SpineNetV2: Automated Detection, Labelling and Radiological Grading Of Clinical MR Scans

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Abstract

This technical paper presents SpineNetV2, an automated tool which: (i) detects and labels vertebral bodies in clinical spinal magnetic resonance (MR) scans across a range of commonly used sequences; and (ii) performs radiological grading of lumbar intervertebral discs in T2-weighted scans for a range of common degenerative changes. SpineNetV2 improves over the original SpineNet software in two ways: (1) The vertebral body detection stage is significantly faster, more accurate and works across a range of fields-of-view (as opposed to just lumbar scans). (2) Radiological grading adopts a more powerful architecture, adding several new grading schemes without loss in performance. A demo of the software is available at the project website: http://zeus.robots.ox.ac.uk/spinenet2/.

Figure 1: An overview of SpineNetV2, shown acting on a T2 lumbar MR scan. Note that the vertebra detection and labelling pipeline works across a range of different MR sequences (T1, T2, STIR, etc.) and fields-of-view (e.g. cervical, thoracic, lumbar and whole spine) as illustrated in Figure 8.
## Contents

1 Introduction .................................................. 3

2 Overview ....................................................... 4
   2.1 Processing Pipeline .................................... 5

3 Methods Used ................................................ 7
   3.1 VB Detection by Vector Field Regression .............. 7
   3.1.1 Splitting Large Scans Into Patches .................. 8
   3.2 Convolutional Labelling of Vertebral Levels .......... 9
   3.3 Extracting Intervertebral Volumes .................... 12
   3.4 Radiological Grading of Intervertebral Volumes .... 12

4 Implementation ............................................... 12
   4.1 Code Implementation ................................... 13
   4.2 Model Architectures .................................... 13
   4.3 Datasets ................................................ 13
      4.3.1 OWS .............................................. 13
      4.3.2 Genodisc .......................................... 13
   4.4 Training ................................................ 15
      4.4.1 VB Detection ..................................... 16
      4.4.2 VB Labelling ...................................... 17
      4.4.3 Radiological Grading of Degeneration Changes .... 18

5 Results ......................................................... 18
   5.1 VB Detection and Labelling ............................ 18
   5.2 Radiological Grading .................................... 20
   5.3 Processing Speed ....................................... 20
   5.4 Example Qualitative Results ........................... 21
   5.5 Online Demo ............................................ 21

6 Conclusions ................................................... 22

7 Acknowledgements ............................................ 22
1 Introduction

Back pain is the most common cause of long-term disability; it affects around 80% people in the UK during their lifetime [11]. As people live longer, incidence will only increase. To combat this, we need methods to diagnose and monitor etiology like degenerative changes that are quick, effective and cheap to perform. This is the motivation behind SpineNet; to offer a completely automated set of tools for performing common gradings & measurements in clinical spinal MR scans.

This report describes the second iteration of the SpineNet software with several improvements over the initial version\(^1\). Namely, the method of detecting and labelling vertebral bodies has been completely overhauled and is now much faster, more robust, and can run across a range of fields of views (cervical, whole spine, lumbar, thoracic etc.) as opposed to just lumbar scans. The grading network has also been improved to perform several new grading types; disc herniation, left and right foraminal stenosis and multiclass central canal stenosis (as opposed to binary classification in the original version). Grading performance across pre-existing tasks is similar or slightly improved from SpineNetV1.

Crucially, unlike SpineNetV1 which was implemented using MATLAB, SpineNetV2 is implemented using open-source python libraries. Therefore, it can be run on a much wider range of hardware without the need for potentially expensive software licences. The time-consuming, HOG-based vertebra detection system of V1 has been replaced with a much faster (on GPUs and CPUs) and more robust deep-learning based approach. Furthermore, the network used to perform radiological grading has now uses a more powerful ResNet34 backbone to extract visual features as opposed to VGG-F. A complete summary of these changes can be seen in Table 1.

This technical report builds on several existing publications on the subject of vertebrae detection and radiological grading, amongst which are \([6, 7, 8, 9, 10, 14]\).

The report is organised as follows; Section 2 describes the operation and functionality of SpineNetV2 at a high level. Section 3 discusses the methods used for vertebral body (VB) detection (§3.1), labelling (§3.2), extracting intervertebral volumes (IVVs) from the detected VBs (§3.3), and performing radiological grading of these detected IVVs (§3.4). Section 4 discusses the implementation of the system, including the libraries (§4.1) and datasets (§4.3) used and methods for training the constituent neural networks (§4.4). Section 5 gives experimental results for the detection and labelling pipeline as well as the radiological grading pipelines, including comparisons with the original version of SpineNet. Finally, Section 6 concludes the report, giving future plans for SpineNet as well as information on how SpineNet software

\(^1\)SpineNetV1 project page: http://zeus.robots.ox.ac.uk/spinenet/
Table 1: Side-by-side comparison of the original SpineNetV1 and SpineNetV2.

| SpineNetV1                                      | SpineNetV2                                      |
|-------------------------------------------------|-------------------------------------------------|
| - Vertebra detection & labelling on lumbar sagittal scans across a range of common clinical MR sequences | - Vertebra detection & labelling on any field of view sagittal scan (e.g. cervical, lumbar, whole spine) |
| - Implemented in MATLAB                         | - Implemented in open-source python libraries only (e.g. PyTorch, PyDicom) |
| - Complete radiological grading of lumbar scan in approx. 5 minutes. | - Complete radiological grading of lumbar scan in approx. 5 seconds. |
| - Grades for (No. Classes): Pfirrmann (5), Disc Narrowing (4), Endplate Defects (2), Marrow Changes (2), Spondylolisthesis (2) and Central Canal Stenosis (2). | - Grades for (No. Classes): Pfirrmann (5), Disc Narrowing (4), Endplate Defects (2), Marrow Changes (2), Spondylolisthesis (2) and Central Canal Stenosis (4), Foraminal Stenosis (2) and Disc Herniation (2). |
| - VGG-F Backbone for Grading Network Backbone. | - ResNet34 Grading Network Backbone. |

2 Overview

SpineNetV2 provides an entire pipeline to go from raw DICOM files (as output by a conventional MRI machine) to 3-D detections localising the each vertebral body visible in the scan and labels describing the level of each detection. In the case of T2 lumbar scans, the pipeline can also output multiple common radiological gradings for each intervertebral disc visible in the scan.

Inputs: DICOM files corresponding to slices of a sagittal MRI spinal scan. This scan can be one of a range of common clinical sequences (e.g. T1, T2, STIR, FLAIR, TIRM, Dixon-technique, etc.), have an arbitrary field-of-view (e.g. lumbar, cervical, whole spine, etc.) and be of varying resolution and slice thickness.

Outputs:

- CSV/JSON file describing the location of vertebral bodies in the scan and the corresponding level of these detections (from S1 to C2).
- **T2 Lumbar Scans Only:** CSV/JSON file with predictions for a range of common radiological grading schemes (itemized in Section 3.4).
each intervertebral disk visible in the scan.

2.1 Processing Pipeline

SpineNet consists of multiple processing steps, each of which is described in detail in the following sections. These are:

1. Splitting each slice of the input DICOM file into a set of smaller patches (for large scans only).

2. Detecting each visible vertebral landmark (vertebral corners & centroid) in each patch/slice.

3. Grouping together these landmarks into vertebrae instances.

4. Determining the level of each detected vertebra.

For T2 Lumbar scans the following stages are added:

5. Locating IVVs (inter-vertebral volumes) using the VB detections.

6. Performing radiological grading of the extracted IVV.

This entire process is shown in Figure 2.
Vertebrae Detections & Labels From Previous Stages

From Previous Stages

Vertebrae Detections & Labels From Previous Stages

Vertebrae Detections & Labels From Previous Stages

(b) **VB Labelling** - Determining the level of each detected vertebra.

(c) **VB Grading** - Grading each detected IVV using a range of common radiological grading schemes. Note this step only applies to T2 Lumbar scans.

Figure 2: The processing pipeline for SpineNetV2. Note that the vertebra detection and labelling section works across a range of sequences and fields-of-view, whereas the radiological grading system only operates on T2 lumbar scans.
3 Methods Used

This section describes methods used for the three main stages of the SpineNet pipeline (VB detection, VB labelling and IVV grading) from an algorithmic standpoint. These stages are illustrated in Figure 1. Broadly speaking, whole spine scans and smaller scans (e.g. lumbar, cervical) are processed identically, with only minor differences in how the patch splitting is done in the VB detection stage. These differences are described fully in Section 3.1.1, however we will initially assume a single lumbar scan when describing the processing pipeline.

3.1 VB Detection by Vector Field Regression

The first stage in the SpineNetV2 pipeline is to detect vertebral bodies (VBs) in the raw scans. This is done using a method called Vector Field Regression (VFR). Operating in each sagittal slice of the scan, a network detects gaussian responses over the centroids and corners (vertebral landmarks) of each visible VB. For each corner detected, a corresponding vector field is also output. At the point of each corner, this corresponding vector field should ‘point’ to the centroid of the vertebra to which it belongs. This allows landmarks from the same vertebra to be grouped together in a simple manner which is robust to rotations, flips and variable vertebra size.

At this point, each detection consists of a centroid and four corners grouped together to make a quadrilateral in an individual sagittal slice. Slicewise 2D quadrilaterals corresponding to the same vertebra must then be grouped together across slices forming 3D volumes. This is done are by measuring the intersection-over-union (IOU) of quadrilaterals in neighbouring slices. If the IOU is large, the quadrilaterals are grouped together into a single vertebral instance. A diagram of this process going from raw scans to 3D volumes is shown in Figure 3.

Specifically, inference proceeds as follows:

1. A raw MR scan of dimension $S \times H \times W$ is split into $S$ sagittal slices. These slices are in turn split into square patches of size 25 cm$^2$ with an overlap of 30% between neighbouring patches on each side. This patch-splitting allows the network to deal with scans of varying dimensions.

2. The patches are resampled by cubic interpolation to resolution of 224×224. The resamples patches are fed as input to a ResNet50-encoded U-Net. This results in a 13×224×224 output per patch; 5 detection channels and 8 grouping channels (see Figure 3).

3. By resampling & concatenating these patch-level outputs using the median output for overlapping regions, an slice-level output tensor is reconstructed of size 13×$H \times W$. 

7
4. The detection channels are then decoded to find the location of detected VB centroids and corners. This is done by thresholding each channel & finding all connected component in the resulting binary map. The exact point-of-detection for each landmark is the point of maximal response in the detection channel for the corresponding connected component.

5. Now that each VB landmark in the slice has been detected, they must be grouped into quadrilaterals corresponding to individual VBs. This is done by measuring the value of the corresponding vector field at the point-of-detection for each corner landmark. Looping through each detected VB centroid, the corner landmark of each type which points closest is assigned as the corresponding corner for that centroid, forming a quadrilateral. If no arrow is within a distance from the centroid of 50% of the arrow length, that centroid is discarded as a spurious detection.

6. Finally the resulting VB polygons are grouped across neighbouring slices if they have an IOU over 0.25. If more than one polygon in a neighbouring slice overlap, then the one with the greatest IOU is chosen.

### 3.1.1 Splitting Large Scans Into Patches

Larger non-square scans (such as whole spine scans) are split into patches before VFR is applied. This is done by splitting the scan into a grid of overlapping squares with edge length 50cm (as determined by the pixel spacing parameter in the DICOM header) and an overlap of 40% between neigh-
bouring patches. The output from the detection and grouping channels are then used to find landmarks in each patch. These landmarks are then transformed back into the frame of the original scan. At this point, the algorithm proceeds as before by grouping landmarks into slicewise polygons and then across sagittal slices. Figure 4 shows the process of patch-splitting for a whole spine scan.

3.2 Convolutional Labelling of Vertebral Levels

The VFR method described above allows us to detect vertebral bodies in a sagittally sliced MR scan. The next step of the pipeline is to determine which vertebral levels the detections correspond to (e.g. S1, L5, L4 etc). This is made more challenging by the fact that SpineNetV2 is not constrained to a single field of view. As such, ‘counting up’ methods, i.e. those that rely on an anchor vertebra being visible (such S1/C2 at the bottom/top of the vertebral column) are unsuitable. Furthermore, such methods are not robust to missed detections or variations in the number of vertebra in the vertebral column (e.g. in cases where a transitional vertebra is present).

There are two pieces of information to consider when labelling a vertebra - its appearance (e.g. intensity pattern, shape, size etc.) and its context (the vertebra’s position relative to other detections in the scan). For example, S1 usually has a very distinctive shape which allows it to be labelled from appearance alone. On the other hand, L5 looks very similar to the other lumbar vertebrae, however can be easily identified from its context - it is the next vertebra up from S1. Our method attempts to use both these sources of information when labelling a vertebra.

Firstly, a 3D volume around each detected VB is fed as input to an appearance network. This outputs a 23-element (from S1 to C3) probability vector predicting the level of the VB from appearance alone. To include information about the spatial configuration of the detections, this is then used to construct a probability-height map, \( P \). At the height of each de-
tection, $P$ has value equal to the output from the appearance network for that detection. Using this as input, a convolutional context network refines the height-probability map, taking into account appearance predictions from spatially nearby VBs to update the probability vectors for each detection. The result is a refined height-probability map $P'$. This process is shown in Figure 5. Finally, $P'$ needs to be decoded into discrete level predictions. Naïvely, this could be done by taking the maximum probability level at the height of each detection in $P'$. However, this would allow for nonsensical outputs, such as the same level for two detections. Ideally, we also want to build in soft contraints such that successive detections are labelled as successive labels. For example, we would expect S1 to be the detection below L5. However, we also wish to remain robust to missed detection.

To build these constraints into our approach, we take inspiration from language modelling. Using a beam search, we can find the most probable valid sequence of levels for the detections. Penalties are added to the sequences probability score in the case of transitional vertebrae or numerical variations to reflect the unlikeliness, yet possibility, of such events. The exact parameterisation of this search is specified in the next paragraph.

Figure 5: The language modelling-inspired approach to vertebra labelling outlined in this section. We begin by constructing a probability-height map $P$ based on appearance information alone. Using a context-aware CNN this map is refined ($P'$). Finally $P'$ is decoded into a valid sequence of levels using a penalised beam search.

The exact specification of this labelling stage is as follows:

1. Given VB detections from the previous stage, a 2-D bounding cube is fit tightly around the union each of detection’s slicewise series of polygons. By expanding this cube by 100% on each side in the axial and coronal directions and by 50% on each side in the sagittal direction a volume around each detection and its nearby anatomical features is created.

2. All extracted volume are resized by cubic interpolation to $224 \times 224 \times 16$ (where 16 is the number of sagittal slices). These are then fed to an
appearance network which outputs a 23-element probability vector, attempting to classify the VB as a level from S1-C3.

3. The output probability vectors are re-calibrated [5] using a softmax temperature $T = 10$. These recalibrated vectors are then used to construct an initial probability-height map, $P \in \mathbb{R}^{H \times 23}$. For a detection polygon with output appearance probability vector $p_a \in \mathbb{R}^{23}$ and spanning from height $h_1$ to $h_2$ in the scan, $P$ is equal to this value between these heights, i.e. $P(h) = p_a \forall h_1 \leq h \leq h_2$.

4. $P$ is then given as input to a image-to-image context CNN. This outputs $P' \in \mathbb{R}^{H \times 23}$, a refined probability-height map which considers the neighbours of each detection to update its probability vector. This refinement step can be seen in Figure 5.

5. The next step is to decode $P'$ into a series of discrete level predictions. Firstly, the probability vector at the centroid of each detection, $p_i$ is extracted. The joint probability of a sequence of levels can then be calculated as the product of elements of these vectors. For example, if detected VB $i$ has a probability of being S1 of $a$ and VB $j$ has probability of being L5 of $b$, then the joint probability of the level sequence is $a \times b$. To reduce search space, we use a beam search to find the most likely sequence, starting from the bottom detection and only storing the 100 most probable level sequences at each step.

6. To impose constraints on sequences of level predictions, penalties can be added to the sequence scores. For example, sequences which predict the same level twice are given a probability of 0. Furthermore, if there is a missed detection (i.e. L4 directly above S1), the joint probability score is multiplied by a penalty score to reflect the rarity of this event. To allow for cases where S2 or C2 are detected, double detections of S1 or C3 are allowed without a score penalty and then relabelled in post-processing.

At this point, each vertebra in the scan from S1 to C3 should have been detected and assigned a level label. These detections can be used in a range of applications. For example in whole spine scans, SpineNet can be used to measure spinal curvature (for scoliosis measurement) or extract regions of anatomical interest such as the spinal chord or vertebral bodies for lesion segmentation (e.g. spinal metastases or ankylosing spondylitis).

One area of particular interest is radiological grading of degenerative changes. The following section describe how this is done in the context of the SpineNet.
3.3 Extracting Intervertebral Volumes

To perform radiological grading in T2 lumbar scans, first volumes surrounding each intervertebral disc must be extracted. This is done using the VB detections from the previous stage. The mid-point between the centroids of two consecutive VB detections is calculated. This defines the centre of each extracted IVV. From this the volume is rotated such that the lower endplate of the upper vertebra is horizontal. The width of the extracted endplate volume is then defined as double that of the larger VB detection. The height of the IVV is then chosen such that the aspect ratio of the extracted patch is 2:1. This is done across all slices in which the vertebrae is detected.

3.4 Radiological Grading of Intervertebral Volumes

Once the IVVs are extracted, they are resampled to have a resolution of $112 \times 224 \times 9$ (height, width and sagittal slices respectively) These volumes are then fed to a radiological grading network which outputs scores for the following radiological gradings:

1. Pfirrmann Grading (5 classes)
2. Disc Narrowing (4 classes)
3. Central Canal Stenosis (4 classes)
4. Upper & Lower Endplate Defects (Binary)
5. Upper & Lower Marrow Changes (Binary)
6. Left & Right Foraminal Stenosis (Binary)
7. Spondylolisthesis (Binary)
8. Disc Herniation (Binary)

The radiological grading network is a standard multi-class classification 3D CNN. We experiment with a range of different architectures, described in Section 5. Each of these grading schemes is described in further detail in Section 4.3.2. Note that the same model is used for all gradings schemes and vertebral levels.

4 Implementation

This section describes the specific design choices made while developing SpineNetV2, as well as details of the datasets and methods used to train the constituent neural networks.
4.1 Code Implementation

All stages of the SpineNetV2 processing pipeline are implemented entirely using open-source python libraries. Deep learning functionality is provided by CUDA-enabled PyTorch v1.7 (or later). Input DICOMs are processed using pydicom.

The software is designed such that detection and grading can be separated. During inference, models can run on CPUs or GPUs for faster processing (the performance and memory constraints of each configuration are given in Section 5.3).

4.2 Model Architectures

There are 4 constituent neural networks in the SpineNetV2 pipeline; the VFR regression network, the appearance network, the context network and the grading network. The VFR regression network is a ResNet18-encoded UNet. The appearance network is a simple VGG-F network as outlined in the original paper [2]. The context network is a simple UNet [12]. Finally, the radiological grading network is a conventional ResNet32 model with 3D 3×3×3 convolutions in the first layer and 3×3 convolutions in all other layers.

4.3 Datasets

Two datasets are used to train SpineNetV2; Oxford Whole Spine (OWS) and Genodisc. OWS is a dataset of whole spine scans across a range of commonly used sequences, used only for training the vertebra detection and labelling sections of the SpineNetV2 pipeline. Genodisc is a dataset of sagittally-sliced lumbar T2 scans used in training all stages of the pipeline.

4.3.1 OWS

OWS consists of 710 sagittally-sliced whole spine scans across 196 patients extracted from local orthopaedic centre’s PACS (picture archiving and communication system) and anonymised under appropriate ethical clearance. These scans are across a range of commonly used clinical sequences (mostly T1, T2, STIR and TIRM). The distribution of sequences can be seen in Figure 6c. Each vertebral body from S1 to C2 is annotated as a quadrilateral in the central slice of each scan by a non-specialist. These are used to generate the ground truths for training, as discussed in section 4.4.

4.3.2 Genodisc

Genodisc is a dataset of sagittally-sliced lumbar T1 and T2 scans from 6 different international clinical spinal imaging centres. This dataset is used for training the detection (T1 & T2) and the radiological grading (T2 only)
Figure 6: Breakdown of scan types in both OWS (196 patients, 719 scans) and Genodisc (2279 patients, 2819 scans). Both datasets are split 80:20:20% down the patient line.
stages of the pipeline. Each T2 scan is annotated by an expert radiologist. The following degenerative changes are graded:

1. Pfirrmann Grading (5 classes) - A general grading system proposed in 2007 by Griffith et al. to categorise the degree of intervertebral disc (IVD) degeneration (originally for older patients). Ranges from 1 (no degeneration) to 5 (severe degeneration)

2. Disc Narrowing (4 classes) - The width of the IVDs. Ranges from 1 (no narrowing) to 4 (extreme narrowing).

3. Central Canal Stenosis (4 classes) - A narrowing of the spinal canal which can in turn lead to compression of the spinal chord. Ranges from 1 (no compression), 2 (mild compression), 3 (moderate compression) and 4 (severe compression).

4. Upper & Lower Endplate Defects (Binary) - Abnormalities/damage to the top or base of the VB’s constituent bodies.

5. Upper & Lower Marrow Changes (Binary) - Lesions/changes in the intensity of constituent VBs.

6. Left & Right Foraminal Stenosis (Binary) - A narrowing of the intervertebral foramina (openings where spinal nerves leave the central canal). In severe cases, this can lead to nerve compression similar to central canal stenosis.

7. Spondylolisthesis (Binary) - A condition when a vertebra slips forward onto the vertebral disc below. This is often caused by a fracture in the *pars interarticularis*, a segment of bone that joins the vertebrae.

8. Disc Herniation (Binary) - A condition where the centre of the IVD (*nucleus pulposus*) breaks through its casing (*annulus fibrosus*). This can lead to nerve compression.

Examples of these degenerative changes from the training dataset are shown in Figure 7.

### 4.4 Training

In total 4 networks are trained for the SpineNetV2 pipeline: 1) a detection network which detects vertebral bodies agnostic to their level; 2) a labelling appearance network which aims to label vertebrae based on their appearance alone; 3) a labelling context network which refines the predictions of the appearance network based on the appearance of neighbouring VB detections 4) a radiological grading network which operates on volumes surrounding IVDs and outputs gradings for the degenerative changes listed in section 4.3.2. Each network is trained independently on data from either Genodisc, OWS or a combination of both.
4.4.1 VB Detection

The network is trained on patches of sagittal slices from Genodisc and OWS. These patches cover an area of approximately 25cm$^2$ and are resampled to 224×224 pixels via cubic interpolation.

Ground truths are constructed from VB polygons marked by annotators. The network’s 13 output channels are divided in two types: detection channels which indicate the location of individual landmarks in the image and grouping channels that show which vertebra each landmark belongs to by ‘pointing’ to the corresponding centroid. The ground truth for each of these two channel types is generated as follows:

- **Detection Channels**: A gaussian response is added to the corresponding channel for each VB vertex, normalised to have a peak value of 1 and have variance proportional to the VB polygon’s surface area. A gaussian response is added to the centroid detection channel at the centre of each annotated polygon.

- **Grouping Channels**: The grouping channels for each vertex are constructed such that, for an area around each vertex proportional to the VB’s surface area, the two corresponding grouping channels together point to the VB’s centroid.

Once the target tensor, $\hat{Y}$, is constructed, the detection network is trained end-to-end using the following composite loss function for output tensor $Y$:

$$\mathcal{L}(Y, \hat{Y}) = \mathcal{L}_{\text{detect}}(Y, \hat{Y}) + \mathcal{L}_{\text{group}}(Y, \hat{Y}).$$

An L1-regression loss is applied to the detection channels;

$$\mathcal{L}_{\text{detect}}(Y, \hat{Y}) = \sum_{k=1}^{5} \alpha_{ijk} |y_{ijk} - \hat{y}_{ijk}|,$$

Figure 7: Example degenerative changes from the Genodisc training dataset.
where $k$ indexes the landmark channel (the four VB corners and centroid), $i$ and $j$ index the position in the patch and $\alpha_{ijk}$ is a weighing factor given by

$$
\alpha_{ijk} = \begin{cases} 
\frac{N_k}{N_k+P_k} & \text{if } \hat{y}_{ijk} \geq T \\
\frac{P_k}{N_k+P_k} & \text{if } \hat{y}_{ijk} < T 
\end{cases} 
$$

(3)

where $N_k$ and $P_k$ are the number of pixels in the target detection channel respectively less than or greater than some threshold $T$ ($T = 0.01$ in this case).

The vector field grouping channels are supervised by an L2-regression loss,

$$
L_{\text{group}} = \sum_{l=1}^{4} \sum_{b} \sum_{(i,j) \in \mathcal{N}_b} \| \mathbf{v}_{ij}^l - \mathbf{r}_{ij}^b \|^2. 
$$

(4)

Here $l$ indexes each corner type/vector field, $b$ indexes the annotated VBs in the patch and $\mathcal{N}_b$ is a neighbourhood surrounding the $l^{th}$ corner of the $b^{th}$ VB annotated in that patch. $\mathbf{v}_{ij}^l$ is the value of the output vector field corresponding to corner $l$ at location $(i,j)$ and $\mathbf{r}_{ij}^b$ is the ground truth value of the vector field, i.e. the displacement vector from the centroid of VB $b$ to location $(i,j)$.

We use heavy augmentation during training including image rotation, rescaling and flipping in the coronal plane. The network is trained using an Adam optimizer with learning rate $10^{-3}$ with parameters $\beta = (0.9, 0.999)$.

### 4.4.2 VB Labelling

The labelling pipeline requires both the appearance and context networks to be trained which is done separately as follows: Firstly a volume is extracted around each annotated VB. This is done by tightly fitting a bounding cuboid around each detection and then expanding the box by 50% in each direction to capture nearby anatomical structures. The resulting volume is the resampled to a size of $224 \times 224 \times 16$ voxels (isotropically in the axial and coronal planes but not in the sagittal plane). These volumes are then given as input to the appearance network which attempt to classify the vertebra from S1 to C3 in a 23-way classification problem. This network is trained on OWS only using a standard cross-entropy loss.

The context network is also trained on OWS. Input height-probability maps are constructed such that for a given VB with detected from height $y_a$ to $y_b$, with centroid at $y_c = \frac{y_a + y_b}{2}$, the height-probability map $P$ has the same value as the temperature-softmaxed ($T=0.1$) predictions from the appearance network from height $y_c - 0.5 \times (y_b - y_a)$ to $y_c + 0.5 \times (y_b - y_a)$. The context network is an image-to-image translation network which takes $P$ as input and then outputs a refined version of $P$, denoted $P'$. $P'$ is then decoded.
into a discrete series of predictions at the height of each VB detection using a beam search. A visual representation of this process is shown in Figure 5. As an augmentation during training each vertebra detection is dropped from \( P \) with probability 0.1. A loss function is still applied to the predictions at height of the missing detection, on the basis that the model should be able to infer the vertebra’s level from the surrounding detections. Both the appearance and context networks are trained using an Adam optimizer with learning rate \( 10^{-3} \) with parameters \( \beta = (0.9, 0.999) \).

4.4.3 Radiological Grading of Degeneration Changes

The grading network is trained on the radiologist-labelled IVDs from the Genodisc dataset from S1-L5 to L1-T12. The model consists of a feature-extracting backbone that encodes each IVD as a 512-dimensional vector, followed by 8 2-layer MLP projection heads, each of which produces predictions for a different grading task. Each of grading task is highly imbalanced in Genodisc and hence a balanced cross entropy loss is used in all cases. During training, augmentation is applied by jittering, rotating, flipping and increasing/reducing the brightness and contrast of each IVD by \( \pm 10\% \). In 50\% of the training cases a random gaussian noise of 10\% is also added. The entire model is trained end-to-end until 10 consecutive validation epochs do not yield an improvement in averaged balanced accuracy. This is done using an Adam optimizer with learning rate \( 10^{-4} \) with parameters \( \beta = (0.9, 0.999) \). Once this is completed, the feature-extraction backbone is frozen and the task-specific projections heads are then trained individually with a learning rate of \( 10^{-5} \), until 10 consecutive validation epochs do not yield improved accuracy for that specific grading task. The results of this training, along with those of the labelling and context networks, are given in the following Section.

5 Results

This section details experimental results from validating the output of the detection, labelling and grading pipelines on withheld data.

5.1 VB Detection and Labelling

The detection and labelling stages of SpineNetV2 are trained on the training splits of Genodisc and OWS. Here, we present results of the labelling and grading pipelines on the test splits from that dataset, as well as on a publically available dataset published by Zukić et al. [16], distributed on SpineWeb[2]. These results are from our initial paper on the method used to detect and label vertebrae used in SpineNet [14].
**Evaluation:** For the detection stage of the pipeline we report the precision and recall of the VB detector. Following [9], we define correct detections to be when the ground truth vertebra centroid is contained entirely within a single detected bounding quadrilateral. For the labelling stage, we report the identification rate (IDR). To be correctly identified, a vertebra must be both detected and assigned the correct level by the labelling stage.

| Dataset (Spine) | Scans | Verts | Method | Prec. (%) | Rec. (%) | IDR (%) | IDR±1 (%) | LE (mm) |
|----------------|-------|-------|--------|-----------|----------|---------|-----------|---------|
| OWS            | 37    | 888   | Windsor† [13] | 99.4 | 99.4 | - | - | 1.0 ± 0.9 |
|                |       |       | Label Baseline | - | - | 88.9 | 93.4 | - |
|                |       |       | Ours | 99.0 | 98.1 | 96.5 | 97.3 | 2.4 ± 1.3 |
| Genodisc (Lumbar) | 421   | 2947  | Lootus [9] | - | - | 86.9 | - | 3.5 ± 3.3 |
|                |       |       | Label Baseline | - | - | 90.1 | 97.4 | - |
|                |       |       | Ours | 99.7 | 99.7 | 98.4 | 99.7 | 1.6 ± 1.1 |
| Zukić (Lumbar) | 17    | 154   | Zukić [16] | 98.7 | 92.9 | - | - | 1.6 ± 0.8 |
|                |       |       | Label Baseline | - | - | 87.0 | 94.3 | - |
|                |       |       | Ours | 99.3 | 98.7 | 90.9 | 98.7 | 2.0 ± 1.5 |

Table 2: Performance of the detection and labelling pipeline on the three datasets. Our approach is compared with other methods using the same datasets and also a LSTM labelling baseline, reported on a per-vertebra level. We also report the percentage of vertebrae within one level of their ground truth value (IDR±1). Lootus [9] is tested on a subset of 291 scans from the Genodisc dataset. Note, Windsor† [13] requires manual initialization by providing the location of the S1 vertebra, so is not directly comparable.

**Baselines:** For each of the three datasets used to assess detection and labelling, we compare to pre-existing methods reporting results on the same dataset. For OWS, we use the method outlined in [13] which detects vertebrae sequentially moving up the spine, starting from S1. It should be noted that this algorithm requires the location of S1 to be known, and is therefore not directly comparable to the our method in that it is only semi-automated. For Genodisc, we compare to results reported in [9], which detects and labels vertebrae using a HOG-template based method in combination with a graphical model. Finally, for the Zukić dataset, we compare to the results reported in the initial paper. It should be noted that several other methods have been proposed to perform vertebra detection and labelling in MRI scan (e.g. [1,3,4,15]). However, these methods do not have publicly available datasets, and thus direct comparison is not possible. To motivate the use of a fully-convolutional context network as opposed to a more standard recurrent network, we also train a bi-directional LSTM labelling baseline. This baseline takes features extracted from each vertebra by the appearance network as a baseline, and outputs a label for each vertebra as output.
5.2 Radiological Grading

This section evaluates SpineNetV2’s agreement with an expert radiologist on withheld data from the Genodisc Dataset. Table 3 compares SpineNetV1 and V2 across all V1 tasks (Pfirrmann, Disc Narrowing, Endplate Defects, Marrow Changes, Spondylolisthesis and Binary Central Canal Stenosis). It also reports results for new grading tasks added in V2, namely 4-class central canal stenosis grading, foraminal stenosis grading, and disc herniation. In all cases the balanced accuracy is reported.

| Task               | Pfirrmann | Disc Narrowing Upper | Disc Narrowing Lower | Endplate Defect Upper | Endplate Defect Lower | Marrow Change Upper | Marrow Change Lower |
|--------------------|-----------|----------------------|----------------------|-----------------------|-----------------------|---------------------|---------------------|
| # Classes          | 5         | 4                    | 2                    | 2                     | 2                     | 2                   | 2                   |
| SpineNet V1        | 71        | 76.1                 | 82.9                 | 87.8                  | 89.2                  | 88.4                |
| SpineNet V2        | 70.9      | 76.3                 | 84.9                 | 89.6                  | 88.9                  | 88.2                |

Table 3: Grading results for withheld data from the Genodisc dataset. It should be noted that SpineNetV2 does not have a separate head for binary central canal stenosis, and instead concatenates together predictions from the multiclass central canal stenosis projection head.

As can be seen from Table 3, performance of SpineNetV2 closely matches that of SpineNetV1 in all tasks. The major changes are the addition of the 4-class central canal stenosis, foraminal stenosis grading, and disc herniation.

5.3 Processing Speed

For application in real-world scenarios, SpineNetV2 needs to be as fast as possible. Here we report the inference time of SpineNetV2 with and without a GPU on lumbar and whole spine scans. We also report the peak memory usage during processing. For a lumbar scan, vertebrae detection and labelling takes approximately 2 seconds and grading takes 1 second, whereas for a whole spine scan, detection and labelling takes approximately 5 seconds on a GPU. Peak GPU memory usage is 1.6GB for a lumbar scan, and 2.5GB for a whole spine scan. On a CPU, lumbar detection and labelling takes 25 seconds, with grading taking 4 seconds. For a whole spine scan, VB detection and labelling takes 2 minutes on a CPU. This is because the scan is split into multiple patches, each of which is ingested separately by the VFR model. This could likely be reduced significantly by changing the patch-splitting strategy to use cover larger areas with smaller overlaps. These results are summarized in Table 4.
| Task Name                  | Scan Type   | Processing Time (s) |   |
|---------------------------|-------------|---------------------|---|
|                           |             | GPU     | CPU |
| VB Detection & Labelling  | Lumbar      | 3        | 25  |
| VB Detection & Labelling  | Whole Spine | 5        | 120 |
| IVV Radiological Grading  | Lumbar      | 1        | 4   |

Table 4: Processing speed of SpineNetV2 on lumbar and whole spine scans. Note that, in all cases, SpineNetV2 is much faster than V1 which takes several minutes to perform detection and grading on a single lumbar scan using a GPU.

Figure 8: Example VB detections for a variety of fields of view.

5.4 Example Qualitative Results

Figure 8 shows example results from the detection pipeline. Example results from the grading pipeline for healthy and pathological scans can be seen at http://zeus.robots.ox.ac.uk/spinenet2/demo.html.

5.5 Online Demo

A demo version of the SpineNetV2 software for T2-weighted lumbar MRIs is available online at http://zeus.robots.ox.ac.uk/spinenet2/. This demo takes as input zipped sagittal slices as DICOMs and outputs a CSV or JSON containing the grading results, depending on preference. Cached results for publically available online samples can be found on this website. These are shown in Figure 9. If you want try the demo software on your own scans please use the contact information provided on the website to be
given access. Input scans are not stored after processing, however should be anonymised prior to submission. Furthermore, please note SpineNetV2 is still a research tool and should not be used for clinical purposes.

6 Conclusions

This technical report describes SpineNetV2, a deep learning framework for detecting and labelling vertebrae in clinical spinal MR scans and to perform radiological grading in T2-weighted scans. We describe the methods used to in each step of the pipeline, as well as the software architecture and datasets for training the constituent neural networks. We also give experimental results for both VB detection and labelling and radiological grading on unseen test data.

SpineNetV2 is an ongoing project. As such we are always looking to validate the existing functionality of SpineNetV2, as well as extend its functionality to new tasks and applications. If you would like to use SpineNetV2 in your own research, or have any questions, please contact us via email: {rhydian,amir}@robots.ox.ac.uk.

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(a) Example healthy spine (radiopedia.org rID:33543, Courtesy: A.F. Galliard).

(b) An example spine with degenerative changes (radiopedia.org rID:56636, Courtesy: H. Knipe)

Figure 9: Outputs from the online web demo for two example lumbar MRIs. Results such as these can be exported in both CSV and JSON format.
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