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Al-Assisted Practical Screening for Diabetic Foot Ulcers Using Focal Attention Network

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ABSTRACT: Diabetic Foot Ulcer (DFU) is characterized by deep tissue lesions linked to peripheral vascular disease and neurological conditions in the lower boundaries. According to National Institute for Health and Clinical Excellence methods early and efficient management of DFU is essential to improve overall quality of life. To classify the DFU image and healthy foot skin the proposed Focal Attention MobileNet (FAM) is developed. Anisotropic Diffusion Filter (ADF) is applied to the DFU dataset that remove noise in the DFU image edges. Using Fuzzy Adaptive Thresholding (FAT) the image region's followed by adjusting the threshold values. Cognitive Contour Descriptor (CCD), extract features by shape, area, boundary box, perimeter, centroid of DFU for further analysis. Finally, FAM is proposed that enhance the classification of DFU images, in foot analysis. Using Python software, the DFU image randomly chosen from DFU dataset and the proposed FAM achieved a higher accuracy of 96% and similarly scores of precision, recall achieved about 96% which is highly efficient compared to the existing method.

Keywords: Diabetic Foot Ulcer, Anisotropic Diffusion Filter, Fuzzy Adaptive Thresholding, Cognitive Contour Descriptor, Focal Attention MobileNet

1. Introduction

Diabetes Mellitus (DM) is a significant global health concern, with an increasing number of diabetic people at risk. It is considered a chronic disease and leads to a significant number of fatalities annually According to the World Health Organization (WHO), over 420 million people worldwide suffer from DM [1]. Furthermore, almost half (50.1%) of people suffering from DM are unaware of their illness. DFU and other foot problems are more likely to develop as a result of rising estimates of the prevalence of DM. According to current estimates, nearly one in fifteen people (6.3%) globally suffer from a DFU [2]. Additionally, DFUs are also expensive to find and a strain on the healthcare system. It is crucial for effective management and prevention DFU since DFUs are likely to reoccur in 8–59% of people with DM [3]. DFU have a substantial impact on mortality rates in addition to their overall quality of life. Consequently, it demonstrated that the mortality rate is two times high for people with DM and also have lower extremity ulcers. However, features like age, type of diabetes, or length of disease, this finding remains constant [4]. Moreover, patients with DM and foot ulcers have an even poorer survival rate (68%), compared to the general population [5]. Moreover, Neuropathy, ischemia, and infection are the three main pathophysiological pillars that define DF. The development and progression of DFU problems are significantly influenced by these factors, although they are difficult to detect the DFU [6].

DFU image is processed using the pre-processing technique such as, Adaptive filtering to remove noise from the DFU image. Flexibility to unstable conditions and effectiveness in reducing noise. Nevertheless, include sensitive to complexity and the possibility of slow convergence [7]. Whereas, Image-level augmentation and pixel-level augmentation to find the pixel vales from the DFU image. Image-level analysis is appropriate for tasks like image processing since it is quicker and requires less processing. Nonetheless, computationally costs and noise sensitivity [8]. Moreover, DFU image is processed using the pre-processing technique such as Shades of Gray color constancy algorithm. It improves illumination normalization, reducing the effects of noise, and improving image quality. A shade of Gray color constancy is to provide more accurate and reliable DFU analysis and identification. Nevertheless, it has trouble to recognizing images with large, consistent color areas, and it could incorrectly identify the dominant color [9]. Thus, the proposed ADF based pre-processing technique is utilized for removes the noise from DFU image for further Processing.

Region of Interest (ROI) based segmentation method segment the DFU with high performance. Using ROI the static thermal data in diabetics with grade-zero foot problems to forecast ulcers is segmented. Drawbacks are potential for bias in analysis, and the difficulty of automatically locating and extracting ROIs [10]. Consequently, K-means clustering based segmentation technique to cluster the severity risk of DFU image. Using K-means clustering it is simplicity and speed to segment the DFU image, which is a direct implementation. However, sensitivity to the unusual centroid placement and inability to handle irregularly sized clusters [11]. Whereas, to segment the DFU image a Semantic segmentation based approach is utilized. Semantic segmentation is a precious segmentation for boundary recognition. Nevertheless, the necessity for large datasets and the possibility of losing area in complex situations [12]. FAT based segmentation approach is proposed in this research that effectively segments the regions with its threshold values.

From the segmented images, the prominent features of DFU are extracted by using techniques such as, Gray Level Co-occurrence Matric (GLCM) feature. GLCM finds the value energy, homogeneity, entropy, correlation, homogeneity, and contrast with good performance. However, high computing cost, when utilized for absolutely DFU detection [13-14]. Moreover, Local Binary Pattern (LBP) extract features from the DFU image by giving the neighbour threshold value based on the center pixel's gray level. It is suitable for texture analysis and computational efficiency and flexibility to grayscale variations. However, it complexity to noise sensitivity, and has an inability to capture color [15]. The proposed feature extraction technique is CCD. It calculates the shape, area, boundary box, perimeter, centroid for DFU image.

However, to classify DFU image Stacking C algorithm is enhanced with high accuracy. Stacking C algorithm utilized the DFU image diversity and increasing the accuracy. But there are drawbacks, such as longer training periods and possible complexity [16]. Whereas, prediction models for discriminating hard-to-heal DFUs were constructed using K-Nearest Neighbour (K-NN) model. The model's parameters realized through the use of cross-validations. Computationally hard, prone to over fitting, have trouble with intricate patterns, and is sensitive to outliers. Computationally costly when dealing with complex datasets, as well as the need to select the appropriate distance measure and 'k' value [17].

Moreover, using Wagner classification the characteristic that had the ability to predict amputation within 30 days. The vascular occlusion and infectious state highlights the classification's indirect description the significance of making early findings for persons have a higher compromise of these two states. However, it takes more time to process the data when large datasets are used [18]. To overcome the limitations of existing classification, a proposed FAM is implemented for depth-wise separable convolutions to get great accuracy and efficiency of DFU prediction and healthy foot skin.

2. Related work

Zhang *et al* (2022) [19] have developed a Logistic Regression (LR) and Artificial Neural Network (ANN) for DFU detection. To improve the performance of LR and ANN is used as an advanced method for DFU identification. The ANN is at learning from data and identifying complex patterns even though LR is simpler to comprehend and interpret. Nevertheless, it has trouble modeling intricate, nonlinear relationships, is difficult to deliver, and requires a lot of processing.

Das *et al.* (2021) [20] have suggested a DFU_Special Network (DFU_SPNet) a stacked parallel convolutional layer to classify the DFU which is used to classify the DFU and normal skin separately with high accuracy. The network is composed of three blocks of parallel convolution layers with various kernel sizes for local and global feature abstractions. Nonetheless, it is computationally complex and need more kernel sizes.

Alzubaidi *et al* (2020) [21] have introduced a novel Deep Convolutional Neural Network called DFU_QUTNet for the automatic classification of healthy skin and abnormal DFU skin. It is constructed with the goal of expanding the network's width while maintaining its depth. This technique have been shown to be highly valuable for gradient propagation. However, there is a possibility of image quality loss and the requirement for meticulous parameter adjustment.

Poradzka *et al* (2023) [22] have presented an ANN to classify the Diabetic Foot Syndrome (DFS). DFS healing is predicted by using an ANN and produce higher accuracy and thereby identifying patient’s condition won't recover in three month. The model reduce the time, effort, and expense of diagnostic procedures. Nonetheless, increased computational burden, over fitting susceptibility for ANN.

Sathya Preiya, V *et al* (2023) [23] have proposed a Deep Recurrent Neural Network (DRNN) called Pre-trained Fast CNN (PFCNN) with U++net to identify DFU. The normal and abnormal diabetic ranges are determined by extracting the DFU image and numerical data independently. PFCNN with U++net is used to segregate and classify foot images of patients with abnormal diabetic ranges. Yet, dependence on pre-trained models, which is suboptimal for specific datasets.

The contribution of this work is follows

- ADF based image pre-processing technique is introduced to DFU for preserving the edge and removed the unwanted noise to get high quality image.
- Segmentation by FAT, fuzziness to adjust the threshold value for further extraction.
- Feature extraction by CCD to find shape, area, boundary box, perimeter, centroid of DFU for further analysis.
- Finally, a FAM is proposed to enhance the classification of DFU images.

3. Proposed work

The proposed block diagram in given figure 1 for DFU prediction using DL technique with DFU datasets. The DFU image is randomly chosen as an input DFU image dataset, initially processed to ADF that enhance the edges and reduce the unwanted noise for better quality image. The pre-processed filtered DFU image is assumed as an input to segmentation step. Segmentation done by FAT it is used to find fuzziness by adjusting the threshold value from the edges. Next, the segmented DFU input image using feature extraction CCD to calculated shape, area, boundary box, perimeter, and centroid of the DFU for further classification. Finally the featured values are as an input to the classification technique the FAM is used. The FAM classifier classifies the DFU disease and healthy foot skin. The FAM process uses depth-wise separable convolutions to get great accuracy and efficiency for DFU disease image.

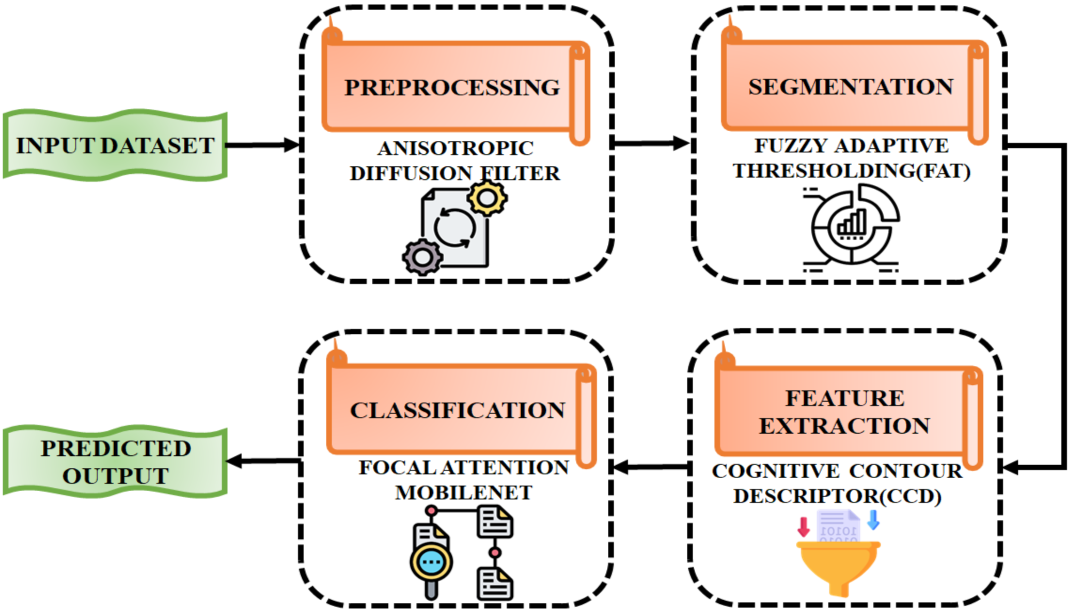

Figure 1: *Block diagram for proposed work*

3.1 Pre-processing for DFU by ADF

In the DFU identification pre-processing using ADF, which is remove unwanted noise from input. Some noise is present in the images due to unprocessed data in the DFU dataset. The accuracy or reliability of data-based findings is impacted by this noise. However, it is required to decrease and correct for noise in order to develop more significant inferences from the data. In medical image processing, ADF is a frequently employed method and goal of this type of image filtering is to reduce noise and enhance the image's edges. ADF functions by limiting diffusion in high-gradient regions and utilizing diffusion exclusively in low-gradient regions to selectively smooth portions of an image while preserving edges and boundaries. This helps in maintaining the clarity and edge sharpness. By reducing small-scale variations in pixel intensity, ADF also reduces noise, creating a clearer, less noisy image. ADF enhances image quality by preserving important details like edges and reducing the impact of noise. ADF are often useful instruments for improving the quality and diagnostic value of DFU images. It enhance the edges and removes noise for better quality DFU image.

3.2 Segmentation by Fuzzy Adaptive Thresholding

The pre-processed DFU image is segmented using FAT methodology for fuzziness detection to find the threshold values in the DFU image. FAT is predicated on fuzzy logic and the length-threshold method which dynamically modifies the assembler's length-threshold by combining fuzzy logic with incoming image. Because FAT is executed each time a rush is generated, it suffers from a high execution image. To analyze and create, such an approach necessitates sophisticated mathematical concepts. Adaptive threshold based on fuzzy logic to solve the delay and loss ratio issues. The following represents a linear combination of K fuzzy basis functions (FBFs) that represent fuzzy systems with singleton fuzzification, product as the fuzzy conjunction operator, addition for fuzzy rule aggregation, and center of average defuzzification

$$y = \sum_{k-1}^{k} y^{-k} \emptyset_k(x) \tag{1}$$

Where $\emptyset_k(x)$ are fuzzy basis functions, which are provided by, and y^{-k} is the output fuzzy set's center of gravity.

$$\emptyset_k(x) = \frac{\prod_j^n \mu_{kj}(x_j)}{\sum_{k-1}^{k} \prod_j^n \mu_{kj}(x_j)} \tag{2}$$

The membership function of input x_j pertaining to the k^{th} rule is shown by $\mu_{kj}(x_j)$ which occurs when fuzzy rule patches not completely cover the input space. Nonetheless, there are a number of simple solutions to this problem. In particular, if there are n inputs, K fuzzy rules, and m outputs, the activation of the k^{th} rule can be expressed as

$$r_k = \prod_j^n \mu_{kj}(x_j) \tag{3}$$

The degree (or firing strength) that the input x matches rule, as determined by the T-norm or product operator, is actually r_k. The Gaussian function is the membership function used in this analysis.

$$\mu_{kj}(x_j) = \exp\left(-\frac{1}{2}\left(\frac{x_j - c_{kj}}{\sigma_{kj}}\right)^2\right) \tag{4}$$

The output value of the i^{th}output is

$$y_i = \sum_{k=1}^{k} \frac{r_k}{\sum_{k=1}^{k} r_k} \overline{y_{\iota k}} \sum_{k=1}^{k} \overline{y_{k=1}} \emptyset_k(X) \tag{5}$$

As a result, fuzzy models that are expressed using fuzzy basis functions are easier to solve for their parameter. The threshold values of DFU are calculated. Next, the segmented output is given as an input to feature extraction technique.

3.3 Feature extraction by CCD

The segmented image is extracted using CCD methodology for feature detection, which have subsequently grown to be a DFU technology in imaging sector. To extract distribution histogram of contour point, this is invariant to the shape's scale. The first and most crucial stage in form matching is examining an object's contour. CCD has two phases involved in generating the extraction of contour points and the structure of CCD under polar coordinates for DFU.

3.3.1 Extraction of contour points

Different forms are created by different alignment techniques for the coordinates of the points on an object contour. In other words, the distribution of points on an object's contour determines its shape. Initially detect the object boundary using the usual canny operator. However, too many contour points are obtained following this technique. The points on the object boundary obtained by the canny operator are sampled using the algorithm. The contour's resulting points is displayed.

$$P = \{(x_1, y_1), (x_2, y_2), \ldots\ldots, (x_n, y_n), \} \tag{6}$$

$$(x_i, y_i) \in R^2 \tag{7}$$

Where n is the contour's number of points. Figure. 2 show the example of CCD that the Canny detected.

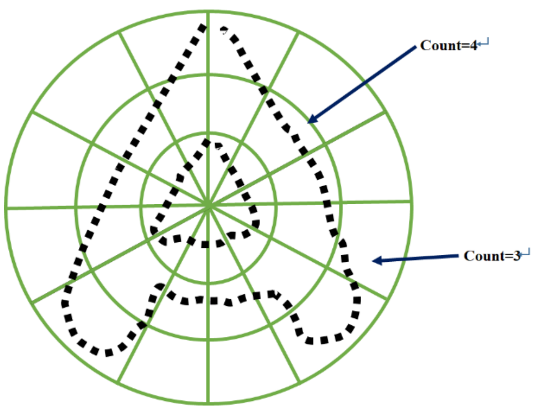

Figure 2: *Show the example of CCD that the Canny detected*

These findings are a summary of the contour point's extraction process. Since all of the contour points on one side of the occlusion boundary are absent, a contour point close to the occlusion boundary has a completely different shape context than the identical contour point in the reference (unoccluded) object contour. As a result, this point significantly contributes to the difference between occluded and unoccluded outlines. The featured output is given as an input to proposed FAM for DFU image. Using CCD the shape, area, boundary box, perimeter, centroid of DFU is calculated for further classification.

3.4 Classification by FAM

In this proposed work Deep Learning method called FAM is utilized for effective classification of DFU disease. The FAM classifies the DFU disease image and healthy foot skin image.

3.4.1 Focal Attention

Focal attention finds and eliminates unnecessary sub-elements from learning alignment. It is difficult for them to recognize irrelevant sub-elements across modalities because they are position-independent. Eliminating a set number of sub-elements, but it is not the best option because the number of irrelevant sub-elements fluctuates. In contrast, a focal attention mechanism that eliminates superfluous sub-elements according to their possibility in figure 3. The DFU in focusing attentions are formulated as follows, assuming that $N\,(v)\;and\;N\,(u)$ are irrelevant sub-elements (i.e., regions and areas) detected by proposed focal attention.

$$I_p = \sum_{u_i \in N_v} w_v, iv_i \tag{7}$$

$$T_p = \sum_{u_i \in N_{(u)}} w_u, iu_i \tag{8}$$

Where w_v, i and w_u, i are attention weights. The focal attention will learn to identify both relevant sub-elements sets $N_{(u)}, N_{(v)}$ and their weights w_v, i and w_u, i.

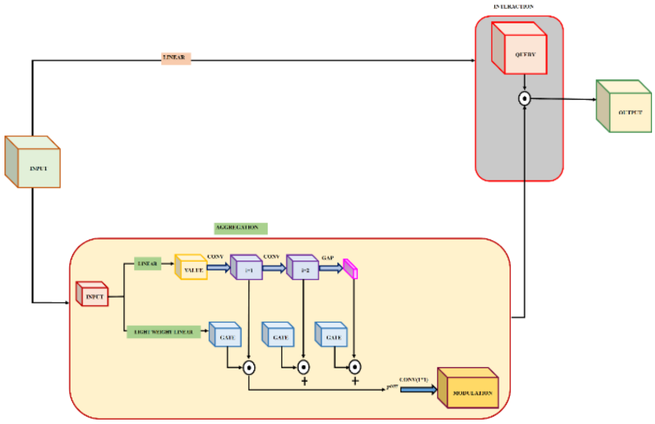

Figure 3: *Architecture of focal attention*

3.4.2 MobileNet Architecture

The proposed MobileNet is used to classify the DFU with high accuracy. A key component of MobileNet is a structure known as depth-wise separable convolutions. Linear bottlenecks between the layers and skip connections between the bottlenecks are two characteristics of this approach. The basis of MobileNet is, made up of two central layers: a depth wise and pointwise convolution that is used to classify DFU disease. The process of filtering data without producing new features is called depthwise convolution. Meanwhile pointwise convolution is a technique for constructing extra features which is integrated. Eventually, the two-layer combination is dubbed separable convolution and this method functional a single filter to every input channel, and formerly it created a linear combination of outputs from the depthwise layer using 1x1 convolution (pointwise). Figure 4 shows the MobileNet architecture.

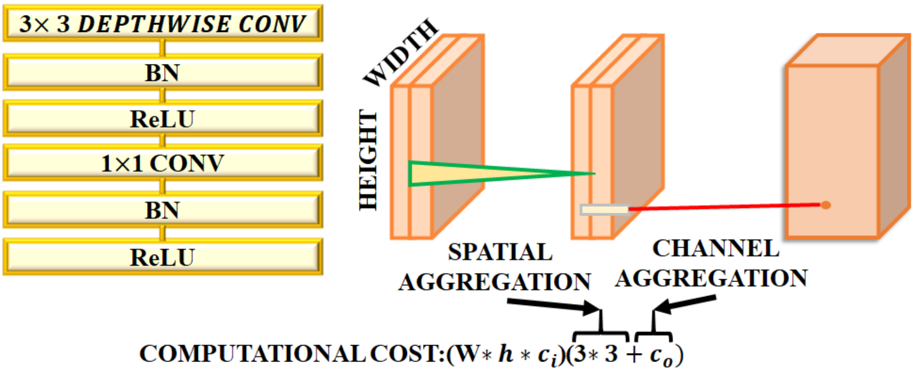

Figure 4: *Architecture of MobileNet*

Following each convolution, the Rectified Linear Unit (ReLU) and Batch Normalization (BN) Approximately four million parameters make up this model, which is incredibly minimal in comparison to other models.

3.4.3 Implementation of MobileNet

In this study, for DFU disease image a deep neural network architecture called MobileNet, which built the lightweight networks using depth-wise separable convolutions. Despite using fewer parameters than other efficiency models for the same depth, Google's MobileNet architecture demonstrated remarkable performance and designed to balance accuracy and latency. MobileNet that effectively categorize the DFU and healthy foot skin for disease analysis.

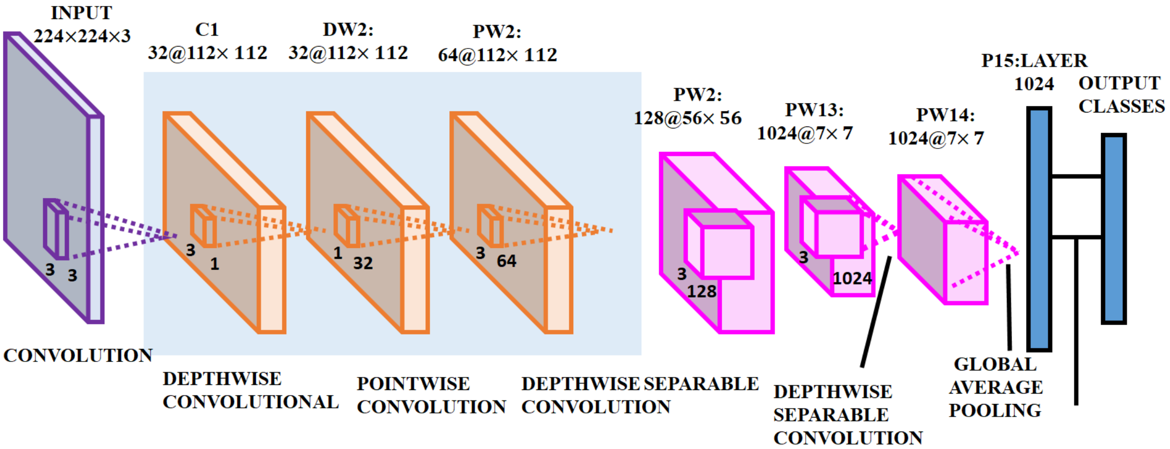

Figure 5: *Implementation of MobileNet architecture*

The MobileNet network layer in figure 5 served as the model for design, which flinches with the first convolutional layer then evolutions over thirteen depthwise convolution layers, each which is prospered by pointwise convolution layers. Following each depthwise and pointwise convolution layer, the Rectified Linear Unit (ReLU) activation function and batch normalization (BN) are used. Finally, FAM method classifies the DFU and healthy skin depth wise to get high accuracy and performance.

4. Result and discussion

In the result and discussion the DFU images are predicted using the proposed FAM. For identifying DFU the DFU dataset is taken from the kaggle.com implemented using Python software. The train images has the count for abnormal image of 409 and normal images of 434. Test images has 103 abnormal images and normal image of 109.

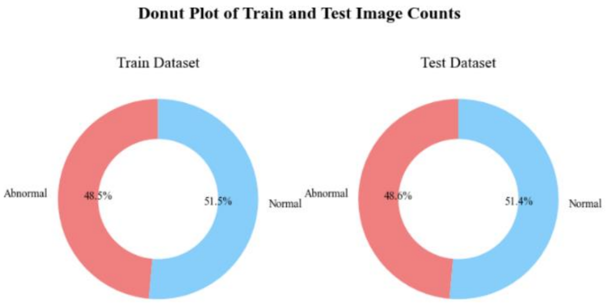

Figure 6: *Donut plot of test and train images count*

Figure 6 shows the donut plot of test and train images count. The train dataset have the abnormal count of 48.5% and normal count of 51.5%. Then the test dataset have the abnormal count of 48.6% and normal count of 51.4%. Both the test and train have the high percentage for normal and lower percentage for abnormal DFU.

Figure 7: *Random test and train images*

Figure 7 shows random images in train and test dataset of DFU and normal skin image. The random images are taken from the DFU dataset for further process. Here, both DFU image and normal skin images are randomly chosen from DFU dataset to test and train for further analysis.

Figure 8: *Input DFU image*

Figure 8 shows the input DFU disease image. The input image is taken from the DFU dataset randomly chosen test and train images. The input DFU image is a raw image taken from DFU dataset from kaggle.com uses the following methods such as pre-processing, segmentation, feature extraction and classification for further processes.

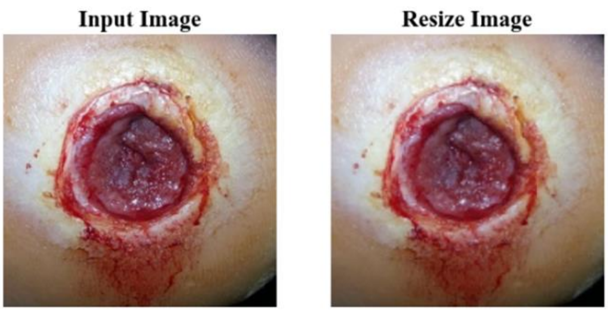

Figure 9: *Input image to resize image*

Figure 9 shows the input image to resize image. Here the input DFU image is resized using image resizing technique. The noises present in the original image are removed and get the better quality image. Next, step the better quality DFU image is given as an input to grayscale conversion technique.

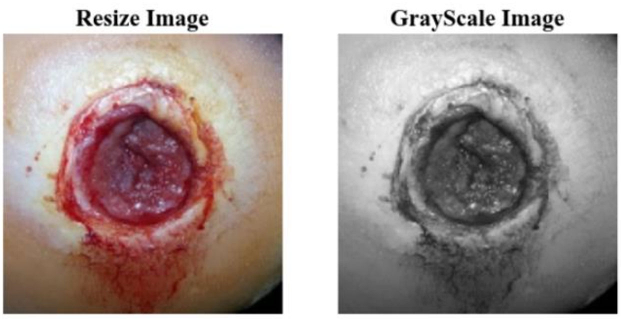

Figure 10: *Resize image into gray scale image for DFU disease*

Figure 10 shows the resized image into gray scale image for DFU disease approach. Here resized image is transformed into grayscale image for enhancing the DFU disease region. DFU disease image is converted in to a gray scale or black and white representation for this gray scale image the grayscale conversion technique is used.

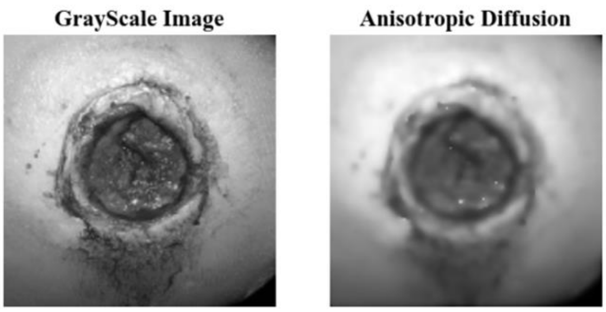

Figure 11: *Grayscale image into ADF image*

Figure 11 shows the grayscale image into ADF image. Here the DFU image is enhanced and preserves the edges by ADF, which also detected and removed the noise from disease affected image. Then the filtered DFU image is given as an input to FAT for further segmentation.

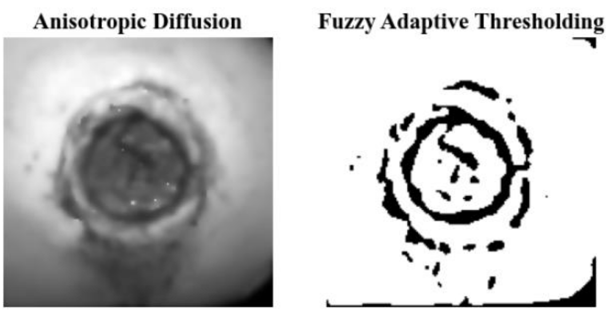

Figure 12: *ADF in to Fuzzy Adaptive Thresholding for DFU image*

Figure 12 shows the ADF in to FAT for DFU image. The FAT calculates the fuzziness of the threshold values from the DFU disease image. Each threshold values are pointed with the variables and these calculated threshold vales are then used as input for feature extraction.

Table 1: *Contour Feature Analysis for DFU*

```
Contour Feature Analysis:
Contour 1:
  Area: 21722.5
  Perimeter: 588.3259004354477
  Centroid: (73, 73)
  BoundingBox: (0, 0, 150, 149)
  ShapeFactor: 0.7886489575109761
```

Table 1 shows the contour feature analysis for DFU disease. The contour feature analysis is nothing but used for analyzing the image and classifies the shape and texture of a wound. The CCD, shows the values for area of 21722.5, perimeter of 588.32, centroid of (73, 73), bounding box of (0, 0, 150, 149) and the shape factor of 0.7886 for DFU disease image.

4.1 Performance metrics

Performance metrics like accuracy, sensitivity and specificity which indicate the likelihood that a DFU be correctly detected and appropriately diagnosed as the probabilities calculated by the FAM. The true positive, true negative, false positive and false negative results are denoted by TP, TN, FP, and FN, respectively. Sensitivity$[TP/(TP + FN)]$, specificity $[TN/(TN + FP)]$, F-value $[2 \times (recall \times precision)/(recall + precision)]$, and accuracy $[(TP + TN)/(TP + FP + FN + TN)]$.

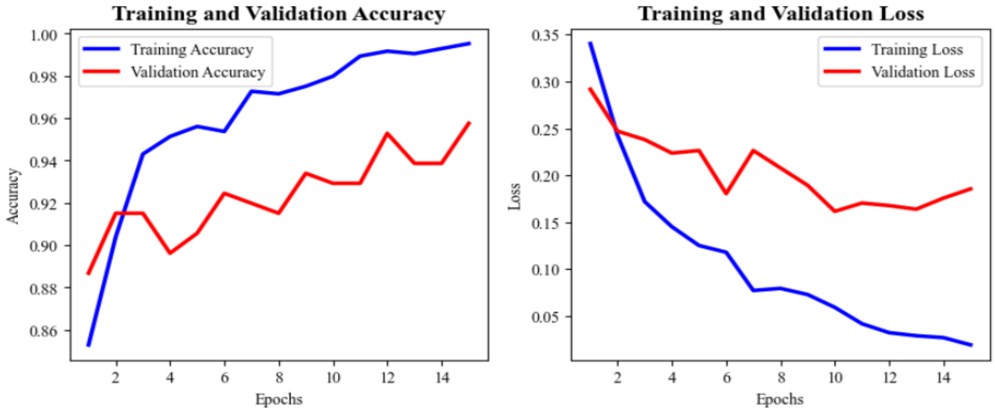

Figure 13: *Training and validation accuracy, training and validation loss*

Figure 13 shows the training and validation accuracy, training and validation loss. The X-axis denotes the epochs and Y-axis is accuracy for training and validation accuracy simultaneously for training and validation loss X-axis for epochs and Y-axis for loss. The Model Accuracy graph illustrates increasing accuracy of 96%, with the model achieving high performance and minimal over fitting. Training and validation loss is reliably declining in training and validation loss, representing improved learning and reduced error.

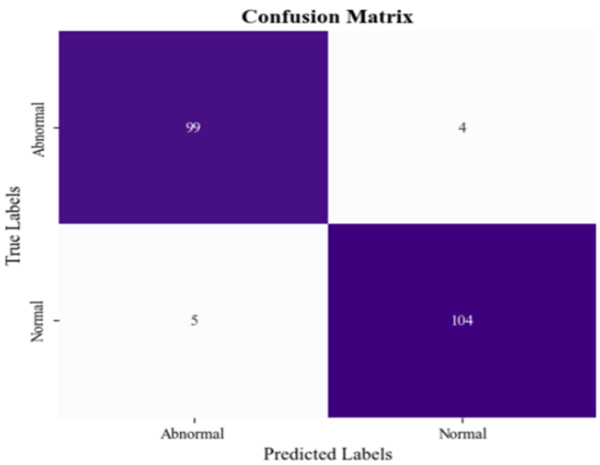

Figure 14: *Confusion matrix for FAM*

The confusion matrix for DFU is shown in figure 14. Proposed method evaluates the model's performance in predicting normal and abnormal levels of DFU. The X-axis indicates the predicted labels and Y-axis indicates the true labels for DFU image. It shows high accuracy for all classes, with 99 for abnormal (DFU) and 104 for normal foot skin.

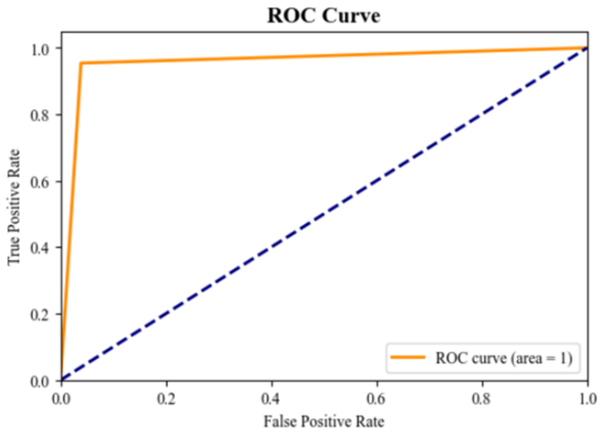

Figure 15: *ROC Curve*

Figure 15 shows the ROC curve for proposed work. The X- axis indicates the false positive rate and Y–axis indicates the true positive rate. The FPR have the values up to 1 and TPR have the value up to 1. By using the ROC calculation formula the proposed FAM method is calculated and have the higher value (area=1) for DFU demonstrating the approach.

4.2 Comparison for the proposed method

The comparison of proposed method with existing method is presented in table 2. The ANN have the classification accuracy of 82.9% [19] and LR and ANN have the accuracy of 91.6% [16]. The proposed FAM have the higher accuracy of 96% and better performance for DFU disease image compared to the existing methods.

Table 2: *Comparison for the proposed method*

Study	Method	Accuracy
Poradzka *et al* [19]	ANN	82.9%
Zhang *et al.*[16]	LR and ANN	91.6%

Proposed approach	**FAM**	**96%**

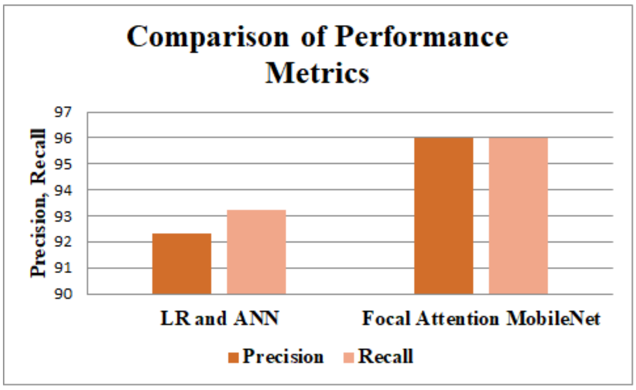

Figure 16: *Comparison for precision and recall value proposed work*

Figure 16 shows the comparison for precision and recall value proposed work and the existing work. The LR and ANN have the precision value of 92.3% and recall value of 93.2% [16] and proposed FAM have the precision value of 96% and recall of 96% for identifying DFU. The proposed precision and recall value is high compared to the existing method.

5. Conclusion

In this study, FAM is proposed for the classification of DFU image. The preprocessing stage effectively preserves the edges and noises are removed using ADF. Next, FAT based segmentation finds the fuzziness of the threshold value for DFU image. Furthermore, CCD-based feature extraction calculates the vales of shape, boundary box, area, perimeter, and centroid, from the DFU disease images. Finally, the proposed FAM classifies the DFU image with better accuracy. The performance evaluation, conducted on the DFU dataset, demonstrates the superior capabilities of the FAM method. The improved accuracy of 96%, precision value of 96% and recall of 96% is achieved as a greater accuracy and performance in contrast to the surviving methods.

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