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Deep Learning-Based Skin Lesion Segmentation Using FCN, U-Net, and SegNet Architectures

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Abstract: Skin disease detection is a critical task in medical image analysis due to its impact on early diagnosis and treatment. This study presents a deep learning-based framework for automated skin lesion segmentation using dermoscopic images. The proposed approach incorporates multiple segmentation architectures, including Fully Convolutional Networks (FCN), U-Net, and SegNet, to evaluate their effectiveness in accurately identifying lesion regions. The preprocessing stage involves image resizing, normalization, and data augmentation techniques such as random rotation and horizontal flipping to enhance model generalization. The models are trained and evaluated using standard benchmark datasets, and their performance is assessed using metrics such as accuracy, Dice coefficient, Intersection over Union (IoU), precision, recall, and loss. Experimental results demonstrate that the U-Net model outperforms FCN and SegNet, achieving superior segmentation accuracy and better generalization capability. The findings highlight the effectiveness of deep learning techniques in improving automated skin disease diagnosis and support the development of reliable computer-aided dermatological systems.
Keywords: Skin Lesion Segmentation, Deep Learning, U-Net, SegNet, Dermoscopic Image Analysis

I. INTRODUCTION

The skin is the largest organ of the human body and serves as a critical protective barrier against harmful environmental factors. It helps prevent dehydration and maintains internal homeostasis [1]. However, skin health is highly influenced by lifestyle and environmental conditions such as excessive sun exposure, pollution, alcohol consumption, smoking, and infections. These factors not only damage the skin's surface but can also negatively impact mental health, self-confidence, and overall quality of life [2].

Skin diseases are among the most common health conditions worldwide, affecting individuals of all ages and backgrounds. Reports indicate that more than 60% of the population in the United Kingdom experiences some form of skin disease each year, while approximately 5.4 million new cases of skin cancer are diagnosed annually in the United States [3]. Beyond physical discomfort, these conditions often lead to psychological issues such as anxiety, depression, and reduced social interaction, further emphasizing their broader impact on well-being [4].

Skin diseases can arise due to bacterial, fungal, or viral infections, as well as allergic reactions [5]. Diagnosing these conditions remains challenging even for experienced dermatologists, as many diseases share similar visual characteristics such as redness, swelling, and irritation. For instance, conditions like contact dermatitis and eczema often appear alike, while measles and keratosis may both present as red patches on the skin [6]. Such similarities increase the likelihood of misdiagnosis, making early and accurate detection essential for effective treatment and improved patient outcomes [7].

Despite the importance of timely diagnosis, several challenges persist, including overlapping symptoms and a global shortage of trained dermatologists, particularly in developing regions. Additionally, the high cost of medical education and healthcare services limits accessibility to proper diagnosis and treatment [8]. These challenges highlight the urgent need for automated, affordable, and efficient diagnostic systems that can operate effectively even in resource-constrained environments.

Recent advancements in machine learning (ML) and deep learning (DL) have significantly transformed the field of medical image analysis. Deep learning models have achieved diagnostic performance comparable to experienced dermatologists by automatically extracting meaningful features from skin images [9]. The availability of large, high-quality datasets such as ISIC, PH2, HAM10000, BCN20000, EDRA, and Med-NODE has further accelerated research in this domain [10–15]. Consequently, AI-based skin disease detection systems offer a promising solution by improving diagnostic accuracy, enabling early detection, reducing healthcare costs, and supporting global dermatological care.

II. LITERATURE REVIEW

T.V. Reddy et al. introduced CNN-based approaches for segmenting and classifying common skin diseases such as acne, eczema, and psoriasis [17]. Their work emphasized the importance of using large and diverse datasets, such as XiangyaDerm, to improve model training and performance. Similarly, Shahid Khan et al. [18] proposed deep learning techniques aimed at enhancing diagnostic accuracy and interpretability. Their study utilized pre-trained CNN architectures including VGG16, GoogleNet, and MobileNetV2, combined with transfer learning and attention mechanisms to improve multi-class skin disease classification. Both studies [17][18] also highlighted the growing role of mobile-based diagnostic applications and discussed key challenges such as dataset diversity, data privacy, and model interpretability for real-world clinical adoption.

Tahseen et al. focused on melanoma detection using advanced deep learning models such as Squeeze Net, VGG-SegNet, and region-based CNNs (R-CNN) [19]. Their research demonstrated improved accuracy, sensitivity, and specificity compared to traditional diagnostic methods and even dermatologists, while also stressing the need for high-quality datasets, explainable models, and generalization across populations. In another study, S.D. Sharam et al. [20] proposed a deep learning-based system for skin disease prediction that integrates machine learning techniques with ensemble methods and feature selection. The authors developed a web-based application using Python Django and employed models such as SVM, ANN, and CNN, achieving an accuracy of approximately 95%. Pai et al. [21] developed a CNN-based approach for classifying bacterial and fungal skin diseases without dermoscopic images, considering multiple disease categories along with healthy skin. Their model, built on a fine-tuned VGG16 architecture with transfer learning, was integrated into a web application for user interaction and achieved an accuracy of 86% with an F1-score of 85%. Similarly, Nigat et al. [22] focused on fungal disease classification using CNNs, where preprocessing techniques such as normalization, grayscale conversion, and augmentation improved model performance, resulting in an accuracy of 93.3%. Muhaba et al. [23] further advanced this field by proposing a smartphone-based diagnostic system using MobileNet-V2, achieving high accuracy (97.5%) along with strong precision and sensitivity. Gautam et al. [24] introduced a CNN-based framework involving preprocessing, feature extraction, and deep learning classification, achieving accuracy up to 98%. Likewise, Sadik et al. [25] utilized pre-trained models such as Mobile Net and Exception with transfer learning and augmentation, reaching accuracies of 96% and 97%, respectively, and enabling real-time web-based diagnosis. Mahum et al. [26] proposed a hybrid method combining traditional techniques like LBP with deep learning (Inception V3 and LSTM), achieving exceptional performance with 99.4% accuracy and high precision and recall. Albawi et al. [27] presented a method for detecting melanoma, nevus, and atypical skin diseases using adaptive filtering, region-based segmentation, and hybrid feature extraction, achieving 96.768% accuracy on the ISIC dataset. Additionally, Yoon et al. [28] focused on detailed skin feature analysis by applying a U-Net-based segmentation model enhanced with attention mechanisms, enabling precise detection of wrinkles and pores and demonstrating strong potential for advanced skin analysis applications.

III.SKIN DISEASE DATASET

The performance of deep learning (DL) and machine learning (ML) models in dermatological image analysis largely depends on the availability of high-quality and diverse datasets. Well-structured datasets enable models to learn meaningful features, improve generalization, and enhance diagnostic accuracy.

Among these, the HAM10000[10] dataset contains over 10,000 dermoscopic images covering various skin lesions such as melanoma, nevi, and other benign and malignant conditions, along with metadata like patient age, sex, and diagnosis. Similarly, the PH2[11] dataset includes 200 dermoscopic images specifically focused on pigmented lesions, providing detailed ground truth information such as lesion boundaries, color, and texture, making it useful for melanoma detection. The ISIC [12] datasets (2016–2020) are also widely used benchmarks that offer diverse, annotated dermoscopic images collected from multiple sources, supporting model evaluation, comparison, and participation in international challenges.

In addition, the DermoFit [13] dataset provides clinical images of multiple skin conditions such as eczema, psoriasis, and carcinomas, enabling classification beyond melanoma. The BCN20000 [14] dataset includes around 20,000 dermoscopic images and is particularly useful for large-scale melanoma classification and improving automated diagnostic performance. Furthermore, the PAD-UFES-20 [15] dataset consists of over 2,000 dermoscopic images across various lesion categories, supporting the development and validation of robust and accurate skin disease detection systems. Together, these datasets play a crucial role in advancing AI-based dermatological research and improving early diagnosis.

IV.METHODOLOGY

The basic workflow for automated skin disease detection using deep learning (DL) consists of several key stages, including data preprocessing, segmentation, feature extraction, deep learning-based classification, and performance evaluation, where each stage plays a crucial role in improving the accuracy and robustness of the model. Fig. 1 illustrates this complete step-by-step process, beginning with dataset input and preprocessing, followed by feature extraction, model construction, skin lesion segmentation, classification, and final performance evaluation.

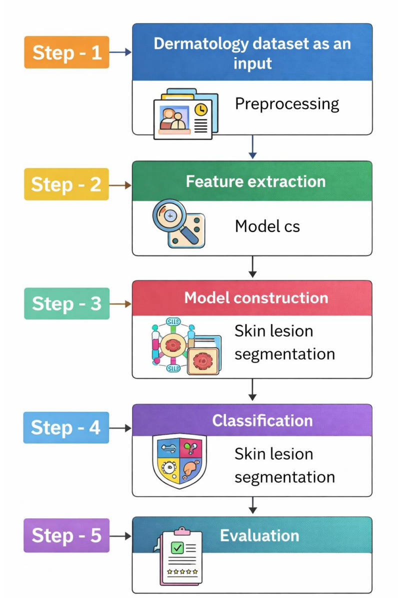

Fig. 1: Proposed workflow of skin lesion analysis using deep learning, showing preprocessing, feature extraction, segmentation, classification, and evaluation stages.

A. Dataset

The PH2 dataset is a publicly available dermoscopic image dataset developed by Pedro Hispano Hospital, Portugal, for skin lesion analysis research [8]. It contains 200 high-resolution images, including common nevi, atypical nevi, and melanoma cases, along with expert annotations such as lesion segmentation masks and clinical features like asymmetry, border irregularity, and colour variation. Fig. 2 presents a sample dermoscopic image from the dataset, while Fig. 3 shows its corresponding ground truth segmentation mask.

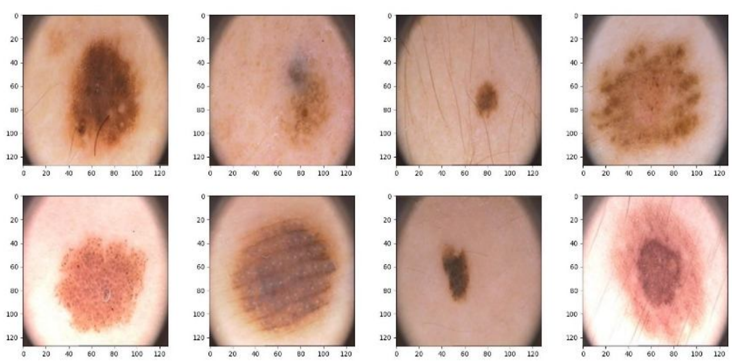

Fig. 2. Example of a dermoscopic image from the PH2 dataset.

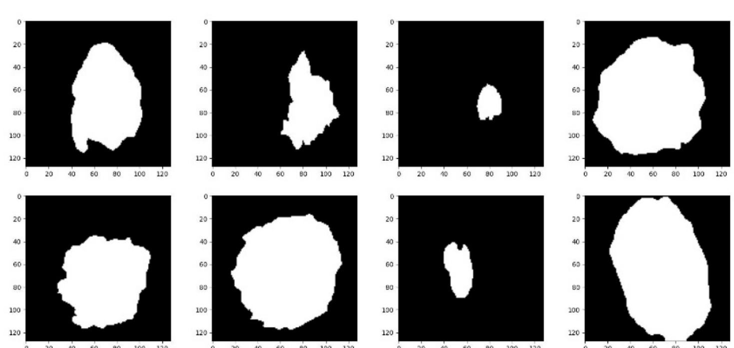

Fig. 3. Ground truth segmentation mask corresponding to the skin lesion image.

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B. Data Preprocessing and Augmentation

Data preprocessing is an essential step that involves resizing images and normalizing pixel values to ensure uniformity across the dataset. To further enhance model generalization and reduce overfitting, data augmentation techniques such as random rotation and horizontal flipping are applied.

Algorithm 1: Data Preprocessing and Augmentation
Input: Training images X_train, corresponding masks Y_train, target size (128 × 128)
Output: Augmented dataset (X_final, Y_final).

Step 1: Dataset Sorting
Initially, the dataset is organized using a numerical sorting function. Filenames are processed using regular expressions to extract numeric values, which are then converted into integers to ensure correct sequential ordering.

Step 2: Image Preprocessing
Each image in the dataset is resized to 128×128 pixels using LANCZOS interpolation for high-quality scaling. The pixel values are then normalized to maintain consistency and improve model training stability.

Step 3: Data Augmentation
To increase dataset diversity, two augmentation techniques are applied:

- Random Rotation: Images and corresponding masks are rotated by a randomly generated angle between −40° and +40° using affine transformation.
- Horizontal Flipping: Both images and masks are flipped horizontally to introduce additional variation.

Step 4: Augmentation Application
For every image-mask pair in the training set, rotated and flipped versions are generated and stored in separate datasets.

Step 5: Dataset Combination
The original, rotated, and flipped datasets are combined to form the final augmented dataset.

Step 6: Output
The algorithm returns the final augmented image set X_final along with the corresponding masks Y_final.

C. Proposed Deep Learning Models for Skin Lesion Segmentation

In this work, multiple deep learning-based segmentation architectures are utilized to accurately identify and segment skin lesion regions from dermoscopic images. The proposed framework incorporates Fully Convolutional Networks (FCN), U-Net, and SegNet, model to exploit their complementary strengths in feature extraction, spatial localization, and boundary refinement. The architectures of these models are illustrated in Fig. 4 to Fig. 5.

1) *Fully Convolutional Network (FCN):* FCN is a pioneering deep learning model designed for semantic segmentation that replaces fully connected layers with convolutional layers, enabling pixel-wise prediction. It uses up sampling (deconvolution) layers to restore spatial resolution and combines coarse, high-level features with fine-grained details through skip connections, making it suitable for segmenting skin lesions.

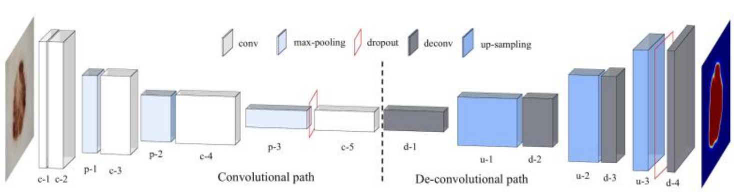

Fig. 1. FCN architectures

2) *U-Net Architecture:* U-Net is a widely used encoder–decoder architecture specifically developed for biomedical image segmentation. It consists of a contracting path (encoder) that captures contextual information and an expanding path (decoder) that enables precise localization. Skip connections between corresponding encoder and decoder layers help preserve spatial details, resulting in accurate segmentation of lesion boundaries.

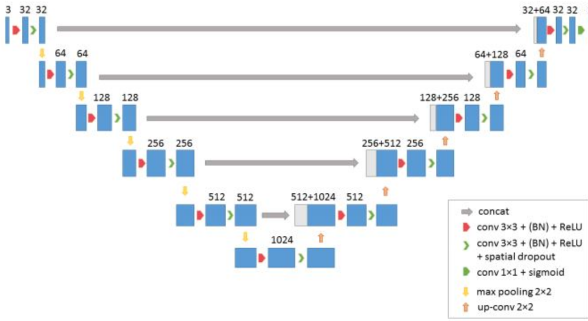

Fig. 2. U-Net architectures

3) *SegNet Architecture:* SegNet is another encoder–decoder-based segmentation model that uses pooling indices from the encoder during the decoding process to perform non-linear up sampling. This approach reduces computational complexity and memory usage while maintaining segmentation accuracy. SegNet is particularly effective for capturing structural information and generating smooth segmentation maps.

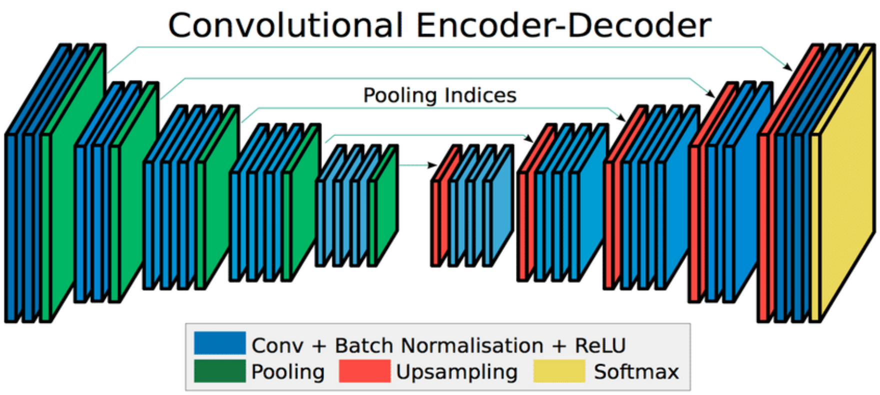

Fig. 3. SegNet architectures

D. Evaluation Metrics

1) *Intersection over Union:* IoU measures the similarity between the predicted segmentation and the ground truth by calculating the ratio of their overlap to their combined area. A higher IoU value indicates better segmentation accuracy.

$$\text{IoU} = (\text{Ground truth} \cap \text{Predicted segmentation})/(\text{Ground truth} \cup \text{Predicted segmentation}) \quad (1)$$

2) *Dice coefficient: The* Dice coefficient evaluates the overlap between predicted and actual segmentation masks. It considers both false positives and false negatives, making it a reliable metric for segmentation tasks.

$$\text{Dice} = (2\times\text{True Positive}) / ((\text{True Positive} + \text{False Positive}) + (\text{True Positive} + \text{False Negative})) \quad (2)$$

3) *Precision:* Precision measures the accuracy of positive predictions by determining the proportion of correctly predicted positive samples among all predicted positives.

$$\text{Precision} = (\text{True Positive}) / (\text{True Positive} + \text{False Positive}) \quad (3)$$

4) *Recall:* Recall evaluates the model’s ability to correctly identify all relevant positive instances of a class [9].

$$\text{Recall} = (\text{True Positive}) / (\text{True Positive}+\text{False Negative}) \quad (4)$$

5) *Accuracy:* Accuracy represents the overall proportion of correctly classified samples (both positive and negative) out of the total number of test samples [9].

$$\text{Accuracy} = (\text{True Positive True Negative})/(\text{Total no of Samples}) \quad (5)$$

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E. Results and Discussion

The performance of different segmentation models, namely FCN, SegNet, and U-Net, is evaluated using standard metrics such as accuracy, Dice coefficient, IoU, precision, recall, and loss across training, validation, and test datasets. The FCN model achieves moderate performance, with a training accuracy of 92.11% and a Dice score of 77.20%, while the validation and test results remain consistent, showing accuracies of 92.83% and 90.13%, respectively. The model demonstrates relatively stable precision and recall values, though its Dice and IoU scores indicate room for improvement in segmentation quality.

The SegNet model shows higher training accuracy (95.71%) and improved Dice performance (82.51%), but its validation and test results slightly decline, suggesting possible overfitting, as indicated by higher loss values. In contrast, the U-Net model outperforms the other architectures, achieving superior segmentation performance with a Dice score of 90.14% on training and 90.90% on the test set. It also maintains high IoU, precision, and recall values with lower loss, demonstrating better generalization and robustness. Overall, U-Net provides the most accurate and reliable results among the evaluated models for skin lesion segmentation. Fig no 6 to 8 show the output of the model.

TABLE 1
EVALUATION OF FCN MODEL

Dataset	Accuracy (%)	Dice Coefficient (%)	IoU (%)	Precision (%)	Recall (%)	Loss (%)
Training Set	92.11	77.20	93.65	83.69	93.35	4.32
Validation Set	92.83	77.93	93.12	84.88	93.97	3.85
Test Set	90.13	75.44	91.71	80.11	93.16	5.27

TABLE 2
EVALUATION OF SEGNET MODEL

Dataset	Accuracy (%)	Dice Coefficient (%)	IoU (%)	Precision (%)	Recall (%)	Loss (%)
Training Set	95.71	82.51	96.02	93.69	92.97	11.87
Validation Set	91.99	75.05	93.98	90.46	83.95	15.65
Test Set	90.58	76.43	93.12	87.03	81.62	20.38

TABLE 3
EVALUATION OF U-NET MODEL

Dataset	Accuracy (%)	Dice Coefficient (%)	IoU (%)	Precision (%)	Recall (%)	Loss (%)
Training Set	92.46	90.14	98.77	93.67	93.11	2.18
Validation Set	91.01	91.07	94.97	91.83	92.63	3.05
Test Set	92.76	90.90	93.61	90.58	91.74	3.36

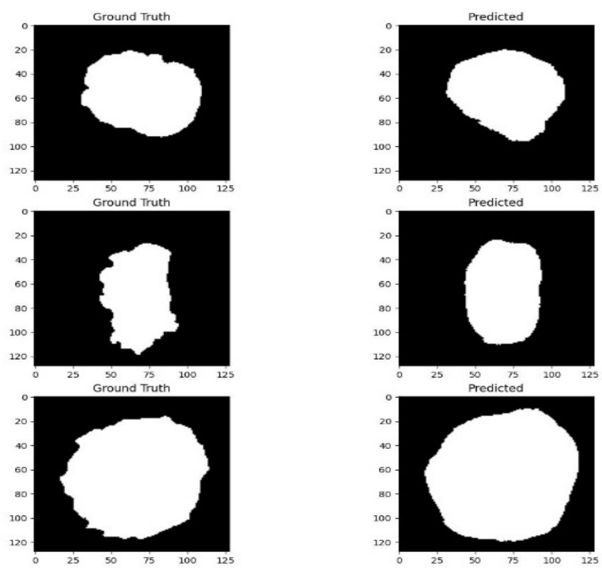

Fig. 6. Ground truth masks and corresponding predicted segmentation outputs generated SegNet model

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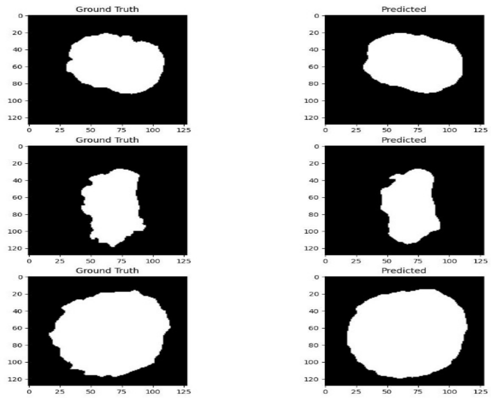

Fig. 7. Ground truth masks and corresponding predicted segmentation outputs generated by U-Net model

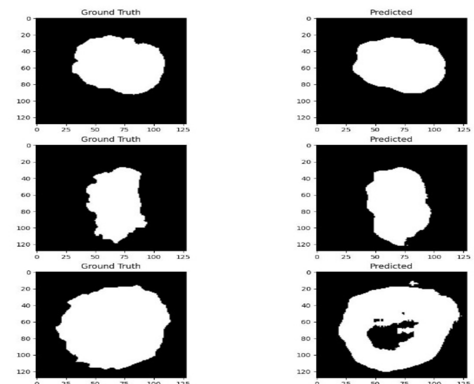

Fig. 8. Ground truth masks and corresponding predicted segmentation outputs by FCN model

V. CONCLUSIONS

This study presents a comparative analysis of deep learning-based segmentation models, including FCN, SegNet, and U-Net, for automated skin lesion detection. The results indicate that while FCN and SegNet provide reasonable performance, U-Net achieves the highest accuracy, Dice score, and IoU, demonstrating superior capability in capturing fine-grained lesion boundaries. The use of preprocessing and data augmentation techniques significantly improves model robustness and generalization. The proposed framework highlights the potential of deep learning in enhancing the accuracy and efficiency of skin disease diagnosis. Future work may focus on integrating hybrid architectures, improving model interpretability, and deploying the system in real-time clinical applications for broader accessibility and practical use.

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