AN AUTOMATED SEGMENTATION ALGORITHM TO IDENTIFY BONES OF THE HAND AND WRIST FOR LARGE SCALE STRUCTUAL DAMAGE QUANTIFICATION

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Background

What Is Psoriatic Arthritis (PsA)

PsA is a destructive inflammatory disease that affects the bones and joints of those with Psoriasis

The Problem

Formal quantification of structural damage in radiographs is **expensive**, **time consuming** and **requires trained experts** [1]

This limits formal quantification to the research setting [2]

The Solution

Automatic structural damage assessment through computer vision and machine learning offering improved speed, reliability and accuracy

We propose the first step in this process, locating and identifying the bones of the hand and wrist

Methodology

Active Latent Space Shape Model (ALSSM)[3]

We extend an existing approach[3] to detect the right index finger, to the whole hand

Allows us to incorporate prior knowledge about the shape of the bones

Provides useful discrepancy and uncertainty information to highlight to users' predictions the model is "unsure" about

Mask RCNN [5]

Instance segmentation model used for the hand and bone detector

Identifies the bones from the textural information in the radiograph

Bayesian GPLVM [4]

Probabilistic generative shape model

Generates shapes from a latent space with uncertainty quantification

Dataset

53 bilateral hand and wrist digital radiographs manually annotated by four trained annotators

3266 bone annotations in total, 481 for reliability testing

Results

The dataset was split into three subsets for training, validation and testing
The model was trained and evaluated three times on different subset splits
Results reported are the average across those three runs

Results are represented as mean (SD)

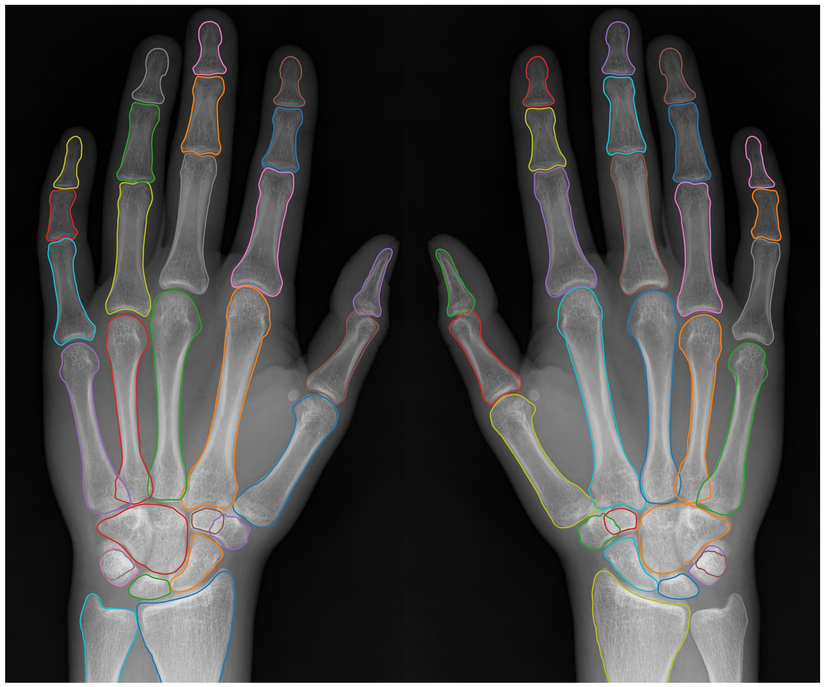
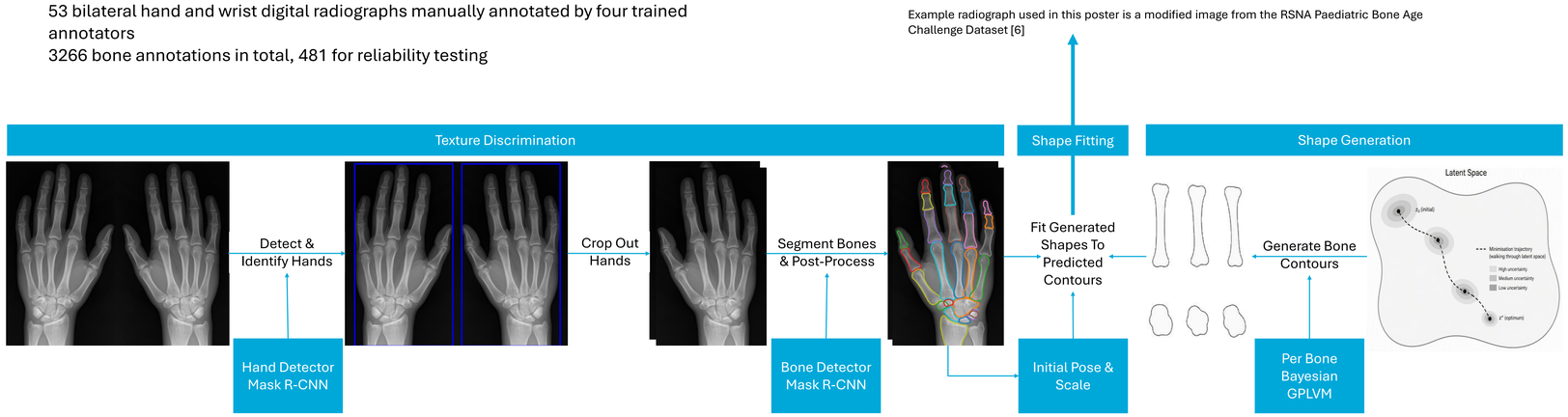


Figure 1 : Example of algorithm annotated hands and wrists.



Chamfer Distance (Pixels)

Chamfer distance is the average nearest-point distance between predicted and target contours lower values indicate better alignment, with 0 = perfect overlap

Human Performance

All bones – 7.3 (7.89)
Phalanges and Metacarpals - 5.0 (1.87)
Carpals – 12.4 (13.7)

Machine Performance

All bones – 11.2 (8.34)
Phalanges and Metacarpals – 7.2 (8.44)
Carpals – 19.6 (8.59)

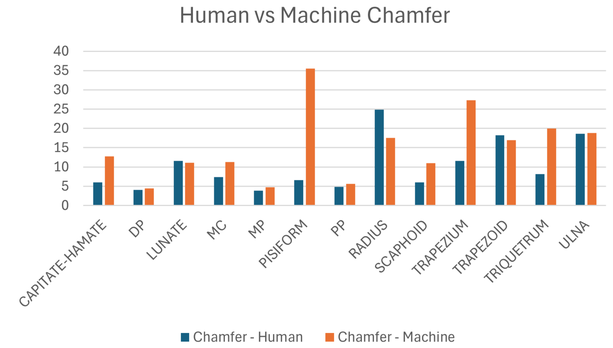


Figure 2 : Human vs machine chamfer distance per bone group performance

Intersection Over Union (IoU)

IoU is the overlap between predicted and target regions divided by their combined area
0 = no overlap, 1 = perfect overlap

Human performance

All bones – 0.93 (0.052)
Phalanges and Metacarpals – 0.95 (0.019)
Carpals – 0.89 (0.088)

Machine Performance

All bones – 0.9 (0.08)
Phalanges and Metacarpals – 0.9 (0.08)
Carpals – 0.8 (0.08)

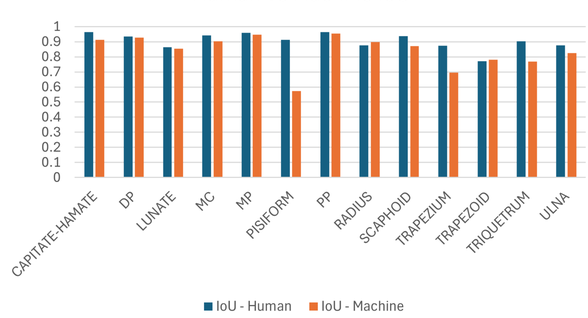


Figure 3 : Human vs machine IoU bone group performance

Conclusion

Novel machine learning approach, with a focus on interpretability and trust
Quickly and accurately locates and identifies the bone contours of the hand and wrist
Provides a solid foundation to move onto the next steps using the identified bone contours to identify the joint space, quantify joint space narrowing and evaluate against the existing gold standard methods

References

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