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Infrared Thermal Signatures for Characterizing Dermatological Disease: A Statistical Investigation

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Abstract
Dermatological diseases are commonly diagnosed through visual examination which may be influenced by lesion appearance imaging conditions and clinical experience. Infrared thermal imaging offers a non-contact and radiation-free approach for capturing physiological changes associated with inflammation blood perfusion and metabolic activity. This paper presents a preliminary exploratory statistical investigation of infrared thermal signatures for characterizing dermatological disease using Gaussian Mixture Modelling (GMM) conducted on a small pilot cohort of two acne-affected and two healthy subjects. Thermal images were analysed through channel-wise decomposition of the red (R) green (G) and blue (B) colour channels and for each channel a four-component GMM was fitted to model the intensity distribution from which statistical descriptors mean standard deviation variance skewness and kurtosis were extracted. Given the limited sample size no inferential statistical testing was performed; the analysis is descriptive and exploratory in nature. Within this pilot dataset diseased subjects showed higher R-channel intensity lower B-channel intensity and greater thermal heterogeneity than healthy subjects while the G-channel showed comparatively limited separation between groups. The probabilistic representation provided by GMM captured the heterogeneous thermal patterns observed in the diseased samples. These preliminary observations while not statistically generalizable due to the small and anatomically unmatched cohort suggest that channel-wise statistical analysis of infrared thermal images may reveal interpretable thermal signatures worth investigating further. The proposed framework is intended as an early step toward a statistical foundation for future machine learning and deep learning studies using larger anatomically matched dermatological thermal image datasets.

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Keywords: Infrared thermal imaging, dermatological disease, Gaussian Mixture Modelling, statistical analysis, thermal signatures

1. Introduction

Skin diseases are the most common diseases in the world and a significant source of non-fatal disease burden. Acne psoriasis eczema fungal infections vitiligo and so on affect millions of people every year and can cause physical pain cosmetic problems and psychological pain which adversely affect the quality of life [1 2]. Therefore, early and accurate diagnosis is crucial for the effective treatment and improved quality of life. Despite advances in dermatological practice skin diseases are still diagnosed mainly on visual examination and on the clinical basis of dermatologists' own experience [3]. Also, variations in illumination skin tone imaging conditions and anatomical location can influence the appearance of a skin lesion and diagnostic variability which has encouraged the development of objective computer-assisted techniques that can provide

physiological information that isn't visible to the human eye. Among the available imaging modalities infrared thermal imaging has emerged as a good non-contact and radiation-free method of medical diagnosis because it measures natural thermal radiation emitted by the human body [4, 5]. Unlike visible-light imaging thermal imaging also provides information about physiological signs including blood perfusion inflammatory response vascular activity tissue temperature and metabolic changes. Since inflammatory skin diseases are often associated with increased blood flow and tissue metabolism characteristic thermal patterns can be captured with infrared thermography [6, 7].

Research on the clinical health benefits of infrared thermography has shown its applications in breast cancer detection diabetic foot examination vascular disease diagnosis musculoskeletal injury wound monitoring and dermatological evaluation [5, 7]. Infrared thermal imaging can measure physiological changes without physical contact and is particularly useful to detect issues which may not be visible during physical examination and the development of such imaging is a good way to detect problems that may not be detected during normal clinical examination.

In dermatology it has been observed that diseased skin exhibits thermal variation compared to healthy skin and infrared thermography can provide physiological information to integrate with conventional clinical examination [8, 9]. It has also been used to provide information for the diagnosis of inflammatory skin disorders wound healing vascular abnormalities and cosmetic dermatology by detecting local temperature changes that result from physiological changes [6, 8]. In fact Raman *et al.* [9] reported significant thermal differences between psoriasis-affected and healthy skin and demonstrated that infrared imaging can be used to detect disease-related temperature changes. Vergilio *et al.* [8] noted the clinical value of infrared thermography for dermatological and aesthetic evaluation in terms of providing objective physiological information that complements visual assessment.

Moreover, to analyse thermal images researchers have investigated different computational methods such as temperature analysis histogram analysis statistical feature extraction texture analysis and artificial intelligence (AI)-based classification [7, 10]. Recent studies have further explored entropy-based texture analysis and DenseNet-169-based deep learning for dermatological disease identification using thermal images demonstrating promising performance for automated skin disease analysis [11, 12]. These methods have shown promising diagnostic performance and have significantly improved the automated analysis of medical images. However most existing studies mainly focus on improving classification accuracy and little attention has been given to understanding the statistical behaviour of thermal image intensities before developing predictive model.The statistical properties of thermal images can offer valuable insight into thermal behaviour of diseases and can provide insights into more informative image features for machine learning and deep learning models. Probabilistic modelling may help in a more accurate representation of the distribution of the intensities in the image rather than statistical measures. Among these methods Gaussian Mixture Modelling (GMM) has been widely used for reconstructing complex image data as a weighted mixture of many Gaussian components [13]. This makes GMM particularly appropriate for infrared thermal images where inflammatory skin lesions may have heterogeneous and multi-modal intensity distributions. By modelling these distributions probabilistically GMM can more accurately predict thermal behaviour and the natural statistical variability present in diseased tissue.

Despite the growing interest in infrared thermography for dermatological assessment there are two important research gaps. First only a few studies have explored channel-wise probabilistic behaviour of thermal image intensities before developing automated classification models. Second the application of Gaussian Mixture Modelling to statistically characterize dermatological thermal signatures has received very little attention. Addressing these gaps could help in the understanding of disease-specific thermal behaviour and provide interpretable statistical features that support the development of robust computer-aided diagnostic systems.

To address these gaps we present a preliminary probabilistic statistical analysis of infrared thermal images taken from acne-affected and healthy skin. The proposed framework applies Gaussian Mixture Modelling separately to the red green and blue colour channels and also to extract statistical descriptors (mean standard deviation variance skewness kurtosis). Rather than developing a classification model the purpose of this research is to investigate if channel-wise statistical analysis can reveal interpretable thermal signatures that differentiate acne-affected skin from healthy skin. The results will support the hybrid machine learning and deep learning framework developed in the follow-up works of this research.

The main contributions of this study are summarized as follows:

- A probabilistic statistical framework based on Gaussian Mixture Modelling is proposed for analysing infrared thermal images of dermatological conditions.
- Channel-wise statistical descriptors are extracted to investigate differences between acne-affected and healthy skin.
- Thermal characteristics of the red green and blue colour channels are analysed to identify interpretable statistical patterns associated with inflammatory skin conditions.
- The proposed statistical analysis establishes a methodological foundation for future machine learning and deep learning studies using larger dermatological thermal image datasets.

The remainder of this paper is organized as follows. Section 2 presents the proposed methodology including data acquisition image pre-processing Gaussian Mixture Modelling and statistical feature extraction. Section 3 presents the experimental results and discussion while Section 4 concludes the study and outlines future research directions.

2. Materials and Methods

2.1. Study Overview

This study presents a preliminary statistical investigation of infrared thermal images to examine whether diseased and non-diseased skin exhibit distinguishable thermal characteristics. The proposed framework combines thermal image pre-processing Gaussian Mixture Modelling (GMM) and channel-wise statistical analysis to characterize the

thermal behaviour of skin. Rather than developing a predictive classification model the objective is to investigate whether probabilistic intensity distributions and their statistical descriptors can reveal meaningful thermal signatures associated with dermatological abnormalities. The overall workflow of the proposed methodology is illustrated in Figure 1.

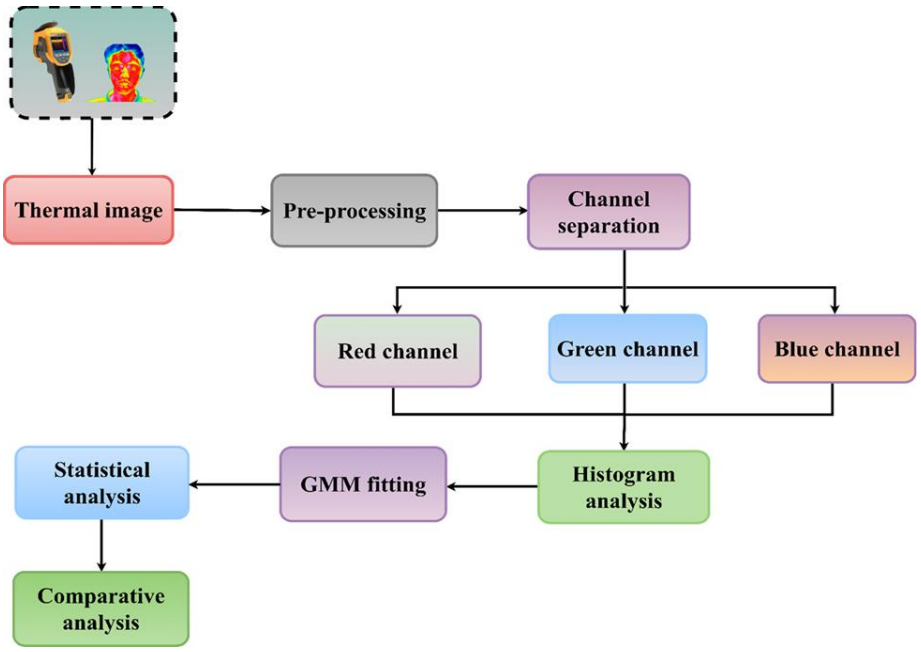

Fig 1: Proposed methodology

2.2. Thermal Image Acquisition

Thermal images were acquired using a "*Fluke Ti480 Pro*" infrared thermal camera under controlled environmental conditions to minimize the influence of ambient temperature individuals. The diseased group comprised two facial thermal images (Subjects D1 and D2) while the healthy group included one facial image (Subject N1) and one hand image (Subject N2). The study was intentionally designed as an exploratory statistical investigation using a limited cohort to examine whether thermal intensity characteristics differ between healthy and diseased skin before conducting large-scale machine learning experiments.

2.3. Image Pre-processing

Prior to analysis the acquired thermal images were processed using SmartView software to obtain calibrated images for quantitative analysis. The images were normalized to ensure consistency across all samples followed by bilateral filtering to reduce sensor noise while preserving edges and thermal gradients. Subsequently each thermal image was analysed separately in the red (R) green (G) and blue (B) colour channels. Channel-wise statistical descriptors and Gaussian Mixture Model (GMM) parameters were then extracted independently for each colour channel.

2.4. Gaussian Mixture Modelling (GMM)

Gaussian Mixture Modelling (GMM) was applied to analyse the thermal intensity distribution of infrared images. The red (R) green (G) and blue (B) colour channels of each thermal image were analysed separately. For each colour channel the intensity distribution was modelled by using four Gaussian components (K = 4) to measure the thermal features. The model parameters like mean standard deviation and mixing weight of each Gaussian component were estimated using the EM algorithm. The GMM parameters of each colour channel are expected to be a probabilistic representation of the thermal intensity distribution and thus can be used for statistical analysis and comparison of patients with and without diseases.

2.5. Statistical Analysis

In order to measure the thermal behaviour of each image five statistical descriptors mean standard deviation variance skewness and kurtosis were extracted from the R G and B colour channels. The extracted descriptors and the corresponding GMM parameters were compared between the diseased and non-diseased subjects to measure the thermal intensity distribution and thermal heterogeneity of dermatological abnormalities.

3. Results

3.1. Subject D1 (Diseased)

Figure 2 shows the thermal image of Subject D1 and the corresponding R G and B channel intensity histograms and their four-component GMM fits. The thermal image shows a heterogeneous intensity distribution with multiple peaks across the three colour channels which indicates that heat is not uniformly distributed over the affected skin region.

The statistical descriptors extracted from the three channels are summarized in Table 1 while the corresponding GMM parameters are listed in Table 2. The R channel recorded a mean intensity of 153.72 whereas the G and B channel means were 170.84 and 162.24 respectively. In addition the R-channel exhibited the highest variance (7041.36) followed by the B channel (4953.33) and the G channel (4812.70).

The relatively high variance observed across all three channels suggests considerable thermal heterogeneity within the diseased region. Such heterogeneous intensity patterns are consistent with localized inflammatory activity where

variations in blood perfusion and metabolic response produce non-uniform temperature distributions across the affected skin. The GMM decomposition further demonstrates that the intensity distribution is represented by multiple Gaussian components with different mixture weights confirming the presence of several underlying thermal populations rather than a single homogeneous distribution.

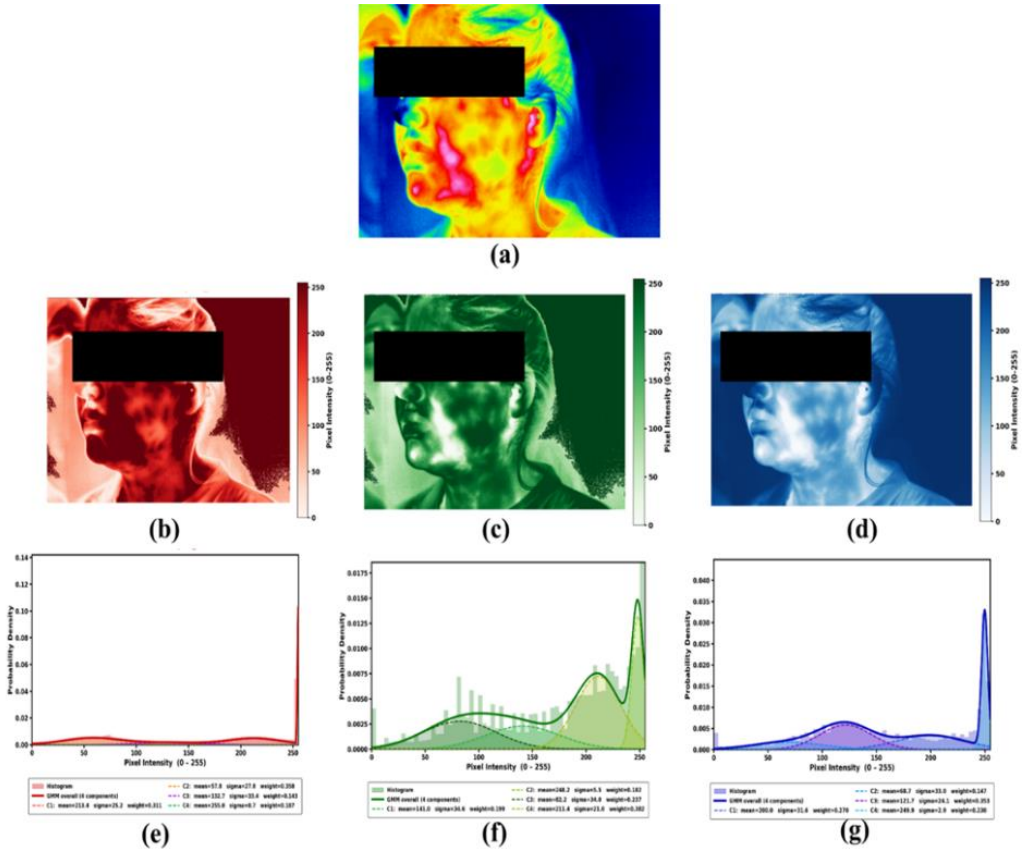

Fig 2: Thermal image of Subject *D1 (Diseased)* together with the corresponding R, G, and B channel histograms and four-component GMM fits

Table 1: Channel-wise statistical analysis D1

Channel	Mean	Std. Dev.	Variance	Skewness	Kurtosis
R channel	153.7181	83.9128	7041.3572	-0.1996	-1.4773
G channel	170.8381	69.3736	4812.6951	-0.6222	-0.7329
B channel	162.2378	70.3799	4953.3286	-0.2165	-1.0021

Table 2: GMM decomposition parameters D1

Comp.	R: μ	R: σ	R: w	G: μ	G: σ	G: w	B: μ	B: σ	B: w
C1	213.40	25.25	0.3109	140.96	34.62	0.1991	199.95	31.60	0.2696
C2	57.78	27.79	0.3582	248.25	5.46	0.1817	68.69	32.96	0.1467
C3	132.75	33.39	0.1434	82.19	34.01	0.2371	121.70	24.07	0.3534
C4	254.96	0.74	0.1875	211.38	21.02	0.3820	249.87	2.86	0.2302

3.2. Subject D2 (Diseased)

The thermal image of Subject D2 shown in Figure 3 demonstrates thermal characteristics similar to those observed in Subject D1. Multiple intensity peaks are visible in the channel-wise histograms indicating a heterogeneous thermal profile associated with inflammatory skin changes.

The statistical descriptors presented in Table 3 reveal that the R channel produced the highest mean intensity (186.25) among all three channels while the G and B channel means were 36.24 and 114.48 respectively. The R channel also exhibited the largest variance (8576.63) indicating substantial variation in thermal intensity across the affected region.

The corresponding GMM parameters listed in Table 4 further illustrate the complex intensity distribution of the diseased skin. The distribution of mixture weights across multiple Gaussian components indicates that the thermal pattern cannot be represented by a single dominant intensity level. Instead the presence of several statistically significant components reflects localized temperature variations that are commonly associated with inflammatory lesions.

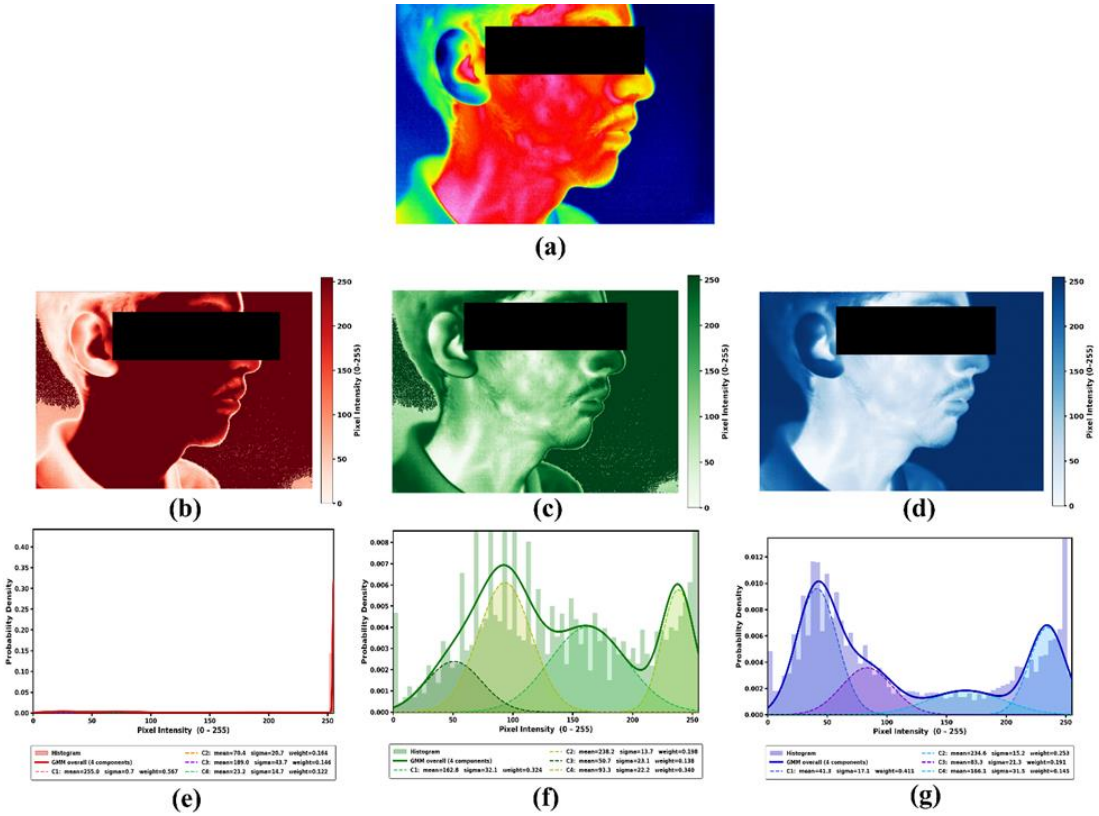

Fig 3: Thermal image of Subject D2 (Diseased) together with the corresponding R, G, and B channel histograms and four-component GMM fits.

Table 3: Channel-wise statistical analysis D2

Channel	Mean	Std. Dev.	Variance	Skewness	Kurtosis
R channel	186.2458	92.6101	8576.6259	-0.8241	-1.0669
G channel	136.2400	69.0833	4772.4978	0.1656	-1.0201
B channel	114.4846	83.3070	6940.0488	0.4691	-1.3561

Table 4: GMM decomposition parameters D2

Comp.	R: μ	R: σ	R: w	G: μ	G: σ	G: w	B: μ	B: σ	B: w
C1	254.99	0.72	0.5674	162.84	32.09	0.3237	41.25	17.06	0.4107
C2	70.35	20.74	0.1641	238.16	13.68	0.1979	234.58	15.22	0.2534
C3	189.04	43.67	0.1464	50.75	23.09	0.1385	83.27	21.30	0.1909
C4	23.21	14.71	0.1221	93.34	22.22	0.3400	166.10	31.54	0.1449

3.3. Subject N1 (Non-Diseased)

The thermal image of Subject N1 and its corresponding channel-wise histograms are presented in Figure 4. Compared with the diseased subjects the thermal image exhibits a more uniform intensity distribution with fewer pronounced peaks in the histogram.

The statistical descriptors summarized in Table 5 indicate R G and B channel mean intensities of 74.64 156.61 and 208.69 respectively. The variances observed across the three channels are consistently lower than those obtained for the diseased subjects indicating a more homogeneous thermal profile.

The GMM decomposition shown in Table 6 demonstrates that the majority of the intensity distribution is concentrated within one or two dominant Gaussian components. This behaviour suggests relatively stable thermal characteristics in the absence of localized inflammatory activity resulting in reduced thermal variability across the image.

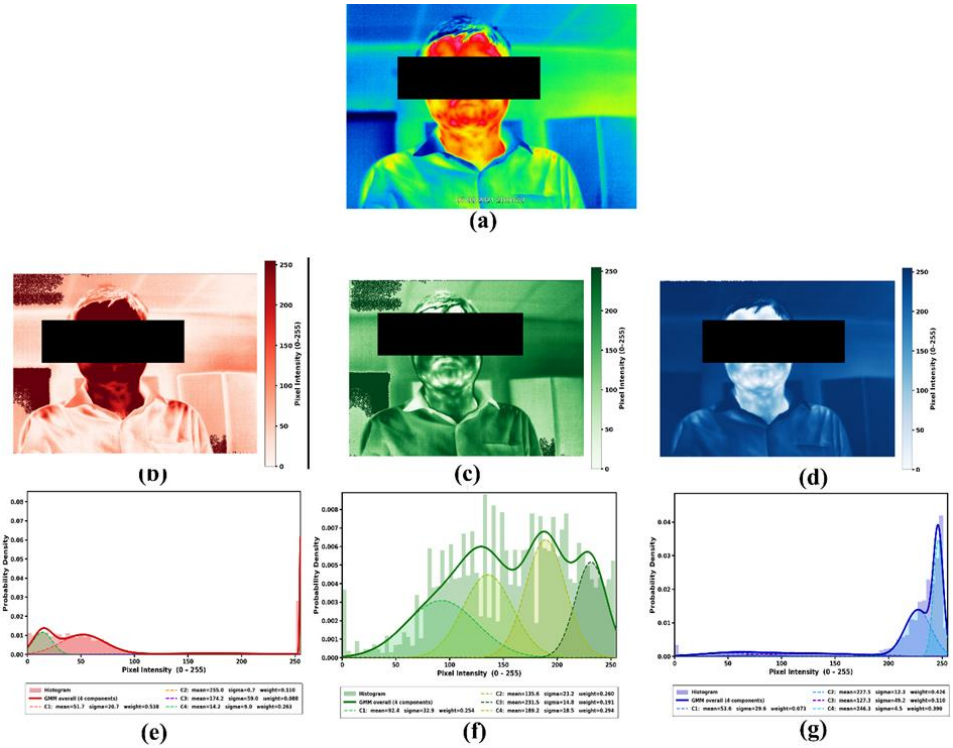

Fig 4: Thermal image of Subject ***N1 (Non-Diseased)*** together with the corresponding R, G, and B channel histograms and four-component GMM fits.

Table 5: Channel-wise statistical analysis N1

Channel	Mean	Std. Dev.	Variance	Skewness	Kurtosis
R channel	74.6366	79.1102	6258.4200	1.4668	0.7426
G channel	156.6087	58.2027	3387.5519	-0.3818	-0.4276
B channel	208.6939	63.6633	4053.0118	-1.9310	2.5026

Table 6: GMM decomposition parameters N1

Comp.	R: μ	R: σ	R: w	G: μ	G: σ	G: w	B: μ	B: σ	B: w
C1	51.75	20.74	0.5384	92.41	32.87	0.2543	53.57	29.60	0.0732
C2	254.99	0.72	0.1102	135.56	23.18	0.2601	227.55	12.31	0.4263
C3	174.18	59.02	0.0884	231.50	14.78	0.1912	127.27	49.19	0.1100
C4	14.24	8.97	0.2630	189.17	18.45	0.2944	246.31	4.49	0.3905

3.4. Subject N2 (Non-Diseased)

Figure 5 illustrates the thermal image and corresponding GMM decomposition for Subject N2. Similar to Subject N1 the statistical analysis indicates a comparatively homogeneous thermal distribution despite representing a different anatomical site. The statistical descriptors listed in Table 7 show R G and B channel mean intensities of 87.25 170.81 and 199.31 respectively. Although slight variations are observed because the image corresponds to the hand rather than the face the overall thermal behaviour remains considerably more uniform than that of the diseased subjects. The corresponding GMM parameters presented in Table 8 reveal that the thermal intensity distribution is dominated by relatively stable Gaussian components further supporting the observation that healthy skin exhibits lower thermal heterogeneity than inflamed skin.

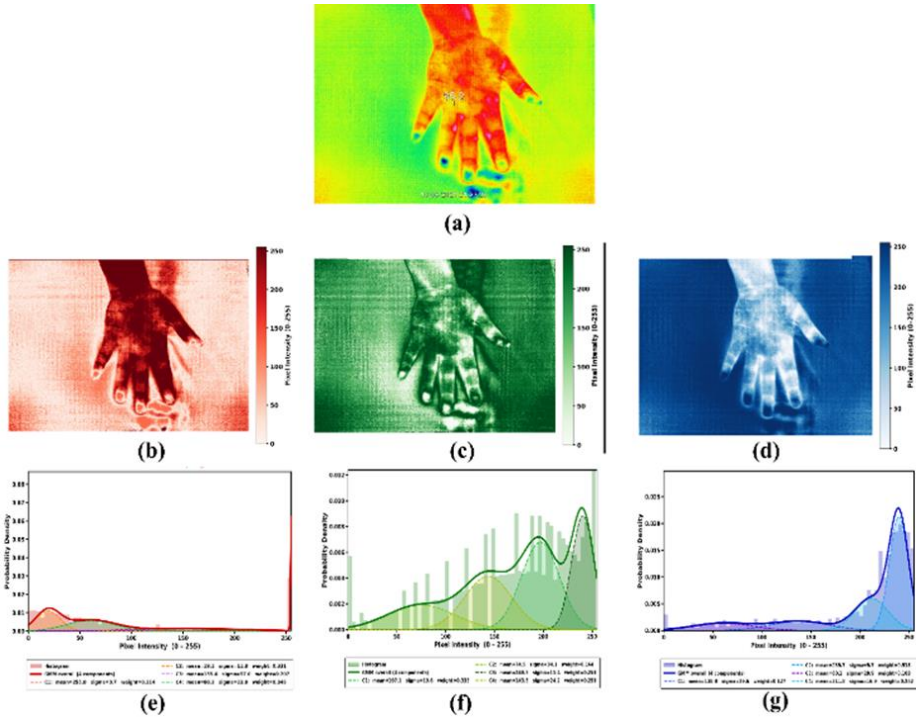

Fig 5: Thermal image of Subject N2 (Non-Diseased) together with the corresponding R, G, and B channel histograms and four-component GMM fits

Table 7: Channel-wise statistical analysis N2

Channel	Mean	Std. Dev.	Variance	Skewness	Kurtosis
R channel	87.2512	82.9589	6882.1753	1.0201	-0.3470
G channel	170.8060	64.7119	4187.6308	-0.7841	-0.0951
B channel	199.3080	63.5125	4033.8388	-1.5575	1.3836

Table 8: GMM decomposition parameters N2

Comp.	R: μ	R: σ	R: w	G: μ	G: σ	G: w	B: μ	B: σ	B: w
C1	254.97	0.73	0.1139	197.11	19.56	0.3328	138.79	29.61	0.1268
C2	19.12	11.84	0.3306	74.52	34.12	0.1643	239.68	9.72	0.5178
C3	155.36	57.03	0.2074	240.51	11.35	0.2514	60.13	29.89	0.1030
C4	60.21	23.81	0.3482	143.54	24.22	0.2515	211.81	16.90	0.2523

3.5. Comparative Analysis

To investigate the overall thermal behaviour of the two groups the channel-wise statistical descriptors were compared using the arithmetic mean calculated across subjects within each group as summarized Table 9.

A clear distinction between the diseased and non-diseased groups is observed in the R channel. The diseased subjects exhibited a substantially higher average R channel intensity (169.98) than the healthy subjects (80.94) with no overlap between the two groups. Conversely the B channel demonstrated the opposite trend where the diseased group recorded a considerably lower average intensity (138.36) compared with the healthy group (204.00). In contrast the G channel showed considerable overlap between the two groups suggesting that it contributes less to discrimination in this preliminary dataset.

The analysis also revealed consistently higher intensity variance in the diseased group across all three colours channels. Increased variance indicates greater thermal heterogeneity reflecting localized fluctuations in surface temperature associated with inflammatory processes. This observation is further supported by the GMM decomposition where the diseased subjects exhibited intensity distributions distributed across multiple Gaussian components whereas the healthy subjects were characterized by fewer dominant components.

Overall these findings indicate that the R and B channel intensity distributions provide the most informative thermal characteristics for distinguishing diseased skin from non-diseased skin within the analysed cohort.

Table 9: GMM decomposition parameters overall comparison (diseased vs. healthy)

Comp.	R: μ	R: σ	R: w	G: μ	G: σ	G: w	B: μ	B: σ	B: w
C1	254.97	0.73	0.1139	197.11	19.56	0.3328	138.79	29.61	0.1268
C2	19.12	11.84	0.3306	74.52	34.12	0.1643	239.68	9.72	0.5178
C3	155.36	57.03	0.2074	240.51	11.35	0.2514	60.13	29.89	0.1030
C4	60.21	23.81	0.3482	143.54	24.22	0.2515	211.81	16.90	0.2523

4. Discussion

The present study demonstrates that probabilistic statistical analysis of infrared thermal images provides meaningful insight into the thermal behaviour of dermatological abnormalities. Although the study was conducted on a small exploratory cohort consistent differences were observed between diseased and non-diseased subjects.

The elevated R channel intensity observed in acne-affected skin is indicative of increased localized heat associated with inflammatory activity while the lower B channel intensity reflects the corresponding reduction in cooler temperature regions. These observations agree with the physiological understanding that inflammation increases blood perfusion and metabolic activity resulting in localized temperature elevation.

An additional finding of this study is the consistently higher thermal variance observed in the diseased subjects. Rather than exhibiting a uniform temperature distribution inflammatory lesions produced heterogeneous thermal patterns that were effectively represented through multiple Gaussian components. Consequently, GMM provides an interpretable statistical framework for describing complex thermal intensity distributions without relying on automated classification algorithms.

The present work should be interpreted in light of several limitations. First the pilot dataset consisted of only four subjects (two diseased two healthy) which is insufficient for formal inferential statistical testing; consequently, no significance testing (e.g. t-test or ANOVA) was performed and the comparisons reported in this study are descriptive rather than statistically generalizable. Second one healthy subject corresponded to a hand image rather than a facial image introducing anatomical variability that is confounded with disease status in the between-group comparison. Third the mapping between R/G/B channel intensity and true radiometric temperature depends on the color palette and scaling applied during image export; while a fixed palette and consistent acquisition protocol were used across all subjects this study does not independently verify pixel-level temperature calibration. These limitations mean the reported channel-wise differences should be regarded as preliminary hypothesis-generating observations rather than validated diagnostic markers. Despite these constraints the observed channel-wise thermal patterns were consistent across the analysed subjects and provide encouraging exploratory evidence that probabilistic statistical modelling may be useful for characterizing thermal signatures associated with dermatological abnormalities in future larger-scale studies.

The statistical observations presented in this work establish the foundation for the larger machine learning and deep learning frameworks developed in the subsequent stages of this research where these thermal characteristics are evaluated using substantially larger multi-class datasets

5. Conclusion and Future Work

This study presented a preliminary probabilistic statistical investigation of infrared thermal images for characterizing dermatological abnormalities using Gaussian Mixture Modelling (GMM). A channel-wise analysis of the red (R) green (G) and blue (B) colour channels was performed to examine the thermal behaviour of acne-affected and healthy skin. The extracted statistical descriptors together with the GMM decomposition parameters provided an interpretable representation of the underlying thermal intensity distributions.

Within this small pilot cohort the experimental results showed noticeable descriptive differences between diseased and non-diseased skin. Diseased subjects showed higher R channel intensity lower B channel intensity and greater thermal heterogeneity than healthy subjects while the G channel showed relatively limited separation between groups. Furthermore, the probabilistic representation obtained through GMM captured the heterogeneous thermal patterns observed in the diseased samples providing a compact statistical description of the observed thermal behaviour. As noted above these observations are descriptive and have not been validated through inferential statistical testing or a larger anatomically matched cohort.

Although the present investigation was conducted on a small pilot dataset the findings demonstrate the potential of channel-wise probabilistic analysis for identifying thermal characteristics associated with dermatological abnormalities. Rather than serving as a diagnostic model the proposed framework establishes a statistical foundation for understanding disease-specific thermal behaviour and provides interpretable thermal descriptors that may support the development of future computer-aided diagnostic systems.

Future work will focus on extending the analysis to a substantially larger and anatomically matched dataset comprising multiple dermatological conditions. Additional statistical descriptors and probabilistic modelling strategies will be investigated to further improve the characterization of thermal patterns. Furthermore the extracted statistical information will be integrated with machine learning and deep learning frameworks to evaluate its effectiveness for automated dermatological disease classification.

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- **Data Availability**

The data associated with this study are provided in the manuscript and are available upon reasonable request from the corresponding author.

- **Consent for Publication**

Informed consent was obtained from all participants for the use of anonymized images and associated data in research and publication.

- **Ethics Approval**

NOC from the ethical committee of University of Jammu had

been taken before recording the dermatological images from the patients (Reference No. RA/24/4843).

- **Competing Interests**

The authors have no conflicts of interest to declare.

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