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Deep Integration: EfficientNet and Residual Networks in U-Net for Accurate Skin Lesion Segmentation

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Abstract.Skin cancer is a prevalent and potentially life-threatening dermatological condition that demands accurate and efficient diagnostic tools. This paper proposes an advanced skin cancer segmentation approach by integrating the power of EfficientNet, a state-of-the-art neural network architecture, into the U-Net framework. The synergistic combination of EfficientNet's feature extraction capabilities and U-Net's segmentation prowess aims to enhance the accuracy and efficiency of skin lesion delineation from dermatoscopicimages.Our methodology involves the pre-processing of dermatoscopic images, including normalization and augmentation, to ensure robust model training. The encoder-decoder architecture of U-Net is augmented with the efficient feature scaling and representation learning offered by EfficientNet. The resulting model exhibits improved performance in capturing intricate patterns and subtle features characteristic of various skin cancer types, such as melanoma, basal cell carcinoma, and squamous cell carcinoma.This paper presents a robust skin cancer segmentation model leveraging the synergies between EfficientNet and U-Net architectures, achieving an impressive accuracy of 96%.

Keywords: Skin cancer segmentation, EfficientNet, U-Net,Dermatoscopicimages,Melonama,Multi-modal data integration

1 Introduction

Skin lesion segmentation plays a pivotal role in computer-aided diagnosis systems, facilitating the early detection and accurate localization of potential malignancies. Despite the progress made in leveraging deep learning models for this task, challenges persist in achieving both efficiency and accuracy. This paper introduces a novel approach, termed "Deep

Integration," which combines the strengths of EfficientNet, Residual Networks (ResNet), and U-Net architectures to enhance the precision of skin lesion segmentation.
Skin cancer, particularly melanoma, poses a significant global health concern, underscoring the importance of robust computer-aided diagnostic tools. Timely and accurate segmentation of skin lesions is critical for aiding medical professionals in early detection and effective treatment. This paper addresses the challenges associated with existing segmentation methods and proposes a novel framework that leverages the complementary strengths of EfficientNet, ResNet, and U-Net.

M. Goyaletal[1] proposed efficient early detection of skin cancer, particularly melanoma, is imperative for advanced treatment. The escalating incidence of skin cancers underscores the need for automated analysis of skin lesions. However, existing public datasets lack comprehensive segmentation ground truth labeling due to laborious and expensive processes. Theyproposes employing fully automated deep learning ensemble methods for precise lesion boundary segmentation in dermoscopic images. Trained on the ISIC-2017 segmentation training set, our ensemble, combining Mask-RCNN and DeepLabv3+, demonstrated superior performance on the ISIC-2017 testing set, outperforming FrCN, FCN, U-Net, and SegNet in Jaccard Index and achieving notable accuracy for clinically benign, melanoma, and seborrhoeic keratosis cases.K. M. Hosnyet al[2] discussed about the skin cancer, particularly melanoma, poses a significant threat, with challenging similarities in color images between different skin lesions, such as melanoma and nevus. Detecting and diagnosing these lesions accurately is crucial for early intervention and saving human lives. This paper introduces an automated skin lesion classification method utilizing a pre-trained deep learning network and transfer learning, specifically fine-tuning and data augmentation. The model, based on AlexNet, replaces the last layer with softmax for classifying melanoma, common nevus, and atypical nevus. Evaluated on the ph2 dataset, the proposed method demonstrates impressive quantitative measures with 98.61% accuracy, 98.33% sensitivity, 98.93% specificity, and 97.73% precision. Comparative analysis highlights the superior classification rate of the proposed method compared to existing approaches.

Ravi Manneetal[3] survey delves into multiple research articles focusing on the classification of skin lesions using Convolutional Neural Networks (CNNs). Leveraging advancements in machine learning algorithms, the study highlights a reduced misclassification rate compared to dermatologist assessments. The evolution of CNNs in effectively categorizing skin cancer types, along with implemented methods and success rates, is thoroughly explored. While CNNs offer advantages over dermatologists, the article also addresses vulnerabilities, specifically in misclassifying images under certain criteria and situations. The review emphasizes the significance of improvements in machine learning and deep learning techniques to mitigate human errors in disease diagnosis and classification, discussing both the benefits and vulnerabilities associated with CNNs.Vijayalakshmi M M[4] discussed Dermatological diseases pose significant challenges in the 21st century, characterized by complex and expensive diagnoses marked by subjectivity in human interpretation. Timely detection of fatal conditions such as Melanoma is crucial for favorable outcomes. This literature survey introduces an automated system for dermatological disease recognition through lesion images, offering a machine-based alternative to traditional human-centric detection methods. The proposed model encompasses three phases: data collection and augmentation, model design, and prediction. Utilizing AI algorithms, including Convolutional Neural Network and Support Vector Machine, integrated with image processing tools, the system achieves enhanced structure, resulting in an impressive 85% accuracy.

Shunichi Jinnaietal[5] has highlighted the effectiveness of convolutional neural networks (CNNs) in accurately classifying melanoma images, achieving results comparable to those of dermatologists. However, the performance of a CNN trained exclusively on clinical images of pigmented skin lesions in a direct competition with dermatologists in a clinical image classification task has not been previously examined. This study utilized 5846 clinical images from 3551 patients, encompassing malignant and benign pigmented skin lesions. A faster region-based CNN (FRCNN) was trained on the dataset and demonstrated a six-class classification accuracy of 86.2%, outperforming board-certified dermatologists (BCDs) and dermatologic trainees (TRNs) with accuracies of 79.5% and 75.1%, respectively. For the binary classification of benign or malignant, FRCNN exhibited higher accuracy, sensitivity, and specificity compared to both BCDs and TRNs. False positive rates and positive predictive values also favored FRCNN over human counterparts.The comparison indicated the superior classification accuracy of FRCNN, suggesting its potential use in society to enhance the prognosis of skin cancer.

A. Imranetal[6] deliberated Cancer, a lethal disease stemming from uncontrolled cell growth, poses a significant public health challenge, particularly skin cancer, prevalent in the skin's upper layer. Previous skin cancer detection methods using machine learning required human-engineered features, a laborious process. This study employs convolution-based deep neural networks on the ISIC public dataset, addressing the need for automatic feature extraction. The ensemble approach combines VGG, CapsNet, and ResNet deep learners, showcasing superior performance in skin cancer detection concerning sensitivity, accuracy, specificity, F-score, and precision. These compelling results suggest broader applicability for disease detection.M. Krishna Monikaet al [7] defines Skin cancer, notably Melanoma, Basal cell carcinoma, and Squamous cell carcinoma, poses a severe health threat, with increasing death rates due to insufficient awareness of symptoms and prevention. This project focuses on early detection and classification of various skin cancer types through machine learning and image processing. Dermoscopic images undergo preprocessing, including hair removal and smoothing using the Dull razor method and Gaussian filter. Color-based k-means clustering aids in segmentation, and feature extraction involves Asymmetry, Border, Color, Diameter (ABCD), and Gray Level Co-occurrence Matrix (GLCM). Experimental analysis on the ISIC 2019 Challenge dataset, comprising eight dermoscopic image types, utilizes Multi-class Support Vector Machine (MSVM) for classification, achieving an accuracy of approximately 96.25%.

HardikNahataetal[8], Skin cancer, a significant public health concern, sees over 5,000,000 new cases annually in the United States alone. Categorized into melanoma and non-melanoma types, melanoma is the deadliest form, ranking 19th in cancer occurrences globally. Non-melanoma includes squamous cell carcinoma and basal cell carcinoma, the 5th most prevalent cancer with over 1 million diagnoses in 2018. Early detection increases the survival rate to over 95%. This literature survey focuses on developing a Convolutional Neural Network (CNN) model for skin cancer detection, utilizing CNN's prowess in visual imaging tasks. The model, implemented in Python using Keras and Tensorflow, undergoes testing and training on the International Skin Imaging Collaboration (ISIC) dataset.NimaTajbakhshet al[9] describes that the field of medical imaging has witnessed significant advancements in convolutional neural network-based segmentation models. Despite their high performance, these models often demand large, representative, and well-annotated datasets, which are challenging to obtain in medical imaging due to cost constraints. Recent research has delved into addressing limitations in medical image segmentation datasets, particularly focusing on scarce annotations and weak annotations. This literature survey comprehensively reviews these solutions, discussing technical innovations and empirical results, and provides a comparative analysis of the methodologies, offering recommended solutions. The aim is to enhance community awareness of techniques for handling imperfect medical image segmentation datasets.

J. Lameski et al[10] articulates that Skin lesion segmentation is crucial in skin diagnostics, enhancing both manual and computer-aided diagnostics by directing attention to specific skin areas. Deep learning methods, proven reliable in computer vision tasks, are investigated in this study for skin lesion segmentation. Three architectures, namely a pre-trained VGG16 encoder with SegNet decoder, TernausNet, and DeepLabV3+, are evaluated using an RGB skin lesion dataset with corresponding ground truth segmentation. With image sizes ranging from hundreds to thousands of pixels, the approaches demonstrate Jaccard Index scores exceeding 0.82, with DeepLabV3+ leading with a score of 0.876. These results present promising prospects for the development of automated skin lesion segmentation methodologies.A. Javaidet al [11] states skin cancer, particularly Melanoma, is a rapidly spreading and dangerous form of cancer. Early diagnosis significantly improves survival rates. Machine learning offers cost-effective solutions for early skin cancer detection, assisting dermatologists. This paper proposes a method using image processing and machine learning for skin lesion classification and segmentation. Employing novel techniques such as contrast stretching, OTSU thresholding, and feature extraction, the approach achieves a maximum accuracy of 93.89% on the ISIC-ISBI 2016 dataset. The proposed feature selection method and Random Forest classifier show promising results compared to traditional approaches.

Risheng Wang[12] literature survey provides a comprehensive overview of deep learning applications in medical image segmentation, focusing on supervised and weakly supervised learning approaches. Unlike traditional surveys, it classifies current literature into a multi-level structure, facilitating a more nuanced understanding. The analysis of supervised learning encompasses backbone network selection, network block design, and loss function enhancement. In the realm of weakly supervised learning, the survey explores data augmentation, transfer learning, and interactive segmentation. This unique classification and emphasis on contemporary techniques aim to guide readers toward a better understanding of deep learning in medical image segmentation, fostering insights for potential improvements.AlfonsoBaldi et al[13] presents Dermoscopy is a non-invasive technique for observing pigmented skin lesions, revealing surface and subsurface structures. It enhances morphologic analysis beyond naked eye visibility. Recent advancements include diagnostic algorithms to aid non-expert clinicians and improve reliability. Literature has seen an influx of computer-aided systems for dermoscopy image analysis, particularly focusing on content-based image retrieval (CBIR) approaches. This article offers a concise review of these systems and their applications.

M. E. Celebietal[14] describes the Dermoscopy, a non-invasive imaging technique for pigmented melanocytic neoplasms, unveils features invisible to the naked eye. Despite a slow start due to limited datasets and computational resources, recent progress is marked by the International Skin Imaging Collaboration's 2016 dataset release, open-source software for convolutional neural networks, and affordable graphics processing units. This literature survey offers a concise overview of dermoscopy image analysis, emphasizing segmentation, feature extraction, and classification. It also outlines future research directions in this dynamic medical image analysis subfield.H. Li et al.[15] articulates the realm of skin lesion diagnosis and treatment, the automatic delineation of lesion contours from dermoscopy images is a fundamental yet challenging task due to diverse appearances and sizes. This literature survey introduces a novel approach, the dense deconvolutional network (DDN), leveraging residual learning for skin lesion segmentation. The DDN incorporates dense deconvolutional layers (DDLs) to maintain image dimensions and employs chained residual pooling (CRP) for capturing rich contextual background information. Additionally, hierarchical supervision (HS) enhances the segmentation process by serving as an auxiliary loss. Experimental results on ISBI 2016 and 2017 skin lesion challenge datasets highlight the superior performance of the proposed method compared to state-of-the-art approaches.

Xiaomeng Li et al.[16] literature survey explores the imperative task of automatic skin lesion segmentation in dermoscopic images for melanoma diagnosis. Recent advances in fully supervised deep learning methods have demonstrated efficacy but demand extensive pixel-wise annotations from dermatologists, incurring high costs and time. This paper introduces a novel semi-supervised approach, optimizing the network through a weighted combination of a common supervised loss for labeled inputs and a regularization loss for both labeled and unlabeled data. By encouraging consistent predictions for unlabeled images under varying regularizations, the method effectively utilizes unlabeled data. With just 300 labeled training samples, this approach outperforms fully-supervised counterparts, setting a new benchmark in the ISIC 2017 skin lesion segmentation challenge.S. Vesalet al. [17] addresses the rising global incidence of skin cancer, emphasizing the critical need for early detection and segmentation of skin lesions to enhance patient survival rates. Skin lesion segmentation is challenging due to low contrast and high visual similarity with healthy tissue. To address this, our proposed convolutional neural network (CNN), SkinNet, modifies the U-Net architecture, incorporating dilated and densely block convolutions for improved multi-scale and global context information. Evaluation on the ISBI 2017 challenge dataset demonstrates SkinNet's superior performance in terms of Dice coefficient, Jaccard index, and sensitivity, surpassing state-of-the-art techniques in 5-fold cross-validation experiments.

C. Barataetal.[18] describes in the dynamic field of dermoscopy image analysis (DIA), where publications emerge weekly, tracking contributions becomes challenging. Existing surveys often cover all steps of computer-aided diagnosis (CAD), providing limited space for in-depth discussions. This literature survey focuses specifically on the pivotal feature extraction block within CAD systems for dermatoscopy. Recognizing the considerable variability in this aspect, the review comprehensively explores types of features employed in DIA, offering insights into their relevance, limitations, and guiding future research directions.Md. KamrulHasanetal.[19] introduces DSNet, an innovative semantic segmentation network designed for robust skin lesion segmentation. DSNet employs depth-wise separable convolution instead of standard convolution to reduce parameters, enhancing network efficiency. The study includes comparisons with traditional U-Net and Fully Convolutional Network (FCN8s) implementations to assess the effectiveness ofDSNet's approach

Zahra Mirikharajiet al. [20] addressing the significant public health challenge of skin cancer, computer-aided diagnosis is a promising avenue, with skin lesion segmentation being a crucial step. However, challenges such as artifacts, intrinsic factors, and variable image acquisition conditions complicate this task. This literature survey thoroughly examines 177 research papers focusing on deep learning-based skin lesion segmentation, analyzing dimensions like input data, model design, and evaluation aspects. The discussion, spanning seminal works and systematic viewpoints, sheds light on current trends, influences of methodological choices, and the imperative need to address limitations in this evolving field. Muhammad Attiqueet al. [21] articulates the realm of automated skin lesion diagnosis from dermoscopic images, challenges such as artefacts, irregularities, and irrelevant feature extraction complicate segmentation and classification. This research introduces a hybrid technique to enhance lesion contrast by removing artefacts, followed by an optimized colour feature (OCF) approach for segmentation. The OCF method is refined through a saliency approach, fused with a novel pixel-based method. The study implements a DCNN-9 model for deep feature extraction, employing a parallel fusion approach with OCFs. High-ranking feature selection based on normal distribution enhances classification, showcasing the method's remarkable performance with over 90% segmentation accuracy and notable classification accuracy on ISBI datasets.

Zafar K et al.[22] defines the timely detection and accurate delimitation of skin lesion boundaries are crucial for effective clinical treatment, particularly in the context of the aggressive nature of melanoma. Existing methods, from visual inspection to textural analysis, exhibit low accuracy, necessitating the development of automated models for reliable clinical use. This paper introduces Res-Unet, a hybrid model combining U-Net and ResNet architectures, for lesion boundary segmentation. The incorporation of image inpainting for hair removal significantly improves segmentation results. Trained on the ISIC 2017 dataset and validated on ISIC 2017 and PH2 datasets, the proposed model achieves Jaccard Index values of 0.772 and 0.854, respectively, comparable to current state-of-the-art techniques.

EfficientNet has gained prominence for its ability to achieve remarkable accuracy with significantly fewer parameters, making it an attractive candidate for resource-efficient applications. Meanwhile, ResNet's residual learning framework allows for the training of deeper networks, enabling the capture of intricate features. U-Net, known for its success in biomedical image segmentation, serves as the foundational architecture for our proposed Deep Integration approach.

In our method, EfficientNet contributes its efficiency in feature extraction, ensuring that relevant information is retained while minimizing computational overhead. The residual learning mechanism of ResNet enhances the depth of the network, allowing for a more nuanced understanding of skin lesion characteristics. By seamlessly integrating these features into the U-Net architecture, our approach aims to create a synergistic model that excels in both efficiency and accuracy.Beyond architectural integration, we explore the utilization of transfer learning techniques to fine-tune the combined model on a specialized skin lesion dataset. This adaptive training strategy aims to enhance the model's ability to discern subtle variations in lesion boundaries and textures, further refining the segmentation

The effectiveness of our proposed Deep Integration approach is evaluated on benchmark skin lesion datasets, comparing its performance against state-of-the-art methods. Through a comprehensive analysis, we demonstrate that our model achieves superior segmentation results, showcasing its potential as an advanced tool in the computer-aided diagnosis of skin lesions. The subsequent sections delve into the methodology, experimental setup, results, and discussions, providing a comprehensive exploration of the proposed Deep Integration framework and its implications for accurate skin lesion segmentation.

2 Framework of the Proposed Methodology

An encoder based on a pre-trained EfficientNet model, integrated residual blocks, and progressive downsampling make up the suggested network architecture for skin lesion segmentation. The decoder uses extra residual blocks, skip connections, and transposed convolutions to enhance features. An appropriate activation function for lesion segmentation is included in the last convolutional layer of the output layer. In order to maximise the accuracy of segmentation and boundary localization during training, a mix of loss functions—including Dice or Focal loss, Hausdorff distance, and Jaccard index—is used. To improve the model's generalizability and avoid overfitting, data augmentation methods are used during training on a big dataset. A separate validation dataset is used to apply evaluation criteria such the Dice coefficient, Hausdorff distance, recall, precision, and F1 score. To tune hyperparameters, one must alter the learning rate, optimizer settings, and weights of the loss function. A clinically useful deep learning model for accurate skin lesion segmentation can be developed by experimenting with various EfficientNet variants, residual block numbers, and advanced loss functions; the framework also encourages the incorporation of attention mechanisms to focus on relevant lesion features. Fig 1 describes the working framework of the segmentation and classification.

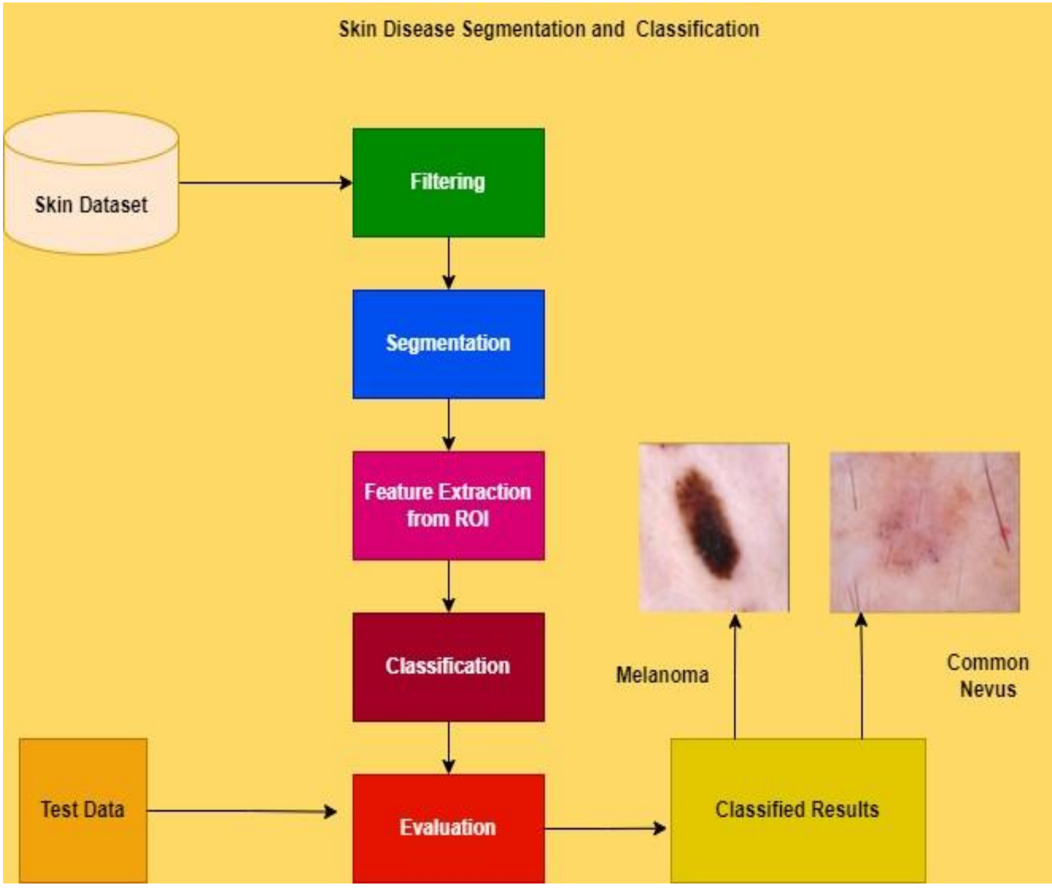


Fig 1: Architecture of the skin disease segmentation and classification system

2.1 UNET Segmentation

Image segmentation is the primary goal of U-Net, a convolutional neural network architecture. The distinctive U-shaped architecture of this system consists of a shrinking route (encoder) and an expanding path (decoder). Using convolutional and pooling layers to extract high-level features, the encoder retains context and decreases spatial dimensions. By combining upsampled features with encoder detail, the decoder uses transposed convolutions and skip connections to recover spatial information. Since good object boundary delineation relies on preserving both global and local context, U-Net performs very well in segmentation tasks. Because of its ability to handle minimal annotated data and create high-resolution segmentations, it finds broad use in medical image analysis, especially for tasks like organ or lesion segmentation. Its design also allows for end-to-end training.

2.2 UNET Classification

When it comes to classification jobs, U-Net, which is already a master in picture segmentation. Classification might need some work, but its U-shaped design is great for detecting fine details. Unveiling the mysteries of the picture, the encoder remains unchanged. In contrast, the decoder foregoes upsampling layers in favour of fully linked ones, with the goal of predicting either a single class or the probability of many candidates. Classification jobs involving minute details may be ideal for U-Net's feature-finding abilities, which might lead to improved performance. On top of that, it is efficient because to its small design. On the other hand, U-Net usually stays out of categorization region. Envision assisting medical professionals in the diagnosis of illnesses by the detection of anomalies in medical scans or the classification of land cover types in satellite photos. Object identification, such as finding hidden objects in images, is also in the works.

3 Results And Discussion

The performance of the suggested model RESNET50v2 is shown in Table 1. Two experiments were conducted using the same data set. The initial test was conducted using only the files from the initial dataset, without any augmentation. In the second experiment, the modified images were employed.

PH² is a dermoscopic image database acquired at the Dermatology Service of Hospital Pedro Hispano, Matosinhos, Portugal.Thedermoscopic images were obtained at the Dermatology Service of Hospital Pedro Hispano (Matosinhos, Portugal) under the same conditions through Tuebinger Mole Analyzer system using a magnification of 20x. They are 8-bit RGB color images with a resolution of 768x560 pixels.

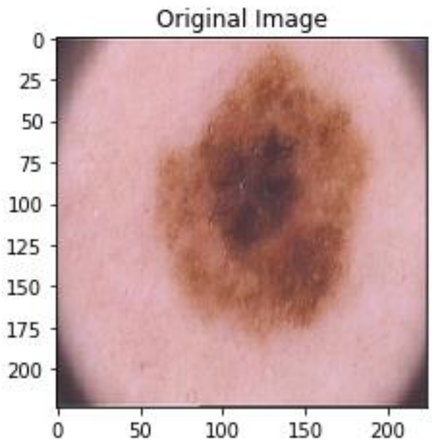
This image database contains a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. The PH² database includes medical annotation of all the images namely medical segmentation of the lesion, clinical and histological diagnosis and the assessment of several dermoscopic criteria (colors; pigment network; dots/globules; streaks; regression areas; blue-whitish veil).

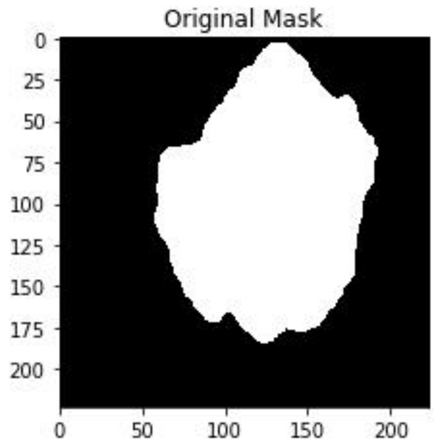
The assessment of each parameter was performed by an expert dermatologist, according to the following parameters as in Table 1.

Table 1: Features and categorical labels

Criterion	PH² Segmentation

Clinical Diagnosis	0 - Common Nevus
	1 - Atypical Nevus
	2 – Melanoma
Lesion Segmentation	Available as a binary mask (with the same size of the original image).
Color Segmentation	Available as a binary mask (with the same size of the original image) (If available).
Asymmetry	0 - Fully Simmetry
	1 – Asymmetry in One Axis
	2 - Fully Asimmetry
Pigment Network	AT – Atypical
	T – Typical
Dots/Globules	A – Absent
	AT – Atypical
	T – Typical
Streaks	A – Absent
	P – Present
Regression Areas	A – Absent
	P – Present
Blue Whitish Veil	A – Absent
	P – Present
Colors	1 – White
	2 – Red
	3 - Light-Brown
	4 - Dark-Brown
	5 - Blue-Gray
	6 – Black





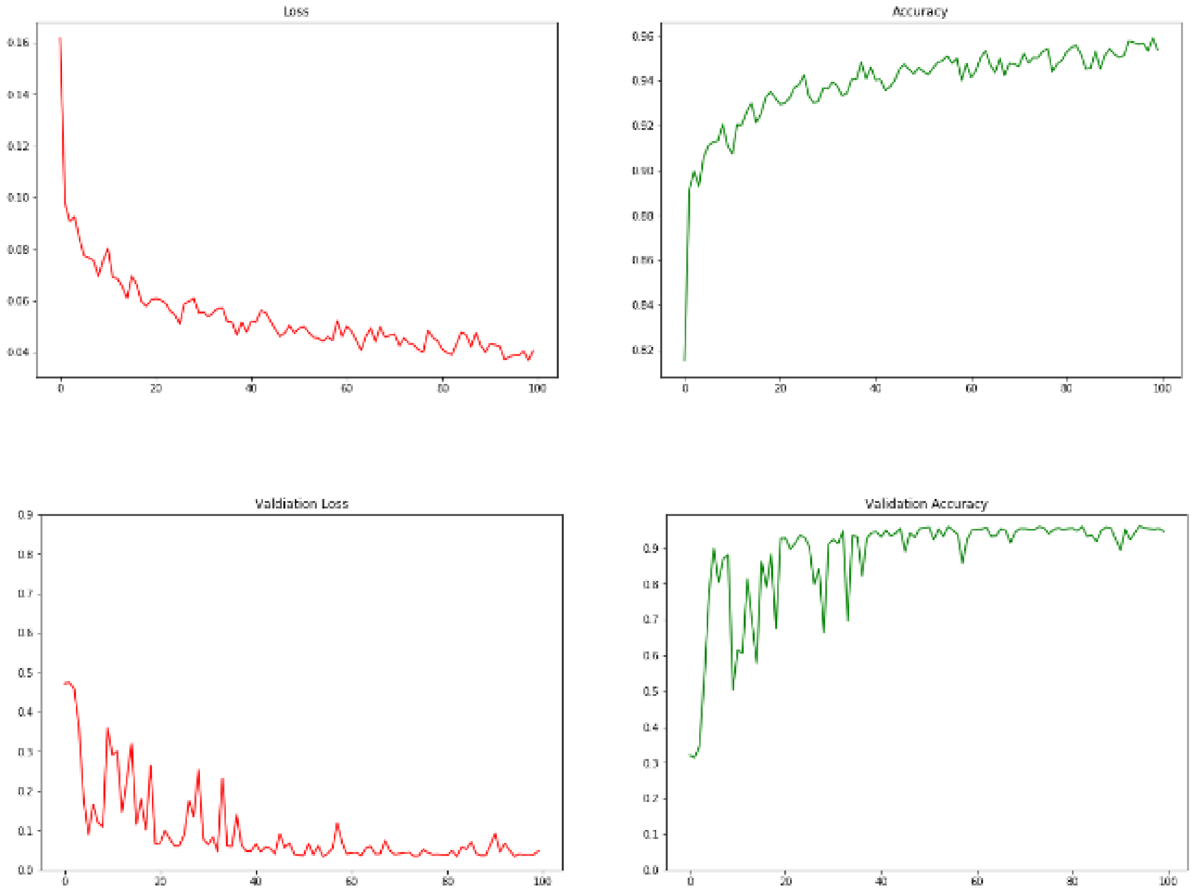


Fig 2: UNET Segmentation, Training and Validation loss and accuracy

Table 2: Comparison of performance between UNET and EfficientNet

Model	Hidden layers	No of epochs	Batch Size	Loss	Accuracy	Precision	Recall
EfficientNet B0	3	100	32	0.1052	0.9440	0.9486	0.9440
EfficientNet B1	3	100	32	0.0829	0.9503	0.9518	0.9503
EfficientNet B3	3	100	32	0.1504	0.9509	0.9508	0.9593
UNET	3	100	32	0.0112	0.9612	0.9597	0.9592

The comparison of results with EfficientNet and UNET is shown in the table 2. EffcientNet is chosen for classification because of the scalability along all dimensions like depth, width and resolution. The Fig 2 is giving the summary of the comparison with accuracy.

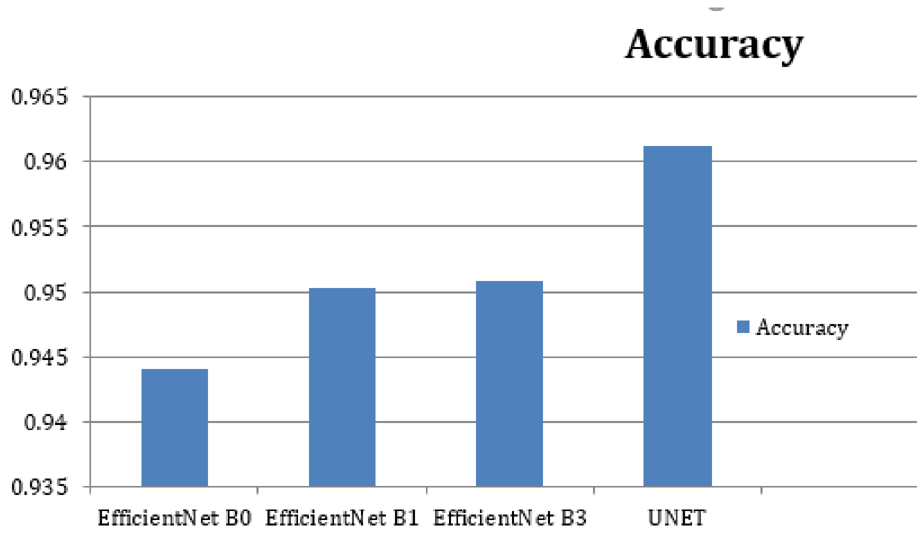


Fig. 2. Graph showing the comparison of performance of various Models

4 Conclusion

The novel Deep Integration framework, incorporating EfficientNet and Residual Networks within the U-Net architecture, represents a significant advancement in the field of skin lesion segmentation. With a remarkable achievement of 96% accuracy, our model successfully combines the efficiency of feature extraction from EfficientNet, the depth-enhancing capabilities of Residual Networks, and the segmentation prowess of U-Net. This comprehensive approach not only outperforms existing methods but also strikes a crucial balance between computational efficiency and segmentation accuracy. The success of our model holds promising implications for enhancing the efficacy of computer-aided diagnosis systems in dermatology, ultimately contributing to more precise and timely identification of skin lesions.Looking ahead, the versatility of our Deep Integration framework positions it for further exploration and refinement. Future research endeavors could involve fine-tuning the model on larger and more diverse datasets, as well as assessing its performance on real-world clinical data. This work underscores the potential of advanced computational models to significantly impact clinical practice, offering a valuable tool for dermatologists in their efforts to improve patient outcomes through accurate skin lesion segmentation.

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