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An Efficient Algorithm for Automated Skin Lesion Detection: A Non-Machine Learning Approach

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ABSTRACT

Skin lesion detection is a very important task in medical applications such as disease diagnostic and cancer detection. This paper suggests an efficient algorithm for skin lesion detection relying on advanced image processing techniques without using machine learning or deep learning algorithms. A set of algorithms is proposed to enhance traditional image processing methods to scrutinize dermatological images, concentrating on melanoma detection. The proposed method combines color space transformation, contrast enhancement, active contour segmentation. ABCD criteria (Asymmetry, Border irregularity, Color variegation, and Diameter) is used in feature extraction. The approach is evaluated on the ISIC (International Skin Image Collaboration) 2020 dataset, accomplishing an accuracy of 84% in differentiating between malignant and benign skin lesions. The results indicate the potential of non-machine learning techniques in dermatological image analysis, providing computationally efficient and interpretable alternative to data-intensive deep learning algorithms.

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1. Introduction

Skin cancer is considered as one of the most prevailing forms of cancer worldwide and the deadliest type is melanoma [1]. The improved patient outcomes and successful treatment depends on the early detection of skin lesion. While recent development in the methods that used machine learning and deep learning models have achieved a remarkable improvement in skin lesion detection, these methods often require significant computational resources and large datasets. The interpretability and the complexity generally represent some difficulties in these models.

The aim of this research is to examine the ability of traditional image processing algorithms that can be used in skin lesion detection, specifically concentrating on melanoma. Well established computer vision techniques are leveraged to seek and develop computationally efficient and transparent methods that can accomplish a comparable result to machine learning procedures. Several image processing techniques are combined in the proposed method. For enhancing feature visibility, color space transformation is used then for image enhancement, contrast-limited adaptive Histogram equalization (CLAHE) is employed. Active contour segmentation is utilized for lesion boundary detection, while feature extraction is implemented depending on (ABCD) criteria (Asymmetry, Border irregularity, Color variegation, and Diameter)

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The proposed method is evaluated on ISIC 2020 dataset which available publicly. Then, the results are compared with the existing algorithms. The main goal of this approach is to manifest that the deliberately configured image processing algorithms can accurately detect skin lesion without the need for the large datasets and complex neural networks.

2. Related Works

Nachbar et al. [2]. introduced the ABCD rule that used widely for evaluating pigmented lesions in dermatology. It produced a systemic approach to estimate the likelihood of melanoma relied on visual characteristics. A method by Celebi et al. (2007) is proposed for border detection using statistical region merging in dermoscopy images [3]. This method performed high accuracy in describing lesion boundaries which is necessary for classification and feature extraction.

Six different segmentations methods for dermoscopy images are compared by Silveira et al. (2009) including adaptive thresholding and active contours [4]. The study provides a valuable understanding of the effectiveness of different segmentation techniques for skin lesion analysis.

Garnavi et al. (2011) developed a diagnostic system for melanoma detection [5]. This system is computer aided and uses color and texture features. Their study demonstrates how the classification accuracy is improved effectively by combining multiple feature types.

A non-invasive real-time automated skin lesion analysis system is developed by Abuzaghleh et al. (2015) for melanoma early detection and prevention[6]. Their system utilizes a combination of image processing techniques where lesion classification is achieved with high accuracy.

A computational approach for detecting pigmented skin lesions in macroscopic images is presented by Oliveira et al. (2016). This paper illustrates the computational methods for pigmented skin lesion classification[7]. Their method investigates diverse feature extraction and image processing techniques, providing a helpful resource for researchers in the field.

Kasmi and Mokrani (2016) developed a new algorithm by using hybrid approach combining edged based and region-based techniques for skin lesion border detection[8]. Their proposed method displays improvement in the performance when comparing with traditional edge detection algorithms.

Chang et al. (2022) developed melanoma detection model that have improvements in some approaches where image features are extracted automatically by applying transfer learning methods[9].

Bhimavarapu and Battineni (2022) published a study in which deep learning model called Fuzzy GC-SCNN is used to detect and classify melanoma in dermoscopic images[10]. This model achieved high classification accuracy when evaluated on public datasets with perfect specificity and sensitivity and made an important advancement in the process of melanoma detection automatically.

Salma W. and Eltrass A. proposed a study in (2022) where they developed a model uses a computer aided diagnostic system for classification of skin lesions into benign and malignant achieving high accuracy with low complexity[11]. The morphological filtering is applied to remove artifact and hair. GrabCut Algorithm in HSV color space is used to automatically segment skin lesion. The ABCD rule is used for enhancement of melanoma detection. Various pretrained convolutional neural network were evaluated for classification.

In (2024), Jaber N. and Akbas A. developed a robust method for detecting melanoma using Convolutional Neural Networks (CNNs)[12]. The aim of this study is to classify Melanoma images as healthy and non-healthy using ISIC dataset (International Skin Imaging Collaboration). The traditional classification algorithms such as Support Vector Machine (SVM), Decision Tree, and K-Nearest Neighbors (K-NN) are compared with their CNN based method. Additionally, the classification performance was enhanced using Harris Hawks Optimization algorithm. The study clarified that CNN based approach was more accurate and efficient in melanoma detection than other algorithms.

3. Methodology

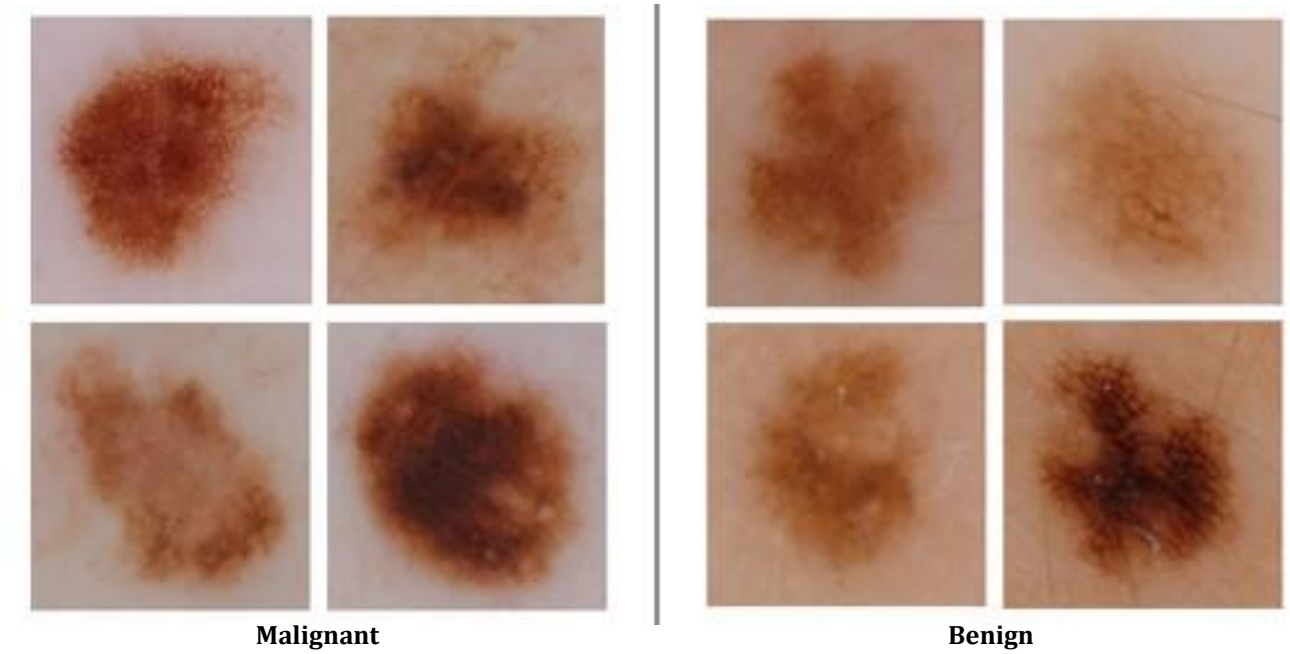
3.1. Dataset Description

For this paper, the ISIC 2020 dataset is used which consist of 33,126 dermoscopic images of skin lesions, each with connected diagnostic [13]. The dataset includes both malignant and benign lesions. The melanoma represents the primary malignant category of interest.

Table 1: Dataset Distribution.

Category	Number of Images
Benign	27,654
Malignant	5,472
Total	33,126

The images format in the dataset is JPEG and the resolution is varied. With each image there is a metadata information including clinical diagnosis and demographic.



Malignant **Benign**

Fig. (1) Examples of ISIC 2020 Dataset

3.2. Proposed Algorithm

The following figure shows the proposed algorithm:

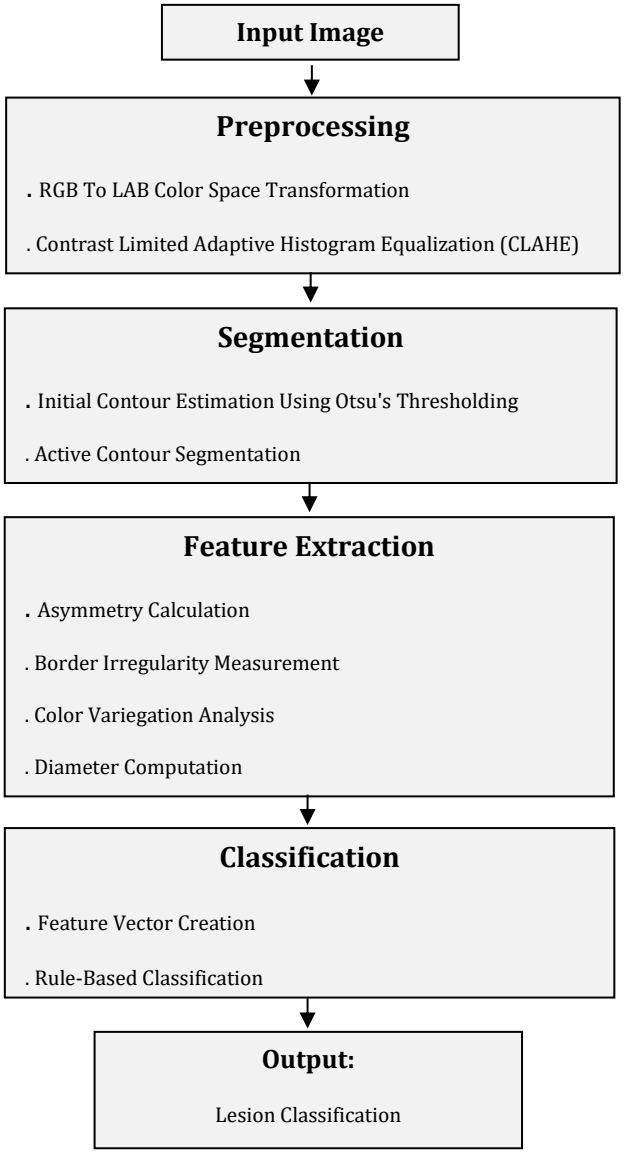


Fig. (2) The Proposed System

3.2.1. *Preprocessing*:

This step includes two stages. In the first stage color space transformation is applied (RGB to LAB). The second stage is performed by using contrast limited adaptive histogram equalization (CLAHE).

Color space transformation (RGB to LAB) is widely used in image processing especially for the purpose of color manipulation or analysis. The structure of LAB color space makes it more perceptually uniform where the same amount of numerical change corresponds to the same amount of visually perceived change[14]. The transformation from RGB to LAB require two steps:

• Convert RGB to XYZ color space.

• Convert XYZ to LAB color space.

Firstly, the RGB values need to be normalized to the range [0,1] if they are not already normalized. Then the normalized RGB values are converted to XYZ color space using the following formulas:

$$X = 0.4124564 \,.\, R + 0.3575761 \,.\, G + 0.1804375 \,.\, B \quad (1)$$

$$Y = 0.2126729 \,.\, R + 0.7151522 \,.\, G + 0.0721750 \,.\, B \quad (2)$$

$$Z = 0.0193339 \,.\, R + 0.1191920 \,.\, G + 0.9503041 \,.\, B \quad (3)$$

After that the XYZ values are converted to LAB using the following formulas:

$$L^* = 116 \cdot f\left(\frac{Y}{Y_n}\right) - 16 \quad (4)$$

$$a^* = 500 \cdot \left(f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right) \quad (5)$$

$$b^* = 200 \cdot \left(f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right) \quad (6)$$

where (X_n), (Y_n), and (Z_n) are the reference white values, and the function $(f(t))$ is defined as:

$$f(t) = \begin{cases} t^{1/3} & \text{if } t > \left(\frac{6}{29}\right)^3 \\ \frac{1}{3}\left(\frac{29}{6}\right)^2 t + \frac{4}{29} & \text{otherwise} \end{cases} \quad (7)$$

Contrast Limited Adaptive Histogram Equalization (CLAHE) is a technique used in image processing to enhance the contrast of image. CLAHE runs on small region in the image called tiles while histogram equalization uses a global transformation. This method enhances image's local contrast and limits the amplification of noise[15]. CLAHE includes the following steps with their formulas:

Key Features of CLAHE:

- **Adaptive Processing:** The image is divided into small blocks called (tiles) and the histogram is computed for each tile allowing for localized contrast enhancement.
- **Contrast Limiting:** The over amplification is prevented where the histogram is clipped at a predefined limit. The excess pixels are redistributed to enhance contrast without introducing noise.
- **Interpolation:** Bilinear interpolation is used to combine tiles after processing to confirm smooth transitions between adjacent tiles.

Equations of CLAHE:

- **Local histogram calculation**: for a local tile *T*, the histogram $H_T(i)$ is the frequency of intensity level (i) in the tile

$$H_T(i) = \sum_{x,y \in T} \delta(f(x,y) - i) \quad (8)$$

Where $f(x, y)$ is the intensity of the pixel at (x, y) and δ is the Kronecker delta function (1 if the condition is met, 0 otherwise)

- **Cumulative Distribution Function (CDF):** The CDF is used to map the old pixel values to new ones and it is calculated from the histogram.

$$CDF_T(i) = \frac{1}{n}\sum_{j=0}^{i} H_T(j) \quad (9)$$

Where:

- n is the total number of pixels in the tile T.
- $H_T(j)$ is the histogram value for intensity level j.
- $CDF_T(i)$ is the CDF for intensity level i.

- **Contrast Limiting (clipping):** A clip limit CL is defined to limit contrast. the histogram is clipped if the frequency of any bin in the histogram exceeds the CL and the excess pixels are redistributed across the histogram uniformly.

$$If\ H_T(i) > CL\ \ then:\quad H_T(i) = CL \quad (10)$$

To maintain the sum of the histogram, the excess pixels, $E = \sum(H_T(i) - CL)$ are distributed across all bins.

- **Histogram Equalization:** The new pixel value after CLAHE is determined by the normalized CDF:

$$g(x, y) = round\left((1 - L).CDF_T\big(f(x, y)\big)\right) \quad (11)$$

Where $g(x, y)$ is the new pixel intensity, L is the number of possible intensity levels (e.g. 256 for an 8-bit image) and $CDF_T\big(f(x, y)\big)$ is the value of the CDF for the pixel intensity $f(x, y)$.

- **Interpolation between Tiles:** Bilinear interpolation is used to blend the borders between adjacent tiles after adjusting the contrast in each tile to avoid artifacts at the boundaries.

3.2.2. Segmentation:

This step also contains two stages. Firstly, Otsu's thresholding is utilized for initial contour estimation and secondly active contour segmentation is applied.

Otsu's thresholding is an image thresholding technique that run automatically. It is used in computer vision and image processing to determine the best value that can separate the pixels into two groups: foreground and background [2], [16]. This is done by minimizing the intra class variance or identically maximizing the intra class variance. The equation that shows Otsu's thresholding is

$$\sigma_B^2(t) = \omega_1(t) \cdot \omega_2(t) \cdot \big(\mu_1(t) - \mu_2(t)\big)^2 \quad (12)$$

Where:

- $\sigma_B^2(t)$ is the between-class variance
- $\omega_1(t)$, $\omega_2(t)$ are the probabilities of the two classes separated by a threshold *(t).*
- $\mu_1(t)$, $\mu_2(t)]^2$ are the means of the two classes.

3.2.3. *Feature Extraction*:

This step requires four operations:

- Asymmetry calculation
- Border irregularity measurement
- Color variegation analysis
- Diameter computation

The ABCD rule commonly used in image processing as feature extraction method especially for melanoma detection in dermoscopy images[2]. The ABCD checks four main criteria:

- **Asymmetry (A):** Measures the asymmetry of lesion. Asymmetry score of (0) is given to the fully symmetrical lesion. Asymmetry can be calculated using the following equation:

$$A = \frac{1}{2} \cdot \left(\frac{|A_1 - A_2|}{A_1 + A_2} + \frac{|B_1 - B_2|}{B_1 + B_2} \right) \quad (13)$$

Where:

- A1 and A2 are the areas of the lesion's halves
- B1 and B2 are the perimeters of the lesion's halves

- **Border (B):** evaluates the irregularity of the lesion's border. higher score is given to more irregular border. The equation that used for this purpose is:

$$B = \sum_{i=1}^{N} \left(\frac{d_i}{D} \right) \quad (14)$$

Where: (di) is the distance of each border point from the lesion's centroid, and (D) is the diameter of the lesion.

- **Color (C):** Assesses the color variation within the lesion. Higher score is gone to more colors present in the lesion. The equation of color is:

$$C = \sum_{i=1}^{M} c_i \quad (15)$$

Where (c_i) represents the presence of different colors (e.g., black, brown… within the lesion, and (M) is the total number of colors.

- **Diameter (D):** Measures the diameter of the lesion. Larger diameters are more important. The Diameter equation is:

$$D = \max(d_i) \quad (16)$$

Where (d_i) is the diameter of the lesion.

3.2.4. Classification:

The classification part of this system includes two main steps: feature vector creation and Rule-based classification

- **Feature vector creation** requires extracting important features from an image to build a vector that denotes the image in a numerical format. These features could include relevant characteristics such as shape, color, and texture. Then the feature vector is used as input to the classification algorithm.

As instance, if three features are extracted from an image (e.g., texture variance, mean color, and shape compactness), the feature vector (v) can be represented as:

$$v = [f1, f2, f3] \tag{17}$$

where:

(f_1) is the texture variance,

(f_2) is the mean color,

(f_3) is the shape compactness.

- **Rule-based classification** utilizes a set of "if-then" rules to classify data. Each rule consists of (if part) as an antecedent and (then part) as a consequent. The rules are applied to the feature vectors to find the class of each image[17].

For example, consider the following rules for classifying skin lesions:

Rule 1: If $(f_1 > \theta_1)$ and $(f_2 < \theta_2)$, then the lesion is benign.

Rule 2: If $(f_1 \leq \theta_1)$ and $(f_3 > \theta_3)$, then the lesion is malignant.

Here, (θ_1), (θ_2), and (θ_3) are threshold values determined through analysis.

The classification decision (C) can be expressed as:

$$C = \begin{cases} \text{Benign} & \text{if } f_1 > \theta_1 \text{ and } f_2 < \theta_2 \\ \text{Malignant} & \text{if } f_1 \leq \theta_1 \text{ and } f_3 > \theta_3 \\ \text{Unknown} & \text{otherwise} \end{cases} \tag{18}$$

The if-then rules were built for classification based on feature thresholds derived from the ABCD rule. For instance, asymmetry values above a specific threshold, combined with irregular borders and multiple color variations, indicate a high probability of malignancy. These thresholds were determined from analysis of the dataset and expert knowledge in dermatology.

Example:

- If asymmetry score > 1.5 AND border irregularity score > 4 AND color variation includes dark brown or blue-gray, THEN classify as malignant.

- If asymmetry score ≤ 1 AND border irregularity score ≤ 2 AND diameter ≤ 6 mm, THEN classify as benign.

4. Results and discussion

The proposed system is evaluated on a subset of 5,000 images from the ISIC 2020 dataset where the original distribution of the malignant and benign lesions is maintained. The cross validation on a separate validation set is used to determine the classification threshold. The following evaluations metrics are used to check the performance of the proposed method:

- **Accuracy:** This metrics often measures how the classifier is correct overall

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{19}$$

- **Sensitivity** (Recall or True Positive Rate): It measures the proportion of actual positives that are identified correctly.

$$\text{Sensitivity} = \frac{TP}{TP + FN} \tag{20}$$

- **Specificity** (True negative Rate): It measures the proportion of actual negatives that are identified correctly.

$$\text{Specificity} = \frac{TN}{TN + FP} \tag{21}$$

- **Precision** (positive predictive value): This metric measures how many of the predicted positive cases are actual positives.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{22}$$

- **F1 Score:** It is the harmonic mean of recall and precision and it balances the two metrics especially if they are imbalanced.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{23}$$

- **AUC-ROC** (Area Under the Receiver Operating Characteristic Curve): It measures the ability of classifier to distinguish between negatives and positives classes. Although there isn't a single formula for AUC-ROC (since it is a curve), it is measured typically using the trapezoidal rule over the ROC curve. The ROC curve itself plots the True Positive Rate (Sensitivity) against the False Positive Rate:

$$\text{False Positive Rate} = \frac{FP}{FP + TN} \tag{24}$$

Table 2: Performance Metrics:

Metric	Value
Accuracy	84.1%
Sensitivity	78.9%
Specificity	85.2%
Precision	63.9%
F1-score	0.81
AUC-ROC	0.848

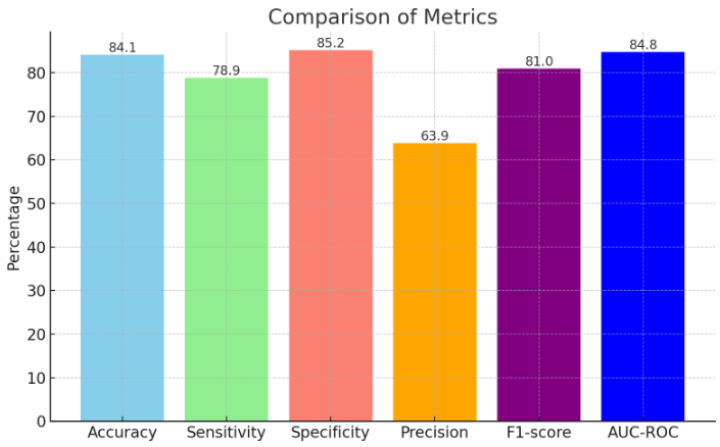


Fig. (3) Performance Metrics

Table 3: Confusion Matrix:

Predicted\Actual	Benign	Malignant
Benign	TP = 3,514	FP = 205
Malignant	FN = 665	TN = 616

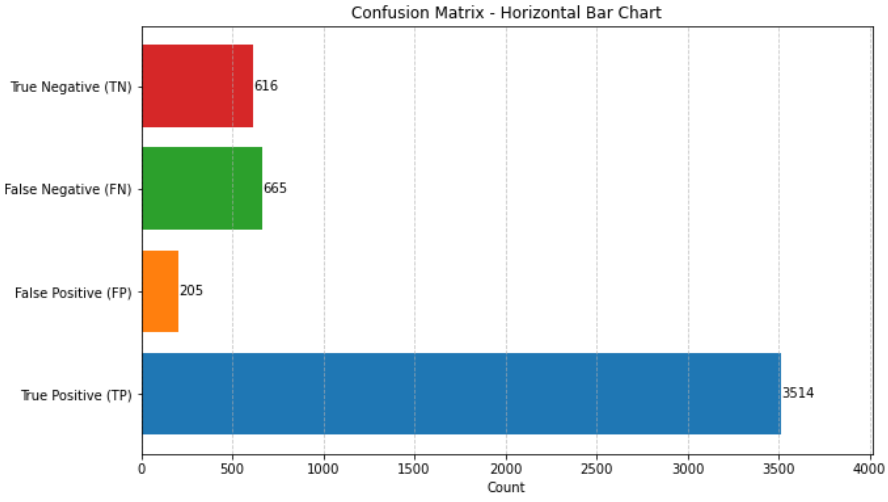


Fig. (4) Confusion metrics

To understand the contribution of each component an ablation study is conducted:

Table 4: Ablation Study Results

Configuration	Accuracy
Full model	84.1%
Without CLAHE	81.7%
Without active contours	79.8%
Without asymmetry feature	82.49%
Without color variegation	79.78%

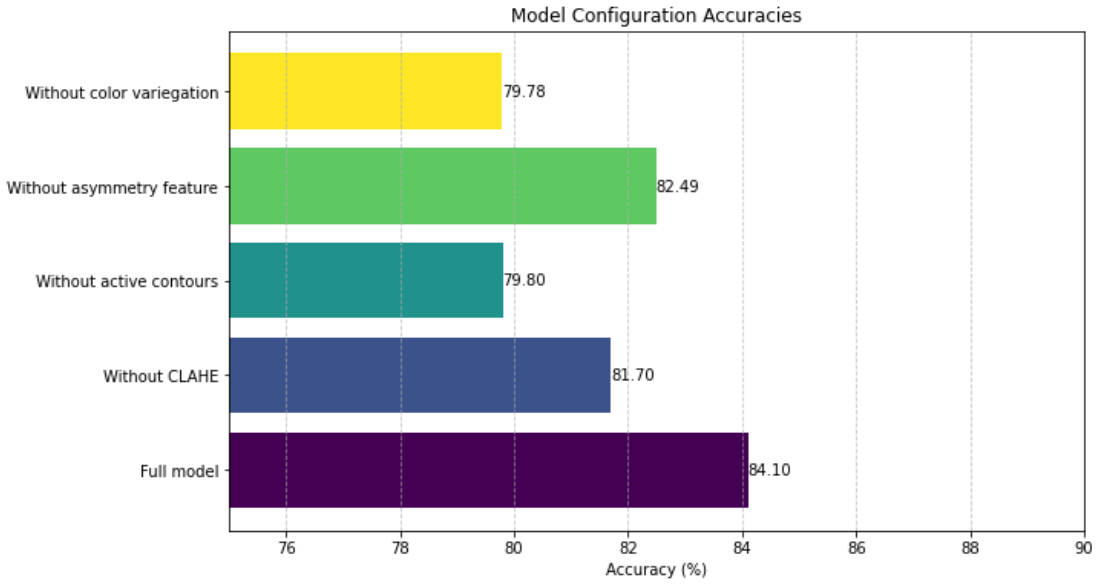


Fig. (5) The ablation Study

The ablation study shows that color variegation analysis and active contour segmentation contribute most significantly to the model's performance.

Our proposed non-machine learning method accomplishes a competitive result in skin lesion detection, with an accuracy of 84.1% and AUC-ROC of 0.848. The method reveals the capability of traditional image processing approaches in dermatological image analysis.

4.1. Advantages of our approach:

There are many advantages of our proposed method, these advantages include:

- **Interpretability:** The medical professionals can easily understand each step of the algorithm because it is simple and transparent.
- **Computational efficiency:** the computational resources require in this method are significantly less than the resources require by deep learning model.
- **Efficiency:** Our proposed method does not require extensive training data so no need for large datasets.

4.2. Limitations:

In spite of the advantages, there are some limitations:

- **Feature engineering:** feature extraction methods and image processing techniques heavily affect the performance.
- **Lack of automatic feature learning:** the proposed approach does not learn hierarchical features automatically, unlike deep learning models.
- **Potential for overfitting:** dataset from different sources or different image characteristics may not work well with rule-based classification algorithm.

4.3. Future work:

- Texture analysis and fractal dimension calculation can be incorporate as additional image processing techniques to achieve more accurate results.
- More sophisticated classification methods that do not depend on machine learning algorithms such as fuzzy logic systems, may be explored and utilized.
- The proposed approach can be extended to be applied on other skin lesion and dermatological conditions.
- A comprehensive comparison with state-of-the-art machine learning algorithms can be conducted on multiple datasets.
- Investigating the potential of merging the proposed approach with lightweight machine learning techniques. This can create a hybrid model that balance interpretability and performance.

5. Conclusion

A new approach is presented in this paper for skin lesion detection where advanced image processing techniques are used to diagnosed melanoma. Color space transformation, contrast enhancement and active contour segmentation are utilized to reach efficient detection and accurate diagnostic without using complicated machine learning algorithms. The ABCD criteria is used to extract features and enhance system's interpretability which makes it simple and easy to use by medical professionals. Evaluating on ISIC 2020 dataset, 84.1% accuracy is reached using the proposed system. This shows the potential of using advanced image processing techniques in image analysis applications. The importance of using color variegation analysis and active contour segmentation is clearly demonstrated in ablation study and emphasized through the efficiency of the proposed system.

Although there are many advantages of the suggested system such as transparency and computational efficiency, some limitations can be found including overfitting to some datasets and manual feature engineering dependency. However, the proposed algorithm draws the way in the field of medical image analysis to explore and develop other algorithms that are not utilize machine learning procedures.

Additional image processing techniques can be incorporated such as texture analysis. some classification methods can be used to keep balance between the interpretability and performance. A comprehensive comparison with state-of-the-art machine learning algorithm may be used to validate the proposed system performance and expand it to other dermatological conditions. A hybrid model that combines strengths of both the suggested system and lightweight machine learning algorithms can be generated to produce a system that have more efficiency and accuracy.

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