 Computer Science and Engineering

A LITERATURE SURVEY ON Localization and

Classification of skin disease with erythema

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## Abstract:

The aim of this paper is to present the problems of customer services and their iortant role for

small and medium companies from the theoretical view and also selected

customer

* The study of skin, the science of dermatology, has undergone significant transformations throughout the centuries. From the first descriptions of skin diseases in Egyptian papyri and in Hippocratic writings to the first treatises on dermatology, important individuals and discoveries have marked the specialty. In the 18th and 19th centuries, the specialty consolidated itself as a field of medical study based on the first classifications of dermatoses, diagnostic methods, and drug treatments. In the 20th century, the scientific and technological revolution transformed dermatological practice, incorporating new therapeutic resources, as well as surgical and aesthetic procedures. In the face of such a vigorous process, it is important to provide a historical synthesis for the medical community to recognize and understand the origins that supported one of the most relevant specialties in the current medical scenario.

## Although computer-aided diagnosis (CAD) is used to improve the quality of diagnosis in various medical fields such as mammography and colonography, it is not used in dermatology, where noninvasive screening tests are performed only with the naked eye, and avoidable inaccuracies may exist. This study shows that CAD may also be a viable option in dermatology by presenting a novel method to sequentially combine accurate segmentation and classification models. Given an image of the skin, we decompose the image to normalize and extract high-level features. Using a neural network-based segmentation model to create a segmented map of the image, we then cluster sections of abnormal skin and pass this information to a classification model. We classify each cluster into different common skin diseases using another neural network model. Our segmentation model achieves better performance compared to previous studies, and also achieves a near-perfect sensitivity score in unfavorable conditions. Our classification model is more accurate than a baseline model trained without segmentation, while also being able to classify multiple diseases within a single image. This improved performance may be sufficient to use CAD in the field of dermatology.

* Introduction:Computer-aided diagnosis (CAD) is a computer-based system that is used in the medical imaging field to aid healthcare workers in their diagnoses[1](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7935891/#CR1). CAD has become a mainstream tool in several medical fields such as mammography and colonography[1](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7935891/#CR1),[2](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7935891/#CR2). However, in dermatology, although skin disease is a common disease, one in which early detection and classification is crucial for the successful treatment and recovery of patients, dermatologists perform most noninvasive screening tests only with the naked eye. This may result in avoidable diagnostic inaccuracies as a result of human error, as the detection of the disease can be easily overlooked. Furthermore, classification of a disease is difficult due to the strong similarities between common skin disease symptoms. Therefore, it would be beneficial to exploit the strengths of CAD using artificial intelligence techniques, in order to improve the accuracy of dermatology diagnosis. This paper shows that CAD may be a viable option in the field of dermatology using state-of-the-art deep learning models.

The segmentation and classification of skin diseases has been gaining attention in the field of artificial intelligence because of its promising results. Two of the more prominent approaches for skin disease segmentation and classification are clustering algorithms and support vector machines (SVMs). Clustering algorithms generally have the advantage of being flexible, easy to implement, with the ability to generalize features that have a similar statistical variance. Trabelsi et al experimented with various clustering algorithms, such as fuzzy c-means, improved fuzzy c-means, and K-means, achieving approximately 83% true positive rates in segmenting a skin disease. Rajab et al. implemented an ISODATA clustering algorithm to find the optimal threshold for the segmentation of skin lesions. An inherent disadvantage of clustering a skin disease is its lack of robustness against noise. Clustering algorithms rely on the identification of a centroid that can generalize a cluster of data. Noisy data, or the presence of outliers, can significantly degrade the performance of these algorithms. Therefore, with noisy datasets, caused by images with different types of lighting, non-clustering algorithms may be preferred; however, Keke et al.[5](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7935891/#CR5) implemented an improved version of the fuzzy clustering algorithm using the RGB, HSV, and LAB color spaces to create a model that is more robust to noisy data. SVMs have gained attention for their effectiveness in high-dimensional data and their capability to decipher “…subtle patterns in noisy and complex datasets”. Lu et al segmented erythema in the skin using the radial basis kernel function that allows SVMs to separate nonlinear hyperplanes. Sumitra et al. combined a linear SVM with a k-NN classifier to segment and classify five different classes of skin lesions. Maglogiannis et al. implemented a threshold on the RGB value for segmentation and used an SVM for classification. Although more robust than clustering algorithms, SVMs are more reliant on the preprocessing of data for feature extraction. Without preprocessing that allows a clear definition of hyperplanes, SVMs may also underperform.

Owing to the disadvantages of these traditional approaches, convolution neural networks (CNNs) have gained popularity because of their ability to extract high-level features with minimal preprocessing. CNNs can expand the advantages of SVMs, such as robustness in noisy datasets without the need for optimal preprocessing, by capturing image context and extracting high-level features through down-sampling. CNNs can interpret the pixels of an image within its own image-level context, as opposed to viewing each pixel in a dataset-level context. However, although down-sampling allows CNNs to view an image in its own context, it degrades the resolution of the image. Although context is gained, the location of a target is lost through down-sampling. This is not a problem for classification, but causes some difficulty for segmentation, as both the context and location of the target are essential for optimal performance. To solve this, up-sampling is needed, which works in a manner opposite to that of down-sampling, in the sense that it increases the resolution of the image. While down-sampling takes a matrix and decreases it to a smaller feature map, up-sampling takes a feature map and increases it to a larger matrix. By learning to accurately create a higher-resolution image, CNNs can determine the location of the targets to segment. Thus, for segmentation, we use a combination of down-sampling and up-sampling, whereas for classification, we use only down-sampling. To further leverage the advantages of CNNs, skip-connections were introduced, which provided a solution to the degradation problem that occurs when CNN models become too large and complex. We implement skip-connections in both segmentation and classification models. In the segmentation model, blocks of equal feature numbers are connected between the down and up-sampling sections. In the classification model, these skip-connections exist in the form of inverted residual blocks. This allows our models to grow in complexity without any performance degradation.

In this paper, we present a method to sequentially combine two separate models to solve a larger problem. In the past, skin disease models have been applied to either segmentation or classification. In this study, we sequentially combine both models by using the output of a segmentation model as input to a classification model. In addition, although past studies of non-CNN segmentation models used innovative preprocessing methods, recent CNN developments have focused more on the architecture of the model than on the preprocessing of data. As such, we apply an innovative preprocessing method to the data of our CNN segmentation model. The methods described above lack the ability to localize and classify multiple diseases within one image; however, we have developed a method to address this problem. Our objective is two-fold. First, we show that CAD can be used in the field of dermatology. Second, we show that state-of-the-art models can be used with current computing power to solve a wider range of complex problems than previously imagined. We begin by explaining the results of our experimentation, followed by a discussion of our findings, a more detailed description of our methodology, and finally, the conclusions that can be drawn from our study.

Objective:

It talks about the versatile use of skin infection location given the picture. Presumably will be intended to identify the skin infection from unfortunate pictures.

**NEED OF STUDY**

The main objective of this study is to diagnosis of skin disease requires both clinical and pathological expertise, which subsequently define the laboratory tests required. Central to these investigations is the biopsy, allowing key architectural features of the skin disease to be analyzed, emphasizing the importance of dermatopathology to the treatment of skin disorders. In addition, and frequently of vital importance, is AI-based image recognition system which tests that sit outside the realms of routine dermatopathology and which assist in the diagnosis and aid in the patient management of skin disease.

**WORK FLOW:**

This Application has been developed to help the customer in processing their complaints. The customers can raise the ticket with a detailed description of the issue. An Agent will be assigned to the Customer to solve the problem. Whenever the agent is assigned to a customer they will be notified with an email alert. Customers can view the status of the ticket till the service is provided.

Diagram: