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Identification of Dermatological Diseases using AI-Driven Entropy and Texture-Based Analysis

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Abstract

Dermatological diseases affect a significant portion of the global population. Traditional diagnostic methods such as visual inspection and biopsies are subjective, invasive, and time-consuming. To address these limitations, this study proposes an entropy-based texture analysis framework combined with Gray Level Co-occurrence Matrix (GLCM) features for the automated identification and classification of skin diseases using standard color dermatological images. The methodology involves pre-processing the input images through normalization and resizing, followed by the extraction of five key texture features: contrast, correlation, energy, homogeneity, and entropy. A comparative evaluation across four dermatological conditions Morgellons, Dermatitis, Psoriasis, and Vitiligo demonstrates that entropy and homogeneity are the most effective features in capturing disease-specific textures, whereas contrast, correlation, and energy exhibit limited discriminative capability. Furthermore, the study examines the impact of varying window sizes (5, 15, and 25) for texture extraction and identifies a 5×5 window as the optimal configuration for preserving critical lesion details. The proposed approach provides a lightweight, interpretable, and non-invasive solution that can serve as a valuable component in clinical decision-support systems. This work contributes to the advancement of AI-driven dermatological diagnostics by offering a cost-effective and accessible methodology for automated skin disease identification.

Keywords: Dermatological diseases; Entropy; Texture analysis; Gray Level Co-occurrence Matrix (GLCM); Image preprocessing; Automated diagnosis; AI in Dermatology.

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1. Introduction

Dermatological diseases are among the most prevalent health conditions worldwide, affecting individuals across all age groups. Despite their widespread occurrence, diagnosing these diseases remains a complex challenge requiring significant expertise. Studies indicate that approximately 24 % of the population consult their general practitioner (GP) with a skin-related issue at least once a year. However, inconsistent dermatological education at the undergraduate level suggests that medical trainees must continuously reassess their knowledge and skills in this field [1]. Furthermore, skin diseases have been identified as the

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fourth leading cause of nonfatal disease burden globally, with three of the most common diseases being dermatological conditions [2]. In countries like India, particularly in rural and small towns, skin diseases are often overlooked, and individuals may not seek timely consultation with dermatologists. The scarcity of dermatologists in these areas further exacerbates the problem, leaving primary healthcare providers, paramedical staff, and community health centers as the primary sources of treatment. Many dermatological diseases, such as bacterial infections, fungal infections, eczema, and scabies, exhibit similar characteristics, making early diagnosis by non-specialists particularly difficult. The impact of skin diseases extends beyond physical discomfort; they can significantly affect a patient's quality of life [3]. Common symptoms include lesions, scales, plaques, and pigmentation, leading to chronic pain, disfigurement, and psychological distress, especially when the condition affects visible areas such as the face [4]. Studies suggest that patients suffering from primary skin diseases like psoriasis, alopecia areata, and vitiligo are more susceptible to mental health issues, including anxiety and depression [5]. According to the 2018 English Skin Establishment Report, an estimated 5.4 million new cases of skin diseases are reported annually in the United States, with one in five individuals at risk of developing a lifelong cutaneous disorder. Additionally, 60 % of the English population reportedly suffers from a skin condition. These disorders not only impact physical health but also affect daily activities, interpersonal relationships, and even internal organs. In severe cases, untreated skin diseases may lead to fatal complications or trigger maladaptive behaviors such as social withdrawal, depression, and even suicidal tendencies [6]. Therefore, there is a pressing need for both effective diagnostic methods and greater awareness in underserved regions.

The skin, as the largest organ in the human body, serves as a protective barrier for muscles, bones, and internal organs. It also functions as a sensor to environmental changes, making it highly vulnerable to external factors such as pollution, climate change, and ultraviolet (UV) radiation. A mere 1% reduction in ozone levels may increase cancer incidence by 2-3 %. In India, photosensitive and infectious skin disorders are highly prevalent, highlighting the urgent need for early intervention to prevent complications beyond the skin. Given the country's rapidly growing population, there is a pressing need for efficient and high-quality dermatological care. Certain skin conditions mimic severe diseases such as AIDS and tuberculosis, which can become life-threatening if not treated promptly. Additionally, even mild skin disorders pose a financial burden, limiting treatment options for many patients. Therefore, it is crucial to develop cost-effective and efficient approaches for diagnosing skin diseases. In recent years, automated technologies have largely replaced traditional manual methods across various fields, including healthcare. However, diagnosing skin diseases remains a challenge due to the structural complexity of the skin and the similarities between different conditions. Many skin disorders share overlapping symptoms, making differentiation difficult. Moreover, segmentation and analysis of skin lesions are complicated by factors such as hair, sweat, and uneven pigmentation. The reliance on color images for diagnosis introduces additional challenges, as variations in lighting, image resolution, and noise can impact accuracy [7-11].

Conventional skin disease detection methods have several limitations. Visual inspection by healthcare professionals is subject to subjective interpretation, and diagnostic accuracy depends on the provider's expertise. Additionally, biopsies, often required for definitive diagnoses, are invasive and may not always capture the full extent of a skin condition. Imaging techniques typically provide only surface-level information, making it difficult to detect abnormalities within deeper skin layers. Furthermore, seasonal variations and evolving disease presentations complicate accurate tracking and diagnosis. Automated detection systems, particularly those based on machine learning, face challenges in handling the complexity and variability of skin conditions. The performance of machine learning models is highly dependent on the quality and diversity of training data, and the availability of large-scale datasets remains a critical bottleneck.

To address these challenges, we propose an entropy-based texture analysis approach for automated skin disease identification and classification. This technique utilizes Gray Level Co-occurrence Matrices (GLCM) and entropy-based texture features to analyze spatial relationships between pixel intensities in dermatological images. Entropy-based analysis provides a quantitative measure of disorder and randomness in skin texture, helping distinguish between different dermatological conditions. By combining GLCM features with CNN-based classification, this method aims to enhance disease detection accuracy while reducing reliance on large annotated datasets. Traditional Convolutional Neural Networks (CNNs) require extensive datasets, which are often unavailable for specific dermatological conditions. However, leveraging entropy-based texture analysis allows for the extraction of meaningful features, enabling more accurate predictions even with limited training data. CNNs have demonstrated remarkable success in skin disease classification, with reported validation accuracies reaching up to 97.1 % [12]. Additionally, CNN-based models have been effective in detecting and classifying skin cancer, achieving performance accuracies ranging from 76 % to 99 % [13].

Recent advancements in deep learning have demonstrated significant potential in transforming dermatological disease diagnosis by offering non-invasive, efficient, and scalable solutions. In particular, Convolutional Neural Networks (CNNs) form the backbone of most deep learning models used in medical imaging. The process begins by feeding raw skin images into the network, where successive convolutional layers automatically extract hierarchical features. Low-level features such as edges, color variations, and textures are learned first, followed by mid-level features like shapes, boundaries, and local patterns, and finally high-level abstract representations that capture lesion-specific characteristics. These progressively refined features are then passed through fully connected layers or classifiers to differentiate between normal and diseased skin conditions. CNNs perform end-to-end learning, thereby reducing subjectivity, minimizing manual intervention, and improving diagnostic scalability and accuracy.

This paper addresses the limitations of conventional approaches by proposing a lightweight alternative that integrates entropy-based texture analysis with Gray Level Co-occurrence Matrix (GLCM) features for automated identification and classification of skin diseases using standard color images. The proposed method emphasizes the extraction of

statistically meaningful texture descriptors particularly entropy and homogeneity which have shown superior capability in capturing disease-specific patterns compared to other features like contrast, correlation, and energy. Furthermore, the study introduces a systematic evaluation of different window sizes for texture computation and identifies the 5×5 window as the most effective for preserving fine lesion details. Unlike deep learning models that typically require large annotated datasets, this lightweight and interpretable approach is capable of delivering accurate results even with limited data, making it particularly suitable for deployment in resource-constrained healthcare settings. By bridging statistical image analysis with machine learning, the proposed framework offers a practical and accessible solution for enhancing early dermatological diagnosis. The remainder of this paper is structured as follows: Section 2 reviews the related literature, Section 3 presents the proposed methodology, Section 4 discusses the experimental results, and Section 5 concludes the paper while outlining future research directions.

2. Literature Review

Researchers have proposed comprehensive automated methods for dermatological disease identification using color image processing. Unlike traditional diagnosis, which relies on medical personnel, these approaches introduce computer-based intervention. The system employs color image processing algorithms, k-means clustering, and color gradient techniques to detect affected skin areas, achieving a skin disease detection accuracy of 99.99 % and an illness identification accuracy of 94.016 % [14]. Convolutional Neural Networks (CNNs), a class of deep learning algorithms, have significantly advanced machine learning applications, particularly in image processing. They have been widely used in diverse fields, including agriculture, aerial image classification [15,16], medical imaging, and dermatological diagnostics. For example, CNNs have been applied in agriculture to detect and classify wheat leaf diseases such as spot blotch, stripe rust, brown rust, and powdery mildew across the plant's life cycle [17].

Convolutional Neural Networks (CNNs) have also been widely applied in image classification, object detection, and predictive modeling. Their ability to extract complex spatial features makes them effective for classification tasks. CNN-based automatic image enhancement has been tested for skin lesion diagnosis, particularly in resource-limited settings [18]. The implementation of a ResNet-152-based technique improved classification accuracy from 87.40 % to 95.85 % when GA-enhanced images were used [19]. CNNs have also been used for classifying dermatological conditions such as dermatitis, eczema, lichen simplex, and ulcers, achieving a precision of 73 % on the DermNet dataset containing 500 images [20]. To enhance skin disease classification, a deep CNN model incorporating a triplet loss function was implemented. For facial skin disease identification, fine-tuning of ResNet-152 and InceptionResNet-V2 was performed, employing moment-based techniques such as Legendre, Zernike, and pseudo-Zernike moments for pattern recognition [21].

Automated techniques for early skin lesion diagnosis have been developed, incorporating color-based lesion segmentation followed by global thresholding. Feature

extraction methods using two-dimensional Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) have been evaluated using the PH2 dataset [22]. Another approach integrates color and texture features, utilizing statistical moments (mean, variance, standard deviation, and asymmetry) and textural features such as Local Binary Patterns (LBP) and Grey Level Co-occurrence Matrices (GLCM), with classification performed using Support Vector Machines (SVM) [23]. Similarly, hybrid frameworks have been applied for automatic dementia diagnosis from T1-weighted MRI scans, combining GLCM-based texture feature extraction with adaptive neuro-fuzzy inference systems (ANFIS). This approach achieved 82.5 % accuracy, outperforming existing machine learning methods [24]. Further advancements in skin lesion classification have been achieved through a probabilistic lesion detection method, followed by feature selection using Bhattacharyya distance and an entropy-controlled variance-based approach. The selected features were then classified using a multi-class SVM [25]. A three-phase automated dermatological disease recognition system was also proposed, incorporating data collection and augmentation, model design, and prediction. This system integrated CNNs and SVMs with advanced image processing techniques for improved accuracy [26]. Machine learning classifier comparisons have been conducted for dermatological diagnosis, evaluating images of lichen planus, plaque psoriasis, and persistent eczema using RGB color features and texture descriptors such as GLCM. The performance of classifiers was assessed using different machine learning techniques with varied feature combinations [27]. Research on skin disease classification has explored differences in color and texture between healthy and affected skin. Texture features such as regularity, smoothness, and coarseness have been leveraged for accurate identification. Maximum histogram values, variance, and entropy of Hue-Saturation-Value (HSV) features were utilized in classification models based on SVMs and Decision Trees (DT) [28]. An advanced pre-trained deep CNN-based automated system for facial skin disease diagnosis has also been developed. To expand the dataset, pre-processing techniques were applied to images collected from various sources, followed by resizing for compatibility with the network. The model successfully classified eight facial skin diseases with an accuracy of 88%, including normal skin and no-face categories [29]. These studies collectively demonstrate the evolution of AI-driven dermatological diagnosis, highlighting the effectiveness of CNNs, texture-based feature extraction, and hybrid machine learning frameworks in automating disease detection and classification across multiple domains, including agriculture and medical imaging.

3. Methodology

The overall methodology of the proposed investigation is presented in the form of a block diagram, as illustrated in Fig. 1. The process is systematically divided into four main subtasks, each constituting a critical phase in the skin disease identification pipeline. These include: (i) image acquisition, (ii) image pre-processing, where the acquired images are prepared through operations such as resizing, normalization, and noise reduction to ensure consistency and enhance quality; (iii) feature extraction using Gray-Level Co-occurrence

Matrix (GLCM) and entropy, where statistical texture features are computed to represent the structural variations in diseased and healthy skin regions; and (iv) result analysis. Each of these subtasks contributes to building a reliable and interpretable framework for automated skin disease detection and is discussed in detail in the subsequent sections.

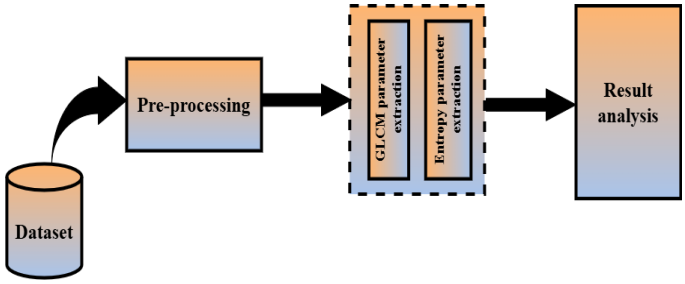

Fig. 1. Block diagram of proposed investigations

a) Image acquisition

A database containing images of skin patches affected by diseases such as Morgellons, Dermatitis, Vitiligo, Melanoma, and Psoriasis was acquired from the DermNet NZ [30], For analysis, an image of normal human skin is used as a reference.

b) Pre-processing

Image pre-processing plays a vital role in enhancing the quality of input images and ensuring consistency for accurate analysis. Raw dermatological images often contain unwanted artifacts such as hair, air bubbles, and noise, which can adversely affect feature extraction and classification. To address these challenges, we applied normalization and resizing techniques. Normalization standardizes pixel intensity values, improving image contrast and reducing variations caused by different lighting conditions. This ensures a uniform intensity distribution across all images, allowing the model to focus on relevant features while minimizing inconsistencies. The normalization process is performed using the following equation:

$$I_{norm} = \frac{I - I_{min}}{I_{\max} - I_{min}} \tag{1}$$

where I is the original pixel intensity, I_{min} and I_{max} are the minimum and maximum intensity values in the image, and I_{norm} is the normalized pixel intensity scaled to the range [0,1]. Additionally, resizing is performed to maintain a uniform image dimension, standardizing all images to a fixed size, which facilitates efficient processing and consistent feature extraction. In this study, all images were resized to 256×256 pixels, preserving essential structural details while reducing computational complexity. By implementing these pre-processing steps, we ensure a high-quality and uniform dataset, which directly contributes to improved performance in feature extraction and classification.

c) GLCM and entropy parameter extraction

Statistical texture analysis plays a crucial role in extracting meaningful patterns from images by analyzing the spatial distribution of pixel intensities. This approach computes texture features based on the statistical distribution of intensity combinations at specific relative positions within the image. Depending on the number of intensity points (pixels) involved, statistical methods are categorized into first-order, second-order, and higher-order statistics. Among these, the Gray Level Co-occurrence Matrix (GLCM) is one of the most widely used second-order techniques, as it provides valuable insights into spatial relationships between pixel intensities.

In this study, we employed the Gray Level Co-occurrence Matrix (GLCM), a widely used second-order statistical method, to characterize the textural properties of dermatological images. Since GLCM operates on grayscale data, all color images were first converted into grayscale. The GLCM was constructed by defining a pixel pair distance d and orientation θ, where d represents the number of pixels between the pair, and θ represents the direction of displacement. Commonly used orientation angles include 0°, 45°, 90° and 135° while the distance d can be varied depending on the scale of texture analysis. For each pixel in the image, the frequency of co-occurring intensity pairs (i, j) separated by the specified displacement (d, θ) was counted, resulting in a co-occurrence matrix $C(i, j|d, \theta)$. Mathematically, it is expressed as in Equation (2):

$$C(i,j|d,\theta) = \sum_{x=1}^{M}\sum_{y=1}^{N}\begin{cases}1, \\ 0,\end{cases} if\ I(x,y) = i\ and\ I(x+d_x, y+d_y) = j \quad (2)$$

where I (x, y) denote the intensity of the pixel at position (x, y), M and N are the image dimensions, and (dx, dy) are determined by the displacement d and orientation θ. The co-occurrence matrix was then normalized to transform the frequency counts into probabilities as given in Equation (3):

$$P(i,j) = \frac{C(i,j)}{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}C(i,j)} \quad (3)$$

where L represents the number of gray levels in the image. Each element $P(i, j)$ thus denotes the probability of occurrence of the pixel pair (i, j). From the normalized GLCM, several texture descriptors were derived, namely contrast, correlation, energy, and homogeneity. The mathematical formulations of these features are presented in Equations (4)-(7).

Contrast: It measures local intensity variation between a pixel and its neighbor

$$\text{Contrast} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} i - j^2\, P(i,j) \quad (4)$$

Correlation: It evaluates the linear dependency of gray levels between pairs of pixels

$$\text{Correlation} = \frac{\sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i\sigma_j} \quad (5)$$

where μ_i, μ_j are the means and σ_i, σ_j are the standard deviations of the marginal distributions of $P(i, j)$.

Energy: It measures textural uniformity or smoothness

$$\text{Energy} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} P(i,j) \quad (6)$$

Homogeneity: It assesses the closeness of distribution to the diagonal, giving more weight to near-diagonal elements

$$\text{Homogeneity} = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{\boldsymbol{P}(i,j)}{\mathbf{1}+|\boldsymbol{i}-\boldsymbol{j}|} \quad (7)$$

These descriptors effectively capture the structural and spatial properties of images, making them highly suitable for disease identification and classification.

Entropy-based analysis quantifies the disorder or randomness present in the pixel intensity distribution of an image, thereby providing insights into its information content, complexity, and visual characteristics. In this context, disorder reflects the irregular distribution of pixel values, where diseased skin typically exhibits higher entropy compared to healthy skin due to increased randomness in texture patterns. To compute entropy, the probability distribution of pixel intensities is first determined. For 8-bit grayscale images, intensity values range from 0 to 255, while for color images, each pixel consists of red, green, and blue (RGB) channel values, allowing entropy to be calculated independently for each channel. For each intensity level *i*, the probability *P(i)* is computed as the frequency of occurrence of that intensity divided by the total number of pixels in the image. This probability distribution forms the basis for entropy analysis, which quantifies the degree of randomness in the image. Mathematically, the entropy *H* of the image is given by in Equation (8):

$$H = -\sum_{i=0}^{L-1} P\,(i)\,log_2 P(\mathrm{i}) \quad (8)$$

where, *P(i)* represents the probability of occurrence of intensity level *i,* while *L* denotes the total number of intensity levels. A higher entropy *(H)* indicates greater irregularity in the pixel intensity distribution, reflecting increased disorder within the image. Conversely, low entropy suggests a more ordered and predictable structure, where certain intensity levels dominate the image.

4. Results and Discussion

The analysis of four dermatological diseases Morgellons, Dermatitis, Psoriasis, and Vitiligo was performed using Gray Level Co-occurrence Matrix (GLCM) and entropy-based texture analysis. The results, presented in Figs. 2 and 3, illustrate the effectiveness of different texture parameters in capturing disease-specific patterns. Each figure consists of multiple subplots, where the leftmost image shows the original dermatological photograph, followed by processed outputs representing different texture attributes. The first column includes the grayscale image along with correlation and homogeneity, while the second column presents contrast, energy, and entropy parameters derived from the grayscale images. These processed feature maps clearly demonstrate how various texture measures highlight different lesion characteristics such as smoothness, irregularity, randomness, and intensity variation providing insights into disease-specific patterns. To further assess the robustness of the framework, the analysis was conducted with varying window sizes of 5, 15, and 25.

4.1. *Morgellons and Dermatitis*

The experimental findings for Morgellons disease indicate that entropy and homogeneity are particularly effective in capturing the complex and irregular texture patterns

characteristic of diseased skin regions. These features enable a distinct visual and statistical separation between affected lesions and surrounding healthy tissue. Entropy, which measures the randomness or complexity within an image, effectively identifies the chaotic and fibrous structures typical of Morgellons. Homogeneity, which assesses the uniformity of pixel intensities, helps differentiate the non-uniform texture of lesions from the smoother patterns of normal skin. In contrast, features such as contrast, correlation, and energy are less effective in highlighting the distinguishing characteristics of Morgellons. Contrast, which is intended to emphasize intensity variation, shows limited sensitivity to subtle differences within the lesions. Correlation, measuring the linear dependency of gray levels between neighboring pixels, fails to adequately capture the disorderly patterns in affected regions. Energy, which typically reflects texture uniformity, also lacks sensitivity to the scattered and fibrous structures. Therefore, these parameters are considered less reliable for characterizing Morgellons disease.

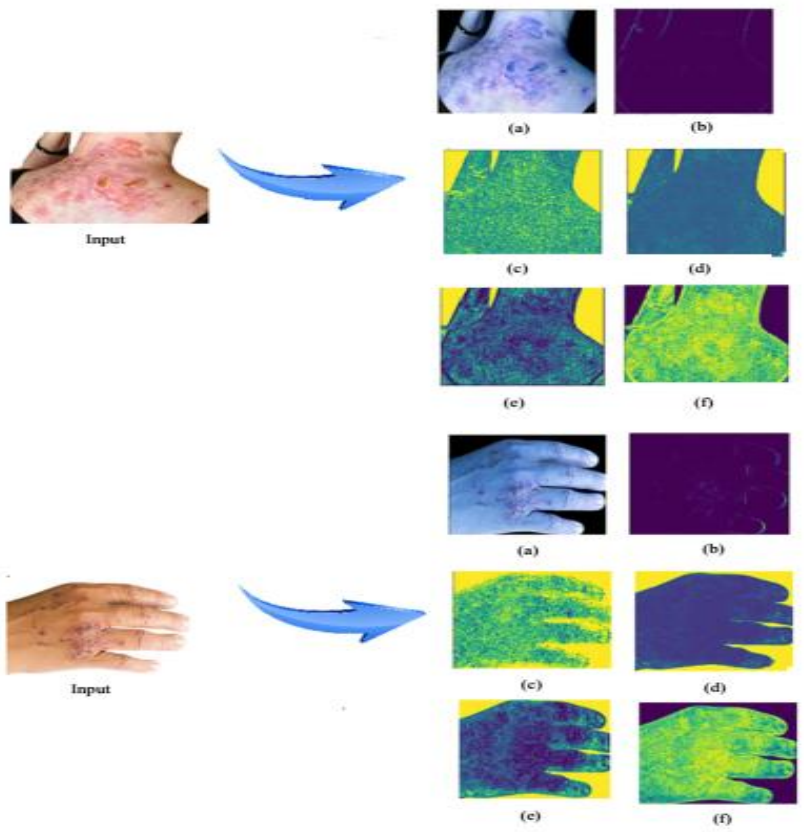

Fig. 2. GLCM and entropy analysis of Morgellons and Dermatitis (a) grayscale, (b) contrast, (c) correlation, (d) energy, (e) homogeneity, and (f) entropy.

A similar pattern is observed for Dermatitis. Entropy and homogeneity successfully capture the inflamed, rough, and disrupted texture associated with this condition. Entropy increases due to the randomness introduced by inflammation, while homogeneity decreases, reflecting the uneven texture of affected skin. In comparison, contrast, correlation, and energy remain less capable of distinguishing diseased regions from healthy tissue. These observations reinforce that entropy and homogeneity-based analysis provides a more reliable and effective framework for accurately identifying dermatological abnormalities such as Dermatitis.

4.2. *Psoriasis and Vitiligo*

For Psoriasis, entropy and homogeneity were the most effective in capturing the texture patterns of thickened, scaly skin, clearly highlighting the roughness and plaque like structures characteristic of psoriatic lesions. In comparison, contrast, correlation, and energy provided less pronounced representations of these patterns and were relatively less reliable for psoriasis detection. Similarly, in Vitiligo, entropy and homogeneity accurately delineated the depigmented patches and irregular skin tone typical of the disease, whereas contrast, correlation, and energy captured these features to a lesser extent, making them comparatively less useful.

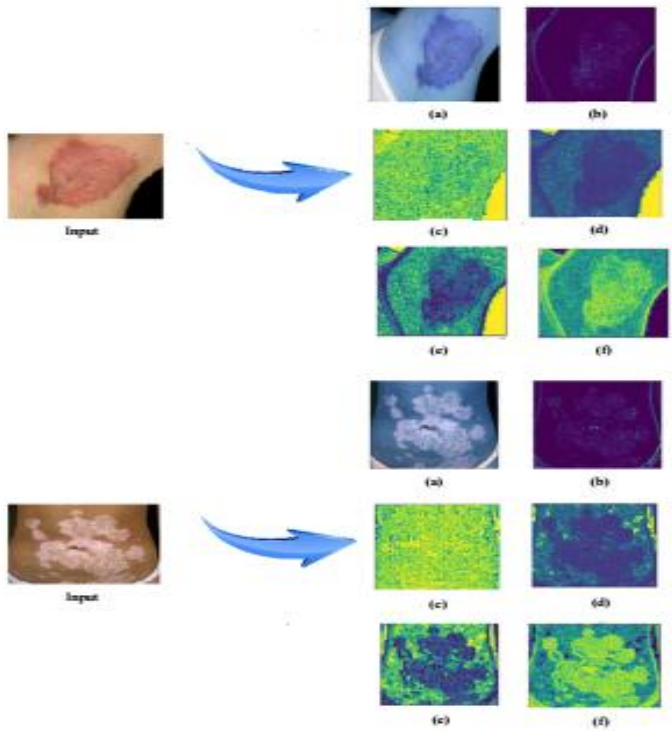

Fig. 3. GLCM and entropy analysis of Psoriasis and Vitiligo (a) grayscale, (b) contrast, (c) correlation, (d) energy, (e) homogeneity, and (f) entropy.

The analysis also revealed that the choice of window size significantly influences texture extraction. Increasing the window size to 15×15 or 25×25 resulted in less distinct texture patterns, reducing classification precision. A smaller window size of 5×5 consistently allowed entropy and homogeneity to capture detailed, disease-relevant textures. Across all four examined skin conditions, these two features demonstrated the strongest discriminative ability for disease identification and classification, while contrast, correlation, and energy contributed to a lesser degree.

Therefore, combining entropy and homogeneity with a 5×5 window size emerges as the most effective approach in this study for distinguishing dermatological diseases. These results underscore the potential of entropy-based texture analysis to enhance automated skin disease detection and provide a solid foundation for developing machine learning–driven diagnostic systems.

5. Conclusions

This study proposed an entropy-based texture analysis framework combined with GLCM features for the automated identification and classification of dermatological diseases. Five statistical descriptors contrast, correlation, energy, homogeneity, and entropy were evaluated across multiple skin conditions, including Morgellons, Dermatitis, Psoriasis, and Vitiligo. The results consistently showed that entropy and homogeneity provided the most reliable diagnostic cues, while contrast, correlation, and energy offered limited discriminative value. A key outcome of this work is the identification of the 5×5 window size as the optimal configuration for texture extraction, as it preserves fine lesion details while avoiding the blurring effects of larger windows. This finding highlights the importance of spatial resolution in medical image analysis, an aspect often overlooked in texture-based studies. Unlike deep learning models that require large annotated datasets, the proposed framework is lightweight, interpretable, and adaptable, making it well-suited for clinical decision-support systems in resource-constrained environments. By bridging statistical image analysis with AI-driven methodologies, this work lays the foundation for cost-effective and accessible diagnostic tools. Future research will focus on integrating these features with deep learning architectures such as CNNs and hybrid classifiers to further improve accuracy and enable real-time clinical deployment.

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