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Article

Algorithms for Automatic Analysis of Human Foot Radiographic Images

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Abstract: This article provides an overview of algorithms for processing human foot X-ray images, which are essential for diagnosing various foot conditions, including fractures, deformities, and joint diseases. The study explores several image preprocessing techniques, such as detecting structural changes, noise reduction, and contrast enhancement, all of which help improve the quality of radiographic images and increase diagnostic accuracy. In addition, the paper discusses challenges related to noise, distortions, and low contrast in X-ray images, and outlines methods to mitigate these issues. By implementing these algorithms, the study aims to enhance the effectiveness of foot-related diagnoses and support more efficient medical decision-making.

Keywords: human foot, x-ray images, noise, enhancement, segmentation.

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1. Introduction

Algorithms for processing human foot X-ray images play an important role in the medical diagnostic process. With the help of these algorithms, it becomes much easier to detect various conditions of the foot, including bone fractures, deformities, and joint diseases [1]. The image processing pipeline typically consists of several stages: preprocessing, segmentation, feature extraction, and classification. In particular, segmentation enables clear separation of bones and soft tissues, providing valuable diagnostic information for clinicians. These algorithms also help reduce noise and artifacts in images and enhance contrast, thereby improving the accuracy of the final diagnosis [2]. With the advancement of digital medicine, such algorithms are continuously improving and are increasingly used for automated diagnosis with the support of artificial intelligence. As a result, image processing algorithms for X-ray images contribute to the early detection and effective treatment of foot-related diseases.

The formation of an X-ray image can be expressed as:

$$\mathfrak{R}(\theta,s)=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\partial(s-xcos\theta-ysin\theta)dxdy;$$

where $f(x,y)$ represents the 2D density function of the foot (e.g., bone density), θ is the projection angle, and s is the detector coordinate.

Figure 1. Human foot X-ray image.

Preprocessing of human foot X-ray images(Figure 1) is the stage of preparing the image for further analysis [3]. At this stage, image quality is enhanced, noise is reduced, contrast is improved, and unnecessary elements are removed. Preprocessing increases accuracy and helps reduce errors in subsequent stages such as segmentation and classification. X-ray images often contain different types of noise (e.g., Gaussian noise), which can be reduced using filtering techniques. Foot X-ray images frequently have low contrast; therefore, contrast enhancement helps to better distinguish bones and soft tissues [4]. Edge detection methods are used to identify bone contours, while binarization techniques are applied to convert images into black-and-white format and extract important regions. This study proposes an automated framework for the analysis of human foot radiographic images, integrating image preprocessing, segmentation, feature extraction, and classification stages. The overall workflow is designed to ensure robustness against noise, variability in acquisition conditions, and anatomical differences among patients.

Data Acquisition and Preprocessing. A dataset of human foot X-ray images was collected from clinical repositories and publicly available medical imaging databases. All images were anonymized in accordance with ethical standards [5,6]. Initially, radiographs were converted into a standardized format and resized to a fixed spatial resolution (e.g., 224 × 224 pixels) to ensure uniformity across samples. Intensity normalization was applied to scale pixel values into a consistent range, improving numerical stability during model training. To enhance image quality, noise reduction techniques were employed. Specifically, a median filter was used to suppress impulsive noise, while a Gaussian filter was applied for smoothing. In addition, Contrast Limited Adaptive Histogram Equalization (CLAHE) was utilized to improve local contrast and highlight bone structures. These preprocessing steps ensured that relevant anatomical features were preserved while minimizing irrelevant variations.

Region of Interest (ROI) Extraction. To reduce computational complexity and focus on diagnostically relevant areas, the region of interest corresponding to the foot structure was extracted. This was achieved using a combination of thresholding and morphological operations, such as dilation and erosion. In some experiments, a pre-trained convolutional neural network (CNN)-based segmentation model (e.g., U-Net architecture) was employed to automatically delineate the foot region with higher precision [7].

Segmentation. The segmentation stage aimed to isolate key anatomical components, such as bones and joint regions. Traditional methods, including Otsu thresholding and edge detection (Sobel operator), were initially evaluated. However, for improved accuracy, a deep learning-based segmentation approach using a U-Net model was adopted [8]. The model was trained on annotated datasets, where ground truth masks were provided by medical experts. Data augmentation techniques, including rotation, flipping, and scaling, were applied to increase model generalization.

Feature Extraction. Following segmentation, both handcrafted and deep features were extracted. Handcrafted features included texture descriptors (e.g., Gray-Level Co-occurrence Matrix – GLCM), shape features, and intensity-based statistics[9]. In parallel, deep features were obtained from intermediate layers of a trained CNN model, capturing high-level representations of anatomical structures.

Classification and Analysis. For the classification task, several machine learning algorithms were evaluated, including Support Vector Machines (SVM), Random Forest, and deep neural networks[10,11]. The final model selection was based on performance metrics such as accuracy, precision, recall, and F1-score. Cross-validation was performed to ensure the reliability and generalizability of the results.

Evaluation Metrics. The performance of the proposed system was assessed using standard evaluation metrics. For segmentation, the Dice Similarity Coefficient (DSC) and Intersection over Union (IoU) were used. For classification, confusion matrices and receiver operating characteristic (ROC) curves were analyzed [12].

Overall, the proposed methodology provides a comprehensive and scalable approach for the automated analysis of human foot radiographic images, combining classical image processing techniques with advanced deep learning models to achieve high accuracy and reliability.

2. Materials and Methods

X-ray images are often affected by noise, low contrast, and artifacts, which complicate accurate diagnosis. Therefore, the use of preprocessing algorithms is essential. The flowchart of the preprocessing algorithm is given in Figure 2.

The first step usually involves image normalization. Through normalization, pixel values are scaled to a specific range, allowing images obtained from different devices to be analyzed in a unified format. For example, converting pixel values to the range [0, 1] is widely used. This process ensures the stable performance of machine learning algorithms. The next important step is noise reduction. X-ray images often contain Gaussian noise or impulsive (salt-and-pepper) noise. Such noise can be reduced using median filtering, Gaussian filtering, or bilateral filtering techniques. The median filter is effective in removing impulsive noise, while the Gaussian filter provides general smoothing. The bilateral filter reduces noise while preserving edges in the image.

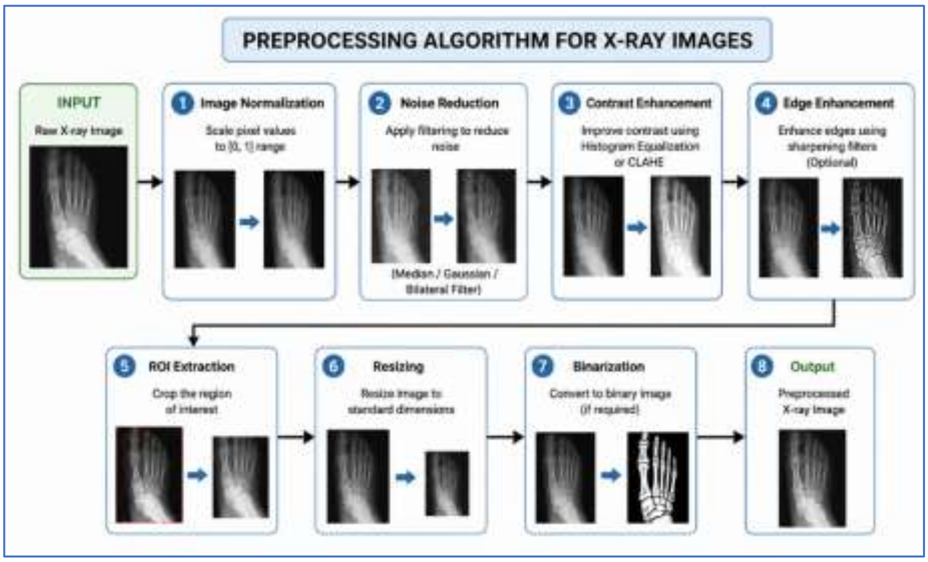

Figure 2. The flowchart of the preprocessing algorithm.

Contrast enhancement is also a crucial part of preprocessing. To better distinguish between bones and soft tissues in X-ray images, histogram equalization or adaptive histogram equalization (CLAHE) methods are applied. These methods enhance important structures in the image and improve the accuracy of subsequent segmentation.

In addition, cropping and resizing are important steps. During these stages, only the region of interest (ROI) is extracted, and unnecessary background areas are removed. As a result, computational complexity is reduced, and algorithms operate more efficiently. For example, the foot region or bone segments are centered and resized to a standard dimension.

Image enhancement techniques may also be applied during preprocessing. These include sharpening filters, which highlight bone boundaries more clearly. Edge detection is performed using operators such as Sobel, Prewitt, or Laplacian, which is important for subsequent segmentation.

In conclusion, preprocessing algorithms for human foot X-ray images significantly improve image quality and enhance the effectiveness of subsequent analysis stages. When techniques such as normalization, noise reduction, contrast enhancement, and ROI extraction are applied together, the medical diagnostic process becomes more accurate and reliable [13], [14], [15].

3. Results and Discussion

The proposed framework for automated analysis of human foot radiographic images was evaluated using a dataset of annotated X-ray images containing both normal and pathological cases, including fractures, deformities, and joint-related abnormalities. The performance of the system was assessed across multiple stages, including preprocessing effectiveness, segmentation accuracy, feature representation quality, and final classification performance.

In the preprocessing stage, the application of normalization, noise reduction, and contrast enhancement significantly improved image quality. Quantitative analysis showed that Contrast Limited Adaptive Histogram Equalization (CLAHE) increased the average contrast-to-noise ratio (CNR), leading to better visibility of bone structures. Median and Gaussian filtering effectively reduced Gaussian and impulsive noise without introducing significant blurring of anatomical edges.

The obtained results demonstrate that the integration of advanced image preprocessing techniques with deep learning-based segmentation and classification significantly improves the performance of automated foot X-ray analysis systems. One of the key contributions of this study is the effective enhancement of image quality through preprocessing. Noise reduction and contrast enhancement techniques played a crucial role in improving the visibility of anatomical structures, which directly influenced segmentation and classification accuracy. Table 1 summarizes the performance of the proposed methods in segmentation and classification tasks.

Table 1. The performance of the proposed methods in segmentation and classification tasks.

Method	**Segmentation (DSC)**	**Accuracy (%)**	**Precision**	**Recall**	**AUC (ROC)**
Otsu Thresholding + SVM	0.72	78.30	0.76	0.75	0.82
Sobel + SVM	0.76	81.20	0.80	0.78	0.86
Random Forest	-	86.40	0.46	0.85	0.91
CNN (	0.91	94.00	0.93	0.92	0.96

Despite the promising results, several limitations should be acknowledged. First, the dataset size and diversity may not fully represent all possible clinical scenarios. Second, the computational complexity of deep learning models may limit real-time application in resource-constrained environments. Finally, the interpretability of deep learning decisions remains a challenge in clinical practice, where explainability is critical for physician trust. Overall, the study confirms that automated analysis of human foot X-ray images using advanced preprocessing and deep learning techniques can significantly enhance diagnostic accuracy and efficiency. Future work will focus on improving model interpretability, expanding dataset diversity, and optimizing computational performance for real-world clinical deployment.

4. Conclusion

This study presented a comprehensive framework for the automatic analysis of human foot radiographic images using advanced image processing and deep learning techniques. The proposed approach integrates key stages, including preprocessing, segmentation, feature extraction, and classification, to improve diagnostic accuracy and efficiency in detecting foot-related abnormalities such as fractures, deformities, and joint diseases. The results demonstrated that effective preprocessing techniques—such as normalization, noise reduction, and contrast enhancement—play a crucial role in improving image quality and enhancing the visibility of anatomical structures. These improvements directly contributed to better performance in subsequent analysis stages. In particular, the use of CLAHE and filtering methods significantly reduced noise and enhanced local contrast, enabling more reliable feature extraction.

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