Exploratory Analysis

IL81.004

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Github Repository

https://github.com/Hadavand-s-Minions/rsna-cervical-spine

Data Source

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

Published Story

https://medium.com/@eishafnu/detecting-cervical-spine-fractures-through-machine-learning-b8e e83636848

Statement of Contribution:

Literature review, context, dataviz analysis (paper writing+publishing): FNU Eisha

Exploratory Data Analysis (coding): Haitham, Stevedavies

Research Question

Our research question is "*How can we quickly detect and locate vertebral fractures in the cervical spine from CT scans to aid in the prevention of neurologic deterioration and paralysis after trauma?*"

Introduction

A cervical fracture is defined as a broken bone in the cervical or neck region and it makes up 50% of all spinal cord injuries per annum (Spoonamore, 2022). It is estimated that over 1 million blunt trauma patients suffer potential cervical injury in a year. (American College of Radiology (ACR), as cited in Radiology Key, 2019). Due to the severity of these cervical fractures leading to potential threat of paralysis or even death, it is crucial that they are diagnosed efficiently and correctly (Salehinejaad, 2021). With more than 17,000 spinal cord injuries in a year (Morano et al. 2021) and over half of them occurring in the cervical or neck region (RSNA 2022 Cervical Spine Fracture Detection 2022), this topic is important due to the number of people it impacts and the severity of said impact.

Furthermore, as can be seen from the literature review below, there is a high rate of inefficiency due to unnecessary radiology for fracture detection. The aim of this project is to use machine learning to detect cervical spine fractures and match the accuracy of a radiologist so as to reduce cost and increase efficiency and accuracy.

Literature Review & Existing Theoretical Methods

Our purpose is the quick detection of vertebral fractures and their locations in order to prevent further adverse effects on health. The common existing theoretical methods for fracture detection include the imaging modalities of radiography and Spiral Computed Tomography (SCT). MRI is reserved for ligamentous and other soft tissue structures (Kumar et. al, 2016). Radiology employs electromagnetic radiation or x-rays whereas computed tomography combines x-rays from different edges such that a cross sectional image is produced without cutting. (Naseera, 2017). The industry standard is that decisions for radiography are affected by the Canadian C-spine rule and NEXUS (National Emergency X-Radiography Utilization Study).

The C-Spine rule reduces the need for imaging by over 40% in order to decrease efficiency for emergency personnel in hospitals. (Stiell, 2022) On the other hand, NEXUS also reduces the need for cervical spine imaging by establishing a criteria. Plain radiographs have a risk of 25-60% missed injuries (Radiology Key, 2022). On the other hand, according to Brown et. al (2005), SCT is sensitive and had a detection rate of above 99% in a retrospective evaluation. Despite the success of SCT scans, it is important to note that this higher dose of radiation has been linked to cancer induction and should therefore be reserved for high risk patients only. According to the Radiology Department of North America imaging diagnosis for adult spine fractures employ more CT scans than radiology. Therefore, we will be using CT scans for our analysis and for training our model due to their efficiency, accuracy and widespread use.

Our Methodology

Based on the aforementioned existing theoretical methods in fracture detection, we are planning on Convolutional Neural Networks (CNN) to learn image features for fracture detection. The accuracy of such models is around 92% with 76% sensitive and 97% specificity (Small et. al, 2021).

We have spent some time understanding what models to use and decompressing the data since it is provided in 3D. Working with large datasets has also been more work than we anticipated and we have come to understand the truth of the statement that data scientist spends more than 70% of their time cleaning up their data. Therefore, we have only started working on the models. This has been a difficult problem for us so far since it is new type of data that we are new to, i.e. medical images. However, we are aiming to try the U-Net Algorithm to provide image segmentations. That way given a certain image, we will be able to highlight parts of that image that form different vertebrae such as C1, or C2. Next, we will use another CNN-like model to make predictions of whether a fracture is present in an image or not.

Some images from our dataset of CT scans can be seen below (Figure 1.0):

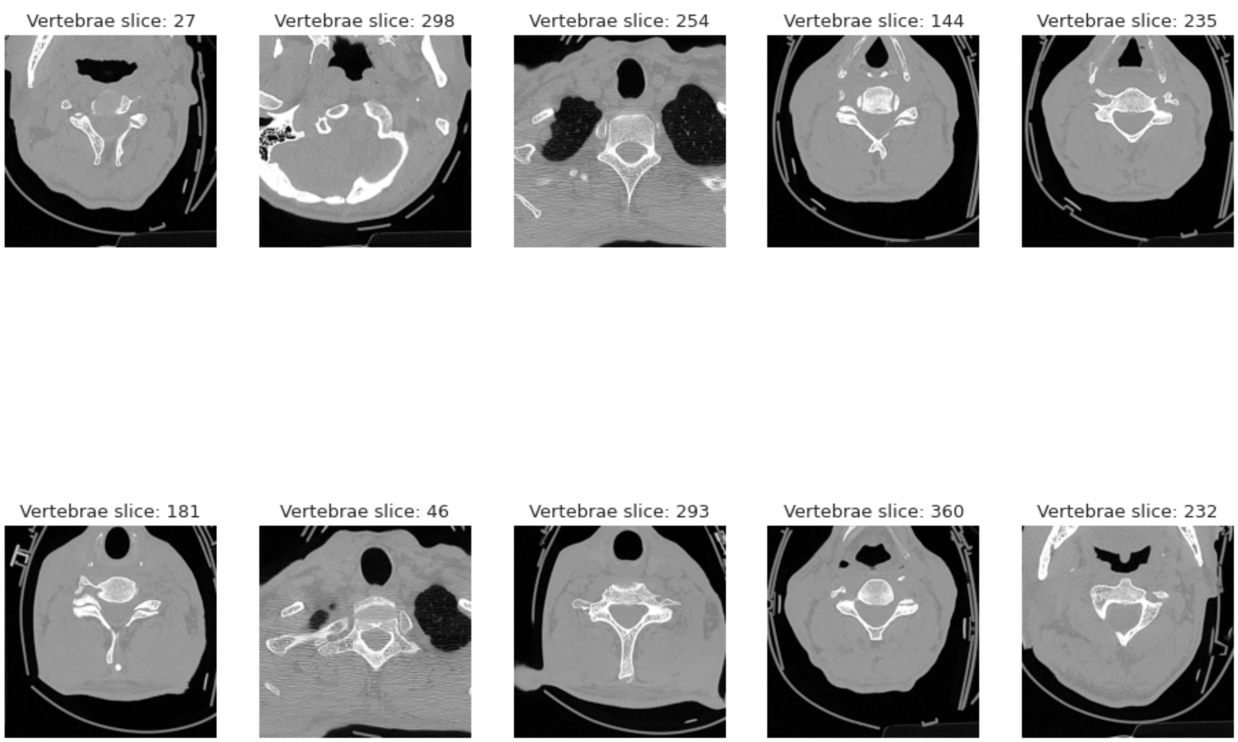


Figure 1.0 CT Scan Images

Our variables can be seen in Figure 2.0:

Variable Name	Label/Description	Variable Codes	Variable Format	Value Indicating Missing Data
StudyInstanceUiD	Study ID for each patient scan (ID corresponding to folders containing multiple images)	1.2.826.0.1.3680043.[int_no_of_images]	Float	None
patient_overall	Whether the patient has a fracture	0 = No Fracture Overall 1 = Has Fracture	Binary: numeric	None
C1	Whether C1 (first vertebrae) has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C2	Whether C2 has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C3	Whether C3 has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C4	Whether C4 has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C5	Whether C5 has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C6	Whether C6 has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None
C7	Whether C7 (last vertebrae) has a fracture	0 = no fracture 1 = has fracture	Binary: numeric	None

Notes:

1. C1 - C7 refers to the cervical spine vertebrae on the neck where C1 is the first vertebrae at the top and C7 is the last neck vertebrae.
2. We are working with image data in multiple folders, the variable names do not correspond to each individual image. Instead, they correspond to all the images in a

Figure 2.0 Variables and their descriptions

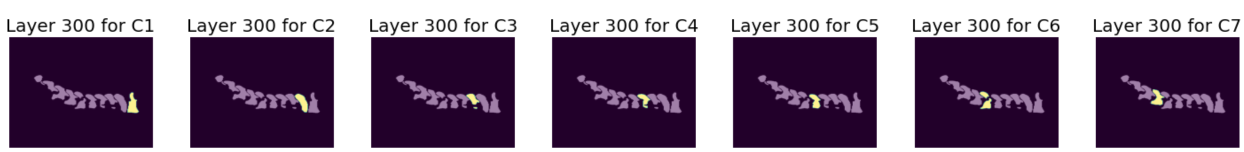
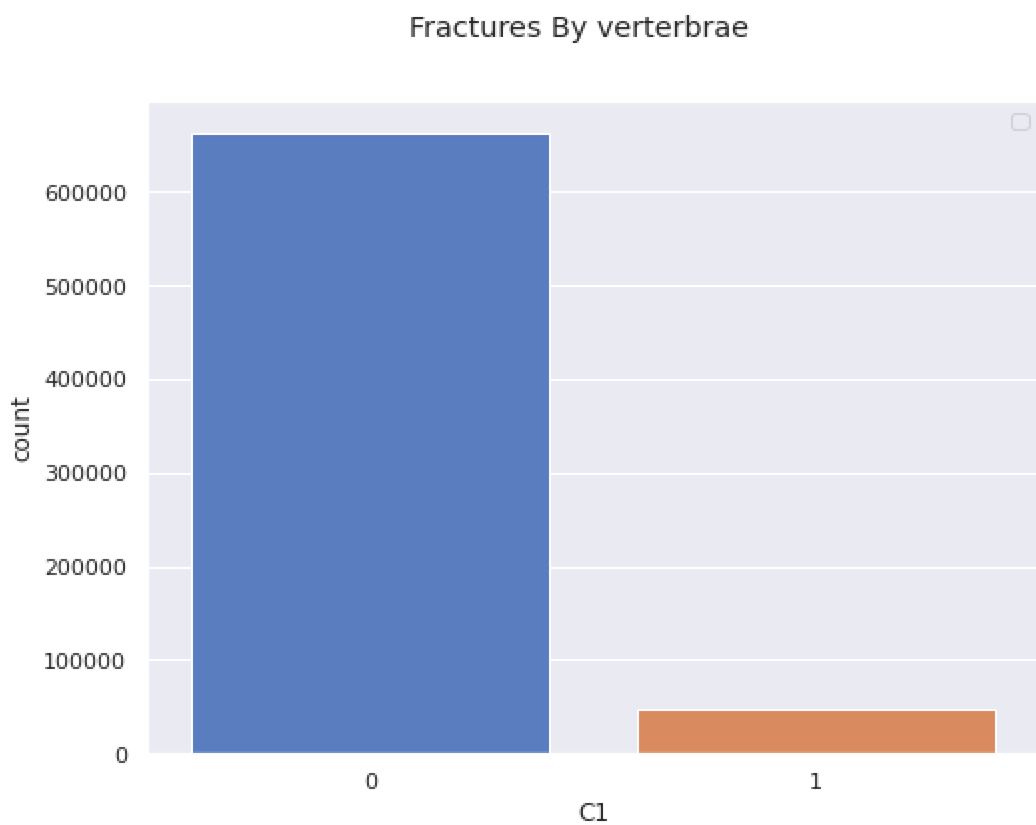
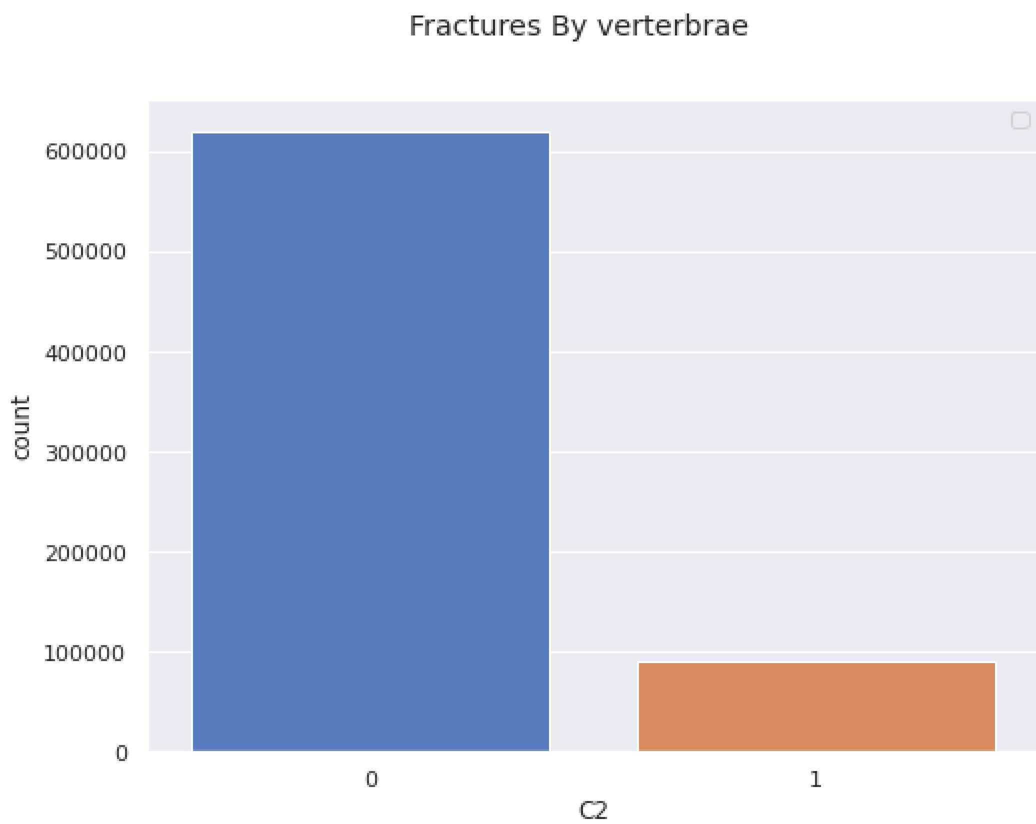
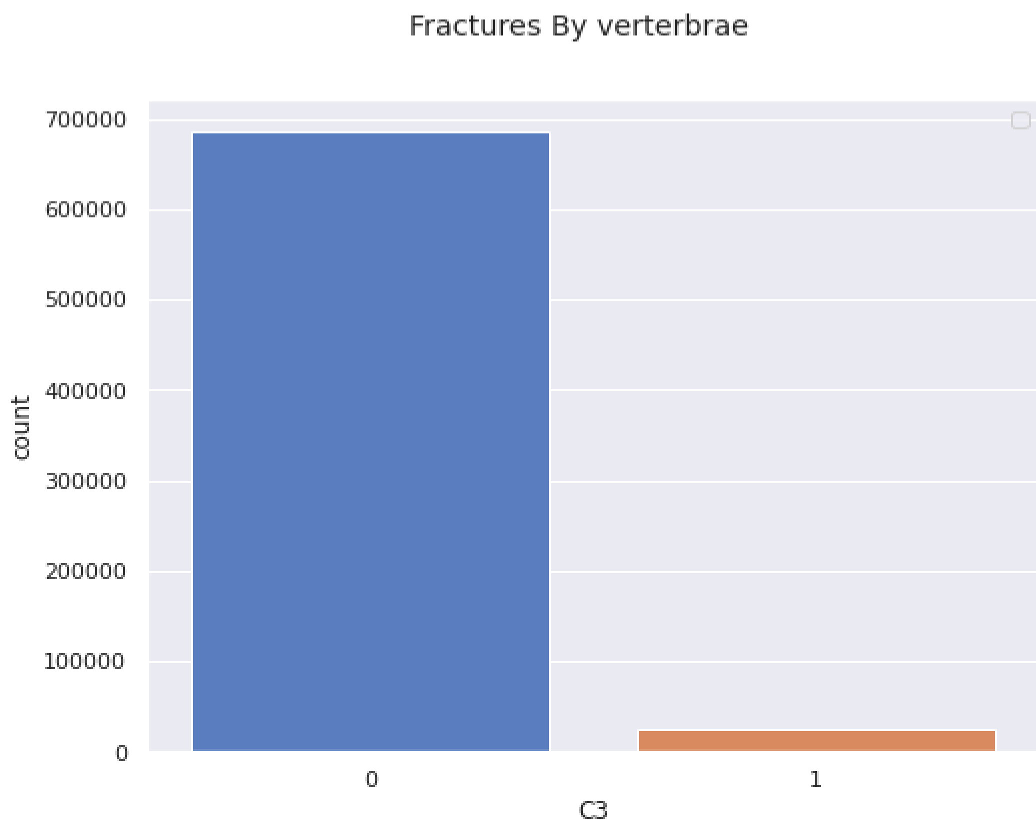


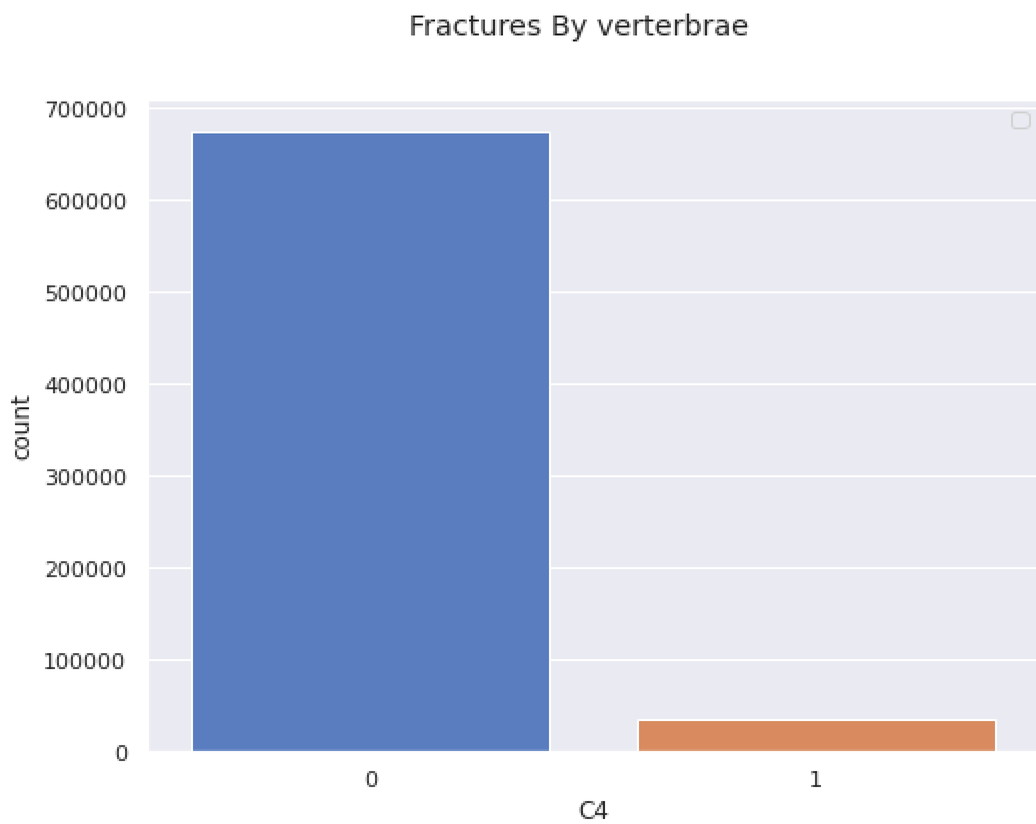
Figure 3.0 C1 to C7 vertebrae

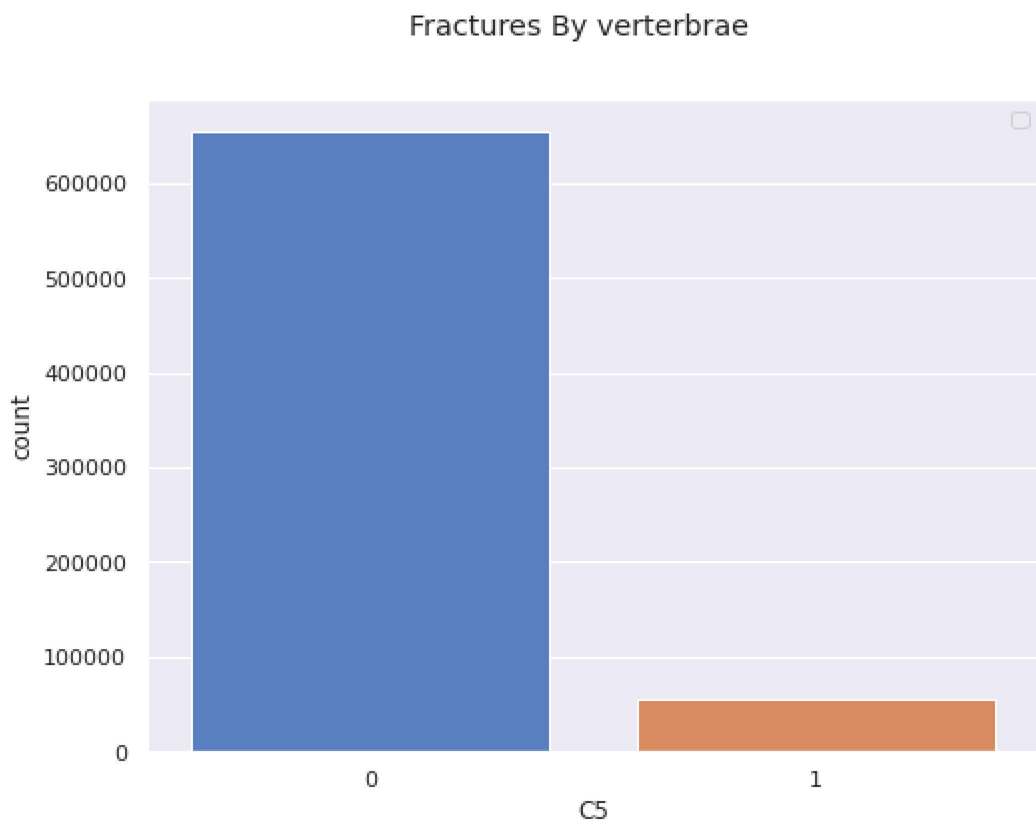
The vertebrae are split in C1 to C7 which can be seen in figure 3.0. According to our exploratory data analysis fractures in C5, C6 and C7 and more common than C1-4 (see data visualisations below). This may be due to the fact that C1-2 fractures are the most severe and can prove to be fatal.

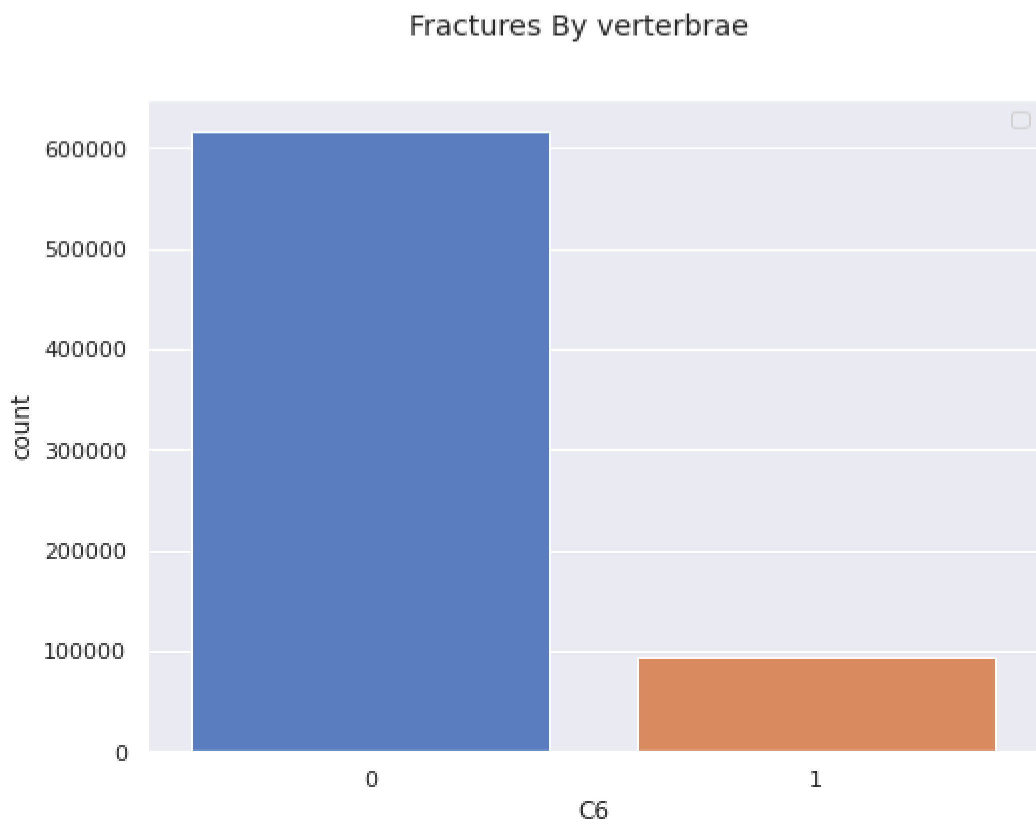


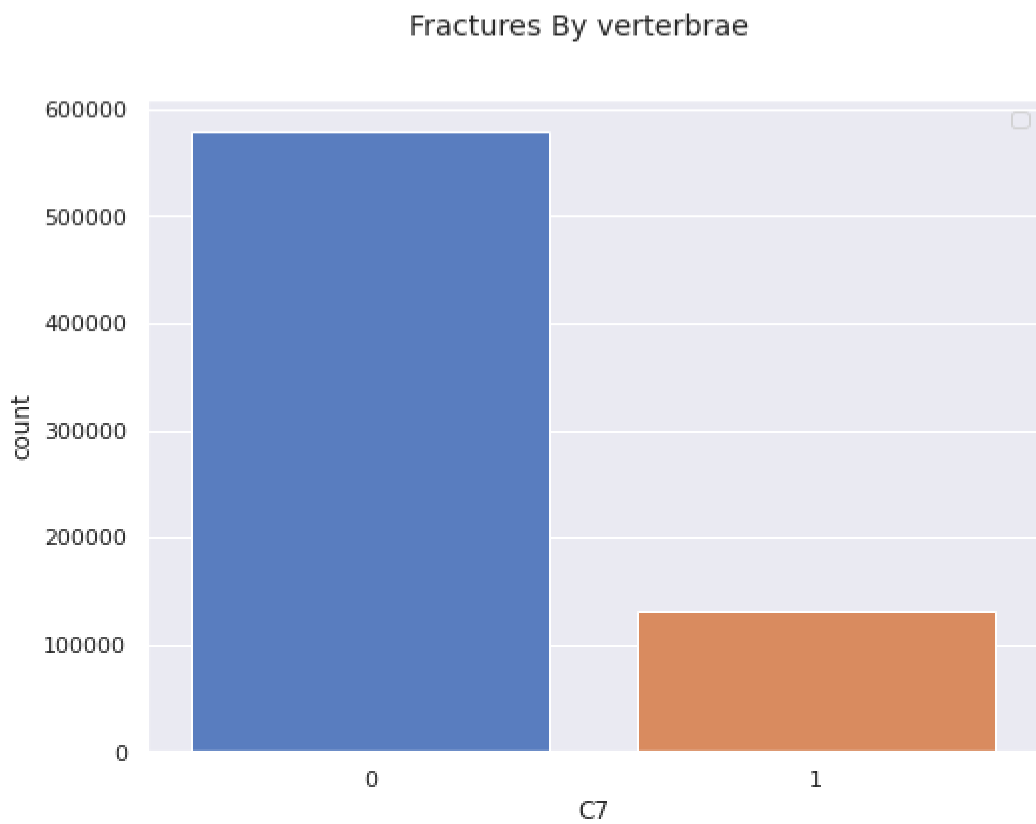

Fractures By verterbrae
600000
500000
400000
300000
200000
100000
0
count
0
1
C2

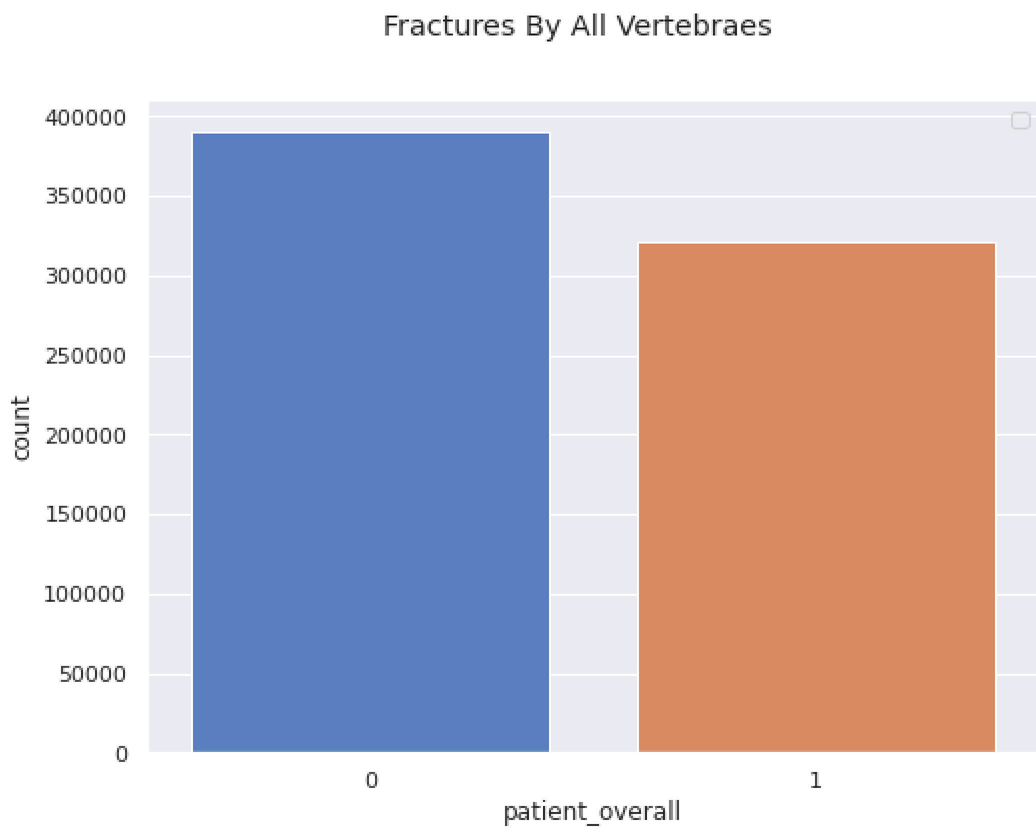

Fractures By verterbrae
700000
600000
500000
400000
300000
200000
100000
0
count
0
1
C3


Fractures By verterbrae
700000
600000
500000
400000
300000
200000
100000
0
count
0
1
C4


Fractures By verterbrae
count
600000
500000
400000
300000
200000
100000
0
0
1
C5


Fractures By verterbrae
600000
500000
400000
300000
200000
100000
0
count
0
1
C6


Fractures By verterbrae
600000
500000
400000
300000
200000
100000
0
count
0
1
C7



The Algorithm

The algorithm we are implementing is multi-step. First, we need to run a semantic segmentation algorithm using the segmentation dataset. The segmentation dataset contains masks of the images with labels from 0 to 19 where 1 to 7 corresponds to C1 to C7. There are only 87 segmentation files provided. The goal of the segmentation dataset is to train the model to what each of the vertebrae looks like before we can train another model of what a fracture looks like. The first model we are building is a U-Net model. The UNet model is an encoder-decoder CNN model that allows images to be masked based on pixel values and a prediction is obtained. The images below show an example of an image and its mask.

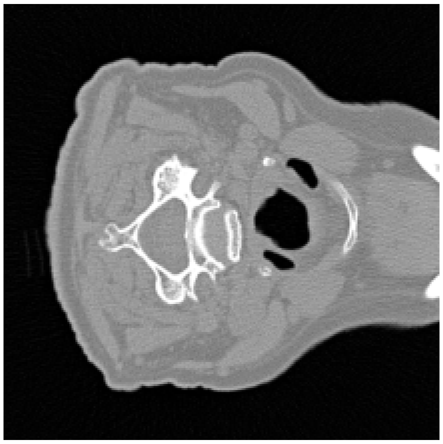
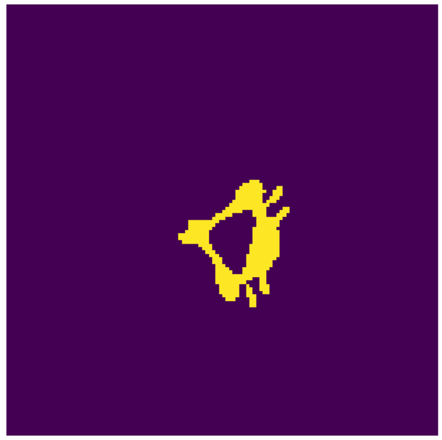



Figure 4.0: Image of one of the C1 to C7 vertebrae and it's mask

As can be seen above, we have a vertebra and its mask. The goal of the U-Net model will be to accurately predict which vertebra it is by learning from the true image and the mask since the mask has labels. From there, we can then build the next model which is able to tell what a fracture looks like on a given vertebra.

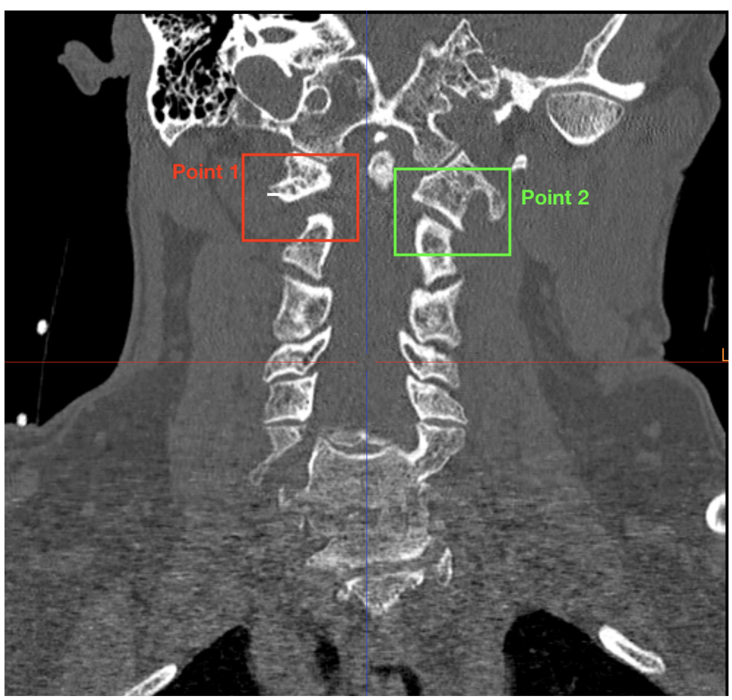


Figure 5.0: An example of an image that shows cervical spine trauma. Point 1 (in red) and Point 2 (in green) have different distances between bones. This view is taken from the front. The two distances are symmetrical in a healthy cervical spine.

As we show in Figure 5, an example of a cervical spine with trauma, we will create a model that can identify trauma by learning the relationship between the images and the labels we provide of what a healthy cervical spine and an unhealthy one are.

References

Morano, Jacqueline M et al. (Apr. 2021). “Management of acute traumatic brain injury and acute spinal cord injury”. en. In: Int. Anesthesiol. Clin. 59.2, pp. 17–24.

RSNA 2022 Cervical Spine Fracture Detection (July 2022). en. https://kaggle.com/competitions/rsna-2022-cervical-spine-fracture-detection. Accessed: 2022-10-21.

Canadian C-spine rule. MDCalc. (n.d.). Retrieved November 19, 2022, from https://www.mdcalc.com/calc/696/canadian-c-spine-rule#pearls-pitfalls

Cervical spine fractures & dislocations. USC Spine Center - Los Angeles. (2019, December 5). Retrieved November 19, 2022, from https://www.uscspine.com/conditions-treated/neck-disorders/cervical-spine-fractures-dislocations/

Salehinejad, H., Ho, E., Lin, H.-M., Crivellaro, P., Samorodova, O., Arciniegas, M. T., Merali, Z., Suthiphosuwan, S., Bharatha, A., Yeom, K., Mamdani, M., Wilson, J., & Colak, E. (2021, February 5). *Deep Sequential Learning for cervical spine fracture detection on computed tomography imaging*. arXiv.org. Retrieved November 19, 2022, from https://arxiv.org/abs/2010.13336#:~:text=Fractures%20of%20the%20cervical%20spine,is%20critical%20to%20patient%20management.

Surgery, F. the D. of. (n.d.). *Spiral computed tomography for the diagnosis of cervical,... : Journal of Trauma and Acute Care Surgery*. LWW. Retrieved November 19, 2022, from https://journals.lww.com/jtrauma/Abstract/2005/05000/Spiral_Computed_Tomography_for_the_Diagnosis_of.2.aspx

Themes, U. F. O. (2019, August 20). *Spinal trauma*. Radiology Key. Retrieved November 19, 2022, from https://radiologykey.com/spinal-trauma-4/

Major trauma & cervical clearance radiation doses & cancer induction. https://www.sciencedirect.com/science/article/abs/pii/S0020138307002434. (n.d.).

A review on image processing applications in medical field - researchgate. (n.d.). Retrieved November 20, 2022, from https://www.researchgate.net/publication/322772022_A_Review_on_Image_Processing_Applications_in_Medical_Field

Kumar, Y., & Hayashi, D. (2016, July 22). *Role of magnetic resonance imaging in acute spinal trauma: A pictorial review*. BMC musculoskeletal disorders. Retrieved November 19, 2022, from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4957861/

Small, J. E., Osler, P., Paul, A. B., & Kunst, M. (2021, July). *CT cervical spine fracture detection using a convolutional neural network*. AJNR. American journal of neuroradiology. Retrieved November 19, 2022, from

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8324280/