# Machine-Learning-Based Skin Lesion Segmentation and Classification

Kunlun Li

***Abstract*—This paper presents a comprehensive examination of segmentation, symmetry detection, and classification of three distinct types of skin lesions: Common Nevi, Atypical Nevi, and Melanoma. Initially, the paper provides an overview of the dataset format and the information it contains. Subsequently, it summarizes and illustrates the connection between previous and related works to this project. Furthermore, the study proposes a methodology section that includes segmenting the lesion and skin using the Otsu's method, along with extracting symmetry information from the segmented images through traditional operations. Additionally, the paper outlines a machine learning approach for feature learning and classification, predicting the type of lesion in new data. Lastly, it discusses the evaluation methods and metrics used in this study, considering the implications of the proposed methods.**

***Index Terms*—Lesion Identification, Classification, Segmentation, U-Net, Random Forest**

## I. Introduction

Skin cancer ranks among the most prevalent and lethal cancers. According to the American Cancer Society, it is projected that there will be approximately 97,920 new cases of melanoma in each year [1]. Early diagnosis and treatment of skin cancer are imperative. Classifying skin diseases, such as melanoma and nevus, is crucial to support physicians in diagnosing skin cancer. Therefore, extracting features and classifying skin diseases are significant components of this study. Over the past few decades, there has been a continuous effort to accurately detect skin diagnosis. Identifying the size and type of skin lesions in dermoscopic images plays a vital role in skin lesion diagnosis[2].This project focuses on three types of skin lesions: Common Nevi, Atypical Nevi, and Melanoma. This paper will discuss the preliminary operations and methods employed for lesion image segmentation, symmetry identification, and classification. Additionally, the dataset, which includes dermoscopic images and lesion information, will be utilized for feature extraction and method application.

## II. Background

### A. Dataset Description

The dataset utilized in this project is referred to as the skin-lesion-dataset, comprising 150 dermoscopic images in BMP format representing various skin lesions. Each image is of the resolution 765x572 pixels. Additionally, for each image, there are corresponding segmented lesion images and a JSON file containing the lesion's type and symmetry information. This segmentation and symmetry data not only facilitate the evaluation of respective tasks but also serve as features for training in the subsequent classification and prediction processes.

Upon statistical analysis, the dataset distribution includes 70 images for Common Nevi, 70 for Atypical Nevi, and 10 for Melanoma. The initial strategy involves using features from 50 images each of Common Nevi and Atypical Nevi, along with 8 images of Melanoma, to train the model. The remaining images will be used for validation purposes. Besides that, the Cross Validation method will also be considered basing on the size of the dataset.

### B. Prior work on Skin Lesion Segmentation

Over the years, a myriad of algorithmic methods for skin lesion segmentation have been proposed, broadly categorized into supervised and unsupervised segmentation approaches. Unsupervised segmentation leverages machine learning techniques like expectation maximization, spectral clustering, and K-means clustering to delineate regions of interest from background regions with minimal computational effort, as exemplified in references [3][4].

Conversely, supervised segmentation methods prioritize the training and learning process, extracting hierarchical image features from extensive datasets through supervised learning techniques such as Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs), noted in [5][6]. CNN-based deep learning approaches, in particular, have emerged as a popular choice for dermoscopic image segmentation due to their ability to achieve high-performance results. Despite their efficacy, these methods are often hindered by computational complexity and a demand for large volumes of annotated training data and extensive parameter tuning to excel in skin lesion segmentation tasks.

### C. Prior Work on Symmetry Identification

Among various features used to train models for classification tasks, symmetry stands out due to its unique presence in most Common Nevi and Melanoma cases. Significant efforts have been made to extract and analyze symmetry information effectively. A prevalent method to assess shape symmetry involves dividing the lesion's area along its principal axis. Subsequently, the mirrored image of one half is superimposed onto the other. This process is repeated using the second principal axis, and a degree of symmetry is calculated based on the area discrepancies between the two overlapping segments. This approach was notably employed by Stoecker et al. [7].

### D. Prior Work on Skin Lesion Classification

In the domain of skin lesion classification, a multitude of research endeavors have used various machine learning and deep learning models to distinguish between different types of skin lesions effectively. An array of machine learning algorithms, including Decision Trees (DT), Random Forests (RF), Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), Gaussian Naïve Bayes (NB), and Linear Discriminant Analysis (LDA), have been utilized to train and test image datasets. These models are evaluated based on several key performance metrics such as Accuracy, Precision, Recall, and F1-score, ensuring a comprehensive assessment of their classification capabilities.

## III. Preliminary Methods and Results

### A. Otsu's-Based Skin Lesion Segmentation

Otsu's method has demonstrated significant effectiveness in image segmentation tasks in previous works. This method relies on analyzing the grayscale histogram of an image to determine an optimal threshold value. This threshold is selected to minimize intra-class variance, or equivalently, to maximize inter-class variance between two key regions: the background (surrounding skin) and the foreground (lesion). For this project, given that the images are originally in color, they are first converted to grayscale. This conversion is necessary because Otsu's method operates exclusively on single-channel images, where pixel intensities indicate levels of brightness.

### B. Symmetry Identification

Following the segmentation process, basic and traditional operations are applied to the segmented mask to extract symmetry information of the lesion. Initially, the mask undergoes a vertical flip, and the difference between the original and flipped masks is calculated through subtraction. This resultant difference is then compared with a pre-determined threshold to assess whether the mask exhibits symmetry along the vertical axis. Subsequently, the mask is incrementally rotated by a small angle, with the same operations applied after each rotation. The comprehensive assessment of symmetry is ultimately determined by the count of axes along which the mask demonstrates symmetry.

### C. Machine Learning-Based Skin Classification

Following the segmentation process and extraction of symmetry information, these results are utilized as key features to train a Random Forest model for classifying three distinct types of skin lesions: Common Nevi, Atypical Nevi, and Melanoma. Additionally, to enrich the feature set, the maximum diameter and area of the segmented lesion mask are calculated. Given the dataset's composition—70 images each for Common Nevi and Atypical Nevi, and 10 for Melanoma—the application of Cross-Validation is deemed appropriate, considering the dataset size. This method ensures a robust evaluation of the model's performance, providing a more accurate reflection of its predictive capability across the varied types of skin lesions.

### D. Evaluation

Since the teaching staff didn't show the evaluation process, some basic evaluation method will be applied to the result in each task.

For segmentation, the Intersection over Union (IoU) metric will be utilized to assess the accuracy of the segmentation results. IoU provides a quantitative measure of the overlap between the predicted segmentation mask and the ground truth, offering insight into the precision of the segmentation task.

For evaluating the symmetry information extraction and the classification accuracy, comparison against the dataset's labels will be conducted, with F1-scores being adopted as the primary metric for assessment. The F1-score, a harmonic mean of precision and recall, is particularly useful for situations where the class distribution is imbalanced.

## IV. Discussion and Conclusion

The methodologies proposed in this study are currently under evaluation, as their effectiveness in delivering the desired outcomes remains to be confirmed. For segmentation, we are considering the implementation of more advanced deep learning models, such as U-Net, should Otsu's method fail to yield satisfactory results. Similarly, for classification, alternatives like Support Vector Machines (SVM) or Convolutional Neural Networks (CNN) are under consideration due to their documented success in skin lesion classification across various studies. Additionally, we plan to explore a broader range of lesion image features, including texture and color, to enhance the robustness of our models.

Our team comprises four members, with each individual responsible for one specific task. For task C, two team members will collaborate. This division of labor mirrors our approach in the MRI project, ensuring each aspect of the project receives focused attention. Detailed assignments and roles will be outlined in the subsequent project phases, facilitating a structured and efficient workflow.

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