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Foot Ulcer Image Based Diabetes Detection Using Feature Extraction and Classification Based on Deep Learning Architectures Integrated With Big Data Analytics

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Abstract:
One of the most common diseases in the world, according to World Health Organization (WHO), is diabetes mellitus (DM). Additionally, a high mortality index is linked to it. One of its most common side effects is diabetic foot, which includes emergence of plantar ulcers that may require amputation. Additionally, diabetic patients may develop various illnesses such as heart disease, eye issues, kidney complications, nerve damage, foot ulcers, skin complications, and dental conditions. Diabetic heart disease (DHD), which is leading cause of mortality for many people, is one of the major consequences of diabetes. In order to treat patients effectively, early detection of diabetic heart disease is aided by a variety of deep learning techniques. So this paper proposed the novel technique in detection of diabetes by the foot ulcer image of patients. Since diabetes patients will have foot ulcer as major complication, the dataset has been collected based on the pre-historic medical data and foot image of the diabetes patients. This dataset has been pre-processed and segmented. Then the segmented data features of foot image using mask recurrent convolution neural network (MRCNN), the extracted features shows the detection of foot ulcer. Then image data and numerical/text data has been extracted separately. The normal diabetes range and abnormal diabetes range has been extracted. Those patients with abnormal diabetes range, their foot images have been separated and classifying the extracted features using fast deep convolution neural network (FDCNN) the normal and abnormal range of diabetes has been detected. The simulation results show confusion matrix for diabetes range detection and parametric analysis of proposed technique. The parameters obtained are Accuracy, precision, recall, f-1 score.
Keywords:DM, DHD, foot ulcer, deep learning,MRCNN, FDCNN, diabetes.

1. Introduction:

High throughput computers, which has made significant advances in biotechnology, as well as the ability to produce data quickly and affordably, have opened field of computational biology to realm of big data. Investigating the steadily expanding biotic data as well as creating a framework for better answers to fundamental questions in biology and medicine are the main objectives. These methods' ability to recognise forms and generate models from data is what gives them their efficiency and dependability. The diagnosis and treatment of diseases that pose a threat to human life is one of the most important applications of science. A illness of this type is diabetes mellitus (DM). According to WHO (2020), DM is one of the most common diseases affecting the elderly in the nation [1]. Globally, 451 million people have diabetes as of 2017, according to the International Diabetes Federation. Over the following 26 years, it is anticipated that this number would increase to 693 million people. Although the basic aetiology of DM is still unknown, scientists think that both environmental and genetic factors are significant contributors to the disease. Despite being incurable, it can be managed with pharmaceuticals and medication. Additional health issues like cardiac arrest as well as organ damage are possible for those with DM. Additionally, early detection and therapy of DM will assist to prevent complications and lessen the threat from serious health problems. A doctor can manually diagnose DM patients or use an automated tool to do so. Each of these methods for measuring DM has advantages and disadvantages. Even a qualified doctor frequently struggles to fully recognise the earliest signs of DM since they are frequently so subtle. [2]. Additionally, poorly managed blood sugar might result in a variety of immediate or long-term consequences. DHD is the name of the cardiac condition that affects diabetics. In addition to raising the risk of DHD and a number of health problems, such as excessive blood sugar and cholesterol, diabetes also dramatically raises the risk of stroke and heart attack. However, due to neurological system abnormalities that can harm the nerves that control the heart, patients with diabetes do not experience any symptoms. One of the leading reasons of death for many diabetics is DHD. The diagnosis of heart illnesses, particularly those that afflict women, is significantly more challenging. Young or diabetic patients are not particularly diagnosed in many incidents of heart attacks in women. According to research, women with diabetes have a sudden death risk that is equal to that of males with the disease. Persons with type 2 diabetes are at a 2 to 4 times greater risk than healthy patients [3]. The majority of diabetic individuals have diabetic foot ulcers, which, if left untreated, can result in partial or complete amputation. Early diagnosis and treatment can stop the development of DF ulcers. Using conventional diagnostic techniques, it is nearly impossible to identify diabetic foot ulcers in their early stages. Due to the patients' progressive lack of sensation, self-examination is also difficult. Additionally, there isn't an automated method for detecting ulcers early on. Previous research indicated a connection between temperature rise and the emergence of diabetic foot ulcers [4]. Several techniques, including infrared imaging, liquid crystal thermography (LCT), infrared (IR) thermometers, and temperature sensors built into a weighing scale, can be utilised for the early detection of diabetic foot ulcers. For the early prediction of DHD, a variety of data mining and machine learning techniques are applied. ML and AI advancements make illness identification and diagnosis by an automated software more likely as well as effective than traditional manual DM recognition technique at an early stage. Benefits include less labour for medical professionals and a lower possibility of human error. Computer-based decision support methods may play a vital role in effective diagnosis as well as profitable management. Big data is generated by the DM field based on laboratory evaluation, patient reports, treatment, follow-ups, medication, etc. It is challenging to manually put together all the necessary data. Unsuitable data management has had an impact on the quality of data organisation.

In order to enable data gathering and sharing in large datamethods, current and new hospitals have employed machines for data collection and inspection. In comparison to manual detection and diagnosis, an automated device is much more competent of identifying DM and handling irregularities. Therefore, automation of the DM diagnosis is crucial. Automated DM systems can be created using artificial intelligence or machine learning techniques. Each ML and AI technique has advantages and disadvantages of its own. As a result, both approaches are employed to create automated DM detection methods. The best-performing ML and AI methods require causability and the capacity to explain how they can function like a human, as many of these techniques are least transparent. Ability of AI systems to explain things helps to increase doctors' confidence in future AI methods. Causability is based on the causal method, which is evaluated in terms of efficacy in comprehending causal relationships and user-friendliness. In recent years, a number of academics have applied ML as well as AI techniques for DM control, self-management, and personalization [5].
The contribution of this paper is as follows:

- To propose the novel technique in detection of diabetes by the foot ulcer image of patients.
- To collect the foot images of diabetic patients and process for noise removal, edge normalization and smoothening
- To extract the features of foot image using mask recurrent convolution neural network (MRCNN), the extracted features shows the detection of foot ulcer.
- Then for those patients with foot ulcer by classifying the extracted features using fast deep convolution neural network (FDCNN) the normal and abnormal range of diabetes has been detected

Remainder of paper is organised as follows: Related study of DF pictures is described in section 2; the system model and specifics of the suggested system are explained in section 3; the simulation results are introduced and discussed in section 4; and conclusions and future work are discussed in section 5.

2. Related works:

Numerous studies have examined how to use thermal imaging to detect changes in skin temperature in order to diagnose diabetic foot conditions. Author in [6] employed thermal foot pictures to distinguish between diabetic feet with and without sympathetic skin response. Images can be divided into six ROI regions to do this: the arch, heel, forehead, lateral sole, hallux, and lesser toes. Then calculate mean temperature difference between them and the temperature of a healthy participant to compare them. A system to detect a diabetic foot using thermal imaging was proposed in [7] by calculating the temperatures of equivalent sites on both feet. According to the findings, neuropathy sufferers' average body temperatures fell between 32.8 and 27.9 oC. The author of [8] described a method for detecting diabetic foot ulcers using thermal image processing. The steps of this technique are segmentation, registration, and abnormality detection. Active contour was used for segmentation to remove the foot from the background, and B-spline non-rigid registration was used for alignment to place both feet in the same place. Finally, the intensity level of the corresponding regions on left as well as right foot were subtracted in order to discover abnormalities. According to this study, an anomalous area is one where the temperature differential exceeds the threshold. Another study [9] used infrared pictures to distinguish between three types of diabetic foot issues: no visual symptom, local complications, and diffuse complications. Calculating the average temperature differential between the contralateral and ipsilateral foot can help with this. By relating the area's temperature to its colour code, the researcher in [10] was able to use thermal imaging to identify the abnormalities of the diabetic foot. Using a rainbow palette, they divided it into ten hues and described the differences between each one in this fashion. A thermal method employing an Android smartphone and MATLAB Mobile platform was suggested in the work in [11]. By comparing four separate ROI locations with the usual test image, this method can forecast ulcers from those places. The study's only focus was on prediction of ulcers in grade 0 diabetic feet based on statically thermal readings and did not include instances that were at high risk of complications. [12] applies image processing on infrared photos to identify the diabetic foot. Additionally, this method had the highest accuracy, 95.66%. However, the focus of this investigation was solely on abnormality detection. In [13], the author simply used a separate convolutional neural network to categorise diabetic foot ulcers. To detect the abnormalities of diabetic foot, [14] suggested a thermal system based on extracting textural and entropy information from decomposed DWT and HOS. Unfortunately, this study was only able to identify the abnormalities with an identification rate of 89.39%, not merely the diabetic foot type. The Authors [15] focuses on an Ensemble model using a majority voting technique using unweighted prediction on various machine learning models. According to the authors [16], non-generative approaches are the main focus. The fundamental classifiers are united by a combination procedure, which depends on how well it can be tailored to the input observations and the demands of the outputs offered by various learning systems.Giving each classifier a weight can make this process better by optimising the behaviour of the combined classifier in the training set.In addition to comparing ensemble learning with sixty techniques, authors [17] advocate ensemble-based methods as being the most appropriate for the challenge of data stream classification. In order to increase accuracy, the author [18] proposes that different classifier systems have grown in recent years in machine learning. He also offers solutions to various machine-related issues.

3. System model:

Based on the foot ulcer for diabetic patients the risk of cardiac disease has been detected by this proposed technique. Initially the medical history of diabetic patients has been collected along with foot ulcer images and dataset is created for CAD system based cardiac risk prediction. The collected data consist of both numerical data and image data. This data has been preprocessed, segmented and finally extracts the feature vector of numerical data and image data. Here data features of foot image using mask recurrent convolution neural network (MRCNN), the extracted features shows the detection of foot ulcer. Then based on the extracted feature of numerical data, the diabetes level has been detected. When diabetes range is higher, further treatment for patient will be carried out and the foot images of particular patient will be sent for classification and when the range is normal the data will be updated in database. Based on this abnormal diabetes range, the foot ulcer image of particular patients will be classified for earlier cardiac disease detection. Here the classification process is carried out by the extracted features using fast deep convolution neural network (FDCNN) for classification of foot ulcer to analyze the abnormal diabetes patients. Proposed architecture is given in figure 1.

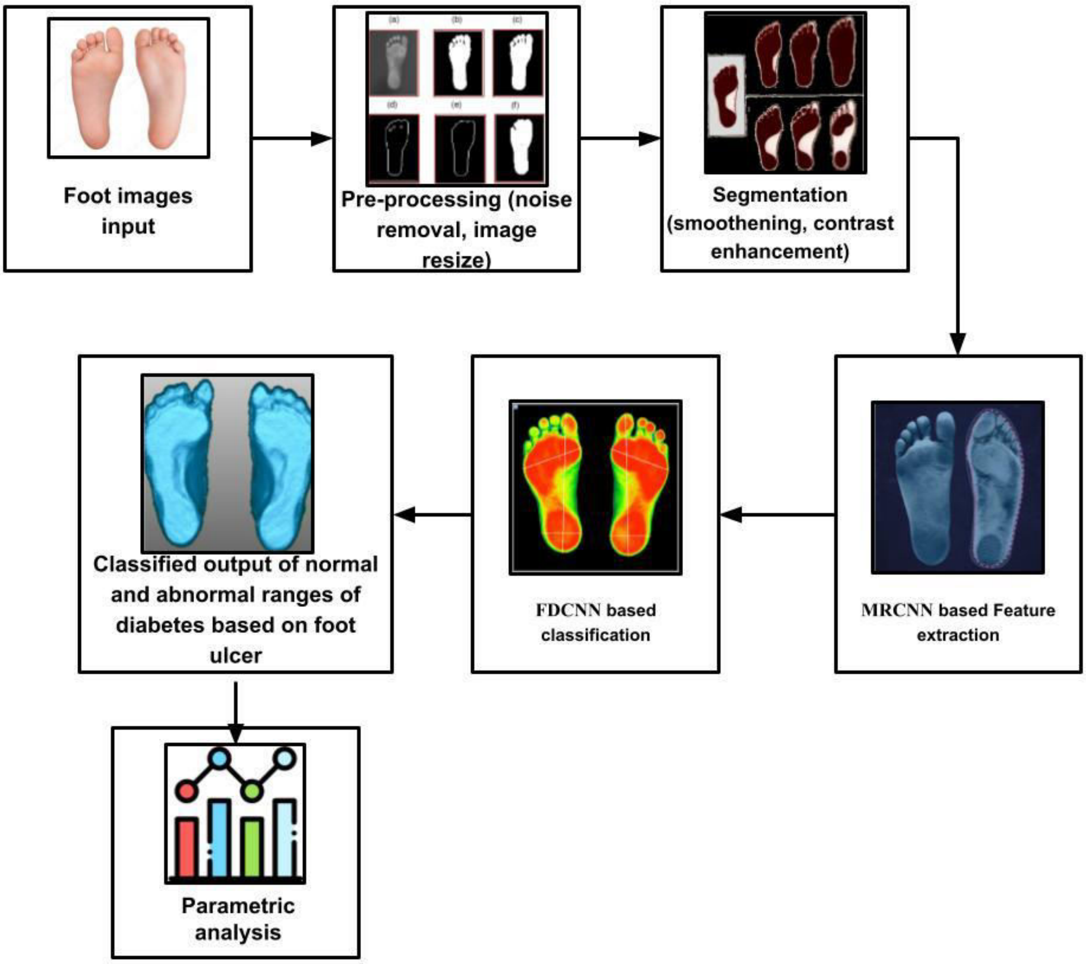


Figure-1 Proposed Architecture

Feature extraction using mask recurrent convolution neural network (MRCNN):

In this study, MRCNN is used to identify the calibration object. FPN, RPN, RoIAlign, and 3 branches make up the majority of the MRCNN. After two branches are joined to the fully connected layer (FC layer), the classification as well as recognition box is regressed. To segment the object, the convolutional (conv) layer is connected behind 3^{rd}branch. They are parallel, all three branches. Fig. 2 depicts the MRCNN's structural layout.

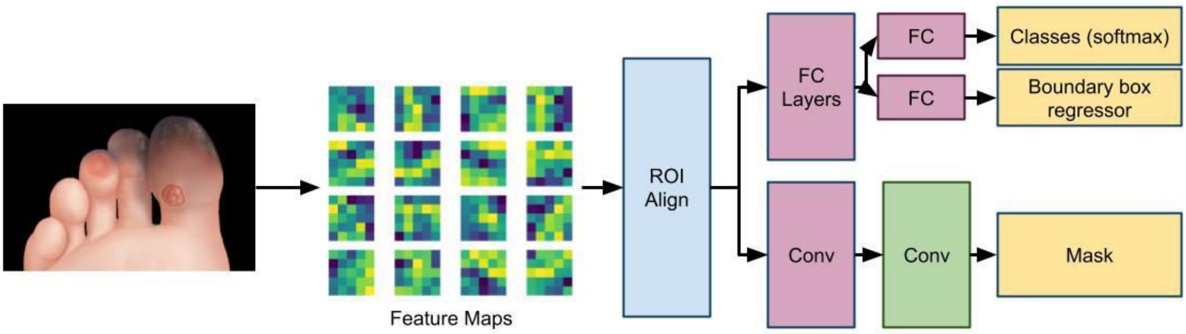


Figure 2. Mask R-CNN framework

The deep learning algorithm's biggest benefit is that it no longer requires artificial feature extraction. FPN, which consists of three components—lateral connections, top-down connections, and bottom-up connections—performs the task of feature extraction. The properties of each layer can be combined in this structure to produce strong semantic as well as strong spatial data. ResNet structure is used by MRCNN to extract features. Fig. 3 depicts the microarchitecture of the FPN.

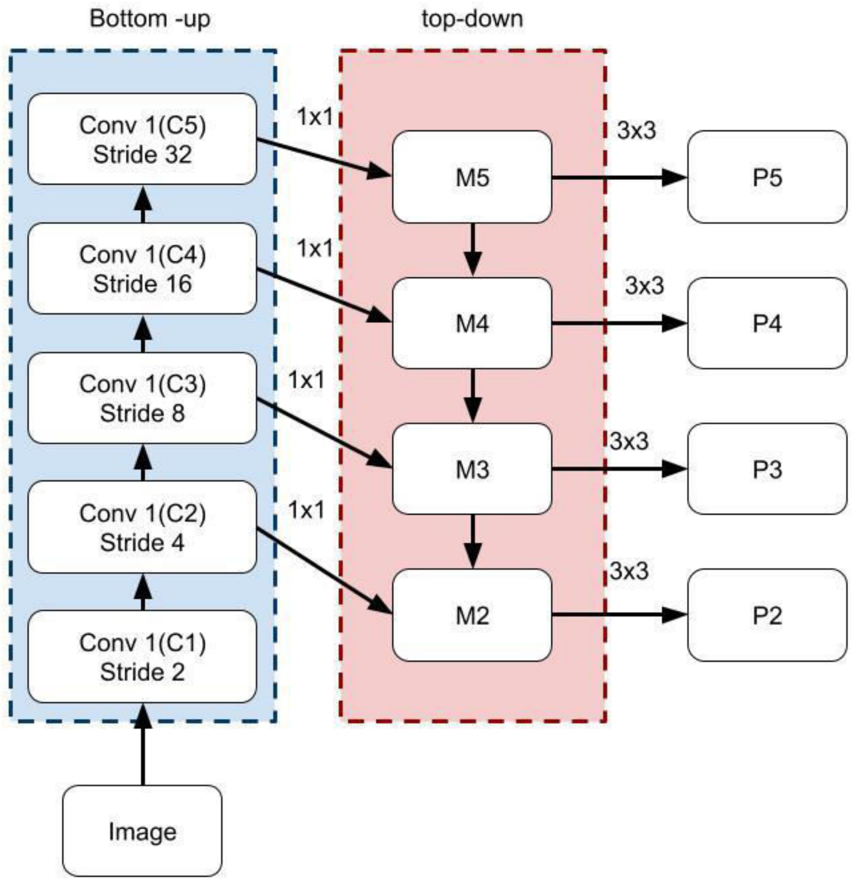


Figure 3. Microarchitecture of FPN

They walk with corresponding strides of 2, 4, 8, 16 and 32. The feature map produced by conv1 is not used to save memory. Upsampling from top layer initiates top-down process, which uses nearest neighbour upsampling to minimise training parameters. Lateral connections combine upsampling findings with a bottom-up, bottom-sized feature map of same size. Each convolutional layer (C2, C3, C4 and C5) has a convolution kernel size of 1, and there are 256 output channels. The result is then supplemented with the upsampling's feature map. The 3 3 convolution kernel is utilized to feed fused features into convolutional layer after fusion, with the goal of removing the aliasing impact of upsampling. In order to obtain P6, M5 is really downsampled using stride 2's maximum pooling. To obtain a 512 512 bigger anchor size, P6 is employed. P6 is, however, only employed by RPN to obtain region suggestions.

RPN:

The MRCNN region proposal is extracted using RPN. The size of the feature map after convolution is 1 1. Convolution kernels of size 1 1 are used in the classification layer and regression layer to extract characteristics that are comparable to a 256-dimensional vector.Purpose of the anchor is to create k potential zones on the sliding window that are various sizes. Essentially, the sliding window and anchor enclose all potential areas where the object might appear. K areas share the 256-dimensional vector features that RPN extracted. The classification (cls) layer generates 2 k scores by predicting the foreground and background probabilities of k areas. The regression (reg) layer outputs 4 k coordinates and predicts the region's four parameters: the coordinates of the region's centre point, its width, and its height. To calculate the loss, it is required to distinguish between the legitimate and invalid k-regions.

RoIAlign

RoIPooling is swapped out for RoIAlign in Mask R-CNN. The RoIPool's issue is that processed feature map is out of alignment with original image, which will decrease effectiveness of detection. RoIAlign, however, has a solution for this issue. Because the RPN creates four parameters for the region proposal, RoIPool causes misalignment. Although they are typically decimals, these parameters are integerized for convenience. To acquire image value, RoIAlign, on other hand, cancels integer operation, keeps decimal, and applies bilinear interpolation. RoI is shown by the solid line box and the dashed box, respectively, on the feature map (RoI). There are two and two cells in the RoI. Each cell is divided into four small squares if there are four sampling sites. The sample point is located in the centre of each small square. These sampling points' coordinates are typically floating-point integers, and value of sample point is determined using its bilinear difference value. To acquire the final RoIAlign result, the maximum pooling operation is lastly applied to each cell's four sampling points.

Loss function

There are three output layers in a Mask R-CNN. We jointly train for classification, bounding-box regression, and mask in eq. (1) using a multi-task loss L on each labelled RoI:

$$\mathrm{L} = \mathrm{L_{cls}} + \mathrm{L_{box}} + \mathrm{L_{mask}} \tag{1}$$

Probability, p, for each of K 1 classes is output by softmax layer. The information about the bounding box is output by the regression layer. In the event when there are K classes, the bounding box's centre coordinates are $\left(\mathrm{t_x^k}, \mathrm{t_y^k}\right)$, its width is $\mathrm{t_w^k}$, and its height is (t hk). Loss for bounding box regression in eq is called Lbox (2).

$$L_{box} = \sum_{i\in\{x,y,w,h\}} \mathrm{smooth}_{L_1}\left(t_i^u - v_i\right)$$

$$\mathrm{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases} \tag{2}$$

Classification using Fast deep Convolution neural network (FDCNN):

Patients with abnormally high levels of diabetes have their foot images classified. Once this classification is complete, diabetes with an abnormal range will be identified as a risk factor for cardiac arrest. As a linear classifier, an FDCNN is utilised. In this design, seven 60 * 40-pixel frames that are centred on the current frame are taken into account as inputs to the FDCNN model. In order to create various channels of information from the input frames, we first apply a series of hardwired kernels. 33 feature maps in five different channels—gray, gradient-x, gradient-y, optflow-x, and optflow-y—in second layer are outcome. The seven input frames' grayscale pixel values are contained in the grey channel. An output layer follows one or more fully connected layers, one or more convolutional layers, and then one or more convolutional layers in a convolutional neural network. Figure 4 illustrates the FDCNN design.

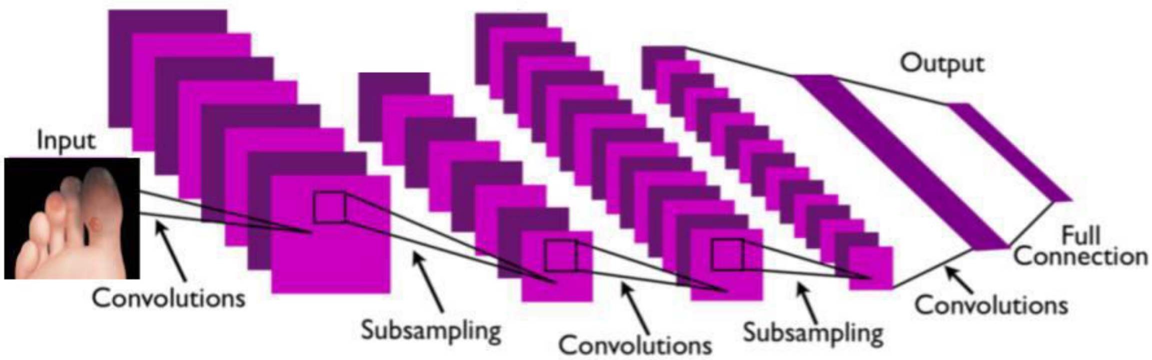


Figure-4 Architecture of FDCNN

Formally, we write $I^{(m)}$for the input to layer m of network. A $n_1^{(m-1)} \times n_2^{(m-1)} \times n_3^{(m-1)}$ 3D object with $n_c^{(m-1)}$ is input to a pre-trained convolutional layer m of a NN. Its constituents are designated by $I^{(m-1)} \epsilon \mathbb{R}^{n1(m-1) \times n_2^{(m-1)\times n_3^{(m-1)}}}$ where I j, and k index the 3D volume and'selects the channel. A convolutional layer's output is determined by both its dimensions, or $n_1^{(m)} \times n_2^{(m)} \times n_3^{(m)}$, and number of filters or channels it generates, $n_c^{(m)}$. $I_{i,j,k}^{(m,l)} = f_{tanh}\left(b^{(m,l)}\right) + \sum_{i,j,k,l} I_{i,j,k}^{(m-1,l)} W_{i-i,j-j,k-k,l}^{(m-l)}$computes layer m's output, which is a convolution of its input with a filter where the parameters that define lth filter in layer m are $W^{(m,l)}$ and $b^{(m,l)}$.Hyperbolic tangent activation function, $f_{\tanh(a)} = \tanh\,(a)$ is our final step.

Convolutional layers build up increasingly sophisticated representations of the input as more layers are added while maintaining the spatial structure of the inputs. A fully connected network layer then receives its input from the output of the convolutional layers. To do this, the output of convolutional layer is considered as a single vector and spatial and channel structure are disregarded. A 1D vector $I^{(m)}$ whose dimension is a component of network design is output of a fully linked network. Equation(3) provides the output of neuron I in layer m.

$$I_i^{(m)} = f_{ReLu}(b^{(m,i)} + \textstyle\sum_j I_j^{(m-1)} W_j^{(m,i)}) \tag{3}$$

The parameters of neuron I in layer m are $W^{(m,i)}$ and$b^{(m,i)}$, and total over j is a sum across all dimensions of input. Here, ReLU with the activation function f (ReLU) with $f_{ReLu}(a) = \max\,(0, a)$The sparsity it causes in the outputs is thought to be particularly useful in classification tasks since it aids in the separation of classes during learning. The output layer receives its input from the last fully connected layer. The specific task determines the output layer's structure and format. Here, two distinct output function types are taken into consideration.The softmax function by equations (4) and (5) is a frequent output function in classification problems with K classes.

$$f_i = \frac{\exp\,(I_i^{(o)})}{\sum_j \exp\,(I_j^{(o)})} \tag{4}$$

$$I_i^{(o)} = b^{(o,i)} + \textstyle\sum_{k=1}^{k} W_k^{(o,i)}\, I_k^{(N)} \tag{5}$$

We additionally take into account a variant of equation (6)'s logistic output function:

$$f = a + (b - a)(1 + \exp\,(b^{(o)} + \textstyle\sum_j W_j^{(o)}\, I_j^{(N)})^{-1} \tag{6}$$

This produces a continuous output f with parameters b((o)) and W((o)) that must fall within the range (a, b). Scaled logistic output function is what we refer to as. We point out that this output function might be anticipated to perform better when taking into account a ranking-type multi-class classification task such forecasting malignancy degree.

Training:

The basic objective is to match the network parameters to the data given a set of data and a network design. To do this, a goal function will be set, and using gradient-based optimization, we will look for network parameters that minimise goal function.

$$E(\theta) = \textstyle\sum_{i=1}^{D} L\left(y_i, f(n_i, \Theta)\right) + \lambda E_{prior}(\Theta) \tag{7}$$

f(ni , Θ)) is a loss function that penalises discrepancies between desired output of network y and prediction of network y, where f(ni , Θ)) is output of network assessed on input n with specifications. By penalising the weights' norm, the weight decay prior $E_{prior}(\Theta) = ||W||^2$ helps prevent over-fitting. It also regulates the prior's strength.

Depending on the output function selected, we take into consideration two possible objective functions in this paper. We utilise common cross-entropy loss function $L(y_i, \hat{y}) = -\sum_{k=1}^{k} y_k \log\,(\hat{y}k)$ for the softmax output function. where y is supposed to be a vector of probabilities for each of the K classes and y is expected to be a binary indicator vector. Formally, $L(y_i, \hat{y}) = (y_i, \hat{y})^2$ with the supposition that y and y are real valued. Parameters are adjusted as follows each iteration t: $\Theta_{t+1} = \Theta_t + \Delta\Theta_{t+1}$,$\Delta\Theta_{t+1} = \rho\Delta\Theta_t - \varepsilon\nabla E_t(\Theta_t)$.

where t is learning rate, $\nabla E_t(\Theta_t)$ is gradient of objective function calculated utilizing only training samples chosen at iteration t, and ρ = 0.9 is momentum parameter.Values of filters and weights are initialised at iteration 0 by uniformly sampling from the interval $(-\sqrt[n]{\frac{6}{f{an}_{in}+f{an}_{out}}}, \sqrt[n]{\frac{6}{f{an}_{in}+f{an}_{out}}}, _$t is set to 0.01 for 2000 epochs.

4. Performance Analysis:

Diabetic Foot Ulcers dataset (DFUC2021) is a dataset is taken for analysis of pathology, focusing on infection as well as ischaemia. 15683 DFU patches, with 5955 training, 5734 for testing and 3994 unlabelled DFU patches are comprised in DFUC2021.

This section shows the performance analysis for diabetic foot image based risk prediction of cardiac attack. The figure 5 and 6 shows Confusion matrix for diabetic range detection for test data and train data respectively.

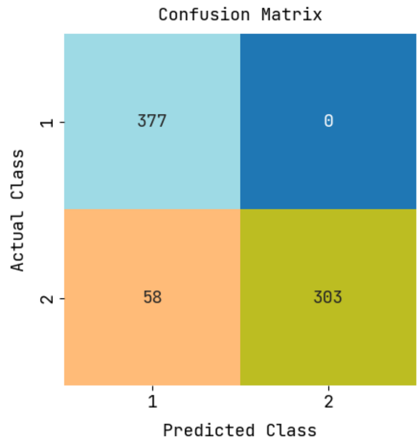


Figure 5: Confusion matrix of test data

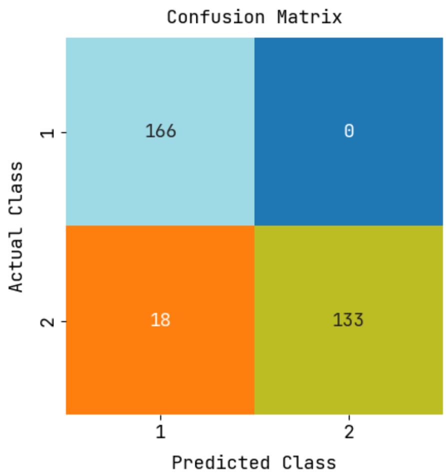
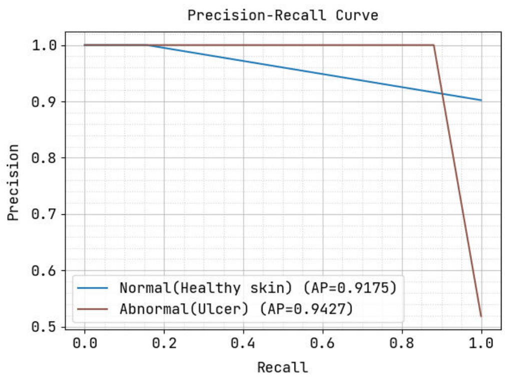


Figure 6: Confusion matrix of test data

ROC curve and the precision – recall curve for prediction of cardiac disease based on testing data of foot ulcer has been determined in 7a &7b. ROC curve and precision – recall curve for prediction of cardiac disease based on training data of foot ulcer has been determined in 8a &8b.



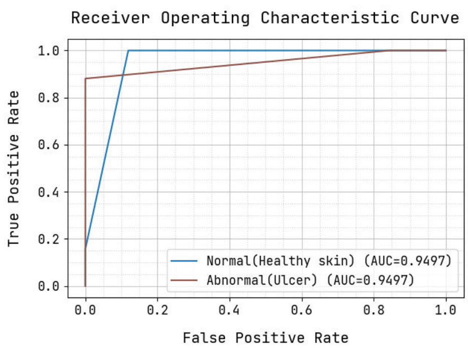


Figure 7a& 7b: ROC curve and precision – recall curve for prediction of cardiac disease based on testing data of foot ulcer has been determined.

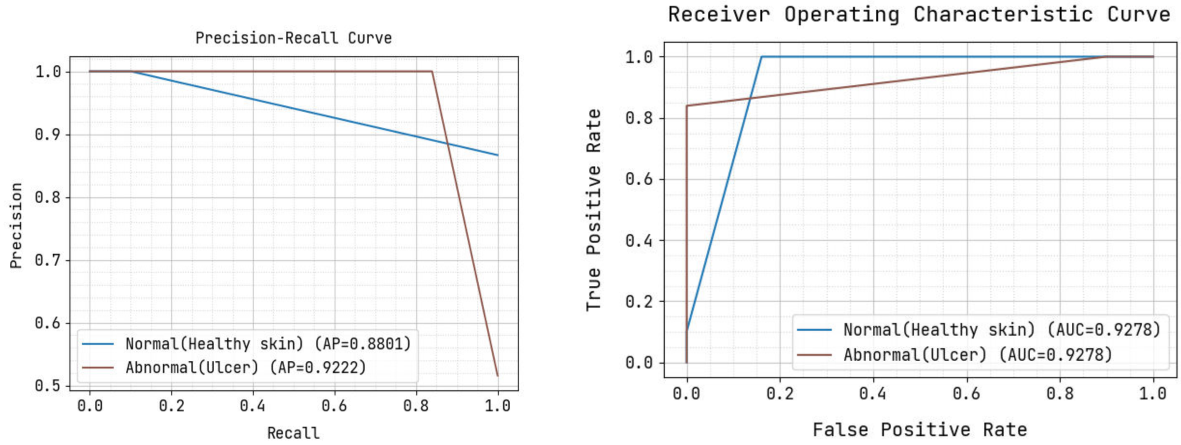
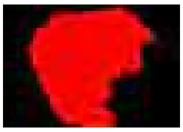
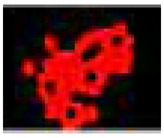
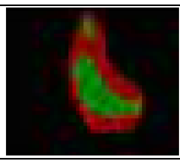
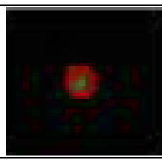
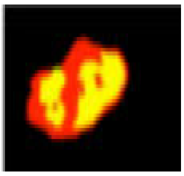
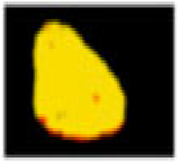
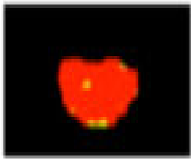
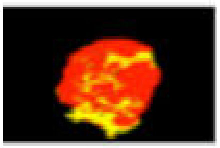
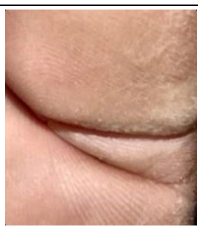


Figure 8a & 8b: ROC curve and the precision – recall curve for prediction of cardiac disease based on training data of foot ulcer has been determined.Table 2 represents the input images of foot ulcer used for training, proceeded with pre-processing, segmentation and the resulted classified output.

Table 2: Classified Results

S.NO	Input Image	Pre-processing	Segmentation	Classified Output
Abnormal Ulcer				
				
				
				
Normal(Healthy skin)				

Abnormal foot ulcers are classified by Fast deep Convolution neural network (FDCNN). The abnormal foot ulcers are normally related to the cardiac diseases. So, the cardiac diseases can be predicted easily.From the results it is observed that classification performance of precision and recall rate obtained 0.9354 for the proposed system.

5. Conclusion:

This research presents the novel technique in detection of diabetes by the foot ulcer image of patients. Since diabetes patients will have foot ulcer as major complication, the dataset has been collected based on the pre-historic medical data and foot image of the diabetes patients. This dataset has been pre-processed and segmented. Then the segmented data features of foot image using mask recurrent convolution neural network (MRCNN), the extracted features shows the detection of foot ulcer. Then image data and numerical/text data has been extracted separately. The normal diabetes range and abnormal diabetes range has been extracted. Those patients with abnormal diabetes range, their foot images have been separated and classifying the extracted features using fast deep convolution neural network (FDCNN) the normal and abnormal range of diabetes has been detected. The simulation results show confusion matrix for diabetes range detection and parametric analysis of proposed technique. The parameters obtained are Accuracy, precision, recall, f-1 score.

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