Title: Skeletal Fracture Detection Using Vision Transformers

Overview:

This project investigates the use of Vision Transformers (ViTs) for detecting skeletal fractures, including normal, hairline, and non-displaced fractures. The system is designed to support radiologists and medical practitioners by offering a fast, reliable, and automated method for screening X-ray images.

Problem Statement:

Traditional fracture detection requires high expertise and careful manual interpretation. Hairline fractures are especially difficult to identify because they appear faint and thin. An automated system can reduce workload, improve accuracy, and assist in early diagnosis.

Objectives:

- Build a deep-learning model that classifies X-ray images into: Normal, Hairline Fracture, or Other Fractures.
- Leverage the powerful feature extraction capabilities of Vision Transformers.
- Improve detection accuracy for subtle hairline fractures.
- Develop a pipeline that can be integrated with clinical workflows.

Tech Stack:

- Vision Transformers (ViT and Swin Transformer variants)
- PyTorch or TensorFlow (depending on experiment)
- Scikit-learn for evaluation
- OpenCV for preprocessing
- Google Colab / Jupyter Notebook for experimentation

Dataset:

A curated dataset consisting of X-ray images of various bone types (hand, wrist, ankle, leg). Images were preprocessed through:

- Contrast enhancement
- Noise reduction
- Image normalization

• Region-of-interest extraction

Method:

1. Preprocess the X-ray images and generate training/validation splits.
2. Fine-tune a ViT model using supervised learning.
3. Extract attention maps to understand fracture-related focus regions.
4. Compare ViT performance with CNN baselines (e.g., ResNet, EfficientNet).
5. Evaluate using accuracy, F1-score, sensitivity, and specificity.

Key Features:

• High-resolution attention-based feature extraction

• Improved identification of faint fracture lines

• Explainability through attention heatmaps

• Modular structure allowing additional classes

Applications:

• Emergency room triage assistance

• Telemedicine screening

• Radiologist decision support

• Medical education and training

Future Enhancements:

• Expand dataset to include more bone categories.

• Add segmentation of fracture regions.

• Deploy as a cloud-based medical assistant tool.

• Integrate DICOM support for clinical use.

This project showcases expertise in deep learning, medical imaging, and the use of modern transformer architectures for practical diagnostic tasks.