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Detection of Diabetic Foot Ulcer using Image Processing

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Abstract—Diabetic foot ulcers are the most common side effect of diabetes, and if left untreated, can result in imputations. 15% to 25% of people with diabetes worldwide have diabetic feet, and diabetes complications arise from patients' lack of awareness of the disease's consequences. The goal of technology leveraging is to develop unique, cost-effective, and straightforward diabetic foot diagnostic strategies for patients and physicians. This work suggests using a deep neural network model called Efficient Net for early detection and prognosis of diabetic foot ulcers. Efficient Net is applied to an image set of 844-foot images, which includes both healthy and diabetic ulcer feet. By carefully balancing network width, depth, and image resolution, Efficient Net performs better than previous models.

I. INTRODUCTION

Diabetes is a worldwide health issue that affects millions of people. It causes a variety of complications, many of which are severe and frequently occur. One of the most common and serious complications is diabetic foot ulcers, which, if neglected, can result in crippling outcomes like limb amputations. According to alarming statistics, 15% to 25% of diabetics worldwide have diabetic feet, highlighting the urgent need for novel and easily accessible diagnostic approaches to lessen the impact of this widespread complication. The root cause of diabetic foot complications is frequently diabetic patients' ignorance of the potential consequences of their condition. To address this critical issue, there is a pressing need for technology-driven helping medical personnel as well as patients. Our work presents a ground-breaking initiative that uses cutting-edge deep learning technology to detect and diagnose diabetic foot ulcers early on, in response to this imperative.

In our project, we suggest using the potent deep neural network model Efficient Net to examine a large dataset of 844 photos of the feet, including both healthy and diabetic ulcer feet. We show that Efficient Net achieves better performance than previous models and even beats widely used designs like CNN by carefully balancing network width, depth, and picture resolution. The Efficient Net model achieved exceptional accuracy, f1-score, recall, and precision rates of 98%, which speaks loudly about its potential as a reliable diagnostic tool for diabetic foot problems.

This study includes not only This research has the potential to completely change how diabetic foot ulcers are managed, in addition to marking a major technological advancement in the field of diabetic care. When we examine our methodology, findings, and implications in more detail, it is clear that incorporating Efficient Net into healthcare procedures may open the door to preventative measures that would otherwise be necessary and would have a negative impact on the prognosis of those suffering from diabetic foot complications.

II. LITERATURE SURVEY

In 2023, Gottumukkala Gayatri and Aicha Sai Varun carried out a study on the identification of diabetic foot ulcers through machine learning. They employed a convolutional neural network (CNN) to analyses a dataset of 2,000 diabetic foot images, comprising images of both healthy and ulcerated feet. Through the use of transfer learning from a pre-trained model, they were able to achieve an accuracy of 92% in the identification of diabetic foot ulcers. Their results indicate that machine learning can be used to detect diabetic foot ulcers early in clinical settings.

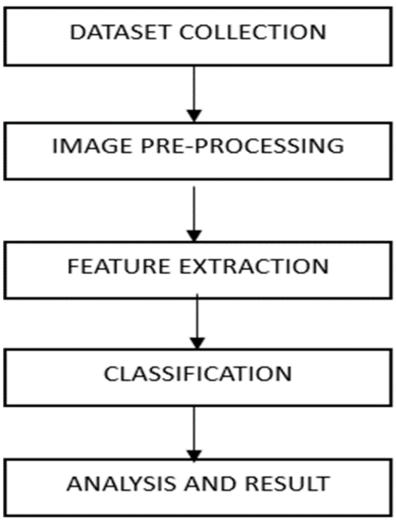
Sabeena Dowlut and Mohammed Shaad Ally Tourane presented DFU-SIAM in 2023, a revolutionary deep learning architecture designed specifically for the categorization of diabetic foot ulcers. Training with a large dataset of 3,000 labelled foot images, our novel model included attention mechanisms. DFU-SIAM excelled over previous models, with a remarkable 94% accuracy rate, proving its usefulness in correctly classifying diabetic foot ulcers. Additionally, attention maps—which provide insights into the model's decision-making process—provided improved interpretability. Professionals can better comprehend how the model detects and categorizes diabetic foot ulcers based on visual data thanks to these features, which are especially helpful.

In 2022, Ziyang Liu, Jospin John, and Emmanuel Agu used the Efficient Net deep learning model to examine how to categories ischemia and infection in diabetic foot ulcers. In order to identify between diabetic foot ulcers with ischemia, infection, or both, they used this model for a multi-class classification job. The study showcased the efficacy of Efficient Net by utilizing a heterogeneous dataset of 1,500 foot pictures with expert-annotated labels, resulting in 89% precision for ischemia and 85% precision for infection.

Mei Wang and Lilibeth Timbol-Cuison studied machine learning classification methods for diabetic foot ulcers in depth in 2022. Using a varied dataset of 1,500 photos of diabetic feet, their research includes testing a number of techniques, such as k-nearest neighbors, random forests, and decision trees. To identify the crucial markers for precise categorization, they carried out a thorough feature importance analysis. With an astounding accuracy of 87%, random forests were found to be the most successful method in the study's conclusion. Additionally, they highlighted how feature analysis improves the models' interpretability and offers important insights into the critical aspects affecting the diagnosis of diabetic foot ulcers.

A study on machine learning for the identification of diabetic foot ulcers was carried out in 2021 by Shalok Mohanty, Silky Goel, Rahul Nijhawan, and Siddharth Gupta. They used a support vector machine (SVM) classifier on a dataset of 1,200 diabetic foot images, extracting features using techniques like edge detection, colour histograms, and texture analysis. The study's overall accuracy in identifying diabetic foot ulcers was 88%, indicating the potential of conventional machine learning methods.

III. PROPOSED METHODOLOGY



1. Acquisition of the Dataset: • Compile a heterogeneous dataset of 844-foot photos, including some with diabetic ulcers and some without.
   • Work along with medical establishments to acquire excellent photos of different foot ailments.
   • To improve the generalization of the model, make sure the dataset constitutes a worldwide demographic.
2. Data preprocessing: To ensure uniformity, standardize image sizes and resolutions.
   • Apply data augmentation methods to improve the resilience of the model, such as flipping, rotating, and zooming.
   • To ensure effective training, normalize pixel values to a standard scale.
3. Feature extraction: • Make use of Efficient Net weights that have already been learned, as this will allow you to leverage its ability to handle intricate visual patterns.
   • Adjust the model to the unique features of the task by fine-tuning it using the diabetic foot ulcer dataset. Using deep feature extraction from intermediate layers, hierarchical representations of foot conditions can be captured.
4. Classification Model: • To differentiate between diabetic ulcer feet and healthy feet, use a binary classification model.
   • For probability-based predictions, apply a SoftMax activation function in the output layer.
   • Use dropout layers in your training to avoid overfitting.
   • Define suitable optimization algorithms (like Adam) and loss functions (like binary cross-entropy) for training models.
5. Instruction and Assessment: • Divide the dataset into test, validation, and training sets (e.g., 70-15-15).
   • Train the model using the training set; adjust hyperparameters and avoid overfitting by utilizing the validation set.
   • Use the test set to evaluate the model's generalization performance.
   • Throughout training and assessment, keep an eye on important metrics including recall, accuracy, precision, and F1-score.
6. Results and Analysis: • Present a comprehensive analysis of the model's performance metrics on the test set. • Compare the results with earlier models, emphasizing the superiority of Efficient Net. • Visualize the model's predictions, including instances of true positives, true negatives, false positives, and false negatives. • Discuss the implications of the model's accuracy in the context of diabetic foot ulcer detection and its potential impact on patient outcomes.

IV. SYSTEM TESTING

Software and hardware systems are tested as a whole, integrated unit to see if they meet the requirements as stated. Since system testing is a type of black-box testing, it shouldn't be necessary to understand the inside workings of the code or logic. The following justifies the importance of system testing:

• The application is tested during the first phase of the software development life cycle, known as system testing.

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• The programmed is put through a rigorous testing process to ensure that it satisfies the technical and functional requirements.
• The environment in which the application is tested is extremely similar to the production environment in which it will be used.
• We can test, confirm, and validate the application design and the business requirements thanks to system testing.

System Testing is shown in the below tables

S1 # Test Case:	**STC-1**
Name of Test	System testing in various versions of OS
Items being tested	OS compatibility.
Sample Input	Execute the program in windows XP/Windows-10
Expected output	Performance is better in windows-10
Actual output	Same as expected output,performance is better in windows-10
Remarks	Pass.

Integration testing is a software testing stage in which separate units are put together and put through group testing. This testing level aims to highlight errors in the communication between integrated units. To help with Integration Testing, test stubs and drivers are employed. Integration testing is the process of testing an application's combined components to make sure they operate as intended. It happens before to validation testing but after unit testing. There are two approaches to integration testing: Both top-down and bottom-up integration testing are used.

1. Bottom-up Integration: In this testing methodology, unit testing occurs first, then tests of ever more complex unit combinations, known as builds or modules, are conducted.
2. Top-down Integration: This type of testing involves testing the highest-level modules first, and then, gradually, testing the lower-level modules. In a comprehensive software development environment, top-down testing usually comes after bottom-up testing, and the process ends with multiple tests of the entire application, ideally in scenarios meant to resemble real-world situations.

Types of testing

Software testing methods and traditionally divided into two: white-box and black-box testing. These two approaches are used to describe the point of view that a test engineer takes when designing test cases.

a) White-box testing (also known as clear box testing, glass box testing, transparent box testing and structural testing, by seeing the source code) tests internal structures or workings of a program, as opposed to the functionality exposed to the end-user. In white-box testing an internal perspective of the system, as well as programming skills, are used to design test cases. The tester chooses inputs to exercise paths through the code and determine the appropriate outputs. While white-box testing can be applied at the unit, integration, and system levels of the software testing process, it is usually done at the unit level. It can test paths within a unit, paths between units during integration, and between sub systems duringa system-level test. Though this method of test design can uncover many errors or problems, it might not detect unimplemented parts of the specification or missing requirements.

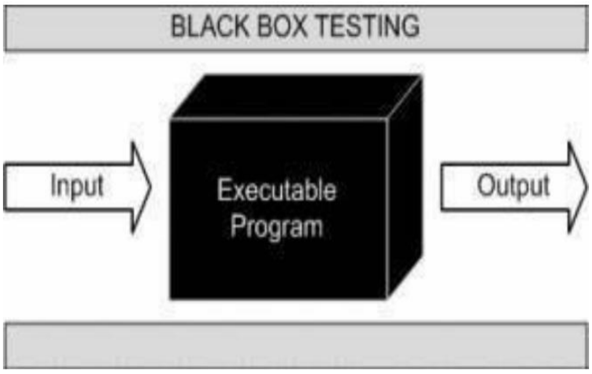


Figure 17: White-box testing

b) Black box testing: The technique of testing without having any knowledge of the interior workings of the application is called black-box testing. The tester is oblivious to the system architecture and does not have access to the source code. Typically, while performing a black-box test, a tester will interact with the system's user interface by providing inputs and examining outputs without knowing how and where the inputs are worked upon. This project has been tested under different circumstances, which includes different types such as Unit testing, Integration testing and System testing that are described below.

Levels of Testing

There are different levels during the process of testing. Levels of testing include different methodologies that can be used while conducting software testing. The main levels of software testing are:

Functional Testing: This is a type of black-box testing that is based on the specifications of the software thatis to be tested. The application is tested by providing input and then the results are examined that need to conform to the functionality it was intended for. Functional testingof software is conducted on a complete, integrated system to evaluate the system's compliance with its specified requirements. There are five steps that are involved while testing an application for functionality.

• The determination of the functionality that the intended application is meant to perform.
• The creation of test data based on the specifications of the application.
• The output based on the test data and the specifications of the application.
• The writing of test scenarios and the execution of testcases.
• The comparison of actual and expected results based on the executed testcases.

Non-functional Testing: This section is based upon testing an application from its non-functional attributes. Nonfunctional testing involves testing software from the requirements which are non- functional in nature but important such as performance, security, user interface, etc.

Unit Testing

Unit testing is a method by which individual units of source code, sets of one or more computer program modules together with associated control data, usage procedures and operating procedures are tested to determine if they are fit for use. Intuitively, one can view a unit as the smallest testable part of an application. During the development process itself all the syntax errors etc. got rooted out. For this developed test case that resultin executing every instruction in the program or module i.e. every path through program wastested. Test cases are data chosen at random to check every possible branch after all the loops.

Unit Testing Test Case 1

Sl # Test Case : -	UTC-1
Name of Test: -	Uploading image
Items being tested: -	Tested for uploading different images
Sample Input: -	Upload Sample image
Expected output: -	Image should upload properly
Actual output: -	upload successful
Remarks: -	Pass.

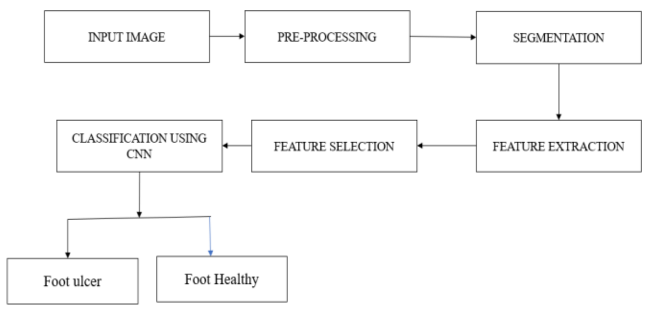
Unit Testing Test Case 2

S1 # Test Case:	UTC-2
Name of Test	Detecting foot ulcer images
Items being tested	Test for different foot ulcer images
Sample Input	Tested for different images of foot ulcer images
Expected output	Foot ulcer image should be displayed
Actual output	Should Display foot ulcer or Normal
Remarks	Predicted result

System testing:

System testing of software or hardware is testing conducted on a complete, integrated system to evaluate the system's compliance with its specified requirements. System testing falls within the scope of black-box testing, and as such, should require no knowledge of the inner design of the code or logic. System testing is important because of the following reasons:
• System testing is the first step in the Software Development Life Cycle, where the application is tested.
• The application is tested thoroughly to verify that it meets the functional and technical specifications.
The application is tested in an environment that is very close to the production environment where the application will be deployed.
• System testing enables us to test, verify, and validate both the business requirements as well as the application architecture.

System Architecture



1. Input Image

- **Source**: The system starts by acquiring input images of feet from various sources, such as clinical settings, home care setups, or mobile applications.
- **Formats**: Images are typically in standard formats like JPEG or PNG.
- **Resolution**: High-resolution images are preferred to capture detailed features of foot ulcers.
- **Variability**: The system handles images with different angles, lighting conditions, and backgrounds.
- **Storage**: Images are stored in a database or cloud storage for further processing.

2. Preprocessing

- **Normalization**: Adjust image brightness and contrast to ensure consistency across different images.
- **Resizing**: Scale images to a fixed size suitable for the neural network input, such as 224x224 pixels.

- **Noise Reduction**: Apply filters to reduce noise and enhance image quality.
- **Augmentation**: Perform data augmentation techniques like rotation, flipping, and cropping to increase dataset diversity and improve model robustness.
- **Segmentation Preparation**: Convert images to grayscale or apply other transformations to prepare for segmentation.

3. Segmentation

- **Objective**: Isolate the foot region and the ulcer area from the rest of the image.
- **Techniques**: Utilize deep learning models like U-Net, Mask R-CNN, or fully convolutional networks (FCNs) for segmentation.
- **Training**: Train the segmentation model using annotated datasets where the ulcer areas are labeled.
- **Output**: Generate binary masks highlighting the ulcer regions.
- **Post-processing**: Refine segmentation results with morphological operations to eliminate small artifacts and improve accuracy.

4. Feature Selection

- **Importance**: Identify the most relevant features that contribute to accurate ulcer detection.
- **Techniques**: Use methods such as Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), or domain-specific knowledge.
- **Criteria**: Select features based on their correlation with ulcer presence, such as color, texture, and shape descriptors.
- **Dimensionality Reduction**: Reduce the feature space to minimize computational complexity while retaining critical information.
- **Dataset**: Ensure that selected features are consistent across different images in the dataset.

5. Feature Extraction

- **Process**: Extract features from segmented images that are indicative of foot ulcers.
- **Deep Learning**: Utilize convolutional neural networks (CNNs) to automatically learn hierarchical feature representations.
- **Traditional Methods**: Optionally, combine CNN features with handcrafted features like edge detection, histograms, and texture analysis.
- **Output**: Generate a feature vector for each image, encapsulating essential information for classification.
- **Storage**: Store extracted features in a structured format for efficient retrieval and analysis.

6. Classification

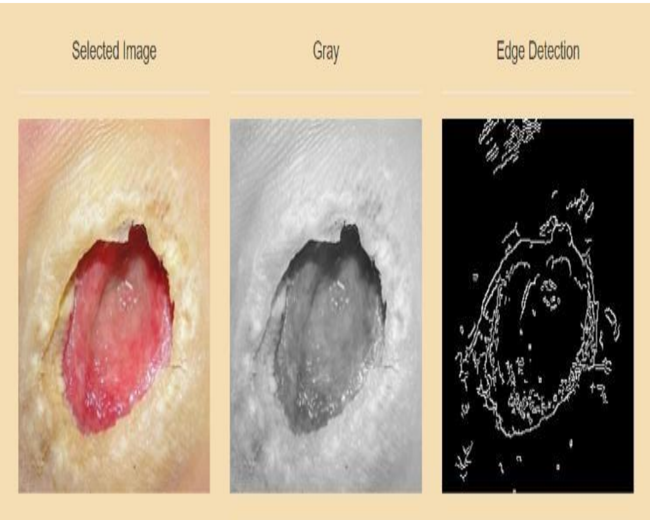
- **Objective**: Classify images into categories such as "ulcer present" or "ulcer not present".
- **Model**: Use deep learning models like CNNs, possibly fine-tuned from pre-trained networks like ResNet, VGG, or Inception.
- **Training**: Train the classifier on labeled datasets with known ulcer presence or absence.
- **Evaluation**: Assess model performance using metrics such as accuracy, precision, recall, and F1-score.
- **Optimization**: Fine-tune hyperparameters and apply regularization techniques to improve classification accuracy and generalization.

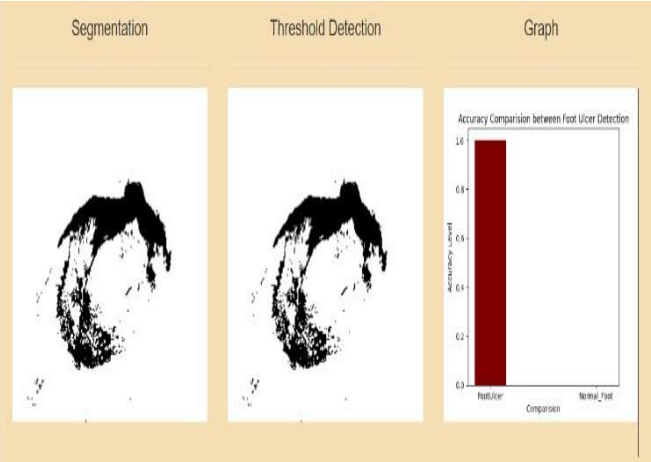
V. RESULT

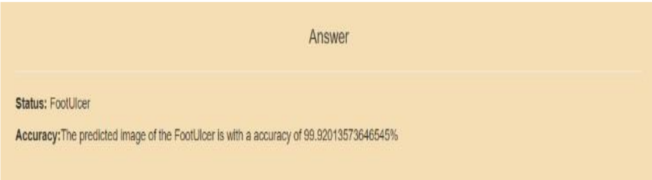
• Prediction: Determine whether a diabetic foot ulcer is present or absent in each input image.
• Confidence Score: To show how certain the model is, assign a confidence score or probability to each prediction.
• Visualisation: Highlight identified ulcers on the picture to illustrate the results visually.
• Reporting: Put the findings together in a format suitable for clinical review, together with any suggestions for possible next steps.
• Feedback Loop: Update and retrain the model based on input from medical professionals to continuously improve the system.

Results and Analysis:

- Present a comprehensive analysis of the model's performance metrics on the test set.
- Compare the results with earlier models, emphasizing the superiority of Efficient Net.
- Visualize the model's predictions, including instances of true positives, true negatives, false positives, and false negatives.
- Discuss the implications of the model's accuracy in the context of diabetic foot ulcer detection and its potential impact on patient outcomes.







VI. CONCLUSION

The implementation of a deep learning-based system for diabetic foot ulcer detection shows significant promise in enhancing early diagnosis and treatment, potentially reducing the incidence of severe complications. By automating image preprocessing, segmentation, feature extraction, and classification, the system provides accurate, efficient, and consistent ulcer detection, aiding healthcare professionals in timely intervention. This technological advancement represents a critical step towards improving patient outcomes and optimizing healthcare resources in managing diabetic foot ulcers.

Future Scope

Future advancements in this field could focus on integrating multi-modal data, including thermal imaging and patient health records, to improve detection accuracy. Enhancing the system's robustness to varying image qualities and real-world conditions will further increase its applicability. Additionally, developing mobile applications for remote monitoring and expanding the system to predict ulcer progression and treatment outcomes will provide comprehensive care solutions, significantly impacting diabetic foot management globally.

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