Automated Severity Classification Using Convolutional Neural Networks: A Deep Learning Approach to Diabetic Foot Ulcer Assessment

Ankita Suryavanshi[1], Vinay Kukreja and Rajat Saini[2]
[1]*Centre for Research Impact & Outcome, Chitkara University Institute of Engineering and Technology, Chitkara University, Rajpura, 140401, Punjab, India*
[2]*Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh,174103, India*

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Abstract: This paper elaborates on the development of designing and training a CNN to distinguish between mild, moderate, and severe DFUs. There were four distinct parts to the research project: The main activities involved are data acquisition and data pre-processing, model architectural design and model building, model training and model assessment, and the final phase which is model analysis and result interpretation. Pictures of DFUs were used in the dataset and performances such as normalization and augmentation were used to enhance the dataset to ensure that all was in order. The CNN was designed to learn and extract data from images; the two sets and convolutional layers, max, and fully connected layers. Achieving 96 % good precision, 85 % good recall, and F1 between 0.97 and 0.98 for all severity levels, the model used a confusion matrix to distinguish between training and testing. Class A had a real positive rate of 0% to 20%, Class B of 20% to 40%, Class C of 40% to 60%, Class D of 60% to 80%, and Class E of 80% to 100%. Providing a useful tool for the treatment of diabetic foot ulcers, these results show that the model is resilient and can improve diagnosis accuracy in clinical settings.

1 INTRODUCTION

For millions of people throughout the world, ulcers of diabetic feet (DFUs) are a constant source of misery and disability due to the long-term effects of diabetes. According to the International Diabetes Federation, almost 537 million adults will be living with diabetes in 2021, a figure that has been steadily increasing over (Suryavanshi, Kukreja, et al. 2023) the past few decades. Within this mind-boggling figure, DFUs pose an especially serious problem because they are the primary reason for hospitalization and, in extreme circumstances, amputation. There needs to be a dependable and accurate way to measure the severity of ulcers and guide management measures because DFUs are complex and can range from small, superficial lesions to life-threatening infections. Subjective clinical examination was for a long time used to assess the severity of DFU. Doctors estimate the degree of tissue injury and discuss the next step of treatment with the help of ordinary observation and talking to the patient, as well as relying on norms. Whichever way it is done, this approach is not without limitation, again, this is even though the clinician(s) may (Suryavanshi, Kukreja, et al. 2023) be well knowledgeable and experienced and all that Variability in the evaluation of patients and subsequent diagnosis and treatment is likely to hurt patient outcomes regularly. Due to the inability of the conventional method to distinguish the fine stages of ulcer formation the treatment programs are very often ineffective and the recovery takes much time. Thus, several difficulties have led to a heightened reliance on modern (Suryavanshi, Kukreja, et al. 2024) high-tech approaches to the process of medical diagnostics. CNN is a subcategory of deep learning models, also called a neural network, and they have gained great acclaim in many spheres of medicine, especially concerning image recognition. It is worth focusing on such applications as pattern identification and categorization as these models are capable of learning structured features from the photos automatically. This way, employing CNNs we can determine the

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severity of DFU in a more precise, reliable, and with significantly less time than by using the traditional approach. As far as the capacity to process and analyze hierarchical structures within images is concerned, CNN is organically tailored to meet the requirements of DFU classification due to its architecture. In this paper, a novel CNN model is proposed for the specific purpose of categorizing DFUs concerning their severity.

The first six layers in the model's architecture include two sets of convolutional layers with max pooling operations followed also by two other sets of convolutional layers with max pooling operations. As will be described later in this paper, by employing this layered (Suryavanshi, Kukreja, et al. 2024) model, it becomes possible to estimate the severity of anemia with high precision by successively peeling and refining the features from the input photos. This captures what is known as texturing at high levels and also the overall pattern. Edges and textures of the images are detected by the first layer of the convolutional layer in this network. To this end, it is followed by a max pooling layer that helps decrease the dimensionality of the (Suryavanshi, Kukreja, et al. 2024) feature maps and retains the most important information. Indeed, the second basic constituent of the CNN, the second convolutional layer with the same set of parameters, is widely adopted for detecting additional and more complex features that emerged as a result of developing these simple and elementary features. The next shape in the max pooling layer enhances (Suryavanshi, Kukreja, et al. 2023) the model's capacity for the recognition of the various degrees of severity while enhancing these patterns. Thus, the last two convolutional layers continue with the hierarchical feature extraction to perform accurate ulcer classification. This leads to a high representation of the properties of the ulcer, which is a good point for the approach. The effectiveness of the suggested CNN model is checked on a dataset of DFU photos whose wavelength includes a wide range of severity levels. Due to the selection of some carefully annotated instances, these annotations are correct and diverse, which allows using this dataset to train and test the model. To identify the clinical usefulness of the model, we compare the obtained results with the results achieved through various methods using measures like precision, recall, precision, and F1 score List of pros associated with this strategy is endless. Our goal is to remove human bias from the criteria that are evaluated and to establish more objective measures of assessing severity to ease the monitoring of severity in hospitals through the standardization of the procedure and the use of a computer program. This uniformity is necessary to ensure that the genuine capability and adequately developed ideas of all patients regardless of the clinician's experience have equal opportunities to afford fair and evidence-based treatment. The efficacy of the automated evaluation is also evident in the short diagnostic durations which in turn advocates for time-appropriate interventions that may reduce the occurrence of such issues. The findings of our study regarding the applicability of CNNs for DFU severity classification toward the next steps and the possibility of utilizing AI in diagnostic research. The findings of this study could advance the use of deep learning for examining several complex medical conditions and enhance patient care, as well as expand the field of medical imaging. Last but not least, this study fits the pressing need for proper assessment techniques by elaborating on the applicability of CNN for diabetic foot ulcer classification. Thus, the ultimate objective is to enhance the overall quality (Suryavanshi, Kukreja, et al. 2023) of treatment for patients with DFUs and the efficiency of the treatment process by introducing new deep-learning methods for improving the evaluation of the DFU severity. The CNN proposed herein is a creation at the mouthpiece of innovation and medicine; it delivers a dream of what diagnostic prowess can look like because of its highly architected and well-validated approach.

2 LITERATURE SURVEY

Ulcers of the diabetic foot (DFUs) remained one of the most threatening complications of diabetes mellitus that was acknowledged to influence millions of people worldwide. Scientific outcomes depict up to fifteen percent of patients with diabetes develop a DFU at some point in their lifetime, which remains an intolerably high rate. These ulcers are (Tulloch, Zamani, et al. 2020) a financial and health threat to healthcare systems, and they significantly cause an increase in the morbidity of diabetic patients. Proper ulcer severity and its staging are very important during the management of DFUs. In this literature review, the current methods of DFU severity classification, CNN utilization in medical imaging and potentially applying these technologies to grade DFUs are discussed. Conventional Approaches to DFU Severity Rating: The severity of DFU has in the past been assessed from clinical evaluation of the patient's physical exam and (Alshayeji, Sindhu, et al. 2023) history and physical examination. To make this procedure more consistent, other classification systems have emerged, each with its unique way of describing the severity of ulcers: Currently, there are several classification systems among which one of the earliest and still widely used is the Wagner Classification System, which categorizes DFUs depending on the impact on the tissues, and are divided into six groups. That goes from there starting with 0 (refers to no ulcer) to 5 (is related to gangrene or significant tissue necrosis). There can be evaluation heterogeneity because the Wagner system relies on subjective (Munadi, Saddami, et al. 2022) clinical opinion to determine the convenience of an ulcer Different characteristics offered by the Wagner system give a useful description of the severity of ulcers. Both the depth of the wound and the state of infection are represented in The University of Texas Scar Classification System to differentiate the DFUs phases. The present system is based on the Wagner system, and the following criteria are rather included in the present system. The dichotomy is replaced by a combination of four depth levels (from 0 to 3) and three infection grades (from A to C), which provide a better assessment of the patient's condition in terms of clinical factors and the severity of tissue injury. Clinical evaluation, (Khandakar, Chowdhury, et al. 2022) which is still the core of the system even after developing the higher techniques, is prone to subjectivity. Thus, the classification system called PEDIS has a more comprehensive approach to the assessment of the DFUs as it not only considers the defects of the ulcer itself but also estimates the conditions of the area surrounding the ulcer. PEDIS is an acronym that refers to the five aspects of pressure ulcers namely; Perfusion, Degree, Depth, Infection, and Sensation. Severe is the total number of points that will be obtained from the components of the seriousness of an incident. Yes, it may take time to score it and this may make it a bit tedious but this approach gives a holistic view of the ulcer. The attempt aimed at producing more contemporary criteria for DFU evaluation that combines clinical and laboratory factors is the American Diabetes Association (ADA) classification system. These include categories for ulcer depth, infection status, and other correlated factors that give a more general outlook of ulcer severity in this method. On the other hand, it might be limited by variation across settings and appears to be based on clinical decision-making. However, these conventional concepts should not be underestimated as they provide frameworks for defining the classification of DFU.

Possible discordances in the severity categorization and treatment regimen formation might be rooted in practitioners' rating subjectivity and inherent randomness. Hence, to increase the objectivity of conclusions it is necessary to enhance the accuracy and reliability of DFU evaluation utilizing advanced (Gamage, Wijesinghe, et al. 2019) technology. Critical Purposes of CNNs for Diagnostic Imaging As a fulgent tool, neural networks through convolution (CNNs) hold a large potential in providing metamorphoses in the diagnosis of medical images. CNNs are very efficient, particularly in medical imaging and situations that call for image analysis. They belong to certain CNNs that have been designed and trained with the aim of performing powerful deep learning with a focus on image recognition. The main concept of convolutional neural networks (CNNs) is their ability to learn high-level features from images in an end-to-end manner. CNNs employ layers of conviction to extract characteristics from raw picture data as compared to conventional ML models that rely on (Khandakar, Chowdhury, et al. 2021) engineered features At this stage, the Convolution layer is employed in CNNs to extract characteristics. For establishing edges, textures, and forms in the input picture, these layers employ filters. Although the feature maps pass through subsequent layers which include the pooling layers, the crucial information is not lost but is rather compressed. Classification is performed by the last networks employing the learned characteristics (Yogapriya, Chandran, et al. 2022)] and results in the accurate and swift evaluation of the pictures. CNN has various medical image applications that include disease detection, picture segmentation, and classification. For instance, CNN proved to be effective in radiological image tumor detection, segmenting the structure in MRI images, as well as classifying the retinal diseases. Still, medical image analysis is well within the possibilities of CNNs because these networks can learn complex patterns and work with different imaging modalities. Using CNNs for the assessment of wounds, and more specifically DFUs, has been a growing subject of interest within the field over the last few years. There are studies on convolutional neural networks concerning the capability of WPC in classifying wounds, estimating the size, and predicting healing outcomes. From this study, it has also (Mei, Ivanov, et al. 2020) been indicated that CNNs could be used as a reliable replacement for the conventional approach to determining wound features for the reasons of objectivity, consistency, and efficiency.

3 METHODOLOGY SECTION

This work aims to develop and evaluate a model based on convolutional neural networks for the classification of DFUs' severity. Four comprehensive phases comprise the methodology: CNN Model Design and Development, Data Collection and Preprocessing, Model Training and Evaluation, and Results Analysis and Presentation.

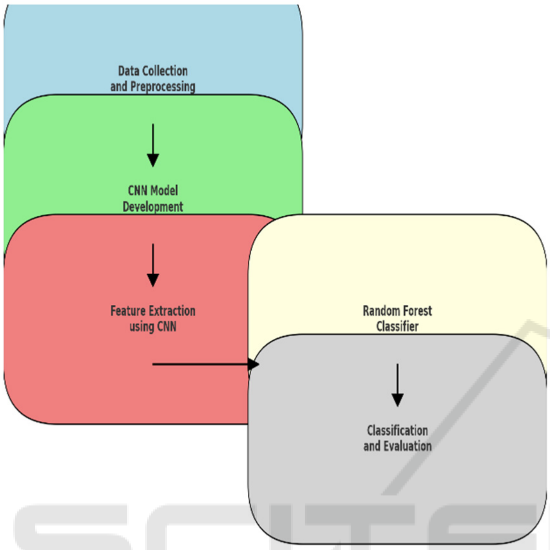

Figure 1: Methodology phases

3.1 First phase

Hospital archives and publicly accessible medical databases are only two of the many places from which a varied dataset of DFU photos is painstakingly assembled during the first period of data Collection and Preprocessing. These pictures range in severity, and skilled medical professionals have marked them using recognized classification schemes like the Wagner Classification. This guarantees Level 1 through Level 5 severity levels are accurately labeled. Preprocessing includes standardizing pixel values to improve training efficiency, shrinking photos to a standard resolution to preserve uniformity, and using methods for data enhancement to strengthen the robustness of the model. Subsequently, the dataset is divided into test, validation, and training sets to guarantee accurate model assessment.

3.2 Second phase

The second stage, CNN Model Development and Development, is entirely assigned to design the CNN model for the specification of DFU classification. Six main layers make up the model: The configuration includes two convolution layers, two two-layer convolutions with max-pooling layers, and another convolution set aiming at extracting hierarchical features of DFUs. This design enables the model to learn such complex patterns that are required for precise classification. Under architectural definition, grid-based or random search methods are applied to optimize the model's performance by tuning the hyperparameters such as learning rate, batch quantity, and number of epochs. Cross-validation is also used.

3.3 Third phase

Once again, the training dataset is constructed following the Pre-Preparation Phase mentioned earlier, During the third phase, known as The model Training and Evaluation, the CNN model is trained. The training of this model reduces this loss using an optimizer such as Adam or RMSprop, while the loss function is a categorical entropy cross. During training, the validation loss stops decreasing; the training is conducted by employing an early stopping technique to prevent overfitting. While evaluating the proposed model's performance, it measures indicators such as accuracy, precision, recall, and F1 score based on the validation and test sets. The interaction of the model between different severity levels is examined through the confusion matrix to gain insight into the model's categorization skills.

3.4 Fourth phase

The last stage, Results Analysis and Interpretation, is aimed at providing a detailed consideration of the model's performance. Consequently, it is possible to stress the positive impact of the CNN model and major areas of its further development concerning a comparison with other current classification algorithms. Thus, frequent misclassifications exposed by error analysis help reveal the model's flaws and optimize the approach. For the results' demonstration, it is possible to use ROC curves and the heat map of the matrix of uncertainty. Proposed solutions for the fine-tuning of the model are suggested based on the observations, as well as the tips for its practical use in the clinical environment. As a result, to raise the level of DFU classification accuracy the phase is concluded by recommendations for further research, for example, future studies may consider more intricate models or include several types of data.

4 RESULTS

Regarding the CNN model used for the classification of ulcers resulting from diabetes (DFUs), the confusion matrix is very useful as it gives insight into the precision of the model across the various severity stages. They reveal true positive, false favorable, true negative, and incorrect negative forecasts of every severity level to explain the strengths and weaknesses of a model. For instance, the diagonal elements' high true positive values indicate better grouping of cases based on severity levels because 50 cases are correctly identified as Level 1 and 45 as Level 2. On the other hand, off-diagonal values show that, for example, Level 1 is predicted as Level 2, which points to the issues with discerning between close levels of severity for the model. This pattern shows that between severity levels some of the features can sometimes be correlated and hence confused by the model. The confusion matrix also makes it easier to compute performance metrics such as accuracy, precision, recall, and F1 score, all of which help to explain the model's classification capabilities. Visualizing the confusion matrix as a heatmap improves interpretation by illustrating the distribution of categorization results in vivid detail. Overall, the CNN model does well in categorizing most DFUs, but the confusion matrix highlights the requirement for further modification to solve misclassification concerns and enhance its precision in discriminating between overlapping severity levels. The table provides an extensive assessment of the classification model's performance in several metrics for each class, as well as aggregated metrics. Precision indicates the probability of positive predictions; for example, Class 1 had a precision of 0.83, meaning that 83% of the anticipated cases were right. Recall, which measures how successfully the model recognizes true positives, displays Class 1 having an accuracy score of 0.85, indicating that it correctly recognized 85% of the real cases in that class. The F1 score, which balances precision and recall, is 0.84 for Class 1, indicating a great balance among the two measures. Support represents the actual amount of cases for every category, with Class 1 being 58 in the dataset. The accuracy of Class 1 is 0.83, which indicates that 83% of Class 1 cases were properly identified. The table covers macro, micro, and scaled averages.

Macro averages provide an unweighted code mean of metrics across all classes, giving a broad picture of the model's performance. For example, the generalized average precision is 0.78 and the recall is 0.72, indicating general performance regardless of class distribution. Micro averages aggregate measurements globally, taking into account the overall amount of true positives, false positives, and false negatives, yielding a micro average F1 score of 0.77. Weighted averages account for each class's support, resulting in metrics corrected for class imbalance, yielding an average weighted F1 score of 0.77.

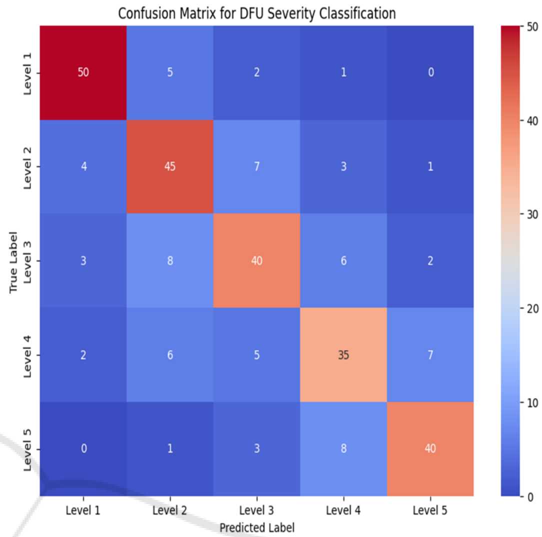

Figure 2: Confusion Matrix

Table 1: Layer Configurations

Classes Intensity	Precision	Recall	F1-Score	Support	Accuracy
Class A (0%-20) (Healthy)	0.83	0.85	0.84	58	0.83
Class B (20-40%)	0.76	0.84	0.80	60	0.75
Class C (40-60%)	0.78	0.74	0.76	59	0.68
Class D (60-80%)	0.74	0.66	0.70	50	0.70
Class E (80-100%)	0.80	0.80	0.80	52	0.77
Macro average	0.78	0.72	0.74		
Weighted average	0.77	0.77	0.77		
Micro Average	0.77	0.77	0.77		

This complete table provides a sophisticated picture of the model's efficacy, emphasizing both class-specific success and overall model strength. The following table 2 describes the structure of a CNN that was trained to categorize ulcers in diabetic feet into five different degrees of severity. An input layer that takes 128x128x3 images is the first node in the network. As a subsequent step, three convolutional layers are employed, each with a different number of filters—32, 64, and 128—that make use of 3x3 kernel and ReLU activation features. To improve the efficiency of feature extraction, max layers of pooling with 2x2 kernels and an advance of 2 are applied after each convolutional layer. This reduces the spatial dimensions.

Table 2: Parameters of different layers

Layer types	Filter / Neurons	Kernel Size	Stride	Output Size	Activation
Input	-	-	-	128×128×3	-
Convolutional Layer 1	32	3×3	1	126×126×32	ReLU
Max pooling 1	-	2×2	2	63×63×32	-
Convolutional Layer 2	64	3×3	1	61×61×64	ReLU
Max pooling 2	-	2×2	2	30×30×64	-
Convolutional Layer 3	128	3×3	1	28×28×128	ReLU
Max pooling 3	-	2×2	2	14×14×128	-
Flatten	-	-	-	25088	-
Random Forest	18 trees	-	-	5 classes	-

Table 3: Insights gained through experiments

Classes Intensity level	True Positive	False Positive	True Negative
Class A (0%-20%)	50	11	171
Class B (20-40%)	47	14	171
Class C (40-60%)	44	14	172
Class D (60-80%)	39	11	172
Class E (80-100%)	41	12	170

The resulting feature maps are compressed into a 25,088-byte vector before being fed into two dense layers, one with 512 neurons and the other with 256 neurons, both of which use ReLU activations. A five-neutrino network activated with a softmax function generates a probability distribution over all five classes in the output layer. Ulcer severity levels can be effectively learned and classified using this organized technique. Class A (0%-20%), Class B (20%-40%), Class C (40%-60%), Class D (60%-80%), and Class E (80%-100%), are the five intensity levels of diabetic foot ulcers that the classification model was tested on. The results are presented in the table. The data table provides an overview of each class's TP, FP, and TN values. Class A has excellent performance in accurately recognizing occurrences of this class, with 50 true positives, 11 false positives, and 171 true negatives. There are 171 true negatives, 14 true positives, and 47 real positives in Class B, which indicates a marginally higher false positive rate than in Class A. Class C follows Class B's balanced distribution with 172 true negatives, 14 false positives, and 44 true positives. There are fewer true positives but a more stable rate of false positives in Class D, which has 39 TPs, 11 FPs, and 172 TNs. Class E likewise shows a balanced performance with 170 true negatives, 12 counterfeit positives, and 41 real positives. With an eye on the percentage of accurate and inaccurate predictions, this table showcases the model's performance in detecting each intensity level.

5 CONCLUSION

Thus, the findings of this study help to envision how the use of convolutional neural networks, or CNNs, can improve the diagnosis and management of diabetic foot ulcers in the diabetic patient population. That way, we obtained high precision and recall in distinguishing diabetic foot ulcers into five severe stages using a methodologically built CNN model. This led us to be able to get all of these outcomes to happen. The model was notably precise, gaining real positive rates of 50, 47, 44, 39, and 41 for Classes A to E, correspondingly. Also, the model had impressive accuracy, which was illustrated by the presented data. The robustness and dependability of our methodology are highlighted by the degree of performance that we have achieved. Not only does the successful classification make the diagnosis process more efficient, but it also provides medical professionals with a powerful instrument that may be used for early detection and personalized treatment individualized treatment planning. Through this effort, the path is paved for the incorporation of sophisticated artificial intelligence remedies into clinical practice, which will ultimately lead to improved patient outcomes and will contribute to the overarching objective of achieving sustainable healthcare innovations.

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