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Project1: RSNA 2022 Cervical Spine Fracture Detection

Problem Statement

What does the topic cover?

A cervical fracture means a bone is broken in the cervical (neck) region of the spine. The cervical spine is made up of the uppermost seven vertebrae. *'A cervical dislocation means that a ligament injury in the neck has occurred, and two (or more) of the adjacent spine bones have become abnormally separated from each other, causing instability. According to a study published by Lasfargues in 1995, over 25,000 cervical fractures occur each year in the United States.'* The majority of fractures and dislocations of the spinal column occur in the cervical spine because it is the most mobile portion of the spinal column, and under--standably, the most vulnerable to injury. Although the lumbar (low back) region is most commonly injured during daily laborious, low-energy activities, the neck is most likely to be injured during high-energy trauma such as motor vehicle accidents. Our goal is to construct a machine learning model that can predict the probability of fracture for each bone in the spine from the input dataset we have.

Why is it important and What it means?

Plain x-rays of the cervical spine are essential to adequately evaluate a cervical fracture and dislocation. It is sometimes difficult to see a non-displaced or minimally displaced fracture or instability, therefore a Computed Tomography (CT) scan is usually ordered. However, due to the increasing tendency of spinal fractures in the elderly, more accurate diagnoses are required since fractures can be more difficult to detect on imaging due to superimposed degenerative disease and osteoporosis, etc.

In this case, Machine learning models with extremely high predictive accuracy will give physicians plenty of references and judgment help, dramatically increasing the speed and accuracy of diagnosis. Quickly detecting and determining the location of any vertebral fractures is essential to prevent neurologic deterioration and paralysis after trauma. Without immediate stabilization, injuries in this area can affect the spinal cord and cause paralysis or death.

Application

What are the applications of the topic?

Artificial intelligence can aid in the detection and localization of cervical spine fractures. Similar machine learning algorithms may be useful in the diagnosis of other emergent injuries. Even the machine learning prediction model can be used in the future for more medical aspects of detection, such as detecting tumors' location, diagnosing whether covid19 is confirmed, etc.

Why is it useful?

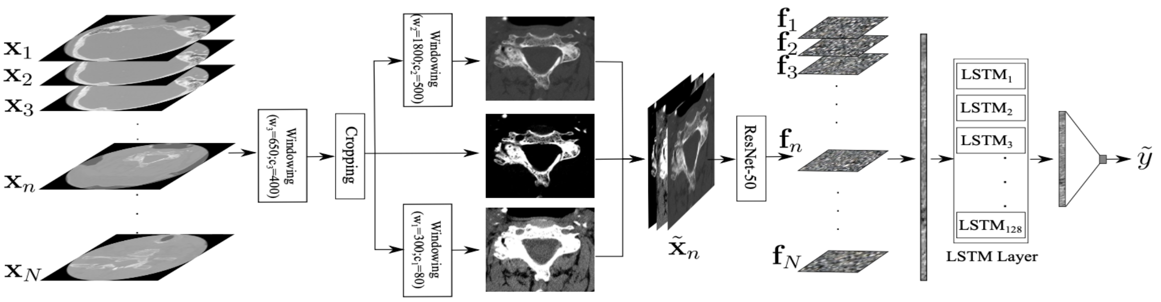
For Doctors, they have more advanced technology to help them make the best diagnosis quickly and accurately. For patients, a faster and more accurate diagnosis allows them to receive the most appropriate treatment faster, reducing the likelihood and impact of post-operative sequelae. Therefore, using machine learning algorithms to detect cervical spine fractures is an effective and useful auxiliary tool to protect our lives and health.

Literature review

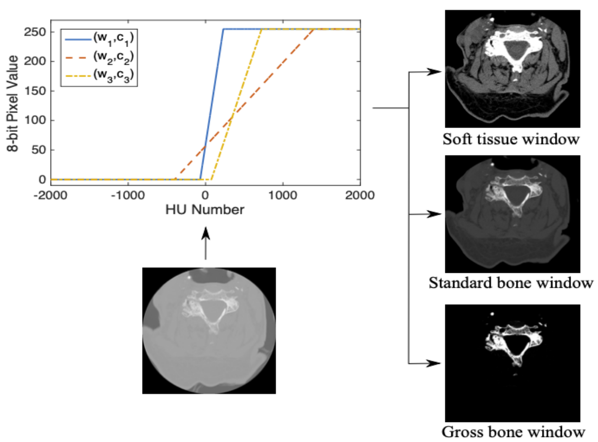
I have carefully read the paper ***Deep Sequential learning For Cervical Spine Fracture Detection On Computed Tomography Imaging*** and ***Detection of Spinal Fracture Lesions based on Improved Yolov2***. After reading these articles which are full of cutting-edge information on cervical s spine fracture detection, I can have a clearer perception and orientation of the application of machine learning in this area and a better understanding of the level of technology that has been applied

Fractures of the cervical spine are a medical emergency and may lead to permanent paralysis and even death. Accurate diagnosis in patients with suspected fractures by computed tomography (CT) is critical to patient management. In ***Deep Sequential learning For Cervical Spine Fracture Detection On Computed Tomography Imaging***, they propose a deep convolutional neural network (DCNN) with a bidirectional long-short term memory (BLSTM) layer for the automated detection of cervical spine fractures in CT axial images. We used an annotated dataset of 3,666 CT scans (729 positives and 2,937 negative cases) to train and validate the model. The validation results show a classification accuracy of 70.92% and 79.18% on the balanced (104 positive and 104 negative cases) and imbalanced (104 positives and 419 negative cases) test datasets, respectively.[1]

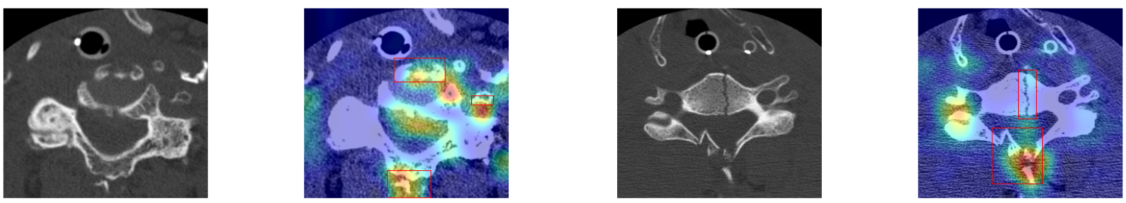
In general, we tend to use a balanced training set to train the model we want to build. But often, in specific scenarios like medical imaging, the ratio of positive and negative samples can be very different. The accuracy obtained by processing the unbalanced data set and pouring it into the designed machine learning model is more informative and close to our real life. We can use spatial transformations, spatial-temporal transformations, and generative adversarial models to reduce this imbalance. In this paper, they propose a DCNN with bidirectional long short-term memory (BLSTM) layer as a baseline model to address this problem on axial cervical spine CT images.



This figure shows that The input scan has N axial images and the BLSTM layer has 128 LSTM units.



Meanwhile, In order to determine the exact location of the cervical spine fracture, we can highlight an axial image in several areas, given different values of Hounsfield unit numbers, to see if there is a fracture or displacement. This allows us to identify the lesion more accurately. In this figure, we can clearly find that different parts of our cervical spines can be Prominently displayed in a single image, which can help find the fracture's location and body structure in trouble.



(a) Axial image with three fractures. (b) Heatmap of (a). (c) Axial image with two fractures. (d) Heatmap of (c).

These are Samples of cervical spine axial images with fractures, we can easily find the location of fractures, and the number of fractures presents on the vertebrae. Compared to doctors who spend 10-15 minutes looking at many CT images to find out where the fracture is, this model will definitely tell doctors more objectively and directly where the fracture is so that they can make the subsequent diagnosis and treatment plan faster. At the same time, this diagnosis is based on a considerable accuracy rate, which means the probability of misdiagnosis and omission is significantly reduced.

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		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		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		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		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

This figure shows some of the data related to the accuracy of the model test. In the unbalanced dataset, the test accuracy tends to increase as the number of BLSTM layers increases, and it can be seen that the test accuracy reaches about 80% when the BLSTM reaches 256 layers.

However, the layers of BLSTM have little impact on the balanced dataset. For the imbalanced dataset, which reflects the natural distribution of negative and positive cases, as more LSTM units are utilized the imbalanced accuracy also increases. However, we observed no significant change in balanced accuracy. The higher performance on the imbalanced dataset is mainly due to the bias of the dataset toward negative cases and images and the bias of the BLSTM layer in capturing the dependency between negative cases.[1]

In addition to the methods in the above paper, there is currently a range of other novel methods and models available in the field of vertebral fracture detection, such as modeling using Yolo[3], SSD, and other network structures that allow for higher accuracy or faster results for the overall detection[4]. It is foreseeable that there is still great potential for machine learning in the field of medical imaging for the benefit of human beings.

Papers and open sources

Open sources:

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

https://www.uscspine.com/conditions-treated/neck-disorders/cervical-spine-fractures-dislocations/

https://github.com/john-james-ai/Cervical-Spine-Fracture-Detection

Papers:

[1] 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.

[2] A. Bekkanti, S. Karimunnisa, S. Gogulamudi, K. Kumar and C. Zeelan Basha, "Enhanced Computerized Bone Fracture Detection Using Harris Corner Detection," 2020 International Conference on Smart Electronics and Communication (ICOSEC), 2020, pp. 572-576, doi: 10.1109/ICOSEC49089.2020.9215240.

[3] G. Sha, J. Wu and B. Yu, "Detection of Spinal Fracture Lesions based on Improved Yolov2," 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA), 2020, pp. 235-238, doi: 10.1109/ICAICA50127.2020.9182582.

[4] Yeh, LR., Zhang, Y., Chen, JH. *et al.* A deep learning-based method for the diagnosis of vertebral fractures on spine MRI: retrospective training and validation of ResNet. *Eur Spine J* 31, 2022–2030 (2022). https://doi.org/10.1007/s00586-022-07121-1

[5]S. S. Sinthura, Y. Prathyusha, K. Harini, Y. Pranusha and B. Poojitha, "Bone Fracture Detection System using CNN Algorithm," 2019 International Conference on Intelligent Computing and Control Systems (ICCS), 2019, pp. 545-549, doi: 10.1109/ICCS45141.2019.9065305.