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Multi-Class Deep Learning-Based Enhanced Image Segmentation and Feature Extraction Technique for Early Classification of Skin Diseases

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Abstract:
Skin disorders pose great health issues among millions of people across the globe and thus require accurate diagnosis and treatment. This research article proposed an enhanced deep learning-based image segmentation and feature extraction approach for the early categorization of human skin diseases utilizing the Dermnet dataset of image samples classified under 23 categories. Input images are applied during the preprocessing stage to an enhanced image segmentation technique known as enhanced holistically nested edge detection (EHNED) toward detail enrichment in edges. Further, for multiple feature extraction, the model used EfficientNet-B0 and extracted 1280 features from an image represented as a 1D array. The extracted features form a baseline for training and testing CNNs on the diagnosis of skin diseases. It tries to bridge all the loopholes from previous research by observing an extremely vast and heterogeneous dataset and uses better techniques for segmentation and feature extraction. The proposed framework is likely to increase the recall performance metric to 91%, specificity to 96%, and ability to enable early diagnosis in case of skin diseases. This enhancement is supposed to follow more effective management and better patient outcomes. Findings in this study are likely to contribute toward dermatology research and promote intelligent systems in diagnostics for automatic classification of skin diseases.

Keywords: Skin disease detection, Classification model, deep learning, Enhanced image segmentation, Feature extraction, CNN, Multi- class, Dataset, Dermnet

1. Introduction:

The body of an individual includes multiple organs. The largest organ represents as the human skin. Skin protects us in many ways and serves as a crucial barrier against pathogens, ultraviolet rays, and other harmful agents found in the external environment(Ahammed et al., 2022a). As the skin acts as a protector, it also requires much attention and care. A skin disorder refers to any ailment which impacts the human skin. The disorders pertaining to skin are common and become more dangerous health problems that impact millions of people around the globe. These problems can take many different forms, including rashes, lesions, and long-term ailments like psoriasis and eczema, therefore a precise diagnosis and course of treatment are essential(Y. Sharma et al., 2024).

The branch that deals with human skin conditions is known as dermatology, several advancements have been made in the dermatological research field which led to an improvised understanding of skin problems and innovative treatments(Jeong et al., 2023). However, dermatology faces problems in the diagnosis process due to the variability of skin conditions and their appearance with an increase in time. Due to this, the examination process of skin infections becomes more complicated and hence delay in treatment. So, the intervention of Machine Learning (ML) and Deep Learning (DL) is more important for early diagnosis and categorization of skin diseases, which is important for better management and effective patient experiences(Reddy et al., 2024)(Ahammed et al., 2022b).

Over the last two decades, due to the widespread use of Artificial Intelligence (AI) (Putatunda, 2019), Machine-Learning (ML) (Ahammed et al., 2022a), and Deep-Learning (DL) (Sazzadul Islam Prottasha et al., 2023), the skin care sector has achieved promising results in medicine, manufacturing, cosmetics, and personal care. Deep learning(Saiwaeo et al., 2023), ML-based techniques are growing very fast and have taken the skin diagnosis process to the next level. DL has enabled algorithms that can analyze images of skin diseases with remarkable accuracy, early identification, and more individualized treatment approaches(Rao, 2021).

1.1 Motivation and Objectives

Although several advances have been made in the realm of deep learning-based skin disease diagnosis, obstacles still impede the successful implementation of these innovations. The motivation behind this study is to enhance the diagnosis process of dermatological conditions using DL approaches. This work aims to improve image segmentation and feature extraction techniques.

This study introduces a Holistically Nested Edge Detection (HNED) technique to improve the edge details of images during segmentation. This step ensures high-quality preprocessing, capturing critical information essential for accurate classification.

The study employs EfficientNet-B0, a powerful DL model proficient in feature extraction from an image and representing them in a 1D array to extract comprehensive and high-dimensional features. This rich feature set is instrumental in capturing the diverse characteristics of skin lesions, enabling a more detailed analysis of disease patterns.

Furthermore, the research evaluates the performance of Convolutional Deep Neural Networks (CNNs) trained on Dermnet dataset encompassing 23 different skin disease classes. This method seeks to improve performance measures, including precision, recall, accuracy, and F1-score, by integrating the feature extraction abilities of EfficientNet-B0 with the categorization strength of CNNs.

In consort with improving the metrics of the designed model, DL-based segmentation models have surged in popularity owing to their capability to produce highly accurate and precise segmentation results(Ahammed et al., 2022a). In the skin disease diagnostic process, these models are very useful since they can delineate the contours of skin diseases even in difficult situations and improve the results(Manerkar et al., 2016). Similarly, numerous DL approaches offer the benefit of autonomous feature extraction from the pre-trained type of CNNs (Shetty et al., 2022)(Benyahia et al., 2022). *Following these advancements, this research paper has some key contributions as follows:*

(1) An advanced image segmentation approach using DL Holistically Nested Edge Detection (HNED) enhances the edge features of the source image during the image segmentation process.
(2) For the multiple feature extraction, a DL-based model EfficientNet-B0 is used, which extracts 1280 features from an image and represents them into a 1D array.
(3) Evaluate convolution deep neural networks (CNNs) for skin disease diagnosis by training 23 different classes of the Dermnet dataset and on the features extracted using EfficintNet-B0 to enhance the categorization performance metrics.

The remnant part of this research paper is outlined as: Section 2 covers the related works done in skin disease diagnosis using DL-based techniques. Section 3 highlights the materials and methodology including the system design workflow of the proposed methodology, dataset, image pre-processing techniques, enhanced CNN-based image segmentation technique, and feature extraction technique. Section 4 expounds on the classification outcomes. Section 5 delineates the experimental configuration and results of the proposed approach while assessing its performance. The research study concludes in section 6.

2. Related works

Researchers have developed many ways to facilitate intelligent diagnostic tools for automated identification of skin problems. According to the many categories of dermatological conditions, image pre-processing, extraction and selection of features methodologies, and classification methods related studies are categorized into various types(R. Sharma & Mehan, 2022). Initially, classification problems were evaluated using several standard ML based algorithms such as Naïve Bayes (NBs)(Balaji et al., 2020)(Hegde et al., 2018), Linear Discriminant Analysis (LDA)(Hegde et al., 2018), K-Nearest Neighbourhood (KNN)(Ballerini et al., 2013)(Rahman et al., n.d.), and Support Vector Machine (SVM)(Hameed et al., 2020) were the preferences of researchers. However, these methodologies have a problem of less data which is further solved by DL techniques.

In (Jagdish et al., 2022) authors suggested a methodology for the categorization of skin diseases using image processing methods. Fuzzy clustering is conducted on 50 sample images using KNN and SVM in conjunction with wavelet analysis. The proposed method achieved an accuracy of 91.2% in identifying skin disease types. In addition, the problem was the model worked only for 50 sample images of two classes.

In(Bandyopadhyay et al., 2022) authors suggested a hybrid approach that integrates ML with DL for choosing features and categorization. Deep neural network techniques such as Alexnet, Resnet50, GoogleNet, and VGG16 were used for feature selection, and ML based techniques corresponding to SVM, Ensemble Adaboost, and Decision Tree (DT) were used for classification. Further literature relevant to the study is summarized in Table 1.

Table 1: Depicts the comparison based on image segmentation and feature extraction

Reference	Research aim	Techniques used	Feature extracted	Sample size	Classification metrics
(Kashyap & Kashyap, 2024; Wei et al., 2018)	Skin disease identification using image segmentation and feature extraction	Median Filter, GLCM & SVM	Color, Texture	90 images	~ 90%
(Roy et al., 2019)	Various segmentation techniques for skin disease detection	Adaptive thresholding, Edge Detection, Morphology-based segmentation and K-means clustering	Not Defined	5	Not Defined
(Gede et al., 2020)	Detection of dermatological conditions using K-means clustering separation and feature extraction techniques	K-means clustering Segmentation, Discrete Wavelet Transform (DWT) and SVM	Color	131 images (4 classes of skin diseases)	Sensitivity- 95% Specificity- 97.9% Accuracy- 97.1%
(Sinthura et al., 2020)	Leveraging technologies for skin diseases using image processing	Otsu's thresholding, GLCM, and SVM	Autocorrelation, homogeneity, entropy, and Energy	100 images	SVM- 89%
(AlDera & Othman, 2022)	Categorization and identification of dermatological conditions with ML and image processing techniques	Otsu's thresholding, Gabor and Entropy for texture, and Sobel for edge	Texture and Edge	Dermnet NZ & Atlas dermatologic (377 images & 5 types of diseases)	Accuracy: SVM- 90.7% RF- 84.2% KNN- 67.1%

Moreover, extensive literature exists detailing the development of several algorithms designed to classify skin illnesses with accuracy and efficiency, enabling the fast identification of many skin-related conditions by these classification methods. From the literature, it is observed that most of the research has been conducted on a few classes of skin diseases. It is also detected that most of the research has been done on small sample-size datasets and the count of features extracted is also less. Furthermore, it is noticed that much literature is available for multiple classes but not more than 20 classes of skin diseases This work seeks to address the constraint by analysing the Dermnet dataset and applying an enhanced image segmentation and feature extraction technique.

3. Materials and Methods

3.1 Proposed Methodology

This research presents a framework for the early categorization of skin disorders, consisting of two primary approaches. The first approach is a pre-processed enhanced edge detection algorithm along with deep learning and the second approach is feature extraction using an EfficientNet-B0 deep learning-based model (Tan & Le, 2019). Figure 1 illustrates the recommended structure for the early categorization of skin diseases. The original images are sourced from the Dermnet dataset. The pre-processing phase involves stages like resizing the image, removing noise, improving contrast, sharpening the image, and feature extraction. The proposed approach employs a CNNs to categorize performance measures.

3.2 Dataset: The initial vital stage in creating an automated system for the early categorization of skin disorders is data collection. The dataset may be obtained from several sources, such as skincare centers, hospitals, open-access platforms, official websites, and other credible archives. This study utilizes the Dermnet dataset, a publicly accessible online resource recognized as the biggest dermatological database for medical teaching purposes. The dataset comprises 23 distinct illness categories. The aggregate quantity of samples is around 19,500. The images are in the form of JPEG and consist of three channels red, green and blue.

At this step, input images are extracted from the Dermnet being collected. The dataset is split into 80% for the training purpose and 20 % for the test purpose. Initially, the images are loaded from the dataset to complete the pre-processing steps. Each image in the dataset represents a particular disease and provides the visual information to train and test the model. Correctly loading and managing these sample images is crucial to guarantee the accuracy and dependability of the processes that comprise the model. Various categories of samples obtained from the Dermnet dataset are displayed in Figure 2.

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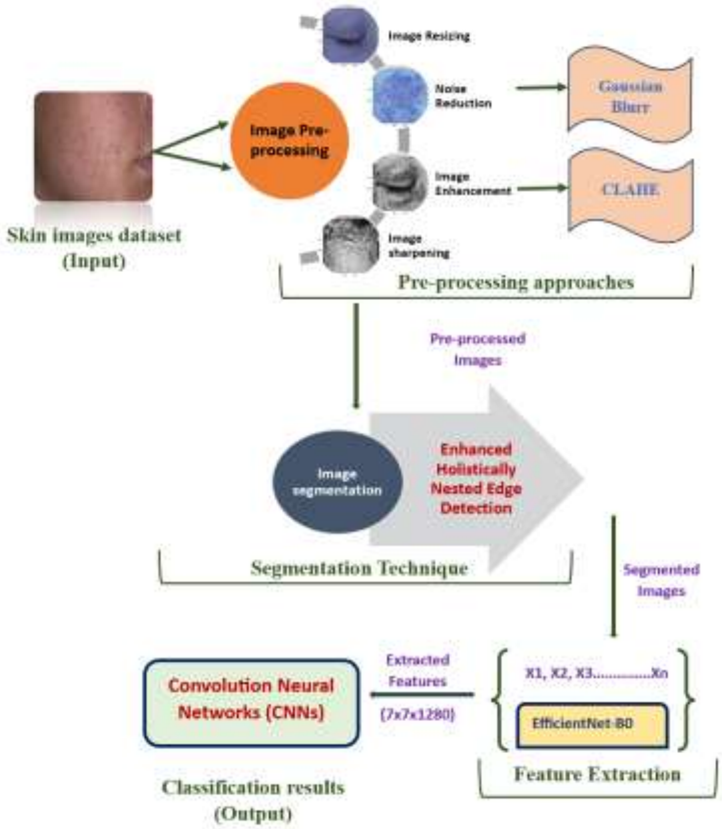


Figure 1: Illustrates a comprehensive description of the proposed system

Acne **Actinic keratosis** **Bullous** **Cellulitis** **Eczema**

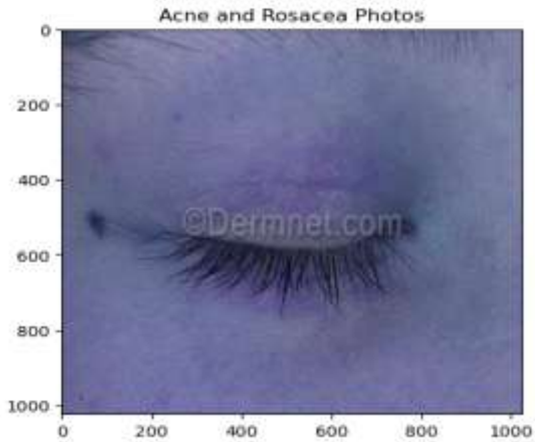
Figure 2: Sample images taken from the Dermnet dataset

3.3 Image Pre-processing: Here, the method of acquiring pictures should be irregular in several ways. In the proposed system, the second phase is image pre-processing. Thus, the primary objective of the preprocessing stage is to improve the picture parameters such as quality, clarity, etc., by eliminating or minimizing the background or other undesirable areas of the image. (Monika et al., 2020). In medical imaging, preprocessing also plays a vital role in enhancing the visibility of significant features in skin images for further analysis and processing, making it easier to classify using deep-learning-based models. In this paper, this is done by using three main steps: a) image resizing b) noise reduction c) image enhancement

3.3.1 Image Resizing: The preprocessing phase encompasses many approaches to ready the images for evaluation and training models. First, image resizing is performed to standardize all sample images to a size of 1024 x1024 pixels. This ensures uniformity across the dataset, crucial for efficient processing and accurate model training. Bilinear interpolation is used to scale up or down the images. The equation for bilinear interpolation is:

$$BI'(x',y') = (1-\delta x)(1-\delta y)BI(x1,y1) + \delta x(1-\delta y)BI(x2,y1) + (1-\delta x)\delta bBI(x1,y2) + \delta x\delta yBI(x2,y2) \quad (1)$$

In Equation (1) (x', y') are the pixel coordinates in the resized image. (x1, y1) and (x2, y2) are the nearest pixel coordinates in the initial image. δa, and δb are the fractional parts of the pixel coordinates. The equation evaluates the value of a pixel in the new image based on its position relative to the original image, for smooth scale up and down. The new dimensions (1024 x1024) represent the width and height in pixels for an image. The original image (size 472 x 720) and resized image data sample are depicted in Figures 3 (a) and (b) respectively.



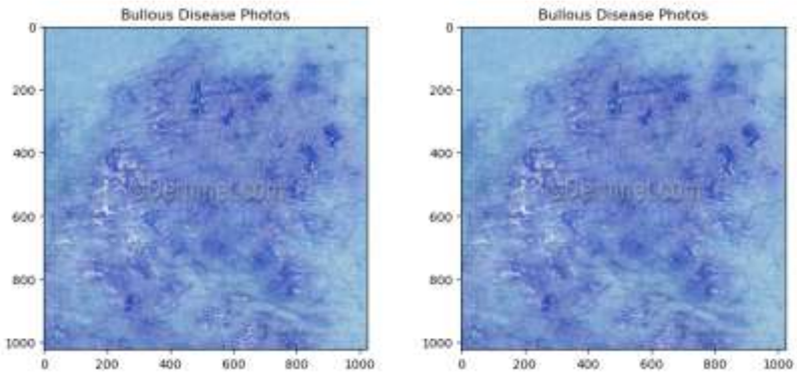
a) b)

Figure 3: a) original image data sample b) resized image data sample

3.3.2 Noise Reduction: After resizing, image blurring, smoothing, and filtering techniques need to be applied to remove or reduce the unwanted noise present in the image data samples. Noise from digital images can be reduced by the commonly used filtration technique which is Gaussian blurring. It is used to smoothen the images by reducing the noise from the images(Ahammed et al., 2022b). In the proposed model, a kernel of size 3x3 matrix is used, to compute the blur for each pixel. The pixel value is calculated as the kernel moves over the image data. The pixel value is further utilized by the Gaussian blur function. The Gaussian function is given by equation:

$$G(x,y) = \frac{1}{\sqrt{2\pi\sigma^2}}\ e^{\left(-\frac{(x2+y2)}{2\sigma^2}\right)} \quad (2)$$

In Equation (2), x and y signify pixel coordinates in the kernel w.r.t. to center. σ (standard deviation) controls the distribution of the Gaussian function. Samples of image data before and after are illustrated in Figures 4(a) & (b) respectively.



a) b)

Figure 4: Noise reduction a) resized image before applying Gaussian blurring b) after applying Gaussian blurring

3.3.3 Image Enhancement: It is used to improve the image contrast and brightness characteristics. (Ajith et al., 2017). The improved contrast of the image ensures accurate performance metrics of the classification model (Saiwaeo et al., 2023) . In our proposed work, we have used histogram equalization to enhance the contrast of the images by stretching the histogram of pixel intensities, which improves the visibility of details across varying lighting conditions as represented in the equation (3), where E’ is the new intensity value, E is the original intensity value, I is the number of possible intensity levels (256 for 8-bit image), N is the total number of pixels of the image, h(j) is count of pixels that have intensity j, and $\sum_{j=0}^{E} h(j)$ is the cumulative distribution function which sums up the histogram values up to intensity E

$$E' = \left(\frac{I-1}{N}\right) * \sum_{j=0}^{E} h(j) \quad (3)$$

Additionally, contrast-limited adaptive histogram equalization (CLAHE) is a new form of adaptive histogram equalization (AHE) that is used locally to enhance contrast in small regions by preventing over-amplification. In the proposed methodology, after applying the image resizing technique and Gaussian blurring to the input image dataset of 23 distinct classes, we have converted our images into grayscale making them suitable for CLAHE. Further, the image is bifurcated into non-overlapping rectangular homogeneous regions of 8x8 tiles (selected by OpenCV), a set of 64 tiles. At the end of this technique, bilinear interpolation is applied to merge all the tiles. Figure 5 depicts the process of the CLAHE method. The main objective of this method is to enhance the visibility of features and textures in low contrast regions by expanding the range of brightness for every tile, so ensuring deeper and lighter parts more apparent. Figures 6 (a) and (b) represent the images prior and after CLAHE.

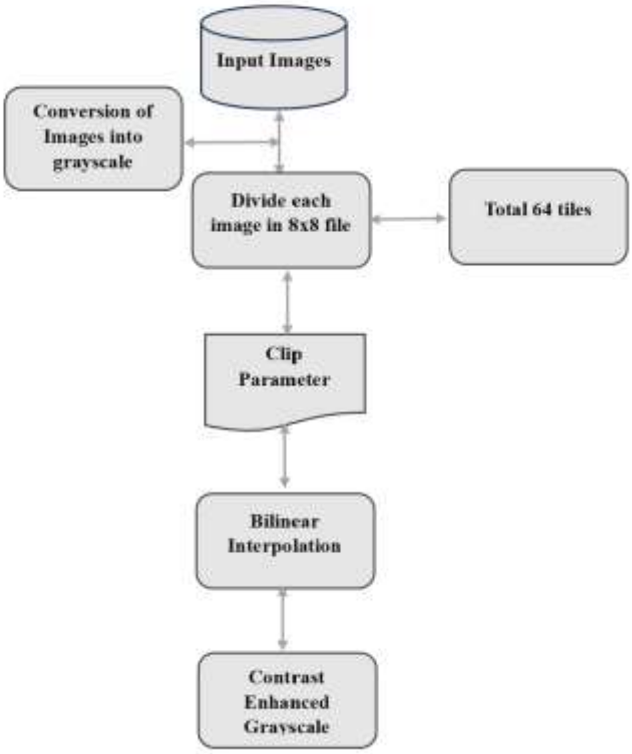
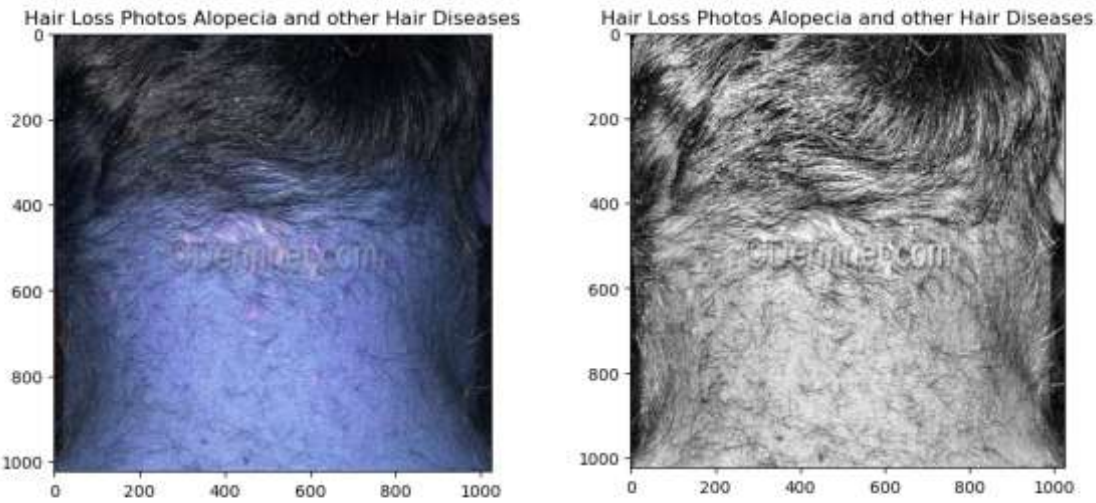


Figure 5: Systematic workflow of CLAHE



a) b)

Figure 6 a) image before applying CLAHE b) after contrast enhancement

3.3.4 Image Sharpening: In the proposed methodology, the last phase of pre-processing is image sharpening. It is applied to enhance the edges and details in the images, making significant features more prominent. We have used an unsharp masking technique of image sharpening. The equation of unsharp masking is:

$$\text{Sharpened Image} = \alpha \times \text{Original Image} - \beta \times \text{Blurred Image} + \gamma \quad (4)$$

Where:

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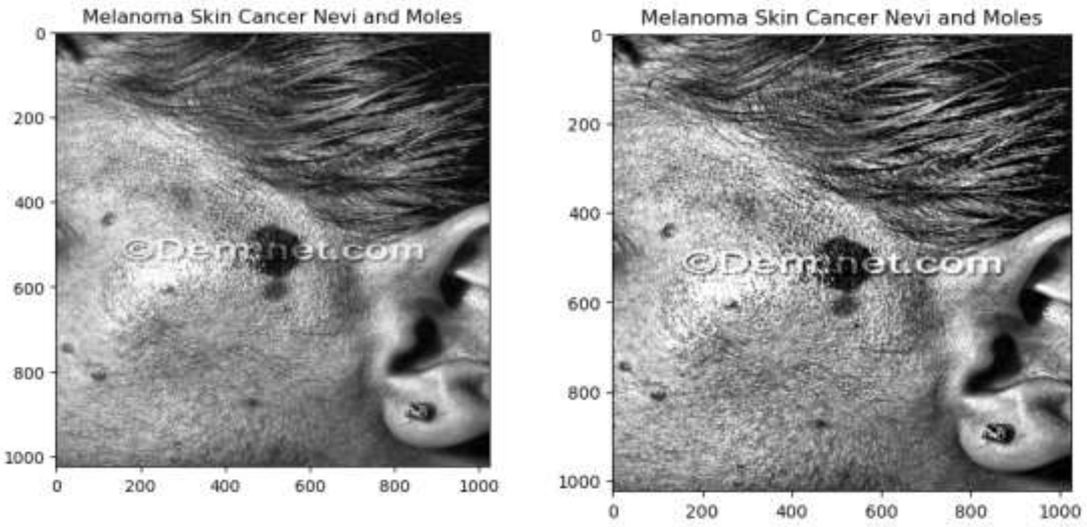
i) α is the positive constant that controls the originality of the image
ii) β is the weight applied to the blurred image
iii) γ it is used to adjust the brightness

For our proposed work, equation (4) corresponds to:

Sharpened Image = 1.5 x original image – 0.5 x blurred image +0

In equation (4) the original image is scaled by a value of 1.5, which enhances the image's intensity. -0.5 is the blurred version of the image, which reduces the smoothed areas and highlights the edges, and no additional brightness adjustments are applied as shown in Figure 6.



a) b)

Figure 7: a) Contrast-enhanced image b) Resultant sharpened image

3.4 Image Segmentation: In the proposed methodology, an enhanced holistically nested edge detection algorithm (E-HNED) combining deep neural networks is used to segment images by detecting edges. E-HNED provides more detailed and accurate edge maps than traditional methods. The use of convolution neural networks (CNNs) in HNED provides significant improvements by predicting edges at various scales and combining these predictions for a comprehensive edge map. The proposed hybrid approach offers more control and fine-tuning results.

3.4.1 Proposed Enhanced CNN-based nested edge detection image segmentation technique

A pre-processed convolution neural networks (CNNs) based holistically Nested edge detection (HNED) algorithm is applied to the input images. However, the conventional holistically edge detection segmentation technique has certain limitations in handling noise, complex structures, semantic segmentation, and lack of post-processing optimization(Xie & Tu, 2017). In order, to remove these problems, some advancements have been accomplished by the proposed work, and termed as enhanced holistically nested edge detection (E-HNED). The Proposed E-HNED works on the following algorithm. Figure 8 depicts the workflow of the proposed architecture for image segmentation

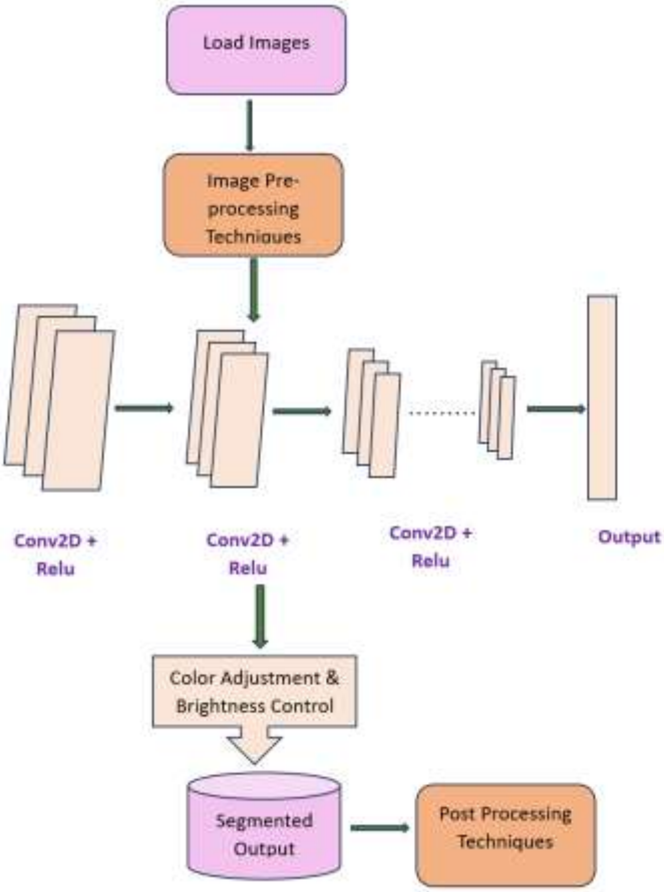


Figure 8: Proposed enhanced holistically nested edge detection system design

Algorithm:

Step1: Input: Load image dataset of 23 different classes of skin diseases

Step 2: Output: Each convolutional layer learns to detect specific features, with lower layers taking basic patterns (such as edges and textures)

Step 3: For each image file in the sub-folder of the image dataset

a) Read image
b) Preprocess image
- Convert image into grayscale
- Apply Gaussian blur to the grayscale image
- Find the minimum and maximum pixel values in the blurred image
- Apply binary thresholding based on a fraction of the maximum value
- Apply median blur to the threshold to the threshold image
- Perform morphological operations: Dilation and closing

c) Contour detection and bounding box
- Identifies contours and finds the largest contour
- Calculate a bounding rectangle and draw the largest contour on the original image.

d) Color adjustment
- Resize the image
- Converts the image from RGB to HSV color space for color manipulation where Hue is reduced by * 0.7, Saturation ↑ *1.5

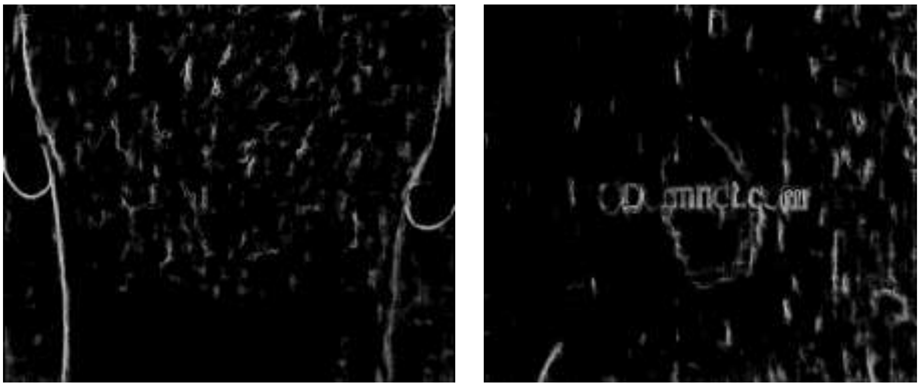
, and value ↓ *0.5.
- Converts the adjusted image back to BGR color space.
- Adjusts the brightness and contrast

e) Convolution neural network-based holistically nested edge detection segmentation:
- Create class
- Create convolution layers: class contains 5 blocks of neural network and each block has multiple convolution layers (maximum 3) followed by relu activation function.

i) 1st layer: Conv2d(in_chan=3, out_chan=64, ker_size=3, stride=1, padding=1)
ii) 2nd layer: Conv2d(in_chan=64, out_chan=64, ker_size=3, stride=1, padding=1)
xiii) 13th layer: Conv2d(in_chan=512, out_chan=512, ker_size=3, stride=1, padding=1)
- Create score layers for each block
- Combine layers to merge output
- Load pre-trained weight

f) Create a forward method to process input images through the CNNs.
g) Color adjustment and brightness control
h) Store the output in the output directory named segmented output.
i) Perform post-processing: resizing the output, converting it back to BGR color space, and saving it.

In the proposed algorithm, the handling of image size plays a vital role in ensuring that the image processing pipeline, functions smoothly and efficiently. By standardizing the input and output dimensions, the algorithm not only meets the requirements of the convolutional neural network but also optimizes performance and enables consistent comparisons between input and output images. This uniformity is critical in image segmentation tasks, where precise delineation of objects or regions in an image is required, as it facilitates the effective evaluation of the model's performance.



a) b)

Figure 9: Segmentation output image samples a) acne b) Melanoma Skin Cancer Nevi

3.5 Feature Extraction: Feature extraction is a critical component in the illness detection process. It is the procedure by which unprocessed visual data is converted into numerical characteristics. This results in a reduction in the resources necessary to display the real data while preserving the initial data for subsequent consequences. Several features such as edge, shape, color, intensity, texture, diameter, asymmetric feature, and more abstract patterns are adjusted in such a way that the hidden characteristics of the image are outshined. Moreover, these derived traits will significantly aid in the efficient, rapid, and accurate detection of skin illnesses (Krishna Monika et al., 2020)(Badiger et al., 2022).

Our proposed system used EfficientNet-B0 to extract maximum numerical features from the image dataset based on the number of convolutional layers (Tan & Le, 2019). EfficientNet-B0 is a type of CNN, curated with a focus on accuracy, sensitivity, and efficiency. The workflow of EfficientNe-B0 is:

a) Input Image: The input layer of the model considers an image of dimensions 224x224x3.

b) Convolution layer (CL): The first layer implements a 3x3 convolution using 32 filters and a stride of 2 and reduces the image size to 112x112. Each Convolution layer applied a filter to the image data for generating feature maps. The mathematical expression for the convolution layer is given below:

$$y_{a,b,c} = \sum_{l=1}^{L} \sum_{m=1}^{M} \sum_{n=1}^{N} x_{a+l,b+m,n} * W_{l,m,n,c} \qquad (5)$$

In the above equation (5) x signifies input image, W signifies kernel, y represents output feature map after the convolution, a, and b are the height and weight of the image, c is the index of the output channel, L and M are the filter dimensions, and N is the count of input channel.

c) Batch normalization (BN): It is employed to regulate the activation mechanisms of a layer for improved stability and accelerated convergence to ensure that the mean activation remains 0 and variance remains around 1. The following equation (6) represents the working of batch normalization where x_a is the activation from the convolution layer, μbatch is the mean value, σ_{batch}^2 is the variance of the batch, and ∈ is the constant.

$$x_a = \frac{x_a - \mu\text{batch}}{\sqrt{\sigma_{\text{batch}}^2} + \epsilon} \qquad (6)$$

d) Activation function: In this model, the swish activation function is used which provides non-linearity and improves the model performance. The equation for the swish function is:

$$\text{Swish}(x) = x.\sigma(x) \qquad (7)$$

Where, $\sigma(x)$ is the sigmoid function.

e) MBConv Blocks (Depthwise separable convolutions): The EfficientNet-B0's layers consist of several mobile inverted bottleneck convolution (MBConv) blocks. For each MBConv block, depthwise separable convolution followed by pointwise convolution is calculated which diminishes the further computational complexity. Depthwise convolution, performed separately to each channel, generally changes the feature by continuously multiplying the result by an identical factor, as shown in the equation (8):

$$y_{a,b,c} = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{a+m,b+n,c} * W_{m,n,c} \qquad (8)$$

Here, x signifies input, W is the depthwise filter, and y signifies output.
Further, equation (9) for pointwise convolution in which a 1x1 filter is applied to the output (Saiwaeo et al., 2023) is represented as:

$$y_{a,b,k} = \sum_{l=1}^{L} x_{a,b,l,} * W_{1,1,l,k} \qquad (9)$$

f) Global average pooling (GAP): It decreases the spatial dimensionality of the output feature map to create a 1x1 feature map. Global average pooling (GAP) takes the average value of each feature map, a 7x7x1280 feature map in this experimental work, which is reduced to a 1D vector of length 1280, by preserving the important characteristics of the image. The feature map of the 1D vector is calculated using the equation (10), where $x_{i,j,m}$ is the value at position (i, j) in channel m, H X W is the spatial dimensionality of the feature map, and f_{m} is the average value of channel c.

$$f_m = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{J=1}^{W} x_{i,j,m} \qquad (10)$$

In this feature extraction technique, each feature map summarizes the image's patterns, edges, textures, etc. The extracted features can be used in many other tasks like classification, clustering, etc. Table 2 depicts the structure of each MBConv block along with input and output layers.

Table 2: Represents the structure of each block of the feature extraction technique

Layer Name	***Output Shape***	***Layer Description***
Input layer	(224,224,3)	Input image size with 3 color channels
Conv2D	(112.112.32)	Starting initial convolution layer with 32 filters and stride 2
MBConv1	(112, 112, 16)	1 block with 16 filters
MBConv6	(56, 56, 24)	2 blocks with 24 filters
MBConv6	(28, 28,40)	2 blocks with 40 filters
MBConv6	(14, 14, 80)	3 blocks with 80 filters
MBConv6	(14, 14, 112)	3 blocks with 112 filters
MBConv6	(7, 7, 192)	4 blocks with 192 filters
MBConv6	(7, 7, 320)	1 block with 320 filters
Con2D(1x1)	(7,7,1280)	Final 1x1 convolution is performed before GAP
GAP	(1280, 1)	It is applied to reduce the feature map to a 1D vector

g) Label mapping: In the proposed work, the label represents the numeric class identifier corresponding to the skin condition category of an image. Image belongs to a specific skin disease category, and these categories are mapped to numerical values using a dictionary called label mapping. Each entry in this list corresponds to a numerical label that matches the extracted features for an image stored in the features list. The label is then appended to the labels list, which stores the numerical labels for each image. In this work, if an image is found in the subfolder 'Acne and Rosacea Photos', the corresponding label is 0. If another image is from the subfolder 'Melanoma Skin

Cancer Nevi and Moles', its label will be 11. These labels help the model learn to associate certain patterns in images with specific categories of skin diseases.

4. **Classification results:**

The proposed framework of enhanced holistically nested edge detection and EfficientNet-B0 used for feature extraction is utilized further using convolution neural networks (CNNs) (Maqsood & Damaševičius, 2023) for the classification of skin diseases. From the given dataset Dermnet 15,500 images (80% data) are used for training the CNN model and 3500 images (20% data) are used for testing the model. In this model, the conv1D layer has 64 filters, each having a 3 x 3 kernel size, and uses the rectified linear unit (ReLU) activation function. Relu introduces non-linearity into the model, allowing it to learn complex patterns. The model is trained for 50 epochs. The achieved performance metrics of this framework are accuracy 77%, precision 75%, recall 91%, F1-score 76%, and specificity 96%.

5. Experimental setup and outcomes

The experiment is implemented with the Python tool using the PyTorch framework. While implementing the proposed framework of EHNED & EfficientNetB0 the initial resolution of each image is resized. The Dermnet dataset is taken from the online open source library. CNN-based image segmentation is implemented to determine edges and the pre-trained EfficientNet-B0 model is used to extract 1280 features for each image and represent them in 1D vector. The CNNs model with the Relu activation is used to determine the performance metrics.

a. Evaluation metrics

To accurately measure the effectiveness of the CNNs model for this framework, five widely used metrics as mentioned below are evaluated. The calculation equations for these five metrics are as follows:

$$\text{Accuracy} = \frac{\text{TP+FN}}{\text{TP+ TN+FP+FN}} \tag{11}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{12}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{13}$$

$$\text{F1-Score} = 2.\frac{\text{Percision X Recall}}{\text{Percision +Recall}} \tag{14}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TP+FP}} \tag{15}$$

b. Outcomes: From the above-discussed metrics, it is observed that the convolution neural networks with the Dermnet dataset of 23 different classes provide promising results of recall of 91% and specificity of 96% for the designed framework of enhanced holistically nested edge detection and deep learning-based feature extraction using EfficientNet-B0 pre-trained model.

6. Conclusion

In conclusion, the study proposed an automated detection of skin disorders by introducing a novel deep learning-based framework that improves image segmentation and feature extraction methods. In this study, enhanced Holistically Nested Edge Detection (HNED) is used for improved edge detail in segmentation and a deep learning-based EfficientNet-B0 model is used to extract a complete set of 1280 features per image, the study effectively captures important information required for correct classification. The assessment of CNNs which is trained on the

Dermnet dataset, comprises 23 skin disease classifications and shows that the framework is capable of achieving promising performance metrics like as 91% recall and 96% specificity. These findings demonstrate the proposed approach's resilience in addressing the challenges of skin disease diagnosis, such as various lesion features and difficult edge delineations. This research highlights the promise of sophisticated DL techniques for improving diagnosis metrics and also provides useful insights into the area of dermatology. Furthermore, in the future, this work intends to increase accuracy by focusing on feature selection approaches and dimensionality reduction techniques.

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