the biomedical and medical sectors [7]. Generally, convolutional neural network (CNN) based techniques are widely employed in medical imaging for segmentation and classification applications [8]. With advancements in hardware and software technologies, deep learning (DL) has emerged as a robust mechanism for feature learning. Feature engineering, the process of defining and extracting features by a human professional, is known for being complex and time-consuming [9]. The DL technique eliminates the need for feature engineering as it automates the learning and extraction of valuable features from fresh information [10]. The DL approach has made significant strides in various domains, particularly in computer vision (CV), marking major achievements in current research.

This research introduces an innovative approach to the detection and classification of Skin cancer diseases through an effective deep learning (DL) model, namely the DSegNet model. The choice of the SegNet model is justified by its ability to address challenges such as the vanishing-gradient problem, enhance feature propagation, promote feature reuse, and significantly reduce parameter count. The proposed model encompasses key stages, including pre-processing, SegNet-based segmentation, MobileNetV3-based feature extraction, and the VGG-19 classifier. Integration of the SegNet model with deep features extracted from the MobileNetV3 model is carried out to assess the efficacy of these features.

The subsequent sections of this study are organized as follows: Section 2 provides a brief overview of related works, Section 3 introduces the Skin cancer disease detection and classification model, Section 4 presents the validation of the proposed model, and Section 5 concludes the study.

2. Literature Review

In a study [11], the authorcreated an Automated Seeded Growing Segmentation with Optimal EfficientNet (ARGS-OEN) method for the SLDC process. This method incorporates the optimal EfficientNet model with hyperparameter tuning using the Flower Pollination Algorithm (FPA). Additionally, a classification method involving the Multiwheel Attention Memory Network Encoder (MWAMNE) was employed to determine suitable class labels for dermoscopy images. Author [12] presented the MAFCNN-SCD method, abbreviated as Optimal Multi-Attention Fusion CNN-related Skin Cancer Diagnosis, for detecting skin cancers in dermoscopy images. The goal of this method is to categorize skin cancers in dermoscopy images. The MAFNet approach, with the Henry Gas Solubility Optimization (HGSO) technique as a hyperparameter optimizer, was adopted as a feature extractor. Finally, the Deep Belief Network (DBN) was utilized for the SLDC model.

The author [13] introduced an efficient computer-based system for analyzing skin cancers using metaheuristic and deep training methods. The main idea is to present a DBN based on the Modified Electromagnetic Field Optimization Algorithm (MEFOA), an improved metaheuristic approach, to provide a robust diagnosis mechanism for skin cancer images. Author [14] developed an automated Deep Learning (DL) approach using a class attention layer-related CAD method for skin lesion detection and classification called DLCAL-SLDC. A DLCAL-related feature extractor was utilized to derive features from segmented lesions by applying CapsNet along with the Adagrad optimizer and CAL. The classification was performed using the SSO-CSAE method.In [15] presented a mechanism that identifies and classifies skin cancers into various classes using CNN. The diagnostic approach incorporates DL and image processing methods, applying different algorithms to dermoscopic images to eliminate noise and improve picture resolution.

3. The Proposed DSegNet Model

The DSegNet technique follows a comprehensive workflow, as depicted in Fig 1. The initial step involves pre-processing to enhance image quality, followed by SegNet-based segmentation to identify infected areas. The MobileNetV3 model is then employed for feature extraction, and finally, the VGG-19 is used for image classification into distinct class labels. The details of each stage are elaborated in the subsequent sections.

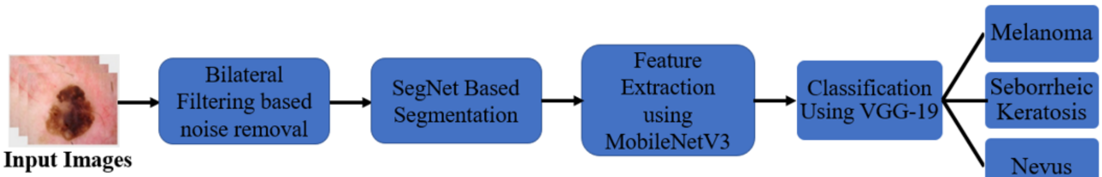

Fig. 1. Overall Architecture of the Proposed Approach

3.1. Bilateral Filtering

Bilateral filtering serves as a valuable technique in image processing for eliminating noise while preserving the edges of the image. In the realm of skin cancer detection and classification tasks, the application of bilateral-based noise removal plays a pivotal role in enhancing image quality, rendering them more conducive to precise classification. This significance arises from the fact that noise present in images can impede the effectiveness of machine learning models, impacting their capacity to accurately identify and classify skin diseases.

The bilateral filtering approach considers both spatial and intensity information during the image-smoothing process, allowing it to discern between noise and genuine edges, thereby preserving the edges of objects within the image. In the context of skin cancer detection and classification, this preservation is critical for maintaining the intricacies of the skin structure, which are essential for accurate disease identification. Bilateral filtering proves effective in mitigating various types of noise, including salt-and-pepper noise and Gaussian noise. By smoothing the image while safeguarding edges, it facilitates the creation of cleaner images, making it more straightforward for machine learning models to concentrate on pertinent features for disease classification [16].

The bilateral filter is typically defined using the following equation:

$$\text{Bilateral}(I)=\frac{1}{W_p}\sum_{q\in\Omega}\exp\left(-\frac{\|p-q\|^2}{2\sigma_s^2}\right)\exp\left(-\frac{\|I(p)-I(q)\|^2}{2\sigma_r^2}\right)I(q)$$

Where:
I is the input image.
p and q are pixel coordinates.
Ω is the neighborhood of pixels.
σ_s controls the spatial decay of the filter.
σ_r controls the intensity decay of the filter.
W_p is a normalization factor.

In the realm of skin cancer detection and classification, the bilateral filter is employed on images to diminish noise while preserving crucial structural details. The denoised images obtained through this process serve as input for machine learning models, enhancing their accuracy in identifying and classifying skin cancer based on the distinctive features present in the skin images.

3.2. SegNet Based Segmentation

SegNet, a deep learning architecture commonly utilized for semantic segmentation tasks like image segmentation, finds application in the realm of skin cancer detection and classification. In the context of skin lesion analysis, SegNet is employed to segment regions of interest, distinguishing between healthy and diseased areas in skin images. The SegNet architecture follows an encoder-decoder structure. The encoder captures hierarchical features from the input skin image, while the decoder reconstructs the segmented output.

The encoder typically comprises multiple convolutional layers with pooling operations, progressively reducing spatial dimensions and extracting high-level features. These features play a crucial role in discriminating between different classes, such as healthy and diseased regions on the skin. During the pooling operations in the encoder, SegNet retains the indices of the maximum values [17], which are essential for subsequent upsampling in the decoder. The decoder utilizes the stored max-pooling indices to perform upsampling, aiding in reconstructing spatial dimensions and recovering finer details from the encoded features.

The final layer of the decoder often incorporates a softmax activation function, assigning probabilities to each pixel for different classes relevant to skin cancer detection, such as healthy and various disease categories. The training process involves optimizing a loss function, such as cross-entropy loss, to minimize the difference between the predicted segmentation and the ground truth segmentation. This optimization guides the network to learn accurate features for effective segmentation in the context of skin cancer detection and classification, as illustrated in Fig 2.

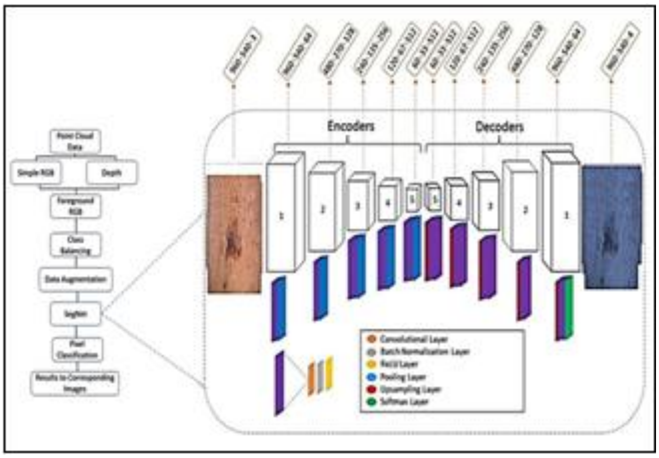

Figure 2: OverallArchitecture of SegNet- Based Segmentation

3.3. Feature Extraction Using MobileNetV3

In the domain of skin cancer detection and classification tasks, the MobileNetV3 model is frequently utilized as a pretrained model for feature extraction. MobileNetV3 is a lightweight convolutional neural network architecture specifically designed for efficient deployment on mobile devices and resource-constrained environments. Pretraining the MobileNetV3 model involves using a large dataset, such as ImageNet, for generic feature learning [18]. During this training phase, the model acquires the ability to recognize a diverse range of features, patterns, and textures from various images.In the specific context of skin cancer detection and classification, the pretrained MobileNetV3 model is repurposed through transfer learning. Transfer learning involves leveraging the knowledge acquired during the initial training on a different task and applying it to the targeted task. The convolutional layers of the pretrained MobileNetV3 model function as feature extractors, proficient at capturing hierarchical and abstract features from input images, including intricate patterns associated with skin diseases.

To reduce the dimensionality of the extracted features, global average pooling is commonly employed. This technique entails calculating the average of each feature map, resulting in a condensed representation that retains crucial information about the input. The extracted features are then inputted into fully connected layers, constituting the classification head of the model, as depicted in Fig 3. These layers further refine the features and generate output predictions for different classes of skin cancer. The final layer typically utilizes a softmax activation function to convert the network's raw output into probability scores for each disease class. The predicted class for a given input image is determined by identifying the class with the highest probability.

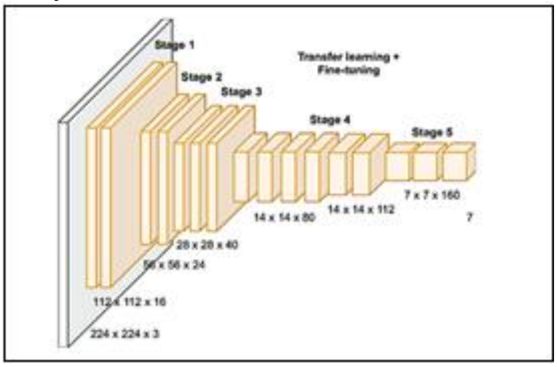

Figure 3: Feature Extraction using MobileNetV3 model

3.4. Classification Using VGG-19

The output from the MobileNetV3 model serves as feature vectors for each skin cancer image. This vector encapsulates the learned representations of the skin's characteristics, capturing both global and local features crucial for disease classification.VGG-19, a deep convolutional neural network architecture, plays a significant role in the classification and detection of skin cancer tasks [19]. In skin cancer applications, VGG-19 is employed as a powerful feature extractor. Its deep layers are capable of capturing intricate patterns and features within dermoscopic images, crucial for discriminating between various types of skin lesions. In classification tasks, VGG-19 extracts hierarchical features from skin cancer images, and these features are then fed into fully connected layers to make predictions about the specific type of skin cancer present. The network is trained on labeled datasets, enabling it to learn patterns associated with different classes of skin lesions, facilitating accurate classification.

For detection tasks, VGG-19 aids in identifying regions of interest within an image that may indicate the presence of skin cancer. By utilizing its convolutional layers as feature extractors, the model learns to highlight relevant features in the input image. This information can be further used to identify potential areas of concern or abnormalities, assisting in the early detection of skin cancer. Utilizing a

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collaborative strategy involving feature extraction with MobileNetV3 and classification through VGG-19 significantly improves the accuracy and efficiency of skin cancer detection and classification as depicted in Fig 4. This integrated approach offers a robust solution for dermatological diagnostics.

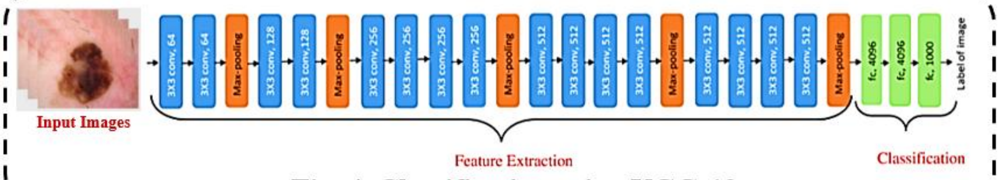

Fig. 4. Classification using VGG-19

4. Performance Validation

4.1. Implementation Setup

In this section, the experimental validation of the DSegNet technique has been conducted, considering various aspects. The simulations were executed using Python 3.6.5 on a PC with an i5-8600K processor, 250GB SSD, GeForce 1050Ti 4GB GPU, 16GB RAM, and a 1TB HDD. The evaluation metrics employed to assess the performance of the DSegNet model include Sensitivity, Specificity, Precision, Accuracy, and F-score. The validation process utilized a benchmark dataset(**ISIC 2017 Dataset)**consisting of skin cancer images [20]. Sample test images representing each class are presented in Fig 5 and the number of samples are depicted in Table 1.

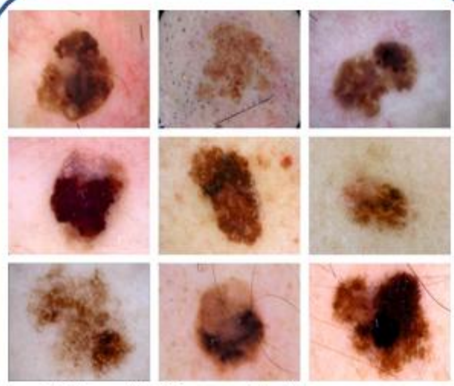

Fig. 5. Sample Images

Table 1. Dataset Description

Class	No. of. Samples
Melanoma	374
Seborrheic Keratosis	254
Nevus	1372
Total	**2000**

4.2. Results and Discussion

Fig. 6 shows the confusion matrix and PR & ROC curves generated during the execution of the DSegNet model revealing accurate classifications in various classes. The performance evaluation of the DSegNet model reveals its effectiveness in classifying applied images are shown in Table 2 and Fig 7. Here 70% is used for training and 30% is used for testing.Notably, the model demonstrates optimal results in classifyingMelanoma disease, achieving maximum sensitivity, specificity, precision, accuracy, and F-score. Additionally, in the classification ofSeborrheic Keratosis, the DSegNet model achieves a notable sensitivity of 83.74%, a high specificity of 93.16%, an impressive accuracy of 95.67%, and a substantial F-score of 87.59%.

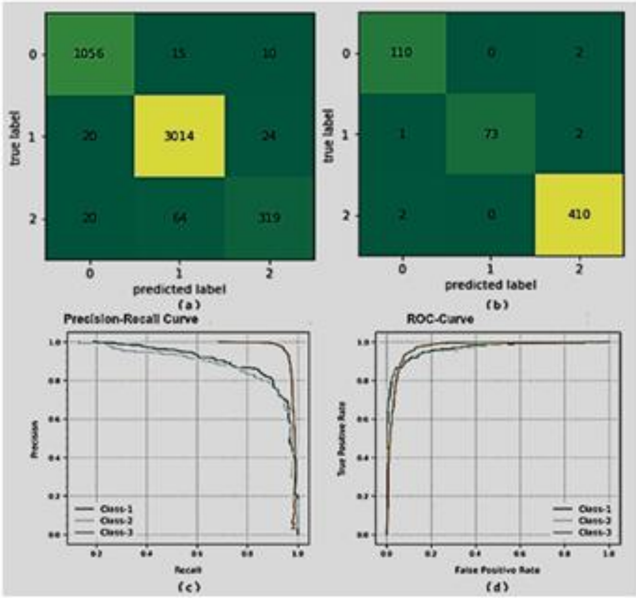

Fig. 6. (a) Confusion Matrix based on TR set (b) Confusion Matrix based on TS set (c) Precision-Recall Curve (d) ROC Curve

Table 2: Performance Evaluation of test images on the proposed DSegNet Model

Labels	Accuracy	Sensitivity	Specificity	F Score	MCC
TR set (70%)					
Melanoma	93.79	77.87	97.30	81.91	78.33
Seborrheic Keratosis	95.43	66.29	99.59	78.38	77.53
Nevus	92.36	98.56	78.27	94.71	81.82
Average	**93.86**	**80.90**	**91.72**	**85.00**	**79.23**
TS set (30%)					
Melanoma	95.00	85.12	97.49	87.29	84.22
Seborrheic Keratosis	94.67	67.09	100.00	8030	79.94
Nevus	93.33	99.00	82.00	95.19	85.04
Average	**95.67**	**83.74**	**93.16**	**87.59**	**83.07**

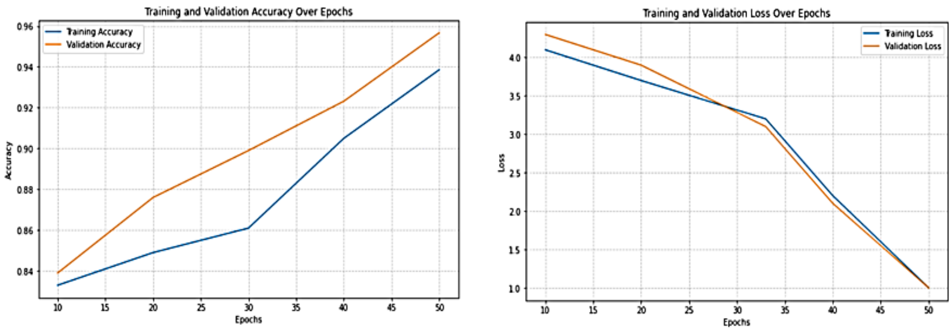

Fig. 7. Accuracy & Loss curve based on TR and TS set

Table 3 presents an accuracy analysis of the DSegNet method in the context of skin cancer detection and classification, in comparison to previously employed approaches [12].Notably, the DSegNet approach surpasses all other methods, achieving a remarkable accuracy of 95.67%. These empirical results affirm the robust detection and classification capabilities of the DSegNet model specifically designed for skin cancer images. The higher performance can be attributed to the inherent strengths of combining the SegNet and MobileNetV3 models. As a result, the DSegNet model stands out as an effective solution for real-time skin cancer diagnosis, offering valuable support to medical professionals and contributing to improved healthcare outcomes.

Table 3: Comparative Outcome of ISIC 2017 Dataset with Existing Systems

Methods	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
DSegNet Model	**95.67**	**83.74**	**93.16**	**87.59**
MAFCNN-SCD	92.22	77.07	88.67	83.05
NB	89.77	74.70	84.02	81.37
KELM	88.04	77.03	84.49	83.02
MSVM	87.15	75.44	83.19	81.45
MobileNet	85.03	74.17	87.98	81.18
DenseNet_169	89.42	76.83	86.28	83.27

5. Conclusion

This study has introduced an automated DSegNet model designed for the detection and classification of skin cancer in Dermoscopy images. The model's experimental evaluation is conducted using the ISIC 2017 dataset. The results of the experiments highlight the system's capacity to accurately distinguish between benign and malignant skin lesions in dermoscopic images. The research represents a significant advancement in improving the precision and efficiency of skin cancer diagnosis, with potential implications for better patient outcomes and advancements in the field of dermatology. The proposed model exhibits noteworthy performance in the differentiation of benign and malignant skin lesions in dermoscopic images. Future research in the realm of skin cancer diagnosis using Deep Learning should focus on developing robust multimodal models that integrate dermoscopic images with clinical data, patient history, and genetic information. Such a comprehensive approach has the potential to enhance diagnostic accuracy and provide personalized treatment recommendations.

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