



Identifying Bone X-rays

Adeyemi Adejuwon

Capstone 2

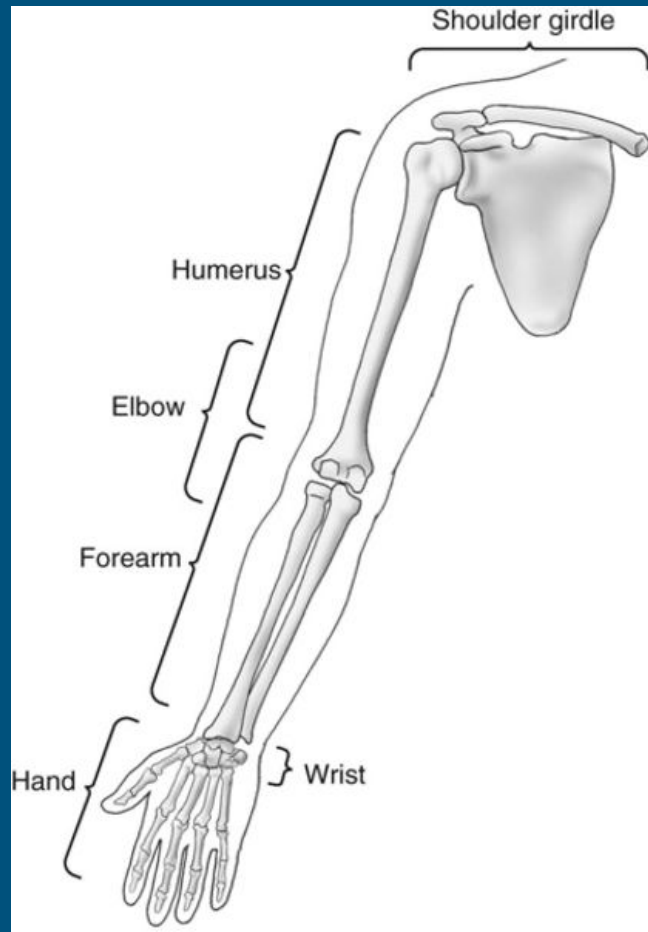
Springboard Data Science

September 2020



Description of Dataset

- **MURA** (**MU**sculoskeletal radiographs) is a large dataset of bone X-rays supplied by Stanford.
- Each study contains one or more images and is manually labelled by radiologists as 'Normal' or 'Abnormal'.
- The images are X-rays of different body parts-wrist, shoulder, elbow, hand, finger, forearm and humerus.
- MURA dataset comes with train and valid folders containing corresponding datasets



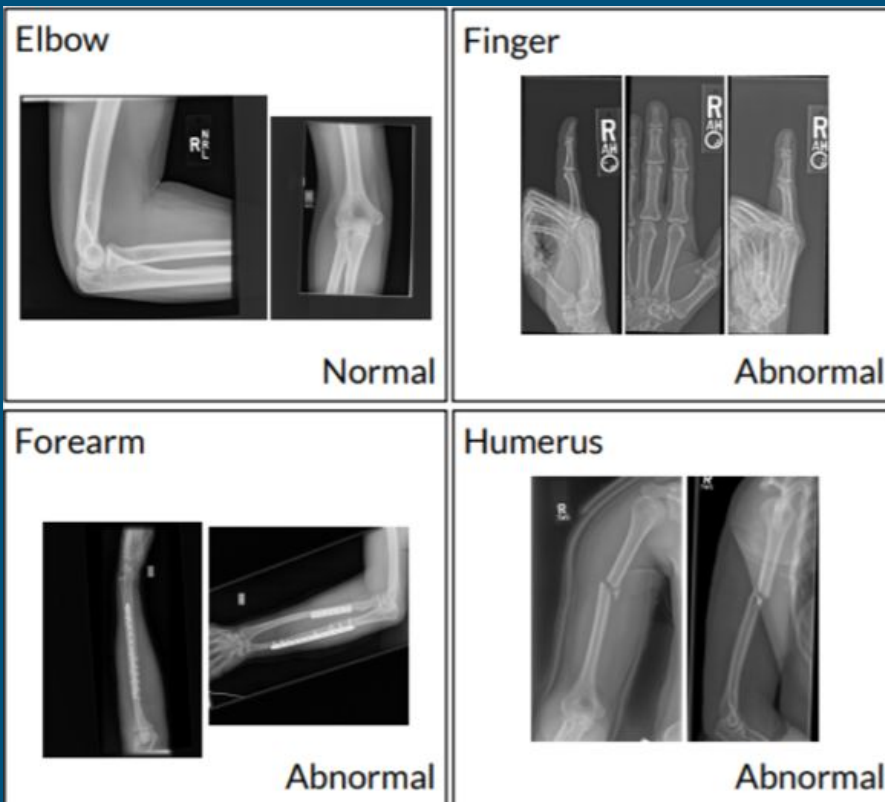
Objective

Classify radiographic images of upper extremity body parts as Normal or Abnormal using machine learning models

The machine learning models used are:

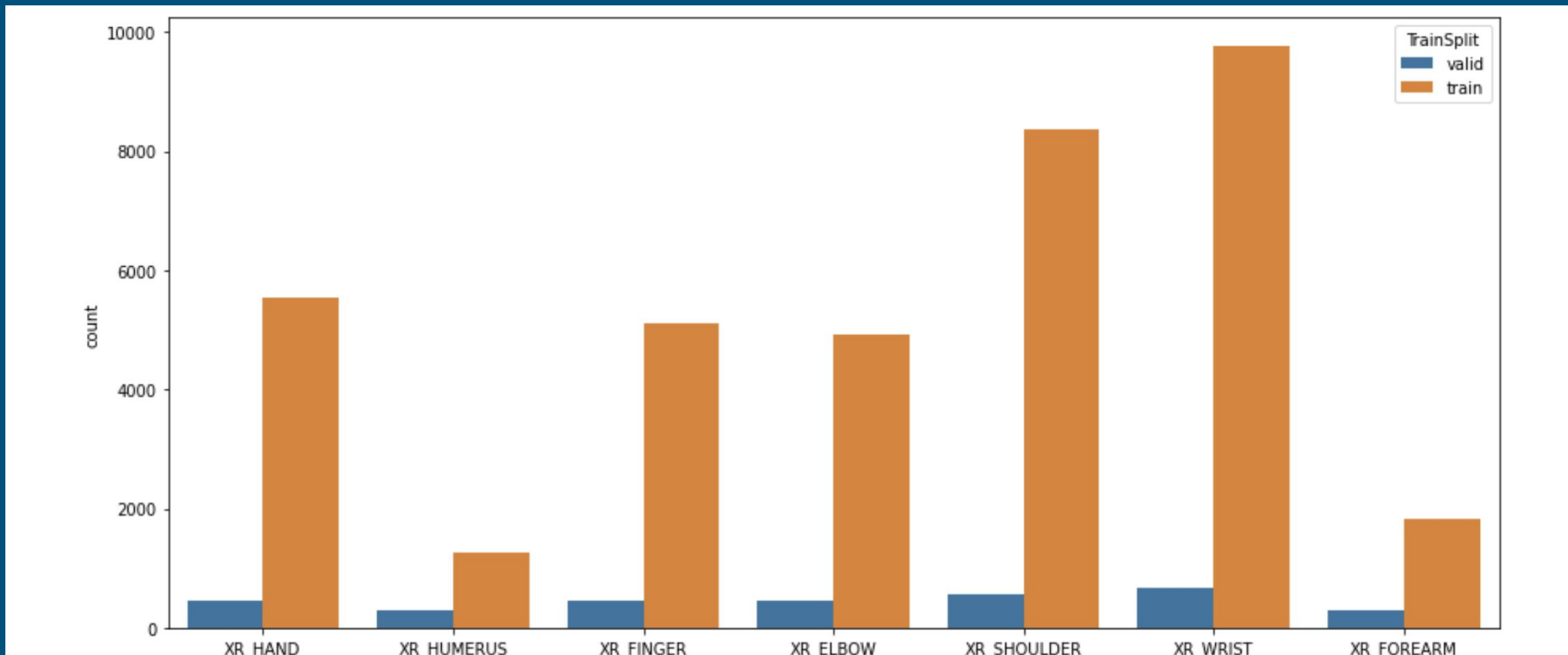
- 1. Logistic Regression**
- 2. K Nearest Neighbor**
- 3. SVM**
- 4. Random Forest**

Summary of Dataset



- ~41,000 images from ~15,000 studies (patients) including train and validation sets
- 9,000 studies of normal (negative condition) and 6,000 of abnormal studies (positive condition)
- Typical image res: 500 x 500 pixels

Dataset



What is the distribution of the abnormal (1 class) and normal (0 class) X-rays in our dataset?

Fig 7: Number of patients versus body parts for both Normal and Abnormal Data for Training data

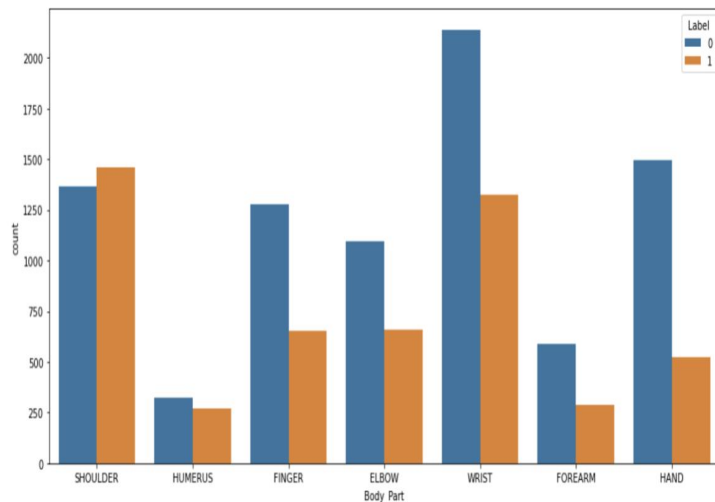
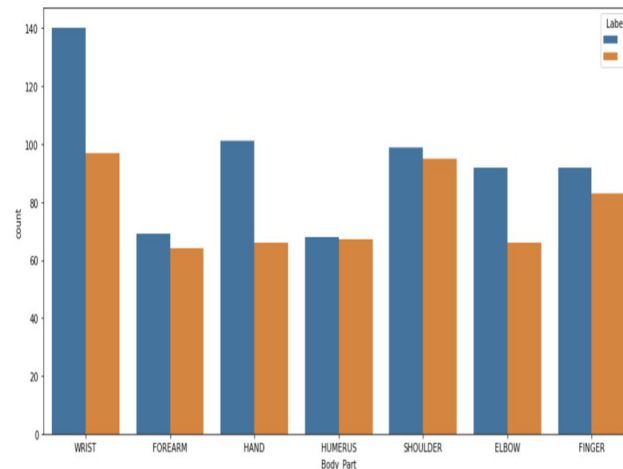
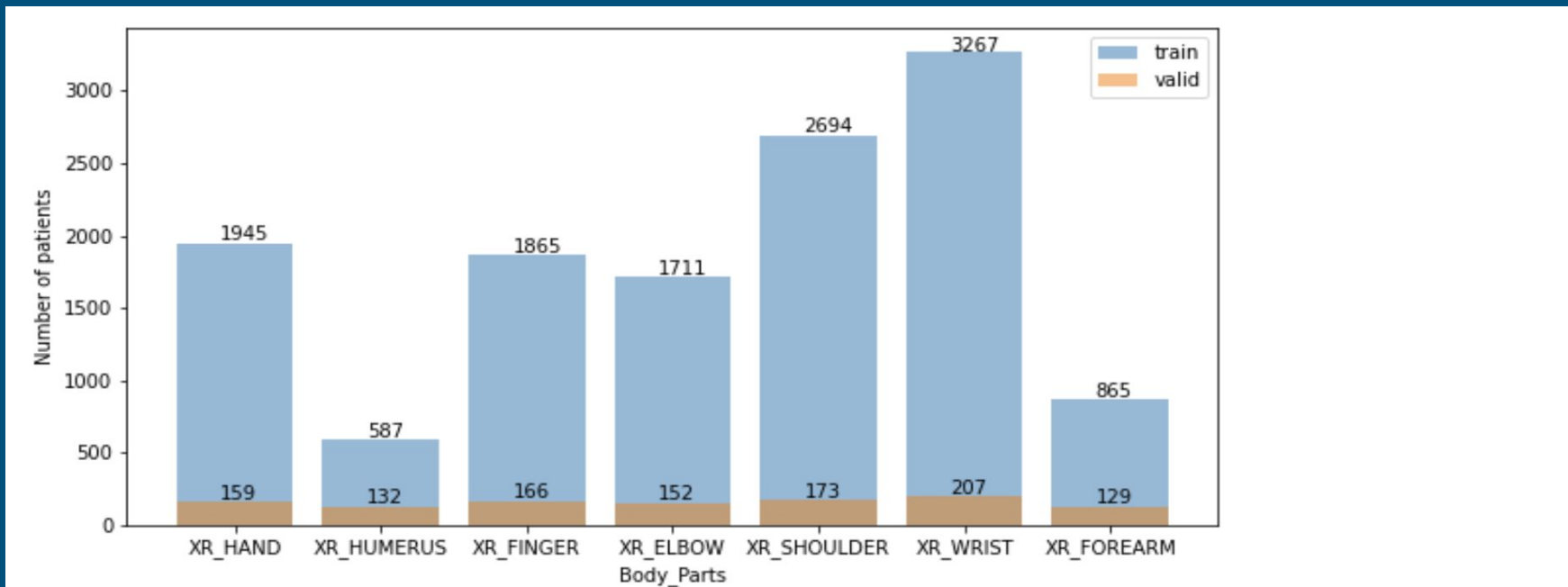


Fig 8: Number of patients versus body parts for both Normal and Abnormal Data for Test data



What is the distribution of X-rays versus the number of patients in the dataset?



Data Wrangling

Preprocessing of Images

- Resizing the images to 224 x 224 to enable the use in the machine learning model
- Normalization of images (scale:0-1) to ensure each input parameter has a similar data distribution

Feature Extraction

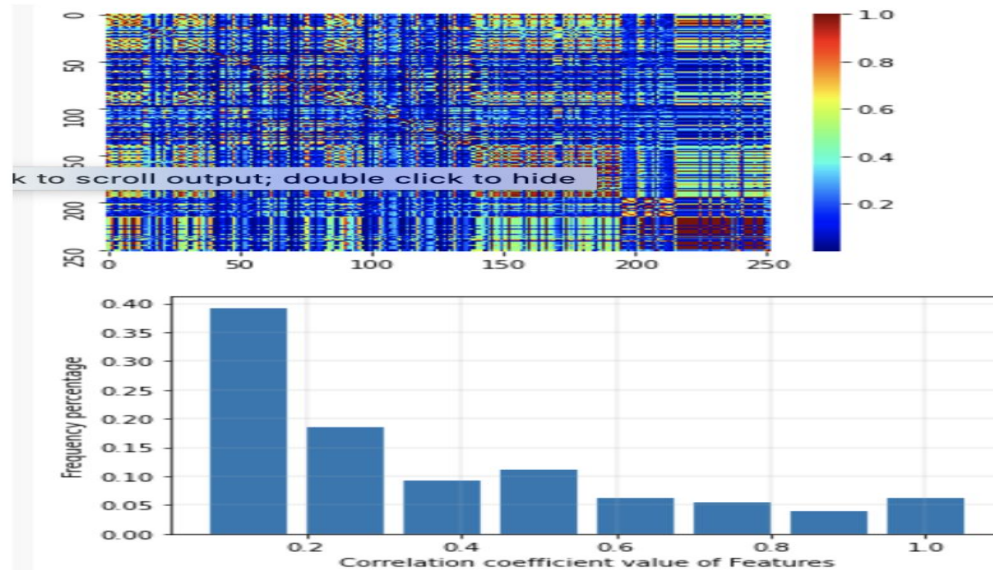
Feature extraction was done using the Gray Level Co-occurrence Matrix (GLCM) method

Results: 252 features for each X-ray image

- 14 features from Texture,
- 14 features from FFT,
- 56 features from GLCM,
- 56 features from GLDM, and
- 112 features from Wavelet

Inferential Statistics

Fig. 11. Heat map and Histogram representation of Pearson correlation Coefficients for the Humerus



Machine Learning Models for Abnormal Class

Model	Logistic Regression			Random Forest		
Body Type	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Forearm	0.67	0.12	0.21	0.74	0.22	0.34
Wrist	0.43	0.19	0.26	0.7	0.4	0.51
Finger	0.76	0.46	0.57	0.78	0.59	0.67
Hand	0.6	0.05	0.08	1.00	0.09	0.17
Humerus	0.56	0.6	0.58	0.69	0.54	0.61
Shoulder	0.5	0.58	0.54	0.62	0.69	0.65
Elbow	0.62	0.12	0.2	0.87	0.2	0.32

Machine Learning Models for Abnormal Class

Model	SVM			KNN		
Body Type	Precision	Recall	F1-Score	Precision	Recall	F1-Score
Forearm	0.73	0.12	0.21	0.59	0.36	0.45
Wrist	0.57	0.32	0.41	0.59	0.48	0.53
Finger	0.81	0.46	0.58	0.68	0.39	0.49
Hand	0.5	0.02	0.03	0.62	0.15	0.24
Humerus	0.65	0.64	0.65	0.63	0.69	0.66
Shoulder	0.54	0.62	0.58	0.58	0.69	0.61
Elbow	0.62	0.12	0.2	0.69	0.27	0.39

Discussion of Results

- Random forest gives best performance metric scores for the abnormal class on all four models.
- Random forest predicts best for the Finger body part
- Classification report for the abnormal class shows that :
 - a. All models offer poor predictions for the Elbow, forearm and hand.
 - b. All models offer good predictions for the humerus and shoulder.

Future & Extension of Project

1. Develop a website for radiologists to upload data. Results from these X-rays are now interpreted with random forest models to see if X-rays are normal or abnormal.
2. Apply deep learning algorithms such as CNN to image dataset, to see if improvements were made to the model predictions.

Works Cited

1. “What Is MURA?” *MURA Dataset: Towards Radiologist-Level Abnormality Detection in Musculoskeletal Radiographs*, stanfordmlgroup.github.io/competitions/mura/.
2. Khuzani, Abolfazl Zargari, et al. “COVID-Classifer: An Automated Machine Learning Model to Assist in the Diagnosis of COVID-19 Infection in Chest x-Ray Images.” *MedRxiv : the Preprint Server for Health Sciences*, Cold Spring Harbor Laboratory, 18 May 2020, www.ncbi.nlm.nih.gov/pmc/articles/PMC7273278/#S6.