

# Bone Fracture Detection using Deep Learning and Computer Vision

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## High-Level Description:

The project aims to address the problem of detecting bone fractures from X-ray images. Early and accurate fracture detection is crucial for timely treatment and better patient outcomes. Traditional methods rely heavily on radiologists, which can be time-consuming and prone to human error. This project will explore how machine learning, specifically computer vision techniques, can automatically detect fractures with high accuracy, thereby serving as a decision-support system in healthcare.

## Type of Data Science Task:

- Classification using supervised learning (fracture vs. no fracture).
- Image recognition and object detection using deep learning.
- Data visualization for model performance (ROC curves, confusion matrices, heatmaps).

## Data:

Two datasets will be used:

- 1) Bone Fracture Detection Computer Vision Dataset [1].
- 2) MURA (Musculoskeletal Radiographs) Dataset published in Nature [2].

The datasets contain thousands of labeled X-ray images of different bones with annotations for fracture detection. Combined, the dataset size is expected to be around 2–3 GB, which is sufficiently large for training deep learning models. Since the data is already available, no web-scraping or new collection will be required.

## Analysis and Methods:

The project will employ convolutional neural networks (CNNs) and transfer learning methods (e.g., ResNet, EfficientNet) for classification. Image preprocessing steps such as normalization, augmentation, and denoising will be applied. Grad-CAM visualization will be used for model interpretability. The evaluation metrics will include accuracy, precision, recall, F1-score, and AUC.

## Anticipated Difficulties:

- **Data imbalance:** Fracture images may be fewer than non-fracture images. This can be mitigated using data augmentation and class-weighted loss functions.
- **Computational resources:** Training CNNs on large image datasets can be resource-intensive. Solutions include using cloud GPUs or pre-trained models with transfer learning.
- **Model interpretability:** Ensuring clinicians can trust predictions will require interpretability techniques such as heatmap visualizations.

## Timeline (8 Weeks):

- 1) **Week 1:** Literature review, finalize problem scope, and dataset exploration.
- 2) **Week 2:** Data preprocessing and cleaning (normalization, augmentation).
- 3) **Week 3:** Baseline model development (simple CNN).
- 4) **Week 4:** Implement transfer learning models (ResNet, EfficientNet).
- 5) **Week 5:** Model training and hyperparameter tuning.
- 6) **Week 6:** Model evaluation and visualization (ROC curves, Grad-CAM).
- 7) **Week 7:** Compare models, optimize performance, and interpretability testing.
- 8) **Week 8:** Final report preparation, results presentation, and documentation.

## REFERENCES

- [1] Bone Fracture Detection Computer Vision Project, ResearchGate. Available at: [https://www.researchgate.net/publication/382268240\\_Bone\\_Fracture\\_Detection\\_Computer\\_Vision\\_Project](https://www.researchgate.net/publication/382268240_Bone_Fracture_Detection_Computer_Vision_Project)
- [2] Rajpurkar et al. (2023). Musculoskeletal Radiographs (MURA). Nature Scientific Data. Available at: <https://www.nature.com/articles/s41597-023-02432-4>