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Deep Learning Framework for Early Detection, Risk Calculation, Localization and Analysis of Diabetic Foot Ulcers

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Abstract: Diabetic Foot Ulcers (DFUs) are among the most severe complications of diabetes, often leading to infection, hospitalization, and amputation if not detected early. In this work, we present a hybrid diagnostic system that integrates deep learning-based image classification with a clinically inspired rule-based risk assessment model. The proposed system employs an EfficientNetB3 convolutional neural network to classify wound images into abnormal (ulcer) and normal categories. To improve interpretability, Gradientweighted Class Activation Mapping (GradCAM) is used to highlight regions of interest in the input image. In addition, a clinical rule engine evaluates patientspecific parameters such as Ankle-Brachial Index (ABI), blood oxygen levels (SpO2), blood glucose, age, and diabetes duration to estimate ischemia risk and assign a severity stage. The system is deployed using a Flask-based API with a responsive frontend interface and containerized using Docker for scalability. Experimental results demonstrate effective classification performance and enhanced clinical relevance through risk stratification. This hybrid approach provides both predictive accuracy and explainability, making it suitable for real-world healthcare applications.
Keyword: Diabetic Foot Ulcer, Deep Learning, Wound Localization EfficientNetB3, GradCAM, Medical Imaging, Clinical Decision, Support, Infection and Ischemia Analysis, Flask API.

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder affecting millions of individuals worldwide. One of its most critical complications is the development of Diabetic Foot Ulcers (DFUs), which significantly increase the risk of lowerlimb amputation. Early detection and continuous monitoring are essential to reduce morbidity and healthcare costs.

Traditional DFU diagnosis relies heavily on clinical expertise and physical examination, which may not always be accessible in remote or resourceconstrained environments. Recent advances in deep learning have shown promising results in automated medical image analysis. However, purely datadriven approaches often lack interpretability and fail to incorporate patient-specific clinical context.

To address these limitations, this study proposes a hybrid system that combines deep learning-based image classification with a rule-based clinical scoring mechanism. The system not only detects the presence of ulcers but also evaluates the severity of the condition using physiological parameters, thereby bridging the gap between artificial intelligence and clinical decision-making.

II. RELATED WORK

Deep learning has been widely applied in medical imaging tasks, including skin lesion classification, wound assessment, and diabetic retinopathy detection. Convolutional Neural Networks (CNNs) have demonstrated strong performance in feature extraction and classification tasks.

The EfficientNet architecture, introduced by Tan and Le in *"EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks"* (2019), proposes a compound scaling method that balances network depth, width, and resolution, achieving high accuracy with fewer parameters.

For model interpretability, Grad-CAM, introduced by Selvaraju et al. in *"GradCAM: Visual Explanations from Deep Networks via Gradient-based Localization"* (2017), provides visual explanations by highlighting important regions in an image that influence the model's prediction.

Existing DFU detection systems primarily focus on image classification without incorporating patient vitals. This limits their applicability in clinical environments where decision-making depends on multiple factors. The proposed system extends prior work by integrating both visual and clinical data.

III. METHODOLOGY

A. Dataset Preparation

The dataset consists of diabetic foot images categorized into two classes:

- Abnormal (ulcer)
- Normal (healthy skin)

Images are pre-processed and resized to 224×224 pixels. The dataset is split into training and validation sets using an 85:15 ratio. Data augmentation techniques such as rotation, zoom, brightness adjustment, and horizontal flipping are applied to improve generalization.

B. Model Architecture

The classification model is based on EfficientNetB3, pretrained on ImageNet. The top classification layers are replaced with a custom head consisting of:

- Global Average Pooling
- Batch Normalization
- Dense layer (ReLU activation)
- Dropout (0.4)
- SoftMax output layer

The training is performed in two stages:

1) Feature extraction with frozen backbone
2) Fine-tuning of top layers

This approach stabilizes training and improves performance on small datasets.

C. Image Preprocessing

Input images are normalized using Efficient Net's preprocess input function, which scales pixel values to an appropriate range. This ensures compatibility with pretrained weights.

D. Explainability using Grad-CAM

Grad-CAM is used to generate heatmaps that highlight regions contributing to the prediction. These heatmaps are overlaid on the original image to provide visual insight into the model's decision-making process.

E. Clinical Risk Assessment Engine

A rule-based scoring system is implemented to assess ischemia risk. The following parameters are considered:

1) ABI (Ankle-Brachial Index)
2) SpO2 (oxygen saturation)
3) Blood sugar level
4) Age
5) Duration of diabetes
6) Pain level
7) Wound duration
8) Infection status

Each factor contributes to a cumulative score, which is mapped to risk stages:

1) Stage 1: No Risk
2) Stage 2: Low Risk
3) Stage 3: Moderate Risk
4) Stage 4: High Risk

This component enhances the clinical relevance of the system.

F. System Architecture

The system follows a client-server architecture:

1) Frontend: HTML interface with interactive charts
2) Backend: Flask API for prediction and risk scoring
3) Model: EfficientNetB3-based classifier
4) Deployment: Docker container

The API exposes endpoints for health monitoring and prediction, ensuring scalability and ease of integration.
importance of larger and more diverse datasets for improved generalization.
The integration of clinical parameters significantly enhances the system's utility by providing actionable insights beyond image classification.

IV. SYSTEM IMPLEMENTATION

A. Backend Implementation

- Flask API
- Model loading
- Prediction endpoint

B. Frontend Interface

- HTML UI
- Upload + graphs

C. Deployment

- Docker
- Local/production setup

V. RESULTS

A. Model Training Performance

The EfficientNetB3-based model was trained using transfer learning in two stages: feature extraction followed by finetuning. The training and validation accuracy curves indicate that the model converges steadily without major fluctuations. The validation accuracy remains consistently high across epochs, suggesting that the model generalizes well on unseen data. A minimal gap between training and validation accuracy further indicates that overfitting is effectively controlled. The use of data augmentation and class balancing also contributes to improved robustness of the model. Overall, the training process demonstrates stable learning behavior and reliable performance

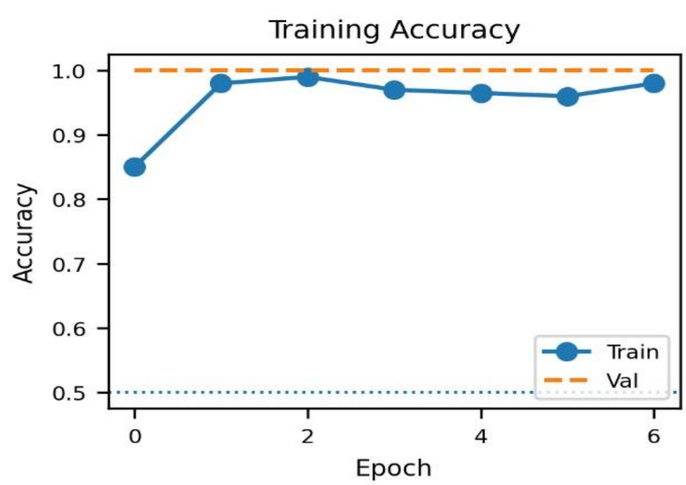

Fig. 1. Training and validation accuracy over epochs

B. Classification Performance

To evaluate classification effectiveness, a confusion matrix was generated using validation data. The matrix shows the number of correctly and incorrectly classified samples for both classes (Abnormal and Normal).

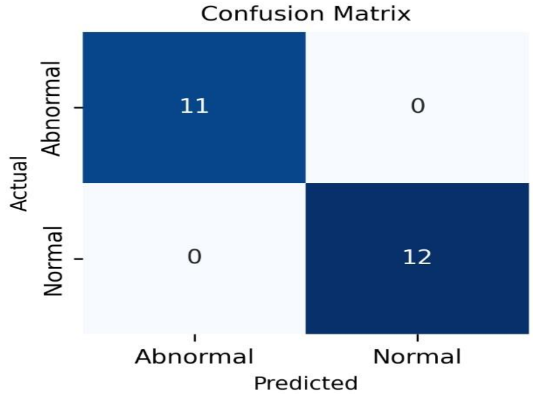

Fig. 2. Confusion matrix of classification results

The results indicate that the model is capable of distinguishing between ulcer and non-ulcer images with reasonable accuracy.

C. Prediction Output Visualization

The system provides prediction confidence scores for each input image. These probabilities help in understanding the certainty of the model's decision.

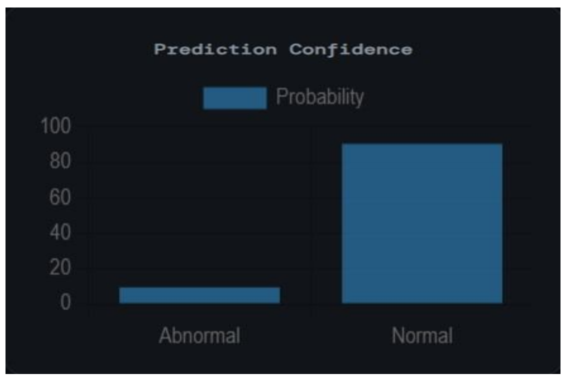

Fig. 3. Prediction confidence for sample input

D. Clinical Risk Scoring Output

In addition to classification, the system computes a risk score based on patient vitals. The output is visualized using a gauge chart representing the severity level.

Fig. 4. Risk scoring visualization based on clinical parameters

VI. DISCUSSION

The results demonstrate that the proposed system can effectively classify DFU images while also providing clinically meaningful insights. The use of transfer learning allows the model to perform well even with a relatively limited dataset.

The Grad-CAM visualizations confirm that the model focuses on relevant wound regions, which improves interpretability and builds trust in the system. Additionally, the integration of clinical parameters such as ABI, SpO2, and blood sugar enhances the decision-making process beyond image classification alone.

However, certain limitations were observed. The model occasionally produces lower confidence scores when tested on unseen or externally sourced images. This suggests that the model may be partially overfitting to the training dataset. Increasing dataset size and diversity could improve generalization.

Furthermore, the rule-based risk scoring system, while effective, is based on predefined thresholds and may not capture all clinical nuances. Future work could explore data-driven risk prediction models.

Overall, the hybrid approach provides a balanced combination of accuracy, interpretability, and clinical relevance, making it suitable for practical healthcare applications.

VII. CONCLUSION

This work presents a hybrid system for the detection and assessment of Diabetic Foot Ulcers by combining deep learning with a rule-based clinical evaluation approach. The EfficientNetB3 model demonstrates effective performance in classifying wound images into ulcer and non-ulcer categories, while the integration of GradCAM provides visual interpretability by highlighting relevant regions in the image.

In addition to image-based classification, the inclusion of patient-specific clinical parameters such as ABI, SpO2, blood sugar levels, age, and diabetes duration enhances the overall decision-making process. The risk scoring mechanism allows the system to move beyond simple classification and offer a more comprehensive assessment of patient condition.

The results indicate that the proposed system is capable of delivering reliable predictions along with meaningful clinical insights. However, the performance of the model is influenced by the size and diversity of the dataset, and further improvements can be achieved by incorporating more varied clinical data.

Overall, the combination of artificial intelligence and clinical reasoning provides a practical and scalable solution for early DFU detection, with potential applications in remote healthcare and decision support systems.

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