EVALUATION OF BACKGROUND SUBTRACTION EFFECT ON CLASSIFICATION AND SEGMENTATION OF KNEE THERMOGRAM

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Abstract— **Presence of inflamed region in knee thermogram indicates the existence of abnormality related to inflammatory diseases. Classification based accurate decision making for knee abnormality and spread of disease analysis is negatively influenced by the unwanted background region of thermogram. In this paper, the effectiveness of background subtraction on knee thermogram classification and segmentation is highlighted depending on accuracy and quantification of segmentation output. The method mainly contains three steps: background subtraction, classification, and segmentation of inflamed region. Automated subtraction of background region is performed using Expectation Maximization method. Extracted features from 50 healthy and 50 arthritis affected knee thermograms are fed to classifiers for accuracy analysis before and after background subtraction. Effect of background subtraction increases the accuracy rate of classification at least by 10%. Popular state of the art segmentation techniques also shows that subtraction of background region enhances the accuracy of knee thermogram segmentation at least by 0.1%.**

Keywords— *Background subtraction; thermogram; classification; segmentation;*

I. INTRODUCTION

Thermoregulation in human body is influenced by pathological abnormality. Due to the involvement of unknown physiological phenomena, measurement of abnormality is a very complex task for joint pain diseases. Presently the quantification of inflammatory joint disease depends on the capability of person to express the condition mainly through words, visual analog scale, and facial expression. Therefore, diagnosis of joint abnormality is a complex task for medical experts, especially in case of children, old age person, and person with impairments. Recording of the distribution of temperature in human body joints provides helpful information associated with physiological abnormality related to inflammatory pain. The skin of human body plays an important role in infrared distribution through preserving or dissipating heat. The heat dissipation through human skin is radiative in nature and mainly falls under the infrared part of
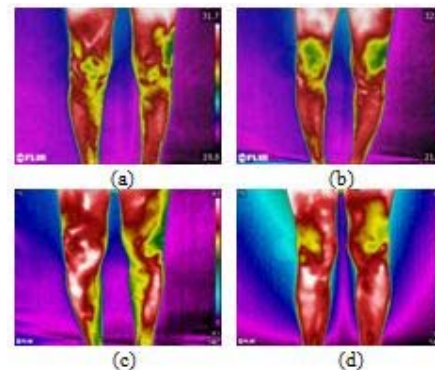

Fig. 1. Row 1: Thermograms of healthy knee; Row 2: Thermograms of arthritis affected knee

the light spectrum. It makes infrared detectors most appropriate for receiving the radiation and recording the distribution of skin temperature. Medical Infrared Thermography (MIT) is the non-invasive method to screen the temperature distribution for detection of abnormality associated with inflammatory joint pain [1]. In present scenario, arthritis is the most commonly occurring inflammatory joint disease, and it causes severe pain in joints. In US, 18% of total disabilities are the result of arthritis and 43.2% of arthritis patients facing limitation in their daily activities [2].

Diagnosis of inflammatory joint disease in the initial stage is helpful in avoiding structural damage of joints which results abnormality. Inflammation oriented accurate extraction of feature using thermal image may help in early diagnosis of disease. As the quantity of inflamed region helps in subjective grading in disease severity, so evaluation of the spread of inflammation by extracting the inflamed region of interest helps in progress of treatment analysis. Figure 1 shows examples of thermogram related to lower part of the body. In each thermogram, two regions are present: background region
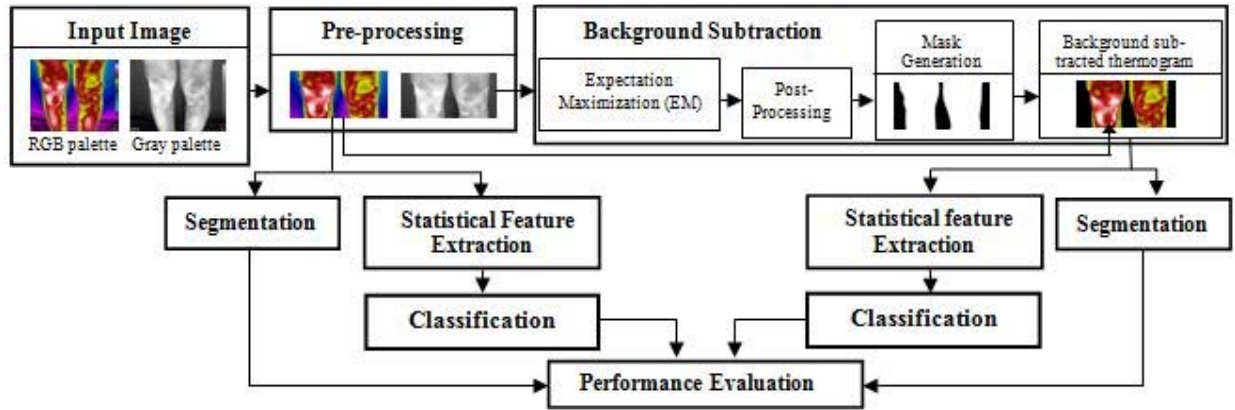
Fig. 2. Overall flowdiagram of analysis

and human leg region. We are mainly concern about the knee region of the thermogram which contains inflammation oriented information related to knee abnormality. The background region contains unwanted information which may lead to erroneous result in classification of knee thermogram for detection of abnormality and also in extraction of inflamed region of interest. Though manual subtraction of background region generates most accurate results, but it is time-consuming, challenging task for a huge number of images and may lead to expert bias. Therefore, automatical subtraction of background region makes an essential contribution to reducing processing time, workload and biases.

Automated segmentation of background region from hand thermogram was performed by X. Font-Aragones et al. [3] using visual and thermal image of hand region. The visual image is binarized by Otsu thresholding. The binary mask generated from Otsu thresholding was further used for subtracting the background region of thermal hand image with additional rotation, translation, and scaling parameters. M. E. Tavakol et al. [4] subtracted the background region from breast thermogram by applying Canny edge detection over the breast region. In their method, manual land mark points were selected and trained for extraction of two lower boundaries from breast region. S.S. Suganthi et al. [5] also subtracted the background region from breast thermogram by segmenting the breast region using non-linear anisotropic diffusion filtering and level set method. The filtering process enhanced the edges, and breast boundary was detected through level set segmentation method. S. Pramanik et al. [6] performed Otsu threshold based segmentation for removal of background region from breast thermogram followed by morphological operation, filtering and edge detection techniques for breast upper and lower boundary detection. M. Milosevic et al. [7] conducted background subtraction using manual segmentation of breast region from breast thermogram. The review shows that use of background subtraction is mostly used in breast thermogram compare to knee and other joint thermograms.

Depending on the phenomenon, this paper mainly highlights the method of automatic back ground subtraction from knee thermal image and also investigated effects of background subtraction over classification and segmentation of knee thermogram. The contributions of the paper contain:

- Hybrid method for subtraction of background region from knee thermogram.
- Effect of background subtraction on classification of knee thermogram for arthritis related abnormality detection.
- Effect of background subtraction on segmentation of inflamed region from knee thermogram.

The remainder of the paper is organized as follows: section II contains details of methodology for background subtraction, classification, and segmentation of knee thermogram. Section III contains the comparison based results and discussion of the methodology output. The final section concludes the overall work stating future direction of research.

II. METHODOLOGY

Evaluation of the effects of background subtraction over knee thermogram has been performed by combining five major steps of image processing: Dataset collection, pre-processing, background subtraction, classification, and segmentation of inflamed region. The overall flowchart of the method is given in figure 2 and described below.

A. Dataset Collection

Effect analysis of knee thermogram background subtraction is applied over 100 frontal thermograms of knee region. Among those 100 thermograms, 50 images are acquired from arthritis patients with complains of pain and restriction of movement in knee region. The other 50 knee thermograms are collected from healthy subjects who have no complaints regarding knee joints. The acquisition of dataset is performed at Physical Medicine and Rehabilitation (PMR) Department, Agartala Government Medical College (AGMC) of Govind Ballav Pant (GBP) Hospital, Agartala, Tripura (W) under the supervision of medical experts and by following standardized method of thermogram acquisition [8]. The FLIR T650sc thermogram acquisition system with sensitivity 0.02°C at 30°C is used for capturing the image based temperature flow from knee region. All the thermograms are saved in RGB and Gray palette using
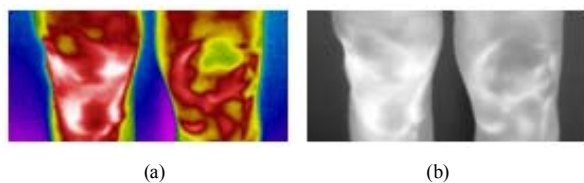
(a)   (b)

Fig. 3. Thermogram preprocessing output on (a) RGB palette (b) gray scale palette

FLIR Tool+ software as shown in input image section of figure 2. The ground truth related to inflamed region of arthritis affected knee thermogram is generated by seven individual technicians using GNU Image Manipulation Program (GIMP) [9, 10] software. Through majority voting policy for each pixel, the final ground truth is generated and examined by medical expert. The rejected ground truths are again followed the same procedure under the supervision of medical expert. The generated ground truth is used for accuracy analysis of segmentation methods.

B. Pre-processing

Pre-processing of image decreases the processing workload, execution time and complexity of an automated system. In our dataset, preprocessing help in elimination of unwanted information, increases the accuracy of image analysis and speed up the execution time. The original captured thermogram contains pixel based inflammatory information regarding the lower part of the body as shown in figure 1. Additionally, it contains company logo, color bar and maximum and minimum temperature range of thermogram. In knee arthritis, abnormality in inflammation distribution mainly affects the knee joints. Therefore, in preprocessing step elimination of unwanted parts is performed by manually rectangular cropping of the knee region from original thermograms. Example of the cropped output is shown in figure 3 for RGB and gray palette of thermogram.

C. Background subtraction

The preprocessing output consists of the information regarding inflammation present in knee area along with background region. To increasing the accuracy of classification and segmentation, the removal of background region from the preprocessing output is performed in this section. The subtraction of background region from the gray palette thermogram is established by automated generation of mask using Expectation Maximization method.

Fig. 4 Mask generated for background subtraction using EM method

Expectation Maximization (EM) is an unsupervised method used for estimating the density of data points. The method relies on iteratively estimating the maximal likelihood parameters where hidden data values are present. This estimation is performed by first approximating the hidden data depending on existing parameter estimation. The final estimation of data (hidden and observed data) is utilized to calculate the parameter values by maximizing the probability of the completely estimated data.

The EM mainly contains two steps: expectation step (E-step) and maximization step (M-step). The E-step estimates the hidden data depending on estimated parameters over the observed data, and the M-step maximizes the existence probability of total data set (data found in the E-step and observed data). The stopping criteria for the iterative process carried out when the maximum difference in between E- step and M- step is reached.

Mathematically, for a given data vector $\{y_1, y_2,...,y_x\}$ and for model $m(y,z)$ where z is hidden data points, we have:

$$p(\theta)=\sum_1^x \log m(y;\theta) \qquad (1)$$

$$p(\theta)=\sum_1^x \log \sum_z m(y,z;\theta) \qquad (2)$$

In the above equation, the variable z is unknown. So instead of z, approximation of z will be placed. The approximation is calculated using E and M steps as described above and formulated below [11, 12, 13]

E-Step:

$$E_i(z^{(i)}) := m(z^{(i)} | y^{(i)}, \theta) \qquad (3)$$

M-Step :

$$\theta := \arg \max_\theta \sum_i \sum_{z^{(i)}} E_i(z^{(i)}) \log \frac{m(y^{(i)}, z^{(i)}; \theta)}{E_i(z^{(i)})} \qquad (4)$$

Here, i = 1 to x

In image, the pixel intensities are considered as processed data points. The segmentation of image pixels is started by initialization of data points through untrained cluster mapping. In each iteration, the label is updated for each pixel intensity. The updation stops, when the labels are unchanged in between n^{th} and $(n-1)^{th}$ iteration. In our analysis, the number of segment is fixed to 2 as we consider the knee region as foreground and rest of the region as background. The outcome of the EM
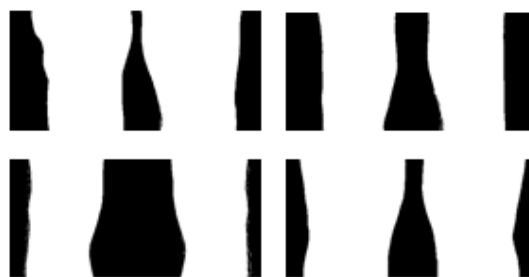
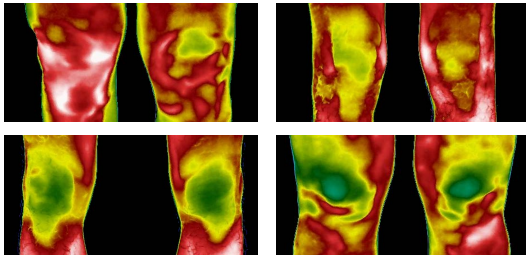

Fig. 5 post processing of EM output

Fig. 6 Background subtracted thermogram in RGB palette

generates a binary mask. In the mask, the pixel value 1 stands for the knee region and 0 represents the background region as shown in figure 4.

In few thermograms, the radiated inflammation from knee region is similar to the background region. Use of EM segmentation for such thermogram may consider some portions of the knee region as background object as shown in second row of figure 4. Therefore in our dataset, accuracy of background subtraction is increased by post-processing of the output of EM segmentation. The post-processing step includes edge detection followed by morphological region fill on the outcome of EM segmentation. In binary mask, use of region fill only consider the region with intensity 0 and surrounded by pixel value 1 and replace the region with value 1. The first image shown in second row of figure 4 can be converted into a correct mask by removing holes present in knee region using region fill. In our dataset, only region fill cannot help in creation of accurate mask due to those 0 intensity pixels which are not surrounded by white pixels in their 8-neighbourhood region but originally part of the knee region as shown in the last mask of figure 4. To overcome such difficulty, the sobel edge detection has been performed on the input of EM segmentation. The detected edges are convolved with the output mask of EM method and region fill is applied over the convolution result. The output of post-processing step for corresponding masks present in figure 4 is shown in figure 5.

In the final step of background subtraction, the output mask generated from post processing of EM method is multiplied with the preprocessed RGB palette thermogram. The multiplication converted the background pixel intensities of RGB image as zero without affecting the intensities of foreground (knee) region as shown in figure 6. The statistical features are extracted from the background subtracted preprocessed RGB thermograms of knee region for further analysis as described in next section.

D. Statistical Feature based Classification

Inflammation oriented classification of knee thermogram for abnormality detection related to arthritis helps in diagnosis of disease in medical science. Higher rate of classifier accuracy tends to proper diagnosis of abnormality. In our system, classification has been performed over two groups of thermograms. One group consists of RGB thermogram of healthy and arthritis affected knee without subtracting background objects as shown in figure 3(a) and the other group consists of the same the thermograms after subtraction of background region as shown in figure 6. In the training dataset 70 thermograms are used. Among those, 35 thermograms belong to healthy knee region and rests are related to arthritis affected knee region. The testing set consists of 30 knee thermograms where 15 thermograms are from healthy subjects and rests 15 are collected from arthritis affected knee. In training and testing set, diagnosis of arthritis knee is performed by medical experts. The classification is performed depending on first and second order statistical features of image for both the groups. From first and second order statistical analysis, ten features are collected by following the publication of M. K. Bhowmik et al.[8]. Features selected from first order statistical analysis are mean, variance, standard deviation, skewness, kurtosis, entropy and from second order statistics Homogeneity, Contrast, Energy and Correlation are computed for classification input. The extracted ten features are fed to the Random Forest, Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) classifier for automated diagnosis of abnormality due to arthritis in knee region. The classification mainly aims at showing the effect of background subtraction of knee thermogram over the accuracy of correct diagnosis. The effect is elaborately discussed in the performance evaluation section of the paper

E. Segmentation of inflamed region of interest

Accurate segmentation of inflamed region of interest from arthritis affected knee thermograms helps medical experts in quantification of the spread of the disease. Depending on the spread of inflammation, progress of treatment is possible to analyze along with grading of arthritis. In this paper, we use five popular states of the art method of segmentation for extraction of inflamed region from 50 arthritis affected knee
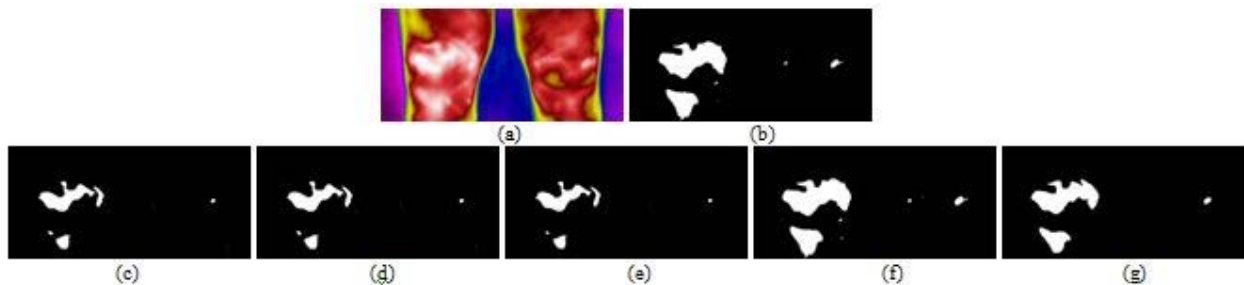

Fig. 7 (a) Preprocesed knee thermogram ; (b) Groundtruth of inflamed region; (c) Output of K-means clustering; (d) Output of FCM clustering; (e) Output of Otsu threshold based clustering; (f) Output of PSO (g) Output of EMO

thermograms. All the five methods are applied separately on the thermograms before and after removal of background region. The methods used for segmentation are:

- K-means clustering (KM) [14,15]
- Fuzzy c means clustering (FCM) [15,16]
- Otsu threshold based clustering (Otsu) [17,18]
- Particle swarm optimization (PSO) [19,20]
- Electro-magnetism Optimization(EMO) [21]

The output of segmentation for each of the method varies depending on user inputs. For clustering based techniques the cluster number(K) is determined depending on the highest accuracy through trial and error method. In case of PSO, the optimal segmentation level(L) is determined by user following trial and error method. In EMO, we performed the Kapur's multilevel thresholding technique [22] for segmenting the inflamed region of interest by following the publication of D. Oliva et al.[21]. The user input intensity level (L) for EMO method is also determined depending on highest accuracy criteria using trial and error technique. All the above mention techniques generate cluster based output. Therefore, in the post-processing step of segmentation, we extract the cluster region representing the inflamed area of interest in thermograms and convert it into binary format for ground truth based comparison of segmentation methods. Figure 7 shows the binary mask based output of segmentation methods applied on the background subtracted knee thermogram for extraction of inflamed region of interest along with ground truth data.

III. RESULT AND DISCUSSION

Application of background subtraction on knee thermogram reduces the interference of unwanted features in classification and segmentation. The first part of the section describes the advantage of background subtraction on classification and the second part explains the same on segmentation of inflamed region of interest.

A. Effect of background subtraction on knee abnormality classification

Classification of knee thermogram has been performed for detection of abnormality related to arthritis for diagnosis of disease. Increase of inflammation in knee joints indicates the presence of arthritis. Using thermography, the inflammation can be visualized through thermogram color palette and by comparing with healthy subjects as shown in figure 1. For computerized automated classification in between healthy and arthritis affected knee thermograms, the Random Forest, SVM and KNN classifier is used on the extracted statistical features as detailed in section II. The background of the thermogram contains unnecessary information regarding inflammation. Therefore classification has also been performed over the features of background subtracted thermograms. To analyze the influence of background subtraction on classification, same features are extracted from the thermograms before subtraction of background region and fed to Random Forest, SVM, and KNN classifiers. Figure 8 shows the accuracy rate of classification using three different classifiers for original
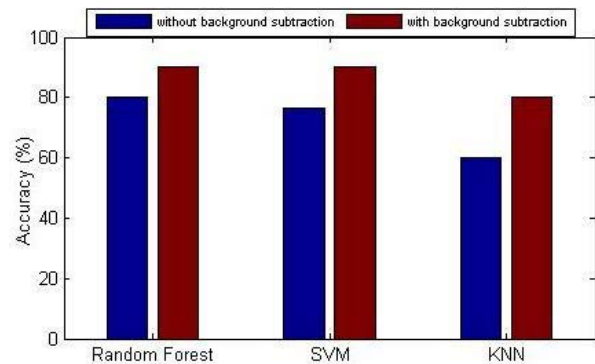

Fig. 8 Classification rate of knee thermogram with and without subtracting background region

knee thermogram and background subtracted knee thermogram. From the figure, it is clearly observed that use of background subtraction in knee thermogram significantly increases the accuracy rate of classification. Without subtracting background region, the highest achieved accuracy is 80% by using Random Forest classifier Application of background subtraction over the thermograms enhance the accuracy to 90% using the same classifier and features. In case of SVM classifier also accuracy reaches to 90% for the features generated from back ground subtracted thermogram and using KNN classifier, 80% accuracy is obtained as shown in figure 8. Without subtraction of background region from knee, thermogram decreases the accuracy of SVM and KNN classifiers by 14% and 20% respectively.

B. Effect of background subtraction on inflamed region segmentation

In arthritis affected knee thermogram, the inflamed region is represented by white color palette as shown in figure 7(a). Segmentation of the inflamed region helps in spread of the disease analysis. In our analysis, we performed five popular states of the art method (as stated in section II-E) for segmenting the inflamed region from 50 arthritis affected knee thermogram. To analyze the effect of background subtraction on inflamed region extraction, all the segmentation techniques are applied before and after background subtraction of knee thermogram. The effect is analyzed depending on quality measurement of segmentation output comparing with ground truth data. Following the publication of M. Belgiu et al. [23], four quality measuring techniques are used for comparative studies, such as: Over Segmentation(OSeg), Under Segmentation(USeg), Root Mean Square (RMS) error, Quality Rate(QR). Along with the four measuring units, the accuracy of segmentation also computed for analysis. Over segmentation (OSeg) generates multiple segmentation of a single region and as a result, the segmented output becomes smaller compared to ground truth region. The Vice versa happens in case of under segmentation(USeg),. The Root Mean Square (RMS) error combines the over and under-segmentation output for quantification. The minimum value of over segmentation, under segmentation and RMS, indicates higher accuracy of segmentation. The Quality Rate (QR) of

TABLE I. QUALITY MEASUREMENT OF KNEE THERMOGRAM SEGMENTATION OUTPUT BEFORE BACKGROUND SUBTRACTION

Method	OSeg	USeg	RMS	OR	Accuracy (%)
KM[K=5]	0.444	0.097	0.348	0.501	97.3
FCM[K=6]	0.301	0.266	0.346	0.495	96.4
Otsu[K=6]	0.37	0.158	0.353	0.491	97
PSO[L=3]	0.257	0.039	0.198	0.711	98.66
EMO[L=3]	0.199	0.036	0.146	0.78	98.9

TABLE II. QUALITY MEASUREMENT OF KNEE THERMOGRAM SEGMENTATION OUTPUT AFTER BACKGROUND SUBTRACTION

Method	OSeg	USeg	RMS	OR	Accuracy (%)
KM[K=6]	0.441	0.026	0.339	0.561	97.43
FCM[K=7]	0.363	0.123	0.325	0.452	96.98
Otsu[K=7]	0.348	0.054	0.308	0.502	97.16
PSO[L=3]	0.061	0.1	0.1	0.844	99.24
EMO[L=3]	0.197	0.034	0.145	0.791	99

segmentation is quantized by calculating the division of the intersection and union in between ground truth and segmented output. As like accuracy, the higher value of QR indicates better segmentation. Table I and II shows the quality measurement output related to extracted features from the thermogram before background subtraction and after background subtraction respectively. Comparing the tables, it is observed that use of background subtraction minimizes the rate of under segmentation and Root Mean Square error for all the segmentation method used in this paper. The Quality Rate decreases in case of FCM method due to the application of thermogram background subtraction which results the increase of over segmentation rate. In spite of that, overall accuracy of all segmentation techniques increases after background subtraction as it is negatively correlated with the value of Root Mean Square error.

IV. CONCLUSION

Thermography helps in diagnosis of inflammatory knee disease related to arthritis by color oriented pixel based plotting of inner body temperature flow. Image based automated classification of knee thermogram for detection of abnormality is highly influenced by the background region. Therefore subtraction of background region increases the accuracy of disease diagnosis. In this paper, background subtraction of the knee thermogram is obtained by the use of EM algorithm followed by edge detection morphological operations. The outcome of normal and abnormal knee classification presented in the paper shows the increase of accuracy due to subtraction of background region from thermogram. The analysis also indicates that in case of segmentation of inflamed region from knee thermogram, background subtraction minorly increases the accuracy by decreasing the rate of under segmentation. In future, the research will be extended toward automated subtraction of background region from the thermogram of other body joint regions along with color feature extraction for disease intensity classification.

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