Musculoskeletal Radiograph Classification Using Deep Learning

A diagnostic AI system for anomaly detection

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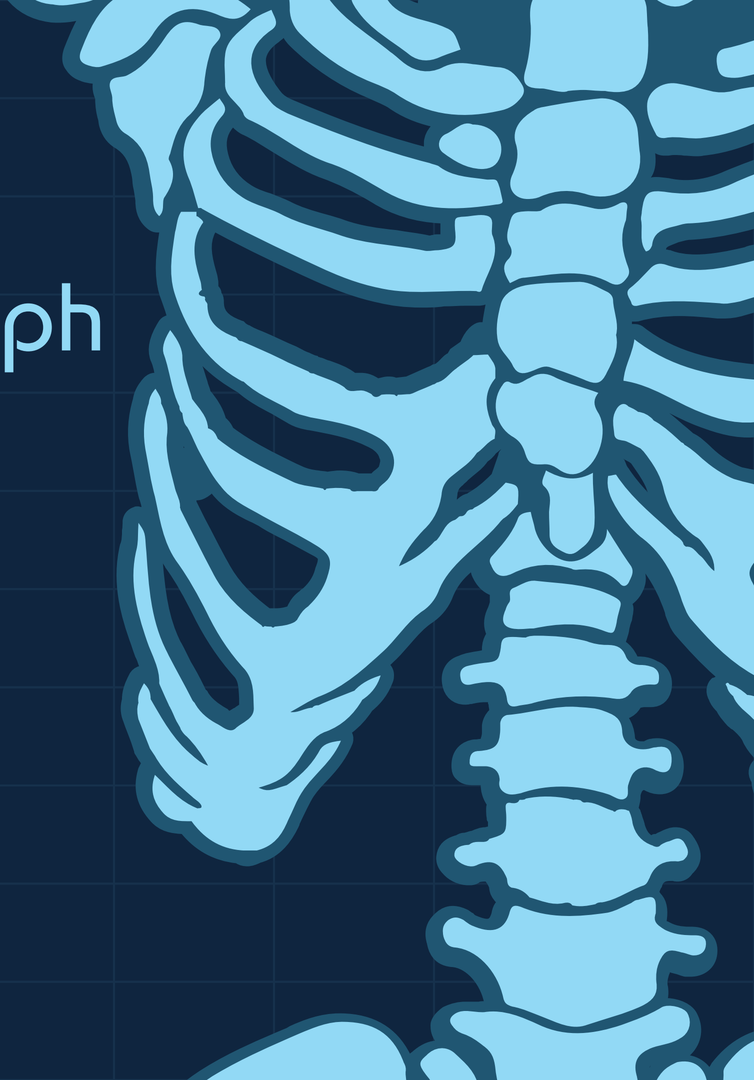

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01 The disease

Business problem:

Automating Anomaly Detection in MSK Radiographs

Diagnostic errors occur mostly when radiologists exceed their average daily production

Marty Stempniak | August 11, 2023 | Radiology Business | Leadership

Work overload and diagnostic errors in radiology

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Using AI to Improve Radiologist Performance in Detection of Abnormalities on Chest Radiographs

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02 Diagnosis

Technical framing:

Understanding the Case & the Data

Dataset: MURA* (Stanford ML Group)

Total Images: ~40,561 musculoskeletal radiographs

Total Studies: 14,863 from **12,173 patients**

Body Parts: Shoulder, Humerus, Elbow, Forearm, Wrist, Hand, Finger

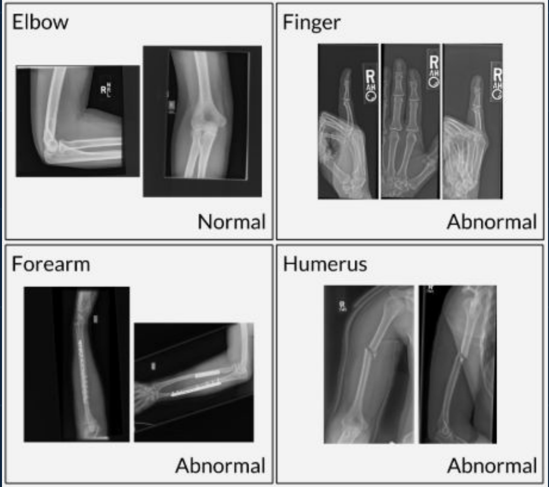
Labeling:

- **Positive (1)** = abnormal finding (fracture, degeneration, etc.)
- **Negative (0)** = normal image

Imbalance: ~58% Negative vs ~42% Positive (varies by study type)

Challenges:

-**High variability** in radiograph quality, orientation, and exposure.
-**Noisy labels:** sometimes based on study-level, not image-level.
-Medical images are visually subtle — anomalies are hard to detect.



Binary classification task:

Is this radiograph **abnormal (1)** or **normal (0)** ?

Other Challenge:

Strong **class imbalance**

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03 Clinical Trials

Model Benchmarking:

Comparison of CNN architectures

MODEL	Accuracy	F1- Score	Notes
ResNet18	91%	0.91	Best Balance & speed
DenseNet121	91%	0.91	Similar to RestNet, more complex
VGG16	82%	0.82	Decent, heavier model
EfficientNet	73%	0.71	Biased to negatives
MobileNet	36%	0.24	Poor anomaly detection

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04 Treatment Plan

Technical framing:

Understanding the Case & the FULL DATA

Version	Main Changes	F1-score	Accuracy
Baseline	Only fc training, no tuning	0.78	78%
V5	Full model trained	0.59	63%
V6	Added class weights + LR scheduler	0.77	77%
V7	Added early stopping	0.79	79%
V8	Better LR tuning + regularization	0.80	80%
V9	+Augmentations & freeze strategy	0.80	80%

No class weighting

Consistent improvement Through fine-tuning and balancing

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05 Surgical Procedure

Architecture:

What the best model looks like

1.Architecture Modification

```
resnet18.fc = nn.Linear(resnet18.fc.in_features, 2)
```

Replaced the fully connected layer to output 2 classes: normal vs. abnormal

2.Advanced Fine-Tuning: Partial Unfreezing

```
for name, child in
resnet18.named_children():
    if name in ['layer3', 'layer4', 'fc']:
        for param in child.parameters():
            param.requires_grad = True
    else:
        for param in child.parameters():
            param.requires_grad = False
```

Unlocked layer3, layer4, and fc for fine-tuning.
Earlier layers remained frozen to preserve ImageNet features.

3. Weighted Loss for Imbalance

```
criterion = nn.CrossEntropyLoss(weight=class_weights_tensor)
```

Applied inverse-frequency class weights to penalize false negatives more

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05 Surgical Procedure

Architecture:

What the best model looks like

4.Regularization with Scheduler and Early Stopping

```
scheduler = ReduceLROnPlateau(optimizer, mode='min', factor=0.5, patience=5)
```

Reduced learning rate automatically if validation loss plateaued

```
if epochs_no_improve >= EARLYSTOP_PATIENCE:
    break
```

Stopped training early to prevent overfitting

5.Clinically Safe Augmentations

Simulated real-world variability in radiograph positioning without distorting key features

```
transforms.Compose([
    transforms.RandomRotation(15),
    transforms.ColorJitter(0.2, 0.2),
    transforms.RandomResizedCrop(IMAGE_SIZE, scale=(0.85, 1.0)),
    ...
])
```

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What comes after treatment?:

Conclusions and next step

Key Takeaways

- **80% F1-score and accuracy** in final model
- Optimizations that worked: **partial unfreezing, class weighting, LR scheduling, safe augmentations**
- Learned from **imbalanced, noisy, and subtle data**
- AI as an **assistive tool**, not a replacement — great for **screening** use cases

Future Improvements

- **Per-body-part performance** (some bones may be harder to classify)
- **Explainability tools** like Grad-CAM or saliency maps
- More **augmentation testing** (blurring, low contrast...)
- **Deployable prototype** (Flask/Gradio for demo or clinical API)
- Feedback loop from radiologists to **continually retrain the model**

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Thanks!

Project available on GitHub

//github.com/alvarosmms/ML_MURA_CLASSIFICATION

Feel free to reach out!

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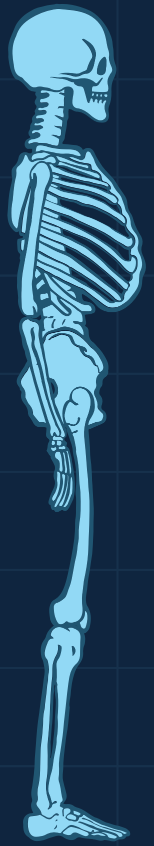

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