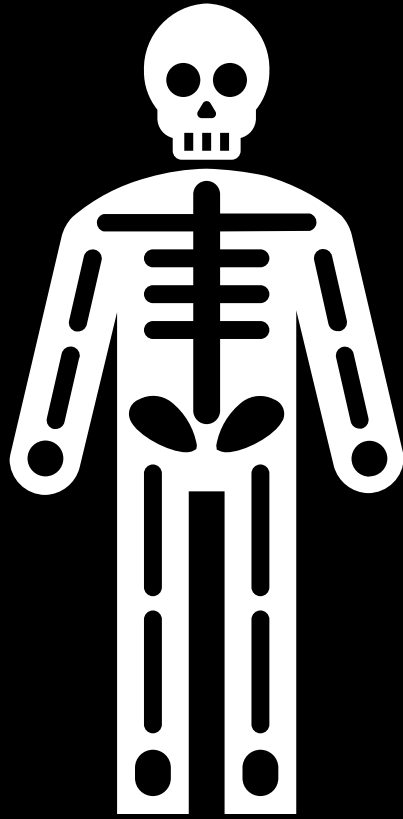


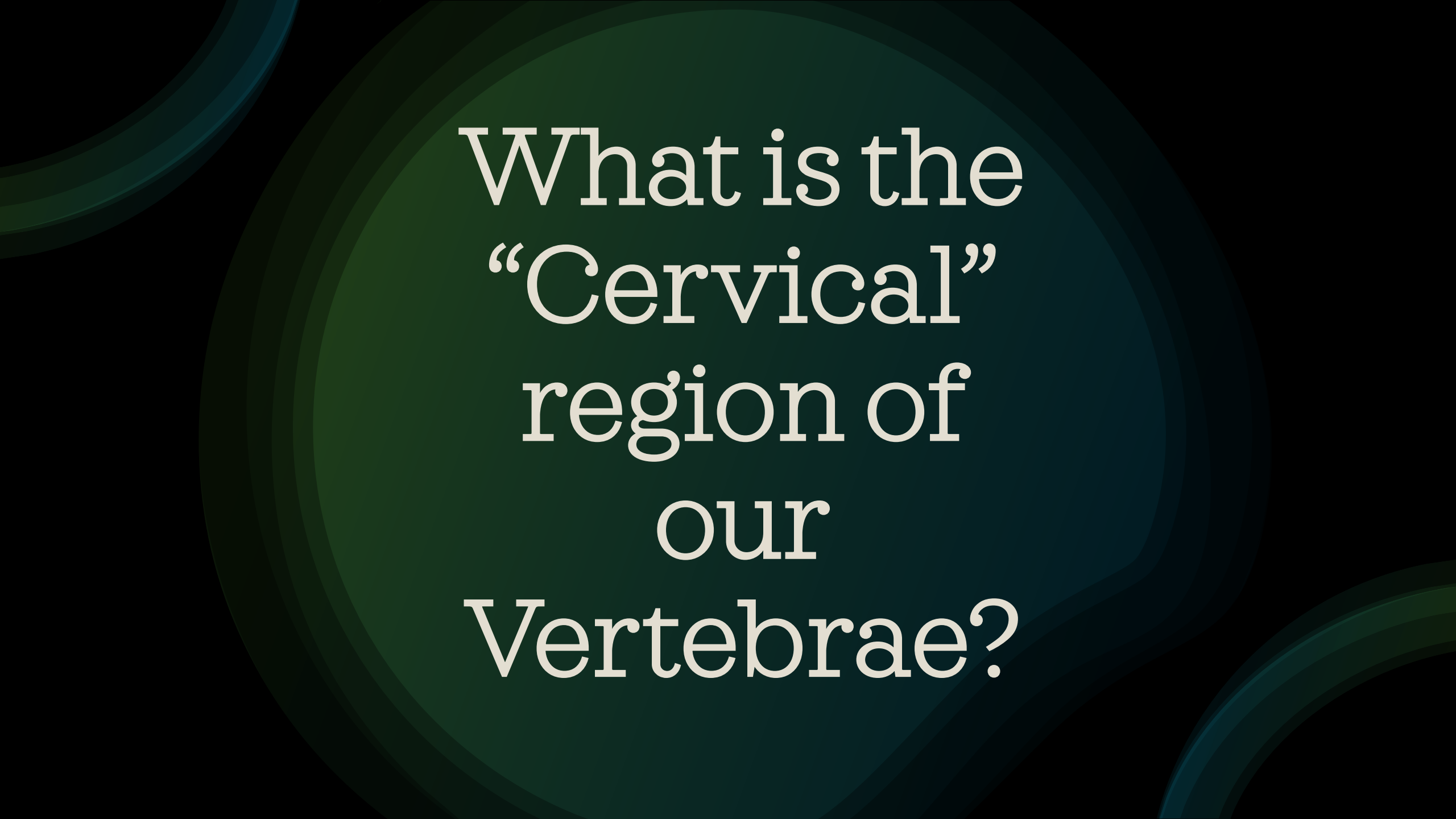
RSNA 2022 Cervical Spine Fracture Detection



Problem Overview

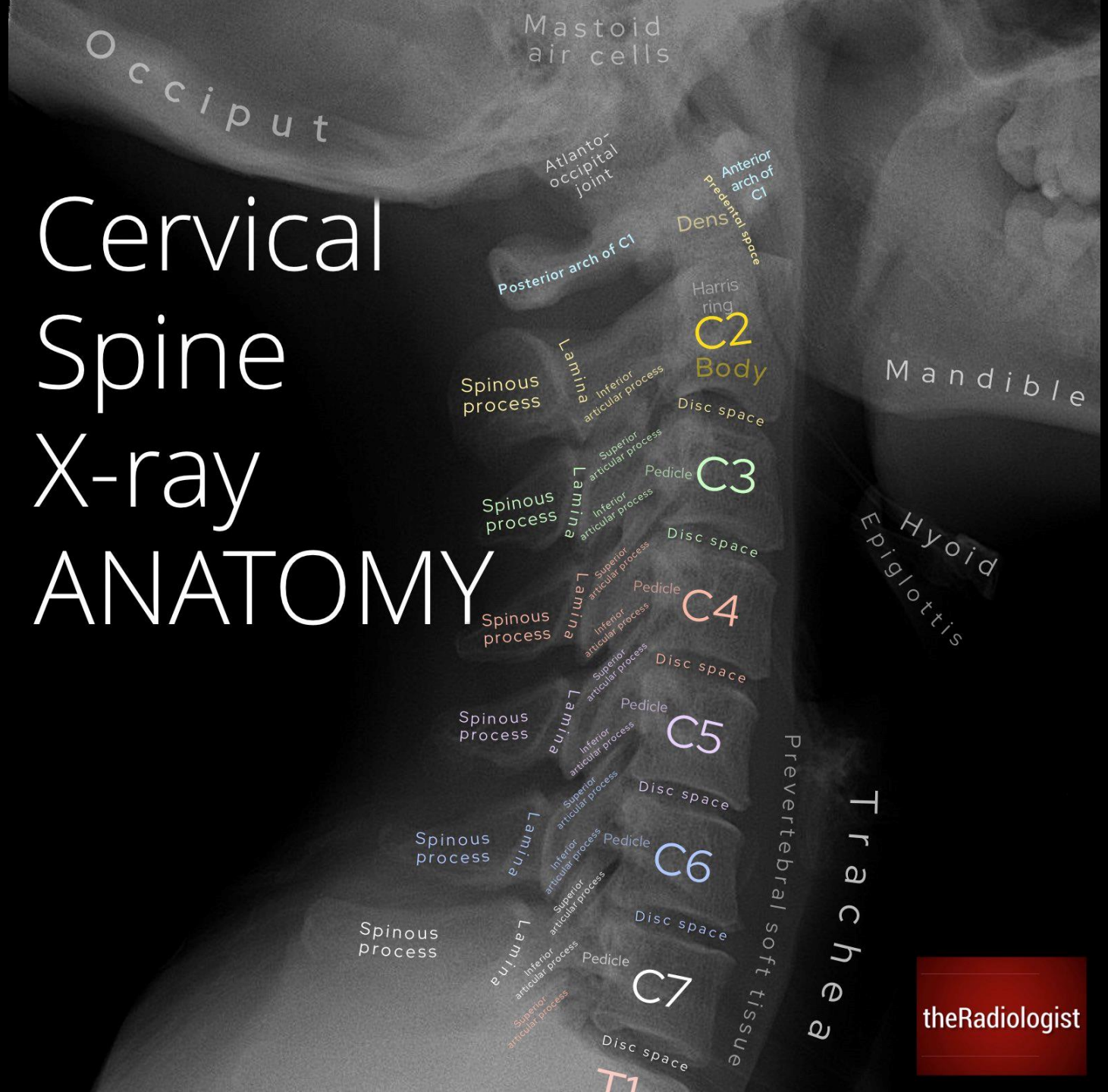
Identify cervical
fractures from scans

The goal of this competition is to identify fractures in CT scans of the cervical spine (neck) at both the level of a single vertebrae and the entire patient.

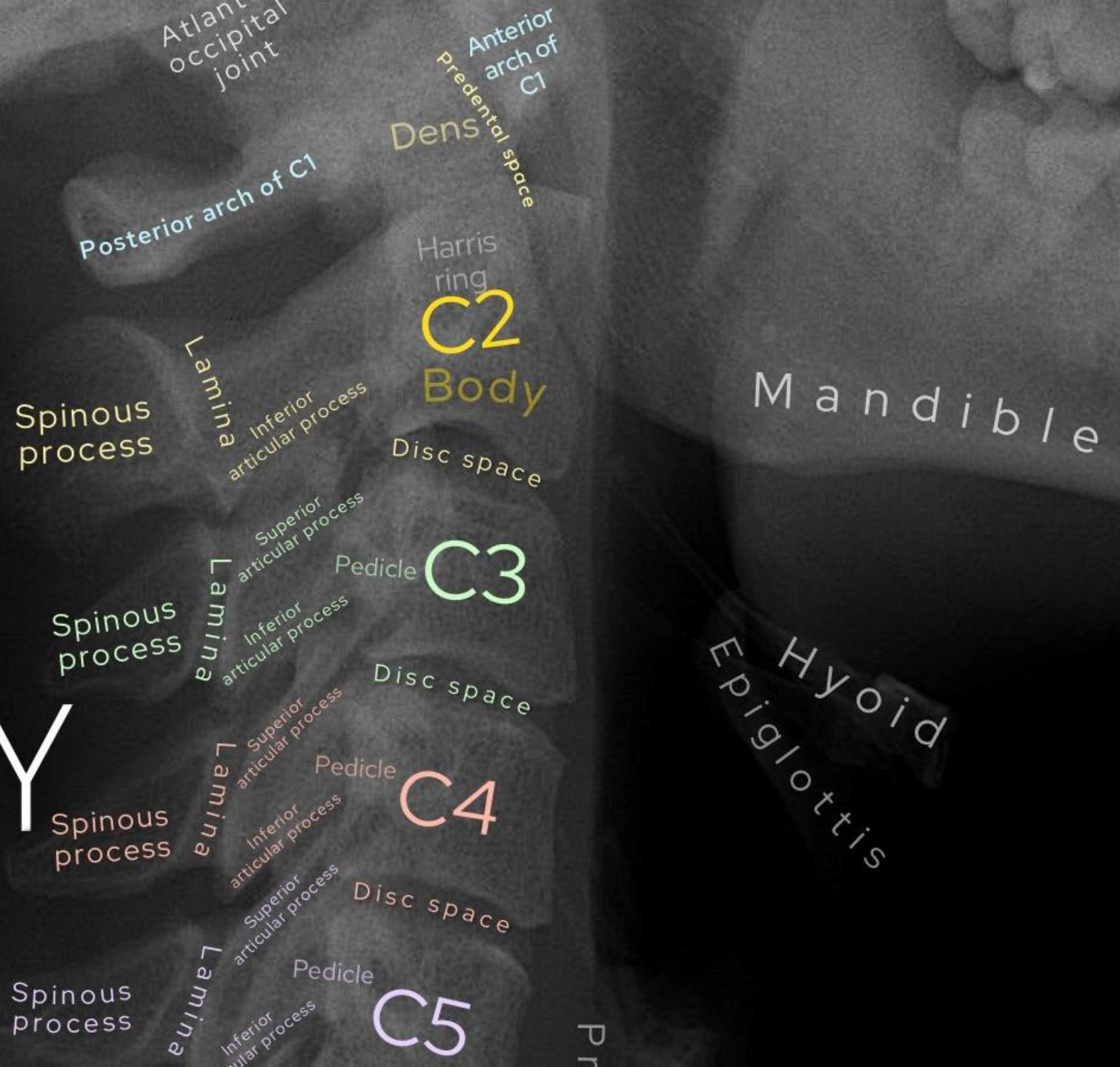


What is the
“Cervical”
region of
our
Vertebrae?

Cervical Spine X-ray ANATOMY

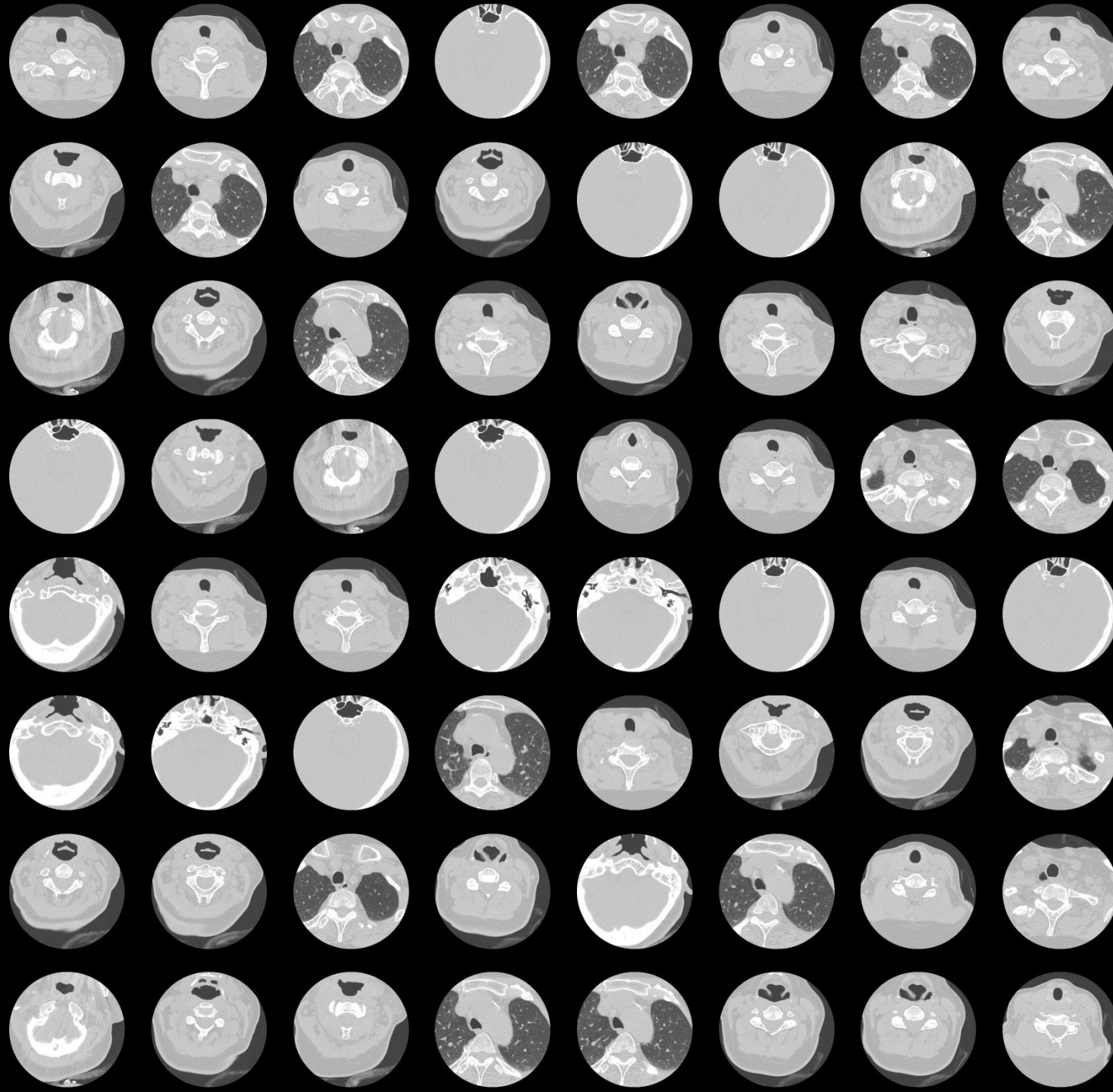


Cervical Spine X-ray ANATOMY





But what do the CT
Scans look like?





DICOM File Format


```

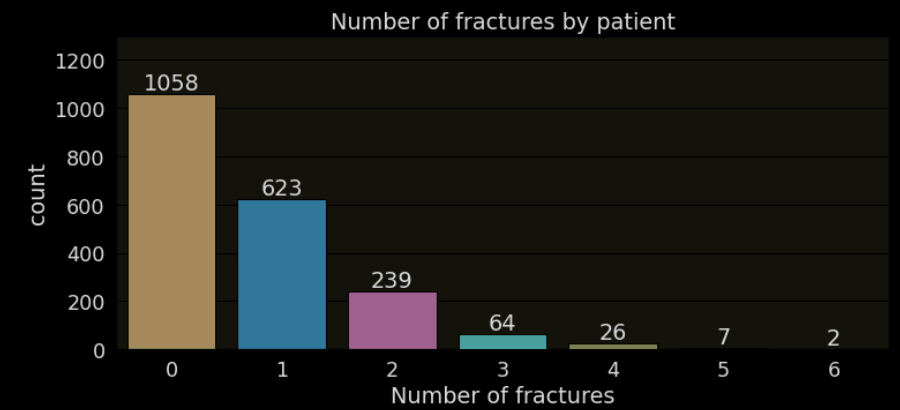
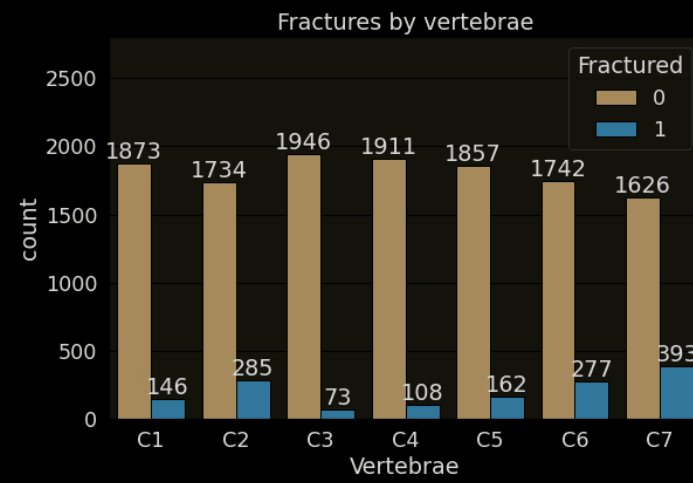
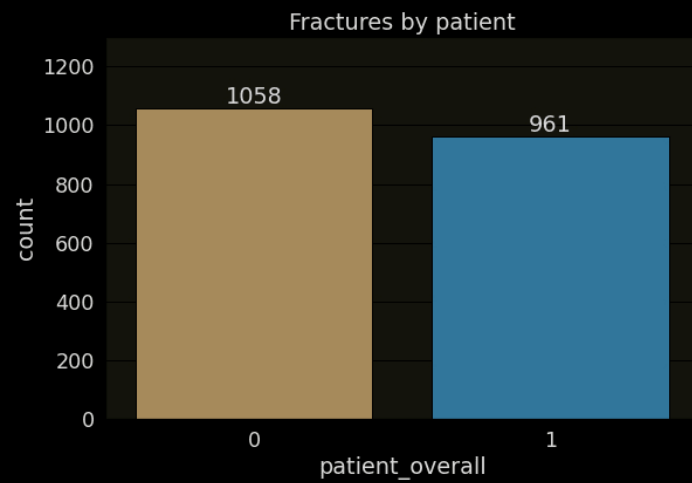
Dataset.file_meta -----
(0002, 0001) File Meta Information Version      OB: b'\x00\x01'
(0002, 0002) Media Storage SOP Class UID        UI: CT Image Storage
(0002, 0003) Media Storage SOP Instance UID     UI: 1.2.826.0.1.3680043.10001.1.101
(0002, 0010) Transfer Syntax UID               UI: Implicit VR Little Endian
(0002, 0012) Implementation Class UID          UI: 1.2.40.0.13.1.1.1
(0002, 0013) Implementation Version Name       SH: 'PYDICOM 2.3.0'
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(0008, 0018) SOP Instance UID                  UI: 1.2.826.0.1.3680043.10001.1.101
(0008, 0023) Content Date                     DA: '20220727'
(0008, 0033) Content Time                     TM: '175846.512627'
(0010, 0010) Patient's Name                   PN: '10001'
(0010, 0020) Patient ID                       LO: '10001'
(0018, 0050) Slice Thickness                   DS: '0.625'
(0020, 000d) Study Instance UID                UI: 1.2.826.0.1.3680043.10001
(0020, 000e) Series Instance UID              UI: 1.2.826.0.1.3680043.10001.1
(0020, 0013) Instance Number                  IS: '101'
(0020, 0032) Image Position (Patient)          DS: [-52.308, -27.712, -55.218]
(0020, 0037) Image Orientation (Patient)       DS: [1.000000, 0.000000, 0.000000, 0.000000,
0, 1.000000, 0.000000]
(0028, 0002) Samples per Pixel                 US: 1
(0028, 0004) Photometric Interpretation        CS: 'MONOCHROME2'
(0028, 0010) Rows                             US: 512
(0028, 0011) Columns                          US: 512
(0028, 0030) Pixel Spacing                    DS: [0.253906, 0.253906]
(0028, 0100) Bits Allocated                   US: 16
(0028, 0101) Bits Stored                      US: 16
(0028, 0102) High Bit                         US: 15
(0028, 0103) Pixel Representation              US: 1
(0028, 1050) Window Center                    DS: '500.0'
(0028, 1051) Window Width                     DS: '2000.0'
(0028, 1052) Rescale Intercept                DS: '-1024.0'
(0028, 1053) Rescale Slope                    DS: '1.0'
(7fe0, 0010) Pixel Data                       OW: Array of 524288 elements


```

HEADER

→ IMAGE

Baseline Solution





BASELINE = Only trying to
predict whether a patient
has a fracture (1) or not (0)

Transfer Learning

Treating each CT Scan as an IMAGE, but instead of 3 RGB Channels, the number of channels equals the number of slices/scans for that patient.

But here we run into a problem. The height of each scan varies from patient to patient, i.e. the number of slices for each patient varies.

We need a constant channel input for using CNN Architectures

Minimum number of scans for a patient = 300

Maximum number of scans for a patient = 1082

Sample N scans for each patient at equally spaced intervals. Thus making the input channel size CONSTANT

Now we can use any 2D-CNN architecture with $\text{in_channels} = \underline{N}$

Using the mobilenetv3_large_100 architecture

Changing the input layers to take 69/300 channels.

Changing the output layer for binary classification.

Freezing the intermediate layers for training.

Setting the value of N as 69 and 300

Validation Accuracy (N=69) = 50%

Validation Accuracy (N=300) = 57 %

All values after 10 epochs

Further Improvements

01

Using 3D-CNN Architectures.

02

Using sequential models (prevent information loss).

03

Using segmentation data to isolate individual vertebrae for prediction.

Thank You

Amey Rambatla

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