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INTERPRETABLE DIABETIC FOOT ULCER LOCALIZATION AND SEVERITY CLASSIFICATION USING YOLOv5, VGG19, RESNET WITH GRAD-CAM AND REST API INTEGRATION

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ABSTRACT
Diabetic Foot Ulcers (DFUs) are among the most severe complications faced by individuals with diabetes, often leading to infection, hospitalization, or amputation if left undiagnosed. This research presents an AI-powered system for early detection and classification of DFUs using medical imaging and deep learning. The VGG19 convolutional neural network, fine-tuned on the DFUC-2024 dataset, demonstrated high accuracy in distinguishing ulcer severity levels. To ensure clinical trust, explainable AI techniques such as Grad-CAM and LIME were integrated, enabling visual interpretation of model predictions. A real-time REST API and mobile-responsive interface facilitate remote ulcer screening and diagnosis. The proposed system not only aids healthcare professionals in decision-making but also enhances access to early intervention for patients in remote areas. Future extensions will include infection risk prediction, time-series ulcer tracking, and integration with wearable health sensors.

Keywords: Diabetic Foot Ulcer (DFU), Deep Learning, VGG19, Medical Imaging, Explainable AI (XAI), Grad-CAM, LIME, Remote Diagnosis, Image Classification, Transfer Learning, REST API, Mobile Health (mHealth), DFUC-2024 Dataset.

I. Introduction
One of the common issues faced by people with diabetes is the development of foot ulcer. These usually begin as open sore or wounds and gradually progress into a serious infection, or in may even lead to death. These ulcers often appear in areas where we apply a large amount of pressure, such as the big toe and the balls of the foot. In severe cases, the infection can reach the bones. To address this issue, researchers have suggested several machine learning techniques for early detection and better treatment outcomes. In this paper, we examine different models for detecting diabetic foot ulcers, including Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Random Forests. We also look at how to integrate these models using REST APIs for practical use. Diabetic foot ulcer detection is a crucial and major area of research, as it plays a vital role in impacting the patient’s health and quality of life. Traditional diagnostic methods depend on manual procedures. Thus, the process can be slow, subjective, and prone to human mistakes. With the help of machine learning algorithms, we can accurately diagnose and detect if the patient has an ulcer or not. It also supports doctors in making better decisions and allows for remote monitoring, which is especially helpful for catching ulcers early in patients who are at risk.

II. Literature
AI & Generative AI in DFU Diagnosis - S. Alkhalefah et al. [1] present an extensive survey on the integration of AI and generative AI—such as GANs and diffusion models—in diabetic foot ulcer (DFU) care. They highlight how these techniques improve DFU classification accuracy, augment limited datasets by producing synthetic images, and enable accessible smartphone-based ulcer monitoring. They recommend the adoption of explainable AI frameworks and the expansion of

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dataset diversity to enhance clinical use. AI-Powered Thermography for Early Detection - M. F. Alwashmi et al. [2] conduct a cross-sectional observational study exploring AI-driven thermography to detect early plantar thermal abnormalities. Using computer vision to compare thermal patterns between diabetic patients without visible ulcers and healthy individuals, the system shows promise in identifying compromised blood supply, which may assist in preventative DFU screening. However, the authors stress the need for further validation in broader populations.AI-Based Remote Monitoring with Smartphone Imaging – In Role of Artificial Intelligence in Diabetic Wound Screening and Early ...‖ [3], the authors review smartphone-enabled AI applications for remote DFU monitoring. They demonstrate that recent AI solutions enable accurate wound assessment via mobile apps, facilitating early diagnosis and proactive management outside clinical settings. Despite this progress, they acknowledge limitations such as variable image quality and patient compliance. AI-Driven Personalized Offloading Device Prescriptions - S. Ahmed et al. [4] introduce a Clinical Decision Support System (CDSS) that uses machine learning to tailor offloading device prescriptions such as insoles and specialized footwear based on patient-specific biomechanical data and preferences. This AI-driven strategy aims to prevent plantar forefoot ulcers by optimizing pressure relief, thereby reducing the onset of DFUs. Wearable Tech & Predictive Analytics for DFU Prevention - A comprehensive review [5] on AI and wearables discusses continuous glucose monitoring, smart insoles, temperature sensors, and predictive analytics. The authors emphasize that wearable data, when combined with AI, facilitates real-time risk identification and personalized interventions. They also highlight implementation challenges like patient adherence, socioeconomic barriers, and validation in clinical trials.

While some papers discuss Machine Learning algorithms for detecting foot ulcers, they often do not consider how to use these algorithms in real-time. This paper outlines a step-by-step approach, similar to an agile development process. It includes all the necessary elements for detecting diabetic foot ulcers (DFUs). The process starts with preparing images, then using a computer model to check for the presence of an ulcer. The results are displayed through a mobile app or website. Most existing studies focus only on finding out if an ulcer is present using Machine Learning algorithms. Yet, in addition to detecting if a region is ulcerous, this paper also annotates the damaged region with a red box. The visual indicator identifies areas presenting signs of tissue damage characteristic of DFUs at a glance. This technique enhances interpretability and informs doctors how the model arrived at its conclusion. Moreover, this study considers applying Explainable Artificial Intelligence (XAI) techniques for foot ulcer detection. It provides explanations of AI models' decision-making, instilling confidence between patients and physicians. This paper also considers the severity of ulcers, either classified as none, mild, moderate, or severe, with the application of a Convolutional Neural Network (CNN) model. A number of other studies have limited their results to a yes or no result to whether there is an ulcer present. This paper also discusses about the use of Support Vector Machine(SVM) in depth. The use of the SVM model is similar to that of the CNN model, but it is limited to a smaller dataset.

III. Methodology

The study proposes an extensive framework to identify and categorize Diabetic Foot Ulcers (DFUs). It can be achieved by employing sophisticated deep learning models and explainable AI methods. This paper mainly attempts to adhere to an agile methodology, which facilitates enhancements in each module of the project pipeline. The process is split into various different components, such as, collecting data, preprocessing of the image, feature design, model classification, deployment of the system. These steps are carried out with the help of API, and integration of explainable AI.

3.1 Data Evaluation

For evaluating the performance of the system, we employed an existing dataset of foot images that could be influenced by Diabetic Foot Ulcers (DFUs). The images were collected from public

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databases and annotated by experts in medicine to provide sound ground truth for validation. In order to verify the efficiency of the system in DFU classification, we experimented with the existing data through a series of tests. The tests were crucial in order to verify that the system works well, not just on familiar instances but also in new cases. The evaluation was done using standard performance measures widely used in the medical industry to measure diagnostic accuracy.
This research is mainly concentrated on four important performance measures.

1. Sensitivity: This metric helps the system in correctly identifying the image in which the foot has been affected by at least one ulcer. If the model has high sensitivity, then it can accurately detect a diabetic foot ulcer; this prevents the possibility of misdiagnosing a positive case.
2. Specificity: This helps us to know how the system can identify an image that does not contain any ulcer correctly. High specificity ensures that the model can accurately distinguish a foot not affected by an ulcer from an affected foot.
3. Accuracy: – This ensures that the model performs correctly across all the images, both with and without ulcers. It delivers a general idea of how the system makes the right prediction.
4. Consistency: This will assess the performances of the system. With the help of machine learning, it ensures that the system always delivers the correct result.

3.2 Image Preprocessing

The foot images came from different origin cameras i.e. had varying image quality, lighting conditions, and had to be cleaned and prepped before doing what was largely uncomplicated and thorough application of the models on the images. This cleaning and prep can be termed preprocessing and introduces consistency for most practical purposes in terms of size quality. The preprocessing contained: Removing noise and correcting lighting: Through some baseline methods (smoothing filters, adjust brightness) unwanted dots/shadow can be removed and images corrected for clarity and less variation in light and contrast.

1. Resizing images: Images were standardized on a resizing operation to ensure that models can read them broadly.
2. Changing/improving Images (Data Augmentation): To actually help our model, substantially improve the model learning process, and also model learning variations beyond the small variations (there are many cases that can be categorized, but are largely defined individually), foot image files were changed to:
    - Color variations (RGB and HSV changes): to change the color very small amounts to give properties to change in the incapability to change in parameters of light.
    - Blurring (Gaussian and Median): sometimes we purposely make the image blurry just to teach the model what to do if in fact the camera was blurred. We will do this to about 10% of the images. Shifting, scaling, and rotation (Affine transformations): images to be moved or shifted randomly and rotated to show the model more angles.

We changed brightness and contrast in a random way to imitate different environments the photograph was taken. There are not too many items to list, but in all situations these will assist the model to recognize foot ulcers better in spite of all the imperfections in all the images. This also allows for better balancing within the dataset and better allows to improve upon the overall efficacy of the model, even with unseen/numerated images

Technique	Purpose
Noise Removal	Remove shadows, dots for clarity
Resizing	Standardize dimensions for model input
Brightness Adjustment	Handle varying lighting
Gaussian/Motion Blur	Teach model robustness to blurry data
Rotation/Scaling	Simulate real-world foot position variation
Color Shift (HSV/RGB)	Improve learning with subtle color differences

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Table 1: Image Preprocessing and Augmentation

Techniques Used for Model Training.

3.3 Feature Engineering and Selection:

Convolutional Neural Networks (CNNs) can autonomously learn features from images. But, traditional machine learning methods can also use methods to compute important features by hand. After collecting structured and well-defined input data, supervised traditional machine learning methods (for example, Support Vector Machines (SVM) and Random Forests) produce outputs that may be efficient at binary classification (i.e. detecting if the ulcer is present), multinomial classification (e.g. what type of ulcer the ulcer is (e.g. neuropathic, ischemic and mixed), but also assessing the severity of the ulcer. For example, a neuropathic ulcer is the result of nerve damage, an ischemic ulcer occurs because there is not enough blood flow to the area, and a mixed ulcer is the result of both nerve damage and poor blood flow. Canadian Association of Optometrists,2022). Models under the category of traditional methods commonly try to identify the type of lesion by showing contours (or outlines) that may be helpful when examining the shape and characteristics of the lesion's anatomy. Edge-based features are effective in identifying margins for differentiation and viewing morphologies of the wounds.

Texture-based features are useful in identifying characteristics on the morphology of the skin with an ulcer. Local Binary Patterns (LBP) is one approach that gives the system information related to the skin that may indicate bumpy, rough, or surface texture based type of characteristics that are often associated with DFUs.

Color features can also be obtained using color histograms which indicates the distribution of different hues within an ulcerated area (sometimes called the dyeing of tissue). These features allow for identifying changes in color that can indicate when tissue is infected or deteriorated for many ulcer types, as ulcers convert appearance many times throughout their lifespan. In addition to color accuracy. Shape features can include the size, depth and regularity of the ulcer's edge. Together these shape features provide the wound and ulcer a more accurate characterization.

3.4 Real-Time Diagnosis API

To facilitate instant and accessible detection of Diabetic Foot Ulcers (DFUs), a RESTful API was developed to allow users to upload images of the foot and then receive the diagnosis in real time. Upon submission of an image, the model in the backend, receives the image and returns the three main outputs; if there is an ulcer or not, if there is, what type of ulcer it is (neuropathic, ischemic or mixed), and if there is an ulcer, what severity grade it is using the International Consensus on Diabetic Foot Ulcer management classification The API was designed to work well through mobile and web endpoints making it easy to use in a telehealth clinical environment. The model ensures patient privacy and data protection by utilizing data encryption, secure transmission of data, and anonymization of the patients details along the pipeline.

3.5 Mobile and Web Interface

In addition to designing a usable API, a clean and responsive interface was developed to support a seamless user experience across mobile and web. A patient or a clinician can upload images of foot, either by taking a real- time picture or selecting it from their local device. The model will process the given image and present a detailed diagnosis, which includes ulcer type, and severity, and relevant treatment recommendations based on its classification. The front end also includes an ability feedback loop approach that allows the doctors review predictions made from the model, add comments or make amendments. Medical oversight and interaction would enhance the development

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of the model, and mechanisms within the clinical encounter would facilitate ongoing improvements in the diagnostic process.

3.6 Explainable AI Integration

To improve the models transparency and trust, Explainable AI (XAI) tools were incorporated into the process of diagnosis. Grad-CAM provides visual heatmaps to delineate the aspects of the image that the model used to predict diagnosis; visual amplification as a response to clinical intuition. LIME offers human interpretable explanations about the model's simplification or summarization of how it views the behaviour of the image in the local area. These transparency artifacts presumably enable clinicians to be better assured and trustful of their models outputs diagnostics to strengthen their medical decision-making confidence in clinical settings.

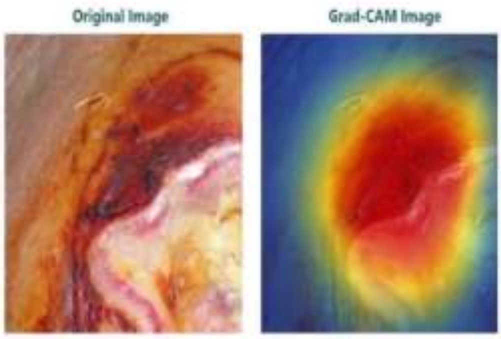

Figure 1: Grad-CAM Visualization of Ulcer Detection

The above figure illustrates the use of Grad-CAM to explain the deep learning model’s decision. The left image shows the original ulcer image, while the right Grad-CAM heatmap highlights the regions most influential in the model’s prediction. The intense red areas indicate the primary focus of the model, confirming that the network concentrated on the ulcerated region when classifying the image.

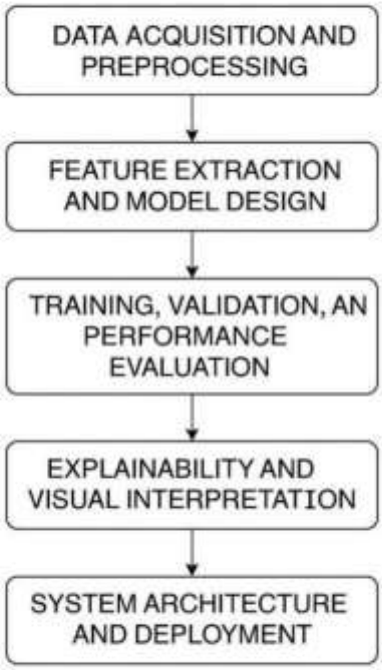

Figure 2: Overview of The System Development Workflow for DFU Detection and Classification

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IV. Result and Discussion

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	Inference Time (ms)
VGG19	91.3	93.5	89.1	120
ResNet50	92.7	94.1	90.8	135
YOLOv5	90.1	91.5	88.4	55
SVM	84.6	87.2	82.3	180
Random Forest	81.5	85.2	78.1	200

Table 2: Evaluation Metrics for Different Classification Models

The system provides a comprehensive pipeline in order to detect and classify diabetic foot ulcers (DFUs) by incorporating deep learning models, traditional machine learning models, and explainable AI (XAI) techniques. By the means of this study, the system was developed using the agile methodology, which allows for continuous improvement of the system through preprocessing, feature extraction, model training, and deployment phases.

This study combines several deep learning models to create a strong framework for detecting and classifying Diabetic Foot Ulcers (DFUs). Each model is incorporated into the pipeline to improve the performance of classification, which determines the ulcer’s nature and severity.

YOLOv5 is the main detection model in the system. It can handle a large collection of diabetic foot images. YOLOv5 processes each image in real time and marks areas likely to have ulcers by creating boxes and giving confidence scores to those areas. Its ability to examine images quickly enables faster and accurate detections. This helps doctors and patients quickly see the affected regions.

After YOLO models identify suspicious areas, VGG19 and ResNet50 are used to improve classification and interpretation. VGG19 can capture fine details in the skin, including surface texture, minor discolorations, and irregularities in tissue structure. This ability to extract features is crucial for distinguishing healthy skin from early stage ulceration, which can look similar to the naked eye. VGG19 helps improve YOLO's raw detections by confirming whether the highlighted area shows an ulcer and giving more context about the lesion's appearance. ResNet50 contributes to this process by offering a deeper layer of analysis with its residual connections. ResNet50 looks at the same areas identified by the YOLO model as VGG19, but it aims to capture higher-level details. This involves assessing the tissue's structural integrity, the extent of damage, and more complex patterns that might indicate severe or worsening ulcers. This multi-model pipeline uses YOLOv5 for detection, YOLOv6 as a developing option, and VGG19 with ResNet50 for classification. It ensures the system identifies ulcers and provides detailed information about the severity and nature of the wounds. By combining speed, accuracy, and deep feature analysis, these models work together to achieve the project's goal of delivering a tool that assists clinicians in early DFU detection and monitoring. The results that are obtained with the help of different machine learning models highlight the effectiveness of the model. Through the help of Convolutional Neural Networks (CNNs), such as VGG19, real-time detection of the ulcer is offered, thus enabling faster diagnosis of the said ulcer. Meanwhile, the traditional manual features, like texture, color histograms, and shape descriptions, are extracted to further classify the ulcer that has already been detected by the CNN model. The models Support Vector Machines (SVM) and Random Forests are used for binary and multiclass classification problems, such as determining the presence of an ulcer, the type of ulcer, and how severe the ulcer is. These models can only handle a restricted quantity of datasets. The real-world application of the system is enabled by a RESTful API that accepts photos and in turn returns predictions on the presence of an ulcer, the type of ulcer (neuropathic, ischaemic, or mixed), and the severity of the ulcer. It provides a clear and easy-to-use experience as the central engine for the web and mobile interfaces. In order to enable ongoing model improvement, patients can upload photos of their feet straight from a smartphone, and clinicians receive comprehensive diagnostic outputs with room for comments or feedback. The expected outcomes of this system are:-

1. A reliable AI system that detects DFU more precisely and quickly.
2. Real-time and mobile-enabled diagnosis that can help detect and prevent the ulcer at an early stage, more specifically in remote areas.
3. The system also ensures that proper rules and measures should be followed in order to protect the safety and privacy of the patients.
4. The system displays the predictions to the doctors in a way where they can easily identify and understand them; this helps in making better decisions without any misdiagnosis.

Fig. 4: Ulcer detection interface showing input and processed image of normal skin.

The above figure demonstrates the model's ability to identify and classify normal, healthy skin. Both the original and preprocessed images were processed by the system, which returned a prediction of "Normal-Healthy skin" with high confidence. No abnormality or ulcer was detected, showing the model's effectiveness in ruling out false positives.

Figure 3:- Deep Learning-Based Ulcer Detection and Model Confidence Visualization –

Case 1 (High Model Confidence)

The above figure demonstrates the model's ability to identify and classify abnormal conditions with high confidence. Both the original and processed images were analyzed by the system, which highlighted the affected region with a box and returned a prediction of "Abnormal Ulcer" with a confidence score of 66.49%. Deep Learning confirmation scores from VGG19 (99.61%) and ResNet50 (87.55%) further validate the detection, demonstrating the model's effectiveness in recognizing and classifying ulcerated skin area.

Figure 4:- Deep Learning-Based Ulcer Detection and Model Confidence Visualization – Case 2 (Moderate Model Confidence)

The above figure demonstrates the model's ability to identify and classify abnormal conditions with high confidence. Both the original and processed images were analyzed by the system, which highlighted the affected region with a box and returned a prediction of "Abnormal Ulcer" with a confidence score of 66.49%. Deep Learning confirmation scores from VGG19 (99.61%) and ResNet50 (87.55%) further validate the detection, demonstrating the model's effectiveness in recognizing and classifying ulcerated skin area.

V. Conclusion

VI. 5.1 Conclusion

The development of the AI-powered Diabetic Foot Ulcer Detection System demonstrates the potential of deep learning technologies in improving early diagnosis and management of chronic complications in diabetic patients. Leveraging the VGG19 model and the DFUC-2024 image dataset, the system achieved high classification accuracy and consistent performance across various ulcer severity levels. The integration of explainable AI tools such as Grad-CAM and LIME ensured that the model's predictions are transparent and interpretable, thereby addressing one of the key limitations in medical AI applications. The real-time deployment using a REST API and user-friendly mobile interface makes the system accessible to patients and healthcare providers, supporting early intervention, especially in resource-constrained environments. Overall, the solution bridges the gap between AI innovation and practical clinical utility.

VII. 5.2 Future Enhancement

While the current system provides reliable ulcer classification, several opportunities exist to extend its functionality and impact. First, future iterations could incorporate multi-label classification to detect not only ulcer presence but also additional clinical indicators such as infection, necrosis, or tissue ischemia. The inclusion of longitudinal datasets would enable tracking ulcer progression over time, allowing for predictive analytics and more personalized care. Integration with wearable devices—such as smart insoles or temperature-monitoring sensors— could offer continuous monitoring and alert systems. Additionally, the system could be enhanced by embedding a chatbot interface for patient education, follow-up reminders, and triage support. Clinical validation in real-world settings, involving feedback from medical professionals, will be essential for refining model accuracy and ensuring regulatory readiness for healthcare deployment.

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