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PARADIGM TO CLASSIFY ISCHAEMIC, NEUROPATHIC AND NEURO-ISCHEMIOC FOOT ULCERS USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Diabetic Foot Ulcers are an extreme compilation of diabetes, significantly impacting a patient's quality of life and leading to amputation and foot pathogenesis if not diagnosed and treated on time. Traditional clinical methods for Diabetic Foot Ulcer classification can be enhanced using deep learning techniques, yielding improved results; however, challenges include limited image data, artifacts, and high computational costs, especially in multi-class classification. Our research unfolds in two distinct phases. Initially, we collected datasets from various sources, while the subsequent phase delved into evaluating diverse Convolutional Neural Network algorithms for multi-class foot ulcer classification. This step performs pre-processing, such as enhancing ulcer region, artifact removal, correcting poor color illumination, ulcer area segmentation, suitable feature selection, and multi-classification of foot ulcers. Convolutional Neural Network techniques such as HYBRID CNN, HYBRID RCNN with YOLOv3, and YOLOv4 are used to achieve better accuracy. Furthermore, we attained the highest accuracy of 99.83\%, 98.06\%, and 97.88\% for Ischaemic, Neuropathic, and Neuro-Ischaemic ulcers, respectively, with YOLOv4. Finally, we summarized our research with an overview of the future trends and challenges in foot ulcer detection classification.

Index Terms: Convolutional Neural Network, Deep Learning, Diabetic Foot Ulcer, Diabetes Mellitus, Ischaema, Neuropathy, Neuro- Ischaemic.

1. INTRODUCTION

Diabetes Mellitus (DM) is a dangerous disease that can lead to foot ulcers and severely impact human life. In some cases, foot or leg amputation becomes necessary to save a person's life.

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The classification of Diabetic Foot Ulcers (DFUs) based on ischaemia or Infection can assist physicians in better understanding the extent of the disease in the patient [1], [2]. The increasing prevalence of diabetic foot ulcers and the fear of higher mortality rates, according to the World Health Organization (WHO), are expected to rise significantly by 2040. If not adequately prevented or treated, it has a high risk. The main reasons for this alarming situation are the adoption of poor lifestyle choices and the consumption of unhealthy food [3]. Expert says people with diabetes are expected to grow by 700 million by 2045. Accordingly, 19\% to 34\% of patients are scaled to develop DFU. It will increase the mortality rate and inject a low quality of life in society [4]. Around 422 million individuals across the globe are affected by diabetes, predominantly in low and middle-income countries. Diabetes stands accountable for approximately 1.5 million annual fatalities. Over the past few decades, both the incidence and prevalence of diabetes have exhibited a consistent upward trajectory [5]. Worldwide, various types of cancers contribute significantly to annual mortality rates, as depicted in Figure 1.

Timely intervention can dramatically improve the chances of preserving the limb and preventing the need for amputation [6], [7] The traditional monitoring method relies on eye inspection and is unsuitable for identifying subtle changes [8], [9]. The development of DFUs is typically attributed to a combination of three factors known as the "triopathy" concept: neuropathy, ischemia, and arteriopathy [10]. There are different factors, which may cause Diabetic Foot Ulcers [11].

(1) Peripheral neuropathy

(2) Mechanical variations in bony structure of the foot.

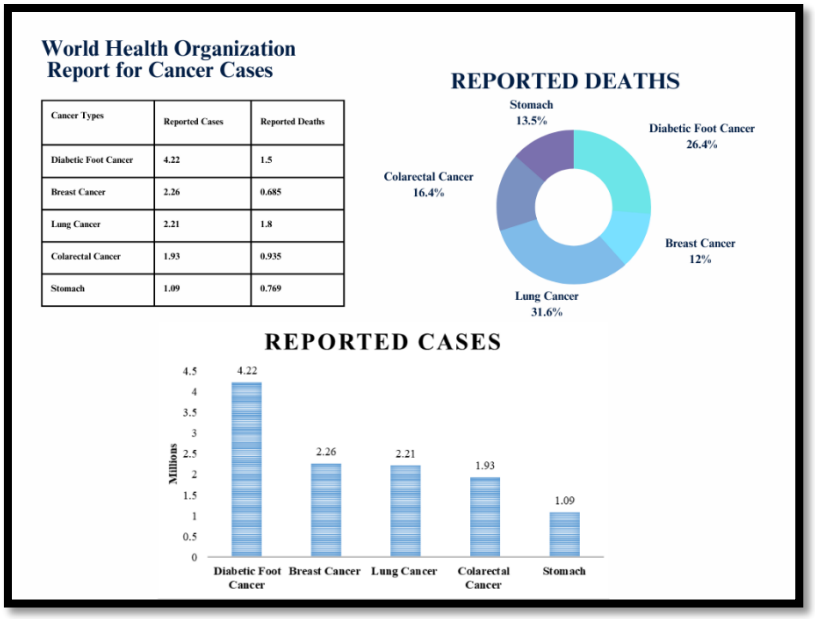

Figure 1: WHO statistics of reported cases and causalities worldwide by cancer

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Regarding classification, there are two types of foot ulcers related to diabetes: Ischaemic and neuropathic. Additionally, there is a third type, Neuro-ischaemic, a combination of Ischaemic and neuropathy [12].

Ischemic ulcer is known as Arterial and is typically caused by low blood circulation in the foot. Ap- pear in black or yellowish tone between the toe and finger on pressure points. Neuropathic: It's another dangerous underlying cause of diabetes. It is pink or red and appears on the pressure point under the foot [13]. Neuro-ischemic: is the combination of both ischemic and neuropathic [14]. All typical features of DFUs, like symptoms, elements, location, and Infection according to etiology, are represented in Table 1.

Table 1: Feature of DFUs According to Etiology [12]

Feature	Neuropathic	Ischaemic	Neuro-ischaemic
Sensation	Diminished sensation	Presence of sensation may reduce if neuropathy	Degree of sensory loss
Foot temperature	warm	Low in temperature	cool
Ulcer location	Fore foot of the foot or toes	Distal or tips of toes, heels, or margins of the foot	Margins of toes and foot
Callus present	Present and often bounding, Dilated, prominent veins	Absent or reduced	Cool with absent pulses
location	Seen on weight bearing areas	Distal, eschar or necrosis	Minimal callus prone to necrosis
Dry skin and infection	Delayed healing fissuring	High risk of infection	Dry skin

1.1 Automated systems with DFU

Different Machine learning predictive models like Support vector machine Linear (SVM-Linear), k-nearest neighbor's algorithm (KNN), artificial neural network (ANN), and Medical Device Reporting (MDR) were applied to various aspects of diabetic foot ulcer management, including early detection, risk prediction, and treatment optimization [15].

The Diabetic Foot Infection Network (DFINET) introduced by Yogapriya [16] has a complex architecture of 22 layers; DFINET includes a parallel convolution layer with Rectified Linear Unit (ReLU) activation, a stabilization-oriented normalization layer, and a dropout-connected fully connected layer. The fusion of DFINET with a specialized technique and advanced image augmentation showcases promising infection detection outcomes. The anticipated 91.98\% % accuracy signifies a notable precision enhancement, supported by a robust 0.84 Matthews correlation coefficient for binary classification. DFUs, a common diabetes complication, often lead to lower limb amputation. Addressing this, an automated DFU diagnostic system employing computer-based techniques offers advantages such as early detection, reduced healthcare workload, cost-effectiveness, standardized treatment, enhanced patient care, and fewer misdiagnoses. Convolutional Neural Network (CNN) models explored with Local Binary Pattern (LBP) inputs for DFU classification, and the innovative CNN architecture incorporates three inputs: DFU- RGB-Net (original RGB images), DFU-TEX-Net (LBP-

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coded textures), and DFU-RGB-TEX-Net (combined RGB and LBP images). It categorized DFU images into healthy or unhealthy, ischaemia or non-ischaemia, and Infection. Integrating computer vision and machine learning enhances DFU assessment precision in a comprehensive diagnostic framework [17].

A novel framework leverages thermal imaging for the classification of DFUs by utilizing Deep Neural Networks (DNN) and decision fusion techniques. This approach involves amalgamating classification outcomes from a parallel classifier using decision fusion. The baseline classifier integrates CNN models, specifically MobileNetV2 and ShuffleNet. The development unfolds in two primary phases. Firstly, MobileNetV2 and ShuffleNet undergo training using datasets containing plantar thermograms. Subsequently, classification results from these models are synchronized using an innovative decision fusion technique to enhance overall accuracy. The proposed framework yields exceptional results, achieving a remarkable 100\% accuracy rate in the binary classification of thermal images linked to DFUs. This accomplishment effectively discerns between positive and negative cases [18].

2. LITERATURE REVIEW

Eid et al [19] combined textural and histogram attributes of thermal foot images and differentiated different classifiers, i.e., Support vector machine, k-nearest Neighbor, and Decision tree. Experimental results exhibit that Fine KNN has a maximum susceptivity of 88.3\% and a loss score of 0.004 using nine different features. Babu et al. [20] described that a Diabetic Foot Ulcer is a wound that must be detected early and treated well in time, classified as DFU, using the Naïve Bayes Classifier and Hoeffding tree, and 90.9\% accuracy was scored. Similarly, researchers proposed [21] feature descriptor, the Superpixel Colour Descriptor, for a handcrafted machine-learning approach to detect ulcers by applying a convolutional Neural Network (CNN) to classify ischemia and Infection. It obtained around 90\% accuracy for ischemia, and for Infection, it got 73\% accuracy. The major limitation of this study is the binary classification, which solves only two class problems. Cui et al. [22] stated that image segmentation gets complex due to skins and noisy image data diversification. The deep learning technique addresses the limitation of the division of wound regions. Gamage et al. [23] investigated that the cause of Neuropathic ulcers is peripheral neuropathy, which leads to continuous stress and unobserved injuries. In this research, the Mask-RCNN model was used to classify ulcers. Their method produced ulcer diagnosis average precision (AP) at the Intersection over union threshold 0.5 of 0.8632 and mean average accuracy at the Intersection over union threshold 0.5 to 0.95 by steps of size 0.05 of 0.5084 for ResNet-101 Bac bone. Physicians diagnose in [24] the diabetic foot ulcers in patients. The present automatic system only works with segmentation. The author designed a deep-learning model for real-time DFU localization. The author took 1175 images of a valid dataset. Utilizing five-fold cross-validation, on the whole, faster R- CNN with InceptionV2 model applying two-tier transfer learning attained a mean average precision of 91.8\%, a speed of 48 ms for inference of a single image, and a model size of 57.2 MB. Padierna et al. [25] explained that factors like smoking, diabetes mellitus, old age, renal insufficiency, etc cause Peripheral Arterial

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Disease identification. So, a non-invasive method based on Infrared Thermography is used to detect type-2 diabetes and diabetic foot ulcers from plantar thermograms. The authors proposed the analysis of relevant features extracted from IRT images of the upper side of the foot and toes. Using this method, the authors worked on two groups of diabetic and non-diabetic people to build a Support Vector Classification model. So, the average performance of the classification model on 1000 randomized and independent runs of 5-fold cross-validations reached 92.64\% accuracy. Rodríguez et al. [26] stated that lower extremity amputation issues in lower extremity amputation occur due to DFU. He proposed a computational method to do cleavage on diabetic foot ulcer images of patients treated with the Heberprot-P. The authors used image data, introduced the Mask R-CNN model, and gave the concept of knowledge transfer to locate the region that delimits the ulcer automatically. This model obtains acceptable results.

Swaminathan et al. [27] illuminated the major complication of Diabetic foot ulcers, which can cause amputation. Researchers have developed an algorithm for early detection of foot ulcers. They extracted different features from 11 regions of interest (ROI) on the foot and conducted a one-sided investigation of the components extracted from ROI regions. They utilized a Support Vector Machine to achieve maximum accuracy results to distinguish between standard and ulcer classifications. Vega et al. [28] pointed out that Diabetes Mellitus is a causative disease for foot amputation and mortality, as estimated by the WHO. They conducted a brief comparison of machine learning and deep learning structures and examined standard systems in the transfer learning mode, including Alex Net and Google Net. Tables 2 and 3 encompass all the related work. Table 2, in particular, offers a comprehensive review of the literature on DFU diagnosis.

The detailed review of literature for DFU diagnosis is presented in table 1.

Table 2: Review of Literature for DFU Diagnosis

Reference	Problem	Proposed solution	Contribution	limitation	Accuracy
[27]	Classification of healthy and DFU	Parallel convolutions using single filter	Feature extraction	Small size Dataset	73.3%
[29]	Binary Classification of ischemia and infection	Ensemble CNN and SVM	Avoid missing region & improving identification	Data unbalance due to Lacking depth and size	90.5%
[30]	Classification of healthy and DFU	Increase DNN width using SVM and KNN classifiers	increase accuracy Better extraction Handling small sizes	No computing increase	95.5%
[31]	Binary Classification	DCNN based on ResKNet	Achieving batter accuracy in ischemia recognition	Not improving classification	90%
[32]	Binary Classification	A pre-trained vision	Improving the performance	weak generalization	Around 92%

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		transformer models with CKBs			
[24]	Wagner Ulcer Grading Scale using DNN	Ensemble DNN	Shows best performance in Diabetic Retinopathy classification	Complex	Around 89%
[33]	Discriminating diabetic foot thermograms	Shallow GoogLeNet	Achieving best sores in Diabetic Retinopathy classification	No sound improvement	Around 90%
[22]	Classify healthy and DFU	Parallel convolutions with a single filter	Adopted first-time Better extraction	Less automatic Fewer images	96%
[35]	Binary Classification	CNN based ResKNet, Res7Net, Res4Net	Archived good accuracy	No Multi-classification	99%

The table reviews all publicly available datasets, both those with open access and those without. It highlights that DFUc contains a notably large number of images. However, it's worth noting that all the images within these datasets are in color and are relatively limited in number. This limitation introduces challenges such as limited representation, noise susceptibility, and overfitting risk. Furthermore, these datasets are primarily used for binary or partial classification of DFU cases. Table 3 provides a comprehensive literature review of datasets used to diagnose Diabetic Foot Ulcers.

Table 3: Review of Datasets used in Diabetic Foot Ulcer Detection

Reference	Problem	Source of Dataset	Open Access	Dataset size	Limitation
[13]	Diabetic Foot Ulcer	Nasiriyah Hospital	No	754-ft images	Weak learning
[21]	Segmentation Diabetic foot Ulcer	Centre of Genetic Engineering and Biotechnology Havana	No	1176 Images	Week learning
[26]	Foot Ulcer Hycare for Wounds	Chennai	No	60 Images	Weak classification due to poor learning
[27]	Segmentation & classification of Diabetic foot thermograms	Not given	No	20 Images	Weak classification due to poor learning, sensitivity to noise, and over-fitting
[33]	Diabetic Foot Ulcer	Lancashire Teaching Hospitals	Yes	1775	Over-fitting

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[34]	Binary classification of foot ulcer ischemia	Lancashire Teaching Hospitals	Yes	DFUC 2,945 images	Sensitive to noise, Over-fitting
[35]	Foot ulcer type 2	Images data was collected 2 Mexican groups	No	43 Images	Images Over-fitting, sensitive to noise
[36]	Ischemia & infection	Lancashire Teaching Hospitals	Yes	1459 Images	Images Over-fitting, sensitive to noise
[37]	Neuropathic Ulcer	Not given	No	400 Images	Weak classification due to poor learning
[38]	Diabetic wound	New York University	No	392 images	Images Over-fitting, sensitive to noise
[39]	Binary classification Diabetic foot Ulcer type 2	Not given	No	50 images	Weak classification due to poor learning
[40]	Ulcer Type 1,type 2	COCO Database over DBI sample	No	108 images	Over-fitting

In summarizing the related work, we address the existing research gap. Despite applying machine learning and deep learning techniques to achieve high accuracy in diabetic foot ulcer (DFU) classification, several limitations and challenges persist. These encompass variations in image quality across different databases, which, in turn, heighten the complexity of addressing artifacts, handling fluctuations in lighting conditions, and mitigating the impact of poor image quality.

Additionally, deep learning often requires a large volume of data for practical training, and DFU datasets may need to be revised in size. Deep learning models also consume significant time and resources during exercise. In the past, most models focused on the binary classification of DFU, and only a few papers discussed multi-class classification involving Ischaemia, neuropathy, and neuro-ischaemic together.

The proposed model addresses these issues and challenges, allowing for a more comprehensive and accurate classification of DFUs by considering all three classes simultaneously. The following research questions lead toward an automatic diagnosis of DFU.

RQ1: What are the problematic issues and artifacts in ulcer images and how to remove them to achieve higher results?

RQ2: How to accurately identify and extract the ulcer area from DFUc images?

RQ3: How to classify Neuropathic, Ischaemic, and Neuro-ischaemic ulcers from DFUc images?

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2.1 Objectives of Research

1) To efficiently improve the quality of Diabetic Foot Ulcer images by removing artifacts, correction of poor color illumination, water-bag, and pus removal, and image resizing to increase the classification accuracy.
2) To accurately segmenting and identifying ulcer area from foot ulcer images and achieving high segmentation results for perfect ulcer classification
3) To provide promising accuracy in the classification of Neuropathic, Ischemic, and Neuro-Ischemic ulcer wounds from DFU images.

2.2 Scope of Research

In this research, modern tools and techniques related to image preprocessing, segmentation, image post-processing, and classification will be used to complete the experiment. To conduct this research study, it is proposed to use CNN for classification and DFU dataset.

2.3 Motivation of Research

The motivations behind this proposed research are:

1) To do something related to humanity
2) To accurately highlight and remove maximum types of noise present in Diabetic Foot Ulcers images
3) To provide promising accuracy on Diabetic foot ulcers segmentation.
4) To classify Ischemic, Neuropathic, and Neuro-Ischemic classes using Deep Learning techniques.

2.4 Significance of Research

The proposed research aims to develop a diabetic foot ulcer recognition system comprising preprocessing images, segmenting the ulcer part, extracting features, and training classifiers to recognize each. It will be helpful for physicians in the early detection of Foot ulcers to help in proper diagnosis at an early stage. The significant contributions of the proposed model include:

2.4.1 Reduce Complexity

Segmentation and ROI helps in faster training because preprocessing result of DFU images mainly focus on the ulcer region. This approach is likely to significantly reduce artifacts up to a certain extent. Similarly water bags or pus area are reduced. It not only reduces the training time but also optimize the resource utilization.

2.4.2 Overcome Dataset Limitation

Image augmentation ensures the generalization and high accuracy without requiring the large dataset. Model is robust for unseen real world data.

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2.4.3 Feature Fusion

Feature fusion from traditional and deep learning approach CNN enables to explore the diverse features of DFU images and more accurately discriminated between multi classes of DFU.

2.4.4 Transfer Learning

As advancements in medical diagnosis with imagery data have become crucial, the proposed model is addressing computer vision queries related to medical diagnosis by utilizing CNN pertained model ResNet50. This model leverages transfer learning during training, emphasizing both the study of low-level features and task-related learning [41]. It avoids overfitting. As a result, the model not only achieves high accuracy but also demonstrates excellent performance on previously unseen data.

This paper presented a hybrid model for multi class classification of DFU using pre-trained ResNet-50 with transfer learning, results of trained model are evaluated via Accuracy and F- score matrix.

2.5 Dataset

The DFU dataset comprises a combination of imagery datasets covering all three classes of ulcers: ischemic, neuropathic, and neuro-ischemic. This State-of-the-art dataset was collected from various sources [42], [43], [44] and is publicly available but only after obtaining proper authorization or consent from the owner of the data. The diversity of the data ensures the inclusion of different DFU and medical datasets related to foot ulcers. The images within these datasets vary in size, ranging from 1600x1200 to 3648x2736 pixels. Over 10437 images have been compiled, and patches of size 255x255 pixels are extracted from them. These images are organized into batches and utilized in the proposed model's training process. Labels indicating ischemia, neuropathy, and neuro-ischemia are assigned to the images to train the model. Table 4 describes a detailed distribution breakdown of the dataset across different platforms for various DFU classes.

Table 4: Data Set Description

References	Dataset	Type of images	cameras	No of images
[42]	DFUC 2020 dataset	Ischemic	Kodak DX4530 (5 megapixel), Nikon D3300 (24.2 megapixel) and Nikon COOLPIX P100 (10.3 megapixel).	4,000
[43]	DFU dataset	Neuropathic, ischemic, neuro-ischemic DFUs	Freely captured by smart phone	1737
[45]	DFU dataset	Neuropathic, ischemic, neuro-ischemic DFUs	Freely captured by smart phone	4700

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3. METHODOLOGY

Our proposed automated system encompasses several critical components to improve the accuracy of diabetic foot ulcer (DFU) classification. It includes image preprocessing techniques to enhance ulcer region visibility, artifact removal, and correction of poor color illumination. Additionally, the system incorporates ulcer area segmentation, feature selection, and classification into Ischaemic, Neuropathic, and Neuro-Ischaemic classes. This comprehensive methodology is designed to operate on a dataset of foot ulcer images, utilizing image processing and specialized deep-learning techniques. The primary objective is to address the limitations associated with each approach and deliver a more precise and dependable classification of DFUs. This paper introduces a hybrid model for multi-class DFU classification, leveraging HYBRID CNN, HYBRID RCNN with YOLOv3, and YOLOv4, resulting in enhanced accuracy. For a visual representation of our approach, please refer to Figure 2.

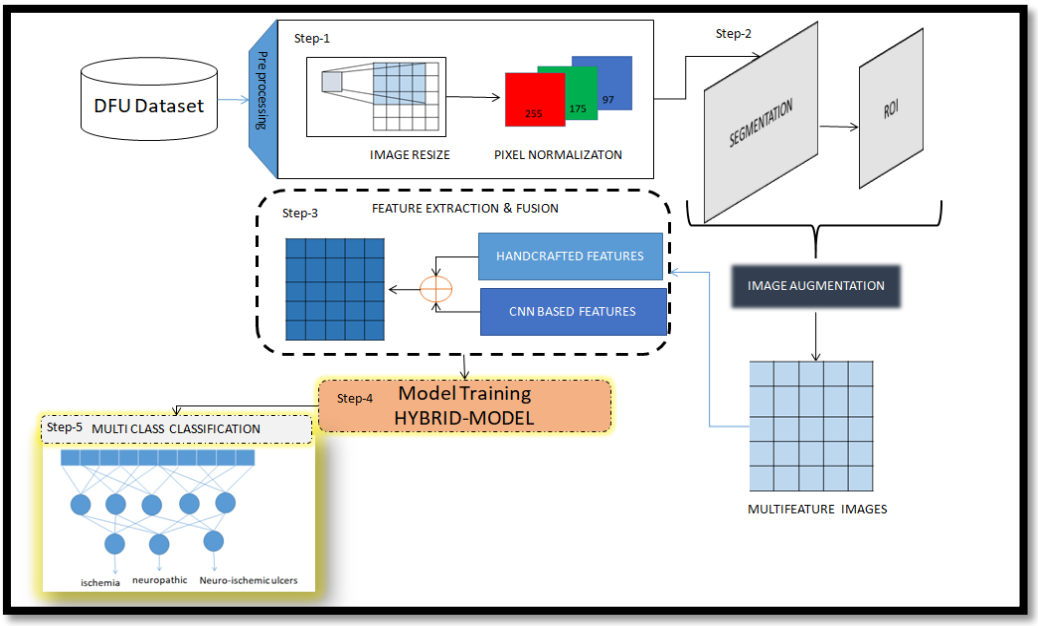

Figure 2: Proposed Solution – An Overview

3.1 Experimental Setup

We implemented all our models using Keras, harnessing the power of the NVIDIA K80 GPU to apply deep learning to our image dataset effectively. Our model training involved the initialization of convolutional layers and utilized a batch size of 4 throughout 150 epochs. We initially set the learning rate (LR) to 1e-3 to optimize learning. However, as we closely monitored the validation F1 score, we dynamically reduced the LR by 0.25 after every five epochs when the F1 score reached a plateau at its minimum value. Additionally, we implemented early stopping during model training for each fold to prevent overfitting. We conducted experiments to assess model performance with highly imbalanced datasets. Out of the extended dataset, we selected 3750 augmented images

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for validation, and the model with the best performance was saved after training for 80 epochs with the lowest validation loss. This model was later used for evaluation on independent test datasets. In a separate set of experiments, where imbalanced datasets were the focus, we utilized 1750 augmented images. Testing and validation were done with a ratio of 20:80, respectively. The Adam optimizer was initialized with a learning rate of 2e-3, which was adjusted downward after 8 epochs when the validation loss showed a decreasing trend. This step allowed us to thoroughly analyze the model's behavior and ability to handle imbalanced datasets. Our experiments featured applying YOLO3 and YOLO4 models with meticulous attention to image selection and augmentation techniques. In Experiment 1, the training dataset comprised 80\% of the data, amounting to 2850 augmented images, while the remaining 20% served as validation data. Throughout these experiments, we fine-tuned the models with specific hyper parameters, following a methodology similar to the sample experiment conducted for loss functions, as mentioned earlier. The primary objective of these experiments was to compare the performance of YOLO3 and YOLO4 models trained with the Focal Tversky loss function and evaluate their effectiveness in handling the given dataset and task. Our proposed solution encompasses a series of carefully executed steps, which collectively contribute to our model's robust performance. The proposed solution is comprised of the following steps, discussed in Table 5:

Table 5: Steps of Proposed solution

Proposed solution	Explanation
Step 1: Input Data	//Load Diabetic Foot Ulcer Colour Image
Step 2: Pre-processing 2.1 Image Registration	// Image rescaling, Resize the image to equal size.
2.2 Enhance image quality	//White spot removal that creates problems in ulcer segmentation
2.3 Binary image conversions	// Water bag and Pus validation removal, enhance image quality
Step 3: Segmentation	//In thresholding, we will convert an image from colour into a binary image, i.e., only black and white. Boundary adjustment and binarization will be handled in the segmentation section.
Step4: CNN feature extraction	/feature vectors obtained from the CNN are considered as sequential inputs to an RNN. Feed the feature vectors to capture temporal dependencies and learn the multi-classification task. Neuropathic, Ischemic, and Neuro-Ischemic ulcers (lesions) from DFUc images
Step 5: RNN Sequence	//feature vectors obtained from the CNN are considered as sequential inputs to an RNN. Feed the feature vectors to capture temporal dependencies and learn the multi-classification task. Neuropathic, Ischemic, and Neuro-Ischemic ulcers (lesions) from DFUc images.
5.1 Hybrid Model RCNN Training	//Training a hybrid CNN and RNN model on a labelled foot ulcer dataset, involving forward and backward passes to adjust parameters using Adam optimization and subsequent testing using k-fold cross-validation
Step 6: Multiclass classification of DFU	//Ischemic, Neuropathic, and Neuro-Ischemic classes
Step 7: Evaluation	// Results are evaluated via Precision, Recall, F1-measure, Accuracy

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3.1.1 Pre-processing

Preprocessing diabetic foot ulcer images is essential for medical image analysis and diagnosis. The following diagram shows Optimizing Diagnostic Clarity and Enhancing Diabetic Foot Ulcer Images through Preprocessing Techniques. The following diagram: 3 shows DFU Image Preprocessing: Unmasking Clarity and Insights(a. Original image, b. Resized image, c. Greyscale image, d. Normalization, e. Smoothing and filtering, f. Median Filtering, g. Gaussian Filtering)

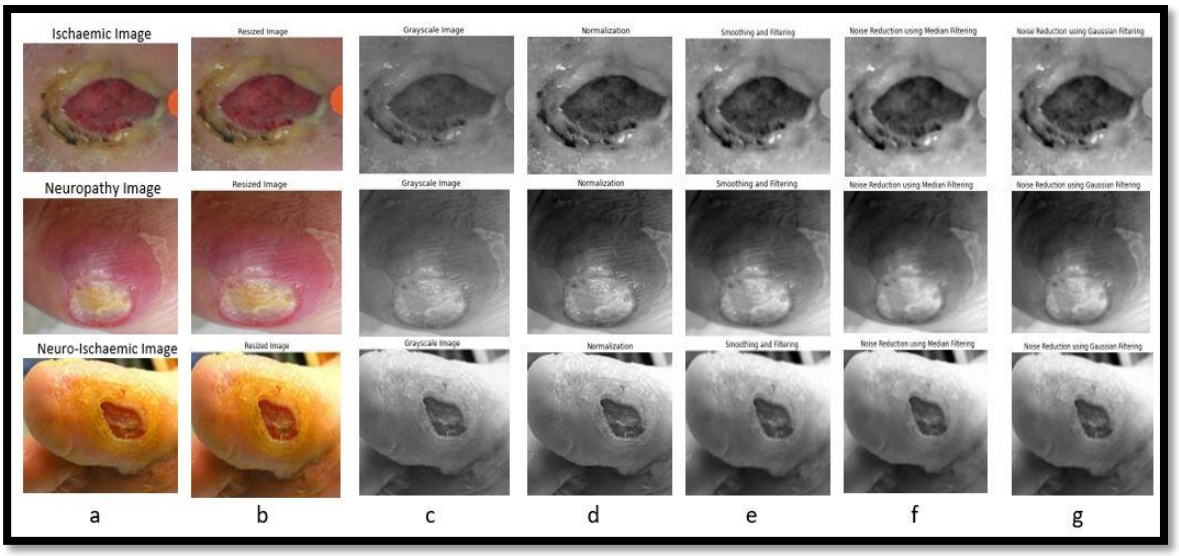

Figure 2: DFU Image Preprocessing: Unmasking Clarity and Insights

Here are some specific pre-processing techniques that we use for diabetic foot ulcer images:

3.1.1.1 Resizing

An image involves changing its dimensions by either increasing or decreasing its width and height. The resizing operation is typically performed using interpolation, which calculates the new pixel values based on the original pixel values.

3.1.1.2 Color Enhancement

Grayscale conversion converts a color image into a grayscale or black-and-white image, where each pixel has a single intensity value representing its brightness. There are several methods to perform a grayscale conversion, but one standard formula is the luminance method, which calculates the grayscale value for each pixel using the following

$$Y= 0 .299.R + 0 .589 .G + 0.114B \qquad 1$$

While Y represents the grayscale value of the pixel. R, G, and B represent the pixel's red, green, and blue color channels, respectively. These values typically range from 0 to 255 in an 8-bit color image.

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3.1.1.3 Normalization

Scaling pixel values to a specific range (e.g., [0, 1] or [-1, 1]) to ensure consistent data for machine learning models. The formula for normalization is straightforward:

Min-Max Normalization (Scaling to [0, 1]). For each pixel value X in the image, the normalized pixel value P norm is calculated as follows:

$$X_{\text{norm}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad 2$$

Where X (original pixel value)

Xmin (minimum pixel value of image)

Xmax (maximum pixel value of image)

Zero-Mean Normalization (Scaling to [-1, 1]). For each pixel value X in the image, the normalized pixel value Pnorm is calculated as follows:

$$X_{\text{norm}} = \frac{X - \mu}{\sigma} \quad 3$$

Where X is the original pixel value

μ is the average pixel value of the whole image.

σ is a standard deviation of the pixel values of the whole image

3.1.1.4 Smoothing and Filtering

Smoothing and filtering of an image involve applying a filter or kernel to the image to reduce noise, remove unwanted details, or enhance certain features. One of the common operations for this purpose is the convolution operation. The general formula for convolution in image processing is as follows:

$$P'(y,z) = (P * K)(y,z) = \sum_{m=-M}^{M} \sum_{n=-N}^{N} P(y-m, z-n) \cdot K(m,n) \quad 4$$

Where P' (y, z) is the resulting pixel value at position (y, z) in the filtered image.

P (y, z) is the original pixel value at position (y, z) in the input image.

K (m, n) is the value of the filter kernel at position (m, n).

K (The summation is performed over a neighborhood of the pixel (y,z), typically defined by the size of the kernel.

M and N represent the half-width and half-height of the kernel, respectively.

We Apply a Gaussian filter to reduce noise and smooth the image.

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3.1.1.5 Noise or artifacts Removal

Removing artifacts from images is an essential preprocessing step in image processing and computer vision tasks. Artifacts can be unwanted elements or noise that degrade the quality of an image and affect subsequent analysis. We used two different techniques for removing artifacts from images

3.1.1.6 Median Filtering

Median filtering is effective at removing salt-and-pepper noise, which appears as isolated white and black pixels in an image. It replaces each pixel's value with the median value in its local neighborhood, effectively eliminating isolated outliers. Mathematically, this can be expressed as:

$$S(x,y) = \text{median}\,(T\,(x,y)) \quad (5)$$

Where S (x, y) is the resulting pixel value at position (x, y) in the filtered image.

T (x, y) represents the list of pixel values within the defined neighborhood centered at (x, y).

The median (T (x, y)) is the median value of the list.

3.1.1.7 Gaussian Filtering

Gaussian filtering can be used to reduce high-frequency noise by smoothing the image. It works well for Gaussian or uniformly distributed noise. Let I (x, y) represent the pixel value at position (x, y) in the filtered image. Define a Gaussian kernel of size N×N. The Gaussian distribution determines the values in the kernel:

$$K(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (6)$$

Where K (x, y) is the value at position (x, y) in the Gaussian kernel.

N is typically an odd number, and (U+03C3) controls the standard deviation or the spread of the Gaussian distribution.

Normalize the Gaussian kernel so that the sum of its values equals 1:

$$K(x,y) = \frac{K(x,y)}{\sum_{i=-M}^{M} \sum_{j=-N}^{N} K(i,j)} \quad (7)$$

Where, M and N are the half-width and half-height of the kernel, respectively.

Perform convolution between the original images

Gaussian filtering effectively removes noise by averaging pixel values in a weighted manner.

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3.1.2 Segmentation

Segmenting diabetic foot ulcer images is crucial in medical image analysis, identifying and isolating diabetic foot ulcers present within medical imagery. Effective segmentation facilitates accurate measurements, ongoing monitoring, and comprehensive analysis of these ulcers, ultimately improving diagnostic procedures and treatment strategizing. The following outlines the typical steps and methodologies in segmenting diabetic foot ulcer images.

3.1.2.1 Thresholding

Binary thresholding is often used to generate binary images. Given a threshold value (N), each pixel value (P) is compared:

$$\text{Binary}\,[y,z] = \begin{cases} 1 & \text{if } P[y,z] > N \\ 0 & \text{otherwise} \end{cases} \qquad 8$$

Where Binary Image (y, z) is the pixel value at position (y, z) in the binary image

P' (y, z) is the resulting pixel value at position (y, z) in the filtered image.

P (y, z) is the input image's original pixel value at position (y, z).

The detailed results for Diabetic Foot Ulcer segmentation are expressed in diagram 4.

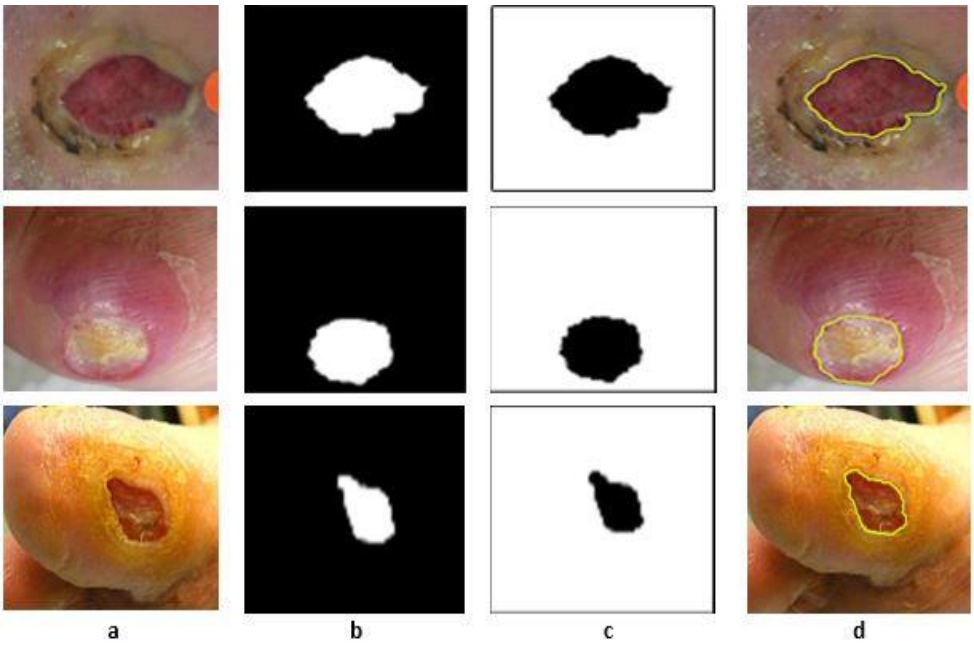

Figure 3: DFU Image segmentation (a: Original Image, b & c: Thresholding, d: Segmented Image)

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3.1.3 Classification

We design a CNN architecture to extract pertinent features from diabetic foot ulcer images, employing common architectures such as HYBRID CNN, HYBRID RCNN with YOLOv3, and HYBRID CNN with YOLOv4.

A detailed algorithm for HYBRID CNN is presented in the table, outlining the model's overall complexity. The detailed Algorithm for HYBRID CNN is explained in the table.

Table 6: Algorithm for HYBRID CNN

Algorithm for HYBRID CNN
1. ***Identification:*** Diabetic Foot Ulcer
2. ***Input***: DFU Dataset
3. ***Output:*** Ischemic, Neuropathic, Neuro-ischemic
4. **Pre-processing:** D_preprocessed = Preprocess(D)
5. **Segmentation:** AR←{Augment(Seg(Preprocess(Image1))),Augment(Seg(Preprocess (Image2))),.,Augment(Seg(Preprocess(ImageN)))}
6. For i = 1 to N:
7. F[i] = ExtractFeatures(AR[i])
8. CF[i] = Concatenate(F[i], CNN(ROI))
9. For each augmented image in AR:
10. TrainHybridModel(CF[i])
11. Multiclass Classification(Ischemic, Neuropathic, Neuro-ischemic)

The overall complexity of the model can be represented as

$$\text{Total Complexity} = \Theta(N * \max(P, S, E, D) + K * T + M * C) \qquad 9$$

Where Θ (N * max (P, S, E, D)) calculates the complexities of data preprocessing, image segmentation, feature extraction, and feature fusion. K * T calculates the complexity of training the hybrid model on K-augmented images. M * C represents the complexity of the multi-class classification, i.e. M is the number of classes, and C is the classification complexity.

It depicts that overall complexity grows at the same rate as the maximum complexity among the preprocessing, segmentation, feature extraction, and feature fusion steps.

The complexities of training and classification contribute to the overall computational cost but may not dominate the growth of complexity.

A hybrid technique has been designed to achieve better accuracy, combining Convolutional Neural Networks (CNN) such as YOLO3 and YOLO4, along with RCNN (Region-based Convolutional Neural Network). This combination allows the model to perform the classification task effectively.

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The following Algorithm 2 table provides a detailed illustration of the proposed hybrid technique:

Table 7: Algorithm for HYBRID RCNN with YOLOv3 and YOLOv4

Algorithm for HYBRID RCNN with YOLOv3 and YOLOv4
1. ***Identification:*** Diabetic Foot Ulcer 2. ***Input*** : DFU dataset df={i1, 12, ….1n} 3. ***Output:*** Ischemic, Neuropathic, Neuro-ischemic 4. **Pre-processing:** x' = ax + by + c, y' = dx + ey + f 5. **Enhance image quality:** g(x, y) = (L - 1) * CDF(f(x, y)) 6. **Segmentation:** {if} f(x, y) >= T g(x, y) = 1 (white) {else} g(x, y) = 0 (black) g(x, y) = 1, if f(x, y) >= T 0, if f(x, y) < T 7. **CNN feature extraction** [model 1: yolov3, model 2: yolov4] bx = σ (tx) + cx by = σ (ty) + cy bw = pw * exp(tw) bh = ph * exp(th) pc = σ (tc) 8. **Bounding box coordinate calculation** pc(i)=exp(tci)/(∑ exp(tcj)) {Loss function for yolov3:} Loss-yolov3 = λ coord* Loss-coord + λ obj * Loss-obj + λ noobj * Loss-noobj + Loss-clas 8. CF[i] = Concatenate(F[i], CNN(ROI)) 9. **Loss function for yolov3:** Loss-yolov3 = λ coord* Loss-coord + λ -obj * Loss-obj + λ -noobj * Loss-noobj + Loss-class 10. **Loss function for yolov4:** Loss-yolov4 = λ - obj * Loss-obj + λ -noobj * Loss-noobj + λ -coord * Loss-coord + λ -obj-cls * Loss-obj-cls + λ -cls * Loss-cls + λ -conf * Loss-conf 11. **RNN Sequence Modeling, Hybrid Model RCNN Training**: h_l = f_l (W_l * h_ {l-1} + b_l) h_ t = RNN (h_ {t-1}, x_t) 11. Multiclass Classification (Ischemic, Neuropathic, Neuro-ischemic) 12. **Prediction:** y = W_out * h_T + b_out

Loss function for Yolov3:

The Yolov3 loss function is a comprehensive metric that encompasses multiple components critical for object detection accuracy. These components include localization loss, classification loss, and confidence loss. The goal of this loss function is to guide the neural network during training to improve its ability to accurately detect and localize objects within images.

$$\mathcal{L}_{3DYOLO} = \lambda_{\text{coord}} \sum_{i=1}^{G} \sum_{j=1}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(t_x^{(ij)} - \hat{t}_x^{(ij)} \right)^2 + \left(t_y^{(ij)} - \hat{t}_y^{(ij)} \right)^2 + \left(t_z^{(ij)} - \hat{t}_z^{(ij)} \right)^2 \right] \quad 10$$

$$\lambda_{\text{coord}} \sum_{i=1}^{G} \sum_{j=1}^{B} \mathbb{1}_{ij}^{\text{obj}} \left[\left(t_w^{(ij)} - \hat{t}_w^{(ij)} \right)^2 + \left(t_h^{(ij)} - \hat{t}_h^{(ij)} \right)^2 + \left(t_l^{(ij)} - \hat{t}_l^{(ij)} \right)^2 \right]$$

$$+ \sum_{i=1}^{G} \sum_{j=1}^{B} \mathbb{1}_{ij}^{\text{obj}} \left(c^{(ij)} - \hat{c}^{(ij)} \right)^2 + \lambda_{\text{noobj}}$$

$$\sum_{i=1}^{G} \sum_{j=1}^{B} \mathbb{1}_{ij}^{\text{noobj}} \left(c^{(ij)} - \hat{c}^{(ij)} \right)^2 + \sum_{i=1}^{G} \sum_{j=1}^{B} \mathbb{1}_{ij}^{\text{obj}} \sum_{k=1}^{K} \left(p_k^{(ij)} - \hat{p}_k^{(ij)} \right)^2$$

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Loss function for Yolov4:

The loss function used in YOLOv4 is a critical component that guides the training of the neural network for accurate object detection. It is composed of multiple elements that collectively contribute to enhancing the model's ability to locate and classify objects within images.

$$L_{\text{ciou}} = 1 - \text{IoU} + \frac{\rho^2(b, b^{gt})}{c^2} + \frac{\beta v^2}{(1 - \text{lou}) + v} v = \frac{4}{\pi^2}\left(\tan^{-1}\frac{w^{gt}}{h^{gt}} - \tan^{-1}\frac{w}{h}\right)^2 \quad 11$$

$$L_{\text{confidence}} = \sum_{i=0}^{S\times S}\sum_{j=0}^{M} - 1_{ij}^{obj}\left[C_i \log C_i + \left(1 - \hat{C}_i\right)\log(1 - C_i)\right.$$

$$-\lambda_{\text{noobj}} \sum_{i=0}^{S\times S}\sum_{j=0}^{M} 1_{ij}^{\text{noobj}}\left[\hat{C}_i \log C_i + \left(1 - \hat{C}_i\right)\log(1 - C_i)\right]$$

$$-\sum_{i=0}^{S*S} 1_{ij}^{\text{obj}} \sum_{\text{class}} \sum_{t\in \text{ classes}} \left[\left(\hat{P}_i(t)\right)^{\gamma} P_i(t)\log \hat{P}_i(t) + \left(1 - \hat{P}_i(t)\right)^{\gamma}\right.$$

$$\left.\left(1 - \hat{P}_i(t)\right)\log\left(1 - \hat{P}_i(t)\right)\right]$$

$$\text{Loss} = L_{\text{ciou}} + L_{\text{confidence}} + L_{\text{class}}$$

3.1.4 Evaluation Metrics:

Precision, recall, F-measure, and accuracy are commonly used evaluation parameters for DFU (Diabetic Foot Ulcer) classification. Each of these metrics provides valuable insights into the performance and effectiveness of a classification model.

Precision:

The proportion of correctly classified positive cases for ulcers was measured using precision, which indicates how reliable the trained model is. A high precision rate means that there are fewer false positives, making the model more dependable in correctly identifying positive cases of ulcers.

$$\text{Precision} = \frac{TP}{TP + FP} \quad 12$$

Recall:

The true positive rate indicates the proportion of correctly classified positive cases in the dataset among the total actual positive cases present. A higher recall indicates good model training.

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$$\text{Recall} = \frac{TP}{TP + FN} \quad 13$$

F-measure:

The F1 score combines precision and recall into a single value by taking their harmonic mean. A higher value of the F1 score indicates that the model's overall performance is good, as it balances both precision and recall effectively.

$$F1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad 14$$

Accuracy:

Correctly classified cases of ulcer are measured via the accuracy of the model. It involves both true positives and true negatives cases among all the cases presented in the dataset. A high accuracy score ensures the model is correctly classifying the ulcer cases.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad 14$$

4. RESULTS AND DISCUSSION

Multi-class classification of DFU (Diabetic Foot Ulcer) using the Hybrid-CNN- Hybrid-CNN-YOLOv3 and Hybrid-CNN-YOLOv4 models are observed as follows:

Table 8: Results for CNN Models

Model	Ulcer Type	Precision	Recall	F-measure	Accuracy
Hybrid-CNN	Ischaemia	99.52%	99.50%	99.51%	99.51%
	Neuropathic	98.49%	97.97%	97.01%	97.80%
	Neuro-ischaemic	97.40%	95.39%	94.68%	95.82%
Hybrid-RCNN-YOLOV3	Ischaemia	99.52%	99.50%	99.51%	99.51%
	Neuropathic	97.40%	95.39%	96.38%	96.02%
	Neuro-ischaemic	94.34%	92.53%	93.43%	93.84%
Hybrid-RCNN-YOLOV4	Ischaemia	99.80%	99.79%	99.80%	99.83%
	Neuropathic	98.49%	97.97%	98.23%	98.06%
	Neuro-ischaemic	98.14%	97.97%	98.05%	97.88%

Hybrid-CNN Result:

For the "Ischaemia" class, the model achieved a precision of 99.52%, recall of 99.5%, F-measure of 99.51%, and accuracy of 99.51%. For the "Neuropathic" class, the model achieved a precision of 98.49%, recall of 97.97%, F-measure of 97.01%, and accuracy of 97.8%. For the "Neuro-ischaemic" class, the model achieved a precision of 97.4%, recall of 95.39%, F-measure of 94.68%, and accuracy of 95.82%.

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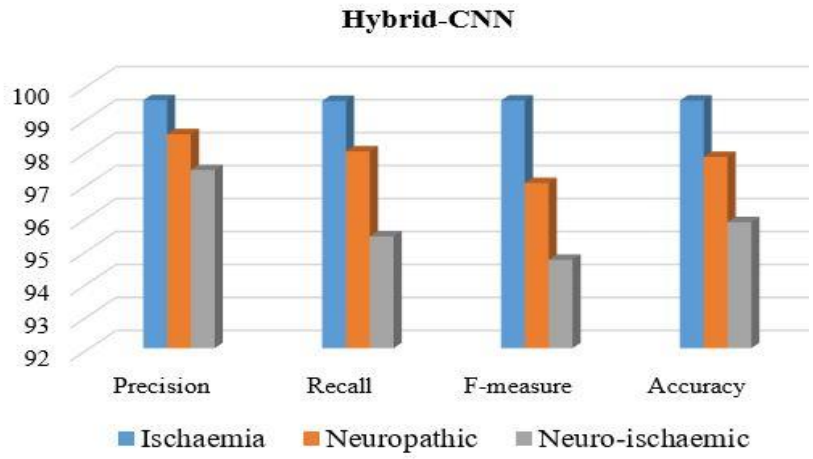

Figure 4: Graphical representation for Hybrid-CNN Result

Hybrid-RCNN-YOLOv3 Results:

For the "Ischaemia" class, the model achieved a precision of 99.52%, recall of 99.5%, F-measure of 99.51%, and accuracy of 99.53%. For the "Neuropathic" class, the model achieved a precision of 97.40%, recall of 95.39%, F-measure of 96.38%, and accuracy of 96.02%. For the "Neuro-ischaemic" class, the model achieved a precision of 94.34%, recall of 92.53%, F-measure of 94.43%, and accuracy of 93.84%.

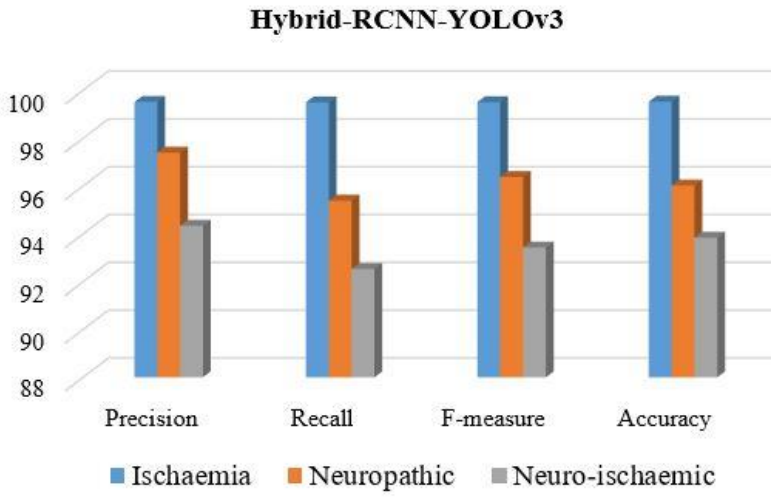

Figure 5: Graphical representation for Hybrid-RCNN-YOLOv3 Results

Hybrid-RCNN-YOLOv4 Results:

For the "Ischaemia" class, the model achieved a precision of 99.80%, recall of 99.79%, F-measure of 99.8%, and accuracy of 99.83%. For the "Neuropathic" class, the model achieved a precision of 98.49%, recall of 97.97%, F-measure of 98.23%, and accuracy of 98.06%. For the "Neuro-ischaemic" class, the model achieved a precision of 98.14%, recall of 97.97%, F-measure of 98.05%, and accuracy of 97.88%.

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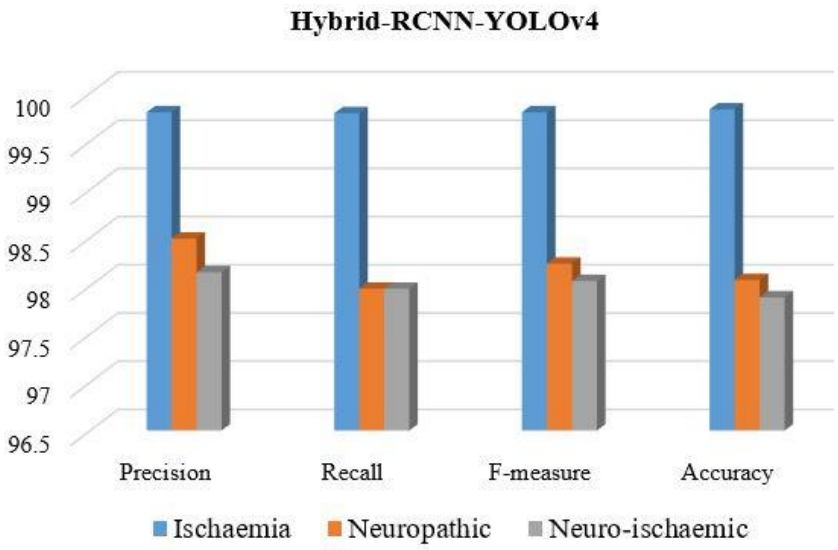

Figure 6: Graphical representation for Hybrid-RCNN-YOLOv4 Results

The related work primarily emphasized Ischemia and infection cases. This table thoroughly compares results between previous and proposed models, aiming to highlight the enhancements introduced by the proposed approach. It focuses on feature fusion and multi-class classification to assess improvements in the latter. We meticulously evaluated the proposed model alongside previous ones, demonstrating its superior capability in handling multiple classes (Ischemic, Neuropathic, and Neuro-ischemic) with enhanced accuracy and efficiency compared to its predecessors.

A detailed Comparative analysis of CNN models that handle DFU in terms of ACCURACY is presented in the following table.

Table 9: Comparative analysis of CNN Models

Reference	Model	Classes	Accuracy	Feature Fusion	Multi - Class classification
[35]	Mask RCN	Ulcer Type 1 & type 2	92.64%	x	x
[36]	ResNet50	Ischemia, infection	99.49%, 84.76%	x	x
[45]	CNNs	Ischemia, infection	90.3%, 72.2%	x	x
[46]	CNNs	Ischemia, infection	99.0%, 74.4%	x	x
[47]	Mask RCNN	DFU	90.50	x	x
[48]	Mask RCNN	Neuropathic (Wagner grade 2)	92.50	x	x
[49]	DFU-VIRNet	Ischemia, Infection	99.82% , 91.21%	x	x
[50]	EfficientNet	Diabetic and Healthy foot	98.97	x	x
Proposed Model	Hybrid-CNN, Yolov3, Yolov4	Ischemia, Neuropathy, Neuro-ischemic	99.83%, 98.06%, 97.88%	✓	✓

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As evident from the related work, the previous studies primarily focused on tasks related to Ischemia and infection cases. In this table, a comprehensive analysis was conducted between the results of the prior and proposed models. This comparison aims to highlight the improvements or differences brought about by the proposed approach. The key areas of focus were feature fusion and multiclass classification to specifically assess the improvements made in the multiclass classification task. The proposed model was meticulously evaluated alongside the results of previous models. This careful analysis aimed to demonstrate the advancements made in multiclass classification, proving the model's ability to handle multiple classes i.e. Ischemic, Neuropathic, and Neuro-ischemic with improved accuracy and efficiency compared to the previous models.

4. CONCLUSION

The prevalence of DFU continues to grow, affecting a significant population daily. Identifying DFU in its early stages is crucial for effective intervention, improving treatment outcomes survival rates, and reducing mortality. Traditional clinical diagnosis methods are susceptible to human error due to subjectivity and less-experienced practitioners. Our primary aim with deep learning techniques was to enable early DFU detection. The "Hybrid-DFUNet" model excelled in classifying all three DFU ulcer types, exhibiting high F-measure and accuracy values. These values indicate a strong balance between precision and recall, ensuring reliability in diagnosing various ulcers. High accuracy underscores the model's precision, achieving a high rate of correct classifications. These outcomes affirm the "Hybrid-DFUNet" model's effectiveness and promise in multi-class DFU ulcer classification.

5. FUTURE WORK AND LIMITATIONS

In the future, we will explore ensemble techniques and incorporate deep-learning approaches to enhance reliability and accuracy. This endeavor aims to benefit medical practitioners, whether experienced or less experienced, mainly when dealing with extensive datasets.

References

1) R. M. Crocker, K. N. Palmer, D. G. Marrero, and T. W. Tan, “Patient perspectives on the physical, psycho-social, and financial impacts of diabetic foot ulceration and amputation,” in Journal of Diabetes and its Complications, vol.35 no, 8.xpp. 1–5, Aug, 2021, DOI..org/10.1016/j.jdiacomp.2021.107960.

2) E. Navarro-Flores, O. Cauli, “Quality of life in individuals with diabetic foot syndrome,” in Endocrine, Metabolic & Immune Disorders-Drug Targets (Formerly Current Drug Targets-Immune, Endocrine & Metabolic Disorders. vol.20 no, 9. x, pp. 1365–1372, Nov, 2020, DOI.org/10.2174/1871530320092010020916 34.

3) M. Goyal, S. Hassanpour, “Refined Deep Learning Architecture for Diabetic Foot Ulcers Detection, in Computer Vision and Pattern Recognition, x, pp1–8, Jul2022,DOI.org/10.48550/arXiv.2007.07922.

4) R. Reardon, D. Simring, B. Kim, J. Mortensen, A. Leslie, “The diabetic foot ulcer,” Australian Journal of General Practice.vol.49no,5.x, pp.250–255, Sep,2020.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
Journal of Tianjin University Science and Technology
ISSN (Online):0493-2137
E-Publication: Online Open Access
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DOI: 10.5281/zenodo.10691791

5) K. M. Shavkatjonovna, A. A. Tolibovich, Y. A. Abduazizovich," Optimization of the Ophthalmic Service in Diabetic Retinopathy". In Central Asian Journal of Medical and Natural Science.vol.4no, 1.x, pp. 308–312, Feb2023, DOI.org/10.17605/OSF.IO/GXWYE.

6) B. Iraj, F. Khorvash, A. Ebneshahidi, G. Askari," O Prevention of Diabetic Foot Ulcer". In International journal of preventive medicine.vol.4no, 3. x, pp.373–376, Mar2013.

7) P. Cavanagh, C. Attinger, Z. Abbas, A. Bal, N. Rojas, Z.R Xu," Cost of Treating Diabetic Foot Ulcers in Five Different Countries". In Diabetes/metabolism research and reviews 28 (2012): 107-111. vol. 28. x, pp.107–111, Jan2012, DOI.org/10.17605/OSF.IO/GXWYE.

8) A. M Reyzelman, K. Koelewyn, M. Murphy, X. Shen, R. Pillai, J. Fu, H.J Scholten, R," Continuous temperature – monitoring socks for home use in patients with diabetes". In Journal of medical Internet research.vol.20no, 12.x, pp.1–13, Dec2020, DOI.:10.2196/12460.

9) B.E Sumpio," Foot Ulcers". In England Journal of Medicine. vol. 343 no, 11.x, pp.787–793, Sep2000, DOI: 10.1056/NEJM200009143431107.

10) R. B Paisey, A. Abbott, C.F Paisey, D. Walker," Diabetic foot ulcer incidence and survival with improved diabetic foot services: An18-yearstudy". In Diabetic Medicine.vol.36no, 11.x, pp.1424–1430, May2019, DOI:10.1111/dme.14045.

11) I. AShaikh, N. MSddiqui, J.H. Shaikh," Diabetic Foot Ulcer: An Easy and Comprehensive Approach. In Diabetic Retinopathy". In eIntech Open. 2020, DOI:org/10.5772/IntechOpen.83159.

12) M. AGERSHATER, LÖNDAHL, Magnus, NYBERG," Complexity of factors related to outcome of neuropathic and neuroischaemic / ischaemic diabetic foot ulcers: a cohort study". In Diabetologia.vol.52no, 11.x, pp. 398–407, Nover2009, DOI:10.1111/dme.14045.

13) L. Alzubaidi, M. A. Fadhel, S. R. Oleiwi, O. Shamma, J. Zhang," DFU_QUTNet diabetic foot ulcer classification using a novel deep convolutional neural network". In Multimedia Tools and Applications.vol.79no, 21.x, pp.315655–15677, Jun2019.

14) S. Gupta, C. Andersen, J. Black, J. de Leon, C. Fife, L.I. JC, R.P. Silverman," Management of Chronic Wounds: Diagnosis, Preparation, Treatment, and Follow-up. Wounds: a compendium of clinical research and practice". In Clinical research and practice.vol.29 no, 9.pp.S19–S36, Sep 2017, PMID: 28862980.

15) J. Yogapriya, V. Chandran, M. G. Sumithra, B. Elakkiya, A. E. Shamila, G. D. Suresh," Automated Detection of Infection in Diabetic Foot Ulcer Images Using Convolutional Neural Network". In Journal of Healthcare Engineering. Apl 2022, Doi.org/10.1155/2022/2349849.

16) N. Garaawi, R. Ebsim, A. F. Alharan, M. H. Yap," Diabetic foot ulcer classification using mapped binary patterns and convolutional neural networks". In Computers in biology and medicine. vol. 140 Jan 2022, doi.org/10.1016/j.compbiomed.2021.105055.

17) K. Munadi, K. Saddami, M.Oktiana, R.Roslidar, K.Muchtar, M. Melinda,F.A.Arnia, "Deep learning method for early detection of diabetic foot using decision fusion and thermal images, in Applied Sciences,vol. 12 no, 15.Jul 2022, doi.org/10.3390/app12157524

18) M. M. Eid, R. N. Yousef, M.A. Mohamed," Proposed Automated System to Classify Diabetic Foot from Thermography." In International Journal of Scientific & Engineering Research.vol.9 no, 12. pp. 371–381, Dec 2018.

19) K. S. Babu, S. Sabut, D.K. Nithya," Efficient Detection and Classification of Diabetic Foot Ulcer Tissue using PSO Technique." In International Journal of Engineering & Technology.vol.7 no, 3.12. pp. 1006 –1010, 2018. Scholar.archive.org

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
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DOI: 10.5281/zenodo.10691791

20) R. Niri, H. Douzi, Y. Lucas, S. Treuillet," A superpixel-wise fully convolutional neural network approach for diabetic foot ulcer tissue classification." In in Pattern Recognition. ICPR International Workshops and Challenges: Virtual Event, vol.10 no, 15. pp. 308–320, Feb 2021, Doi.org/10.1007/978.

21) C. Cui, H. K. Thurnhofer, R. Soroushmehr, A. Mishra, J.Gryak, E.Domínguez, E.RLópez" Diabetic Wound Segmentation using Convolutional Neural Networks.".in In Pattern Recognition. IEEE Engineering in Medicine and Biology Society (EMBC). pp. 1002–1005, Jul 2019, DOI: 10.1109/EMBC.2019.8856665.

22) H. V. L. C. Gamage, W. O. K. I. S. Wijesinghe, I. Perera, E. RLópez" Instance-based segmentation for boundary detection of neuropathic ulcers through Mask-RCNN." In in International Conference on Artificial Neural Networks. pp. 511–522, Sep 2019, DOI:doi.org/10.1007/978-3-030-30493-5_49.

23) L. Fraiwan, M. AlKhodari, J. Ninan, B. Mustafa, A. Saleh, M. Ghazal," Diabetic foot ulcer mobile detection system using smartphone thermal camera: a feasibility study." In Biomedical engineering online.vol.16 no, 1. pp. 1–19, Oct 2017.

24) S. Das, P. Roy, A. Mishra," Recognition of ischaemia and infection in diabetic foot ulcer: a deep convolutional neural network based approach.".in Int J Imaging Syst Technol.vol.32 no, 1. pp. 192—208, May 2022, Doi: 10.1002/ima.22598.

25) R. I. I. Álvarez, E. T. Castaño, D.G. García, R.C. Reynoso, P.J.E.Elton, A.P.Barajas, R.I.F. Pérez," Non-targeted metabolomic analysis reveals serum phospholipid alterations in patients with early stages of diabetic foot ulcer.".in Biomarker Insightsl.vol.15 no, 1. pp. 1177271920954828, Sep 2020, Doi.org/10.1177/1177271920954828.

26) J. Saminathan, M. Sasikala, V. B. Narayanamurthy, K. Rajesh, R. Arvind, A.P. Barajas, R.I.F. Pérez," Computer-aided detection of diabetic foot ulcer using asymmetry analysis of texture and temperature features.". In Infrared Physics & Technology.vol.105 no, 1. pp. 103219, Mar 2020, Doi.org/10.1016/j.infrared.2020.103219.

27) V. I. Cruz, C.D. Hernandez, B.H. Peregrina, M.J.J. Rangel, C.J.M. Ramirez," Deep learning classification for diabetic foot thermograms".in Sensors.vol.20 no, 6. pp. 1762, Mar 2020, Doi: 10.3390/s20061762.

28) I. Wijesinghe, C. Gamage, I. Perera, C. Chitraranjan," A smart telemedicine system with deep learning to manage diabetic retinopathy and foot ulcers". In Moratuwa Engineering Research Conference (MERCon) Moratuwa: IEEE. pp. 686—691, Jul 2019, Doi:10.1109/MERCon.2019.8818682.

29) N. Y. J. Laptev, R. Rajagopal," Reconstruction and regression loss for time-series transfer learning".in Moratuwa Engineering Research Conference (MERCon) Moratuwa: IEEE. pp. 686—691, Jul 2019, Doi: 10.1109/MERCon.2019.8818682.

30) M.Goyal,N.D.Reeves, A.K.Davison, S.Rajbhandari, J.Spragg, M.H. Yap," Convolutional neural networks for diabetic foot ulcer classification".in IEEE Trans. Emerg. Top. Comput. Intell. vol. 4 no, 5.pp. 728—739, Sep 2018, Doi: 10.1109/TETCI.2018.2866254.

31) M. Goyal, N.D. Reeves, S. Rajbhandari, N. Ahmad, C. Wang, M.H. Yap," Recognition of ischaemia and infection in diabetic foot ulcers: dataset and techniques". In Computers in Biology and Medicine. vol. 117 no, 5. pp.103616, Feb 2020, Doi: org/10.1016/j.compbiomed.2020.103616.

32) L. Alzubaidi, M. A. Fadhel, S. R. Oleiwi, O. Al-Shamma,J. Zhang," DFU_QUTNet: diabetic foot ulcer classification using novel deep convolutional neural network". In Multimedia Tools and Applications. vol. 79 no, 21. pp.5655—15677, June 2019, Doi: org/10.1007/s11042-019-07820-w.

33) M. Goyal, N. D. Reeves, S. Rajbhandari, M.H. Yap," Robust methods for real-time diabetic foot ulcer detection and localization on mobile devices". In IEEE J Biomed Health Inf. vol.23 no, 4. pp.1730—41, Sep 2018, Doi:10.1109/JBHI.2018.2868656.

Tianjin Daxue Xuebao (Ziran Kexue yu Gongcheng Jishu Ban)/
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ISSN (Online):0493-2137
E-Publication: Online Open Access
Vol: 57 Issue: 02:2024
DOI: 10.5281/zenodo.10691791

34) S.K.DAS, ROY, Pinki, MISHRA, K. Arnab," Recognition of ischaemia and infection in diabetic foot ulcer: a deep convolutional neural network-based approach". In International Journal of Imaging Systems and Technology.vol.32 no, 1. pp. 192–208, May 2022, Doi.org/10.1002/ima.22598.

35) L. C. Padierna, M. L. F. Amador, O. B. Murillo, M. C. Villaseñor," Classification method of peripheral arterial disease in patients with type 2 diabetes mellitus by infrared thermography and machine learning". In Infrared Physics Technologyvol.111. pp.103531, Dec 2020, Doi.org.10.1016.j.infrared.2020.103531.

36) M. Goyal, N. D. Reeves, S. Rajbhandari, N. Ahmad, C. Wang, M.H. Yap," Recognition of ischaemia and infection in diabetic foot ulcers: Dataset and techniques". In Computers in biology and medicine vol 117.pp.103616, Feb 2020, Doi.org/10.1016/j.compbiomed.2020.103616.

37) H. V. L. C.Gamage, W. O. K. I. S.Wijesinghe, I. Perera," Instance- based segmentation for boundary detection of neuropathic ulcers through Mask-RCNN". In In International Conference on Artificial Neural Networks.pp.511–522, Sep 2019, Doi.org/10.1007/978-3-030-30493-5-49.

38) P.L.Muñoz, R.Rodríguez, N.Montalvo," Automatic segmentation of diabetic foot ulcer from mask region-based convolutional neural networks". In Journal of Biomedical Research and Clinical Investigation vol.1 no, 1.pp.511–522, Aug 2019, DOI: Doi.org/10.31546/2633-8653.1006.

39) M.S. Prabhu, S.Verma," A Deep Learning Framework and its Implementation for Diabetic Foot Ulcer Classification".in Infocom Technologies and Optimization, Trends and Future Directions vol.1 no, 1.pp.1–5, Sep 2021, DOI: Doi.org/10.31546/2633-8653.1006.

40) L.A Izubaidi, M. A. Fadhel, S. R. Oleiwi, O. Shamma, J.Zhang," A Deep Learning Framework and its Implementation for Diabetic Foot Ulcer Classification". In Infocom Technologies and Optimization, Trends and Future Directions vol.1 no, 1. pp. 1–5, Sep 2021, DOI: Doi.org/10.31546/2633-8653.1006.

41) Y. Xu, K. Han, Y. Zhou, J.Wu, X.Xie, W.Xiang," Classification of diabetic foot ulcers using class knowledge banks".in Front Bioengineer Biotechnol vol.9 no, 1.pp.1–5, Feb.2022, Doi: 10.3389/fbioe.2021.811028.

42) B. Cassidy, C. Kendrick, N. D. Reeves, J. M. O. Pappachan, C. Shea, D. G. Armstrong, M. H. Yap," Diabetic foot ulcer grand challenge 2021: Author et al.: Preparation of Papers for IEEE TRANSACTIONS and JOURNALS evaluation and summary. In Diabetic Foot Ulcers Grand Challenge ".in Springer International Publishingl.pp.90–105, 2021, Doi.org/10.1007/978- 3-030-94907-5-7.

43) M. Meloni, V. Izzo, L. Giurato, M.J.L. Lázaro, L. Uccioli," revalence, clinical aspects and outcomes in a large cohort of persons with diabetic foot disease: comparison between neuropathic and ischemic ulcers.". In Journal of clinical medicine, vol.9 no, 6. pp.1780, Jun 2020, doi.org/10.3390/jcm9061780.

44) R. R. Yotsu, N. M. Pham, M. Oe, T. Nagase, H. Sanada, H. Hara, T. Tamaki," Comparison of characteristics and healing course of diabetic foot ulcers by etiological classification: neuropathic, ischemic, and neuro-ischemic type. ".in Journal of Diabetes and its Complications vol.28 no, 4. pp. 528–535, Aug.2014, Doi.org/10.1016/j.jdiacomp.2014.03.013.

45) M. Ahsan, S. Naz, R. Ahmad, H. Ehsan, A.A Sikandar," deep learning approach for diabetic foot ulcer classification and recognition". In (Biomedical Informatics) vol.14 no, 1. pp.36, Jan.2023,Doi.org/10.3390/info14010036.

46) N. Garaawi, R. Ebsim, A. F. Alharan, M. H. Yap," Diabetic foot ulcer classification using mapped binary patterns and convolutional neural networks." In Computers in Biology and Medicine. vol. 140. pp. 105055, Jan.2022,Doi.org/10.1016/j.compbiomed.2021.105055.

47) C. Cao, Y. Qiu, Z. Wang," Nested segmentation and multi-level classification of diabetic foot ulcer based on mask R-CNN.". In Multimed Tools Appl vol.82 no, 1. pp.18887—18906, May.2023,Doi.org/10.1007/s11042-022- 4101-6.

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Journal of Tianjin University Science and Technology
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DOI: 10.5281/zenodo.10691791

48) N. Sharma, S. Mirza, A. Rastogi, P.K. Mahapatra," Utilizing Mask R-CNN for Automated Evaluation of Diabetic Foot Ulcer Healing Trajectories: A Novel Approach.". In Traitement du Signal vol.40 no, 4. pp. 1601–1610, Jan.2023,Doi.org/10.3390/info14010036.

49) J. L. Reyes, J. V. Guerrero, J. R. Andrade, M. F. Gallanzi," DFU_VIRNet: A novel Visible-InfraRed CNN to improve diabetic foot ulcer classification and early detection of ulcer risk zones...". In Biomedical Signal Processing and Control vol.86. pp. 105341, Sep.2023,Doi.org/10.1016/j.bspc.2023.105341.

50) Thotad, N. Puneeth N, R. Geeta, Bhaamagoudar, S. A. Basavaraj," Diabetic foot ulcer detection using deep learning approaches. "In Sensors International vol.4. pp.100210, 2023, doi. org/10.1016/j.sintl.2022.10021