RSNA 2022 Cervical Spine Fracture Detection

Problem Statement

Spine fractures occur about 1.5 million times every year in the US [1]. Through computer-aided diagnosis, spine fractures are possible to be detected automatically with limited human verification [2]. The topic is to develop a feasible machine learning model to detect and segment the spine fractures based on patients' CT images.

Applications

Common causes of cervical fractures are high-energy traumas like traffic accidents, high-level falls, and strong physical contact in sports activities [3]. However, low-energy falls are enough to cause cervical fractures in elderly people [4], and they are more difficult to detect than in young people due to superimposed degenerative disease and osteoporosis [5]. Without appropriate treatment, these fractures can lead to serious results like nerve injuries and paralysis [6]. Therefore, through computer-aided fracture detection, cervical fractures can be quickly detected and located, thus decreasing the risk to patients.

Literature Review

Article Name: DEEP SEQUENTIAL LEARNING FOR CERVICAL SPINE FRACTURE DETECTION ON COMPUTED TOMOGRAPHY IMAGING [7]

In this paper, the author proposed a deep learning model to detect the spine fractures based on Computed Tomography (CT) images. Figure 1 shows the workflow for training the model.

During the preprocessing part, each CT image is rescaled from its original HU value to a gray scale image. Different scales can show different part of human body clearly because bones and water have significant different HU values. In this study, we are more interested in bones and soft tissues. As a result, three different viewing windows are chosen to display images in different scales, including soft tissue window, gross bone window, and standard bone window. Later, the images are cropped and translated to the center of spine bones and resized to affixed resolution of 384*384.

After the preprocessing, the images are stacked together and fed into a Resnet-50 to extract feature maps by convolution layers. The feature maps are further input to Bidirectional Long Short-Term Memory (BLSTM) networks to generate the predicted label, which indicates the fracture probability for this image slice. is used as the network backbone to extract the feature maps. The feature maps are fed into a BLSTM to generate the fracture labels for the image.

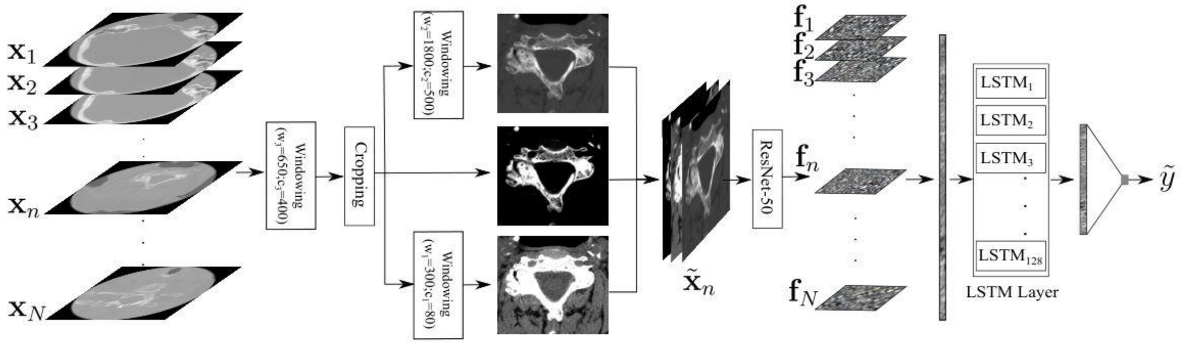


Figure 1

The models are trained with both balanced and imbalanced datasets. The training dataset size is 104 positive cases and 419 negative cases for imbalanced dataset and 104 cases for each condition for balanced dataset. The models are evaluated with a 7-fold cross validation.

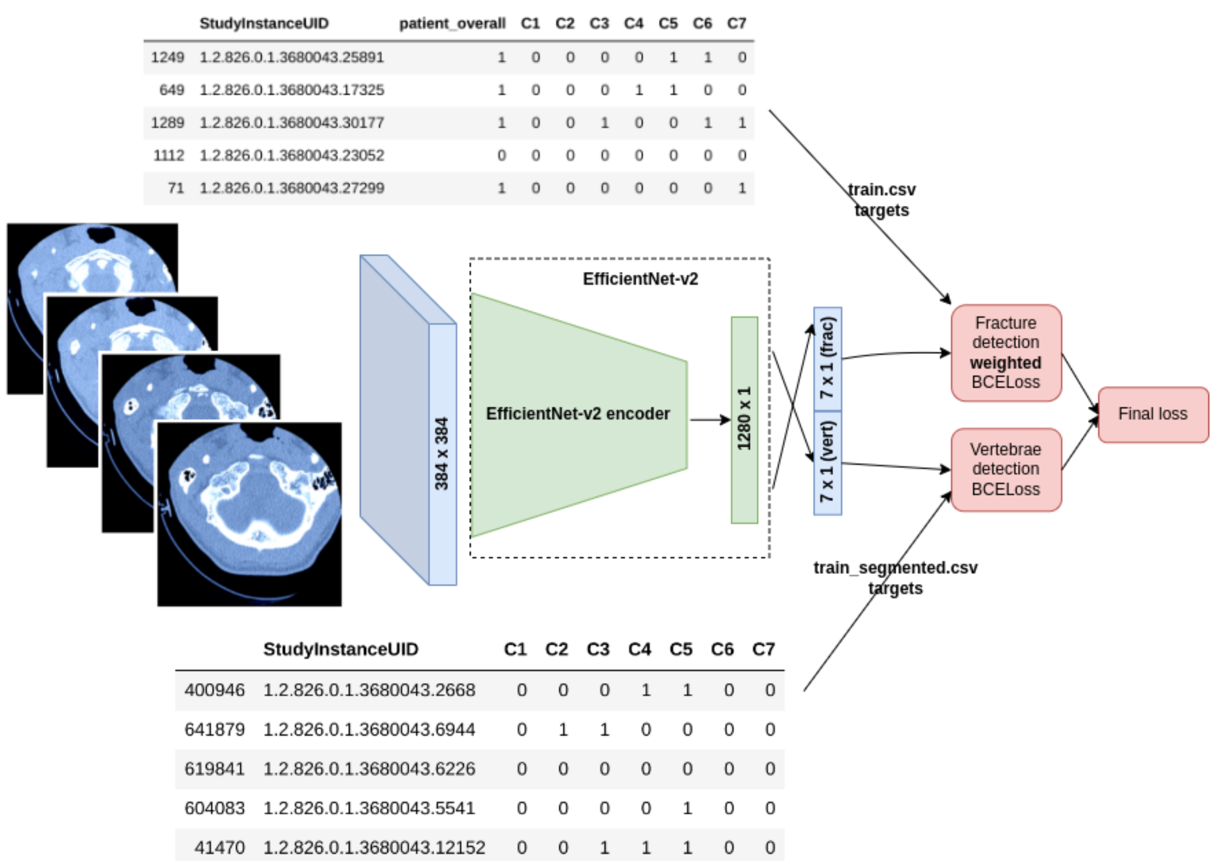
Figure 2 shows the evaluation result for this model. The accuracy result of predicting a spine fracture is 79.18% for imbalanced dataset and 71.06% for balanced dataset. According to the author, the balanced dataset is less dependent on the number of LSTM units. The better result achieved in imbalanced dataset is due to the bias toward negative cases, which allows the LSTM units learn the features between negative cases.

Model	Data	TPR	TNR	PPV	NPV	F1	Acc	MCC	AUC
ResNet-50 + BLSTM-96	Imblcd.	64.19 ± 5.7	78.67 ± 6.6	43.62 ± 6.3	89.83 ± 1.5	51.66 ± 5.5	75.79 ± 5.2	37.84 ± 7.6	71.43 ± 3.9
ResNet-50 + BLSTM-128	Imblcd.	62.28 ± 6.0	80.84 ± 2.9	44.83 ± 4.8	89.62 ± 1.6	52.06 ± 4.9	77.15 ± 2.9	38.54 ± 6.7	71.56 ± 3.7
ResNet-50 + BLSTM-256	Imblcd.	59.01 ± 5.7	84.12 ± 4.9	48.54 ± 6.7	89.34 ± 1.5	52.92 ± 4.6	$\mathbf{79.18 \pm 3.8}$	40.36 ± 6.5	71.57 ± 3.1
ResNet-50 + BLSTM-96	Blcd.	64.19 ± 5.7	77.11 ± 7.3	74.14 ± 5.4	68.36 ± 3.1	68.58 ± 3.8	70.65 ± 3.5	41.90 ± 7.1	70.65 ± 3.5
ResNet-50 + BLSTM-128	Blcd.	62.28 ± 6.0	79.84 ± 3.1	75.55 ± 3.0	68.06 ± 3.5	68.17 ± 4.2	$\mathbf{71.06 \pm 3.1}$	42.86 ± 5.9	71.06 ± 3.1
ResNet-50 + BLSTM-256	Blcd.	57.75 ± 4.9	84.09 ± 5.3	78.87 ± 4.9	66.63 ± 1.8	66.44 ± 2.8	70.92 ± 1.9	43.62 ± 4.3	70.92 ± 1.9

Figure 2

Opensource Research

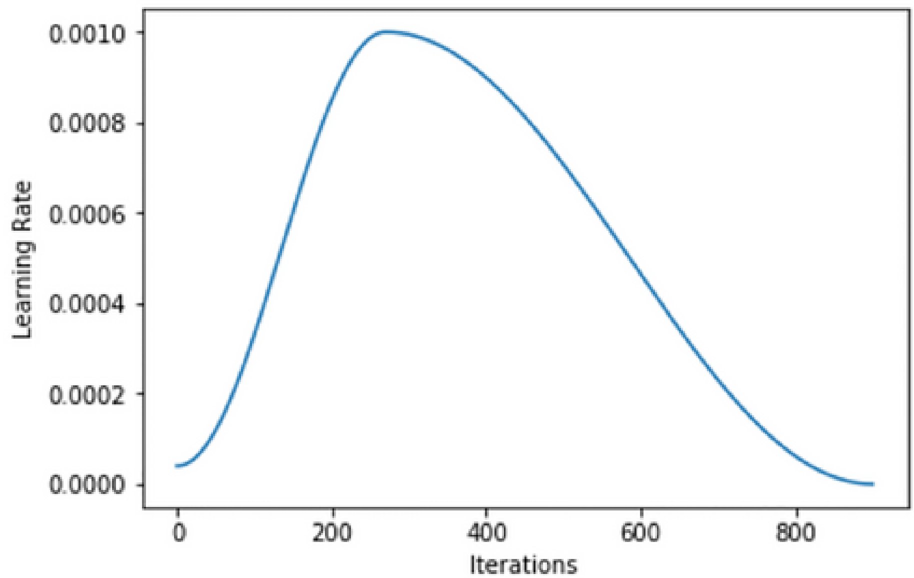
1. EffNetV2 baseline [8]
   (a) This model is based on EffNetV2 and implemented in PyTorch
   (b) The code uses mixed precision training (fp16 and fp32) to accelerate the training process
   (c) 5-fold cross-validation is used to evaluate the model performance



	StudyInstanceUID	patient_overall	C1	C2	C3	C4	C5	C6	C7
1249	1.2.826.0.1.3680043.25891	1	0	0	0	0	1	1	0
649	1.2.826.0.1.3680043.17325	1	0	0	0	1	1	0	0
1289	1.2.826.0.1.3680043.30177	1	0	0	1	0	0	1	1
1112	1.2.826.0.1.3680043.23052	0	0	0	0	0	0	0	0
71	1.2.826.0.1.3680043.27299	1	0	0	0	0	0	0	1

	StudyInstanceUID	C1	C2	C3	C4	C5	C6	C7
400946	1.2.826.0.1.3680043.2668	0	0	0	1	1	0	0
641879	1.2.826.0.1.3680043.6944	0	1	1	0	0	0	0
619841	1.2.826.0.1.3680043.6226	0	0	0	0	0	0	0
604083	1.2.826.0.1.3680043.5541	0	0	0	0	1	0	0
41470	1.2.826.0.1.3680043.12152	0	0	1	1	1	0	0

(d) use a OneCycle learning rate function to achieve best training efficiency



2. DenseNet [9]
   (a) This approach utilizes MONAI deep learning framework for PyTorch to train a DenseNet
   (b) Multiple image slices are stacked together to train the patients' overall fracture probability
   (c) Use a weighted loss function to calculate the loss value for different prediction conditions.

References

[1] https://orthoinfo.aaos.org/en/diseases--conditions/osteoporosis-and-spinal-fractures/

[2] Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Comput Med Imaging Graph. 2007;31(4-5):198-211.

[3] https://en.wikipedia.org/wiki/Cervical_fracture

[4] https://orthoinfo.aaos.org/en/diseases--conditions/cervical-fracture-broken-neck/

[5] https://www.kaggle.com/competitions/rsna-2022-cervical-spine-fracture-detection/overview

[6] Marcon, Raphael Martus et al. "Fractures of the cervical spine." Clinics (Sao Paulo, Brazil) vol. 68,11 (2013): 1455-61.

[7] H. Salehinejad et al., "Deep Sequential Learning For Cervical Spine Fracture Detection On Computed Tomography Imaging," 2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI), 2021, pp. 1911-1914, doi: 10.1109/ISBI48211.2021.9434126.

[8] https://www.kaggle.com/code/vslaykovsky/train-pytorch-effnetv2-baseline-cv-0-49/notebook

[9] https://www.kaggle.com/code/andradaolteanu/rsna-fracture-detect-pytorch-densenet-train/notebook