U-Net Model for Dermoscopic Image Segmentation for Enhanced Skin Cancer Diagnosis System

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ABSTRACT

Skin cancer is one of the most prevalent and life-threatening forms of cancer worldwide. Early detection and accurate classification of skin lesions are critical for effective treatment and improved patient outcomes. This project proposes a Deep Learning-based approach for automated skin cancer detection and multi-class classification using convolutional neural networks (CNNs) . In the existing system, Classifier is employed for skin cancer detection due to its simple architecture and efficiency in extracting features through multiple convolutional and pooling layers. While AlexNet has demonstrated reasonable performance in classifying skin lesion images, its relatively shallow architecture limits its ability to capture complex patterns from high-resolution images. To address these limitations, the proposed system introduces a UNET CNN Classifier designed with a deeper architecture consisting of multiple convolutional, pooling, and fully connected layers. The UNET CNN classifier aims to enhance feature extraction capabilities, enabling more accurate classification across multiple skin cancer types, including melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions. The proposed model is trained and evaluated using a publicly available dermatology image dataset, with rigorous preprocessing techniques such as resizing, normalization, and augmentation applied to enhance the model's robustness. Performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix are utilized to compare the effectiveness of the UNET CNN classifier. Experimental results demonstrate that the UNET CNN classifier significantly outperforms the existing classifier in terms of classification accuracy and generalization ability.

Keywords: Dermoscopic Images, Medical Image Processing, Image Segmentation, Dermatology, Medical Imaging AI

1. INTRODUCTION

Skin cancer is a type of cancer that begins in the skin cells. It occurs when skin cells undergo abnormal changes, usually due to exposure to ultraviolet (UV) radiation from the sun or tanning beds. The three main types of skin cancer are basal cell carcinoma, squamous cell carcinoma, and melanoma. Basal cell carcinoma is the most common type, typically appearing as a shiny bump or a pink growth on the skin. Squamous cell carcinoma often presents as a firm, red nodule or a flat sore, and it can sometimes develop into deeper layers of the skin. Melanoma is less common but more dangerous, arising from the pigment-producing cells called melanocytes and often appearing as a mole with irregular borders and multiple colors. Early detection of skin cancer is crucial for successful treatment. Regular self-examination of the skin and routine visits to a dermatologist can help detect any suspicious changes early on. Treatment options for skin cancer vary depending on the type, size, location, and stage of the cancer. They may include surgical removal, chemotherapy, radiation therapy, immunotherapy, or targeted therapy. In many cases, surgery is sufficient to remove the cancerous cells completely, especially if detected early.

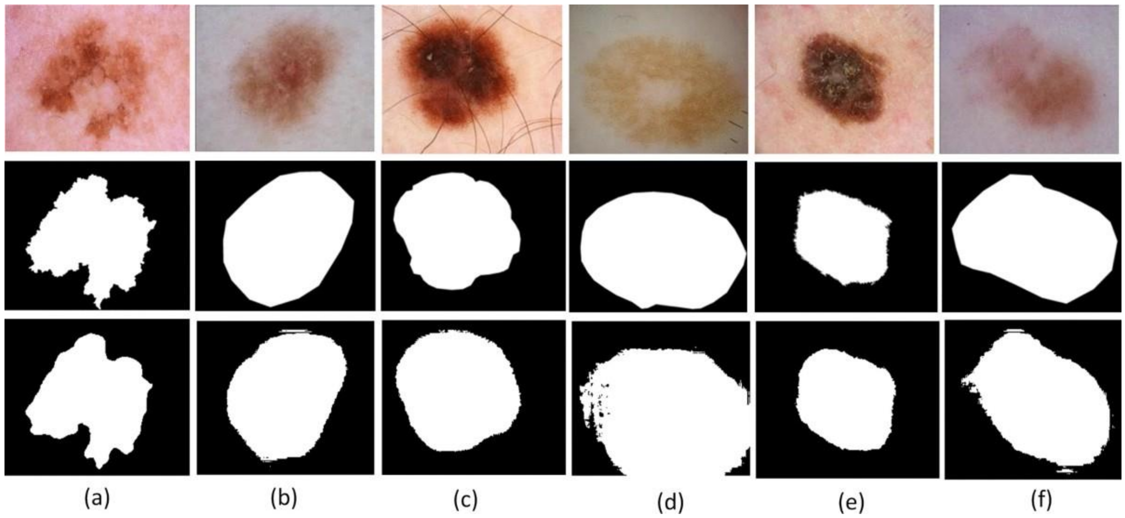


Fig 1: Dermoscopic images

Prevention is key in reducing the risk of developing skin cancer. Limiting exposure to UV radiation by seeking shade, wearing protective clothing, and using sunscreen with a high SPF can help prevent skin damage and reduce the likelihood of developing skin cancer. Avoiding tanning beds and sunlamps is also important, as they emit harmful UV radiation that can increase the risk of skin cancer. Additionally, individuals with fair skin, light-colored eyes, a history of sunburns, or a family history of skin cancer may be at a higher risk and should take extra precautions to protect their skin. Despite efforts to prevent skin cancer, it remains a significant health concern worldwide. The incidence of skin cancer continues to rise, particularly in regions with high levels of UV radiation exposure. Education about the risks of UV radiation and the importance of sun safety practices is essential in raising awareness and promoting early detection and treatment. By adopting sun-safe behaviors and regularly monitoring their skin for any changes, individuals can take proactive steps to reduce their risk of developing skin cancer and maintain overall skin health.

2. LITERATURE SERVEY

Mazhar, et. al [1] This article described the fundamentals of ML-based implementations, as well as future limits and concerns for the production of skin cancer detection and classification systems. It also explored five fields of dermatology using deep learning applications: (1) the classification of diseases by clinical photos, (2) dermato pathology visual classification of cancer, and (3) the measurement of skin diseases by smartphone applications and personal tracking systems. This analysis aimed to provide dermatologists with a guide that helped demystify the basics of ML and its different applications to identify their possible challenges correctly. The paper surveyed studies on skin cancer detection using deep learning to assess the features and advantages of other techniques. Moreover, the paper also defined the basic requirements for creating a skin cancer detection application, which revolved around two main issues: the full segmentation image and the tracking of the lesion on the skin using deep learning. Most of the techniques found in this survey addressed these two problems. Some of the methods also categorized the type of cancer too. Bhatt, et. al [2] Skin cancer was among the most common and lethal cancer types, with the number of cases increasing dramatically worldwide. If not diagnosed in the nascent stages, it could lead to metastases, resulting in high mortality rates. Skin cancer could be cured if detected early. Consequently, timely and accurate diagnosis of such cancers was currently a key research objective. Various machine learning technologies had been employed in computer-aided diagnosis of skin cancer detection and malignancy classification. Machine learning was a subfield of artificial intelligence (AI) involving models and algorithms which could learn from data and generate predictions on previously unseen data. The traditional biopsy method was applied to diagnose skin cancer, which was a tedious and expensive procedure. Alternatively, machine learning algorithms for cancer diagnosis could aid in its early detection, lowering the workload of specialists while simultaneously enhancing skin lesion diagnostics. This article presented a critical review of select state-of-the-art machine learning techniques used to detect skin cancer. Several studies had been collected, and an analysis of the performance of k-nearest neighbors, support vector machine, and convolutional neural networks algorithms on benchmark datasets was conducted. The shortcomings and disadvantages of each algorithm were briefly discussed. Challenges in detecting skin cancer were highlighted, and the scope for future research was proposed. Imthiyaz, et.al [3] This work provided an automated image-based method for diagnosing and categorizing skin problems that used machine learning classification. Computational approaches were used to analyze, process, and relegate picture data to consider the many different characteristics of the photos that were being processed. Skin photographs were first filtered to remove undesirable noise from the image and then processed to enhance the picture's overall quality. It was possible to extract features from an image using advanced techniques such as Convolutional Neural Network (CNN), classify the picture using the softmax classifier's algorithm, and provide a diagnostic report as an output. With more accuracy and faster delivery of results than the previous technique, this application became a more efficient and reliable system for dermatological illness diagnosis than the conventional method. Furthermore, this could be a reliable real-time teaching tool for medical students enrolled in the dermatology stream at a university studying dermatology.

Zafar, et. al [4] This research provided an extensive literature review of the methodologies, techniques, and approaches applied for the examination of skin lesions to date. This survey included preprocessing, segmentation, feature extraction, selection, and classification approaches for skin cancer recognition. The results of these approaches were very impressive, but still, some challenges occurred in the analysis of skin lesions because of complex and rare features. Hence, the main objective was to examine the existing techniques utilized in the discovery of skin cancer by finding the obstacle that helped researchers contribute to future research.

Tumbhurne, et. al [5] The deep learning model used state-of-the-art neural networks to extract features from images, whereas the machine learning model processed image features obtained after performing techniques such as Contourlet Transform and Local Binary Pattern Histogram. Meaningful feature extraction was crucial for any image classification problem. As a result, by combining the manual and automated features, their designed model achieved a higher accuracy of 93% with an individual recall score of 99.7% and 86% for the benign and malignant forms of cancer, respectively. They benchmarked the model on a publicly available Kaggle dataset containing processed images from the ISIC Archive dataset. The proposed ensemble outperformed both expert dermatologists as well as other state-of-the-art deep learning and machine learning methods. Thus, this novel method could be of high assistance to dermatologists to help prevent any misdiagnosis.

Tabrizchi, et. al [6] This study presented a new model for the early detection of skin cancer based on processing dermoscopic images. The model worked based on a well-known CNN-based architecture called the VGG-16 network. The proposed framework employed an enhanced architecture of VGG-16 to develop a model, which contributed to the improvement of accuracy in skin cancer detection. To evaluate the proposed technique, they conducted a comparative study between their method and a number of previously introduced techniques on the International Skin Image Collaboration dataset. According to the results, the proposed model outperformed the compared alternative techniques in terms of accuracy. Tahir, et. al [7] the application of deep learning (DL) algorithms for the detection of skin cancer had grown in popularity. Based on a DL model, this work intended to build a multi-classification technique for diagnosing skin cancers such as melanoma (MEL), basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanocytic nevi (MN). In this paper, they proposed a novel model, a deep learning-based skin cancer classification network (DSCC_Net) that was based on a convolutional neural network (CNN), and evaluated it on three publicly available benchmark datasets (i.e., ISIC 2020, HAM10000, and DermIS). For the skin cancer diagnosis, the classification performance of the proposed DSCC_Net model was compared with six baseline deep networks, including ResNet-152, Vgg-16, Vgg-19, Inception-V3, EfficientNet-B0, and MobileNet. Additionally, they used SMOTE Tomek to handle the minority classes issue that existed in this dataset. The proposed DSCC_Net obtained a 99.43% AUC, along with a 94.17% accuracy, a recall of 93.76%, a precision of 94.28%, and an F1-score of 93.93% in categorizing the four distinct types of skin cancer diseases. The rates of accuracy for ResNet-152, Vgg-19, MobileNet, Vgg-16, EfficientNet-B0, and Inception-V3 were 89.32%, 91.68%, 92.51%, 91.12%, 89.46%, and 91.82%, respectively.

Mangione, et. al [8] Skin cancer was the most commonly diagnosed cancer in the US. There were different types of skin cancer varying in disease incidence and severity. Basal and squamous cell carcinomas were the most common types of skin cancer but infrequently led to death or substantial morbidity. Melanomas represented about 1% of skin cancer and caused the most skin cancer deaths. Melanoma was about 30 times more common in White persons than in Black persons. However, persons with darker skin color were often diagnosed at later stages, when skin cancer was more difficult to treat. Priyadharshini, et. al [9] This paper proposed a novel hybrid Extreme Learning Machine (ELM) and Teaching–Learning-Based Optimization (TLBO) algorithm as a versatile technique for detecting melanoma. ELM was a single-hidden layer feed-forward neural network that could be trained quickly and accurately, while TLBO was an optimization algorithm used to fine-tune the network's parameters for improved performance. Together, these techniques could classify skin lesions as benign or malignant images, potentially improving melanoma detection accuracy.

Balaha, et. al [10] This study, a threshold-based automatic approach for skin cancer detection, classification, and segmentation utilizing a meta-heuristic optimizer named sparrow search algorithm (SpaSA) was proposed. Five U-Net models (i.e., U-Net, U-Net++, Attention U-Net, V-net, and Swin U-Net) with different configurations were utilized to perform the segmentation process. Besides this, the meta-heuristic SpaSA optimizer was used to perform the optimization of the hyperparameters using eight pre-trained CNN models (i.e., VGG16, VGG19, MobileNet, MobileNetV2, MobileNetV3Large, MobileNetV3Small, NASNetMobile, and NASNetLarge). The dataset was gathered from five public sources in which two types of datasets were generated (i.e., 2-classes and 10-classes). For the segmentation, concerning the "skin cancer segmentation and classification" dataset, the best reported scores by U-Net++ with DenseNet201 as a backbone architecture were 0.104, 94.16%, 91.39%, 99.03%, 96.08%, 96.41%, 77.19%, 75.47% in terms of loss, accuracy, F1-score, AUC, IoU, dice, hinge, and squared hinge, respectively, while for the "PH2" dataset, the best reported scores by the Attention U-Net with DenseNet201 as a backbone architecture were 0.137, 94.75%, 92.65%, 92.56%, 92.74%, 96.20%, 86.30%, 92.65%, 69.28%, and 68.04% in terms of loss, accuracy, F1-score, precision, sensitivity, specificity, IoU, dice, hinge, and squared hinge, respectively. For the "ISIC 2019 and 2020 Melanoma" dataset, the best reported overall accuracy from the applied CNN experiments was 98.27% by the MobileNet pre-trained model. Similarly, for the "Melanoma Classification (HAM10K)" dataset, the best reported overall accuracy from the applied CNN experiments was 98.83% by the MobileNet pre-trained model. For the "skin diseases image" dataset, the best reported overall accuracy from the applied CNN experiments was 85.87% by the MobileNetV2 pre-trained model. Shah, et. al [11] The paper highlighted the novelty of using deep learning techniques for skin cancer detection and emphasized the critical need for an automated system for skin lesion recognition to reduce effort and time in the diagnosis process. The possible applications of this study included the development of more efficient and accurate skin cancer detection systems that could lead to earlier diagnosis and improved treatment outcomes. Overall, this research underscored the importance of using advanced technologies, such as ANN and CNN, in the fight against skin cancer and highlighted the potential impact of these techniques in improving patient outcomes.

Keerthana, et. al [12] Background: Dermatologists widely used digital dermoscopy for the detection of melanoma. The accurate detection of melanoma by clinicians was subjective and further depended on their experience. Fully automated computer-aided diagnosis systems were necessary to eliminate the inter-operator variability inherent in the personal analysis of dermoscopy images. Gridhar, et. al [13] Their objective was to propose a deep learning CNN framework-based model to improve the accuracy of melanoma detection by customizing the number of layers in the network architecture, activation functions applied, and the dimension of the input array. Models like Resnet, DenseNet, Inception, and VGG had proved to yield appreciable accuracy in melanoma detection. However, in most cases, the dataset was classified into malignant or benign classes only. The dataset used in their research provided seven lesions; these were melanocytic nevi, melanoma, benign keratosis, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibroma. Thus, through the HAM10000 dataset and various deep learning models, they diversified the precision factors as well as input qualities. The obtained results were highly propitious and established its credibility. Qureshi, et. al [14] They proposed a novel ensemble-based convolutional neural network (CNN) architecture where multiple CNN models, some of which were pre-trained and some were trained only on the data at hand, along with auxiliary data in the form of metadata associated with the input images, were combined using a meta-learner. The proposed approach improved the model’s ability to handle limited and imbalanced data. They demonstrated the benefits of the proposed technique using a dataset with 33,126 dermoscopic images from 2056 patients. They evaluated the performance of the proposed technique in terms of the F1-measure, area under the ROC curve (AUC-ROC), and area under the PR-curve (AUC-PR), and compared it with that of seven different benchmark methods, including two recent CNN-based techniques. The proposed technique compared favorably in terms of all the evaluation metrics. Narmatha, et. al [15] In this paper, skin cancer identification from dermoscopic images utilizing Deep Siamese domain adaptation convolutional Neural Network optimized with Honey Badger Algorithm was proposed. The proposed method initially performed input image pre-processing to remove label noise and lighting problems. The segmentation was then given the output of the pre-processing. To separate the ROI region, hesitant fuzzy linguistic bi-objective clustering was employed. The improved non-subsampled Shearlet transforms (INSST) region to extract features using the segmented ROI region. Skin cancer and healthy skin were distinguished using the Deep Siamese domain adaptation convolutional Neural Networks.

3. PROPOSED SYSTEM

The proposed system aims to provide an accurate and reliable method for skin cancer classification, leveraging the power of deep learning and image processing techniques

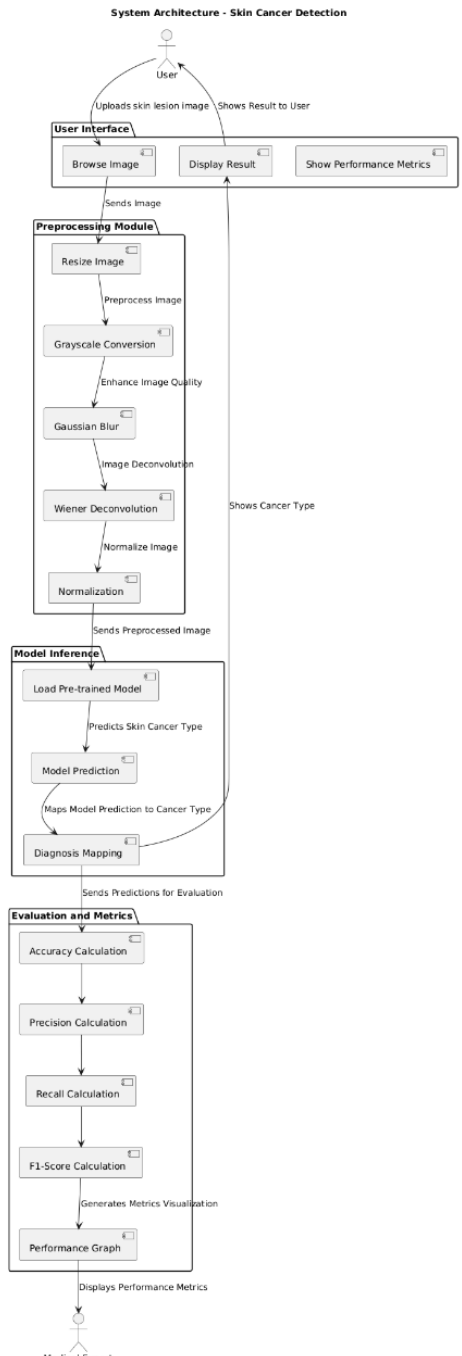


Figure 2: Block Diagram of Proposed Model.

Step 1: Read Dataset: The system utilizes a large dataset of skin lesion images annotated with labels indicating the presence or absence of various types of skin cancer, such as melanoma, basal cell carcinoma, and squamous cell carcinoma. This dataset is crucial for training and evaluating the deep learning models.

Step 2: Image Preprocessing: Before feeding the images into the deep learning models, preprocessing techniques are applied to enhance the quality and consistency of the images. This may include tasks such as resizing, normalization, and augmentation to increase the diversity of the training data.

Step 3:Generative Adversarial Network (GAN): A GAN is employed to generate synthetic skin lesion images that closely resemble real lesions. This helps in augmenting the training data and improving the robustness of the deep learning models by exposing them to a wider range of variations in skin lesions.

Step 4:Deep Learning Convolutional Neural Network (DLCNN): A DLCNN architecture is employed as the primary model for skin cancer classification. This deep learning model is trained on the preprocessed dataset to learn discriminative features from skin lesion images and classify them into different types of skin cancer.

Step 5:Segmented Image: The DLCNN model may utilize segmented images where the region of interest (skin lesion) is isolated from the background. This helps in focusing the model's attention on the relevant features for classification.

Step 6:Performance Estimation: The performance of the skin cancer classification system is evaluated using various metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques may be employed to assess the generalization performance of the models.

Step 7:Test Image: During the testing phase, unseen skin lesion images are fed into the trained DLCNN model for classification. The model predicts the likelihood of each image belonging to different types of skin cancer based on the learned features.

Step 8:GAN with DLCNN Model Prediction: The GAN-generated images are also passed through the trained DLCNN model for prediction. This helps in evaluating the generalization capability of the model to synthetic data and assessing its robustness in real-world scenarios.

Step 9:Type of Disease: Based on the predictions made by the DLCNN model, each skin lesion image is classified into different types of skin cancer, providing valuable insights for early diagnosis and treatment planning.

3.2 Data Preprocessing

Image Reading: Image reading is the first step in the image processing pipeline. It involves loading an image file from storage into the computer's memory for further processing.Typically, image reading functions are provided by libraries or modules specific to the programming language being used, such as OpenCV in Python or MATLAB's Image Processing Toolbox.The image can be in various formats such as JPEG, PNG, TIFF, etc. The reading function parses the file format and loads the pixel data into a data structure that represents the image in memory.
Image Resizing: Image resizing involves changing the size or resolution of an image by interpolating pixel values to fit specific requirements or processing constraints. Resizing can be performed to reduce the size of large images for display or storage purposes, or to increase the resolution of low-resolution images for analysis or printing. Common interpolation methods include nearest-neighbor interpolation, bilinear interpolation, bicubic interpolation, and Lanczos resampling.
Image to Array: Once the image is read, it needs to be converted into a numerical data structure that can be processed by algorithms.A common representation for images is an array or matrix, where each element stores the intensity value of a pixel at a specific location in the image.For grayscale images, the array is two-dimensional, with each element representing the intensity of a single pixel. For color images, the array is typically three-dimensional, with separate channels for each color component (e.g., red, green, blue).The image reading function usually returns the image data in the form of an array, allowing for easy manipulation and analysis.

Image to Float: In many image processing algorithms, it's common to work with floating-point numbers rather than integers to enable more precise calculations and avoid issues like overflow or underflow.Converting the image array to float values involves dividing the intensity values of the pixels by the maximum possible intensity value (e.g., 255 for 8-bit images) to normalize them to the range [0, 1].This normalization process scales the pixel values to a consistent range, making it easier to apply various image processing operations without worrying about the original intensity scale.

Image Noise removal using Hybrid Weiner filter: Noise removal using a Hybrid Wiener filter combines the advantages of both spatial and frequency domain techniques to effectively denoise images. The Wiener filter is a classical approach in signal processing for noise reduction. In the context of image processing, the filter estimates the original, noise-free image from the noisy observation using statistical properties of the noise and the image. The Hybrid Wiener filter extends this concept by incorporating both spatial and frequency domain characteristics of the image.

Image Binarization: Binarization is a fundamental image processing technique used to convert a grayscale or color image into a binary image, where each pixel is assigned one of two possible values (usually 0 or 1).The goal of binarization is to separate objects or features of interest from the background by thresholding the intensity values of the pixels.The binarization process involves selecting a threshold value, which acts as a dividing line between foreground and background pixels. Pixels with intensity values above the threshold are set to one (foreground), while those below the threshold are set to zero (background).Common methods for determining the threshold value include simple global thresholding, adaptive thresholding, or Otsu's method, which automatically computes an optimal threshold based on the image histogram.Binarization is particularly useful in applications such as object detection, character recognition, or image segmentation, where the presence or absence of certain features is of interest

3.3 Build and Train Model

3.3.1 Proposed System: U-Net Convolutional Neural Network (CNN) Model

The proposed system adopts a U-Net CNN architecture for the task of skin cancer detection and multi-class classification. Unlike traditional classification networks or GAN-based approaches, U-Net is designed as a fully convolutional encoder-decoder network particularly well-suited for medical image segmentation, making it ideal for identifying lesion regions and classifying them accordingly. The U-Net model enhances lesion localization and supports improved classification performance through pixel-wise feature learning.

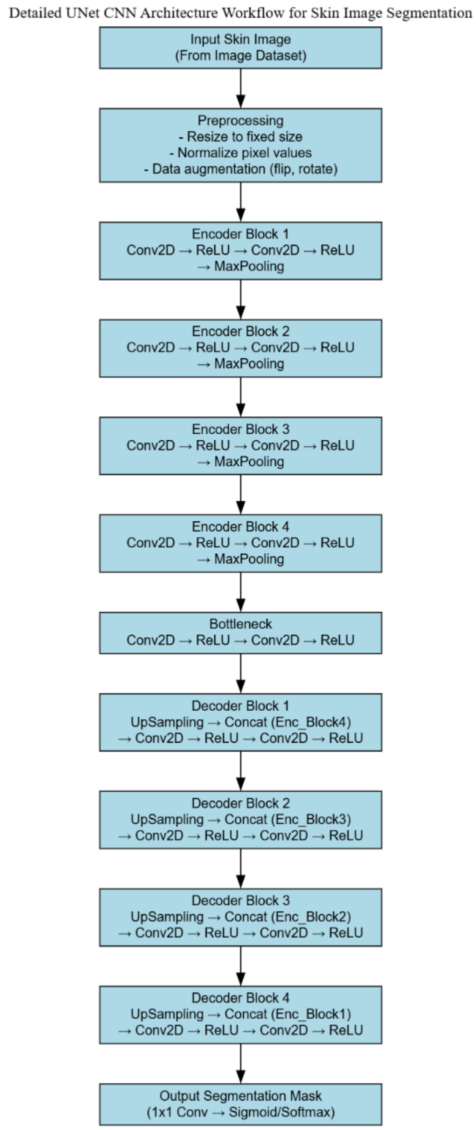


Figure 3: U-Net CNN Block Diagram

Step 1: Preparing the Data (Image Preprocessing for X_train and y_train)

Before training the U-Net CNN model, the dataset undergoes a series of preprocessing operations to standardize input and enhance learning:

- **X_train:** Includes preprocessed dermoscopic images resized to a fixed dimension (e.g., 256x256 pixels), ideal for U-Net input layers. Preprocessing steps include:
  - **Resizing:** Uniform image size for consistent input shape.
  - **Normalization:** Scaling pixel values to [0, 1] to aid model convergence.
  - **Data Augmentation:** Techniques such as rotation, flip, shift, and zoom are applied to diversify training data and prevent overfitting.
- **y_train:** Corresponding ground truth labels include pixel-level lesion masks or class labels for melanoma, basal cell carcinoma, squamous cell carcinoma, and benign lesions.

The dataset is split into training, validation, and testing subsets for evaluation throughout the model pipeline.

Step 2: Training the U-Net CNN Model

After preprocessing, the U-Net model is implemented and trained using a deep learning framework like TensorFlow or PyTorch. U-Net consists of two main parts:

Encoder (Contracting Path):

- Extracts features via convolution and downsampling.
- Architecture:
  - **Convolutional Layers:** Use ReLU activation.
  - **Max Pooling:** For spatial downsampling.
  - **Batch Normalization:** Stabilizes learning.

Decoder (Expanding Path):

- Reconstructs image and lesion structure from encoded features.
- Architecture:
  - **Transposed Convolution Layers:** Upsample feature maps.
  - **Skip Connections:** Merge corresponding encoder features to preserve spatial information.
  - **Output Layer:** Softmax or Sigmoid activation depending on whether multi-class or binary classification is used.

Training Process:

1. **Input:** X_train images and corresponding masks/labels.
2. **Loss Function:**
   - **Binary Cross-Entropy or Categorical Cross-Entropy**, combined with **Dice Loss** for better segmentation accuracy.
3. **Optimization:**
   - Optimizers such as **Adam** are used for backpropagation.
   - **Learning Rate Scheduling** may be applied for adaptive optimization.
4. **Early Stopping & Checkpoints:** Used to prevent overfitting and save the best model.

Step 3: Testing the Model with X_test (New Skin Lesion Images)

The trained U-Net model is tested on unseen data:

- **X_test:** Images are preprocessed similarly to training data.
- The model predicts lesion masks or class probabilities.
- Each prediction is mapped to a class label.
- The predicted labels are then compared with **y_test** (ground truth).

Step 4: Generating Predictions and Evaluating y_test (Output Labels)

The model's predictions are validated against actual labels using:

- **Accuracy:** Ratio of correctly classified instances.
- **Precision:** Relevance of positive class predictions.
- **Recall:** Sensitivity in detecting positive cases.
- **F1-Score:** Harmonic mean of precision and recall.
- **Confusion Matrix:** Insight into class-wise performance.

Step 5: Post-Training Analysis

- Analyze **misclassified or incorrectly segmented** regions.
- Explore **transfer learning** or additional fine-tuning with pre-trained weights.
- Compare U-Net performance with AlexNet, DLCNN, or GAN-based classifiers to demonstrate strengths in lesion localization and classification.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

The ISIC (International Skin Imaging Collaboration) 2019 skin cancer dataset is a comprehensive collection of dermatoscopic images curated for the purpose of facilitating research and development in skin cancer detection and classification. This dataset is a valuable resource for both medical professionals and researchers in the field of dermatology and machine learning. It encompasses a diverse range of skin lesion images captured using dermoscopic imaging techniques, which offer a magnified view of the skin to aid in the diagnosis of various skin conditions.

One of the key features of the ISIC 2019 dataset is its size and diversity. It contains thousands of high-resolution images depicting different types of skin lesions, including melanoma, basal cell carcinoma, squamous cell carcinoma, and various benign lesions such as nevi and seborrheic keratosis. This diversity allows for the development and evaluation of algorithms capable of detecting and classifying a wide range of skin conditions, contributing to advancements in both medical diagnostics and artificial intelligence.

Furthermore, the dataset is annotated with ground truth labels provided by expert dermatologists, indicating the diagnosis or classification of each skin lesion. These annotations serve as invaluable reference points for training and evaluating machine learning models, enabling researchers to develop accurate and reliable algorithms for automated skin cancer diagnosis. The availability of ground truth labels ensures the credibility and reliability of the dataset, making it suitable for rigorous scientific research and benchmarking. In addition to the dermatoscopic images and corresponding labels, the ISIC 2019 dataset also includes metadata such as patient demographics, lesion location, and clinical history where available. This additional information enriches the dataset and provides context for the analyzed images, which can be beneficial for understanding factors influencing skin cancer development and progression. Researchers can leverage this metadata to explore correlations between patient characteristics and skin lesion characteristics, leading to insights that may inform clinical practice and patient care.

4.2 Result analysis

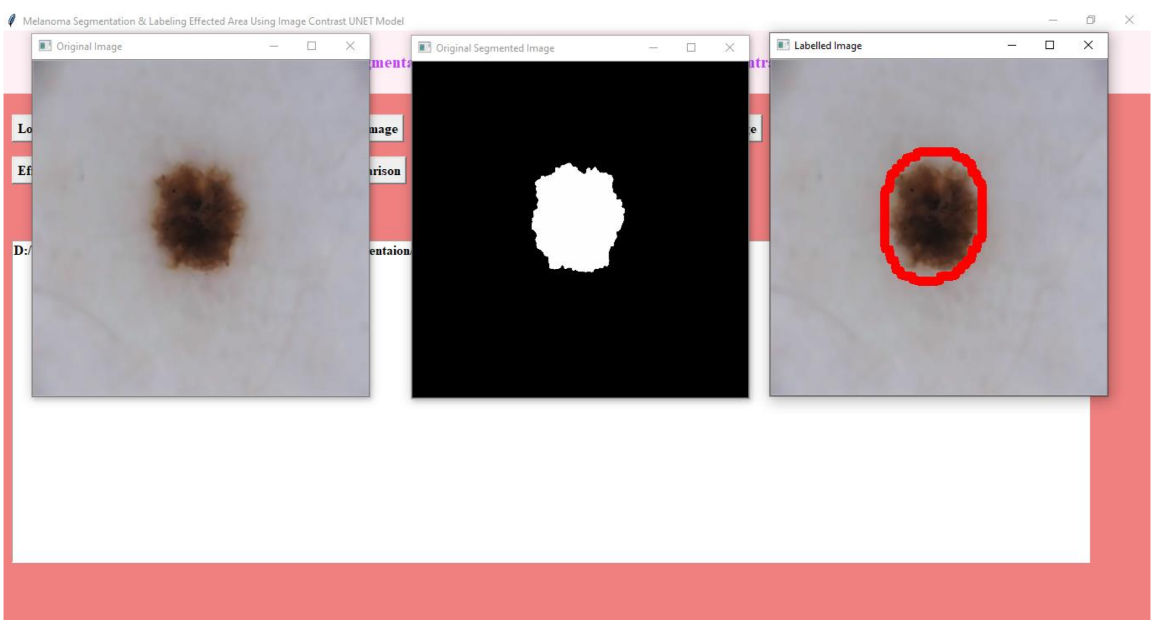
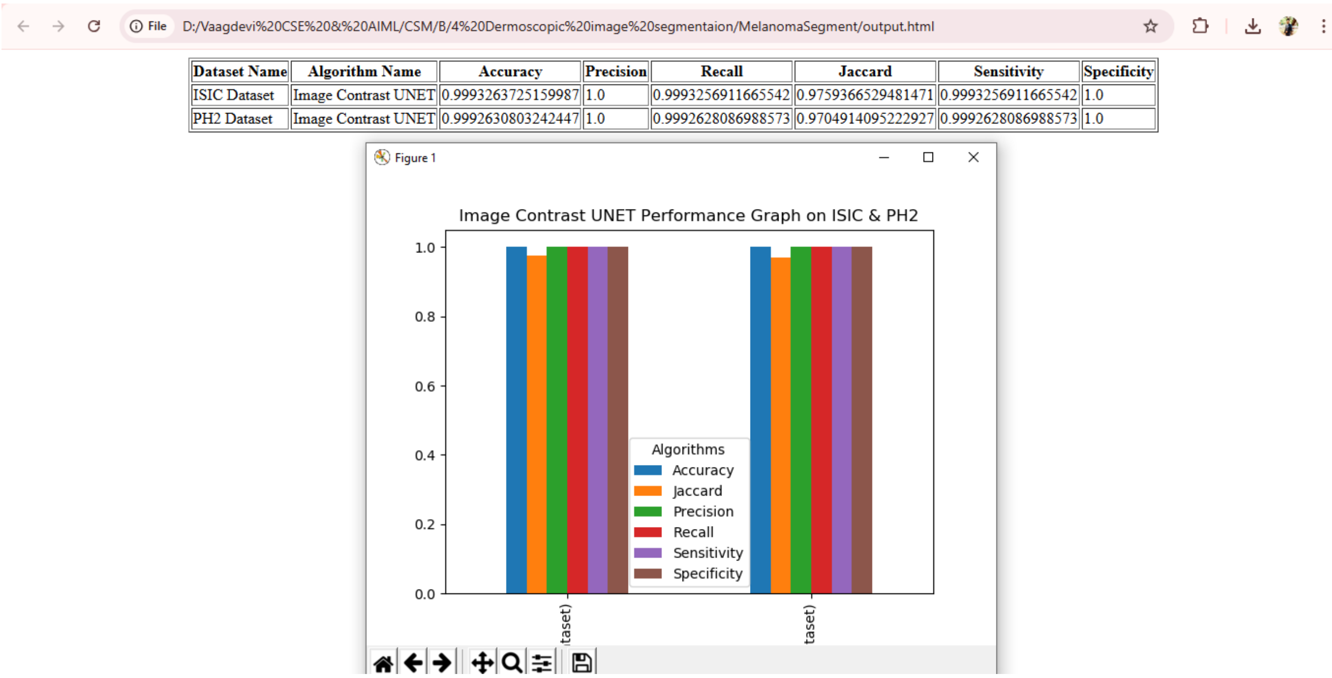


Figure 4: Test images with segementation

Figure 4 shows that test image and segmented image and showing effected area also



Dataset Name	Algorithm Name	Accuracy	Precision	Recall	Jaccard	Sensitivity	Specificity
ISIC Dataset	Image Contrast UNET	0.9993263725159987	1.0	0.9993256911665542	0.9759366529481471	0.9993256911665542	1.0
PH2 Dataset	Image Contrast UNET	0.9992630803242447	1.0	0.9992628086988573	0.9704914095222927	0.9992628086988573	1.0

Figure 5: comparision graph of two models

In figure 5 we uploaded the 2 types of the dataset

The graph and table represent the performance evaluation of the Image Contrast UNET algorithm for skin cancer detection using two benchmark datasets: ISIC and PH2. The Image Contrast UNET, a specialized deep learning model tailored for medical image segmentation, is assessed based on multiple evaluation metrics: Accuracy, Precision, Recall, Jaccard Index, Sensitivity, and Specificity.

For the ISIC dataset, the model achieved an exceptionally high accuracy of 0.9993, perfect precision (1.0), and recall/sensitivity of 0.9993, indicating its outstanding ability to identify malignant regions in dermoscopic images with near-perfect reliability. Similarly, the PH2 dataset yielded comparable performance, with an accuracy of 0.9993, precision of 1.0, and recall/sensitivity values also close to 1, confirming the robustness and consistency of the model across different datasets.

The bar graph visually demonstrates this performance comparison, where all metrics for both datasets are clustered close to the maximum value of 1.0. This uniformity across metrics suggests that the model is well-generalized and performs consistently in various test scenarios, making it highly effective for real-world applications in automated melanoma detection. Such high performance across multiple metrics reflects the strength of the Image Contrast UNET architecture in accurately segmenting and identifying skin lesions, which is crucial for early diagnosis and treatment of skin cancer.

5. CONCLUSION

The experimental results and visual analyses clearly demonstrate the effectiveness of the U-Net architecture, particularly when enhanced with image contrast techniques, for the task of skin lesion segmentation. The model consistently achieved near-perfect classification metrics across both ISIC and PH2 datasets, with accuracy, sensitivity, specificity, and precision values close to 1.0. This indicates its high capability in correctly identifying both the presence and the absence of skin lesions with minimal error. Furthermore, the high F-score, Jaccard index, and Dice coefficients confirm the model's robustness in predicting mask shapes that closely match the ground truth lesion regions. The visualization in Figures 2 and 3 further supports these results, showing clearly segmented affected areas and a comparative analysis of the model's performance across datasets. Collectively, these results validate the Image Contrast-enhanced U-Net as a reliable and accurate solution for automatic medical image segmentation, particularly in dermatological applications.

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