



Exploring the feasibility of using deep learning and artificial intelligence for OA type distal radius fracture classification

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Introduction:

Distal radius fractures (DRF) are amongst the most common surgically treated fractures. All receive plain radiographs before and after application of plaster. Often, intra-articular fractures receive a CT in the emergency department prior to discharge. This results in significant delays and utilisation of resources, for an injury which is best treated in the outpatient setting.

In an experienced surgeon's hands, approximately 20% of distal radius fracture require a CT as most distal radius fractures have a predictable injury pattern.

The aim of this study was to utilise deep learning to classify distal radius fractures and therefore allow an artificial intelligence program to predict which fractures require a CT scan prior to an outpatient surgical consult.

Materials and Methods:

X-rays of 439 DRFs, which underwent surgical fixation were extracted from PACS. Each fracture was classified according to the AO classification by 3 independent orthopaedic training registrars under consultant supervision. These images and classifications were used for deep learning.

YOLOv5, an open-source object detection network, was used to localize the region of interest (ROI) on the distal radius for each X-ray. YOLOv5 was trained to narrow the ROI over the distal radius to obtain more accurate results (Figure 1).

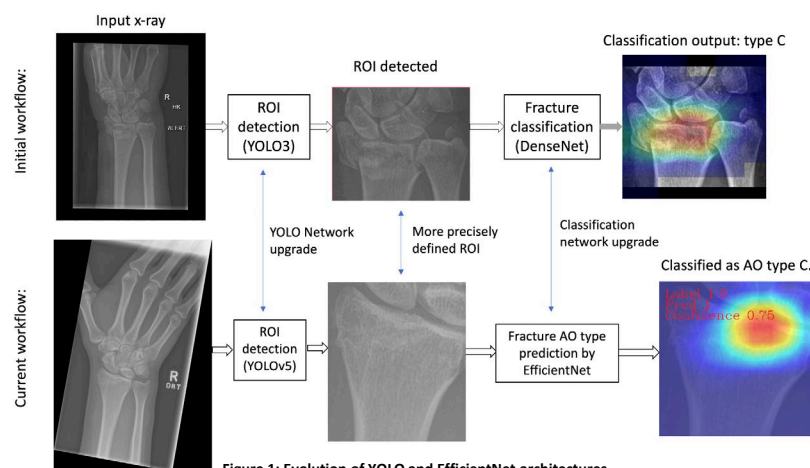


Figure 1: Evolution of YOLO and EfficientNet architectures

For the classification stage, we used the new ROIs, the EfficientNet-b3 architecture and RandAugment augmentation method for training. EfficientNet is a sophisticated network currently used to classify fracture. RandAugment randomises (5-fold cross validation) the experiment setting, allowing the network to learn generalised features rather than memorise characteristics.

In our current experiment, the image data are randomly partitioned into 5 folds. In each validation round, 4 folds of the data are used for training the classification network and 1 fold is used for testing the performance of the trained model.

Results:

The results were graphed on a receiver operating characteristics (ROC) curve (Figure 2). EfficientNet-b3, was trained to achieve an area under receiver operating characteristic (AUROC) of 0.74.

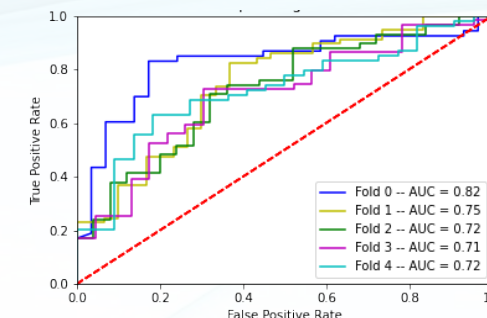


Figure 2: Receiver Operating Characteristics (ROC) Curve.
Average area under the curve (AUROC) = 0.74

Conclusions:

The deep learning architecture, EfficientNet, has been successfully trained to correctly classify DRF 74% of the time for a randomly selected image. This result is based on AP radiographs only. Further evaluation of lateral radiographs and use of patient demographics will certainly improve the accuracy of the architecture.

Although early in its evolution, there is scope for deep learning and artificial intelligence to have a significant positive impact in the clinical setting to streamline processes, improve efficiency and overall patient care.