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Multi-Level Diabetic Foot Ulcer Detection Using Transfer Learning with Deep Convolutional Neural Networks

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ABSTRACT: Diabetic Foot Ulcer (DFU) is a serious complication of diabetes that can lead to severe infections, tissue damage, and even lower-limb amputation if not detected and treated at an early stage. Early identification and accurate assessment of ulcer severity are essential for effective medical intervention and patient care. However, traditional diagnosis methods rely on manual examination by healthcare professionals, which can be time-consuming and may not always be accessible in remote or resource-limited areas. Recent advancements in artificial intelligence and deep learning have enabled the development of automated medical image analysis systems that can assist clinicians in diagnosing diseases more efficiently.

This research proposes a deep learning-based system for the automated detection and multi-level classification of diabetic foot ulcers using transfer learning techniques. Pretrained convolutional neural network models such as ResNet, MobileNet, and EfficientNet are utilized to classify foot images into three severity levels: **Normal, Mild, and Severe**. The dataset used in this study is obtained from Kaggle and consists of diabetic foot ulcer images collected from clinical sources. Image preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve model performance and reduce overfitting.

The experimental results demonstrate that transfer learning significantly improves classification accuracy and reduces training time compared to training deep learning models from scratch. Among the evaluated models, EfficientNet shows strong performance in extracting relevant features from medical images and accurately classifying ulcer severity levels. The proposed system can assist healthcare professionals in early diagnosis, improve screening efficiency, and support remote patient monitoring. In the future, the system can be integrated into mobile or web-based healthcare platforms to enable real-time diabetic foot ulcer detection and support telemedicine applications.

I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder affecting millions of people worldwide, and one of its most serious complications is the development of diabetic foot ulcers (DFUs). A diabetic foot ulcer is an open wound that typically occurs due to nerve damage (neuropathy) and poor blood circulation in the lower limbs of diabetic patients. If not diagnosed and treated at an early stage, these ulcers can lead to severe infections, tissue damage, gangrene, and even lower-limb amputation. Therefore, timely detection and accurate assessment of ulcer severity are critical for effective treatment and prevention of life-threatening complications.

Traditional diagnosis of diabetic foot ulcers relies on manual examination by healthcare professionals, which can be time-consuming and highly dependent on clinical expertise. In many rural or resource-limited areas, access to specialized medical professionals is limited, making early detection difficult. Recent advancements in artificial intelligence and deep learning have opened new possibilities for automated medical image analysis. Deep Convolutional Neural Networks (CNNs) are particularly effective in identifying patterns and abnormalities in medical images, enabling faster and more consistent diagnosis. Additionally, transfer learning techniques allow pretrained models to be adapted to medical datasets, improving performance even when data is limited.

This research focuses on developing an automated system for the detection and multi-level classification of diabetic foot ulcers using advanced transfer learning models such as ResNet, MobileNet, and EfficientNet. The system classifies foot images into different severity levels, helping in early diagnosis and treatment planning. By integrating deep learning into healthcare, the proposed approach aims to assist medical professionals in improving diagnostic accuracy, reducing workload, and enhancing overall patient care.

II. LITERATURE SURVEY

Several research studies have explored the application of deep learning techniques for automated medical image analysis and disease detection. In recent years, deep learning models have been widely used in healthcare applications such as skin cancer detection, diabetic retinopathy analysis, and wound classification. Convolutional Neural Networks (CNNs) are particularly effective in medical imaging because they can automatically extract complex patterns and visual features from images. These models learn hierarchical features such as edges, textures, color variations, and spatial structures, which are essential for identifying abnormalities in medical images.

A significant contribution to medical image analysis using deep learning was made by Varun Gulshan and colleagues, who developed a deep learning algorithm for detecting diabetic retinopathy from retinal fundus images. Their research demonstrated that deep neural networks could achieve performance comparable to trained ophthalmologists in identifying diabetic eye disease. This study highlighted the effectiveness of CNN-based architectures for large-scale disease screening and encouraged further research in automated medical diagnosis using artificial intelligence.

Transfer learning has become an important technique in medical image classification, especially when dealing with limited medical datasets. Pretrained models such as ResNet and MobileNet have been widely used because they are trained on large-scale datasets like ImageNet. These models can be fine-tuned for specific medical imaging tasks, allowing researchers to achieve high accuracy without requiring extremely large training datasets. Transfer learning also reduces computational cost and training time.

Recent advancements in deep learning architectures have introduced more efficient models such as EfficientNet, which balances network depth, width, and resolution using a compound scaling technique. EfficientNet has demonstrated superior performance in many image classification tasks while maintaining lower computational complexity. Studies have shown that EfficientNet models can provide higher accuracy compared to traditional CNN architectures, making them suitable for medical image classification applications.

Although several studies have focused on automated detection of diabetic foot ulcers using deep learning, most of them concentrate on binary classification, where images are classified only as ulcer or non-ulcer. However, in clinical practice, understanding the severity level of the ulcer is crucial for determining appropriate treatment strategies. Multi-level classification systems that categorize ulcers into stages such as mild, moderate, and severe are still limited in existing research. Therefore, this study proposes a multi-class classification approach using transfer learning models to classify diabetic foot images into three severity categories: **Normal, Mild, and Severe**, which can assist healthcare professionals in early diagnosis and effective treatment planning.

III. METHODOLOGY

The proposed system follows a structured workflow consisting of **dataset preparation, image preprocessing, model training, evaluation, and deployment**. The objective of this methodology is to develop an automated deep learning-based framework capable of detecting and classifying diabetic foot ulcers according to their severity levels. The system leverages transfer learning techniques using advanced convolutional neural network architectures such as ResNet, MobileNet, and EfficientNet to improve classification accuracy and computational efficiency.

1. Dataset Collection

The dataset used in this project is obtained from Kaggle and specifically from the **Diabetic Foot Ulcer (DFU) dataset**. This dataset contains images of diabetic feet collected from clinical environments and includes both healthy foot images and ulcerated foot images. The images represent different stages of ulcer severity and are captured under varying lighting conditions and backgrounds.

Dataset Link:

<https://www.kaggle.com/datasets/laithjj/diabetic-foot-ulcer-dfu>

To perform multi-level classification, the dataset is organized into three main categories representing the severity levels of diabetic foot ulcers:

- **Normal Foot** – Foot images without any visible ulcer or wound.
- **Mild Ulcer** – Early-stage ulcer with small wounds or minor tissue damage.
- **Severe Ulcer** – Advanced ulcer stage showing deep wounds, infection, or extensive tissue damage.

All images are standardized to a resolution of **224 × 224 pixels**, which is suitable for training most deep learning models. This classification enables the system to not only detect ulcers but also determine their severity level, which is essential for medical diagnosis and treatment planning.

2. Data Preprocessing

Before training the deep learning model, several preprocessing techniques are applied to improve the quality and consistency of the dataset. Image preprocessing plays a critical role in medical image analysis because it enhances important features and reduces noise that could affect the performance of the model.

First, all images are resized to **224 × 224 pixels** to match the input size required by the convolutional neural network models. Pixel values are then normalized to scale the image intensity values within a consistent range, which helps stabilize the training process and accelerates model convergence.

To increase dataset diversity and prevent overfitting, **data augmentation techniques** are applied. These techniques generate additional training samples by applying various transformations to the existing images. The augmentation methods used in this research include:

- **Rotation** – Rotating images at different angles to simulate different camera perspectives.
- **Horizontal flipping** – Mirroring images to increase variability in foot orientation.
- **Zooming** – Slightly enlarging or reducing image regions to capture scale variations.
- **Brightness adjustment** – Modifying image brightness to simulate different lighting conditions.

Finally, the dataset is divided into **training, validation, and testing sets**. The training set is used to train the model, the validation set is used to tune hyperparameters and monitor model performance during training, and the testing set is used to evaluate the final performance of the trained model.

3. Model Architecture

The deep learning framework used in this research is based on transfer learning with pretrained convolutional neural network architectures. Transfer learning allows models trained on large-scale datasets to be adapted for specific tasks such as medical image classification. This approach significantly reduces training time and improves classification accuracy.

The proposed system uses three well-known CNN architectures:

- **ResNet**

ResNet introduces residual connections that allow gradients to flow through deep networks without degradation. This architecture helps overcome the vanishing gradient problem and enables the training of very deep neural networks.

- **MobileNet**

MobileNet uses depthwise separable convolutions to reduce computational complexity while maintaining good accuracy. It is particularly suitable for real-time and mobile-based healthcare applications.

- **EfficientNet**

EfficientNet improves model performance by scaling network depth, width, and resolution in a balanced manner using a compound scaling strategy. This results in higher accuracy with fewer parameters compared to traditional CNN architectures.

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In this system, the pretrained models are used as **feature extractors**, and the final classification layers are modified to perform multi-class classification. Additional **fully connected layers** are added, and the final output layer uses a **softmax activation function** to classify images into the three ulcer severity categories.

The model is implemented using the **TensorFlow** and **Keras** deep learning frameworks, which provide efficient tools for building, training, and deploying neural networks.

4. Model Training and Evaluation

The deep learning models are trained using the preprocessed dataset. During the training process, the network learns to identify important visual features associated with diabetic foot ulcers, such as ulcer boundaries, color variations, tissue texture, and wound depth.

The performance of the trained models is evaluated using several standard classification metrics, including:

- **Accuracy** – Measures the overall correctness of predictions.
- **Precision** – Indicates the proportion of correctly predicted positive cases among all predicted positive cases.
- **Recall (Sensitivity)** – Measures the ability of the model to correctly identify actual positive cases.
- **F1-score** – Provides a balanced measure of precision and recall.
- **Confusion Matrix** – Shows the distribution of correct and incorrect predictions across all classes.

These evaluation metrics provide a comprehensive understanding of the model's ability to distinguish between **Normal, Mild, and Severe** diabetic foot ulcers.

5. Web Application Deployment

After training and evaluating the deep learning model, the system can be integrated into a web application for real-time usage. The web application is developed using the **Flask framework**, which allows users to upload foot images and obtain instant predictions from the trained model.

The workflow of the web application includes the following steps:

1. The user uploads a foot image through the web interface.
2. The uploaded image is automatically preprocessed and resized to the required input dimensions.
3. The trained deep learning model analyzes the image and extracts relevant features.
4. The system predicts the severity level of the diabetic foot ulcer and displays the result along with a confidence score.

This deployment demonstrates the practical applicability of the proposed system for **real-time screening and remote healthcare monitoring**, enabling doctors and healthcare professionals to detect diabetic foot ulcers more efficiently.

IV. RESULTS

The trained deep learning models successfully classified diabetic foot images into Normal, Mild, and Severe categories.

Experimental results indicate that transfer learning models achieve high classification accuracy. Among the tested models, EfficientNet demonstrated superior performance due to its optimized architecture and efficient scaling strategy.

The confusion matrix analysis shows that the model can effectively differentiate between normal and severe ulcers. However, minor misclassifications may occur between mild and severe stages due to visual similarities.

User Evaluation Results

The system interface starts with a **home page** that introduces the Diabetic Foot Ulcer (DFU) detection application. The navigation bar includes **Home, Login, and Register** options. *Figure 1* shows the registration page, where users can create an account.



Figure 1: home page

Along with the home page, *Figure 2* shows the **registration page**, where new users can create an account by entering their basic details.

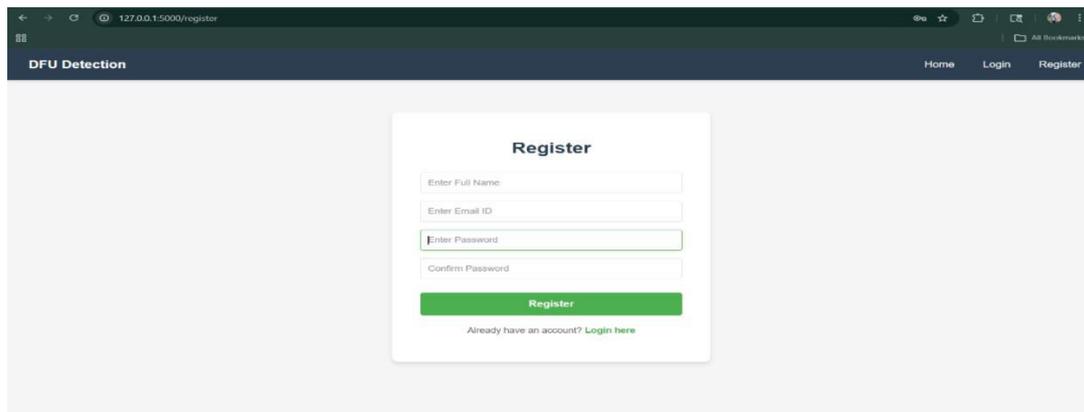


Figure 2: Registration page

After registration and login, the user is taken to the prediction page, as shown in *Figure 3*. Here, the user can upload a foot image for analysis. The system accepts **.jpg and .png** image formats. Once the image is uploaded, the model processes it and generates the result.



Figure 3: Prediction page

The final output is displayed on the results page, as shown in *Figure 4*. The system shows the uploaded image along with the predicted class (Normal, Mild, or Severe) and a confidence score.

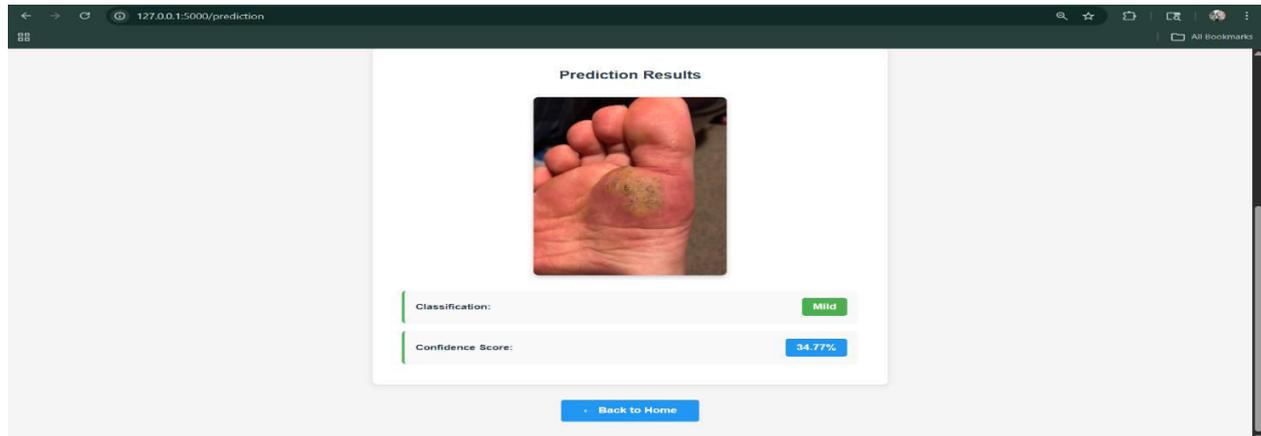


Figure 4: Result

V. LIMITATIONS

Although the proposed system demonstrates promising results in detecting and classifying diabetic foot ulcers using deep learning techniques, several limitations still exist that may affect the overall performance and real-world applicability of the model.

One of the major limitations is the **limited size and diversity of the available medical dataset**. Deep learning models typically require large amounts of labeled data to learn robust and generalized features. However, medical datasets are often relatively small due to privacy concerns, limited patient availability, and the complexity of data annotation by medical experts. As a result, the model may not fully capture the wide variations that occur in real clinical environments, which could affect its ability to generalize to unseen data.

Another challenge is **class imbalance within the dataset**, where certain ulcer severity levels may contain significantly fewer images than others. This imbalance can cause the model to bias toward majority classes while underperforming on minority classes. Consequently, the system may misclassify rare or less represented ulcer stages, which can affect the reliability of predictions in clinical scenarios.

The proposed system is also limited by its reliance on **image-based analysis alone**. In real-world medical diagnosis, clinicians consider multiple factors such as patient medical history, blood glucose levels, duration of diabetes, and other clinical indicators when assessing the severity of diabetic foot ulcers. Since the current model only analyse visual features from images, it may not capture the complete clinical context required for accurate diagnosis.

Furthermore, **image quality and environmental variations** can influence the performance of the system. Differences in lighting conditions, camera quality, image resolution, and background noise may affect feature extraction and classification accuracy. Poor-quality images may reduce the model's ability to identify subtle ulcer characteristics, especially in early stages of the disease.

Finally, the proposed model has primarily been evaluated in an experimental research environment. **Extensive clinical validation and collaboration with medical professionals** would be necessary before deploying the system in real healthcare settings. Additional testing on larger and more diverse clinical datasets would help improve the reliability, robustness, and trustworthiness of the proposed diabetic foot ulcer detection system.

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Future research can focus on several improvements to enhance the performance, reliability, and practical usability of the proposed diabetic foot ulcer detection system. One important direction is the expansion of the dataset by collecting larger and more diverse medical images from multiple hospitals and clinical environments. A larger dataset with varied patient conditions, lighting settings, and imaging devices would help the model learn more robust features and improve its ability to generalize to real-world scenarios.

Future work can also incorporate **Explainable Artificial Intelligence (XAI)** techniques to improve the interpretability of the deep learning model. Methods such as Grad-CAM can be used to highlight important regions of the foot image that influence the model's predictions. This visual explanation can help healthcare professionals understand the reasoning behind the system's decisions and increase trust in AI-assisted medical diagnosis.

Another promising direction is the integration of the proposed system into **mobile healthcare applications** for remote monitoring of diabetic patients. By embedding the trained model into smartphone-based applications, patients or healthcare providers can capture foot images using mobile cameras and obtain instant predictions regarding ulcer severity. This approach can significantly improve early detection and regular monitoring, especially in rural or underserved areas where access to specialized healthcare services may be limited.

Finally, the system can be extended through **cloud-based deployment and telemedicine integration**. Hosting the trained model on cloud platforms would enable real-time image analysis and remote consultation between patients and healthcare professionals. Such a system could support large-scale screening programs, improve accessibility to medical diagnosis, and contribute to more efficient management of diabetic foot ulcer cases.

VII. CONCLUSION

This research presents an automated deep learning-based system for multi-level classification of diabetic foot ulcers. Transfer learning models including ResNet, MobileNet, and EfficientNet were used to classify foot images into Normal, Mild, and Severe categories.

The experimental results demonstrate that deep learning can effectively assist in early detection and severity classification of diabetic foot ulcers. The proposed system has the potential to support healthcare professionals in faster diagnosis and improved patient monitoring.

With further improvements and larger datasets, AI-based diagnostic systems can significantly contribute to better diabetic foot ulcer management and prevention of serious complications.

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