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DIABETIC FOOT ULCER CLASSIFICATION USING SEQUENTIAL CNN ALGORITHM

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ABSTRACT: The occurrence of diabetic foot ulcers (DFUs) and their possible consequences provide a major healthcare challenge. For prompt care and the avoidance of serious problems, early and accurate detection of DFUs is essential. This study proposes a novel approach for automatic DFU detection utilizing Convolutional Neural Networks (CNNs), a powerful deep learning technique proven effective in image analysis. A large dataset of foot photos covering a variety of DFU types, phases, and circumstances is used to train the suggested CNN model. The training process involves learning intricate patterns and features indicative of DFUs, enabling the model to generalize well to unseen data. The CNN algorithm's effectiveness in feature extraction and spatial hierarchy learning is harnessed to identify subtle visual cues associated with DFUs, enhancing diagnostic accuracy. The proposed system is designed to operate on medical images, particularly those obtained through various imaging modalities such as digital photography or thermal imaging. Through rigorous validation and performance evaluation, the CNN model exhibits promising results, showcasing its potential as a reliable tool for automated DFU detection. The integration of this technology into clinical practice holds the promise of expediting the diagnostic process, facilitating timely medical interventions, and ultimately improving patient outcomes. This research contributes to the ongoing efforts in leveraging advanced technologies to address critical healthcare challenges, particularly in the realm of diabetic care and wound management.

Keywords: Diabetic foot ulcer, Convolutional neural network, Medical imaging, Deep learning, Diagnosis system.

1. INTRODUCTION

Diabetic Foot Ulcers(DFUs) are a serious healthcare concern due to their frequence and implicit consequences. Beforehand and precise DFU discovery is pivotal for timely care and the forestallment of major issues. The present work suggests a new system for automatic DFU discovery that makes use of Convolutional Neural Networks(CNNs), a potent class of deep literacy algorithms that are well-known for their effectiveness in image analysis operations. A large dataset of bottom prints covering a variety of DFU types, phases, and circumstances is used to train the suggested CNN model. A number of causes can lead to the conformation of ulcers, including diabetes for an extended period of time, trauma, poor rotation, abnormalities of the bottom, and vexation from disunion or pressure. Cases with diabetes for an expanded period of time may create neuropathy, which may be a reduced or total misfortune of feeling within the bases due to whim-whams harm caused over time by tall blood sugar circumstances. whim-whams harm as often as possible happens in an inert state, with the influenced existent being insensible of the issue. Your podiatrist can utilize a monofilament, a clear and easy instrument, to appraise your bases for neuropathy. Vascular complaint can complicate a foot ulcer by waning the body's capability to recuperate and including the risk of disease.

Diabetic bottom ulcers can be offered using the Wound, Ischemia, and Foot Infection(WIfI) Threatened branch Bracket System.This approach offers threat categorization for major amputation and facilitates communication between clinicians. When infection is suspected, blood tests including a complete blood count(CBC),a thorough metabolic panel, haemoglobin A1c(HbA1c), and seditious labels should be attained. Get weight- bearing radiographs of the branch that's injured. Deciphering the fissure, applying saline or comparable dressings daily to create a moist crack landscape, administering antibiotics with or without surgical measures in cases of osteomyelitis or soft cloth infection, sustaining optimal blood glucose management, and evaluating and addressing additional arterial insufficiency are all imperative for the management of diabetic foot ulcers. A professed podiatrist or vascular surgeon should assess every case with diabetic bottom ulcers. They should take into account possibilities for soft towel covering, vascular reconstruction and reconstructive surgery on the bony armature. Fig 1 shows the normal foot vs diabetic foot ulcer

Fig 1: Normal foot vs Diabetic foot ulcer

2. RELATED WORK

Lihong chen md, et.al,…[1] Put the system in place for The degeneration of the skin and tissues of the foot in individuals with diabetes is known as a diabetic foot ulcer (DFU), and it is typically accompanied with peripheral arterial disease (PAD) and/or neuropathy.1. According to a 2017 meta-analysis, the global prevalence was estimated to be 6.3%, with significant regional variations.2. The number of patients with DFU is expected to rise significantly as the population with diabetes continues to grow. DFU can result in a higher rate of hospitalization and lower limb amputation and is linked to severe morbidity and mortality. According to our meta-analysis, approximately half of all deaths were caused by cardiovascular illnesses. It is often recognized that the top causes of death globally are cardiovascular illnesses, including ischemic heart disease and stroke.47 The World Health Organization estimates that cardiovascular illnesses account for close to 32% of all fatalities worldwide. The findings in the general population and the population with diabetes are consistent with the high percentage of cardiovascular disease-related deaths among patients with DFU.47, 48 Patients with DFU could live longer if cardiovascular risk factors were aggressively managed.49. Therefore, it is imperative to identify and treat cardiovascular disorders as well as the risk factors that are linked to them. It was discovered that infections—not just foot infections—were the second most common cause of death. Infection prevention, identification, and management have not received much attention in clinical practice, despite the fact that infections have been reported to be one of the most common causes of death in patients with DFU50. Furthermore, it hasn't gotten much attention in the global recommendations that have been issued. As a result, when developing guidelines and conducting clinical procedures, infection prevention and control should be considered more frequently.

Dewa ayu rismayanti, et.al,…[2] expanded quickly, coinciding with a rise in the regular usage of cell phones and the internet for communication. Furthermore, android is the primary operating system used on smartphones nowadays, and it's also a way to get health information through telemedicine and telemarking. A number of strategies for the early diagnosis of DFU in diabetic patients are influenced by the usage of technology in the health sector. It has been extensively developed to use cameras and computers to detect neuropathic problems in individuals with diabetes mellitus. Additionally, early DFU detection is accomplished through direct intervention utilizing standard instruments like pin-prick testing and footwear with sensors. There are currently just a few studies discussing one model of early DFU detection in DM patients, and no studies that describe multiple strategies that can be employed for early identification in DM patients have been found. The purpose of this systematic review is to clarify the many digital and conventional-based early detection approaches, together with their advantages and disadvantages, in order to assess risk factors for DFU in patients with diabetes mellitus. The most widely used method in a range of treatment contexts is the early detection of diabetic foot ulcers in patients by conventional methods or direct physical examination. Since the patient walks frequently, the footwear-based method of ulcer diagnosis is believed to be beneficial. Not only can the gait of individuals with DM evaluate the pressure in their legs, but it can also reveal an anomaly that may be indicative of a neuropathic condition. Meanwhile, because the pinprick test is a straightforward process that accurately determines the risk of DFU, using it to diagnose DFU early on is also seen to be beneficial. Mccague, cathal, et.al,…[3] Applied medical image interpretation is based on a visual evaluation that is primarily qualitative and is influenced by the experience and training of the observer. For example, contouring a three-dimensional volume of interest (such as a tumor or surrounding structures) is a crucial stage in the planning of radiotherapy treatment in oncological practice. When done by hand, this is a tedious and possibly inconsistent operation. Over the past ten years, advances in high-performance computers have transformed medical images into high-dimensional data that can be digitally mined to extract new insights. Simultaneously with these advancements, sophisticated AI algorithms have surfaced. These algorithms perform tasks in a highly automated, practically instantaneous, and consistent manner in contrast to traditional radiography. Medical image analysis is a specialty of artificial intelligence (AI) tools, which can automatically detect complex aberrant patterns in radiological pictures and quantitatively identify disease. These methods are currently being applied in clinical research settings for lesion categorization, screening, diagnosis, prognosis evaluation, and to enhance our comprehension of basic disease processes and therapeutic response evaluation. The adaptation of AI-based contouring tools, also known as segmentation tools, from research to a clinical setting is one such instance. A robust and reliable automated segmentation technique would have clinical utility by automatically segmenting medical images, a critical and time-consuming step in radiation planning and the development of predictive radionics biomarkers. Currently, the most often used methods for assessing the efficacy of AI-based segmentation systems are quantitative metrics, like the overlap-based dice similarity coefficient. But this approach can't identify or classify the errors an algorithm might be making. This lack of openness could make it possible to hide serious flaws or poor algorithmic performance.

Rene markovič, et.al,…[5] entailed using a range of drugs, many of which are recommended in accordance with the unique characteristics of each patient. It is still difficult to comprehend medication use patterns and how they relate to clinical outcomes, though. In this study, we developed a unique natural language processing (NLP) method to extract information on prescription medications from the lab test results and medical records of diabetes patients. One key challenge that we have managed to tackle is the usage of simple text files created by doctors and the chronological organization of all relevant information extracted from the files for our use. It is crucial to note that medical records made by doctors are not connected to any other databases or registries. We were forced to create a language model that could extract every piece of information as a result. Consequently, this solution is able to independently examine Slovenian plain text files in an orderly and methodical fashion, and it may also facilitate further research as required. This publication offers insightful information about the medication features of diabetics in different age groups. Using the data, we have developed a system that allows us to identify groups of patients with diabetes who use comparable medications and to construct patient-specific profiles. Important distinctions between the extracted profiles have also been assessed by us. One of the study's main accomplishments is the development and implementation of a novel natural language processing (NLP) algorithm that successfully extracts prescription information from diabetes patients' electronic medical records (EMRs). The language model can interpret a large amount of textual data and provide relevant information on the characteristics and usage patterns of pharmaceuticals because it was trained on specific medical records. Another notable aspect is the extensive analysis of the EMR, which allowed for the identification of medication clusters and the tracking of diabetics' movements among age groups within clusters. This thorough investigation provides information on drug consumption trends and possible effects on patient care and diabetes management.

3. EXISTING METHODOLOGIES

The realm of diabetic foot ulcer (DFU) classification is undergoing transformative advancements through the integration of machine learning techniques. Recognizing the critical importance of early detection and treatment, researchers are delving into feature-rich datasets, particularly comprising medical images of diabetic patients' feet. Advanced feature extraction methods, including wavelet transforms, Gabor filters, and machine learning algorithms, are employed to capture intricate patterns and textures essential for distinguishing between healthy tissues and ulcerations. Ensemble techniques, which combine the predictive strength of several models to improve classification resilience, are widely used. K-Nearest Neighbor algorithms, Random Forests, decision trees, and support vector machines are a few examples of these methods. While some research handle restricted DFU datasets by using transfer learning from pre-trained deep learning models, others investigate a multimodal method that integrates data from multiple imaging modalities. Integrating clinical data, such as patient history, demographics, and real-time processing capabilities, contributes to a holistic understanding of DFUs, promoting accurate and timely classifications. Furthermore, efforts towards enhancing the interpretability of machine learning models aim to facilitate trust and comprehension among healthcare professionals, paving the way for practical and effective applications in diabetic foot ulcer management.

Data Collection and Preprocessing:

Gather a comprehensive dataset of foot images, ensuring it includes a balanced representation of both normal and ulcerated cases. Preprocess the images, applying techniques such as resizing, normalization, and possibly feature extraction to represent key aspects of the foot images numerically.

Feature Selection:

Identify relevant features that contribute to the classification of DFUs. These could include texture patterns, color information, or any other characteristics specific to diabetic foot ulcers.

Labeling:

Assign labels to the dataset indicating whether each image represents a normal foot or a foot with a diabetic ulcer.

Data Splitting:

The dataset is isolated into preparing and testing sets. The show learns from the preparing information and its execution is assessed on the testing information.

Decision Tree Model Training:

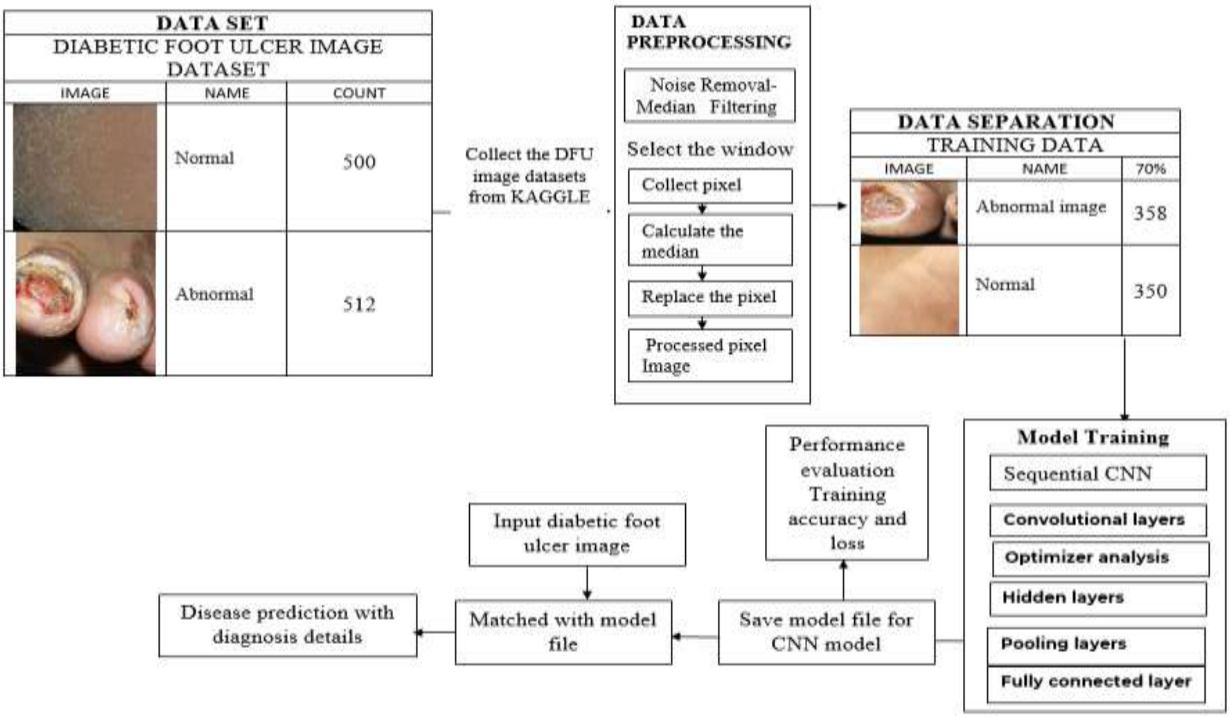
Implement a Decision Tree classifier using a machine learning library (such as Scikit-learn in Python).Utilizing the annotated training data, train the Decision Tree so that the algorithm may discover the patterns connected to photos of both normal and ulcerated feet.

Model Evaluation:

Utilize measurements like exactness, accuracy, review, and F1 score to evaluate the prepared model's execution on the testing set in arrange to find out how well it generalizes to modern, unidentified information.

4. PROPOSED METHODOLOGIES

The proposed system for diabetic foot ulcer(DFU) classification introduces a sophisticated approach to leveraging Convolutional Neural Networks(CNNs) for enhanced accuracy and efficiency in the classification process. Beginning with the collection of a diverse and well-annotated dataset encompassing normal and ulcerated foot images, the system emphasizes data preprocessing, including resizing, normalization, and augmentation, to optimize the dataset for training. Robust model training and evaluation are facilitated by the split of datasets into training, validation, and testing sets. The CNN architecture, which is intended primarily for image classification, incorporates convolutional layers for feature extraction, pooling layers for spatial down sampling, and fully linked layers for classification. The CNN learns to automatically identify essential features that differentiate between normal and ulcerated instances through rigorous training on the heterogeneous dataset. The system incorporates hyperparameter tuning and model evaluation, leveraging metrics like accuracy and precision. Optionally, visualization techniques aid in interpreting the CNN's decision-making process. If the model meets performance criteria, deployment in clinical settings offers potential support to healthcare professionals in DFU diagnosis. Continuous learning mechanisms, though optional, enable adaptation to new data over time, ensuring the system's ongoing relevance and effectiveness in diabetic care. Overall, this proposed system stands to significantly advance the capabilities of DFU classification, fostering early detection and intervention in the management of diabetic complications.



This suggested system uses convolutional neural networks (CNNs) to present a fresh approach to DFU image categorization. Our suggested approach makes use of deep learning to automatically classify DFU photos into various groups, allowing for prompt intervention and improving the standard of care. The CNN architecture that serves as the foundation of the system has been specially modified for DFU classification. This deep convolutional neural network (CNN) with pooling and fully connected layers effectively recognizes and extracts fine details from ulcer images (Fig 2).

Fig2: Proposed architecture

Building a Convolutional Neural Network (CNN) involves a systematic series of steps to effectively process and classify images. The initial phase entails collecting a well-labelled dataset, such as images of diabetic foot ulcers for classification purposes. Data preprocessing, which entails scaling photos to a uniform dimension, standardizing pixel values to a standardized scale, and incorporating augmentation procedures to diversify the dataset, is therefore essential for standardization. At the heart of this process lies the Convolutional Neural Network(CNN) armature. This armature is strictly drafted with structure blocks like convolutional layers to prize features, pooling layers to epitomize information, and completely connected layers to perform bracket. Once this armature is in place, the model is fine- tuned by opting applicable functions a loss function(like categorical cross-entropy) to measure crimes and an optimizer(like Adam or SGD) to acclimate the model's internal parameters. Eventually, the model undergoes training, where it learns from the data by iteratively conforming its internal connections(weights) through backpropagation and optimization algorithms. Throughout this training phase, the model refines its ability to recognize patterns and features in the data, ultimately achieving a level of proficiency in distinguishing between different classes. These steps collectively form a comprehensive framework for developing a CNN, a powerful tool in image classification tasks like the detection of diabetic foot ulcers.

Initialization: To start constructing the CNN armature, determine the volume of convolutional layers, pooling layers, completely connected layers, activation functions, and affair layers.

Input Processing: Input the labeled dataset of images into the CNN.Implement preprocessing techniques include uniformly resizing photos, standardizing pixel values, and maybe enhancing the dataset with transformations like flips or rotations.

Convolution and Feature Extraction: Utilizing filters or kernels carry out convolution operations in the CNN's initial layers to extract features from the input images. After every convolutional operation, add non-linearity using activation functions (such as ReLU).

Pooling or Subsampling: Utilize pooling layers, such as max pooling, to minimize the retrieved features' spatial dimensions while maintaining their crucial information.

Flattening and Fully Connected Layers: Flatten the pooled feature maps into a single vector.

Join the flattened vector with fully connected layers to create a classifier that uses the collected data to identify high-level features.

Output Layer and Activation: To generate class probabilities, add an output layer with an activation function appropriate for the task (softmax for multi-class classification, for example).

Loss Computation: Determine the difference between the true labels and the predicted outputs (e.g., categorical cross-entropy for classification problems) using a chosen loss function.

Optimizer and Backpropagation: Set up an optimizer (such as Adam or SGD) to update the weights of the network by taking the calculated loss into account.

Iteratively update weights using backpropagation to reduce loss and enhance model performance.

Training Loop: Iteratively feed batches of training data through the network.

Compute the loss, backpropagate the gradients, and update the weights in each iteration (epoch) of the training loop.

Validation and Hyperparameter Tuning: Examine the model's performance on a different validation set to keep an eye on its recall, accuracy, and precision.

Adjust hyperparameters (learning rate, batch size, etc.)in response to validation outcomes to enhance the model's generalization capabilities.

Testing: Assess the trained CNN's performance on unseen data and validate its efficacy by evaluating it on a held-out test dataset.

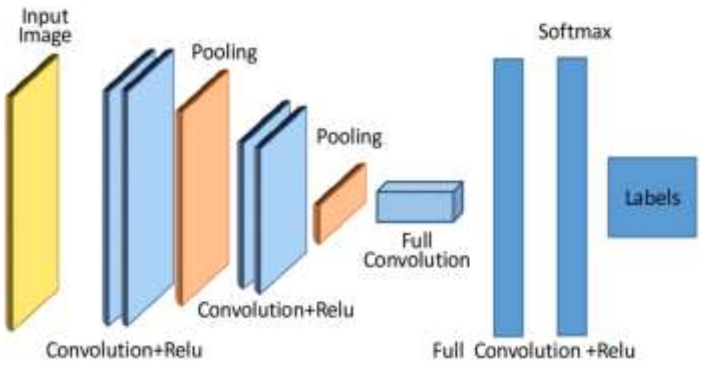


FIG 3. CNN ARCHITECTURE

5. RESULTS AND DISCUSSION

In this consider, we will collect the datasets from KAGGLE interface it incorporates typical and irregular pictures. Preparing exactness and preparing misfortune can be utilized to evaluate the system's execution. The performance conversation is displayed in Figs. 4 and 5. A deep learning model's "training accuracy" is a measurement of how well it operates on the training set of data. It displays the percentage of cases in the training dataset that are correctly classified.

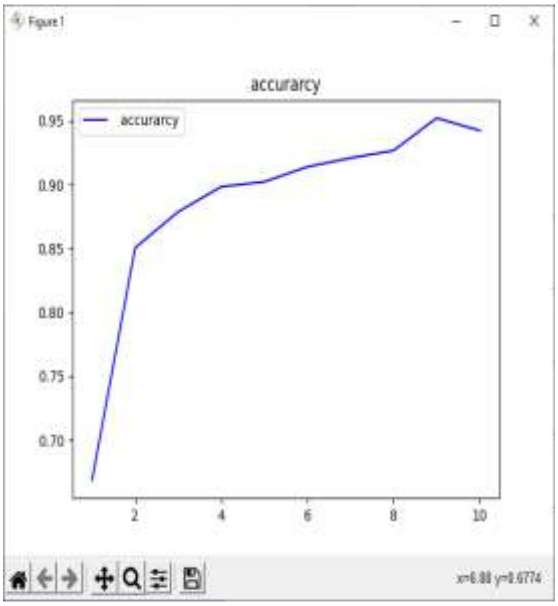


Fig 4: Training accuracy

In the context of deep learning, "training loss" refers to a model's performance during the training phase. It displays the error or discrepancy between the model's predictions and the target values found in the training set. Usually, the goal of training is to reduce this loss, indicating that the model is become ng more predictive.

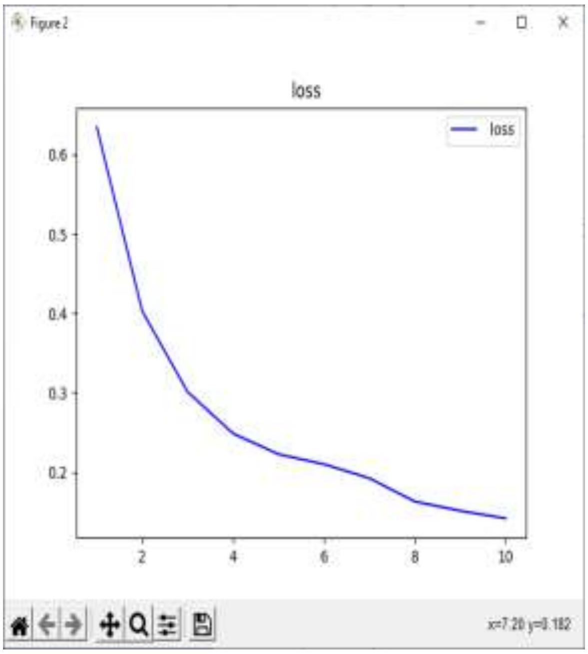


Fig 5: Training loss

From the above figures proposed system achieve the accuracy upto 95% and loss values 0.01.

6. CONCLUSION

In conclusion, using machine learning-more especially, Convolutional Neural Networks (CNNs)-to the field of diabetic foot ulcer (DFU) detection has enormous promise for enhancing early diagnosis and intervention. Creating accurate and efficient models for DFU classification requires a lot of meticulous steps, from obtaining and preparing datasets to training models and making real-time inferences. Multiclass classification methods provide a thorough grasp of the severity and characteristics of diabetic foot ulcers, allowing for more sophisticated categorization. The CNN-based DFU classification system that is being suggested makes use of deep learning to increase efficiency and accuracy. The model's real-time analysis of diabetic foot ulcer photos has the potential to greatly improve patient care by facilitating quick treatments and knowledgeable clinical decisions. However, there are still problems that need to be handled, like the necessity for a range of carefully annotated datasets, moral dilemmas with handling medical data, and continual model monitoring and modification in response to evolving clinical situations. Addressing these challenges is essential for the successful integration of machine learning technologies into clinical practice p.

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