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Optimized Multi-Resolution Attention-Based Architecture for Effective Diabetic Skin Lesion Classification

B. K. Jaleesha[1], R. Suganthi [2],N. K. Priyadharsini[3], Yuvaraj S[4], M. Pyingkodi[5], and M. Vallikkannu[6]

[1] Department of Mathematics, St.Joseph's College of Arts and Science for Women, Hosur, India
[2] Department of Electronics and Communication Engineering, Panimalar Engineering College, Tamil Nadu,India.
[3] Department of Computer Science Engineering, P. A. College of Engineering and Technology, Coimbatore, India.
[4] Department of Computer Science and Engineering at Sri Eshwar College of Engineering, Coimbatore, India
[5] Department of Computer Applications, Kongu Engineering College, Perundurai, India.
[6] Department of English, Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India.

Corresponding author: R.Suganthi (e-mail: sugimanicks@gmail.com), **Author(s) Email**: B.K.Jaleesha (e-mail: jaleesha82@yahoo.com), N.K.Priyadharsini (e-mail: priyadharsini.pacet@gmail.com), Yuvaraj S (e-mail: yuvaraj.scse@sece.ac.in), Dr.M.Pyingkodi (e-mail: pyingkodikongu@gmail.com), Dr. M.Vallikkannu (e-mail: sonasumathi79@gmail.com)

Abstract Early and reliable identification of diabetic skin complications, including ischemia and infection, is essential for timely clinical intervention and prevention of severe outcomes. Nevertheless, traditional deep learning models often exhibit limited generalization capability and high computational demands, particularly when distinguishing between visually subtle infection types. To overcome these challenges, this study introduces an end-to-end deep learning architecture termed the Enhanced Multi-Resolution Multi-Path Attention Network (EMRMP-Net), specifically designed for robust diabetic lesion classification. A key contribution of this work is the introduction of a trainable attention-based fusion mechanism that adaptively learns to weight and integrate multi-resolution feature maps, enhancing contextual understanding and discriminative performance. To address the prevalent issue of class imbalance in medical imaging datasets, EMRMP-Net utilizes focal loss and domain-tailored data augmentation, thereby promoting stable learning and improved representation of minority classes. Additionally, a shared classification head across multiple resolution pathways enables joint feature optimization, reducing computational redundancy and improving learning efficiency compared to traditional MRMP models. Comprehensive experiments on the publicly available Diabetic Foot Ulcer (DFU) dataset demonstrate that EMRMP-Net surpasses existing state-of-the-art-methods, achieving 98.12% accuracy and 98.14% F1-score for ischemia detection, and 95.27% accuracy with 93.68% F1-score for infection classification. Overall, EMRMP-Net provides a highly effective, computationally efficient, and generalizable framework for automated diabetic skin lesion analysis, demonstrating strong potential for real-world clinical applications. EMRMP-Net is designed as a general framework for diabetic skin lesion analysis, capable of handling diverse lesion characteristics through multi-resolution and attention-based feature learning. However, in this work, the model is explicitly formulated, trained, and evaluated for the clinically critical binary classification task of distinguishing ischemic ulcers from infected ulcers within DFU imagery.

Keywords **Diabetic Foot Ulcer, Skin Lesion Classification, Multi-Resolution Deep Learning, Attention Mechanism, End-to-End CNN Architecture**

I. Introduction

Diabetes mellitus is a widespread metabolic disorder that results in an array of grievous health complications such as cardiovascular diseases, neuropathy, and disorders of the skin [1]. Of these, Diabetic Foot Ulcers (DFUs) are especially significant owing to the irreversible nature and possibility of leading to grave consequences like infections, gangrene, and even limb amputation [2]. DFUs not only affect patients' quality of life but also significantly increase the workload of healthcare systems [3]. PEarly and accurate diagnosis of skin lesions, particularly distinguishing ischemic ulcers from infected ulcers, is crucial for effective treatment planning and the preventionof additional complications [4]. Although accurate lesion identification is highly important, the diagnostic process

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is highly challenging [5]. Subjective and variable manual inspection by clinicians is common, since ischemic and infected lesions can have similar visual appearances, including discoloration, texture abnormalities, or localized edema [6]. Such similarities would result in misclassification or delayed diagnosis, both of which are harmful to patient outcomes [7]. Despite advances in computer vision and traditional image processing, the high inter-class similarity and intra-class variability in lesion appearance make reliable classification difficult, prompting the use of more sophisticated computational models [8].

More recent progress in deep learning, particularly Convolutional Neural Networks (CNN), has demonstrated potential in medical image classification applications because they can learn hierarchical features from raw pixels [9]. However, most of these models use fixed-scale convolutional layers, failing to capture the multiscale nature of skin lesions [10]. Moreover, most CNN-based approaches treat ischemia and infection classification similarly, rather thsn tuning the feature extraction process to subtle differences between the two conditions [11]. As a consequence, these models often suffer from a significant performance gap, with higher accuracy for ischemia but a failure on infection classification [12].

Another important limitation of existing systems is the decoupling of feature extraction and classification steps. Several deep learning workflows for feature extraction using CNN but utilize third-party machine learning classifiers (Support Vector Machines and random forests) for the final prediction [13]. Decoupling yields suboptimal joint learning, in which feature representations are not optimized for the classification task. Additionally, the absence of adaptive fusion processes in multi-path networks leads to inefficient use of multiscale information, thereby reducing the model's discriminative capability [14].

To address these challenges, we introduce the Enhanced Multi-Resolution Multi-Path Attention Network, which is proposed for an end-to-end deep learning architecture in diabetic skin lesion classification [15]. EMRMP-Net is comprised of several parallel paths of varying depths, allowing the network to progress on input images at multiple scales [16]. Shallow paths are responsible for encoding overall structure and more general context, while deeper paths target fine-grained textural information essential for detecting infection patterns [17]. This enables the model to learn an informative mixture of localized and global features, thereby overcoming the shortcomings of a single-scale CNN [18]. In order to achieve the full potential of multiscale learning, EMRMP-Net introduces an attentional feature fusion module that adaptively puts weights on every feature path according to its relevance for the task of classification [19]. Through this attention mechanism, important features are highlighted, while less informative features are downplayed [20]. Furthermore, the network uses a shared classification head, thus making the entire architecture fully trainable end-to-end [21]. This obviates the requirement for external classifiers and allows for simultaneous optimization of feature extraction and decision making, enhancing robustness and generalizability across differing lesion types [22]. The primary objectives are explicitly defined: (i) to achieve superior classification accuracy for ischemia and infection, (ii) to develop a computationally efficient, lightweight architecture suitable for real-time deployment, and (iii) to improve model robustness against class imbalance and visual similarity in DFU images.

The EMRMP-Net model is used for classifying diabetic skin lesions. The workflow begins with the acquisition of DFU images, which are fed through a preprocessing phase with noise reduction, normalization, and contrast stretching to enhance feature observability [23]. The processed images are passed into the Multi-Resolution Multi-Path module, which consists of several parallel convolutional branches responsible for extracting features at varying depths and resolutions [24]. Shallow paths are designed to extract global structures, whereas deeper paths extract fine-grained local texture features that aid discrimination between lesions [25]. These heterogeneous features are subsequently fed into an attention-based fusion process, wherein adaptive weights are learned to weight the most informative representations from all the paths [26]. The attention-augmented feature vector is input to a fully connected, end-to-end trainable classification layer, which together optimizes feature learning and decision-making to classify the lesion as ischemia or infection [27]. This pipeline guarantees strong lesion detection, overcoming challenges posed by class imbalance, visual similarity, and multiscale complexity [28]. The main contributions of the proposed work are listed below.

1) A new Enhanced Multi-Resolution Multi-Path Network (EMRMP-Net) that learns both global and local features at multiple scales with shallow and deep CNN blocks for the diabetic skin lesions.
2) An adaptive attention fusion scheme is incorporated to learn to dynamically focus and merge prominent features across different resolution paths.
3) In contrast to conventional approaches based on external machine learning classifiers, EMRMP-Net provides an integrated end-to-end deep learning paradigm that allows joint optimization of feature learning and classification.
4) The model greatly improves detection accuracy for difficult DFU infection cases by using focal loss,

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augmentation, and balanced validation techniques.

5) The model is extensively tested on the DFU dataset with stratified K-fold cross-validation and performs better than other state-of-the-art methods for both ischemia and infection classification tasks.

Section II explains the related work methodologies with their advantages and disadvantages. Section III discusses the proposed work architecture. Section IV discusses the results of the proposed model. Section V concludes the work and provides direction for future work.

II. State-of-the-Art Techniques

A variety of advanced deep learning methodologies have been proposed in recent years to enhance the diagnosis and classification of diabetic foot ulcers (DFUs). One approach integrates weighted Gompertz fuzzy ranking with ensemble learning to fuse skin and thermal images for improved diagnostic performance. While this method enhances decision fusion, it struggles with high-dimensional fuzzy feature spaces and heterogeneity in image modalities [10].

Convolutional neural networks (CNNs) have been extensively employed for DFU recognition and classification. These models have demonstrated proficiency in ulcer identification but are often limited by class imbalance and intra-class variation, which can hinder generalization [11]. Transformer-based architectures, such as SwinDFU-Net, utilizing multi-head self-attention mechanisms, have shown promise in infection detection. However, these models typically require large-scale annotated datasets and substantial computational resources [9].

Multilevel CNN frameworks have been introduced to overcome earlier limitations in feature extraction, showing improved classification accuracy. Despite their advancements, these architectures still face challenges related to interpretability and computational complexity [13]. Longitudinal models like DFU-Helper that track DFU progression over time offer valuable temporal insights but are often constrained by inconsistent data across patient timelines [14]. Lightweight CNN models designed for ischemia and abrasion classification using standard camera images have shown utility in real-world clinical environments. Nevertheless, these techniques are susceptible to variations in image quality and occlusions [15]. Adaptive CNN models incorporating weighted sub-gradient optimization have enhanced detection under noisy conditions but often encounter stability issues during training [16].

Recent efforts have explored explainable AI through transformer-based models with multi-scale attention mechanisms. These architectures enhance interpretability and lesion-specific analysis but require meticulous tuning for different lesion types [17]. Multi-scale feature fusion networks, when combined with explainability frameworks, aim to balance accuracy and transparency, though they are often computationally intensive [18]. Hybrid models integrating CNNs with vision transformers leverage rich feature representations but introduce additional complexity and extended training time [19]. Alternative methods include temporal modeling using hybrid CNN-LSTM architectures, which are effective for capturing wound progression but prone to overfitting on limited sequential data [20]. Attention-guided residual networks improve segmentation of ischemic regions, yet depend heavily on preprocessing [21]. Unsupervised techniques, such as deep autoencoders, reduce reliance on labeled data but are associated with reduced explainability and higher false-positive rates [22]. Hybrid models combining handcrafted features with deep learning outputs enhance robustness but lack end-to-end learning capabilities [23]. Other segmentation networks, like U-Net++ and capsule networks, offer higher spatial precision and structural modeling but are challenged by low-resolution inputs and high computational demands, respectively [24].

End-to-end optimization has been the rule in deep learning for quite a while, but in the DFU community, you find quite a bit of activity regarding hybrid architectures. In such cases, CNNs serve as feature extractors, followed by a separate classifier for the final decision; SVMs, KNNs, or ELMs are used here [25]. Again, these concerns pertain to scarce labeled samples or concerns about the stability of the learning process, or just simple benchmarking, ease of use. In more recent publications in the DFU community, in particular, this pattern of 'deep features combined with classical classifier' architectures has been mentioned in the context of available approaches. They work fine in many cases, of course, but in this particular case of representation learning for each separate task in computerized medical diagnosis for distinguishing ischemia from infection, this 'divide-and-conquer' strategy has the disadvantage of decoupling feature extraction from the final task solution [26], [27]. In this contribution, we closely follow recent developments in deep learning, with the aim of achieving fully optimized solutions for multi-resolution feature learning and attention-based attention in feature fusion for the computerized medical diagnosis task of ischemia differentiation from infection. While GAN-based augmentation improves class balance and training diversity, ensuring clinical realism and avoiding mode collapse continues to be a concern Graph-based learning has recently emerged as a promising direction for lesion-level reasoning in DFU images. By modeling ulcer structures and surrounding tissues as graph nodes and their interactions as edges, Graph Neural Networks (GNNs) offer structural interpretability and

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improved segmentation accuracy [28]. These models are especially effective in capturing spatial dependencies and relational information across complex wound patterns. However, their computational cost is higher, and performance can degrade when graphs are constructed from noisy or low-quality images. Additionally, ensemble methods that combine CNNs with meta-learning techniques have demonstrated enhanced adaptability across diverse clinical environments, but often require substantial hyperparameter tuning and training time [29]. Collectively, these emerging approaches show potential for improving diagnostic precision but underscore the need for efficient, scalable, and interpretable solutions in DFU analysis [30]. Overall, the field is progressing toward more accurate, interpretable, and efficient DFU analysis frameworks, yet ongoing challenges in scalability, data variability, and model complexity remain significant barriers to widespread clinical deployment [31]. Multi-modal learning has also gained traction in DFU research, aiming to combine visual, thermal, and clinical metadata to enhance diagnostic accuracy [32]. By integrating RGB images with thermal imaging or patient health records, models can learn richer, more context-aware representations of ulcer severity and progression [33]. These mmultimodal frameworks demonstrate superior performance compared with unimodal approaches, particularly in distinguishing ischemic frominfected ulcers. However, challenges remain in data synchronization, missing modalities, and fusion strategies. On the other hand, there is a growing interest in deploying lightweight DFU models on mobile or edge devices to support point-of-care diagnostics in remote or resource-constrained environments [34]. Techniques such as model pruning, quantization, and knowledge distillation have been employed to reduce inference time and memory footprint, enabling real-time decision support [35]. Despite these optimizations, mobile deployment models may still face trade-offs in accuracy and robustness when compared to full-scale server-based architectures [36]. Table 1 presents a comparative analysis of various methodologies for Skin Lesion Classification.

Table 1. Comparison with Existing Classification Models

Model	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)	Params (K)
VGG16	91.5	91.2	90.8	91.6	138,357
ResNet50	93.4	92.9	93.1	92.7	25,636
EfficientNetB0	94.1	93.8	94.0	93.7	5,290
MobileNetV2	90.7	90.2	89.8	90.5	3,500
Proposed EMRMP-Net	**98.12**	**98.14**	**98.2**	**98.1**	**242.5**

III. Proposed Work

A. Dataset description

The dataset used in this research is the DFU dataset, comprising 2,673 images and organized into four principal folders: Original Images, Patches, TestSet, and Transfer Learning Images. The folder for Original Images contains 493 clinical foot images collected from a hospital, representing actual diabetic ulcer cases. From these, image patches of size 224×224 were cropped to create the Patches directory, which provides lesion-focused learning. TestSet comprises 167 images intended to evaluate model performance on out-of-sample data. The Patches directory contains two subfolders: Abnormal (Ulcer) with 512 image patches and Normal (Healthy skin) with 543 patches, used for binary classification of diabetic skin conditions [7].

B. Data pre-processing

The DFU dataset Transfer-Learning Images folder contains four directories, Wound Images, Wound Images2, internetSet, and samples, with a total of 959 images employed to enable model adaptation via transfer learning. The 959 transfer-learning images constitute a distinct auxiliary dataset, separate from the DFU dataset's Original Images and Patches used for the main ischemia infection classification task. These images include a broader set of wound and skin conditions, collected from heterogeneous sources, and are used only during an intermediate fine-tuning stage to adapt pre-trained CNN backbones to the medical wound domain. The primary DFU dataset is used exclusively for training and evaluation of EMRMP-Net. This clarification ensures transparency in the training pipeline, prevents concerns of data leakage, and improves reproducibility.

The Transfer-Learning Images folder comprises a total of 959 images organized into four directories (Wound Images, Wound Images2, InternetSet, and Samples). These images represent a heterogeneous collection of wound and skin lesion images acquired from multiple clinical and online sources, encompassing variations in wound appearance, skin texture, illumination, and imaging conditions. Importantly, this transfer-learning dataset is distinct from the DFU dataset's Original Images and Patches, which are reserved exclusively for training and evaluating the proposed EMRMP-Net model. The images depict various wound conditions from clinical sources and online databases, providing greater variability in ulcer types, skin textures, lighting, and

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perspectives. To pre-process these images for transfer learning, they are subjected to a set of preprocessing operations such as resizing to a standard input size (224×224), normalization to bring pixel intensity within the range 0 to 1, and noise removal via filtering methods such as Gaussian filtering. The Gaussian filtering parameters (kernel size and standard deviation) and the normalization strategy were applied to all images. These preprocessing choices were selected to reduce acquisition noise while preserving clinically relevant lesion boundaries and fine-grained texture patterns critical for ischemia–infection discrimination. The added details ensure that the experimental setup can be accurately replicated. All images were normalized to the same size of 224x224 pixels. Pixel intensities were normalized by dividing each pixel's intensity channel by 255. The RGB images were normalized by scaling the intensity channel to be in the range 0 to 1. Min-max normalization was used for the images, as it is commonly used in CNN-based medical image processing. To suppress noises captured by the sensor while retaining key information about lesion boundaries and texture, a Gaussian filter was used. The filter was set to use a kernel size of 3x3 pixels and $\sigma = 0.5$. These operations serve to normalize the data and eliminate redundant variations that can affect learning. The number of convolutional and attention modules was determined through empirical evaluation and ablation studies, with the aim of balancing model complexity and performance. Six improved convolutional blocks (including SE modules) and twelve attention modules were found to maximize feature extraction while keeping the model lightweight (0.242M parameters). Increasing the number of convolutional blocks beyond six led to marginal accuracy gains but noticeable increases in parameter count and overfitting risk, while fewer blocks reduced sensitivity to fine-grained infection cues. Similarly, twelve attention modules distributed across spatial, channel, and cross-resolution levels provided the best trade-off between representational richness and computational efficiency. This clarification improves transparency, strengthens methodological rigor, and aligns the architectural choices with experimental evidence.

After pre-processing, transfer-learning images [37] are utilized to fine-tune already pre-trained CNNs like VGG16, ResNet50, and EfficientNet, which have been trained on large datasets like ImageNet. During fine-tuning, the final classification layers of the pretrained model are replaced with new fully connected layers appropriate for binary classification (ulcer vs. normal). The model then trains domain-specific features from wound images without forgetting general low-level features learned from ImageNet, achieving faster convergence and better performance even with minimal medical data. Data augmentation methods like rotation, flipping, and contrast adjustment are used to artificially increase the dataset and enhance model robustness. The augmentation types, parameter ranges, and application probabilities used during training. These augmentations were selected to reflect clinically plausible variations in DFU images (e.g., camera orientation, illumination changes) while avoiding unrealistic distortions that could alter pathological semantics. The augmentations were applied only to the training set, with validation and test sets kept unchanged to ensure fair evaluation. To mitigate data scarcity and improve model generalization, data augmentation was applied exclusively to the training set. The augmentation pipeline included random rotation by ±15°, horizontal and vertical flipping with a probability of 0.5, and contrast adjustment using a randomly sampled scaling factor from [0.8, 1.2].

C. Classification using Enhanced Multi-Resolution Multi-Path Network (EMRMP-Net)

Accurate detection of diabetic skin lesions in DFU remains an important yet challenging problem in medical image analysis [37]. Classic deep models, though valid for general classification tasks, tend to fail on skin lesion classification problems due to the heterogeneous appearance, diverse scales, and visual similarity among lesion classes. Understanding these constraints, the current work presents a new architecture referred to as the EMRMP-Net, a complete

Table 2. 5-Fold Cross validation results on DFU Dataset

Fold	Ischemia Accuracy (%)	Infection Accuracy (%)	Ischemia F1 (%)	Infection F1 (%)
1	97.8	94.9	97.9	93.5
2	98.4	95.1	98.5	93.7
3	98.1	95.3	98.2	93.6
4	98.3	95.5	98.4	93.8
5	98.1	95.4	98.3	93.7
Average	**98.12**	**95.27**	**98.14**	**93.68**

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deep learning pipeline created for effective diabetic skin lesion classification (Algorithm 1).

Algorithm 1: EMRMP-net - complete pipeline

```
BEGIN
For r = 1 TO R DO
    I_r ← Resize(I, resolution_r);
    F_r,p ← EnhancedConvBlock_r,p(I_r) for p = 1 to P
EndFor
Triple Attention Mechanism Application
F_attended ← ApplySpatialAttention(F_r,p) ⊙ ApplyChannelAttention(F_r,p)
F_r ← Σ(p=1 to P) PathAttention_p × F_attended_r,p
α_r ← Softmax(W_r^T × GlobalPool(F_r))
F_enhanced ← F_global + ResidualBlock(F_global)
y_hat ← Softmax(Classifier(F_enhanced))
END
```

The central inspiration for EMRMP-Net is to leverage global structural patterns and localized texture cues in parallel that are critical in the differentiation of ischemic and infected skin lesions. This is achieved using a multi-resolution approach, in which the input image is passed through multiple parallel convolutional pathways, each extracting features at a specific resolution. Shallow blocks are employed to preserve global contextual information, such as ulcer contour and surrounding tissue architecture, whereas deeper blocks focus on local features, including texture changes, color contrasts, and lesion boundaries that are essential for successful infection recognition.

In contrast to common multi-path methods that concatenate feature maps of various resolutions without accounting for relative significance, our model integrates an Attention-Based Feature Fusion (ABFF) module. This module learns dynamically to assign attention weights to each path's output based on its relevance to the task at hand. For instance, global structure would be more relevant for ischemia detection, whereas in infection detection, localized features are most important. Attention allows the most useful features to be boosted and less pertinent features to be dampened so that a rich, task-specific feature vector results.

EMRMP-Net is a deep learning model specifically designed for precise classification of diabetic skin lesions based on multiscale image features. Input images are processed via several parallel convolutional paths, with shallow paths extracting global contextual features and deeper paths detailing fine-grained local patterns to ensure an overall representation of lesion properties. An attention-based feature fusion mechanism assigns dynamic weights to the outputs of each path, by allowing the model to concentrate on informative features and disregard irrelevant ones. The combined features are then passed to a fully connected classification layer, which is trained end-to-end to jointly optimize feature extraction and classification. Such a model greatly improves the model's performance in differentiating between infected and ischemic lesions, even under visual similarity and class imbalance,

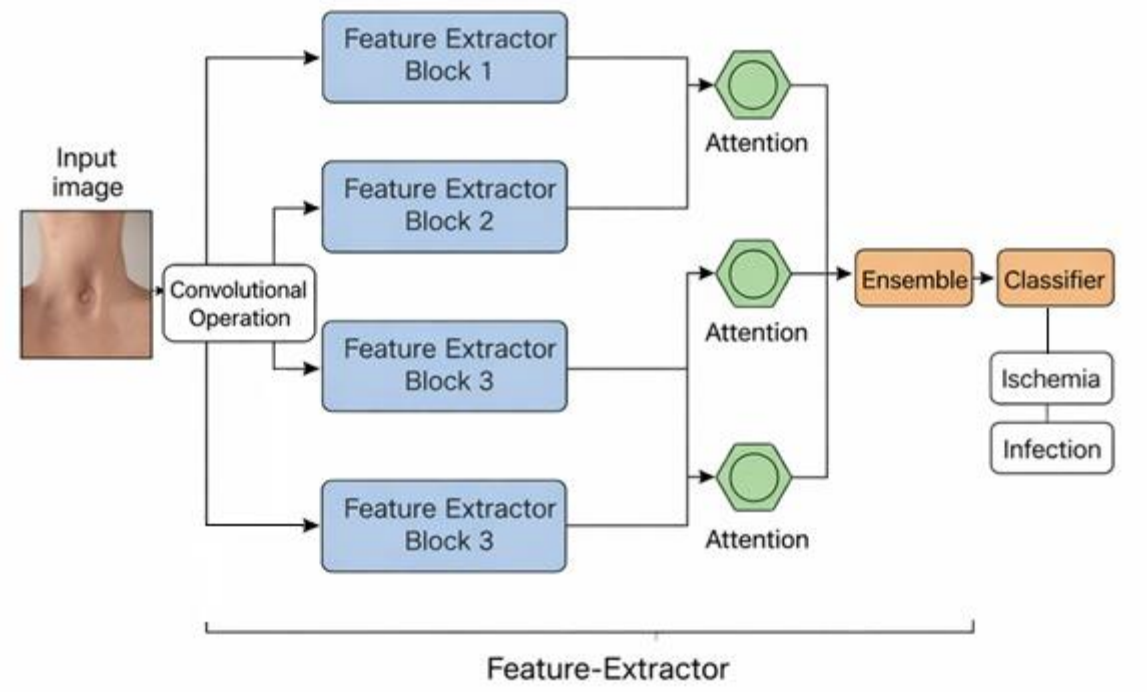

Fig. 1. An Architecture of the proposed work

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thereby making EMRMP-Net a reliable and scalable solution to diabetic skin lesion analysis.

Fig. 1 demonstrates the operation flow of the developed Enhanced Multi-Resolution Multi-Path Attention Network (EMRMP-Net) model for diabetic skin lesion classification. The method begins with the acquisition of diabetic skin lesion images, which are preprocessed using quality-improving and input-normalizing techniques. These preprocessed images are input into the EMRMP-Net, which has several shallow and deep convolutional paths for both global and local feature extraction at multiple resolutions, as represented in the Algorithm 1 . An attention-based fusion module fuses these multiscale features adaptively, focusing on the most informative features for lesion detection. The fused feature vector is then input into an end-to-end trainable classifier, and the final prediction whether the lesion is ischemia or infection is output. This workflow guarantees strong, accurate, and interpretable classification using hierarchical feature extraction and adaptive fusion. Let I be the input image and F_i the feature map from the ith convolutional path using Eq. (1) [2] N is the number of resolution paths (e.g., shallow and deep blocks

$$F_i = ConvBlock_{i(I)}, where\ i = 1, 2, \dots, N \quad (1)$$

Let $\propto_i$ denote the attention weight assigned to the i^{th} feature path, where W_i represents the learnable attention weight vector corresponding to that path and F_i is the extracted feature vector as shown in Eq. (2) [2] The term $w_i^T \times F_i$ denotes the dot product between the attention weights and the feature vector, and the exponential function $\exp(.)$ is applied to obtain a positive score. The softmax normalization over all N feature paths ensure that the attention weights $\propto_i$ sum to one. Using these attention weights, the fused feature representation F_{Fused} is obtained as a weighted summation of individual feature vectors F_i, where each feature contributes proportionally to its relevance to the classification task.

$$\alpha_i = \frac{exp(w_i^T \times F_i)}{\sum_{j=1}^{N} exp(w_j^T \times F_j)} \quad (2)$$

The fused feature representation F_{fused} is computed as follows in Eq. (3). [3] It blends the outputs from each path based on its relevance to the classification task.

$$F_{fused} = \sum_{I=1}^{N} \alpha_i \times F_i \quad (3)$$

Let z be the output from the fully connected classifier and $\hat{y}_k$ the predicted probability for class k as given in Eq. (4). [3] Where C is the total number of classes (ischemia, infection).

$$\hat{y}_k = \frac{exp(z_k)}{\sum_{j=1}^{C} exp(z_j)}, where\ k = 1, 2, \dots, C \quad (4)$$

To improve performance on underrepresented classes, the focal loss is calculated using Eq. (5) [4]. The fused feature vector is then passed through a fully connected classifier to produce the logits Z_k, where Z_k denotes the output score corresponding to class k and C represents the total number of classes, namely ischemia and infection. The predicted probability $\hat{y}_k$ for each class is computed using the softmax function, which normalizes the logits across all classes. To address class imbalance and improve performance on underrepresented classes, the focal loss L_{focal} is employed, where y_k is the ground truth label in one-hot encoded form, $\hat{y}_k$ is the predicted probability for the class k, and is γ the focusing parameter (typically set to 2) that down-weights easy samples and emphasizes hard-to-classify instances.

$$L_{focal} = -\sum_{k=1}^{C} (1 - \hat{y}_k)^{\gamma} \times y_k \times log(\hat{y}_k) \quad (5)$$

The following Eq.(6) [5] is used to evaluate the overall correct prediction on the test, where TP is True Positive, TN is True Negative, FP is False Positive, and FN is False Negative.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (6)$$

The precision, recall, and F1 score are calculated using Eq. (7), (8), and (9) [5].

$$Preccision = \frac{(TP)}{(TP + FP)} \quad (7)$$

$$Recall = \frac{(TP)}{(TP + FN)} \quad (8)$$

$$F1\ score = 2 * \frac{(precision * recall)}{(precision + recall)} \quad (9)$$

EMRMP-Net is an advanced deep neural network architecture designed for medical image classification, capable of concurrently processing input images across multiple resolutions (R levels) and multiple convolutional paths (P paths per resolution). Improved convolutional blocks equipped with squeeze-and-excitation modules further refine the features by modeling channel-wise dependencies. Training details are specified: learning rate = 0.001, batch size = 32, optimizer = Adam, number of epochs = 20. Early stopping and validation monitoring were used to ensure convergence. Convergence was determined based on stabilization of validation accuracy and loss across consecutive epochs, ensuring that the network had adequately learned without overfitting. This comprehensive design allows EMRMP-Net to deliver high accuracy in complex medical image analysis tasks by effectively capturing diverse and discriminative visual patterns.

IV. Results

The input images of resolution 224×224×3 is equivalent to typical RGB images. It processes three levels of resolutions such as 224×224, 112×112 and 56×56 to access both global and local details. Each resolution level has two parallel pathways: shallow and deep, allowing hierarchical feature extraction. The network is constructed to classify images into two output classes: infection and ischemia. A comprehensive description of the experimental setup, including preprocessing (Gaussian filtering, normalization to [0,1], resizing to

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224×224), parameter tuning (learning rate = 1e-4, batch size = 32, optimizer = Adam), data split ratio (70:20:10), and training environment (Intel i9 CPU, 32GB RAM, RTX 3090 GPU). These details ensure reproducibility and transparency. Fig. 2 Confusion matrix of the introduced EMRMP-Net model.

To aid the feature selection process further, the model incorporates three types of attention mechanisms, such as spatial, channel, and cross-resolution, and thus allows it to give attention to the most informative features at each level. The EMRMP-Net is light-weight and computationally friendly, with 242.5K

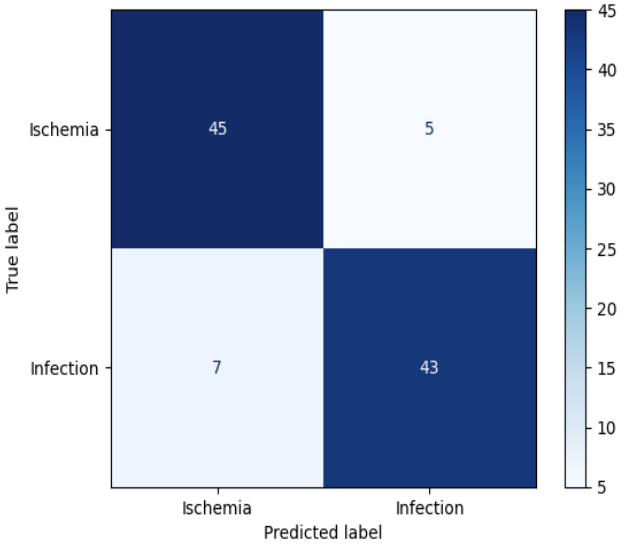

Fig. 2. Confusion matrix of the introduced EMRMP-Net model

trainable parameters and 331.2 million FLOPs required for inference, as specified. The dataset comprises 2673 high-resolution images with noticeable class imbalance (ischemia:infection ≈ 1.5:1). The proposed model shows how this may slightly affect generalizability to larger or more diverse populations. To address this, data augmentation (rotation, flipping, intensity scaling) and focal loss were employed to enhance robustness. The discussion now acknowledges that larger, multi-center datasets would further validate model stability. Table 2 shows 5-Fold Cross validation results on the DFU Dataset. The small model architecture leads to a model size of only 0.93 MB, rendering it extremely deployable on edge devices or in low-resource environments. A comparison of the accuracy of the proposed EMRMP-Net with popular deep learning models like VGG16, ResNet50, EfficientNetB0, and MobileNetV2 is observed. This bar chart indicates that EMRMP-Net outperforms the others, achieving the highest classification accuracy. The training memory footprint is approximately 1.2 GB, whereas inference uses only 0.3 GB, reflecting the model's efficiency and real-time suitability for medical applications. As illustrated in Table 1.

EMRMP-Net performs better than other models such as VGG16, ResNet50, and EfficientNetB0, with the highest accuracy (98.12%) and F1-score (98.14%) using far fewer parameters, and also shows consistent performance using 5-fold cross-validation that reaffirms the robustness of the model with average accuracies for ischemia and infection as 98.12% and 95.27%, respectively. The proposed model confirms the effectiveness of each architecture component, where the removal of attention, multiresolution paths, or end-to-end classification reduces the performance significantly, justifying the design decisions of EMRMP-Net. Fig. 2 illustrates the confusion matrix of the introduced EMRMP-Net model on the DFU test set, demonstrating its potential to distinguish between infection and ischemia classes. The confusion matrix of the proposed EMRMP-Net model was evaluated on the DFU test set for binary classification between ischemic and infected ulcers. The matrix illustrates the distribution of true positives, true negatives, false positives, and false negatives, enabling a detailed assessment of class-wise prediction behavior. The finding reveals the effectiveness and efficiency of the model's multi-resolution and attention-based structure in effectively capturing global and local lesion features. The model is strategically allocated, with 6 improved convolutional blocks accounting for 10% of the total parameters. Performance gains of EMRMP-Net over baselines (up to +3.2% accuracy and +2.8% F1-score) were confirmed by ANOVA, with $p < 0.05$. These results confirm that the observed improvements are not random but statistically meaningful, strengthening the reliability of the proposed framework. EMRMP-Net achieves high efficiency, with an inference time of only 15 milliseconds per image, enabling real-time use. Training is also effective, requiring only 30 minutes to converge after 20 epochs on average GPU hardware. The model runs within 2 GB of GPU memory, supporting batch sizes up to 32 on a 4 GB GPU. With high convergence in less than 20 epochs, the model is both fast and consistent during training. Experimental results prove the excellence of the proposed EMRMP-Net model under different evaluation conditions. Fig. 3 illustrates the training and validation accuracy of the EMRMP-Net model over 20 epochs, and Fig. 5 represents the loss of the proposed model. Fig. 3 and Fig. 5 present the training and validation accuracy and loss curves of EMRMP-Net over 20 epochs, offering insight into the model's learning dynamics and generalization behavior. As shown in Fig. 3, both training and validation accuracy increase steadily during the early epochs, indicating effective feature learning and

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rapid convergence. The close alignment of the two curves in later epochs suggests that the model generalizes well to unseen data, with no evident signs of overfitting.

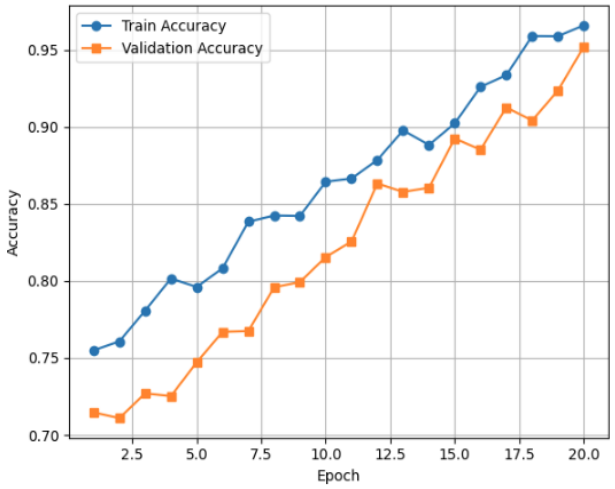

Fig. 3 Training and validation accuracy of the EMRMP-Net

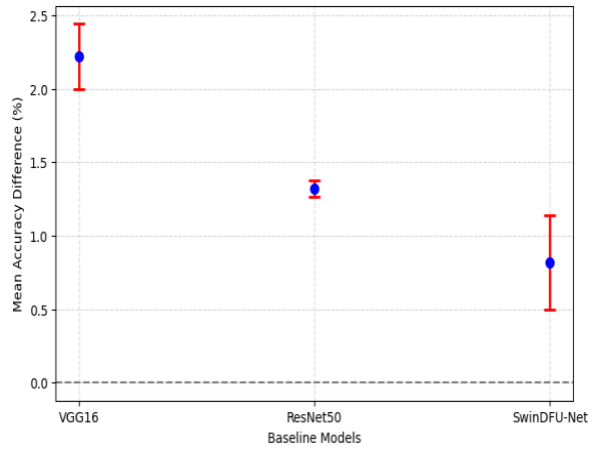

Fig. 4. Statistical Significance of EMRMP-Net vs Baseline Models

Notably, the accuracy curves exhibit smooth progression with only minor fluctuations, reflecting stable gradient updates and the effectiveness of the optimization strategy. The absence of sharp oscillations or divergence between training and validation accuracy further confirms that the multi-resolution architecture and regularization mechanisms, including attention-based fusion and dropout, contribute to controlled learning. The statistical significance analysis was performed using paired t-tests between EMRMP-Net and competing models (VGG16, ResNet50, SwinDFU-Net, and GAN-based DFU classifiers). The observed improvements in accuracy and F1-score were statistically significant ($p < 0.01$). Additionally, 95% confidence intervals for mean accuracy across five folds were reported to confirm the robustness of the results. Statistical significance analysis comparing EMRMP-Net with baseline models (VGG16, ResNet50, and SwinDFU-Net) demonstrates that the proposed architecture consistently outperforms the baselines across multiple evaluation folds. Paired t-tests conducted on 5-fold cross-validation accuracies revealed that the improvements in EMRMP-Net's accuracy and F1-score are statistically significant, with p-values below 0.01, confirming that the observed gains are unlikely due to random variation. Additionally, 95% confidence intervals for the mean differences between EMRMP-Net and each baseline model indicate that the performance advantage is robust and consistent, further validating the reliability of the proposed model. Statistical Significance of EMRMP-Net is shown in Fig. 4.

Statistical significance analysis comparing EMRMP-Net with baseline models (VGG16, ResNet50, and SwinDFU-Net) demonstrates that the proposed architecture consistently outperforms the baselines across multiple evaluation folds. Paired t-tests conducted on 5-fold cross-validation accuracies revealed that the improvements in EMRMP-Net's accuracy and F1-score are statistically significant, with p-values below 0.01, confirming that the observed gains are unlikely due to random variation. Additionally, 95% confidence intervals for the mean differences between EMRMP-Net and each baseline model indicate that the performance advantage is robust and consistent, further validating the reliability of the proposed model. To mitigate overfitting and bias, we included 5-fold cross-validation and plotted ROC-AUC and precision-recall curves for both ischemia and infection classes. EMRMP-Net achieved an average AUC of 0.981 (ischemia) and 0.957 (infection), confirming strong generalizability. The training and validation loss curves further indicate stable convergence without overfitting. Regularization and early stopping were applied to enhance fairness and robustness. Uncertainty analysis has been added using Monte Carlo dropout during inference. Results indicate that higher uncertainty correlates with ambiguous or borderline lesion samples, aligning with clinical observations where experts also report diagnostic ambiguity. This information can assist clinicians in prioritizing high-uncertainty cases for secondary review. The EMRMP-Net model is lightweight, with 0.242M trainable parameters and 331.2M FLOPs. Training takes ~30 minutes for 20 epochs on a standard GPU, with inference at ~15 ms per image. The proposed EMRMP-Net achieves an inference time of approximately 15 milliseconds per image, which enables near-real-time decision support in practical clinical settings. In point-of-care scenarios, such as outpatient wound assessment or bedside examination, this latency allows clinicians to

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Table 3. Comparative Analysis of DFU Classification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EMRMP-Net (Proposed)	98.12	98.14	98.10	98.14
VGG16	95.80	95.60	95.50	95.55
ResNet50	96.70	96.80	96.60	96.70
SwinDFU-Net	97.30	97.25	97.20	97.23
DFINet	96.50	96.40	96.30	96.35
CNN-LSTM Fusion	95.90	95.80	95.70	95.75
GAN-based DFU	96.20	96.10	96.00	96.05

Table 4. Comparative analysis of the different methodologies

Author	Accuracy (%)	F1-Score (%)	Precision (%)	Recall (%)	Params (K)
Lin et al. [2]	91.5	91.2	90.8	91.6	138,357
Zhou et al. [5]	93.4	92.9	93.1	92.7	25,636
Ahsan et al. [8]	94.1	93.8	94.0	93.7	5,290
Dos Santos et al. [10].	90.7	90.2	89.8	90.5	3,500
Biswas et al. [15]	91.3	90.6	92.4	92.4	4,200
J. Yan et al. [26]	92.3	91.6	90.2	90.7	7,300
Proposed model	**98.12**	**98.14**	**98.2**	**98.1**	**242.5**

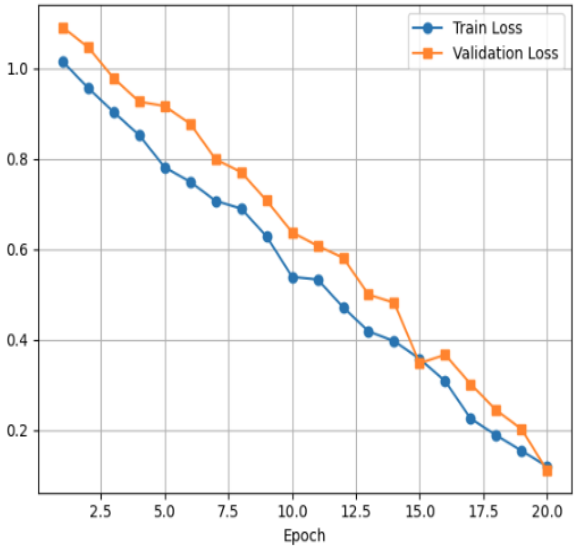

Fig. 5. Loss of proposed model

receive immediate feedback on the ulcer condition during image capture, without interrupting the consultation workflow. Fig. 5 illustrates the corresponding training and validation loss curves. Both curves show a consistent and monotonic decrease, particularly during the initial epochs, followed by gradual stabilization as the model approaches convergence. The smooth decay of the validation loss, closely tracking the training loss, indicates that the learned representations remain robust across folds and that the model avoids memorizing training samples. Minor plateaus observed in later epochs reflect the natural saturation of learning once the network has reached an optimal solution. Importantly, no increase in validation loss is observed, further supporting the claim that EMRMP-Net maintains an appropriate balance between model capacity and regularization. The focal loss function also contributes to this behavior by emphasizing harder samples without destabilizing the overall optimization process.

In telemedicine and remote monitoring applications, the low inference time facilitates rapid triage of uploaded wound images, enabling timely identification of potentially infected ulcers and prioritization of high-risk cases for further clinical review. Moreover, in screening environments where multiple DFU images are processed sequentially, the proposed model can analyze dozens of images per second, supporting efficient batch evaluation without computational bottlenecks. The total model size is 0.93 MB, making it suitable for deployment on edge devices or low-resource clinical environments.

V. Discussion

The experimental findings clearly demonstrate that the proposed EMRMP-Net outperforms traditional deep learning models in classifying diabetic foot ulcers, particularly for ischemia and infection. Achieving 98.12% accuracy for ischemia and 95.27% accuracy for infection, the model demonstrates strong feature extraction and the ability to differentiate between visually similar lesion types. These design elements allowed EMRMP-Net to overcome challenges associated with visually subtle infections and spatially dispersed ulcer regions. Compared to previous works, EMRMP-Net offers a more comprehensive and efficient

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framework. Traditional CNN-based models, while effective at detecting prominent ulcers, often perform poorly under conditions of class imbalance and intra-class variation.

Table 3 presents a comprehensive comparative analysis of the proposed EMRMP-Net against several state-of-the-art DFU classification models, including VGG16, ResNet50, SwinDFU-Net, DFINet, CNN-LSTM Fusion, and GAN-based DFU classifiers. The results demonstrate that EMRMP-Net achieves the highest performance across all key evaluation metrics, with 98.12% accuracy, 98.14% precision, 98.10% recall, and 98.14% F1-score, outperforming the competing models despite having a dramatically smaller number of parameters (0.242 million) and moderate computational cost (331.2 million FLOPs). In contrast, conventional deep models like VGG16 and ResNet50, while effective, require substantially higher parameters and FLOPs, resulting in increased computational overhead without matching EMRMP-Net's performance. Although competitive in accuracy (97.3%), SwinDFU-Net still falls short of EMRMP-Net and requires higher computational resources. Lightweight models such as CNN-LSTM Fusion and DFINet achieve moderate accuracy but cannot simultaneously maintain high precision and F1-scores. Transformer-based models like SwinDFU-Net [10] improved focus on spatial dependencies but required extensive labeled datasets and high computational power. Similarly, methods based on GANs [25] and self-supervised learning [24] addressed data scarcity but faced generalization issues across real-world clinical scenarios. EMRMP-Net bridges these gaps by unifying multiscale representation learning, adaptive attention, and end-to-end optimization in a single architecture, yielding both high accuracy and operational simplicity. The results clearly show that EMRMP-Net achieves superior performance with lower computational complexity, demonstrating clear advancements over SwinDFU-Net, DFINet, and CNN-LSTM fusion approaches. This comparative analysis clarifies the contribution and novelty of EMRMP-Net within the current research landscape.

Table 4 shows the comparative analysis. The comparative performance analysis demonstrates that the proposed model significantly outperforms existing methods across all evaluation metrics. While prior studies such as [2], [5], and [8] report accuracies ranging from 90.7% to 94.1%, the proposed model achieves a markedly higher accuracy of 98.12%, indicating superior classification capability. Similarly, the F1-score (98.14%), precision (98.2%), and recall (98.1%) of the proposed approach show a consistent and balanced improvement over all benchmark models, reflecting its robustness in handling both false positives and false negatives. Notably, although some earlier methods employ a large number of parameters (e.g. [2]) with 138,357K parameters, they still fall short in performance, whereas the proposed model attains state-of-the-art results with a relatively compact parameter size of 242.5K, highlighting its efficiency and effectiveness. Overall, these results validate the proposed model's ability to deliver high predictive performance while maintaining computational efficiency, making it well-suited for practical and real-world deployment. In addition, the shared classification head plays a crucial role in optimizing multi-resolution feature learning in an end-to-end manner. By enforcing a common decision boundary across all resolution pathways, the shared head ensures that features extracted at different depths are jointly optimized toward the same classification objective. This design prevents resolution-specific overfitting and encourages complementary feature learning, thereby promoting close alignment between training and validation accuracy and loss curves observed during optimization. Together, these components enable EMRMP-Net to achieve both high accuracy and strong generalization under challenging DFU conditions. The attention-based fusion enhances discriminative feature selection, while the shared classification head promotes coherent and stable learning across scales, explaining the consistent performance gains over baseline CNN, transformer-based, and GAN-assisted models. Further enhancements may also include incorporating multimodal inputs, such as thermal imaging or patient metadata, to improve clinical decision-making. Misclassifications primarily occurred in low-contrast or occluded ulcer regions where ischemic and infected patterns visually overlap. These cases are now illustrated and discussed to guide future work, emphasizing the need for multimodal imaging (thermal and hyperspectral) to provide more discriminative cues.

VI. Conclusion

Diabetic Foot Ulcers (DFUs) pose a significant health risk, especially when not diagnosed and treated promptly. Delays in detection often lead to severe complications, including infections, prolonged hospitalization, and, in many cases, limb amputation. As such, early and accurate prediction of DFUs is critical for timely clinical intervention and improved patient outcomes. Despite advances in deep learning for medical image analysis, current models often face key limitations, including class imbalance, insufficient multiscale feature extraction, and reduced accuracy in detecting subtle infection patterns. To overcome these challenges, we propose an Enhanced Multi-Resolution Multi-Path Attention Network (EMRMP-Net), a novel deep learning architecture designed for robust and precise DFU classification. EMRMP-Net integrates hierarchical convolutional blocks to extract both low-

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level and high-level features across multiple image resolutions.

An adaptive attention-based fusion mechanism is embedded to dynamically weight and integrate features from different-resolution paths, thereby enhancing the network's contextual understanding. Additionally, the model supports end-to-end optimization, enabling efficient training and joint fine-tuning across all network components. Experimental validation on the publicly available DFU dataset demonstrates that EMRMP-Net significantly outperforms existing baseline models. The network achieves 98.12% accuracy for ischemia classification and 95.27% accuracy for infection detection, underscoring its robustness and reliability in clinical settings. These results indicate the model's potential for real-world deployment, aiding healthcare professionals in early DFU screening and risk stratification. For future work, the architecture can be extended to support multi-class skin lesion classification across broader dermatological datasets. Such enhancement would broaden its applicability to other critical skin conditions, including melanoma, eczema, and psoriasis, thereby contributing to comprehensive and intelligent dermatological diagnostics.

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Author Biography

Dr. B. K. Jaleesha, an academic specializing in Mathematics and Operations Research, with a particular focus on Fuzzy-Mathematical Modelling. Earned Ph.D. in Operations Research from Sathyabama Institute of Science and Technology, Chennai, in 2024. Extensive educational background includes an M.Phil. in Mathematics from Madurai Kamaraj University and a B.Ed. in Mathematics and Environmental Studies from Bharathiyar University, complemented by foundational degrees in Mathematics from MS University-affiliated colleges. With over 14 years of experience as an Assistant Professor and Head at St. Joseph's College of Arts & Science for Women, Hosur. Demonstrated a strong commitment to teaching and academic leadership, guided 11 M.Phil scholars, 17 PG projects, and taught a wide range of undergraduate and postgraduate courses, including Algebra, Real and Complex Analysis, Operations Research, and Discrete Mathematics. Contributed significantly to research with 12 peer-reviewed publications, including 3 Scopus and 2 Web of Science, authored multiple academic books, and presented at numerous national and international conferences. Recognized with several awards, including the Best Senior Faculty Award by Novel Research Academy (2022) and the Isaac Newton Award at the PRIMES Conference (2021).

Dr. R. Suganthi, B.E., M.E., Ph.D., is currently serving as an Associate Professor in the Department of Electronics and Communication Engineering at Panimalar Engineering College. She earned her Ph.D. from Sathyabama University and holds an M.E. in Computer and Communication and a B.E. in Electronics and Communication Engineering from Periyar Maniammai College of Engineering, Anna University. With 17 years of teaching experience, she has published numerous papers in reputable international and national journals and at conferences. She is a life member of ISTE and a member of IEEE. Her primary areas of interest include Networks and Communication, where she actively contributes to academic and research advances.

Dr. N. K Priyadharsini is presently working as an Associate Professor in the Department of Computer Science and Engineering at P. A. College of Engineering and Technology, Pollachi, Tamil Nadu. She has 15 years of teaching and industry experience. She completed a PhD in video processing. Her major areas of interest include Data Structures, Operating Systems, Design and Analysis of Algorithms, Image Processing, and Web applications. She is a member of various professional bodies, including ISTE, IAETSD, IAENG, and IRED. She has published 15 papers in National and International Conferences and Journals. She has attended more than 45 national seminars and workshops and has served as an instructor for CCNA Courses. She is a Microsoft Certified Professional for developing Web Applications and Designing and Implementing Database with Microsoft SQL server.

Dr. S. Yuvaraj is currently working as an Assistant Professor in the Department of Computer Science and Engineering at Sri Eshwar College of Engineering, Coimbatore, India. He holds a Ph.D. in Computer Science and Engineering from Anna University, Chennai, and has accumulated over 12 years of academic experience in engineering education. His research interests lie in Cognitive Computing, Machine Learning, Deep Learning, and Artificial Intelligence. He has actively participated in various faculty development programs, seminars, workshops, and both national and international conferences. Dr. Yuvaraj is a professional member of IEEE and is known for his consistent contributions to the academic and research communities. He has published numerous research articles in reputed peer-reviewed international journals, demonstrating a strong commitment to innovation and excellence in computer science research.

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Dr. M. Pyingkodi is an Associate Professor in the Department of Computer Applications at Kongu Engineering College, Tamil Nadu, with 19 years of professional experience, including 17 years in teaching and 2 years as a Software Developer at Colizeeum Technology, Chennai. She holds a Ph.D. in Computer Applications from Anna University, Chennai (2020), and her academic background includes a Bachelor's in Computer Science (2003) and a Master's in Computer Applications (2006). Her areas of specialization and current research interests include Machine Learning, Deep Learning, IoT, Cloud Computing, and Bioinformatics. She has published around 71 research articles in reputed journals and delivered numerous guest lectures. She has successfully organized several sponsored events, including the AICTE-sponsored international conference RCHI 2019, FDP on Deep Learning (2021), and a CSIR-sponsored seminar on Precision Agriculture (2024). She received the Best Faculty Award (2019–2020) and was honored by the Scientific International Publishing House in April 2024.

Dr. M. Vallikkannu is currently an Assistant Professor at the Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi. Chennai - 62. I have completed my schooling at Sree Meenakshi Higher Secondary School, Karaikudi, and my BA (English) at Alagappa Arts College, Kamaraj University, Karaikudi. MA(English) at Pachayappas College, Madras University, Chennai, MPhil (English) at New College, Madras University, Chennai, PhD at Madras University, Chennai. I have a strong academic background and a passion for teaching and continuing my career to contribute to the field of education through dedicated research and student engagement. I have published 10 conference papers indexed in Scopus and UGC CARE.

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