

Image-Based Classification of Diabetic Foot Ulcers Using CNNs

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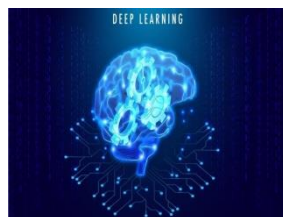
Abstract: Diabetic foot ulcers (DFUs) pose a significant healthcare challenge due to their prevalence and potential complications. Early and accurate detection of DFUs is crucial for timely intervention and prevention of severe complications. This study proposes an innovative approach for automated DFU detection utilizing Convolutional Neural Networks (CNNs), a powerful class of deep learning algorithms widely recognized for their proficiency in image analysis tasks. The proposed CNN model is trained on a comprehensive dataset of foot images, encompassing a diverse range of DFU types, stages, and conditions. 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.

I. INTRODUCTION

Deep learning is a subset of machine learning, which is essentially a neural network with three or more layers. These neural networks attempt to simulate the behaviour of the human brain—albeit far from matching its ability—allowing it to “learn” from large amounts of data. While a neural network with a single layer can still make approximate predictions, additional hidden layers can help to optimize and refine for accuracy. Deep learning drives many artificial intelligence (AI) applications and services that improve automation, performing analytical and physical tasks without human intervention. Deep learning technology lies behind everyday products and services (such as digital assistants, voice-enabled TV remotes, and credit card fraud detection) as well as emerging technologies (such as self-driving cars). It has emerged as one of the most promising areas of research in artificial intelligence and has been applied to a wide range of applications such as image and speech recognition, natural language processing and robotics.

II. DEEP LEARNING APPLICATIONS

Real-world deep learning applications are a part of our daily lives, but in most cases, they are so well-integrated into products and services that users are unaware of the complex data processing that is taking place in the background. Some of these examples include the following robotics.



Deep learning structure

LAW ENFORCEMENT

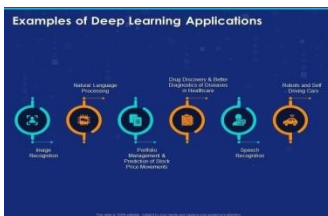
Deep learning algorithms can analyze and learn from transactional data to identify dangerous patterns that indicate possible fraudulent or criminal activity. Speech recognition, computer vision, and other deep learning applications can improve the efficiency and effectiveness of investigative analysis by extracting patterns and evidence from sound and video recordings, images, and documents, which helps law enforcement analyze large amounts of data more quickly and accurately.

FINANCIAL SERVICES

Financial institutions regularly use predictive analytics to drive algorithmic trading of stocks, assess business risks for loan approvals, detect fraud, and help manage credit and investment portfolios for clients.

CUSTOMER SERVICES

Many organizations incorporate deep learning technology into their customer service processes. Chatbots—used in a variety of applications, services, and customer service portals—are a straightforward form of AI.



DL Application

ADVANTAGES OF DEEP LEARNINGS

FEATURE GENERATION AUTOMATION

Deep learning algorithms can generate new features from among a limited number located in the training dataset without additional human intervention. It means deep learning can perform complex tasks that often require extensive feature engineering. For businesses, it means faster application or technology rollouts that deliver superior accuracy.

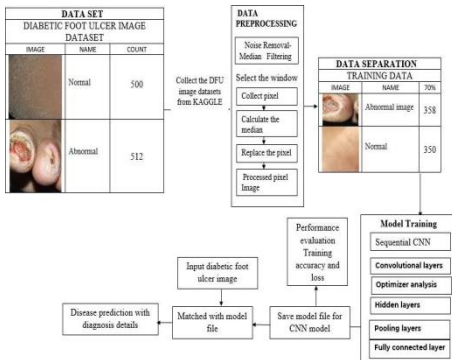
WORKS WELL WITH UNSTRUCTURED DATA

One of the biggest draws of deep learning is its ability to work with unstructured. In the business context, it becomes particularly relevant when you consider that the majority of business data is unstructured. Text, images, and voice are some of the most common data formats that businesses use

III. PROPOSED SYSTEM

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. Dataset division into training, validation, and testing sets facilitates robust model training and evaluation. The CNN architecture, tailored for image classification, integrates convolutional layers for feature extraction, pooling layers for spatial down sampling, and fully connected layers for classification. Through meticulous training on the diverse dataset, the CNN learns to automatically discern relevant features distinguishing normal from ulcerated cases. 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, it is a proposed system stands to significantly advance the capabilities of DFU classification, fostering early detection and intervention in the management of diabetic complications. It is a proposed system presents a novel system for DFU image classification based

on Convolutional Neural Networks (CNNs). Leveraging the power of deep learning, our proposed system automates the classification of DFU images into different categories, facilitating timely intervention and enhancing the quality of care. System is built around a customized CNN architecture optimized for DFU classification. The network consists of multiple convolutional layers,



pooling layers, and fully connected layers, enabling the model to learn and extract intricate features from the ulcer images.

ADVANTAGES

- Extract the all features
- Dimensionality can be reduced
- Improve the classification accuracy
- Automated segmentation

SYSTEM ARCHITECTURE

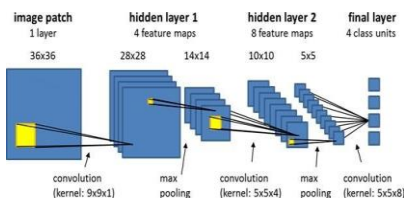
MODULES

- Data Collection And Preprocessing
- Convolutional Neural Network (Cnn) Architecture
- Training And Validation
- Multi-Class Classification
- Real-Time Inference

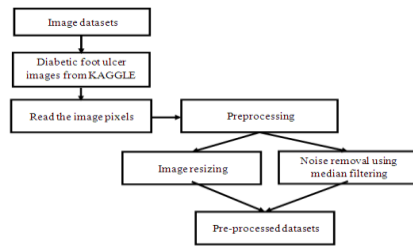
MODULES DESCRIPTION

DATA COLLECTION AND PREPROCESSING

Diabetic foot ulcers (DFUs) are visual representations of a critical complication arising from diabetes, captured through various imaging modalities. These images typically depict the affected foot, showcasing skin lesions, wounds, or ulcerations resulting from poor circulation, nerve damage, or other diabetes-related



complications. The images play a pivotal role in medical diagnosis and treatment planning, allowing healthcare professionals to assess the severity, size, and characteristics of the ulcers. In clinical settings, digital photography, thermal imaging, or other medical imaging techniques are employed to document DFUs, providing a visual basis for monitoring the progression of wounds, evaluating the effectiveness of interventions, and facilitating collaborative decision-making between healthcare providers and patients.



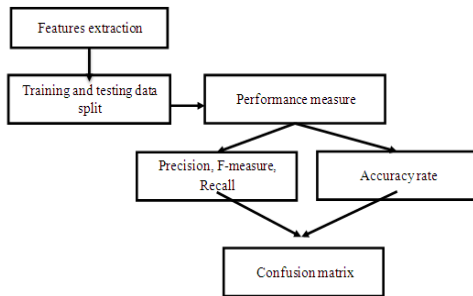
Data Collection And Preprocessing

CONVOLUTIONAL NEURAL NETWORK (CNN) ARCHITECTURE

A convolutional neural network is a feed-forward neural network that is generally used to analyze visual images by processing data with grid-like topology. It's also known as a ConvNet. A convolutional neural network is used to detect and classify objects in an image Convolutional Neural Network (Cnn) Architecture

TRAINING AND VALIDATION

The training and validation phases are integral components in the development of Convolutional Neural Networks (CNNs) for tasks such as diabetic foot ulcer detection. During the training phase, the CNN learns from a labeled dataset, adjusting its internal parameters through backpropagation and optimization algorithms to minimize the computed loss function.



Training And Validation

MULTI-CLASS CLASSIFICATION

In a module, the CNN model is designed to perform two-class classification. It involves configuring the output layer to produce predictions for various DFU categories, such as ulcer type (normal or abnormal). Various evaluation metrics, such as accuracy, precision, recall, and F1-score, are calculated to measure how well the system can classify DFUs.

REAL-TIME INFERENCE

Once the model is trained and validated, it is a module enables the system to perform real-time inference. It allows for the automated classification of new DFU images as they are input into the system, providing quick and accurate diagnosis.

VI. CONCLUSION

On the basis of the symptoms seen on the leaves, a limited amount of study has been done on the automated diagnosis of coffee leaf diseases. Therefore, the goal of it is an article was to create a model to identify coffee leaf disease at its early stage. It is a model would be extremely helpful to farmers, extension agents, and agricultural experts, and it will also boost the quality and quantity of coffee crops produced for the export market. As a result, we put forth a method for employing a convolutional neural network to identify and categorize coffee leaf disease in Ethiopian coffee leaves. The Resnet50 model's experiment on transfer learning produced a 99.89% accuracy result, outperforming the approaches that were examined over training from scratch and MobileNet. As a result, the four classes of coffee leaf diseases can be readily identified and classified with high performance utilizing our constructed model employing Resnet50.

FUTURE ENHANCEMENT

In future we can extend the framework implement various deep learning algorithms to improve the accuracy in disease prediction. An integrated approach involving multimodal data, including novel imaging techniques, could provide a more comprehensive understanding of DFUs. Prioritizing the development of models with explainable AI (XAI) capabilities ensures transparency and trust in the decision-making process for clinicians. Continuous learning mechanisms will allow models to adapt to evolving clinical scenarios and emerging patterns in DFUs over time.

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