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Automated Classification of the Diabetic Foot Using Comprehensive Encoding and Feature Transform Techniques

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Abstract: Diabetes Mellitus type 2 (DM2) is a disease with the leading cause of death in the world. Recent statistics from world health organization projects that by 2030 this disease will be the seventh leading cause of death. The major complications of the disease relate to lower limb amputation and pathogenesis of foot. The main focus of this paper is developing a diagnostic method for classifying the feet images for early detection of Diabetes Mellitus type 2 (DM2) based on thermal images and support vector machine (SVM) classifier. Foot images of 50 patients are considered, where the left and right foot are separately taken to train and test the model. The proposed methodology contains the joint information of scale-spaces and feature across the images. The work is mainly divided into four stages to obtain the extracted features. The Gaussian derivative filter is considered in the first stage, feature transform is done in the second stage. The third stage is feature extraction via discrete pixel codes and integrated coding is the last stage. The SVM classifier is considered to build the predictive model, where extracted feature vectors and class labels are fed as input to the classifier. The experimental results showed that the proposed model got a 97.24% prediction accuracy. When comparing the proposed system with the relevant systems our algorithm has the best predictive accuracy.

Keywords: Image Processing, Infrared (IR), Support Vector Machine (SVM), Classification & Diabetes

1. INTRODUCTION

Diabetes Mellitus (DM) is mainly caused due to deficiency in the production of insulin in the human body [1]. As time progress it will largely affect the body parts such as kidneys, eyes, and blood vessels. The disease is growing globally and according to the World Health Organization (WHO), in the year 2015 around 69.2 million people were living with diabetes in India. The rate is predicted to go with approximately 98 million people with type 2 diabetes by the year 2030 [2]. The number is alarmingly increasing and the main complication that may arise from DM is foot ulcers. A study shows that up to 15% of diabetic patients may get affected by ulcers. Every diabetic patient has a 20-25% risk of developing ulcers in their lifetime [3]. By early detection and proper treatment foot ulcers can be prevented and to avoid the risk of foot ulcers, there is a necessity that the patients must undergo foot screening at least once a year [4].

Infrared thermography is a very fast technique. It is a non-contact, non-invasive, and safe process as it only captures the invisible heat radiation emitted by the human body [5]. Due to this fact it is gaining popularity in various medical applications. The technique also allows us to visualize the changes in temperature [6]. The temperature of the body has been extensively used as a natural disease indicator since the fact that in general, the body temperature remains constant to 37°C [7]. The thermos-grams helps in providing the clues which are very useful for early diagnosis of diseases like diabetes [8]. The thermal image approach provides complete details of temperature distribution and also reveals information that is associated with tissue damage to detect diabetes [9]. The infrared thermography has become the leading technique compared to vibration sensation tests to detect the foot ulcers as it is a fast and contactless process [10]. The unnecessary contact will be eliminated and thus it will avoid the risk of infection spread. Regardless of the shape and size of the foot, the thermography accurately measures the temperature pattern and has emerged as an effective approach for early detection of diabetic foot ulcers.

Many diabetic foot studies have used an infrared thermography approach to explain the relationship

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between the variation in temperature distribution and diabetic foot. An asymmetric analysis technique with the help of color image segmentation [11] was used to detect diabetic foot ulcers including the serious condition of Charcot foot syndrome. The approach used in [12] for classification of thermal images was manual and hence there is scope for automatic classification by appropriate technique. An approach for the classification of thermal images using independent component analysis was proposed [13] to identify diabetic patients. There were some limitations as few initial frames are not taken for analysis purposes.

In this paper, the main concern is to distinguish between healthy and diabetic feet. We proposed four sequential stages to obtain the extracted feature. Stage one is the foundation step and majorly used to get the multi-gage rotationally features, but these features are not sufficient for the discriminative texture information. Therefore, stage two is considered where a feature transform is performed by steerable filters to obtain a more discriminative rotation-invariant set of features. Afterward, to get the histogram-based features, the scalar quantization process is considered to transform features into the discrete pixel codes and to provide optimal computational efficiency. Subsequently, a cross-scale integrated coding is considered to obtain the final texture features from combining the initial texture codes and to get the feature representation. At last, a support vector machine is considered to detect the diabetic thermal foot images, where extracted feature vectors and class labels are fed as inputs to the SVM classifier to build the predictive model. To get the effectiveness of our proposed model, the various evaluation parameters are considered in the result analysis section.

2. LITERATURE SURVEY

The number of studies has considered that the variations of temperature in the plantar area can be linked to diabetic foot complications. IR thermography has been considered to be very successful to detect the problem associated with the diabetic foot. In [14], an overview was proposed which detects the diabetic feet by comparing the temperature values at corresponding points of both the feet. A machine learning approach was proposed in [15] for the classification process. The work mainly focused on extracting several features i.e., color descriptors and texture descriptors on small patches of the wound images, which is followed by an algorithm to classify them into abnormal and normal type skin patches [16].

A FootSnap application was developed in [17], which is generally used for standardizing the diabetic foot images. This application uses the basic image-processing methodologies like segmentation to provide the apparition images of the foot, which is further useful to track the progress in diabetic foot ulcers. However, this type of design is done for standardizing the capture conditions of image, while it will not execute any automatic detection. Nevertheless, the research in [18] has already provided that some traditional clustering approaches are not efficient enough to provide the precise diabetic ulcer segmentation of the foot images.

In machine learning, hand-crafted features are generally exaggerated via skin shades, image resolution, and illumination, moreover these methodologies are writhed to segment the uneven outline of wounds or ulcers. However, approaches like unsupervised learning depend upon the methods of image processing, morphological operations, edge detection, and clustering approaches by using diverse color space to segment the wound region at images [19][20]. In [21], a capture box was considered to capture the image data and it can resolute the foot ulcer area through a cascaded two-layer based SVM classifier. Besides, the super-pixel approach was used for the process of segmentation and feature extraction. Though this system has obtained significant results unfortunately very limited dataset was used that hinders the robustness of the proposed system. Moreover, the box of image capture is very unfeasible for the collection of data because the patient's barefoot needs to be properly placed right way in contact with the image capture box. Therefore, considering the healthcare condition such settings are not preferred due to the apprehensions about infection control. These details highlight the scope for incessant development of algorithms to faster and accurate analysis of thermal deviations in the diabetic foot.

3. PROPOSED METHODOLOGY

Here, the proposed methodology contains the joint information of scale-spaces and features across the images. A total of four stages are involved to obtain extracted features. Figure 1 shows the proposed model block diagram. In general, the thermal image is taken as the input will be initially convolved with the Gaussian derivative filter to calculate the minimum and maximum responses at the multiple scales. Afterward based upon the obtained responses, the transform feature set is generated with the help of steerable filters [22]. Subsequently, scalar quantization is used to get the discrete pixel codes from obtained transform features and lastly, the texture codes are generated via integrating all obtained features. Besides, all the extracted features are fed as an input to the SVM classifier to build a predictive model to classify the diabetic foot images. The mathematical analysis of various image processing steps is provided in subsequent sections.

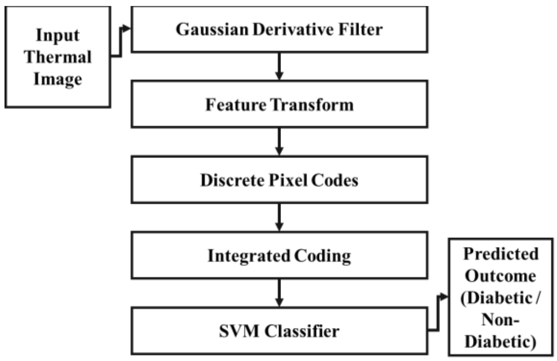


Figure 1. Proposed Model Block-Diagram

A. Gaussian Derivative Filter

Initially, the Gaussian derivative filter [23] is considered to provide minimum and maximum filtering in multi-fold. It will capture the necessary information in 1st and 2nd order differential structures at scale range. Additionally, it synthesizes considering the linear combination of various basic filters. The circularly symmetric Gaussian function by considering two-dimension is given as;

$$D(x, y; z) = \frac{1}{2\pi z^2} \exp\left(-\frac{x^2+y^2}{2z^2}\right) \quad (1)$$

The 1st and 2nd order derivatives of Gaussian function at arbitrary orientation [11] are given as;

$$D_1^{\chi} = \cos(\chi)\, D_x + \sin(\chi)\, D_y \quad (2)$$

Where, D_x denotes the first derivative of D at x-axis and D_y denotes the first derivative of D at the y-axis.

$$D_2^{\chi} = \cos^2(\chi)\, D_{xx} + \sin(2\chi)\, D_{xy} + \sin^2(\chi)\, D_{yy} \quad (3)$$

Similarly, D_{xx} denotes the second derivatives of D at x-axis and D_{yy} denotes the second derivatives of D at the y-axis. The term $(x, y; z)$ is not shown for the simplicity of the argument.

On image M, the initial computation of first and second-order derivatives of the image is given by $E_x = D_x \otimes \mathrm{M}$, $E_y = D_y \otimes \mathrm{M}$, $E_{xx} = D_{xx} \otimes \mathrm{M}$, $E_{xy} = D_{xy} \otimes \mathrm{M}$ and $E_{yy} = D_{yy} \otimes M$.

The convolution is denoted by $\otimes$. Therefore, the first and second derivative responses of Gaussian filter at χ are given as;

$$M_1^{\chi} = D_1^{\chi} \otimes M = \cos(\chi)\, E_x + \sin(\chi)\, E_y \quad (4)$$

$$M_1^{\chi} = \sqrt{E_x^2 + E_y^2}\, \sin(\chi + \Phi) \quad (5)$$

Where $\Phi = \arctan(E_x/E_y)$

$$M_2^{\chi} = D_2^{\chi} \otimes M = \cos^2(\chi)\, E_{xx} - \sin(2\chi)\, E_{xy} + \sin^2(\chi)\, E_{yy}$$

$$= 0.5\left(E_{xx} + E_{yy} + \sqrt{\left(E_{xx} - E_{yy}\right)^2 + 4E_{xy}^2}\, \cos(2\chi - \Psi)\right) \quad (6)$$

Where $\Psi = \arctan(2E_{xy}/E_{yy} - E_{xx})$ and the computation of minimum and maximum value at first-order derivative for all θ is given by;

$$M_{1max}^{\chi} = \sqrt{E_x^2 + E_y^2} \quad (7)$$

Furthermore, the computation of second-order derivative min and max values over all χ is given by;

$$M_{2max}^{\theta} = 0.5\left(E_{xx} + E_{yy} + \sqrt{\left(E_{xx} - E_{yy}\right)^2 + 4E_{xy}^2}\right) \quad (8)$$

$$M_{2min}^{\theta} = 0.5\left(E_{xx} + E_{yy} - \sqrt{\left(E_{xx} - E_{yy}\right)^2 + 4E_{xy}^2}\right) \quad (9)$$

Here, the image M rotates in the clockwise direction from its center point through β° arbitrary angle and M' denotes the rotated image. While considering the rotation operation at (x, y) point for image M it is changed to (x', y') for M'. The arbitrary angle β° gets added with $\hat{\chi}$ at the directional derivative filter, which provides the minimum and maximum responses for both the corresponding points.

B. Feature Transform

From the obtained minimum and maximum responses, we will construct an informative set of transform feature considering the subsequent coding and quantization. Afterward, we consider the linear and non-linear type of operator on the minimum and maximum responses to characterize their correlation and local texture structures quantitatively [24]. The maximum response of 1st derivative Gaussian directional filter is denoted by gradient magnitude.

$$d = M_{1min}^{\chi} = \sqrt{E_x^2 + E_y^2} \quad (10)$$

Moreover, the differences between maximum response and minimum response at 2nd order Gaussian directional filter is denoted by g, which is the extrema difference.

$$g = M_{2max}^{\chi} - M_{2min}^{\chi} = \sqrt{\left(E_{xx} - E_{yy}\right)^2 + 4E_{xy}^2} \quad (11)$$

The shape index h, which is used to provide the quantitative local measurement of second-order local curvature is given by

$$h = 0.5 - 1/\pi \arctan\left(\frac{M_{2max}^{\chi} + M_{2min}^{\chi}}{M_{2max}^{\chi} - M_{2min}^{\chi}}\right) \quad (12)$$

$$h = 0.5 - 1/\pi \arctan\left(\frac{-E_{xx} - E_{yy}}{\sqrt{\left(E_{xx} - E_{yy}\right)^2 + 4E_{xy}^2}}\right) \quad (13)$$

The index shape is initially defined by the traditional geometry theory [25]. It can also be provided via the principle of surface curvatures [26]. The Eigenvalues of Hessian Matrix F are denoted by l_2 and l_1 .

$$F = \begin{bmatrix} E_{xx} & E_{xy} \\ E_{xy} & E_{yy} \end{bmatrix} \quad (14)$$

$$h' = 2/\pi \arctan\left(\frac{l_2+l_1}{l_2-l_1}\right) ; (l_2 \le l_1) \quad (15)$$

All the values at (15) can be mapped to [0, 1] interval for easy subsequent progression. The mixed min-max ratio is denoted by k that captures the information of correlation of 1st and 2nd order differential structures to provide the low dynamic range output.

$$k = 2/\pi \arctan\left(p.\frac{g}{d}\right)$$
$$= 2/\pi \arctan\left(p.\frac{M^{\chi}_{2max} - M^{\chi}_{2min}}{M^{\chi}_{1max}}\right)$$
$$= 2/\pi \arctan\left(p.\sqrt{\frac{\left(E_{xx}-E_{yy}\right)^2+4E^2_{xy}}{E^2_x+E^2_y}}\right) \quad (16)$$

Where scale factor is denoted by p to adjust g to d ratio. The obtained features of transform are given by $R = \{d, g, h, k\}$, which have properties of rotational and compact invariant.

C. Discrete Pixel Codes

Here, we consider the scalar quantization [27] to transform features into the discrete pixel codes. This helps in providing the optimal computational efficiency, illumination changes, and rotation robustness. The value of non-negative interval from transform feature $\{d, g\}$ is considered to adopt a mean-value dependent binary quantizer.

$$A = S_1(x) = \begin{cases} 0, & if\ \frac{x}{u_x} > l \\ 1, & \text{otherwise} \end{cases} \quad (17)$$

Where, $x \in \{d, g\}$and u_x denotes the mean of x, which is a transform feature map and l denotes a tuning parameter. The usage of u_x provides robust image rotation and averaging operator [28]. Based on the value, ranges of [0, 1] from transform features $\{h, k\}$, the uniform quantizer is adopted.

$$A = S_2(x) = \begin{cases} 0, & x \in [0, \mu] \\ 1, & x \in [0,2\mu] \\ \quad \dots . & \\ E-1, & x \in [(E-1)\mu, 1] \end{cases} \quad (18)$$

Where, $x \in \{h, k\}$and E denotes the quantization level. The quantization step is $\mu = 1/E$. E_k and E_h denotes the quantization levels for k and h, both are related in terms of feature dimension and texture discrimination.

D. Image Representation and Integrated Coding

A cross-scale integrated coding for initial multiple features is considered and it is concatenated to provide image feature representation. However, the transform feature such as $\{ d, g, h \}$ are cooperatively encoded through two adjacent scales (e.g., (z_1, z_2), (z_2, z_3)) and so on. The pair of adjacent scale (z_m, z_{m+1}) where $(m = 1, 2, 3, .. \, ., \lambda_z - 1)$ of the pixel (x, y) for image M is calculated as;

$$p_m(x, y) = \sum_{n=1}^{2} (E_h)^{n-1} \mathrm{A}_h(x, y; z_{m+n-1}) + (E_h)^2 \sum_{n=1}^{2} \left(E_g\right)^{n-1} \mathrm{A}_G(x, y; z_{m+n-1}) + \left(E_g\right)^2 (E_h)^2 \sum_{n=1}^{2} (E_d)^{n-1} \mathrm{A}_d(x, y; z_{m+n-1}) \quad (19)$$

Where,
$\mathrm{A}_d(x, y; z_m)$, $\mathrm{A}_g(x, y; z_m)$ and $\mathrm{A}_h(x, y; z_m)$ represents the quantized texture-codes in correspondence with the levels A_d, A_g and A_h for features d, g and h at σ_i scale. The k transform features are encoded through all scales $(z_1, \dots .\, , z_{\lambda_z})$ and the full-scale pixel value (x, y) in image M is calculated as;

$$p\lambda_z(x, y) = \sum_{n=1}^{\lambda_z} (E_k)^{n-1} \mathrm{A}_k(x, y; z_n) \quad (20)$$

Where, $\mathrm{A}_k(x, y; z_n)$ denotes quantized texture-code for the k feature at z_n and the quantization level is given by E_k. The extracted final feature for image M is given as;

$$B_m(v) = \sum_{(x,y)\in M} f(p_m(x, y), v) \quad (21)$$

Where, $v \in \{0, 1, \dots .\, , P_m \}$ and P_m represents the maximum value. The local image derivative filter consists of the information for characterizing essential image structures like blobs, lines, and edges. Therefore our proposed methodology enhances such type of information through comprehensive encoding and feature transform for ensuring the several invariances of illumination changes and image rotation.

E. Support Vector Machines (SVM)

SVM is a very well-known methodology in the field of machine learning to solve binary classification problems. SVM technique constructs a single hyper-plane or many of them to separate between classes [29]. The hyperplane acts as a decision-maker. It searches for a margin to divide the data points belonging to different classes by keeping the maximum margin. Therefore, extracted feature vectors consider being input to SVM classifier to detect the diabetic thermal foot images in association with ground-truth considered from datasets that are approved by physicians in the thermography center.

The basic function in SVM is the kernel function which can transform nonlinear spaces into linear ones. The Gaussian kernel function [30] is calculated by:

$$k(x, y) = \exp(-\gamma * (x-y)^2) \quad (22)$$

Gamma is a positive scalar value which refers to kernel scale value. If the value of gamma is large, this means that the separation between x and y is large and vice versa.

This study has used a linear SVM classifier. To train the model [31], randomly 60% of data is considered and the remaining 40% for testing purposes.

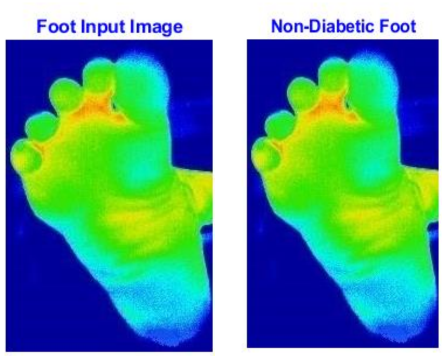
4. RESULTS AND ANALYSIS

In this section, we provide the result analysis that is obtained by our proposed model. The simulation of code is done using Matlab 2016b. The datasets are taken from Digital Infrared Thermal Imaging (DITI, India). A total of 50 patients were included in this study. The mean age of the participants was 52.6 ± 9.2 years.

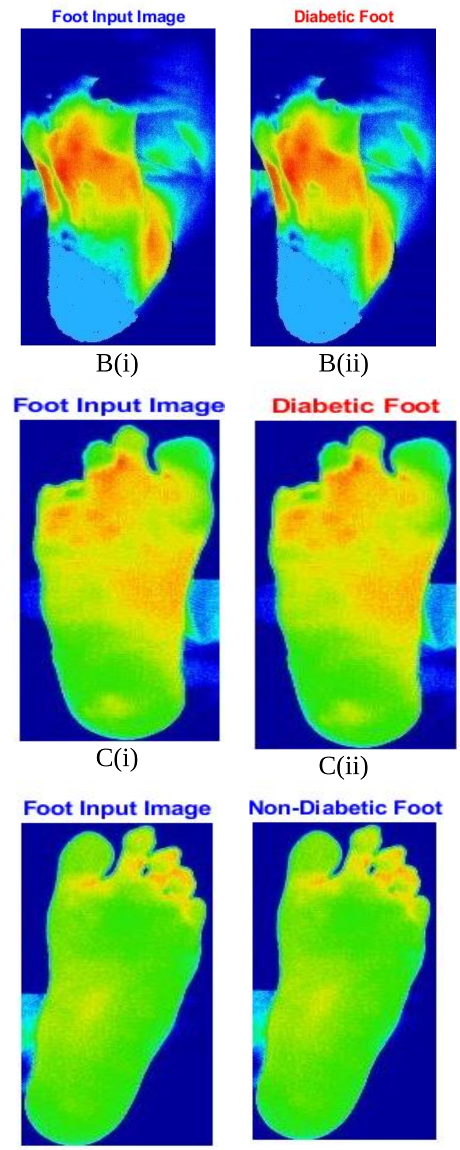
TABLE I. DEMOGRAPHIC INFORMATION

Characteristics	Subjects,n
Normal group	10
Diabetic Group	40
Normal group – Male	6
Normal group – Female	4
Diabetic group – Male	24
Diabetic group – Female	16

Figure2 shows the diabetic and non-diabetic detection of the foot on sample images, where suffix i denotes the input images and *ii* denotes the output images.



A(i) A(ii)



D(i) D(ii)

Figure 2. Diabetic and Non-Diabetic Foot Detection

The image set A(i) belongs to 42 years non-diabetic male patient and the results confirm the same in set A(ii). The 70 years male diabetic patient foot image is shown in set B(i) and the algorithms classify it as diabetic as shown in B(ii). Image set C(i) and C(ii) corresponding the classification of 42 years male diabetic patient. The image set D(i) and D(ii) shows the analysis feet image corresponding to non-diabetic female aged 53 years. The proposed model obtained very satisfactory results and the performance is validated with specialist physicians at the thermography center. The ground truth completely matches with the result obtained from the proposed model.

The proposed approach achieved the maximum prediction accuracy of 97.24%, sensitivity of 88.5%, and specificity of 99.58% using five features. Thus our method has achieved the highest performance also the accuracy is enhanced when compared with the past researches. The reason for increased classification accuracy is combining comprehensive encoding and feature transform techniques instead of using a single approach. The limitations of the proposed system are the limited number of subjects taken for study and the expensive technique of infrared thermography. The table2 provides the performance comparison to measure the effectiveness of the proposed system

TABLE II. PERFORMANCE COMPARISON

Reference	Diagnostic method	Validation (%)
Purnima [32]-(2017)	Segmentation, Feature extraction and SVM classifier	Accuracy: 75.13 Sensitivity: 86.8 Specificity: 61.93
Adam [10]-2018	Wavelet (characteristics vector) and (SVM) (classifier)	Accuracy: 89.39 Sensitivity: 81.81 Specificity: 96.97
Marwa M. Eid[33]-2018	Feature fusion and SVM classifier	Accuracy: 96.8 Sensitivity: 88.3 Specificity: 99.1
Maldonado [34]-2020	Difference pixel-to-pixel, normalized threshold, Temperature filter threshold	Accuracy: 90.28 Sensitivity: 90.29 Specificity: 90.28
Proposed system	Gaussian Derivative Filter, Feature Transform, Discrete Pixel Codes, Integrated Coding, and SVM Classifier	Accuracy: 97.24 Sensitivity: 88.5 Specificity: 99.58

5. CONCLUSION

An infrared scanning device is generally used to capture the IR radiation emitted from the surface of the skin and convert into the electrical impulses that can be visualized on a monitor for further analysis. This image visually graphically draws the temperature of the body. The proposed model got the 97.24% prediction accuracy while considering the other evaluation parameters also it performed considerably well. The proposed system can be introduced in health centers as a supportive instrument to help the physicians to validate their diagnosis related to DM. In the future, instead of using the SVM classifier, some other novel machine learning algorithms [35] can be considered to get a more optimal outcome. Also, a mobile application can be developed for the automatic diagnosis of the diabetic foot which will be useful to the community to a larger extent.

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