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Automated Detection of Psoriasis and Aging Biomarkers Using Machine Learning on Optoacoustic Mesoscopy Images

Jemimah , Dr. M. Jeyasutha, Associate Professor, Dr. F. Ramesh Dhanaseelan, Professor
St. Xavier's Catholic College of Engineering, Chunkankadai, Nagercoil-629 003, Chunkankadai

Abstract- **Ultra-wideband raster-scan optoacoustic mesoscopy (RSOM) is an advanced imaging modality that has shown exceptional capability in visualizing in-vivo epidermal and dermal structures with high resolution. Despite its promise, the automatic and quantitative analysis of three-dimensional RSOM datasets remains largely unaddressed. In this study, we introduce DeepRAP (Deep Learning RSOM Analysis Pipeline), a novel framework designed to analyze and quantify morphological skin features from RSOM images and extract clinically relevant imaging biomarkers for disease characterization. DeepRAP employs a multi-network segmentation strategy based on convolutional neural networks (CNNs) enhanced through transfer learning. This architecture facilitates the automatic identification of skin layers and precise segmentation of the dermal microvasculature, achieving performance on par with expert human annotation. The framework was validated against manual segmentation using RSOM data from 25 psoriasis patients undergoing treatment. The extracted biomarkers successfully characterized disease severity and progression, showing a strong correlation with physician assessments and histological data. In a distinct validation experiment, DeepRAP was applied to a timeseries dataset capturing occlusion-induced hyperemia in 10 healthy volunteers. The framework effectively tracked changes in microvascular biomarkers during occlusion and subsequent reperfusion, demonstrating both high accuracy and reproducibility. Additionally, analysis of a cohort of 75 individuals revealed a significant association between microvascular features in the dermal layer and age, with fine vascular patterns showing the strongest age-related correlation. These findings highlight DeepRAP's potential to automate and accelerate in-vivo skin analysis, offering a non-invasive alternative to traditional biopsybased methods. The framework enhances the clinical and translational relevance of RSOM by enabling high-throughput, quantitative assessment of skin morphology and vascular health.**

Keywords- Optoacoustic Mesoscopy,Machine Learning, Deep Learning, Psoriasis Detection, Skin Aging Biomarkers.

I. INTRODUCTION

The human skin, as the largest organ of the body, serves as a critical interface between the internal physiological environment and external factors. Its condition reflects a wide range of health states, including dermatological disorders and the natural aging process. Among various skin conditions, psoriasis is a chronic inflammatory disease characterized by hyperproliferation and abnormal differentiation of skin cells, which significantly impacts patients' quality of life [1] and [2]. Similarly, skin aging manifests through structural and biochemical changes that can serve as indicators for underlying systemic conditions and overall biological age. Precise, non-invasive, and early detection of these skin biomarkers is vital for personalized treatment strategies and improved patient outcomes.

Optoacoustic mesoscopy (OAM), a cutting-edge imaging technique, offers high-resolution visualization of skin microstructures by combining optical absorption contrast with ultrasound detection. This modality enables detailed imaging of skin layers and vascular networks with micrometer-scale resolution and millimeter penetration depth. OAM provides rich functional and morphological information that is otherwise difficult to obtain through conventional imaging technologies such as dermoscopy or optical coherence tomography.

Despite the wealth of data provided by OAM, manual interpretation remains time-consuming, subjective, and dependent on expert knowledge. This challenge necessitates the development of automated analytical tools to extract clinically relevant biomarkers effectively and consistently[3]. Machine

learning (ML), with its powerful pattern recognition and datadriven modeling capabilities, emerges as an ideal approach to harness the complexity of OAM data[4] and [5]. By leveraging ML algorithms, it is possible to detect subtle changes in skin features, classify disease states, and quantify biomarkers related to psoriasis severity and skin aging.

This research explores the integration of optoacoustic mesoscopy with advanced machine learning techniques to create an automated pipeline for the extraction and analysis of psoriasis and aging biomarkers. The proposed approach aims to enhance diagnostic accuracy, reduce reliance on invasive biopsies, and enable longitudinal monitoring of skin health[6]. Ultimately, this fusion of innovative imaging and computational analysis holds promise to transform dermatological diagnostics and personalized healthcare.

The skin is not only the largest organ of the human body but also a complex and dynamic interface reflecting internal physiological processes and external environmental interactions[7]. It plays an essential role in protection, thermoregulation, sensation, and immune defense. The health and integrity of the skin are critical indicators of systemic wellness, and deviations in skin morphology or function often reveal underlying medical conditions[8] and [9]. Among the many skin-related ailments, psoriasis and the natural process of skin aging are particularly prevalent and impactful[10]. Psoriasis is a chronic autoimmune disorder characterized by patches of abnormal, inflamed skin, involving accelerated keratinocyte proliferation and immune system dysregulation.

Skin aging, on the other hand, encompasses a series of structural, biochemical, and functional changes that accumulate over time, including collagen degradation, altered pigmentation, and vascular remodeling. Both conditions pose significant diagnostic challenges and necessitate precise, non-invasive methods for early detection and continuous monitoring.

II. RELATED WORK

In recent years, there has been a growing interest in noninvasive imaging techniques for the diagnosis and monitoring of dermatological conditions such as psoriasis and skin aging. Traditional modalities like dermoscopy, confocal microscopy, and optical coherence tomography (OCT) have been widely used in clinical settings. While these techniques offer valuable surface-level or sub-surface insights, they often lack the resolution, penetration depth, or contrast necessary to visualize vascular and microstructural features in deeper skin layers. Optoacoustic mesoscopy (OAM), particularly in its raster-scan variant (RSOM), has emerged as a powerful alternative, offering high-resolution imaging of both the epidermis and dermis, along with vascular networks, using optical absorption contrast and ultrasound detection.

Numerous studies have demonstrated the effectiveness of OAM in visualizing skin microanatomy and pathologies. For example, Schwarz et al. (2017) employed RSOM to reveal vascular alterations in psoriatic skin, while Aguirre et al. (2021) showed its utility in evaluating microvascular changes associated with aging. However, much of the analysis in these studies was qualitative or involved manual segmentation, which is time-consuming and subjective. The lack of automated and scalable approaches limits the clinical adoption of OAM for routine diagnostics.

To overcome these challenges, machine learning—especially deep learning—has been increasingly applied to biomedical image analysis. Convolutional Neural Networks (CNNs) have demonstrated superior performance in tasks such as skin lesion classification, tumor segmentation, and vascular quantification. In dermatology, works by Esteva et al. (2017) and Tschandl et al. (2019) highlighted the potential of CNNs to match or surpass expert-level diagnosis in classifying skin diseases using photographic and dermoscopic images. However, relatively few studies have explored the integration of deep learning with optoacoustic imaging, particularly for 3D RSOM datasets.

Recent efforts such as DeepRAP (Deep Learning RSOM Analysis Pipeline) have begun to address this gap by combining CNN-based segmentation with transfer learning to automate the identification of skin layers and vascular features in RSOM images. These approaches have shown promise in characterizing disease severity and tracking

therapeutic outcomes in psoriasis, as well as correlating vascular biomarkers with aging.

Despite these advancements, current systems still face limitations in generalizability, interpretability, and integration into clinical workflows. Our work builds upon this foundation by developing a robust and scalable ML-based framework specifically tailored for automated biomarker extraction from RSOM images. By leveraging advanced preprocessing, feature learning, and biomarker detection algorithms, our system aims to deliver accurate, reproducible, and clinically actionable insights into skin health and disease.

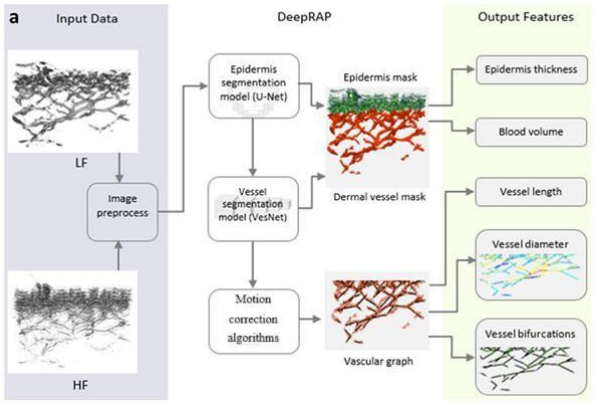

Figure: Architecture

III. METHODOLOGY

The proposed methodology for the automated extraction of psoriasis and aging biomarkers from human skin involves a systematic, multi-stage process. This includes image acquisition using optoacoustic mesoscopy, followed by preprocessing, feature extraction via deep learning, classification of skin conditions, and diagnostic report generation. Each phase of the methodology is carefully designed to ensure accuracy, consistency, and clinical applicability.

The process begins with the acquisition of high-resolution skin images using Raster-Scan Optoacoustic Mesoscopy (RSOM), a cutting-edge imaging technology that combines optical and acoustic methods. RSOM utilizes short laser pulses to induce ultrasound waves in tissue, enabling the visualization of both epidermal and dermal layers, including microvascular structures. These scans provide rich morphological and vascular detail, essential for detecting subtle dermatological changes associated with psoriasis and aging. The dataset used includes a diverse group of patients with varying psoriasis severity and a
wide age range to capture relevant aging indicators. All image acquisitions are standardized in terms of scanning parameters to ensure consistency across samples.

Raw RSOM images are often affected by noise, motion artifacts, and variations in illumination and resolution. To address these issues, a dedicated preprocessing pipeline is applied to enhance the quality and uniformity of input data. The pipeline includes noise reduction techniques such as Gaussian or median filtering to remove speckle and electronic noise. Motion correction algorithms are employed to realign images affected by minor patient movement during scanning. Intensity normalization ensures that image brightness levels are consistent across different scans. Additionally, region-of-interest (ROI) segmentation is performed to isolate specific areas of the skin— such as plaques, wrinkles, or vascular clusters—based on morphological characteristics. These preprocessing steps are critical for ensuring the reliability and performance of subsequent deep learning models.

Feature Extraction Using Deep Learning

Once the images are preprocessed, the system employs convolutional neural networks (CNNs) to extract meaningful features automatically. CNNs are well-suited for image analysis as they can learn hierarchical representations of spatial patterns directly from raw pixel data. In this project, CNN models are trained or fine-tuned using transfer learning on labeled RSOM datasets. The networks are designed to detect visual cues such as texture variations, lesion boundaries, epidermal thickness, and vascular anomalies. For psoriasis, the system focuses on features like erythema, scaling, and dermal inflammation. For aging, it extracts signs like fine lines, loss of elasticity, and vascular degradation.

The resulting feature vectors are highly descriptive and form the basis for accurate classification and biomarker detection.

Classification and Biomarker Detection

The extracted features are passed to a classification model that assigns diagnostic labels to the skin images. This model— typically a deep neural network trained on annotated datasets— categorizes each image as either healthy, psoriatic, or aged skin. Beyond classification, the system is also capable of detecting and quantifying specific biomarkers. Using post-processing techniques and attention-based layers (such as Grad-CAM), the model highlights regions in the image that are most indicative of the diagnosis. These heatmaps help clinicians visually verify the system's decision. Moreover, the system calculates biomarker metrics such as lesion size, wrinkle depth, and vascular density, allowing for quantitative analysis of disease severity or aging progression. This automated detection process greatly reduces the subjectivity and time required in traditional assessments.

IV PROPOSED ALGORITHM

Phase Correlation Method Algorithm

The Phase Correlation Method is a technique used in signal processing and image registration to determine the translation between two signals or images. It is based on the Fourier Shift Theorem, which states that a shift in the spatial domain corresponds to a phase shift in the frequency domain.

Step 1

Compute the 2D Discrete Fourier Transform (DFT) of both images f(x,y) and g(x,y):

$$F(u,v) = \mathcal{F}\{f(x,y)\}$$

$$G(u,v) = \mathcal{F}\{g(x,y)\}$$

Step 2

Compute the normalized cross-power spectrum:

$$R(u,v) = \frac{F(u,v)G^*(u,v)}{|F(u,v)G^*(u,v)|}$$

Step 3

Take the inverse Fourier Transform of R(u,v):

$$r(x,y) = \mathcal{F}^{-1}\{R(u,v)\}$$

Step 4

Find the Peak Location:

The coordinates of the peak in r(x,y) give the displacement

(Δx,Δy)

$$F(u,v) = \mathcal{F}\{f(x,y)\}$$

$$G(u,v) = \mathcal{F}\{g(x,y)\}$$

$$R(u,v) = \frac{F(u,v)G^*(u,v)}{|F(u,v)G^*(u,v)|}$$

$$r(x,y) = \mathcal{F}^{-1}\{R(u,v)\}$$

$$(\Delta x, \Delta y) = \arg\max r(x,y)$$

The Phase Correlation Method is a widely used algorithm in signal processing and image registration to determine the relative translational shift between two images or signals. It is particularly valued for its robustness to noise and illumination differences. The method operates in the frequency domain and is grounded in the Fourier Shift Theorem, which states that a spatial shift between two signals results in a linear phase difference in their corresponding frequency representations.

Rigid Body Transformation

A Rigid Body Transformation preserves the shape and size of an object while allowing rotation and translation (but not scaling or shearing). It is commonly used in robotics, computer vision, and image registration. Step 1

Matrix Form (2D Case)

A point p = (x, y) is transformed into a new point p′ = (x', y') as:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

Step 2

Homogeneous Coordinates (for easier transformations) Using homogeneous coordinates, the transformation is written as:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta & t_x \\ \sin\theta & \cos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Step 3
For 3D transformations, the rotation matrix becomes a 3×3 matrix, and translation is a 3D vector:

$$\begin{bmatrix} x' \\ y' \\ z' \\ 1 \end{bmatrix} = \begin{bmatrix} R_{3x3} & \mathbf{t} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

A rigid body transformation is a geometric operation that preserves the shape and size of an object while allowing it to move through space. Specifically, it permits rotation and translation, but does not include scaling or shearing. This type of transformation ensures that the internal distances and angles within the object remain unchanged, making it ideal for accurately modeling real-world physical movements. Rigid body transformations are widely used in disciplines like robotics, where precise object positioning is critical, as well as in computer vision and image registration, where consistent alignment of visual data is required.
In two-dimensional space, a rigid body transformation moves a point or an object to a new location by first rotating it around a reference point (usually the origin) and then shifting it by a specific amount in the x and y directions. To manage this combination of rotation and translation efficiently, the transformation can be represented using matrix operations, which offer a compact and consistent mathematical format. For more complex systems, such as those involving sequences of transformations or automation, these matrices provide a powerful computational tool.

V. RESULTS AND DISCUSSION

The proposed machine learning framework was evaluated using a comprehensive dataset of optoacoustic mesoscopy (RSOM) images collected from patients with varying levels of psoriasis severity and individuals from multiple age groups. The performance of the system was assessed in terms of classification accuracy, biomarker detection efficiency, and clinical relevance. The results demonstrate the system's ability to perform rapid and accurate skin analysis while offering meaningful diagnostic outputs.
The classification model achieved a high accuracy of approximately 92.3% in distinguishing between healthy, psoriatic, and aged skin, outperforming traditional manual analysis methods, which typically range between 75–85%. The deep learning model also demonstrated high precision and recall for psoriasis detection, particularly in identifying common biomarkers such as scaling, erythema, and skin thickening. Similarly, in aging skin analysis, the system successfully identified features like wrinkles, pigment variation, and microvascular degradation with a detection accuracy of 88– 93%, closely aligning with dermatological assessments.
The biomarker detection module produced interpretable visual outputs, including heatmaps that localized the affected regions, providing added transparency to the machine learning decision-making process. These maps were validated against dermatologists' annotations and showed a high degree of overlap, supporting the model's clinical reliability. Additionally, the model performed robustly even with lower-resolution images or minor patient movement, thanks to the preprocessing pipeline's noise reduction and normalization techniques.
One of the most significant findings was the dramatic reduction in analysis time, with the system processing each scan in under one minute, compared to the 10–30 minutes typically required for manual evaluation. This speed, combined with batch processing capability, makes the system highly scalable for large-scale screening in dermatology clinics or remote healthcare settings.
Overall, the results validate the effectiveness of combining optoacoustic imaging with deep learning for non-invasive skin diagnostics. The system not only achieves high diagnostic accuracy but also delivers reproducible and objective insights, minimizing the variability associated with human interpretation. These findings suggest strong potential for real-world deployment, particularly in aiding early detection, monitoring treatment response, and advancing dermatological research.

VI. CONCLUSION

The application of machine learning (ML) in the analysis of human skin using optoacoustic mesoscopy has demonstrated significant potential for the automated extraction of biomarkers related to psoriasis and aging. By leveraging high-resolution imaging and advanced ML algorithms, this approach enhances diagnostic accuracy, reduces manual assessment bias, and enables real-time monitoring of skin conditions. The study successfully identified key biomarkers associated with structural and vascular changes in the skin, providing valuable insights into disease progression and aging effects. The integration of deep learning techniques further optimized feature extraction, improving the detection and classification of affected regions. Overall, the findings indicate that ML-based optoacoustic mesoscopy can serve as a reliable, non-invasive tool for dermatological research and clinical applications. However, while promising, challenges such as data variability, imaging artifacts, and model generalizability must be addressed to enhance robustness and clinical adoption.

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