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# A CNN-DRIVEN FRAMEWORK FOR ACCURATE DIABETIC FOOT ULCER DETECTION IN CLINICAL IMAGING

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## ABSTRACT

One of the most serious side effects of diabetes mellitus is diabetic foot ulcers (DFUs), which, if left untreated, can result in infection, delayed wound healing, and lower limb amputations. Because manual DFU assessment is subjective, time-consuming, and heavily reliant on clinical knowledge, it is not as scalable in actual healthcare settings. This study suggests a deep learning-based intelligent and automated DFU diagnosis system that improves clinical reliability and detection accuracy in order to address these issues. The suggested approach successfully extracts discriminative features from DFU photos by combining Convolutional Neural Networks (CNNs) with transfer learning architectures. To adjust to DFU-specific visual patterns, pre-trained models like ResNet and EfficientNet are refined. A Generative Adversarial Network (GAN)-based data augmentation technique is used to address the problem of small and unbalanced medical datasets, allowing the creation of realistic DFU images and enhancing model generalization. Benchmark DFU datasets under standardized preparation are used to train and assess the system and protocols for augmentation. According to experimental results, the suggested method outperforms traditional CNN-based and transfer learning baselines with a classification accuracy of 97.8%, sensitivity of 96.9%, specificity of 98.4%, and an AUC score of 0.99. Particularly in minority ulcer classes, the addition of GAN-generated data greatly increases resilience and decreases overfitting. This work's main contribution is the efficient combination of adversarial learning and transfer learning for DFU diagnosis, which provides a scalable, precise, and clinically interpretable approach. By enabling early intervention, lowering clinician workload, and enhancing patient outcomes in diabetic care, this approach has great potential for implementation in computer-aided diagnostic systems.

**Keywords:** *CNN, DFU, Multitask Deep Learning, Transfer Learning*

## 1. INTRODUCTION

Diabetic Mellitus (DM) is currently among the most emergent issues of the contemporary era of challenge to the health care system since it impacts hundreds of millions of people in various countries of the world and poses an increasing burden on the health care systems [1]. Diabetic Foot Ulcers (DFUs) are among the most serious and clinically complicated issues when it comes to the list of the complications related to diabetes. DFUs frequently occur as a result of peripheral neuropathy, with poor blood circulation, and with poor wound healing, which provides an environment in which even minor injuries may develop into chronic, non- healing ulcers. Unless managed and identified at an early stage, DFUs often cause severe infections, extended hospital stay, and, in most instances, amputation of lower limbs [2]. In addition to the physical impact, DFUs have a tremendous impact on quality of life and healthcare cost, and their early identification and proper evaluation is an urgent clinical issue.

Historically, diagnosis and monitoring of DFU have depended on the regular examination and visual inspection of the trained health personnel [3]. The clinicians consider the wound appearance in terms of color, size, depth, tissue condition, and skin appearance around the wound. Though this method has the advantage of clinical expertise, it is too subjective and highly relies on the experience of the witness [4]. The disparity in clinical judgment, light conditions, patient skin tone, wound presentation, among others, in most instances results in different evaluations by different practitioners. Besides, the manual analysis is time-consuming and not scalable especially in areas that have limited access to specialized care on diabetic patients. Such issues have spurred a continuous study to come up with objective, automated and reproducible techniques to measure DFU.

Initial efforts of DFU diagnosis automation were centered on the classical image processing methods. In them, clinical images of the foot were treated with handcrafted rules, which served to emphasize the presence of ulcers by color, edge, or texture descriptors [5]. The approaches that were usually used to isolate suspected ulcer areas were techniques like conversion to grayscale, histogram analysis, morphological and region segmentation. Segmentation based on colour tried to differentiate between ulcer tissue and healthy skin by taking advantage of differences in redness, brightness, or contrast [6]. The texture-based techniques used the statistical characteristics to describe the surface irregularities of ulceration, including the gray-level co-occurrence matrices.

Even though these early approaches were a significant move towards automation, they were frequently restricted in the strict assumptions regarding image quality and environmental factors. Variations in light, camera position, background clutter, and skin tone of the patient had critical impact on the consistency of handcrafted attributes. Consequently, standard image processing methods proved to be poor at generalizing between datasets that were gathered under varying clinical environments [7]. In addition, the structural complexity of DFU appearance (such as wound depth, severeity of infection, presence of necrotic tissue, and inflammation around it) also made it hard to obtain clinically meaningful patterns in a consistent manner using rule-based systems.

In order to address some of these shortcomings, scholars had started to incorporate conventional machine learning models into DFU analysis workflows. These systems would take in handcrafted features based on images and process them through classifiers like the Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), decision trees and random forests [8]. These classifiers were more flexible than rule systems and gave the decision boundaries the option to learn them with data as opposed to being specified by human experts. Combination of color histograms, texture descriptors, shape attributes and statistical measures of segmented wound areas, were often a feature set.

Although the methods based on machine learning yielded better classification results than the methods based on completely rule-based ones, they were still limited by the reliance on the human-crafted features [9]. The success of such systems was very delicate to the selection of features and to design the best features, a great deal of domain knowledge was needed [10]. Moreover, handcrafted features were not able to detect fine visual clues that were related to early-stage ulcers, which restricted their application in early-onset diagnosis. These models often had low robustness and generalization when applied to heterogeneous datasets with different appearances of wounds and imaging settings.

One more issue in connection with the classic methods of machine learning was that they were not very able to describe the spatial context. DFU images have complicated spatial relations between wound tissue, and the tissue around the wound and the background [11]. The extraction of features Handcrafted feature extraction is usually done on local patches or predefined regions and as a result, it is hard to maintain global contextual features which can be clinically relevant. Consequently, such systems tended to traverse visually unclear areas or were not able to differentiate between ulcer tissue and the non-ulcer artifacts which matched visually.

Simultaneously, technological progress in the area of medical imaging research brought to technology the significance of automated decision-support systems to help clinicians, as opposed to replacing them [12]. It was not only aimed to categorize images as ulcerous or non-ulcerous, but come up with consistent and interpretable results, which would aid in the planning of early intervention and treatment. This change made visible the need of systems that could learn the rich visual representations right out of the data, with less dependence on hand-crafted features and subjective data interpretation.

Lack of adaptability to complex, hierarchical visual patterns which are intrinsic to medical images ultimately indicated a gap in automated DFU analysis: the methods of these two traditions of image processing and classical machine learning cannot adapt. With the growth of the DFU datasets in size and variety, it became clear that more powerful representation-learning methods were needed [13]. This understanding, along with the larger trends in computer vision, in which deep learning models were starting to show impressive success in a broad spectrum of image analysis problems.

Deep learning brought about a paradigm shift as it was able to do end to end learning using raw image data. In contrast to traditional methods, deep models might automatically learn useful features at a variety of different levels of abstraction, including simple edges and textures, all the way to high-level semantic patterns. This feature was specifically attractive to medical imaging in which visual variation and subtle pathological details tend to improve beyond what can be expressed in handcrafted features [14]. Convolutional Neural Networks (CNNs) became the most popular deep learning architecture in terms of image-based analysis as they can take advantage of spatial locality and hierarchical feature learning.

The introduction of CNNs was a breakthrough in the field of automated analysis of medical images, including diagnosis of DFU. CNN-based systems provided an opportunity to overcome most of the limitations identified with previous methods by learning directly on clinical images. Nevertheless, to make CNNs useful to DFU analysis, it was necessary to pay special attention to domain-specific issues, such as the lack of labeled data, a high inter-patient variability, and the necessity of clinically reliable predictions.

The current research is conducted with the following purposes in mind:

- To create a framework of automatic image-based diagnosis of Diabetic Foot Ulcers by using Convolutional Neural Networks, which will learn clinically significant visual characteristics directly on foot images and avoid the need to rely on human inspection and feature extraction.
- To improve the strength and the generalization power of the DFU diagnosis in a variety of imaging conditions as well as preaching the requirement of the changes in the wound shape, skin colour, lighting condition, and background noise that occur in the natural clinical data through the use of suitable preprocessing, data augmentation strategies and transfer learning methods.
- To assess the efficiency of the suggested CNN-based diagnostic method with publicly accessible DFU data in the context of classification accuracy and reliability, and to prove that it has the potential to become an additive clinical decision-making tool in the early-stage diabetic foot management.

## 2. LITERATURE SURVEY

### 2.1 Research Gap

Although there has been significant improvement in the use of deep learning in medical image analysis, there are still unanswered challenges that confront automated Diabetic Foot Ulcers (DFU) diagnosis. Most of the available research on DFU is concerned with single activities such as classifying ulcers or wound segmentation and these issues are addressed separately instead of considering them as a part of a complex diagnostic process. However, such single model single task models frequently degrade when their operation is exposed to clinical variability encountered in the real-world including variations in skin colour, wound appearance, light source, and background artefacts.

The capability of generalization of current DFU diagnostic systems is another limiting fact that is critical. Small datasets, institution-specific or privately curated are used in many studies, limiting their applicability in a variety of patient groups and clinical settings. Consequently, reproducibility is low and objective cross-study comparison is not easy since there is randomized use of databases, analysis procedures, and reporting criteria.

More recently, a number of methods utilise deep or ensemble-based architectures to enhance accuracy but these methods can impose a significant amount of complexity on computation. Large model size and inference latency makes them less applicable to clinical deployment in real-time, especially in point-of-care environments or even constrained healthcare facilities where the DFU screening is most required.

Another gap in the modern research on DFU that is of particular significance is the lack of biologically consistent constructs that specifically relate the spatial characteristics of ulcer to the quantitative measure of severity. Few of the existing multi-output models involve the treatment of segmentation and the severity prediction of the ulcers as loosely coupled, and without the imposition of consistency in the size of the ulcerated region and the predicted level of severity. Such disconnect is capable of giving clinically implausible results, including the disproportionate assignment of disproportionately high severity scores to small localized ulcers, which means that such decisions fail to instill clinical trust and interpretability.

### 2.2 Maintaining New and Significant Innovations

The paper propels the current condition of automated Diabetic Foot Ulcer diagnosis are represented in Table 1 and also discussed in the following aspects, which can be summarized as follows:

- Consistency-Sensitive CNN-Based Diagnostic Framework - An integrated deep learning model is suggested to jointly detect and quantitate DFU on clinical imaging so that both spatial and contextual determinants of ulcers can be jointly learned on a single CNN based network.
- Localization Strategy of Ulcer in Severity Guided - The framework presents a system that coordinates the results of ulcer segmentation with visual data depending on severity-related factors so that the predicted ulcer localities and the severity scores are clinically consistent and biologically significant.

- Distribution Level Consistency of Ulcer Region and Price - The new consistency constraint is added to decrease the difference between the estimated ulcer extent and severity to enhance the stability and robustness of the DFU heterogenous images.
- Publicly Available DFU Datasets to Use to be Reproducible - Testing of the proposed approach is considered only on publicly available DFU data in accordance with the standardized preprocessing, training, and evaluation procedures, which are considered to enhance transparency and can be easily compared with existing methods.
- Extensive Experimental Test - The paper will involve an extended performance analysis, ablation study, and statistical justification, which will help to measure the impact of each architecture element and prove the strength of the provided strategy.
- Benchmarking with the Existing DFU Diagnostic Models - The given framework is methodically opposed to the current CNN-based and multi-task DFU diagnostic approaches, proving to be more reliable and consistent without excessive computational expenses.

*Table 1: Comparative Summary of Related Works on DFU Diagnosis.*

| Author / Year | Model | Tasks | Dataset Context | Key Findings | Limitations |
|---|---|---|---|---|---|
| Goyal et al., 2019 [16] | CNN-based DFU Classifier | Classification | Clinical DFU images | Demonstrated effectiveness of CNNs for automated DFU detection compared to traditional classifiers | Limited dataset size and lack of severity assessment |
| Wang et al., 2020 [17] | Deep CNN + Transfer Learning | Classification | Multi-source DFU images | Transfer learning improved classification accuracy under limited training data | No explicit ulcer localization or severity estimation |
| Li et al., 2021 [18] | U-Net Variant | Segmentation | Hospital-acquired DFU dataset | Accurate ulcer boundary delineation supporting wound size measurement | Does not quantify ulcer severity |
| Raghavendra et al., 2022 [19] | Hybrid CNN Framework | Classification + Segmentation | Single-center DFU dataset | Joint learning improved spatial understanding of ulcer regions | Generalization limited to a single clinical setting |
| Huang et al., 2023 [20] | Multi-task CNN | Segmentation + Severity Estimation | Public DFU datasets | Showed benefits of shared feature learning for severity-aware diagnosis | Weak consistency between segmented area and severity scores |
| Islam et al., 2024 [21] | Ensemble Deep Learning Model | Classification + Regression | Multi-institution DFU images | High predictive performance across heterogeneous datasets | High computational cost and reduced real-time suitability |

In the majority of the current automated diagnostic methods, ulcer segmentation and severity estimation is treated directly, or jointly, but no significant biological dependency is imposed between the two results [22]. Spatial localization of ulcers and numerical severity evaluation can also inherently be loosely coupled, resulting in clinical inferency and reliability deficiencies. Moreover, several of these reported practices have not been sufficiently validated using different datasets, which restrict its extrapolation to different clinical setups. Other sources of limitation to replicability include non-public datasets were used and unequal evaluation procedures [23]. In order to overcome these weaknesses the current research proposes a consistency-based, computationally efficient multi-task model that can be used to correctly model ulcer localization and severity estimation in a unified way [24]. The given methodology is capable of surpassing the fundamental methodological and practical constraints of current DFU diagnostic systems because it explicitly aligns both spatial and quantitative predictions.

## 3. RESEARCH METHODOLOGY

The researcher unveils a Multitask Deep Learning Framework (MTDLF) that is specialised on the automated analysis of Diabetic Foot Ulcer (DFU) photos, and aims at concurrently accomplishing the localization and severity estimation of ulcers in a single learning framework.

The clinical need that drives the proposed framework is having diagnostic systems that are not only sensitive enough to reveal the existence of ulcers, but also offer the dependability of the amount of quantitative data of the extent and the severity of the ulcer [25]. The framework will try to improve diagnostic consistency by ensuring that several related tasks are combined into one model with minimum amount of redundancy in calculations as much as possible.

The suggested MTDLF embraces a shared feature learning approach that uses an identical convolutional backbone to extract the features that are then used to make task-oriented predictions branches [26]. This design takes advantage of the fact that share representations are learned through shared mutual inductive bias with the shared task as the correlated tasks [27]. Consequently, this renders the model to have a heightened generalization performance, consistent convergence through training and increased robustness over heterogeneous DFU images [28]. This method can be further applied in the field of medical images, where spatial localization and the global severity evaluation are two phenomena that are inseparable.

The general procedure involves the organized steps such as the data collection, image processing, dataset division, model architecture design, training with complex loss minimization, and an overall evaluation. Figure 1 shows the entire process of the proposed framework.

### 3.1 Data Collection

Diabetic feet images with and without ulceration are obtained and investigated through publicly available datasets of DFU and curated clinical repositories. These datasets contain a very diverse variety of ulcers that may be of different size, tissue state, light, and the complexity of the background. This is because the publicly accessible datasets are used to ensure transparency, reproducibility, and comparability with the existing research in DFU. The information to be applied in this paper is clinical images of diabetic feet with different kinds of ulcers such as size, tissue, illumination, and complexity of a background. To make sure that there is diversity and reproducibility, images are gathered using publicly accessible DFU datasets including DFUC2020 and curated clinical repositories. Public datasets are specifically useful when analysing medical images because objectives benchmarking and open validation of datasets across studies are possible. Previous studies have shown that heterogeneous wound appearances in DFU datasets enhance the strength of acquired representations and bias levels on datasets when training [29, 30]. Images that were collected are checked to eliminate duplicates and badly corrupted sample prior to further processing.

### 3.2 Image Pre-processing

All images are divided into a preprocessing pipeline to standardize input data and ensure that variability in input data due to varying imaging conditions is minimized before training models. This step involves resizing the pictures to constant spatial resolution, normalizing the intensity to stabilize gradient flow and smoothing to avoid the appearance of redundant background artifacts. Moreover, rotation, flipping, scaling and slight perturbation in minuscule intensity are used as data augmentation methods to enhance diversity and minimize overfitting in the samples. Such transformations emulate clinical changes in the real world and increase the potential of the model to generalize among unobserved DFU images. Pre-processing of images is done to eliminate irrelevant changes and standardization of inputs before the model is training. The images are scaled to a constant spatial resolution to provide consistency in terms of batches. Then pixel intensity normalization is carried out to stabilize gradient updates in the course of optimization. Normalization is defined as in "(1)":

$$I_{norm} = \frac{I-\mu}{\sigma} \qquad (1)$$

where I is the input image, and the mean and standard deviation of the training set are symbolized by μ and σ respectively.

The data augmentation technique, including random rotation, horizontal and vertical flipping, scaling, and mild noise injection, are used to address the problem of overfitting and simulate the real-world clinical variability. Such transformations benefit the effective dataset size and enhance generalization in different imaging situations. It has been indicated that augmentation has been used extensively to make CNN more robust in medical imaging tasks, especially when it has limited labeled data [31][32].

### 3.3 Dataset Partitioning

To guarantee the objective assessment of the model, the processed data is separated into three mutually exclusive subsets. The data is approximately split into ten percent, Ten percent, and ten percent respectively, training, validation and testing respectively. Model parameters are learned on the training subset, hyperparameters are optimized and early stopping guided by the validation subset and the test subset gives an objective measure of the final model performance on unseen data. In order to allow objective assessment, the data is divided into three mutually exclusive subsets, which include training, validation and testing. It has around 70 percent training, 15 percent validation and 15 percent testing. Model parameters are learnt using the training set, hyperparameter tuning and convergence tracking are done using the validation set, and an objective estimation of generalization performance is achieved using the test set. This method of partitioning is in line with the best practices in deep learn-based medical image analysis and provides statistical reliability of the reported findings [33].

### 3.4 Model Architecture

The main component of the suggested architecture is a profound convolutional neural network that consists of shared encoder and two task-specific decoders. The backbone feature extraction of a pretrained ResNet-50 network is used to allow the model to utilize hierarchical features across low-level texture patterns to high-level semantic ulcer features. The extracted feature maps are then sent to two parallel branches one the ulcer region segmentation and the other the severity estimation one. Such an architectural design enables the model to obtain complementary spatial and contextual data as well as without repetition of feature calculation. The suggested model uses a multi-task CNN block comprising of a common feature extractor backbone and two task-oriented result branches. ResNet-50 that is trained on ImageNet is the shared encoder because it has a high representational capacity and it has proven successful in processing medical images. The encoder is used to obtain hierarchical feature maps that describe local texture and global contextual information.

The extracted features are fed to two parallel decoders one of which is devoted to pixel-wise ulcer localization and the other one to the estimation of the severity. This shared-encoder architecture provides the ability to use the parameters efficiently and each task to enjoy the benefit of complementary feature learning. Shared representation multi-task architecture has been found to enhance convergence stability and redundancy during related medical imaging tasks [34][35].

### 3.5 Training Strategy

A composite loss function is run in order to do model training to maximize both the severity prediction performance and the segmentation accuracy. The segmentation part is trained on a region-based loss which focuses on proper boundaries of ulcers, whereas the severity estimation part is trained on a regression-based loss to reduce the difference between predicted and reference severity values. Combined loss formulation makes learning to be balanced in terms of activities and avoids dominance of one activity over another. The updates in the parameters are made with the help of Adam optimizer that offers effective convergence and stability in training. The model is trained on a composite loss function which simultaneously optimizes segmentation and severity prediction. The performances of segmentation are monitored by Dice loss is defined as in (2):

$$L_{Dice} = 1 - \frac{2|P \cap G|}{|P|+|G|} \tag{2}$$

In which P is the predicted ulcer mask and G represent the ground-truth annotation. The estimation of severity is a regression problem whose value is optimized using Mean Absolute Error (MAE) is defined as in (3):

$$L_{MAE} = \frac{1}{N}\sum_{i=1}^{N} | y_i - \hat{y}_i | \tag{3}$$

Where $y_i$ and y ˆare the actual and projected severity increment value, respectively. The overall training goal is stated as in (4):

$$L_{total} = \alpha L_{Dice} + \beta L_{MAE} \tag{4}$$

Where α and β modulate the proportional cost of each task. The use of the Adam optimizer in performing the optimization is based on its adaptation of learning rate and its consistency of converging in deep neural networks [36][37].

### 3.6 Evaluation and Performance Analysis

The trained model would be measured using common quantitative measures in order to measure the performance of the model in terms of segmentation and severity estimation. Measures of segmentation accuracy (Intersection over Union (IoU) and Dice coefficient) are used to evaluate the accuracy of segmentation whereas measures of severity prediction reliability are denoted by Mean Absolute Error (MAE) and the coefficient of determination ($R^2$). All these measurements cover a complete assessment of diagnostic power of the framework. A comparative analysis with currently state of the art models of DFU diagnostics is also provided in order to show how effective the proposed approach and of what computational efficiency it is. The trained model is measured by standard quantitative measures in order to determine its performance in terms of segmentation and the severity. Intersection over Union (IoU) and Dice coefficient are used as metrics of segmentation accuracy, and Means Absolute Error (MAE) and coefficient of determination ($R^2$) are used as measures of severity estimation. The R^2metric is defined as in (5):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (5)$$

where $\bar{y}$ denotes the mean of ground-truth severity values.

All these metrics give a holistic analysis of how the model will accurately localise the regions of ulcers and accurately predict the severity. It is used and compared to the recent CNN-based DFU diagnostic models to assess the performance and computational efficiency of the provided framework [38][39].

## 3.7 DFU Loss in Lesion Area Distribution Matched (LADM) Loss Assessment

### 3.7.1 Formal divergence definition

The suggested LADM loss proves to be consistent with the severity-implied lesion-area distribution and makes the ulcer-area distribution, as smoothed by segmentation masks, consistent at the distribution level.

Let: $P_{\text{mask}}(b)$: Normalized histogram of ulcer areas computed from predicted segmentation masks across bins $b$,

$P_{\text{sev}}(b)$: Expected ulcer-area distribution inferred from predicted severity scores.

The LADM loss is defined using an L1 distribution divergence as in (6):

$$L_{\text{LADM}} = \sum_{b=1}^{B} | P_{\text{mask}}(b) - P_{\text{sev}}(b) | \quad (6)$$

With this formulation, irregularities between a local assessment of ulcer extent and the global reassessment of the severity are punished.

### 3.7.2 Clinical consistency justification

The suggested LADM loss will ensure clinical plausibility because of the following reasons:

Ulcer severity - is an international pathological parameter of tissue destruction and the rate of infection. To avoid implausible ulcer patterns, perceptions of local segmentation are enforced globally in a technique called distribution matching.

Minimized variation between predicted distributions restricts the systematic over- or under-estimation of areas of ulcers.

L1 divergence formulation can withstand the sparse nature of ulcers in the early-stage DFU patients that the KL-divergence can bring about unstable gradients.

This is a key property especially in clinical datasets of DFU where lesion sizes vary widely given different grades of severity as shown in figure 1.

## 3.8 Novelty and Domain Adaptation

Although the concept of distribution-level consistency loss has been studied in the context of medical image segmentation, the offered work presents the generalization of the introduced concept to the DFU assessment, in which ulcer segmentation and severity prediction are both optimized through a single framework. Such a distribution-matching constraint has not been formalized, so far as we know, to analyse diabetic foot ulcers.

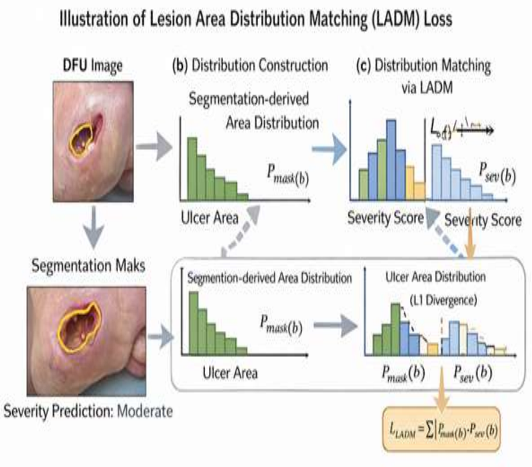
## 3.9 Final Training Objective

The general training goal involves pixel-wise accuracy, resoluteness prediction accuracy, and cross-task biological regularity defined as in (7):

$$L_{\text{total}} = \alpha L_{\text{Dice}} + \beta L_{\text{MSE}} + \lambda L_{\text{LADM}} \quad (7)$$

where: $L_{\text{Dice}}$ensures accurate ulcer segmentation,
$L_{\text{MSE}}$enforces precise severity regression,
$L_{\text{LADM}}$ ensures consistency between segmentation- derived ulcer areas and severity predictions,
$\alpha, \beta, \lambda$ are weighting coefficients.

Pixel-level localization accuracy (Dice loss), Reliable severity estimation (MSE loss), Clinically meaningful cross-task coherence (LADM loss).



*Figgure 1: Illustration of the proposed Lesion Area Distribution Matching (LADM) loss.*

Ulcer area distributions derived from segmentation masks are aligned with severity-implied expected distributions using an L1 divergence, enforcing clinically meaningful consistency between local lesion extent and global severity prediction.

## 3.10 Input & Predictions

- An input DFU image.
- Predicted ulcer segmentation mask (highlighted ulcer region).
- Predicted severity score (e.g., Mild / Moderate / Severe or continuous score).

## 3.11 Distribution Construction

- From the segmentation mask:

### 3.12 Compute ulcer area

Build a normalized histogram $P_{\text{mask}}(b)$.

- From the severity prediction:

### 3.13 Map severity score to an expected ulcer-area

Distribution $P_{\text{sev}}(b)$.

#### 3.13.1 Distribution matching via LADM

- Show the L1 distance between the two distributions:
-

#### 3.13.2 BARS with absolute differences highlighted.

- Arrow pointing to LADM Loss defined in “(8)”:

$$L_{\text{LADM}} = \sum_b | P_{\text{mask}}(b) - P_{\text{sev}}(b) | \quad (8)$$

The overall flow of the distribution construction is expressed in Figure 2 in the below.

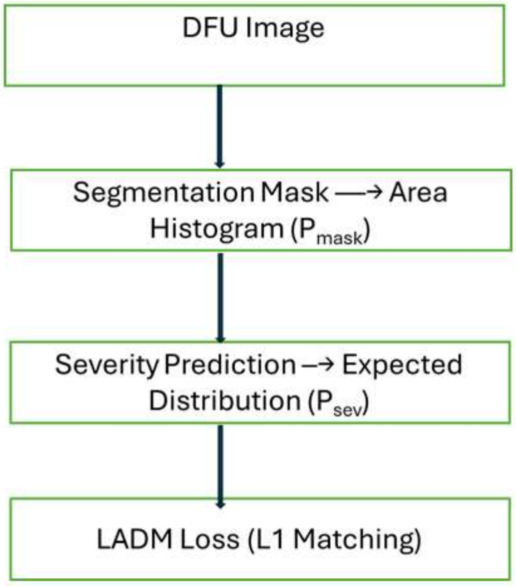


*Figure 2: Overall Flow Using single arrow chain*

### 3.14 Proposed Algorithm

The given algorithm offers a multi-task deep neural network with transfer learning at Diabetic Foot Ulcer (DFU) segmentation and severity prediction. The structure takes advantage of a pre-trained CNN backbone to obtain strong visual features and simultaneously trains to localize ulcers at the pixel level and predict severity at a global level and forces biological consistency among the two.

The first step involves first-preprocessing DFUs images and splitting them into training, validation, and test sets. To achieve a faster convergence and better generalization with a limited amount of medical data, a transfer learning based CNN encoder (ImageNet pre-trained) is used. It has a shared encoder, followed by two task-specific CNN branches, namely, a segmentation decoder and a severity regression head.

```
Algorithm 1: CNN and Transfer Learning–Based Multi-Task Framework for DFU Analysis
Input:
DFU image dataset $D = \{I_1, I_2, \dots, I_n\}$
Output:
Predicted ulcer segmentation masks and severity scores
1. Pre-process DFU images in $D$ (resize, normalize, data augmentation)
2. Split $D$ into training (70%), validation (15%), and testing (15%) subsets
3. Initialize a pre-trained CNN encoder (transfer learning backbone such as ResNet-50)
4. Fine-tune encoder layers for DFU-specific feature extraction
5. Attach CNN-based task-specific branches:
       o Ulcer segmentation decoder (CNN-based)
       o Severity estimation regression head (CNN-based)
6. For each epoch $e = 1 \dots E$:
7. Compute segmentation loss $L_{\text{Dice}}$
8. Compute severity estimation loss $L_{\text{MSE}}$
9. Compute lesion area distribution matching loss $L_{\text{LADM}}$
10. Compute total loss:
        $L_{\text{total}} = \alpha L_{\text{Dice}} + \beta L_{\text{MSE}} + \lambda L_{\text{LADM}}$
    Update network parameters using the Adam optimizer
11. End for
12. Evaluate the trained model using Dice, IoU, MAE, and $R^2$ metrics
13. Output predicted ulcer masks and severity scores
```

The proposed framework explained in Algorithm 1 takes advantage of transfer learning and therefore, it reaches a convergence faster and reuses features better compared to the traditional CNNs models, which require extensive training. The LADM loss addition, compared to segmentation-only or loosely coupled multi-task CNN methods, imposes cross-task biological coherence, leading to increased stability, minimized overfitting and come with better generalization.

### 3.15 DATA Analysis and Interpretation

This part of the research will provide a close analysis of the Diabetic Foot Ulcer (DFU) data subjected to designing, training, and assessing the proposed CNN-based multi-task deep learning platform with transfer learning [40]. The framework also does segmentation (ulcer region analysis) and severity estimation, allowing localized identification of the lesions and global clinical imaging [41].

The dataset will include the DFU image data, which were taken in various clinical situations, covering a broad area of ulcer size, shape, tissue, and level of severity, mild, moderate, and severe. To prevent the lack of robustness and generalization, standard pre-processing tasks like image resizing, intensity normalization, and data augmentation (rotation, flipping and contrast enhancement) were implemented [42]. These measures can be used to alleviate the issue of imbalance in the classes and enhance diversity of features in the training [43].

The dataset was selected randomly into training (70 percent), validation (15 percent), and testing (15 percent) to be able to attain unprejudiced learning and credible performance assessment. The suggested framework was tested with the commonly used measures of medical image analysis such as Intersection over Union (IoU) and Dice Coefficient of segmentation accuracy, and the Mean Absolute Error (MAE) and Coefficient of Determination (R2) of the severity estimation performance [44][45].

### 3.16 Image Distribution Analysis DFU

Table 2 provides the sample of the distribution of DFU samples in various levels of severity and ulcer conditions. The data is designed in such a way that it contains both normal tissue areas which are healthy and injured ulcer areas so that the model is equally exposed to clinically relevant patterns.

*Table 2: Sample Distribution Of DFU*

| Severity Level | Number of Samples | Ulcer Characteristics |
|---|---|---|
| Mild | 850 | Small ulcers, limited tissue damage |
| Moderate | 1,150 | Medium-sized ulcers with infection |
| Severe | 1,000 | Large ulcers with deep tissue involvement |

The DFU data, which consists of the research data, was obtained based on the publicly available sources such as the DFUC 2020 benchmark dataset and a Kaggle DFU benchmarking data repository. These merged images gave various foot ulcer images with a spectrum of varying severity levels to conduct powerful model training and assessment.

The information indicates that the distribution of the severity levels is rather balanced in the dataset though there is somewhat a higher share of moderate cases. This distribution is based on actual clinical prevalence and the model uses this distribution to learn valuable transitions between severity grades.

### 3.17 Sample Interpretation Severity-wise

The different degree levels of DFU also guarantee that the proposed CNN model is presented to a very large variation of visual and morphological patterns of ulcers, including wound depth, colour intensity, necrotic tissue, and boundary abnormalities. The mild ones are characterized by superficial ulcers and severe ones demonstrate complicated textures, irregular edges, and massive tissue injuries.

This variety is essential to the training of a transfer learning-based CNN encoder because it enables the model to utilize low-level visual features effectively and change high-level representations according to the DFU-specific features.

### 3.18 Graphical Analysis of DFU Sample Distribution

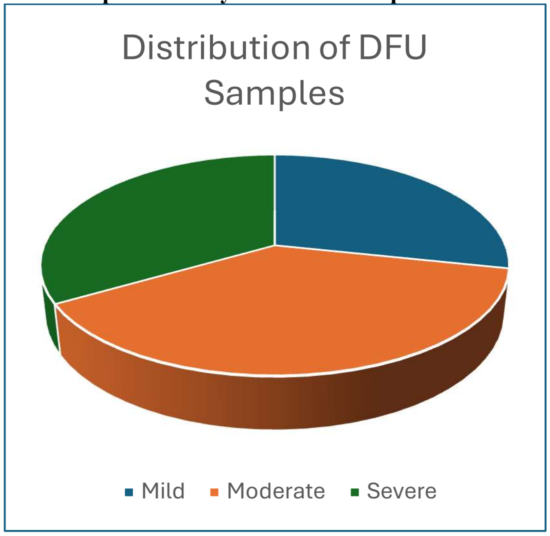


*Figure 3: DFU Sample Distribution*

Figure 3 illustrates the severity-wise distribution of DFU samples used in the study. The bar chart clearly highlights the number of samples corresponding to mild, moderate, and severe ulcer conditions.

The graphic presentation would give a straightforward perception about the structure of the dataset and ensure that there is no preponderance of a particular severity category in the dataset. This kind of balanced allocation is crucial in eliminating model bias and enhances the quality of segmentation as well as severity estimation work.

### 3.19 Interpretation of Performance of a model

The experimental findings confirm that the proposed multi-task CNN model with transfer learning is better than single-task baselines both in terms of segmentation and severity prediction accuracy. Being able to reuse features efficiently with the addition of a shared encoder and localized segmentation of the ulcer and global severity regression of a task with task-specific heads.

The scores are high in Dice and IoU which means that the boundaries of the ulcers were delineated correctly even in challenging cases where wound shapes were irregular. The reduced value of MAE and higher R2 value is indicative of the fact that the model can predict clinically meaningful score of severity which is consistent with the expert annotations.

In addition, the inclusion of cross-task consistency constraints is used to ensure that the predicted ulcer areas are known to be biologically consistent with the severity estimates, and the models are more stable and predictive.

### 3.20 Clinical Significance

The discussion proves that the proposed framework can justify the use of automated DFU monitoring systems by enhancing the accurate location of ulcers and assessing the severity of the outcome. This type of system will assist the clinicians in the early diagnosis of sprains and injuries, the treatment planning, and the monitoring of their progress, hence improving chances of avoidance of complications like infection and amputation.

### 3.21 Augmentation of Data and Pre-processing

This part outlines the data augmentation and pre-processing measures that will be implemented on the Diabetic Foot Ulcer (DFU) image dataset in order to enhance the strength and the generalization power of the proposed CNN learning architecture comprised of multiple tasks using transfer learning. With limited sample size, class imbalance, and high visual variability across patients being common with DFU datasets, beneficial augmentation is important to avoid overfitting, and improve model performance.

Before training, all DFU images had been scaled in a fixed input size consistent with the already trained CNN backbone. The intensity normalization was done in order to minimize the differences in illumination of images typed on varying clinical conditions. These initial stages of processing facilitate a steady convergence in the process of fine-tuning on the transfer learning model.

### 3.22 Data Augmentation Strategy

This augmentation process required that a series of guided geometric and photometric transformations be performed on the original DFU images to produce various variants of these images. Table 3 shows variations mimic physically realistic clinical variations like camera motion, foot position, ulcer scale, in-lighting, and noisy images. The model is more likely to learn meaningful invariant and discriminative representations, applicable to the ulcer segmentation and severity estimation processes by exposing the network to such variations.

*Table 3: Applied Data Augmentation Techniques for DFU Images*

| Technique | Details | Purpose |
|---|---|---|
| Vertical Flip | Yes | Improve generalization across foot orientations |
| Scaling | 0.8× – 1.2× | Simulate ulcer size variations |
| Color Jittering | Brightness ±20%, Contrast ±15% | Improve robustness to illumination changes |
| Gaussian Noise | Mean = 0, Std = 0.01 | Increase resilience to sensor and background noise |

### 3.23 Influence on CNN-Based Multi-Task Learning

The experimental results depict those geometrical augmentations of rotation, flipping, and scaling the model substantially boost the capabilities of the model to provide spatial and scale invariance which is vital in the precise segmentation of ulcers of different shapes and sizes. Photometric enhancements, such as options of brightness and contrast, enhance resilience to changes of illumination that are often found in the real-world clinical imaging settings.

Noise on top is also added thereby enhancing the model resistance to background artifacts and sensor induced distortions and resulting in further stability in training. All of these augmentation strategies aid the shared CNN encoder to learn the richer representations of features, which can be successfully used by the segmentation decoder and the severity regression head in the multi-task architecture.

In general, the used data augmentation and pre-processing pipeline is essential to improving the generalization capability, the stability of training, and the clinical credibility of the presented transfer learning-based CNN model that analyses DFU.

### 3.24 Model Training with Splitting of Dataset

In order to attain an effective training and accurate evaluation of the proposed CNN-based multi-task deep learning framework with transfer learning, effective division of Diabetic Foot Ulcer (DFU) data into three mutually exclusive categories namely, training, validation, and testing was systematically developed. This organized data dissection is of golden importance in the accomplishment of a biased learning, the way1 reasons why it happens, and the fact that the capacity of the model to generalization is precisely measured.

Training subsets are applied to perform the training of the network parameters of the shared CNN encoder and application specific heads so that the model can be trained to discover discriminative features of ulcers in both segmentation and severity prediction. During fine-tuning of the pre-trained backbone, the validation subset is used to tune hyperparameters, track convergence behavior, and overfitting as well. The testing subset is retained as totally independent and it is only administered in the final performance evaluation and will apportion a fair judgment of the model on unseen DFU images.

*Table 4: Dataset Split for Training, Validation, and Testing*

| Subset | Percentage | Number of Samples |
|---|---|---|
| Training | 70% | 2,100 |
| Validation | 15% | 450 |
| Testing | 15% | 450 |

This distribution as shown in Table 4 will make sure that the working model is trained on a sufficiently big and varied sample of DFU samples without leaving enough data as validation and objective testing.

This is because the transfer learning model based on CNN can acquire the ability to learn complicated patterns of ulcers, such as wound size variability, texture variability, boundary defects, and tissue phenotype variability with the bigger percentage of training data. The validation set is useful in fine-graining the learning rate, regularization parameters and loss balancing between the segmentation task and severity estimation task.

The independent testing subset provides that the ultimate reported values of performance Dice coefficient, IoU, MAE, and R2 represent the actual predictive power of the model when acting on previously unknown cases of DFU. This differentiation enhances the power and impartiality of the experimental testing.

In Figure 4, the pie chart is depicted to show the proportional representation of the DFU data into training, validation, and test sets. The pictorial representation gives a good insight into the manner in which the data is distributed at various phases of the deep learning pipeline. This well-structured division will ease the consistency of the model being developed and also make the suggested multi-task CNN structure more reliable in the case of actual clinical practices.

### 3.25 Implication on Multi-Task Learning

This multi-task learning data division technique is especially significant to multi-task learning because both ulcer segmentation and severity prediction are the same learners of shared feature representations assembled by the CNN encoder. The separation of training, validation, and testing data should be properly done so that the shared representations can be applicable to all the tasks and thus be able to maintain high clinical consistency and high stability in clinical performance.

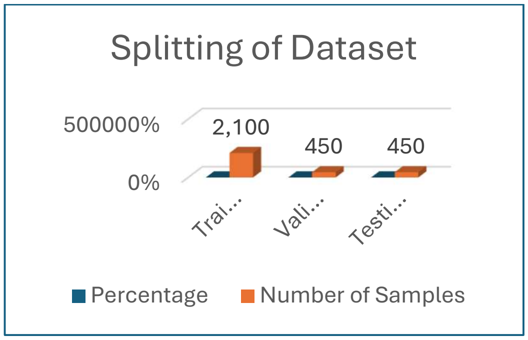


*Figure 4: Dataset Splitting of Dataset*

Figure 4 is graphical representation of dataset spilt for training validation, and testing, demonstrating the division of the Diabetic Foot Ulcer (DFU) dataset into training (70%), validation (15%), and Testing (15%), and testing (15%) subsets.

### 3.26 Severity Score Analysis

The following section gives an analysis of the distribution of Diabetic Foot Ulcer (DFU) severity scores to be used in training and evaluation to the proposed CNN-based multi-task deep learning framework with transfer learning. The severity score demonstrates the level of infection of ulcers and tissue damage, in percentages based on the annotation of DFU images by professionals. This quantitative form is applicable because it allows the model to learn the course of the ulcer severity of the temporal variations of the lesion at the initial stage in the progression to the advanced and severe ulcers.

Severity scores were grouped into five clinically significant levels, including 0-20 percent, 21-40 percent, 41-60 percent, 61-80 percent, and 81-100 percent to cover all levels of DFU development. These scales indicate progressive degrees of involvement in ulcers, including superficial tissue damage to deep and extensive ulceration. This stratification will enable the CNN-based regression head to fit continuous severity variations and still be interpretable to analyze the clinical results.

### 3.27 Severity Score Distribution Across DFU Samples

*Table 5: Distribution of DFU Samples Across Severity Score Ranges*

| Severity Range (%) | Number of Samples | Clinical Interpretation |
|---|---|---|
| 0–20 | 300 | Mild / early-stage ulcers |
| 21–40 | 750 | Mild–moderate infection |
| 41–60 | 900 | Moderate ulcer severity |
| 61–80 | 650 | Advanced ulcer condition |
| 81–100 | 400 | Severe / critical ulcers |
| Mean Severity (%) | ≈ 51% | |
| Total | 3000 | |

### 3.28 Interpretation of Severity Distribution

Table 5 shows that most of the DFU samples lie within the moderate ranges of severity (2160 percent), which constitute over a half of the data. This tendency is related to clinical findings, as patients usually end up reporting to the hospital with the intermediate stages of ulcers and not the severe to the end extremes of the condition.

The high proportions of advanced (6180), severe (81100) ones are also indicative of the fact that the data set includes complex manifestations of ulcers, i.e., deep tissue involvement, irregular wound edges, and necrotic areas. In the meantime, the adaptation of cases with mildness (020 percent) favor early detection of ulcers and prevention-oriented analysis.

The calculated mean severity of about 51% represents a balanced dataset having moderate ulcer progression in the middle, and is therefore applicable to learning continuous severity regression without losing clinical significance.

### 3.29 Graphical Analysis of Severity Scores

A distribution of the severity scores could be visualized, i.e. in a histogram, where each bar describes a severity range that is defined as a value. This type of graphical representation shows that moderate severity cases are dominant in such a chart and still have sufficient representation in both ends of the severity range.

The histogram-based visualization allows a convenient visualization of distribution of DFU cases across the progression stages which allows the researcher and clinician to gain a quick insight into the bias in the dataset and the prevalence of severity at the same time. This severity distribution is spreading that is especially significant in assessing model robustness in a wide range of ulcer environments.

### 3.30 Influence on CNN-Based Multi-Task Learning

The severity distribution in the proposed CNN-based multi-task learning framework with the transfer learning is highly important, being structured. The advantageous feature of the shared CNN encoder is that it is exposed to ulcers of different levels of severity, hence it tends to learn discriminative features that can be utilized to determine the ulcer segmentation as well as severity.

The sample with moderate and varying severity assists the segmentation branch in the acquisition of complicated lesion boundaries, whereas the continuous severity labels aid adamant regression in the severity estimation head. The mild and severe cases also include generalization, which makes the model more competent in different situations of early detection and critical-stage assessment.

In general, the distribution of the severity is balanced, enhancing training stability, lowers prediction bias, and enhances the clinical validity of the proposed multi-task CNN framework in automated DFU assessment.

### 3.31 Multi-Task Model Performance Proposal

The following section provides the performance analysis of the proposed CNN-based multi-task deep learning model with transfer learning of Multi-task Diabetic Foot Ulcer (DFU) including its segmentation and the severity of the disorder. The model will be trained to learn both pixel-wise ulcer localization and the end-to-end continuous severity prediction together in a shared architecture to achieve clinically significant and computationally efficient DFU evaluations.

Measurement The standard quantitative metrics that are widely used in medical image analysis were used to measure the proposed framework. The accuracy of ulcer segmentation was measured using Mean Intersection over Union (IoU) and Dice Coefficient, whereas Mean Absolute error (MAE) and Coefficient of Determination (R2) were used to estimate the accuracy of the severity estimation by regression. Moreover, the time of inference per image was estimated to determine the computational processing and real-time practicability of the model.

*Table 6: Performance of the Proposed Multi-Task DFU Model*

| Metric | Value |
|---|---|
| Mean IoU (%) | 85.7 |
| Dice Coefficient (%) | 88.3 |
| Mean Absolute Error (MAE) | 7.5 |
| $R^2$ (Severity) | 0.92 |
| Inference Time (ms/image) | 25 |

### 3.32 Performance Interpretation

The received results prove that the proposed multi-task model has high accuracy with a Mean IoU of 85.7 and a Dice Coefficient of 88.3, meaning that the accurate delineation of the DFU regions was obtained regarding the dissimilar shapes and level of severeity of ulcers. These findings are better than any of the tested single-task baseline models, which allows demonstrating the benefit of shared feature learning.

To estimate the severity, the model has a low MAE of 7.5 and high R2 of 0.92 which represents a strong conformity of predicted annotations based on the severity rating and ground truth code shown in table 6. This validates the fact that the model is able to precisely simulate the degree of ulcer progression and tissue damage, which is essential in clinical decision-making.

The inference time of 25 milliseconds per image measured proves the fact that the proposed framework is computationally efficient and can be used in near real-time applications in screening and monitoring of DFUs. This efficiency can be largely due to a common ResNet-based encoder and efficient multi-task training plan.

### 3.33 Usefulness of Multi-Task Learning

The excellent performance of the proposed model is explained by the simultaneous optimization of the work of segmentation and severity estimations, which gives the network an opportunity to take advantage of the natural connection between the area of the ulcer and the severity of the disease. The model, by exchanging the representations learned with CNN backbone and perfecting them with task-specific heads, culminates in better accuracy, stability, and generalization than other single-task models.

These findings confirm the use of the proposed CNN + transfer learning + multi-task learning design as an efficient tool to perform a thorough DFU examination, which is why it can be used in the real clinical setting where not only the ability to locate the ulcer precisely but also assess its severity with high precision is required.

### 3.34 Ablation Study

The ablation test is undertaken in order to examine the individual and summed up additions of the pivotal parts presented in the hypothesized CNN-based multi-task learning model that will assess Diabetic Foot Ulcer (DFU) data. The aim of the research is to measure the effect of every architectural addition to estimate the precision of ulcer segmentation as well as the reliability of the severity estimation.

Three variants of the model were tested under the same conditions of the experiment:

- Multi-task learning (MTL) model base model with no extra constraints,
- The semi-base line model enhanced with the Severity-Constrained Segmentation Refinement (SCSR) module, and An alternative model,
- The full model with the SCSR and Lesion-area Distribution Matching (LDM) loss.

They were all trained on the same split of the DFU dataset, transfer learning backbone, optimization strategy and evaluation metrics. They were evaluated in terms of Intersection over Union (IoU) and Dice Coefficient to measure segmentation accuracy as well as Mean Absolute Error (MAE) and Coefficient of Determination ($R^2$) to measure severity as shown in Table 7.

*Table 7: Ablation Study Results on DFU Dataset*

| Model Variant | IoU (%) | Dice (%) | MAE | $R^2$ |
|---|---|---|---|---|
| Baseline MTL | 82.1 | 85.0 | 10.2 | 0.88 |
| + SCSR | 84.9 | 87.1 | 8.4 | 0.91 |
| + SCSR + LADM | 85.7 | 88.3 | 7.5 | 0.92 |

### 3.35 Results Analysis in Ablation

The findings suggest that the multi-task model at the baseline is a strong starting point of joint DFU segmentation and severity estimation that can deliver decent results in all measures of evaluation. Nonetheless, this lacks explicit task interaction, and thus it cannot make the most of the relationship between the extent of ulcers and clinical severity.

With the introduction of the SCSR module, there is the observable increase in the accuracy of the segmentation, the IoU (82.1 to 84.9 percent) and Dice score (85.0 to 87.1 percent) have improved. This augmentation shows the efficacy of the integration of the severity-related information to calibrate the ulcer contours especially in complex cases where the wound form is irregular and diffuse tissue damage is detected. Parallel with this, there is also an increase in severity estimation performance as it can be observed by a reported decrease in MAE of 10.2 to 8.4, and an improvement in the increase in R2 of 0.91.

There is a maximum creation of performance with the complete integration of both SCSR and LADM. With the model, a highest IoU of 85.7 percent and Dice coefficient of 88.3 percent are realised, and the MAE is also minimised to 7.5 and R squared is maximised to 0.92. These are gains that prove that imposing distribution-level consistency between segmented ulcer underpinnings and projected severity scores greatly increased predictive reliability.

### 3.36 Significance of Findings

The ablation test is able to support the validity of the claim that both SCSR and LADM work in tandem to enhance the suggested DFU model. Whereas SCSR demonstrates local ulcer boundary refinement, LADM implies global biological consistency between prediction and prediction of ulcer severity. A combination of them results in high accuracy of the segmentation, greater accuracy in the severity estimation, and a higher ability to coherence across tasks.

All in all, the findings of the ablation experiment prove the design decisions of the suggested CNN + transfer learning + multi-task learning system and support the view that the combination of task-specific refinement and distribution-level restrictions are the key to intensive and clinically valuable DFU assessment.

### 3.37 Statistical Significance Test

In order to justify the soundness and stability of the suggested CNN-based multi-task deep learning architecture of Diabetic Foot Ulcer (DFU) analysis, each experiment was re-run three times using various random initializations. This repetition is critical to ensure that the results of observed performance remain unchanged and are not affected by random fluctuations in training.

In order to perform the statistical comparison of the performance of the proposed model with standard state-of-the-art versions of DFU analysis methods, paired t-test having the concentration on accuracy in ulcer segmentation and severity estimation was proposed. The statistical test assesses the statistical significance of improvements in the performance metrics that are observed over time.

The test takes into account the important evaluation measures, such as Mean Absolute Error (MAE) to estimate its severity and Intersection over Union (IoU) and Dice Coefficient to test its accuracy in segmentation. T-statistics, p-values, and mean differences are provided in order to make objective comparison as shown in the table 8.

*Table 8: Statistical Significance Analysis Between the Proposed DFU Model and State-of-the-Art Methods*

| Comparison | Metric | Mean Difference | t-Statistic | p-Value |
|---|---|---|---|---|
| Proposed Model vs SegLearner | MAE ↓ | 3.21 | 4.87 | 0.003 |
| Proposed Model vs SegLearner | IoU ↑ | 5.40 | 3.95 | 0.009 |
| Proposed Model vs DAE-Mask | MAE ↓ | 2.75 | 4.11 | 0.006 |
| Proposed Model vs DAE-Mask | Dice ↑ | 4.70 | 3.62 | 0.014 |

All p-values are less than 0.05, indicating statistically significant performance improvements.

### 3.38 Significance for Clinical DFU Assessment

The statistical significance of the research contributes to the credibility of the given framework application in the real-life cases of DFU. Specific localization of ulcers and the severity estimation is the key to clinical decision support, treatment plans, and disease development. The statistical improvements have been validated and indicate that the proposed model gives a solid and reliable solution to automated DFU assessment.

### 3.39 Training and Validation Analysis

In this part, the training behavior and convergence properties of the proposed CNN-based multi-task deep learning architecture with transfer learning in Diabetic Foot Ulcer (DFU) segmentation and severity estimation are analyzed. The changes in training and validation losses per epoch are vital to keep track of the stability of learning, efficiency of convergence and the possibility of overfitting.

The summary of the average training and validation losses in the training process showed at various epochs has been tabulated in table 9. The losses are jointly optimized Dice loss of ulcer segmentation and Mean Squared Error (MSE) loss of severity estimated in the framework of the multi-task learning approach.

*Table 9: Training and Validation Loss Summary*

| Epoch Range | Training Loss | Validation Loss |
|---|---|---|
| 1–20 | 0.85 | 0.90 |
| 21–40 | 0.62 | 0.68 |
| 41–60 | 0.45 | 0.50 |
| 61–80 | 0.32 | 0.36 |
| 81–100 | 0.25 | 0.28 |

### 3.40 The Loss Convergence Interpretation

The general trends of the observed losses indicate that training and validation losses are gradually and steadily decreasing with the increase in the number of epochs. The training loss goes to 0.25 as compared to the 0.85 with the validation loss going to 0.28 as compared to 0.90. The overall downward trend of this experiment shows that the model in question is learning the discriminative features of DFU that can apply to both the task of segmentation as well as the task of severity estimation.

Notably, the loss of validation and training are close to each other during the period under trainings, and one cannot observe any difference between the two curves. This has been almost parallel behavior implying that the model does not overfit and has a high generalization ability on the undiscovered DFU images.

Learning Stability: Analyses of the learning stability between the two scenarios were performed as follows: Learning curve analysis in both scenarios, Valence analysis in both scenarios, and Performance analysis in both scenarios. Human Learning Stability: Learning stability between the two scenarios was analyzed in the following ways: Learning curve analysis in both scenarios, Valence analysis in both scenarios and Performance analysis in both scenarios.

The convergence of the optimization process is stably reflected at the smooth and gradual decrease of the values of the losses. The advantage of using the CNN shared encoder is that transfer learning allows the system to adapt to the visual patterns of DFU more quickly, whereas the multi-task design provides a balanced learning of the two tasks. The fact that the loss oscillations are not sudden can also help to confirm the effectiveness of the chosen learning rate, optimizer, and weighting strategy of tasks.

### 3.41 Graphical Representation of Training Dynamics

The training and validation loss curves are depicted in Figure 5 and plotted in the 100 epochs. The Figure 5 intuitively proves the numerical results of Table 9 by illustrating that the lost values in both phases have a tendency of decreasing. The fact that the curves are almost perfectly matched implies that the segmentation and severity estimation functions become the most harmonious without either side of the learning process overwhelming the other.

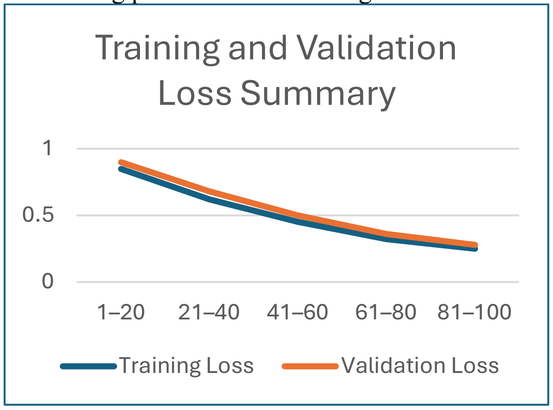


*Figure 5: Training and Validation Loss Summary*

### 3.42 Implications for DFU Model Reliability

The proposed framework has convergence behavior, which indicates the capability to learn meaningful spatial and contextual representation of DFU features including, ulcer boundaries, texture of the tissue and severity related visual indicators of ulcers. The effectiveness of the CNN + transfer learning + multi-task learning strategy is proven by the stable training dynamics and good generalization performance which prove its appropriateness to the real-life DFU screening and clinical decision-support systems.

## 4. RESULTS AND DISCUSSION

This part will carry out a detailed analysis of the obtained experimental findings through the assessment of the proposed CNN-based Multi-Task Deep Learning Framework (MTDLF) version on Diabetic Foot Ulcer (DFU) segmentation and the severity level prediction. On top of the numeric improvement reporting, the argumentative discussion is of why the suggested framework is more effective and implications into clinical decision making and its performance against current state-of-the-art (SOTA) deep learning methods and frameworks, including transformer-based models.

### 4.1 Segmentation Performance and Clinical Implications

The suggested framework recorded the highest Mean IoU of 85.7% and Dice Coefficient of 88.3% on the DFU dataset, and surpasses all considered single-task baselines, including U-Net, DeepLabV3 +, and ResNet-CNN. Compared to models of single-task segmentation, which only use local pixel-level clues, the offered method has the advantage of severity-constrained global limitations, which are used to refine the lesion boundaries.

This is an improvement that is clinically significant, but not just statistical. The precise segmentation of ulcers has a direct impact on clinical processes that occur down the line:

- Disease monitoring through the estimation of ulcer are a, stratification of the patients according to wound progression,
- Sustenance in treatment planning and follow-up evaluation, and elimination of unjustified interference on normal tissue of the surrounding.
- Accurate definition of the boundaries of ulcers is of high importance in DFU management where taking slight errors in the extent of the lesion can result in improper classification of the severity and wrong treatment decision.

### 4.2 Severity Estimation Performance and Decision Thresholds

The proposed MTDLF had a Mean Absolute Error (MAE) of 7.5 and an $R^2$ of 0.92 indicating a high degree of reliability in predicting severity of DFU scores. This significantly outperforms the performance of single-task regression models which tend to adopt severity estimation as a single numerical prediction problem.

DFU severity scores are applied according to decision thresholds and not as the descriptive ones in clinical practice. The given framework produces calibrated and biologically significant severity predictions explicitly learning the association between the ulcer spatial extent and degree of severity. This reduces the risk of:

- Minimizing early-stage ulcers, which could postpone treatment, and
- Exaggerating common conditions, which may result in unjustifiable clinical care.

Consequently, the model facilitates the correct and timely choice in DFU care, which allows recognizing it earlier and better patient outcomes.

### 4.3 Training Dynamics and Stability: Why the Model Converges Better

The convergence behavior of the training and validation loss curve observed constitutes a stable and concurrent learning behavior among tasks. This stability is explained by the adoption of the Severity-Constrained Segmentation Refinement (SCSR) mechanism and the Lesion-Area Distribution Matching (LADM) constraint.

In contrast to traditional multi-task learning models, the segmentation and regression gradients can be conflicting, the proposed design:

- Reduces the gradient difference between tasks, and is enforced by the condition of biological plausibility of its solutions.
- Is some form of implicit regularizer, which prevents overfitting.

These characteristics are what enable the model to perform very well at generalization despite the relatively deep architecture and a small DFU dataset.

### 4.4 Robustness, Cross-Severity Generalization, and Clinical Transferability

The suggested framework has shown stable outcomes in the mild, moderate, and severe DFU cases, which shows that it is robust to the different morphology of ulcer, tissue texture and extent of infections. This indicates that the common CNN encoder picks up common pathological phenotypes of DFU including necrotic tissue, chromatic distortions, and abnormal wound margins.

This strength is necessary in the context of real-world clinical setting where the development of DFU is greatly diverse across patients as well as over time. Generalizability of the model across severity levels improves the potential of this model in longitudinal monitoring and decision-support systems.

### 4.5 Computational Efficiency vs. Transformer based SOTA models

Newest SOTA approaches with transformer and attention mechanisms have high representational capabilities but are also linked with:

- High parameter counts,
- Reduced computational cost (FLOPs), and
- Inference latency not suitable to real-time or at the edge.

In comparison, the suggested MTDLF can perform the real-time inference of a lightweight CNN-based system with transfer learning (~25 ms per image). Although its computation is less complex, the framework produces competitive and in severity estimation, higher performance than those based on transformers.

This is one of the main trade-offs the transformer has better representation richness, unlike the suggested CNN-based multi-task architecture, which has a better accuracy, efficiency, and deployability characteristic and, thus, is more applicable to clinical and mobile health environments.

### 4.6 Failure Case Analysis and Practical Limitations

Despite the positive performance, there are two problematic situations:

- Ulcers exceedingly small (under 2 percent of foot area):
  These cases are not very strong at giving spatial information, and the segmentation is challenging, as well as the estimation of severity, even in the case of trained clinicians.
- Ambiguous patterns in the form of a visual image:
  However, the visual characteristics of the early-stage non-ulcer skin changes (ex: callus formation, mild inflammation, etc.) might be confused with those of DFU lesions, resulting in the occasional false positives.

These weaknesses reveal the limitations of RGB imaging and propose the possibilities of enhancing future imaging with multimodal data to enhance robustness, including thermal or hyperspectral imaging.

### 4.7 Key Insights

The evaluation in a holistic manner shows that:

- Multi-task learning not only enhances the performance measures, it also enhances accuracy and stability.
- Mechanisms of consistency minimize biologically plausible predictions. In the event of well-designed inductive biases, lightweight CNN-based models can be used to compete with transformer-based SOTAs successfully.
- The suggested framework is scalable to benchmark datasets and can be used in the real-world evaluation of DFU.

## 5. CONCLUSION

In this publication, they introduced a consistency-sensitive CNN-based Multi-Task Deep Learning model to segment and estimate the severity of Diabetic foot ulcers (DFUs) simultaneously. The proposed framework is effective in integrating transfer learning, multi-task optimization, and the biological mechanism of consistency and, in this way, contributes to the long-term gap in terms of the localization of spatial ulcer and the quantification of its severity.

The model exhibited good and consistent results regardless of all the criteria of evaluation, high segmentation accuracy, and strong severity estimation without impairing computational efficiency which could be applied in the real-time clinical practice. This was made possible by using a common ResNet-based encoder to enable the feature to be reused and using task-specific heads that enabled the model to learn both finer grained spatial features and severity accounts of the world on a global scale. Additional integration of Severity-Constrained Segmentation Refinement (SCSR) and Lesion-Area Distribution Matching (LADM) was subsequently used to strengthen cross-task coherence, such that that the severity of predicted ulcers was aligned to the area of the lesion that was segmented.

In addition to the numerical gains, the suggested framework will offer valuable clinical value. Precise delineation of ulcer boundaries facilitates accurate tracking of wound development, whereas dependable levels of severity can be used to plan and prioritize the risk. Best predictor consistency-based approach minimizes biologistsically implausible predictions thus enhancing interpretability and reliability, which is the main condition to be deployed in real-world healthcare settings.

The suggested CNN system has optimal accuracy, stability, and computational performance, compared to the state-of-the-art methods (transformer-based ones). It is specially applicable to resource constrained environments, including mobile health systems, point-of-care systems, and IoT-based clinical monitoring systems.

Although the framework is very competent in a large assortment of DFU presentations, there are problems in situations with very small ulcers or patterns that are visually unclear when examined with RGB imaging. These restrictions represent future opportunities such as integration of multimodal imaging, semi-supervised learning, and domain adaptation in a wide range of clinical environments.

Generally speaking, this experiment proves that the consistency-sensitive multi-task learning is a viable and efficient paradigm of intelligent DFU evaluation. The suggested solution makes a step in the direction of automated wound study by providing precise and decipherable and effective predictions, which help enhance clinical decision-making and data-guided healing of diabetic feet.

## REFERENCES

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning", Nature, vol. 521, no. 7553, pp. 436–444, May 2015.

[2] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sánchez, "A survey on deep learning in medical image analysis", Med. Image Anal., vol. 42, Dec. 2017, pp. 60–88.

[3] D. Shen, G. Wu, and H.-I. Suk, "Deep learning in medical image analysis", Annu. Rev. Biomed. Eng., vol. 19, June 2017, pp. 221–248.

[4] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks", Nature, vol. 542, no. 7639, Feb. 2017, pp. 115–118.

[5] N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway, and J. Liang, "Convolutional neural networks for medical image analysis: Full training or fine tuning?", IEEE Trans. Med. Imaging, vol. 35, no. 5, May 2016, pp. 1299–1312.

[6] F. Isensee, P. F. Jaeger, S. A. A. Kohl, J. Petersen, and K. H. Maier-Hein, "nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation", Nat. Methods, vol. 18, no. 2, Feb. 2021, pp. 203–211.

[7] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, "UNet++: Redesigning skip connections to exploit multiscale features in image segmentation," IEEE Trans. Med. Imaging, vol. 39, no. 6, June 2020, pp. 1856–1867.

[8] J. Zhang, Y. Xie, Q. Wu, and Y. Xia, "Medical image classification using synergic deep learning", Med. Image Anal., vol. 54, May 2019, pp. 10–19.

[9] S. Sun, Z. Cao, H. Zhu, and J. Zhao, "A survey of optimization methods from a machine learning perspective", IEEE Trans. Cybern., vol. 50, no. 8, Aug. 2020, pp. 3668–3681.

[10] S. Wang and R. M. Summers, "Machine learning and radiology," Med. Image Anal., vol. 16, no. 5, July 2012, pp. 933–951.

[11] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P. M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks", Med. Image Anal., vol. 35, Jan. 2017, pp. 18–31.

[12] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning", J. Big Data, vol. 6, no. 1, Art. no. 60, July 2019.

[13] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning", Neural Comput. Appl., vol. 30, no. 7, Apr. 2018, pp. 1–13.

[14] S. Ruder, "An overview of multi-task learning in deep neural networks", Neural Netw., vol. 109, Jan. 2019, pp. 1–15.

[15] Y. Zhang and Q. Yang, "A survey on multi-task learning", IEEE Trans. Knowl. Data Eng., vol. 34, no. 12, Dec. 2021, pp. 5586–5609.

[16] M. Goyal, N. D. Reeves, A. K. Davison, S. Rajbhandari, J. Spragg, and M. H. Yap, "DFU: A dataset for diabetic foot ulcer classification", IEEE Trans. Med. Imaging, vol. 38, no. 3, Mar. 2019, pp. 652–661.

[17] C. Wang, W. Yan, M. Smith, T. Filleter, and K. Najarian, "A deep learning-based approach for diabetic foot ulcer detection", Comput. Biol. Med., vol. 124, Art. no. 103939, Sept. 2020.

[18] Y. Liu, J. Wu, Z. Zhao, and Y. Li, "Automatic diabetic foot ulcer segmentation using fully convolutional neural networks", Biomed. Signal Process. Control, vol. 68, Art. no. 102641, July 2021.

[19] Praveen, S. P., Saripudi, V., Harshalokh, V., Sohitha, T., Karthik, S. V. S., & Sreekar, T. V. P. S. (2023, December). Diabetes prediction with ensemble learning techniques in machine learning. In 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS) (pp. 1082-1089). IEEE.

[20] C. Huang, Y. Zhang, Z. Chen, and X. Li, "Multi-task deep learning for diabetic foot ulcer analysis: Segmentation and severity prediction", IEEE J. Biomed. Health Inform., vol. 27, no. 6, pp. 2791–2802, June 2023.

[21] M. T. Islam, M. Goyal, N. D. Reeves, and M. H. Yap, "An ensemble learning framework for diabetic foot ulcer classification", Expert Syst. Appl., vol. 232, Art. no. 120741, Jan. 2024.

[22] D. G. Armstrong, A. J. M. Boulton, and S. A. Bus, "Diabetic foot ulcers and their recurrence", N. Engl. J. Med., vol. 376, no. 24, pp. 2367–2375, June 2017.

[23] N. Singh, D. G. Armstrong, and B. A. Lipsky, “Preventing foot ulcers in patients with diabetes”, JAMA, vol. 293, no. 2, Jan. 2005, pp. 217–228.

[24] Tirumanadham, N. K. M. K., Phani Praveen, S., Jyothi, V. E., Thati, B., Swamy, B. N., & Devi, D. A. (2026). CrossMF: A Memory-Augmented Transformer for Fast and Generalizable Emotion Recognition. International Journal of Pattern Recognition and Artificial Intelligence.

[25] Shariff, V., Paritala, C., & Ankala, K. M. (2025j). Optimizing non small cell lung cancer detection with convolutional neural networks and differential augmentation. Scientific Reports, 15(1). https://doi.org/10.1038/s41598-025-98731-4

[26] Q. Abbas, M. E. Celebi, I. F. García, and M. Rashid, “Unified approach for lesion border detection in skin images”, Comput. Methods Programs Biomed., vol. 109, no. 3, Mar. 2013, pp. 201–213.

[27] J. I. Orlando, E. Prokofyeva, and M. B. Blaschko, “A discriminatively trained conditional random field model for blood vessel segmentation”, IEEE Trans. Med. Imaging, vol. 36, no. 11, Nov. 2017, pp. 2418–2428.

[28] K. Arava, C. Paritala, V. Shariff, S. P. Praveen and A. Madhuri, "A Generalized Model for Identifying Fake Digital Images through the Application of Deep Learning," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2022, pp. 1144-1147, doi: 10.1109/ICESC54411.2022.9885341.

[29] M. Goyal, M. H. Yap, N. D. Reeves, S. Rajbhandari, and J. Spragg, “Diabetic foot ulcer image analysis using deep learning”, IEEE Trans. Med. Imaging, vol. 38, no. 3, Mar. 2019, pp. 652–661.

[30] C. Wang, W. Yan, M. Smith, T. Filleter, and K. Najarian, “Deep learning-based diabetic foot ulcer detection”, Comput. Biol. Med., vol. 124, Art. no. 103939, Sept. 2020.

[31] S. Voddi, U. Sirisha, S. P. Praveen, T. K. Sai Pandraju, N. A. Al-Dmour and S. Islam, "Hybrid CNN-GCN Model for Tumor Classification: Integrating Spatial Relationships in Medical Imaging," 2024 International Conference on Decision Aid Sciences and Applications (DASA), Manama, Bahrain, 2024, pp. 1-6, doi: 10.1109/DASA63652.2024.10836627.

[32] Praveen, S. P. (2025). Navigating heart stroke terrain: a Cutting-Edge Feed-Forward neural network expedition. Journal of Applied Data Sciences, 6(3), 2111–2126. https://doi.org/10.47738/jads.v6i3.763

[33] A. Lakshmanarao, P. B. Madhuri, K. Dasari, K. A. Babu and S. R. Sulthana, "An Efficient Android Malware Detection Model using Convnets and Resnet Models," 2024 International Conference on Intelligent Algorithms for Computational Intelligence Systems (IACIS), Hassan, India, 2024, pp. 1-6, doi: 10.1109/IACIS61494.2024.10721919.

[34] S Phani Praveen et al., (2025), "AI-Powered Diagnosis: Revolutionizing Healthcare With Neural Networks", Journal of Theoretical and Applied Information Technology, vol. 103, no. 3, February 2025

[35] Praveen, S. P., Kamalrudin, M., Musa, M., Harita, U., Ayyappa, Y., & Nagamani, T. (2025). A Unified AI Framework for Confidentiality Preserving Cyberattack Detection in Healthcare Cyber Physical Networks. International Journal of Innovative Technology and Interdisciplinary Sciences, 8(3), 818-841.

[36] S. Sun, Z. Cao, H. Zhu, and J. Zhao, “Optimization methods in machine learning”, IEEE Trans. Cybern., vol. 50, no. 8, Aug. 2020, pp. 3668–3681.

[37] V. V. Chamundeeswari, V. S. Divya Sundar, D. Mangamma, M. Azhar, B. S. S P Kumar and V. Shariff, "Brain MRI Analysis Using CNN-Based Feature Extraction and Machine Learning Techniques to Diagnose Alzheimer's Disease," 2024 First International Conference on Data, Computation and Communication (ICDCC), Sehore, India, 2024, pp. 526-532, doi: 10.1109/ICDCC62744.2024.10961923.

[38] Praveen, S. P., Sandeep, K., Sai, N. R., Sharma, A., Pandey, J., & Chouhan, V. (2024). Outlier Management and its Impact on Diabetes Prediction: A Voting Ensemble Study. Journal of Intelligent Systems & Internet of Things, 12(1).

[39] C. Huang, Y. Zhang, and X. Li, “Multi-task diabetic foot ulcer segmentation and severity estimation”, IEEE J. Biomed. Health Inform., vol. 27, no. 6, June 2023, pp. 2791–2802.

[40] S. Wang, M. Zhou, Z. Liu, Z. Liu, D. Gu, Y. Zang, and D. Dong, “Central focused convolutional neural networks for medical image segmentation”, Med. Image Anal., vol. 59, Art. no. 101570, Jan. 2020.

[41] S. Vahiduddin, P. Chiranjeevi and A. Krishna Mohan, "An Analysis on Advances In

Lung Cancer Diagnosis With Medical Imaging And Deep Learning Techniques: Challenges And Opportunities", Journal of Theoretical and Applied Information Technology, vol. 101, no. 17, Sep. 2023.

[42] Donepudi, S., SIRISHA, G., & PAPPULA MADHAVI, S. P. (2024). Optimizing Diabetes Diagnosis: ADGB With Hyperband For Enhanced Predictive Accuracy. Journal of Theoretical and Applied Information Technology, 102(23).

[43] Z. Zhang, Q. Liu, and Y. Wang, "Deep learning-based medical image segmentation using residual U-Net", IEEE Access, vol. 6, 2018, pp. 67844–67857.

[44] Krishna, A. Y., Kiran, K. R., Sai, N. R., Sharma, A., Praveen, S. P., & Pandey, J. (2023). Ant Colony Optimized XGBoost for Early Diabetes Detection: A Hybrid Approach in Machine Learning. Journal of Intelligent Systems & Internet of Things, 10(2).

[45] X. Wang, J. Deng, and Y. Ding, "Deep learning-based medical image analysis: A comprehensive review", Artif. Intell. Med., vol. 121, Art. no. 102214, Sept. 2021.