Uncertainty for Proximal Femur Fractures Classification

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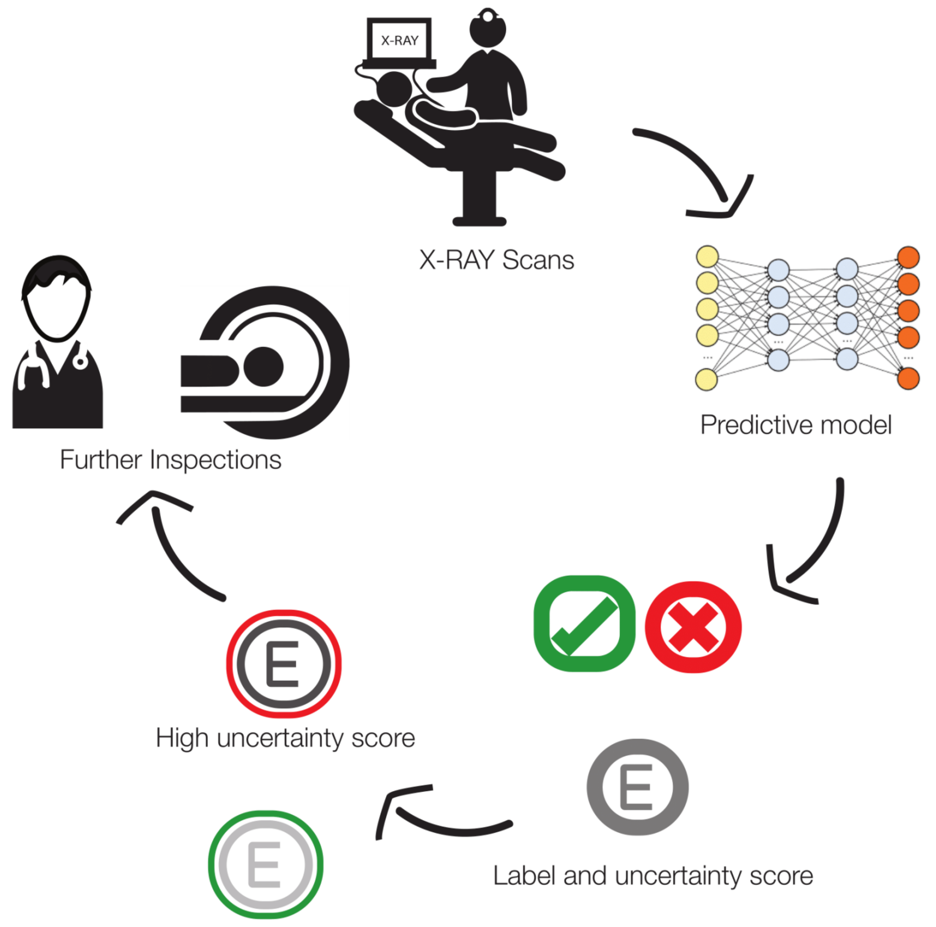
Motivation

- **Goal:** reliable score of uncertainty as quality control for automated Proximal Femur Fracture classification



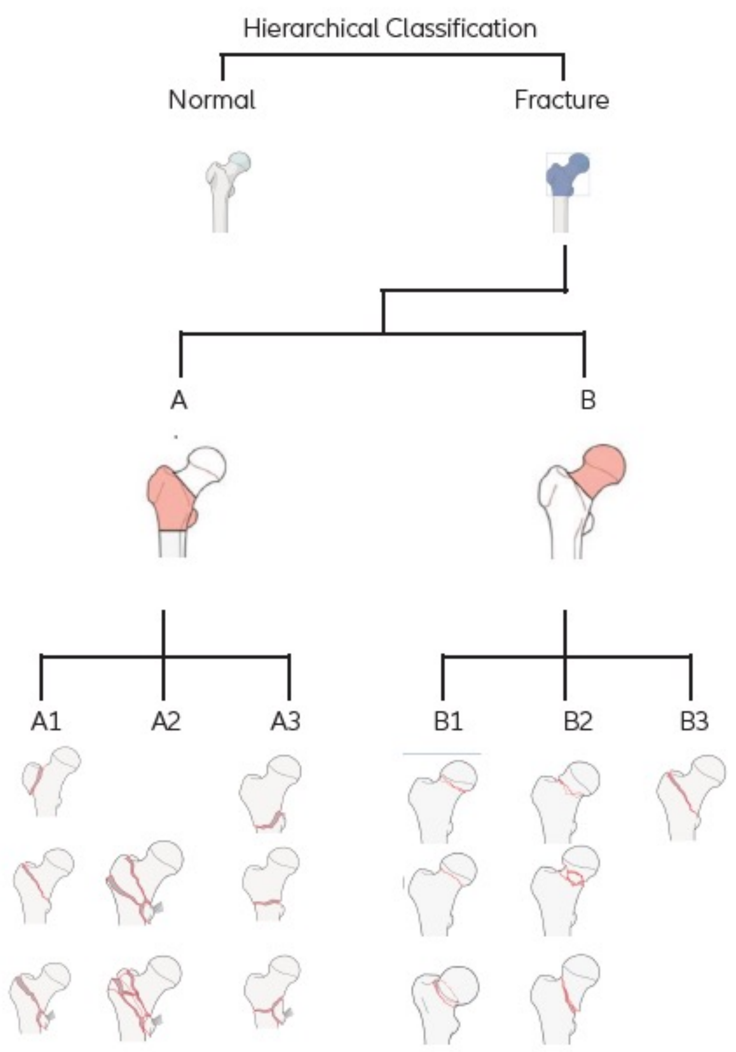
- **CADs**: achieving state-of-the–art results in diagnosis (1,2), improve accuracy of diagnosis (3), reduction of medical error and support time, cost.efficient treatment in future medicine (6)
- **Proximal femur fractures:** high incidence, early diagnosis and treatment are essential for the patient's outcome and survival (4), depends on the examiners' experience (5).

Database

- 672 patients from trauma surgery department of Klinikum Rechts der Isar, Munich, 1347 X-ray images & corresponding labels – using the work of (8) as baseline

Method

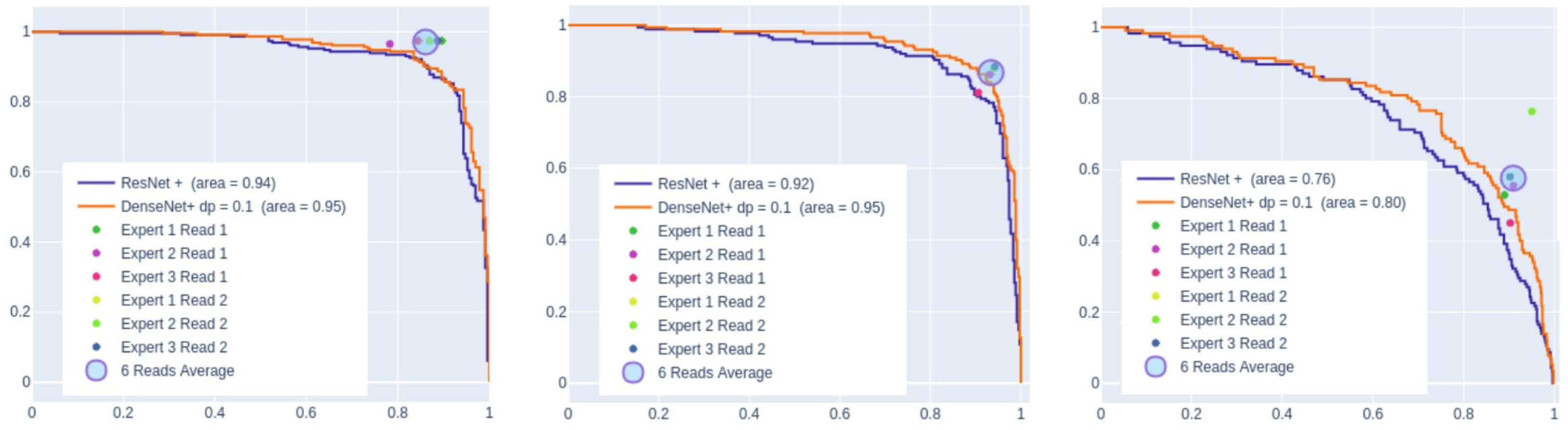
- Three different classification scenarios:
  - –C ∈ {C1, C2, C3}; C1 ⊂ {Fracture, Normal} = fracture detection scenario
  - –C2 ⊂ {A, B, Normal} = 3 classes scenario
  - –C3 ⊂ {A1, A2, A3, B1, B2, B3} = 6 classes scenario



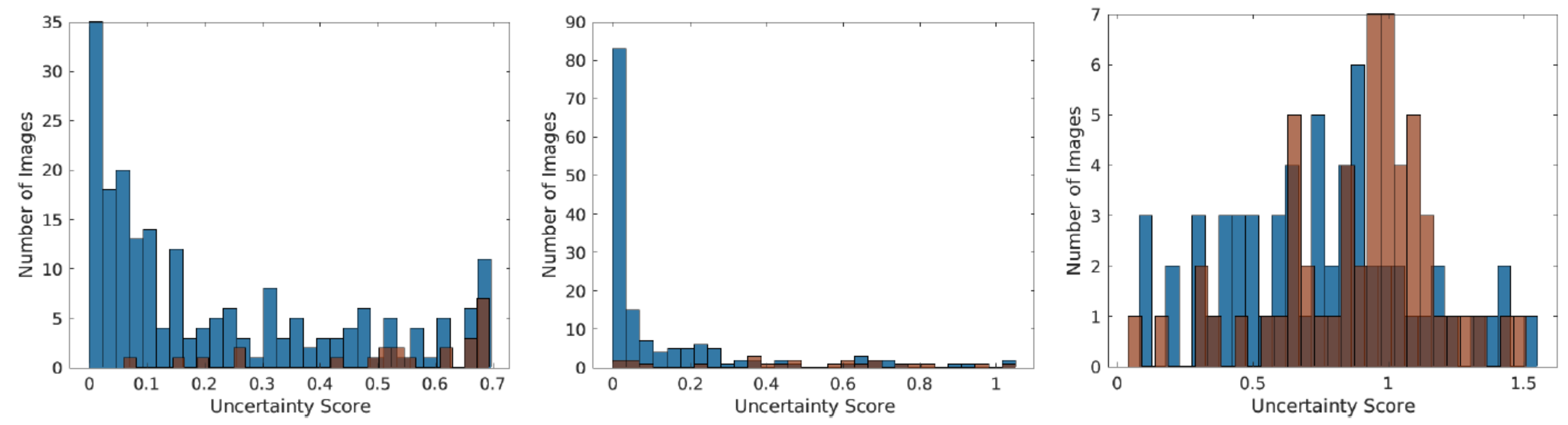
- **Ground truth**: three different experts, confirmed by senior radiologist
- **Monte Carlo dropout**, as an approximation of Bayesian Neural Networks (7) providing a quality control measure.
- ResNet adopted from (8), where the MCDO was introduced only at the last dense layer, treating the rest as a deterministic network.
- Stochastic DenseNet121 model, the dropout layers were introduced at each convolutional layer and in the transition blocks, hyper-parameters adopted from (9). 5-fold cross validation were conducted for the DenseNet models.

Experiments & Results

- Clinical experts vs. CAD system for the 3 classification scenarios



- Uncertainty coherence with miss-classication for DenseNetCE+



(d) Fract. (e) 3 classes (f) 6 classes

- Uncertainty scores on test and validation set

- **Qualitative assessment** - re-evaluation 30% of the test dataset by an independent radiologist & In-depth analysis - further annotations from three independent experts, each with two independent reads in different occasions as different shifts and lighting conditions

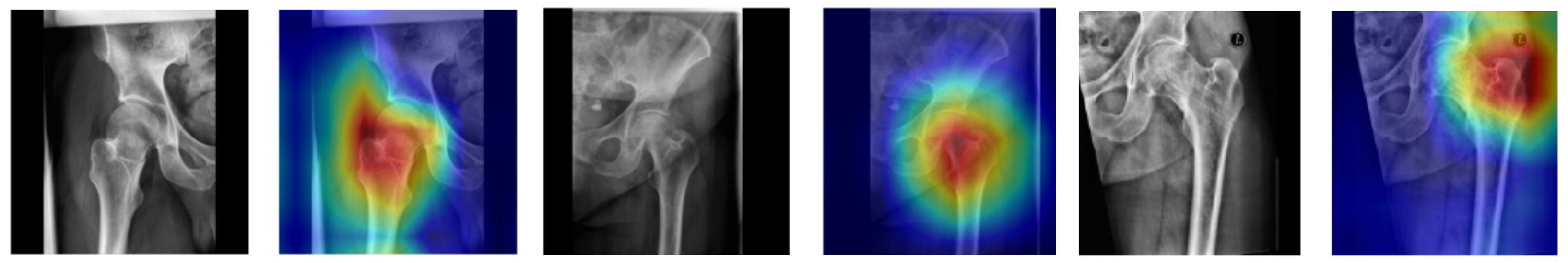


Image is clear			
App.	No	**Frac.**	No
	Exp.1	**Exp.2**	**Exp.3**
Read1	B	B	B
Read2	B	B	B
GT.	A	**Pred.**	B

Low uncertainty-missclassfied → false ground truth

Overlapping soft tissue artefacts as disturbing factor			
App.	Yes	**Frac.**	No
	Exp.1	**Exp.2**	**Exp.3**
Read1	B	N	B
Read2	N	B	B
GT.	N	**Pred.**	B

High uncertainty-missclassfied → high uncertainty among experts

Image is taken after operation Healed fracture with sclerotic transformations after screws removal			
App.	Yes	**Frac.**	Yes
	Exp.1	**Exp.2**	**Exp.3**
Read1	N	B	N
Read2	N	N	N
GT.	B	**Pred.**	B

High uncertainty-correctly classified → false ground truth

- ***Two key outcomes***:

1. Uncertainty score = reliable measure for detecting mistakes in the model performance and a valid robustness quality control.
2. Model's performance is reflected on how well and coherent is the modelling of uncertainty, i.e. ResNet+ vs. DesneNet+ 1

Conclusion

- Coherency between misclassification and uncertainty scores - high uncertainty score means high risk for error in prediction.
- Uncertainty measures mimicking the actual radiologist's uncertainty for challenging and complex examples reflected on intra- and inter-experts variability.
- Possible key element for clinical applicability of CADs

Future work

- Improving robustness of the model
- Extending the work on different datasets/ other parts of the human body

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