

Classification of Femur Fracture in Pelvic X-ray Images Using Meta-learned Deep Neural Network

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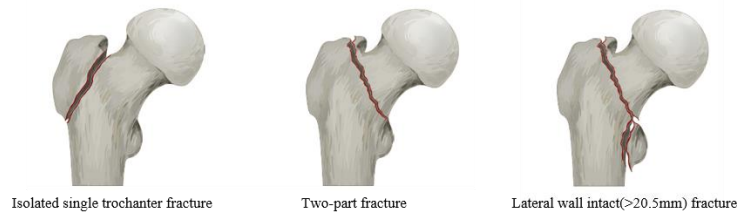
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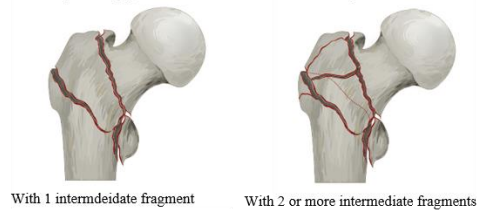
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Group A – trochanteric region fracture

- A1- simple pertrochanteric fracture



- A2- multifragmentary pertrochanteric, lateral wall incompetent ($\leq 20.5\text{mm}$) fracture



- A3- intertrochanteric (reverse obliquity) fracture

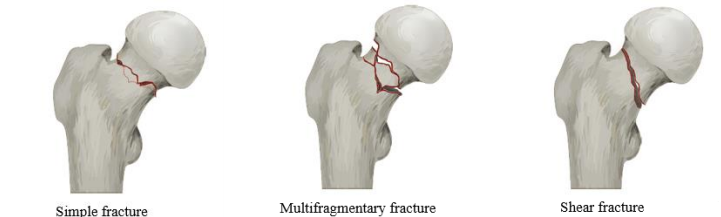


Group B – femoral neck fracture

- B1- subcapital fracture



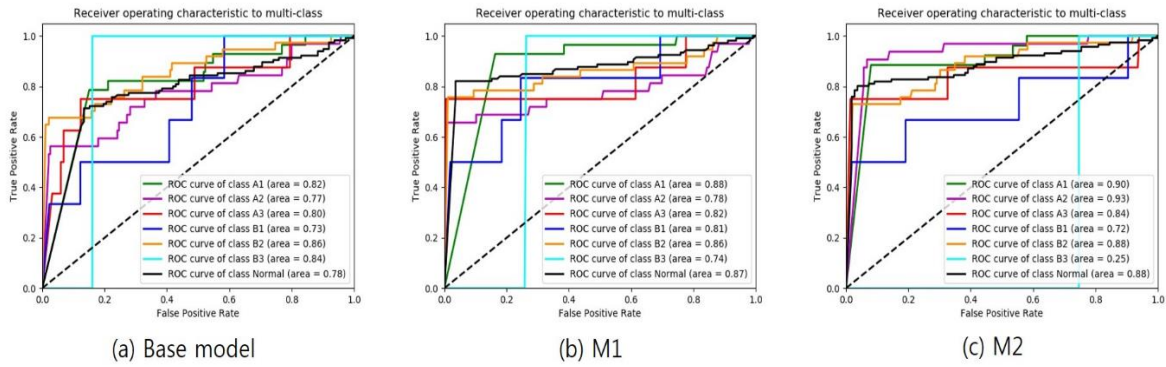
- B2- transcervical fracture



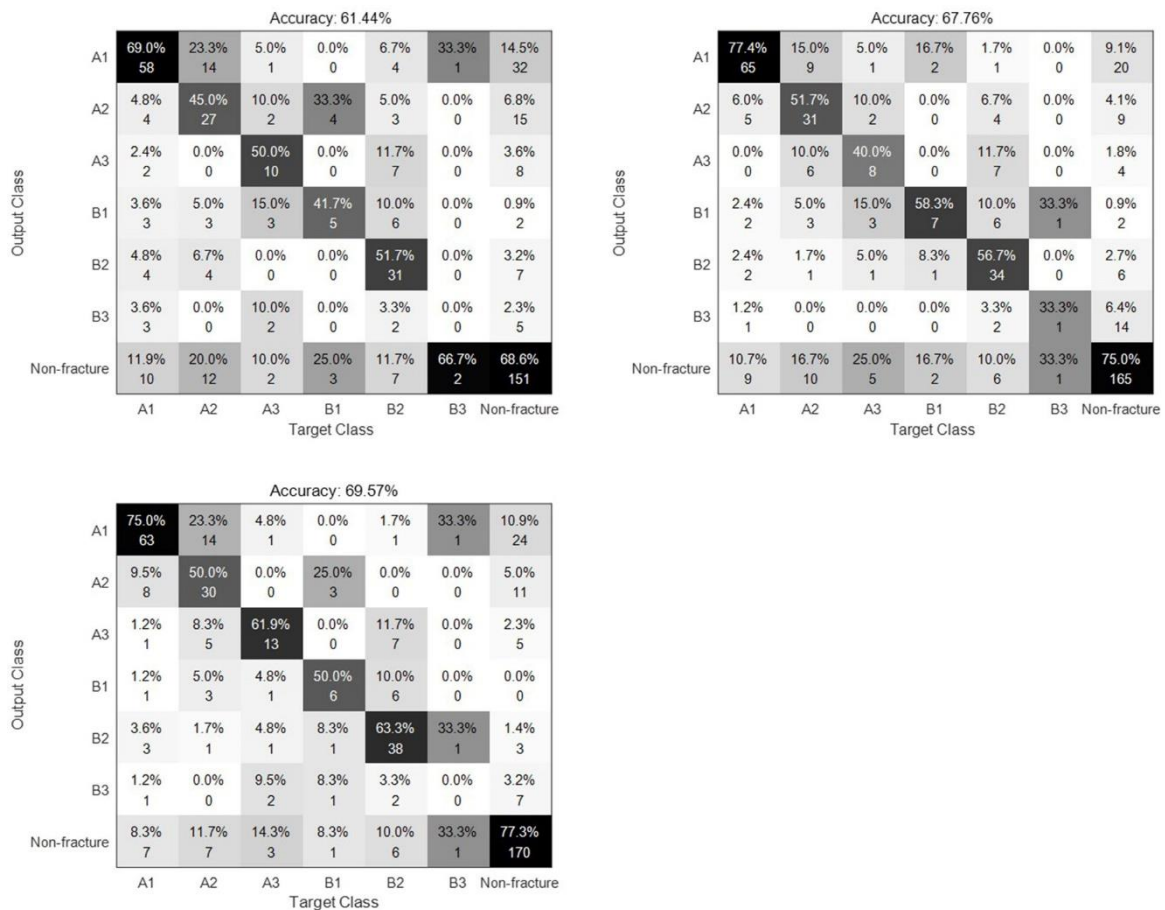
- B3- basicervical fracture



Supplementary Fig. 1 | Example proximal femur fracture images with AO/OTA classification standards. A1: Simple pertrochanteric fracture, A2: Multifragmentary pertrochanteric fracture, A3: Intertrochanteric (reverse obliquity) fracture, B1: Subcapital femoral neck fracture, B2: Transcervical femoral neck fracture, B3: Basicervical femoral neck fracture.



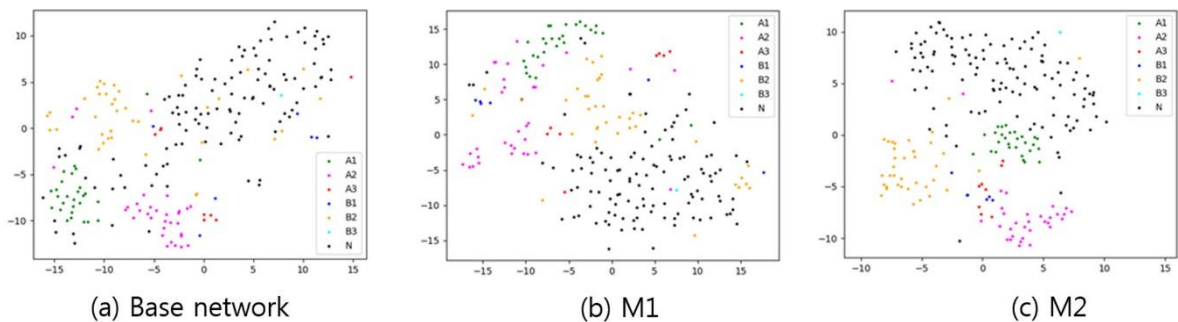
Supplementary Fig 2. | ROC curves for (a) base model, (b) M1, and (c) M2 for multilabel classification of the test dataset.



Supplementary Figure 3 | Overlapping results of confusion matrix obtained with five-fold cross validation for the dataset of 459 paired X-ray images and the radiology reports.

Model	Measure	2 Class	3 Class	7 Class
Base Network (Inception V3)	Avg. Overall Accuracy(%)	76.12 ± 2.04	67.18 ± 1.43	62.24 ± 1.75
	Avg. F1 score	0.768 ± 0.021	0.658 ± 0.016	0.451 ± 0.010
M1	Avg. Overall Accuracy	81.75 ± 2.19	73.85 ± 1.76	67.76 ± 1.68
	Avg. F1 score	0.805 ± 0.022	0.728 ± 0.013	0.487 ± 0.017
M2	Avg. Overall Accuracy	82.58 ± 2.67	76.73 ± 1.40	69.57 ± 1.37
	Avg. F1 score	0.838 ± 0.025	0.767 ± 0.016	0.492 ± 0.014

Supplementary Table. 1 | The average overall accuracy and F1-score obtained with five-fold cross validation for the dataset of 459 paired X-ray images and the radiology reports.



Supplementary Fig. 4 | t-SNE visualization of each latent representation vector for (a) Base network, (b) M1, and (c) M2. N=Normal.

Focal loss for multi-class classification

The original focal loss [21] was designed to address the class imbalance for binary classification, but it can be extended to the multi-class classification tasks. The Cross Entropy (CE) loss for an example is given in equation (1):

$$L_{CE} = -\sum_{i=1}^C t_i \log(y_i) \quad (1)$$

where C denotes the number of categories, t_i denotes a real probability distribution, y_i denotes a probability distribution of the prediction. $t_i = 1$ if i belongs to the true label, else it is 0.

The multi-class focal loss can be designed to address the class imbalance via down-weighting easy examples such that their contribution to the total loss is small even if their number is large. In other words, it focuses training on minority examples. A method for addressing class imbalance is to add a modulating factor $(1 - y_i)^\gamma$ to the cross entropy loss, with adjustable focusing parameter $\gamma \geq 0$. We define the multi-class focal loss, as formulated in equation (2):

$$L_{fl} = -\sum_{i=1}^C (1 - y_i)^\gamma t_i \log(y_i) \quad (2)$$

The focusing parameter γ is utilized to control the rate at which easy examples are down-weighted. Especially, when $\gamma = 0$, L_{fl} is equivalent to L_{CE} . The effect of the modulating factor $(1 - y_i)^\gamma$ is increased with γ . Secondly, when an example is misclassified and y_i is small, the modulating factor nearly tends to 1, and thus the loss is unaffected. As y_i increases to 1, the modulating factor nearly tends to 0 and the loss for well-classified examples is down-weighted. We adopt the multi-class focal loss in our experiments with $\gamma = 1.5$, which is determined empirically.