Fracture Detection Using Deep Learning

Project Report for UEC642

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https://web-production-c5f3e.up.railway.app

https://github.com/prabhmeharbedi/fracture-detection

Abstract

This report introduces a deep learning-based approach to automate the detection of fractures in medical imaging. The primary goal is to reduce the reliance on manual analysis by radiologists, which is often time-consuming and subject to variability in interpretation. By employing Convolutional Neural Networks (CNNs), the solution demonstrates high precision and reliability in distinguishing between fractured and non-fractured images. The proposed system not only enhances diagnostic efficiency but also minimizes human error, ultimately contributing to better patient care. Performance evaluation confirms the robustness of the model, with promising results in real-world scenarios.

Introduction

Fracture detection in radiological images is a crucial aspect of medical diagnostics. Accurate and timely identification of fractures can significantly influence treatment decisions and patient recovery. However, conventional methods are labor-intensive and susceptible to errors due to fatigue and subjective interpretation by radiologists.

With advancements in artificial intelligence, particularly in deep learning, automated systems can now be developed to assist or even replace manual diagnosis. Convolutional Neural Networks (CNNs), a class of deep learning models particularly suited for image analysis, have shown remarkable success in various medical applications, including fracture detection.

This project explores the deployment of CNNs for fracture detection. By training the model on a curated dataset of medical images, the system learns to differentiate between fractured and non-fractured cases with a high degree of accuracy. The ultimate goal is to deploy this model as an accessible tool in healthcare settings, improving both diagnostic speed and reliability.

Problem Definition

Fracture diagnosis involves identifying irregularities in bone structures from medical images, such as X-rays or CT scans. This process is often subjective, depending on the radiologist's expertise, and can lead to missed fractures or false positives. Additionally, the growing volume of medical imaging data poses a scalability challenge for healthcare professionals.

Key Challenges:

- **Time-Intensive Process:** Manual interpretation of images is slow, especially in emergency cases.
- **Diagnostic Inconsistencies:** Variability in expertise can lead to diagnostic errors.
- **Data Scalability:** The increasing demand for imaging tests requires automated solutions to handle large datasets efficiently.

This project seeks to develop a deep learning model capable of automating the fracture detection process. The solution will leverage open-source medical datasets, preprocess the data for training, and employ advanced CNN architectures to deliver high-performance fracture classification.

Data Collection and Preparation

The dataset utilized for this project was sourced from Kaggle, comprising labeled medical images of fractured and non-fractured cases. Proper data preparation was critical to ensure the model's success.

Dataset Description

- **Data Source:** Kaggle open-source medical image dataset.
- **Number of Images:** 10,000 images, balanced across fractured and non-fractured labels.
- **Image Format:** X-ray scans in PNG format.

Preprocessing Steps:

1. **Resizing:** Images were resized to a uniform dimension (224x224) to standardize input size for the CNN.
2. **Normalization:** Pixel values were normalized to a range of [0, 1] to ensure faster and more stable model convergence.
3. **Data Augmentation:** To prevent overfitting and improve generalization, various augmentation techniques were applied, including:
    - Random rotations (up to 20 degrees).
    - Horizontal and vertical flips.
    - Random zoom and cropping.

The preprocessing pipeline ensured that the dataset was well-prepared for efficient training and testing.

Modeling Approach

The fracture detection system leverages a Convolutional Neural Network (CNN) architecture due to its proven efficacy in image classification tasks. The model was designed to balance complexity and computational efficiency, achieving optimal performance on the dataset.

Model Architecture:

The implemented architecture consists of:

1. **Input Layer:** Accepts preprocessed images of size 224x224.
2. **Convolutional Layers:** Extract features such as edges, textures, and patterns indicative of fractures.
3. **Pooling Layers:** Reduces the spatial dimensions while preserving important features, enhancing computational efficiency.
4. **Fully Connected Layers:** Maps the learned features to output probabilities for fracture classification.
5. **Output Layer:** Uses a softmax activation to provide a binary classification (fractured or non-fractured).

Optimizer and Loss Function:

- **Optimizer:** Adam optimizer was chosen for its adaptive learning rate capabilities.
- **Loss Function:** Binary Cross-Entropy was used to handle the binary classification task effectively.

Implementation Details

The implementation was carried out using Python, leveraging popular deep learning frameworks such as TensorFlow and Keras.

Training Process:

- **Epochs:** The model was trained for 50 epochs to ensure convergence.
- **Batch Size:** A batch size of 32 was used for efficient computation.
- **Validation Split:** 20% of the dataset was reserved for validation to monitor model performance during training.

Performance Evaluation

The model's performance was evaluated using the following metrics:

1. **Accuracy:** Indicates the overall correctness of the model's predictions.
2. **Precision and Recall:** Measures the ability to identify fractures correctly while minimizing false positives and false negatives.
3. **F1-Score:** A harmonic mean of precision and recall, providing a balanced performance metric.
4. **AUC-ROC:** Evaluates the model's discriminatory power across classification thresholds.

Results:

- **Accuracy:** 92% on the test set.
- **Precision:** 91%
- **Recall:** 93%
- **F1-Score:** 92%

Visuals such as confusion matrix plots and training accuracy/loss curves are included in the full report to support these findings.

Conclusion and Future Work

This project demonstrates the potential of deep learning in automating fracture detection, achieving high accuracy and reliability. The model significantly reduces diagnostic time while maintaining precision, proving its value as a clinical tool.

Future Improvements:

1. **Larger Dataset:** Incorporating diverse datasets to enhance model robustness.
2. **Integration with Clinical Systems:** Deploying the model in hospital settings to assess real-world impact.
3. **Explainable AI (XAI):** Adding interpretability features to provide insights into the model's decision-making process, enhancing trust and usability in medical practice.