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Efficient DL diabetic foot, Thermogram Classification

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Abstract: In this paper, a new approach to practical and utilization of technology within a Diabetic foot complications continue to be a major public health concern, causing significant suffering and economic burden. Timely and accurate diagnosis is paramount to prevent severe complications, such as amputations. This proposal introduces a cutting edge approach to diabetic foot thermogram analysis, utilizing Deep Convolution Neural Networks (DCNNs) to enhance diagnostic precision. Our research endeavors to develop a robust DCNN based model tailored explicitly for the analysis of diabetic foot thermograms. DCNNs incorporate structured information and hierarchical feature learning, making them particularly well-suited for capturing intricate patterns and subtle abnormalities within these thermal images. Leveraging a thermograph image dataset, we aim to create a highly effective diagnostic tool. Moreover, our study aims to advance the interpretability of DCNNs, shedding light on the decision process of the model and providing clinicians with valuable insights into the detected anomalies By enhancing diabetic foot thermogram analysis with DCNNs, this research holds the potential to revolutionize diabetic foot care, enabling earlier intervention and improved patient outcomes

Keywords: Deep Convolution Neural Network (DCNN) Diabetic Foot Thermogram classification in Deep learning

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I. INTRODUCTION

Diabetes Mellitus (DM) is a metabolic disorder characterized by increased blood glucose, known as hyperglycemia [1]. The pathogenesis of DM is due to immune disorders or insulin resistance, generated by genetic predisposition or environ mental factors [2], [3]. In general, risk factors associated with DM are first-degree relatives with the pathology or a high Body Mass Index (BMI). In fact, high BMI has increased the number of cases worldwide due to poor eating habits and excessive sugar consumption [4], [5]. The impact is seen in alarming statistics worldwide. For example, World Health Organization (WHO) reported DM as the leading cause of death in 2019, with approximately 1.5 million cases [6].

Projections indicate that this number could increase to approximately 1.6 million by 2025 [7].

Similarly, the Interna tional Diabetes Federation (IDF) reported 537 million adults (20-79 years) with diabetes in 2021, i.e., one in ten adults are living with diabetes, where more than half are undiag nosed. Estimates project a global increase to 643 million by 2030 and 784 million by 2045. In addition, the IDF estimated approximately 6.7 million deaths by 2021 [8]. DM manifests as a group of metabolic disorders that can range from heart disease, stroke, renal failure, blindness, ischemia, and peripheral vascular disease, among the most common conditions [9]. Peripheral vascular disorders gener ate the well-known diabetic foot, being this also the main neu ropathic alteration [10]. The disorder generates infections, ulcerations, or destruction of deep tissue in the lower limb, limiting the patient's mobility [11]. In this order of ideas, the pathology requires early and continuous medical attention to prevent complications such as lower limb amputation [12]. On the other hand, body temperature change is a widely used strategy to identify abnormalities in the medical field [13]. The research addresses different applications in the medical field, and diabetes is no exception to this trend. For example, different studies are currently based on foot thermography and even on the detection of type 2 DM from facial or tongue thermography, as explored by Thirunavukkarasu et al. in 2020 [14], [15]. Thermography is presented as a novel method for the exploration of different conditions [16], [17]; even such images have presented a significant growth in recent decades due to their noninvasive nature, being used even in face detection [18]. Additionally, thermographic images can be integrated with different Artificial Intelligence (AI) strategies due to their digital character. Advances have not been long in coming, and there are already several research studies aimed at diagnosing DM or the detec tion of conditions that are a consequence of it, such as neuro pathic complications or diabetic foot [19]–[24]. The growing interest has even motivated the development of low-cost proprietary systems to register such thermographic images, as has been done by Bayareh [25] and Sruthi et al. [26]. At the same time, the topic has been approached from different perspectives, covering topics ranging from image processing to state-of-the-art deep learning networks. For example, Christy Evangeline et al. suggest a method of asymmetry analysis between angiosomes for the exclusive characterization of subjects with diabetes [27]. Filipe et al. propose a new coefficient like the Thermal Change Index (TCI). The method consists of parceling the foot into different regions based on the clustering algorithm applied to the intensity levels of the image (temperature). The average temperature is estimated from the regions, and they calculate the coefficient called Classification Temperature Threshold (CTT) [28]. Prabhu et al. developed an automatic system for segmentation of the plantar foot region in thermographic images, as it is an inherent need for feature extraction in such images. The development was done using the C means algorithm [29]. On the other hand, Carlos Padierna et al. extract 12 features from the top of the foot to train a Support Vector Machine (SVM) [30]. Similarly, Adam et al. also rely on a support vector machine for classification. The model uses Gray Level Co-occurrence Matrix (GLCM), Hu's invariant moment, Local Binary Pattern (LBP), Laws Texture Energy (LTE), and entropy, extracted from the decomposed form of the Discrete Wavelet Transform (DWT) and HigherOrder Spectrum (HOS). The development achieves an accuracy of over 89%. However, the authors point out that the work was based on a reduced database; moreover, the system is semi-automated, as it requires feature extraction [31]. In the same year, Adam et al. present new research on diabetic foot classification. The authors report higher values than in their previous research.

II. METHODOLOGY

This section describes all the steps followed to obtain a final comparison of the machine learningbased classifiers mentioned above. For purposes of this work, 110 thermograms of DM subjects obtained from a public thermogram database were used [53]. In order to use the MLP and SVM algorithms, a process of selection of the region of interest (ROI) for segmentation is required in addition to the further extraction of relevant features. In this case, we use a histogram-based segmentation method represented by fuzzy sets and optimized with an evolutionary optimization technique. This process is mentioned briefly in this section, but it is expanded in the appendices at the end of the work. Finally, we briefly mention the description of the three machine learning-based classifiers and the new proposed DL structure

A .Dataset

When DL structures are trained from scratch, they require a large number of images because of the enormous number of parameters trained in them. Data augmentation is an affordable technique to obtain such quantity of data when we do not dispose of it. Data augmentation consists of a combination of various processing techniques, like rotation, flipping, contrast enhancement, using different color, space, and random scaling. In this work, rotation is performed at angles of 90◦ , 180◦, and

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270° . We used three types of flipping (horizontal flip, vertical flip, and horizontal+vertical flip) performed on the original patches. We also obtained several patches of each image, allowing us to increase the data set tenfold. Figure 1 shows five classes of thermal change that can be found in the database and an example of the extracted patche

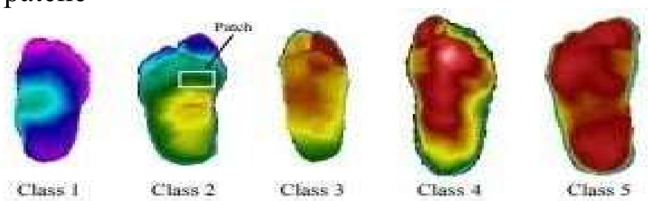

Fig 1

B. Data Preprocessing

The .csv files were converted to single-channel images in the 'float32' format. The size was set to 199 × 88, padding with zeros the edges of all images that did not meet that size.

C. Deep Convolutional Neural Network

Artificial intelligence is one of the areas of computational sciences with many ramifications. AI ranges from the most straight forward systems composed of linear models to the most recent deep learning methods. One of the fundamental elements in AI is convolutional artificial neural networks or simply convolutional networks (See Appendix A). Networks are one of many bioinspired systems based on the function ing of the central nervous system, more specifically, the brain. Convolutional networks emulate the primary visual cortex to perform tasks such as detection, classification, or feature extraction to achieve a specific task [65]. This concept has led to the emergence of a large number of networks; in fact, there are currently several networks that differ from the first convolutional model developed by Lecun et al. in 1998 [66] or from the first convolutional DL model, known as Alex Net [65]. The various architectures and their depth allow them to perform increasingly complex tasks. However, the increase in depth has two drawbacks. First, the depth implies a more significant number of layers and, consequently, a larger number of training parameters. Consequently, a more significant number of training data is needed to fit many model parameters. In this sense, this is one of the reasons that motivated us to use data augmentation methods and include new strategies to address this problem.Secondly, augmentation limits the model's training generated by gradient fading [66]. For this reason, in this research, we chose to use the ResNet50v2 network [50], which has an elegant solution to this drawback. The network is based on the concept of connection or residual mapping. In general, the connection creates parallel paths to the convolutional layer sequences, allowing smooth transmission of the gradient through the layers and preventing the gradient value from being zero. In addition, the connection forces the network to learn the residual mapping f (x)−x, being easier to train if the residual mapping is the identity function f (x) = x [50], [67].

D. Data Augmentation

The MLP and SVM require the extraction of relevant features to be introduced to the classifiers before training them. In this paper, the ROI of DM patients is segmented before the feature extraction using a histogram-based method. In the process of obtaining the partition of a digital image into multiple segments, a variety of image segmentation methods have been developed, such as thre scolding, clustering-based methods, compression based methods, histogram-based methods, and edge detection, among others. This work uses a histogram-based method, mainly using fuzzy logic, representing the segments of the image. The fuzzy logic approach for image processing allows us to use membership functions, defining the degree to which a pixel belongs to one segment or another. Furthermore, we obtain a better definition of segments by using fuzzy logic according to the measure of entropy. The optimized parameters are obtained by using a Heuristic optimization technique based on Differential Evolution. The Appendices A and B contain an expanded explanation of this, and Figure 2 represents the basic steps of this process

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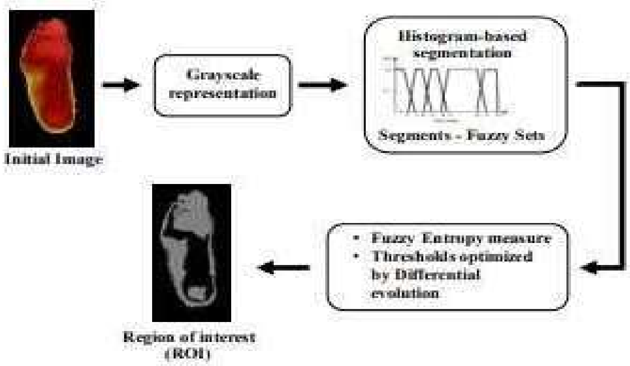
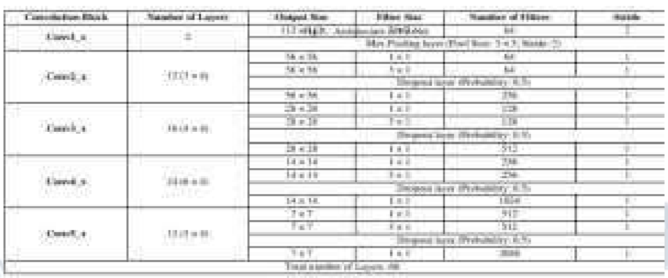


Fig 2. Automatic segmentation process

A. Figures

The performance metrics for all the (Alex Net, Resnet101 and ProNet) accuracy, precision, sensitivity, specificity follows:



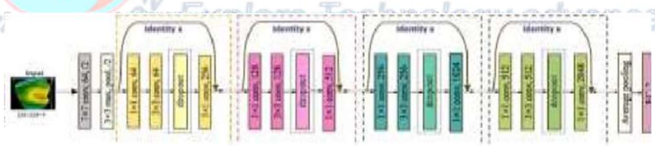


Table I: Confusion Matrix

It is an N×N matrix that is utilized for assessment of performance of classification technique as shown by Fig. 1. N is the no. of target groups. Confusion matrix compares the projected target values obtained by DL model to the actual target class values.

Training Parameter	Deep Neural Network		
	AlexNet	ResNet-101	ProNet
Input Image Size	227×227×3	224×224×3	224×224×3
Solver	SGDM	SGDM	SGDM
Maximum epochs	30	10	10
Mini Batch Size	128	10	10
Initial Learn Rate	1E-4	1E-3	3E-3

Table II Training Parameter Specification

B. Training Parameters Training input parameters that are used in this work, as listed in Table II. Are described as:

1) Solver: SGDM (Stochastic-Gradient-Descent with Momentum) solver is a technique that aids in enhancing gradient vectors in correct directions.Quicker convergence is the result of this. It is amongst major prevalent algorithms for optimization purposes and a lot of models are trained with its help.

2) Maximum epochs: An epoch designates that the no. of passes of complete dataset training by ML methodology has finished. If data amount is extremely huge, databases are generally congregated into batches.

3) Initial Learn Rate: It is a hyper parameter (configurable) utilized in neural network training. Its value lies between 0 and 1 (a little positive value). It controls the adaptability of the model to situation

4) Mini Batch Size: Before updating of the internal parameters of model, a number of samples are there which have to be worked through. This number is denoted by mini batch size.

Deep Neural Network	Training Time
AlexNet	t
ResNet-101	7t
ProNet	4t

Table III Training Time Observation

Techniques implemented is given in Table III. It can be observed that if the time taken by AlexNet is denoted by ‘t’, ResNet-101 takes seven times the time consumed by training AlexNet. ProNet, the Proposed network, consumes four times the time. (96.8%) than that of classification models in the Alex Net consumes minimum training time due to previously reported work [5,6,8]. least number of layers but also has the lowest accuracy.

ProNet, proposed network takes more time for training than AlexNet. But, it is less complex and tedious than ResNet because of reduction in the number of layers. depict testing output samples (of diabetic foot thermograms) of AlexNet, ResNet101

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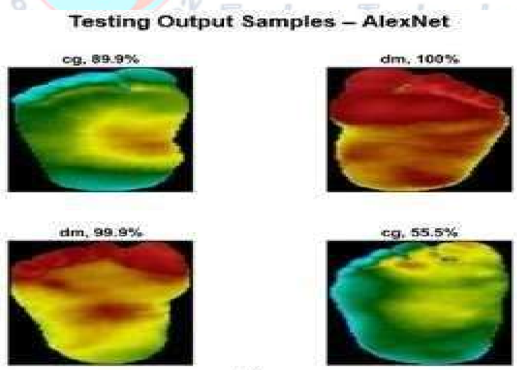
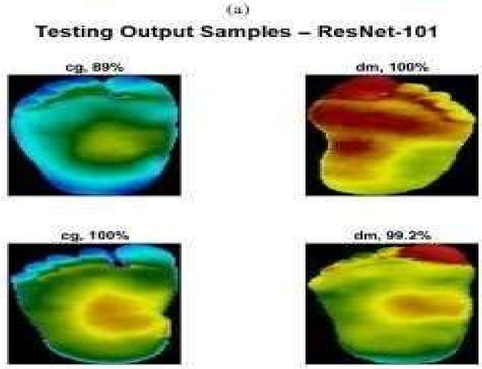
and ProNet with their prediction probability percentages. Control Group sample is denoted by 'cg' and that of Diabetes Mellitus group is represented by 'dm'.

It can be observed that two out of every four samples tested have 100% probability of being predicted correctly in case of AlexNet and ResNet101. The rest two samples have a higher percentage of being predicted incorrectly by AlexNet than by ResNet-101. In case of ProNet, three out of every four samples have complete chances of correct estimate. Only one out of every four samples has probability of being predicted slightly inaccurately (as small as 0.1%).

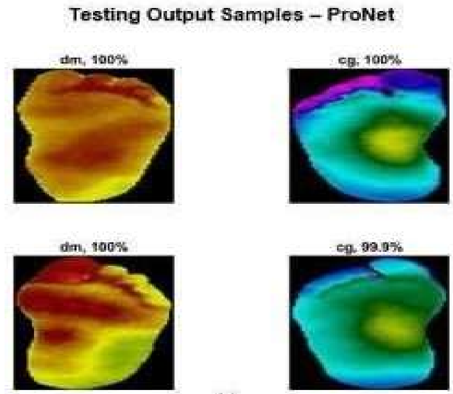
Confusion matrices obtained for the methods implemented are shown in Fig. 5 (a)-(c). The matrices depict the number of TPs, FNs, FPs and TNs along with prediction percentages for each class – CG and DM. Also, percentage accuracy is represented for each DL technique. The values for all performance parameters are calculated as recorded in Table IV. It can be observed from Table IV. that AlexNet has greater accuracy



(a)

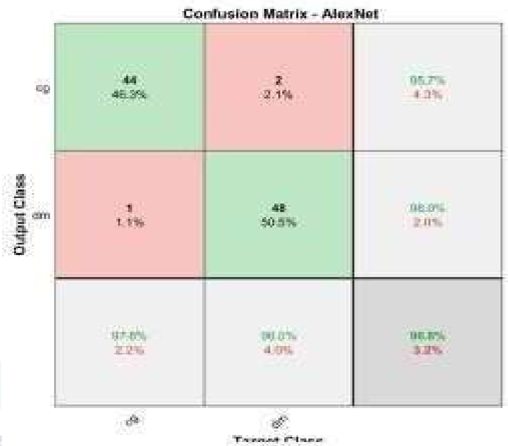


(b)



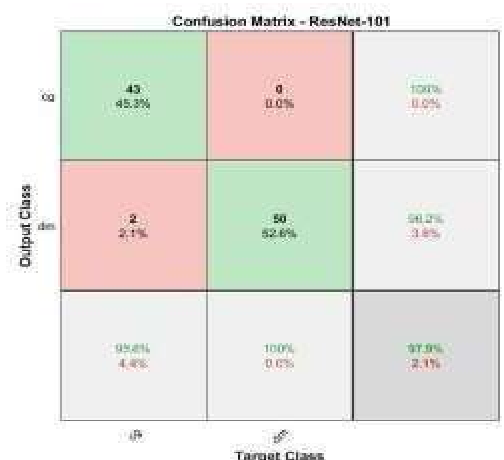
(c)

Fig 3



(a)

Fig 4 Testing Output Samples for (a) AlexNet; (b) ResNet (c) pronet



(c)

Fig 5 Confusion Matrix for (a) AlexNet; (b) ResNet- 101; (c) ProNet

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Table IV Performance metric calculation

Performance Metric	Deep Neural Network		
	AlexNet	ResNet-101	ProNet
Accuracy	0.968	0.979	0.989
Precision	0.956	0.955	1.000
Sensitivity	0.977	1.000	0.978
Specificity	0.960	0.962	1.000
F1 Score	0.966	0.976	0.988

Although ResNet-101 has higher values than AlexNet for most of the metrics, it has lower accuracy, precision, specificity and F1-Score than the DL network proposed in this work. Except for the fact that ProNet has lower than ResNet-101 (which has a perfect sensitivity value of 1), it gives the best results amongst the other two in terms of accuracy (as high as 98.9%) and all other parameter values. Also, it has optimal precision and specificity.

a. ***Accuracy:*** It is the ratio of correct predictions to total predictions made for a dataset as depicted in (1). Here, TP: no. of true positives; TN: no. of true negatives; FN: no. of false negatives and FP: no. of false positives.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP}$$

b. ***Precision:*** It is a parameter which measures the no. of right positive predictions. It is formulated as the ratio of rightly predicted positives to the total positive examples predicted as in (2)

$$\text{Precision} = \frac{TP}{TP+FP}$$

c. ***Sensitivity:*** It is a parameter that computes correct positive estimates of all positive examples which could have been predicted. It is equated as the ratio of TPs to the total TPs and FNs as represented in (3).

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

d. ***Specificity:*** It is the quantity of real negatives, that are also forecasted as negative. It is equated as the ratio of TNs to the total TNs and FPs as shown corpus of thermographic image data. The in (4). augmentation consisted of 4 conventional methods and eight proposed methods based on dimension

$$\text{Specificity} = \frac{TN}{TN+FP}$$

reduction methods: principal component analysis,

kernel PCA, incremental PCA, factor analysis, independent component analysis, non-negative matrix factorization, dictionary learning, and LDA. Initially, the images were taken to latent spaces of lower dimensionality using the afore mentioned methods. The latent variables were altered with a random noise vector and returned to the original image space, generating new synthetic images with characteristics like the reference images. All methods were shown to be statistically significant with a significance level below 0.05, which is a f. F1-Score: It provides a method to combine both relevant contribution to data enhancement.

sensitivity and precision into a sole measure which Additionally, a comparative analysis was has both the properties. It is harmonic mean of two performed, we studied the behavior of the network fractions as given by (5). under three training conditions. First, the network was trained from scratch. Secondly, we used

$$\text{F1-Score} = \frac{2*(\text{Precision}*\text{Sensitivity})}{(\text{Precision}+\text{Sensitivity})}$$

transfer learning from the conventional ImageNet image database, and finally, we performed the same process, but from a thermographic database.

III. CONCLUSION

The results showed that data augmentation and A framework for exploring different approaches learning transfer are statistically significant for screening subjects with diabetes mellitus (DM) strategies to improve the performance of was proposed. Initially, we planned to study a new convolutional neural networks. Furthermore, it was discrimination coefficient of the subjects based on also shown that learning transfer has the same the characteristics of average temperature, age, impact regardless of the nature of the images, as overall TCI of right and left feet. The new long as the data corpus is large enough to generate coefficient was able to exceed the accuracy of the transferable learning patterns. TCI by up to 17%, which is a useful tool for the stratification of subjects with DM. Secondly, the ResNet50v2 network was explored to accurately classify subjects by integrating it with 12 data augmentation methods to make up for the low

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