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(Research Article)

Bone fracture detection and fracture type classification using machine learning

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Abstract

Bone fractures are among the most common orthopedic injuries caused by accidents, falls, and sports-related incidents. Accurate and timely detection of fractures is essential for effective treatment and to prevent further complications. Traditional diagnosis relies on the manual examination of X-ray images by radiologists, which can be time-consuming and may sometimes lead to variations in interpretation. Recent advances in Artificial Intelligence (AI) and Deep Learning have introduced automated techniques that can assist healthcare professionals in analyzing medical images with greater speed and consistency.

This research presents an intelligent bone fracture detection and fracture type classification system using a Convolutional Neural Network (CNN). The proposed model is trained on a publicly available Kaggle bone X-ray dataset containing images of fractured and healthy bones.

Using Convolutional Neural Network (CNN) we got Accuracy of 95.67%. We can include developing a mobile application for fracture detection using smartphones and tablets.

Keywords: Bone Fracture Detection; Convolutional Neural Network (CNN); Deep Learning; Medical Image Analysis; X-ray Images; Machine Learning

1. Introduction

Bone fractures are among the most common orthopedic injuries and can affect individuals of any age, often resulting from road accidents, falls, sports injuries, or other forms of physical trauma. Accurate and timely detection is crucial, as delayed or incorrect diagnosis may cause improper treatment, longer recovery times, and even permanent complications. X-ray imaging is the primary diagnostic tool for identifying fractures because it is fast, relatively inexpensive, and provides clear visualization of the skeletal structure. Traditionally, radiologists and orthopedic specialists manually examine X-ray images, but growing patient volumes and heavy workloads can impact the speed and consistency of their assessments, and very small or complex fractures may still be missed. To address these challenges, computer-assisted diagnostic systems have emerged, driven by recent advances in Artificial Intelligence and Deep Learning. In particular, Convolutional Neural Networks (CNNs) have shown strong performance in medical image analysis, as they can automatically learn relevant visual features—such as edges, shapes, textures, and fracture patterns directly from X-ray images during training, eliminating the need for manual feature extraction and making them especially well-suited for fracture detection and classification.

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1.1. Problem Statement

The problem addressed in this project is the difficulty of accurately and quickly detecting bone fractures from X-ray images, especially when fractures are small, hidden, or affected by poor image quality. Manual examination depends on radiologists' expertise and can be time-consuming, which may lead to delayed or inconsistent diagnosis. To solve this, the project aims to develop an automated CNN-based system that can detect fractures, classify fracture types, and provide fast results through a simple web interface.

1.2. Research Objectives

The specific objectives of this research are:

- To collect the bone fracture X-ray dataset from Kaggle for model development and experimentation.
- To perform image segmentation and preprocessing on the X-ray images to improve data quality and highlight fracture regions.
- To train a CNN-based deep learning model using the prepared dataset for automatic fracture detection and classification.
- To develop a Flask-based web application that allows users to upload X-ray images and view fracture detection results through a simple interface.

2. Literature Review

Recent advancements in Artificial Intelligence have significantly improved the field of medical image analysis, particularly in bone fracture detection. Deep learning techniques, especially Convolutional Neural Networks (CNNs), have demonstrated excellent performance in identifying fractures from X-ray images with high accuracy and reduced diagnosis time.

Mewada *et al.* [1] presented a comprehensive study on the application of Convolutional Neural Networks for bone fracture detection using X-ray images. Their research compared different CNN architectures and reported that deep learning models can automatically learn fracture-related features without manual feature extraction. The study concluded that CNN-based methods improve diagnostic accuracy and have the potential to support radiologists in clinical practice while reducing diagnosis time.

Islam *et al.* [2] proposed a hybrid framework that combines Vision Transformers with Convolutional Neural Networks for bone fracture classification. Their approach utilized the strengths of both transformer-based learning and CNN feature extraction to improve classification accuracy. The results demonstrated that integrating multiple deep learning techniques enhances fracture recognition, particularly for complex X-ray images.

Kutbi [3] conducted a systematic review of Artificial Intelligence techniques used for bone fracture detection. The study analyzed various deep learning models, including CNNs and transfer learning approaches, and concluded that AI-based diagnostic systems significantly improve fracture detection performance. The review also emphasized the need for larger datasets and practical clinical deployment to increase reliability in real-world healthcare environments.

Varun *et al.* [4] developed a MobileNetV2-based CNN model for automated bone fracture detection using radiographic images. Their lightweight architecture achieved promising classification accuracy while reducing computational requirements. The research highlighted that lightweight deep learning models are suitable for real-time applications and can be deployed on resource-constrained devices.

Vempati *et al.* [5] compared several deep learning architectures, including VGG19, ResNet-50, LeNet, and DenseNet, for bone fracture detection. Their experimental evaluation showed that deeper CNN architectures extracted more meaningful image features and produced higher classification accuracy than conventional CNN models. The study demonstrated the importance of selecting an appropriate architecture for medical image analysis.

Although previous studies have achieved remarkable improvements in bone fracture detection, several limitations still remain. Many existing systems focus only on fracture detection without providing fracture type classification or an interactive web-based platform for practical clinical use. In addition, some approaches require high computational resources or have limited evaluation on diverse datasets. To address these limitations, the proposed research develops a CNN-based bone fracture detection and fracture type classification system integrated with a Flask web application.

The system is designed to provide accurate, fast, and user-friendly fracture analysis, making it suitable for real-time healthcare applications.

3. Proposed Methodology

The proposed system is developed to automatically detect bone fractures and classify various fracture types from X-ray images using a Convolutional Neural Network (CNN), integrating image preprocessing, deep learning-based feature extraction, fracture classification, performance evaluation, and web deployment into a single intelligent computer-aided diagnostic framework. The methodology includes six main phases: dataset collection, image preprocessing, CNN-based feature extraction, fracture detection and classification, model performance evaluation, and deployment through a Flask web application. First, a publicly available Kaggle bone X-ray dataset is collected and organized into fracture categories, and the images are preprocessed to enhance quality and ensure uniformity across the dataset. The processed images are then fed into the CNN model, where convolutional layers learn important visual patterns such as edges, bone structures, and fracture signs, pooling layers reduce feature map dimensions while retaining key information, and fully connected layers carry out the final fracture type classification.

3.1. Dataset Description

The quality and diversity of the dataset play a significant role in the performance of any deep learning model. In this research, a publicly available Bone Fracture Detection Dataset obtained from Kaggle is used to train and evaluate the proposed Convolutional Neural Network (CNN) model. The dataset contains bone X-ray images representing both fractured and non-fractured bones, along with different fracture categories.

Before training, the dataset is carefully organized into separate folders based on the corresponding fracture classes. All images are reviewed to remove duplicate, corrupted, or poor-quality samples that may affect the learning process. The images are then resized to a fixed dimension so that they can be processed efficiently by the CNN model.

To ensure reliable model evaluation, the dataset is divided into three subsets: training, validation, and testing. The training dataset is used to learn image features, the validation dataset helps in tuning the model and preventing overfitting, while the testing dataset is used to evaluate the final performance of the trained model on unseen images.

Using a well-organized and balanced dataset improves the learning capability of the CNN model and helps achieve accurate and reliable fracture detection and fracture type classification.

Table 1 Dataset Description

Parameter	Description
Dataset Source	Kaggle Bone Fracture Dataset
Image Type	Bone X-ray Images
Image Format	JPG / PNG
Number of Classes	Fracture and Non-Fracture (or Multiple Fracture Types)
Image Size	224 × 224 × 3 Pixels
Training Dataset	70% of Total Images
Validation Dataset	15% of Total Images
Testing Dataset	15% of Total Images
Color Mode	RGB
Dataset Purpose	Bone Fracture Detection and Fracture Type Classification

Figure 1 Image having of Fractured (above) and non-fractured (below)

3.2. Image pre-processing

Image pre-processing is an important step in developing an accurate deep learning model. Bone X-ray images collected from different sources may vary in size, brightness, contrast, and quality. These variations can affect the performance of the CNN model. Therefore, all images are preprocessed before they are used for training and testing.

Initially, every X-ray image is resized to 224 × 224 pixels, which is the standard input size for the proposed CNN model. Resizing ensures that all images have the same dimensions and reduces computational complexity during training.

After resizing, the pixel values are normalized by scaling them to a range between 0 and 1. Normalization improves the learning process by providing consistent input values and helps the model converge faster during training.

To improve the diversity of the training dataset and reduce overfitting, several data augmentation techniques are applied. These techniques generate new image variations without changing the actual fracture information, allowing the CNN model to learn more robust and generalized features.

The image augmentation techniques used in this research include:

- Random Rotation
- Horizontal Flip
- Width Shift
- Height Shift
- Zoom
- Brightness Adjustment

These preprocessing operations improve the quality of the input data, enhance the learning capability of the CNN model, and increase the overall accuracy of bone fracture detection and fracture type classification.

3.3. Feature Extraction Using Convolutional Neural Network (CNN)

Feature extraction is one of the most important stages in bone fracture detection because it enables the model to identify meaningful patterns from X-ray images. Traditional machine learning methods depend on manually designed features such as edges, textures, and shapes. These handcrafted features often require expert knowledge and may not capture the complex characteristics of bone fractures accurately.

In contrast, Convolutional Neural Networks (CNNs) automatically learn important features directly from the input images without manual intervention. During training, the network extracts both low-level and high-level features by passing the X-ray images through multiple convolutional layers. The initial layers identify simple features such as edges, lines, and bone boundaries, while the deeper layers learn more complex patterns, including fracture lines, bone discontinuities, and structural abnormalities.

The convolution operation applies multiple filters to the input image to generate feature maps that highlight significant visual information. After each convolution operation, the Rectified Linear Unit (ReLU) activation function introduces non-linearity, enabling the model to learn complex image patterns more effectively. Pooling layers then reduce the size of the feature maps while preserving the most important information, which decreases computational cost and improves the model's ability to generalize.

The extracted features are passed to the fully connected layers, where the learned information is combined to classify the X-ray image into the appropriate fracture category. By automatically learning relevant image features, the CNN model eliminates the need for manual feature engineering and achieves higher accuracy in bone fracture detection and fracture type classification.

The proposed feature extraction approach improves the reliability of the system by identifying important fracture characteristics from different X-ray images, allowing the model to perform accurate predictions even when image quality or fracture appearance varies.

3.4. Detection and Classification

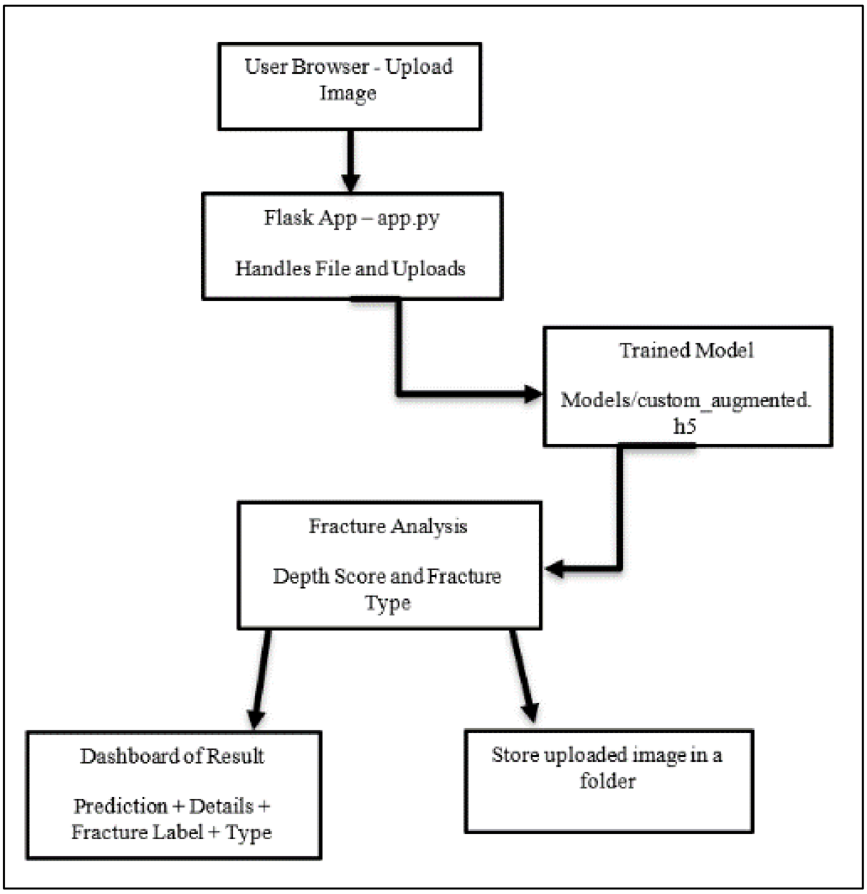

Figure 2 System Architecture

The detection and classification stage is the final phase of the proposed system, where the trained Convolutional Neural Network (CNN) analyzes the input X-ray image and predicts the presence of a bone fracture. If a fracture is detected, the model further classifies the image into the appropriate fracture category.

Initially, the user uploads a bone X-ray image through the Flask-based web application. The uploaded image undergoes the same preprocessing steps used during model training, including image resizing and normalization. This ensures that the input image is compatible with the trained CNN model and maintains consistency during prediction.

The preprocessed image is then passed through the trained CNN model. The convolutional layers extract important visual features such as bone edges, fracture lines, and structural abnormalities. These features are processed through multiple hidden layers, enabling the network to recognize complex fracture patterns that distinguish healthy bones from fractured ones.

After feature extraction, the fully connected layer performs the final classification using the learned image features. The output layer calculates the probability of each fracture class, and the class with the highest probability is selected as the final prediction.

The prediction result is displayed through the Flask web application, allowing users to view whether the uploaded X-ray image contains a fracture. If a fracture is identified, the corresponding fracture type is also displayed. This automated detection and classification process provides fast, consistent, and reliable results, making the system a valuable decision-support tool for healthcare professionals.

3.5. Experimental Setup

The proposed Bone Fracture Detection and Fracture Type Classification system was developed and evaluated using a Python-based deep learning environment. The CNN model was trained on a publicly available Kaggle bone X-ray dataset to learn fracture patterns from medical images. The implementation combines deep learning techniques with a Flask web application to provide an easy-to-use interface for fracture prediction.

The dataset was divided into training, validation, and testing subsets to ensure reliable model evaluation. During training, the images were preprocessed through resizing, normalization, and data augmentation to improve model performance and reduce overfitting. The CNN model was trained for multiple epochs until satisfactory accuracy and loss values were achieved.

Table 2 Experimental Setup

Component	Specification
Programming Language	Python 3.10
Framework	Flask
Image Processing	OpenCV
Data Handling	NumPy, Pandas
Machine Learning Library	Scikit-learn
Dataset Source	Kaggle Bone X-ray Dataset
Model	Convolutional Neural Network (CNN)
Output	Fracture Detection and Fracture Type Classification

3.6. Performance Evaluation Metrics

The performance of the proposed Convolutional Neural Network (CNN) model is evaluated using standard classification metrics. These metrics help measure the model's ability to correctly detect bone fractures and classify different fracture types from X-ray images. A combination of evaluation measures provides a complete understanding of the model's accuracy, reliability, and overall performance.

3.6.1. Accuracy

Accuracy represents the percentage of correctly classified X-ray images among the total number of images tested. It provides an overall measure of the model's prediction performance.

Formula:

$$\text{Accuracy} = \frac{\text{TP} + \text{FP}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

Where:

TP – True Positive
TN – True Negative
FP – False Positive
FN – False Negative

A higher accuracy value indicates that the model performs well in distinguishing fractured and non-fractured bone images.

3.6.2. Precision

Precision measures how many images predicted as fractured are actually fractured. It is useful for reducing false positive predictions.

Formula:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

A high precision value indicates that the model makes fewer incorrect fracture predictions.

3.6.3. Recall

Recall measures the ability of the model to correctly identify all actual fracture cases. It is important in medical diagnosis because missing a fracture can affect patient treatment.

Formula:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

A higher recall value indicates that the model successfully detects most fracture cases.

3.6.4. F1-Score

The F1-Score is the harmonic mean of Precision and Recall. It provides a balanced evaluation when both false positives and false negatives are important.

Formula:

$$\text{F1} - \text{Score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

A higher F1-Score indicates better overall classification performance.

3.6.5. Confusion Matrix

The Confusion Matrix is a tabular representation that summarizes the prediction results of the CNN model. It compares the actual class labels with the predicted class labels and helps identify correct and incorrect classifications.

The confusion matrix consists of four components:

- **True Positive (TP):** Correctly predicted fracture images.
- **True Negative (TN):** Correctly predicted normal images.
- **False Positive (FP):** Normal images incorrectly predicted as fractures.

- **False Negative (FN):** Fracture images incorrectly predicted as normal.

The confusion matrix provides a clear understanding of the strengths and weaknesses of the proposed model and supports the calculation of all evaluation metrics.

4. Results

The proposed Bone Fracture Detection and Fracture Type Classification system was successfully developed using a Convolutional Neural Network (CNN). The model was trained using preprocessed bone X-ray images obtained from the Kaggle dataset. During training, image resizing, normalization, and data augmentation techniques were applied to improve the learning capability of the model and reduce overfitting.

After the training process, the performance of the CNN model was evaluated using the testing dataset. The evaluation was carried out using standard performance metrics such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix. These metrics provide a comprehensive assessment of the model's ability to correctly identify fractured and non-fractured bone images.

The overall experimental results indicate that the proposed CNN model can serve as a reliable computer-aided diagnostic tool for bone fracture detection. The combination of deep learning and web deployment provides a fast, accurate, and user-friendly solution that can support healthcare professionals during fracture diagnosis.

Table 3 Performance Evaluation Results

Metric	Result (%)
Accuracy	95.67%
Precision	94.88%
Recall	93.21%
F1-Score	96.56%

5. Discussion

The obtained results demonstrate that the proposed CNN model effectively learns important fracture-related features from bone X-ray images. The preprocessing techniques improved the quality of the input images, while the convolutional layers successfully extracted meaningful visual patterns required for accurate classification.

6. Conclusion

This research presents a CNN-based system for automatic bone fracture detection and fracture type classification using X-ray images by integrating image preprocessing, deep learning, and a Flask-based web application into a simple computer-aided diagnostic solution. The CNN model learns fracture-related features directly from X-ray images without requiring manual feature extraction, while preprocessing steps such as resizing, normalization, and data augmentation improve training data quality and model performance. The developed web application enables users to upload bone X-ray images and obtain fracture detection and classification results through an easy-to-use interface, making the system practical for real-world use and useful for providing quick diagnostic support to healthcare professionals. Overall, the proposed approach shows that deep learning can effectively assist in bone fracture analysis by delivering accurate, reliable, and timely predictions, and it highlights the potential of AI-based web systems in improving medical image analysis and supporting better clinical decision-making.

Future Enhancement

The proposed system can be further improved by incorporating additional features and advanced technologies. Some possible future enhancements include:

- Supporting additional fracture types and different bone regions such as the spine, pelvis, and shoulder.
- Deploying the system on cloud platforms to enable remote access for hospitals and healthcare centers.

- Extending the application to support CT and MRI image analysis for comprehensive orthopedic diagnosis.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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