



X-RAY PROJECT - RESEARCH

How should we classify between injury and not?

How should we differentiate limbs?

Should we fine tune a pretrained model from Image NET?

I took these questions before starting up the action plan.

For the classification of Whether it's a injury or not, we can approach this with two process. First one we should focus on the Data Preprocessing step and the second one is Model selection, Transfer Learning, Model Training and Fine tuning.

Data Preprocessing:

Dataset Requirements as far as I researched for Task 1 (Injury Classification)

1. Diverse set of X-ray images from various angles
2. Dataset images should be having
 - a. Variations of Injuries
 - i. Bone Injuries - Simple Fractures
 - ii. Soft Tissue Injuries - Ligament Injury, strains,
 - iii. Joint Injuries - Dislocations

- b. Different types of Fractures, Ligament tears
 - i. Fractures
 - ii. Ligament Tears
 - c. Severities of Fractures, Ligament tears
 - i. Fractures - Minor Fractures, Compound Fractures
 - ii. Ligament Tears - Mild Tear, Partial Tear, Complete Tears
 - d. Wide range of injury types based on Patient Demographics
 - i. Children
 - ii. Women
 - iii. Adults
 - iv. Elders
 - v. Senior Citizens
3. Annotations of all the images should be done by the medical professionals

Dataset Requirements for Task 2 (Body Part Identification / Detection)

- 1. Variety in Imaging Techniques
 - a. X-rays taken with the different imaging techniques such as CT, MRI
- 2. Annotations for reference points or landmarks on the body can help in more accurate body part identification

Datasets from the document:

- **FracAtlas**
 - Dataset features 4,083 X-ray images focusing on the hand, leg, hip, and shoulder regions, with patient ages ranging from 8 months to 78 years.
 - Expert radiologists reviewed and annotated the images for fractures, with the dataset containing a mix of fracture severities and types, as well as orthopedic fixation devices.
 - Images come in different views (frontal, lateral, oblique)
 - Available in JPG format, with annotations in COCO JSON format for segmentation and localization tasks

- **UNIFESP**

- The dataset labels represent 22 different body parts, each assigned a unique integer.

Datasets which can be helpful:

1. **VinDr-BodyPartXR** - This dataset contains 16,093 X-ray images specifically collected and manually annotated for classifying body parts from X-ray scans - <https://vindr.ai/datasets/bodypartxr#:~:text=This challenge raises the need,are collected and manually annotated>
2. **GRAZPEDWRI-DX** - This is a large dataset containing 20,327 scans with annotations for localization collected from 6,091 patients. It is focused on wrist fractures and thus covers only a specific part of the human body - <https://www.nature.com/articles/s41597-022-01328-z#:~:text=GRAZPEDWRI,were included%2C tagged and annotated>
3. **MURA** - MURA is a dataset of musculoskeletal radiographs consisting of 14,863 studies from 12,173 patients, with a total of 40,561 multi-view radiographic images. Each belongs to one of seven standard upper extremity radiographic study types: elbow, finger, forearm, hand, humerus, shoulder, and wrist. Each study was manually labeled as normal or abnormal by board-certified radiologists from the Stanford Hospital at the time of clinical radiographic interpretation in the diagnostic radiology environment between 2001 and 2012 - <https://stanfordmlgroup.github.io/competitions/mura/>
4. **VinDr-SpineXR** - It consists of 10,466 spine X-ray images from 5,000 studies, each manually annotated with 13 types of abnormalities by experienced radiologists. This dataset provides detailed spinal injury classifications - [https://vinlab.io/datasets#:~:text=Vingroup Big Data Institute \(VinBigdata\) has created and,each scan was annotated by an expert radiologist.#:~:text=Vingroup Big Data Institute ,annotated by an expert radiologist](https://vinlab.io/datasets#:~:text=Vingroup Big Data Institute (VinBigdata) has created and,each scan was annotated by an expert radiologist.#:~:text=Vingroup Big Data Institute ,annotated by an expert radiologist)
5. **Bone Fracture Identification Dataset** - Utilized in a study for the automatic detection of fractures, this dataset comprises 300 X-ray bone images of upper and lower extremities. This would be useful for models focusing on fracture identification in those specific body areas - <https://universe.roboflow.com/roboflow-100/bone-fracture-7fy/g/dataset/2>

Model selection, Transfer Learning, Model Training and Fine tuning:

For the Task 1:

After my research I feel these are all the models could be helpful for the Classification of Fractures.

1. ResNet

- a. <https://www.mdpi.com/2076-3417/10/4/1507>
- b. <https://arxiv.org/abs/2102.00515>
- c. https://link.springer.com/chapter/10.1007/978-981-15-3075-3_20

2. Inception

- a. <https://ieeexplore.ieee.org/document/8861312>
- b. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7903219/>
- c. <https://www.mdpi.com/2075-4418/12/5/1280>

3. DenseNet

- a. <https://iopscience.iop.org/article/10.1088/1742-6596/1848/1/012030>
- b. <https://dl.acm.org/doi/10.1145/3453892.3461632>
- c. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9080057/>

I've collected some of the research papers based on these models related to our task.

I'm just going through some of the papers whenever I get time.

Once I read all of the papers, I might be getting some ideas related to how does the model performs for the specific classification. Until that we could try the model comparison analysis parallely.

There are some other models like AlexNet, GoogleNet and EfficientNet. we can try these model for the model selection analysis.

For the Task 2:

R-CNN would be best option for the object identification / detection

Faster R-CNN - https://link.springer.com/chapter/10.1007/978-3-319-54526-4_33#:~:text=%23%20Multiple,detecting%20persons%20and%20their%20parts

I've to read about this paper to get more insights about the Faster R-CNN.

I've read about the YOLO model, it's excellent for the object detection but for our case, precision is high likely important when comparing to the speed. In that case R-CNN outperforms the YOLO model.

Should we perhaps combine steps 1 and 2? Are there resources that can help us with this challenge?

This could be a effective approach. I read about one approach for this combination

I've got some of the research papers

- https://link.springer.com/chapter/10.1007/978-981-15-3075-3_20#:~:text=Computer,stage classification step
- <https://ieeexplore.ieee.org/document/1529959>

Multi-Task Learning:

- We can use a multi-task learning framework where a single model is trained to perform both tasks simultaneously.
- This can be achieved by having a shared feature extraction backbone (like ResNet or EfficientNet) and two separate heads at the end of the network: one for classification and another for detection.
 - <https://www.sciencedirect.com/science/article/pii/S1361841521001717#:~:text=In this paper%2C we review,segmentation%2C localization%2C image>
 - <https://www.semanticscholar.org/paper/Self-supervision-and-Multi-task-Learning%3A-in-from-Ridzuan-Bawazir/b48f7a3ba1c3c16e0b70dc867182e549ca90be94#:~:text=In this work%2C we investigate,supervised>

