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IVRA INTERNATIONAL VETERINARY RADIOLOGY ASSOCIATION

EVDI European Veterinary Diagnostic Imaging

O-2.14: AUTOMATIC DETECTION OF BODY AREAS IN CANINE COMPUTED TOMOGRAPHY (CT) USING ARTIFICIAL INTELLIGENCE (AI)

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Introduction

Collaborative endeavour: VetCT + University of Cambridge (Dpt of Applied Mathematics)
3 months Internship funded by VetCT, through Cambridge Mathematics Placement program (CMP)

University of Cambridge

- Experience in machine learning
- Team of computer scientists (2 interns in mathematics + senior research associate)

VetCT

- Clinical expertise
- Diagnostic images (CT) dataset, IT infrastructure
- Interpretation of outputs

UNIVERSITY OF CAMBRIDGE

VETCT
Teleradiology | Teleconsulting | Education

Introduction

- **Background** :
  - Multiple body areas (BA) CT commonly submitted for interpretation
  - Some of the BA acquired not always necessary for the diagnosis
  - Need to standardise and provide tools to help Vets to recognise anatomy
  - Lack of reliable AI tools in Veterinary CT
- **Objective** : Develop a prototype AI algorithm capable of recognizing body areas in CT
- **Significance** :
  - Provide practical tools to Vets to improve imaging workflows
  - AI developments should start with basic applications

Methods – study design

- Study design: Retrospective study
- Data sources:
  - 160 CT of adult Jack Russel Terrier from VetCT database
  - Normal CT reviewed by 1x DipECVDI
  - Good to excellent imaging quality (scores 4&5 out of 5)
  - Anonymised using OsiriX DICOM viewer
  - Extracted subset of 5 body areas

Body area	Head	Thorax	Abdomen	Pelvis	Spine
# studies	26	26	30	29	16

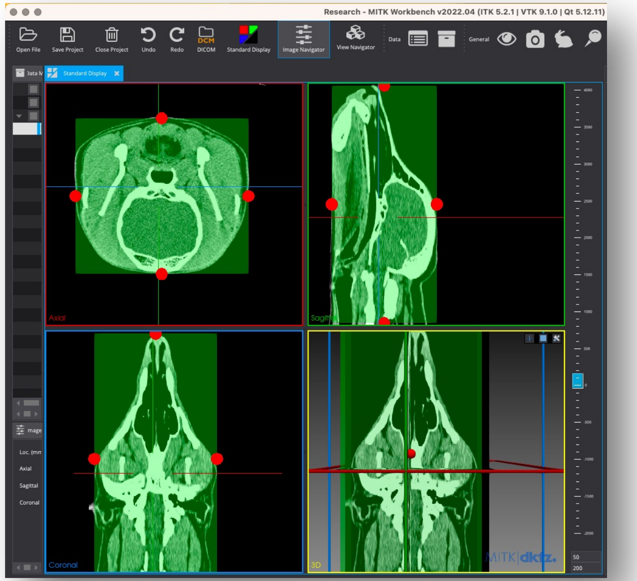
Methods - goal

Supervised* Machine Learning Model to detect body areas in CT scans

* supervised: because trained on a labelled dataset

Methods – ground truth and labelling

- Manual curation of data
- Open source : Medical Interaction Toolkit (MITK)
- DICOM import
- Image cropped function to generate 3D bounding box containing the BA
- Export mathematical coordinates and store in a *.mitkgeometry* file



MITK Workbench


```xml
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<GeometryData>
    <Version Writer="/Users/jenkins/jenkins-
agent/MITK/Release/src/MITK/Modules/Core/src/IO/mitkGeometryDataWriterService.cpp"
FileVersion="1"/>
    <ProportionalTimeGeometry NumberOfTimeSteps="1">
        <Geometry3D ImageGeometry="true" FrameOfReferenceID="0" TimeStep="0">
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z="-217.51499999999999"/>
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                <Min type="Vector3D" x="122.99999999999983" y="136.00000000000045"
z="65"/>
                <Max type="Vector3D" x="411.00000000000011" y="422.00000000000063"
z="332"/>
            </Bounds>
        </Geometry3D>
    </ProportionalTimeGeometry>
</GeometryData>
```
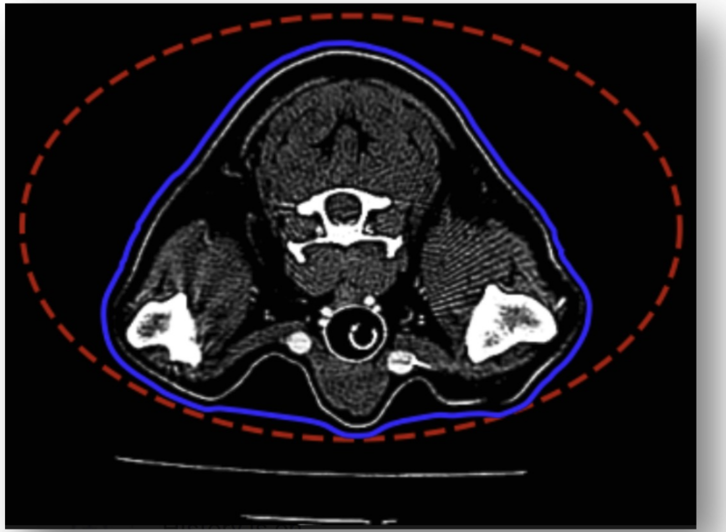


Mathematical coordinates

Methods – data pre-processing

- AI Model perform better if **images are normalised** before training
  - Convert DICOM data into HU units, saved in a 3D array
  - All images normalised to scale with real-world distances
  - Convert images to PNG and apply a HU clip (0 – 255)
  - Morphological closing to remove image noise

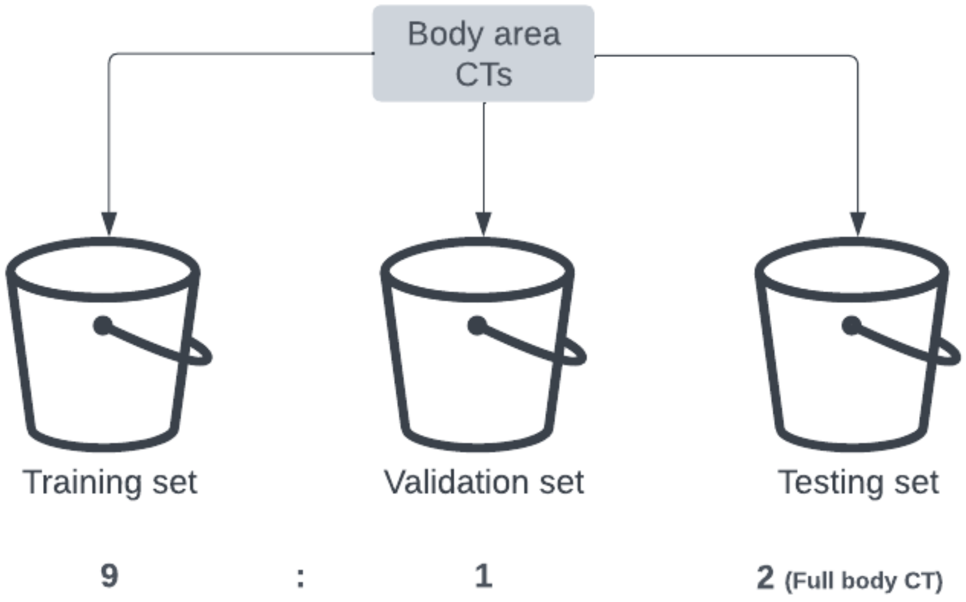
- Generate **tighter bounding boxes** around each BA
  - Interns created the program called [*auto.py]*
  - Apply an active-contour function to the shape in the bounding box
  - “Snake enclosing” the main body area



$$E = E_{\text{Int}} + E_{\text{Image}}$$

Methods – data partition

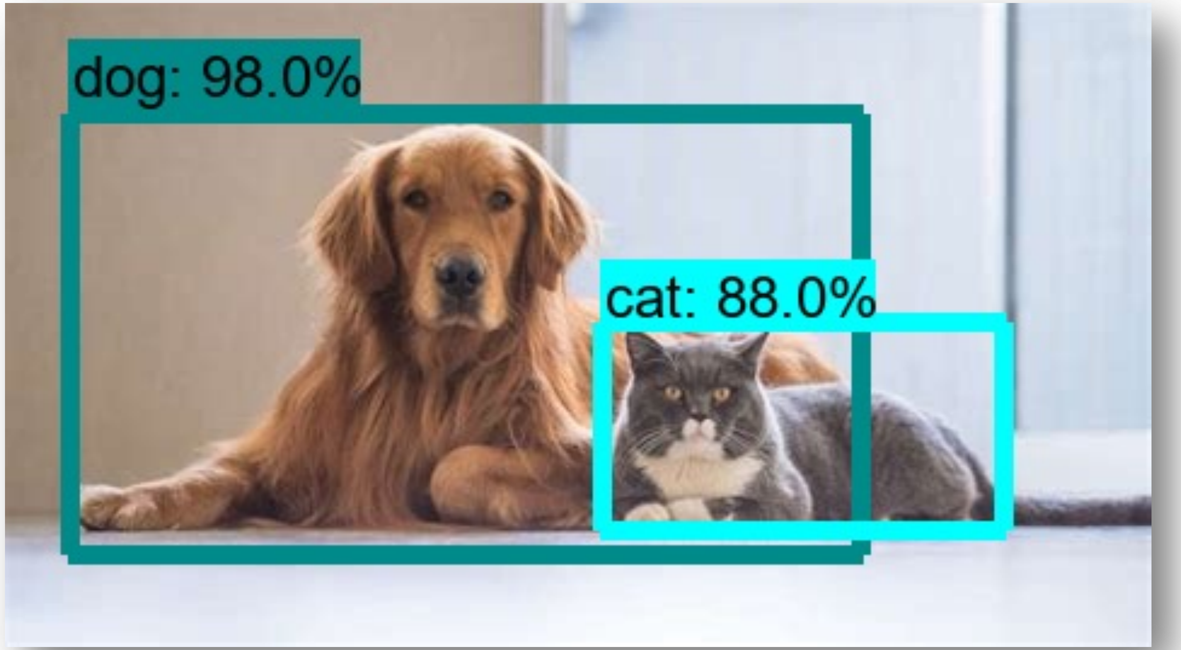
- For each BA, CTs distributed in 3 different datasets (google drive "buckets")
- Each dataset disjoint at patient level to avoid data leakage
- Ratio of CTs used for training and validation sets was 9 : 1
- 2 full body scans for testing set that the model has never seen



Methods – model training

YOLOv5

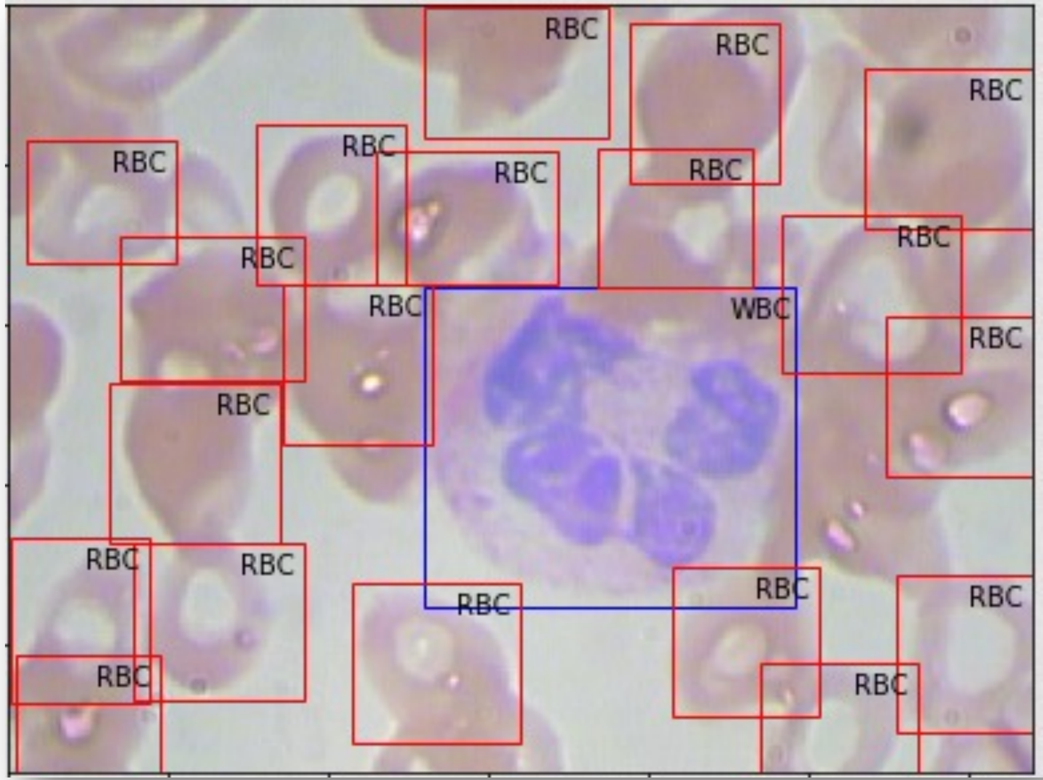
- AI model used is a neural network called YOLOv5 (version 5)
- YOLO [You Only Look Once] real time object detection algorithm used in images / videos
- Draw a bounding box and assign a probability that the object detected is correct



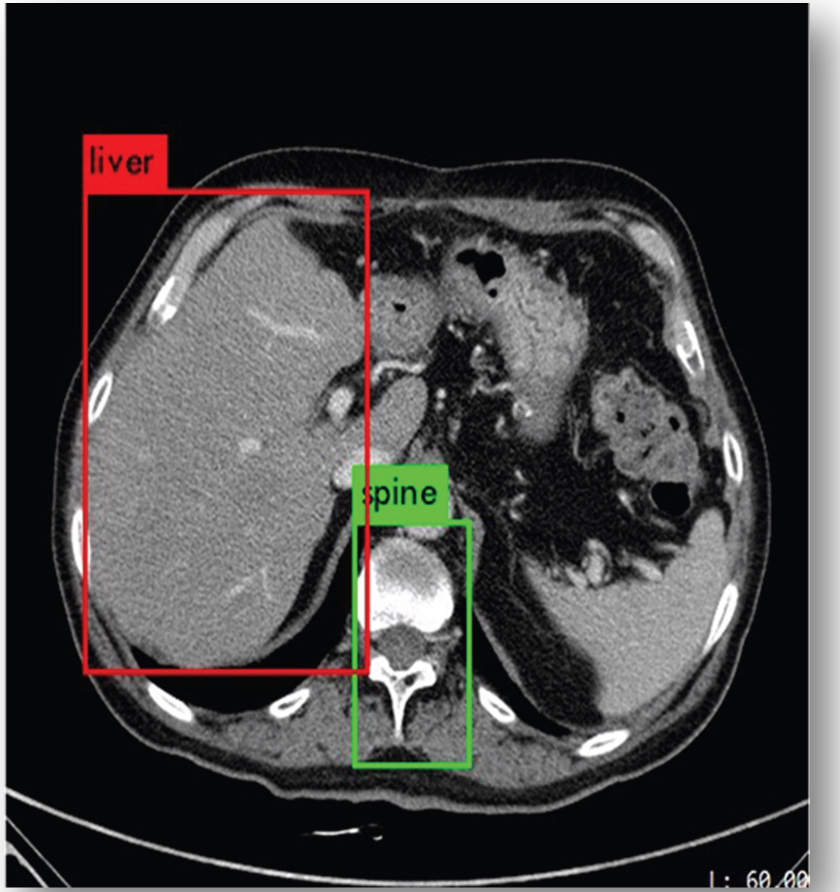
Object Detection using Region-based Convolutional Neural Network (RCNN). (2019, September 23). OpenGenus IQ: Computing Expertise & Legacy. https://iq.opengenus.org/object-detection-using-r-cnn/

Methods – model training

- Human medicine



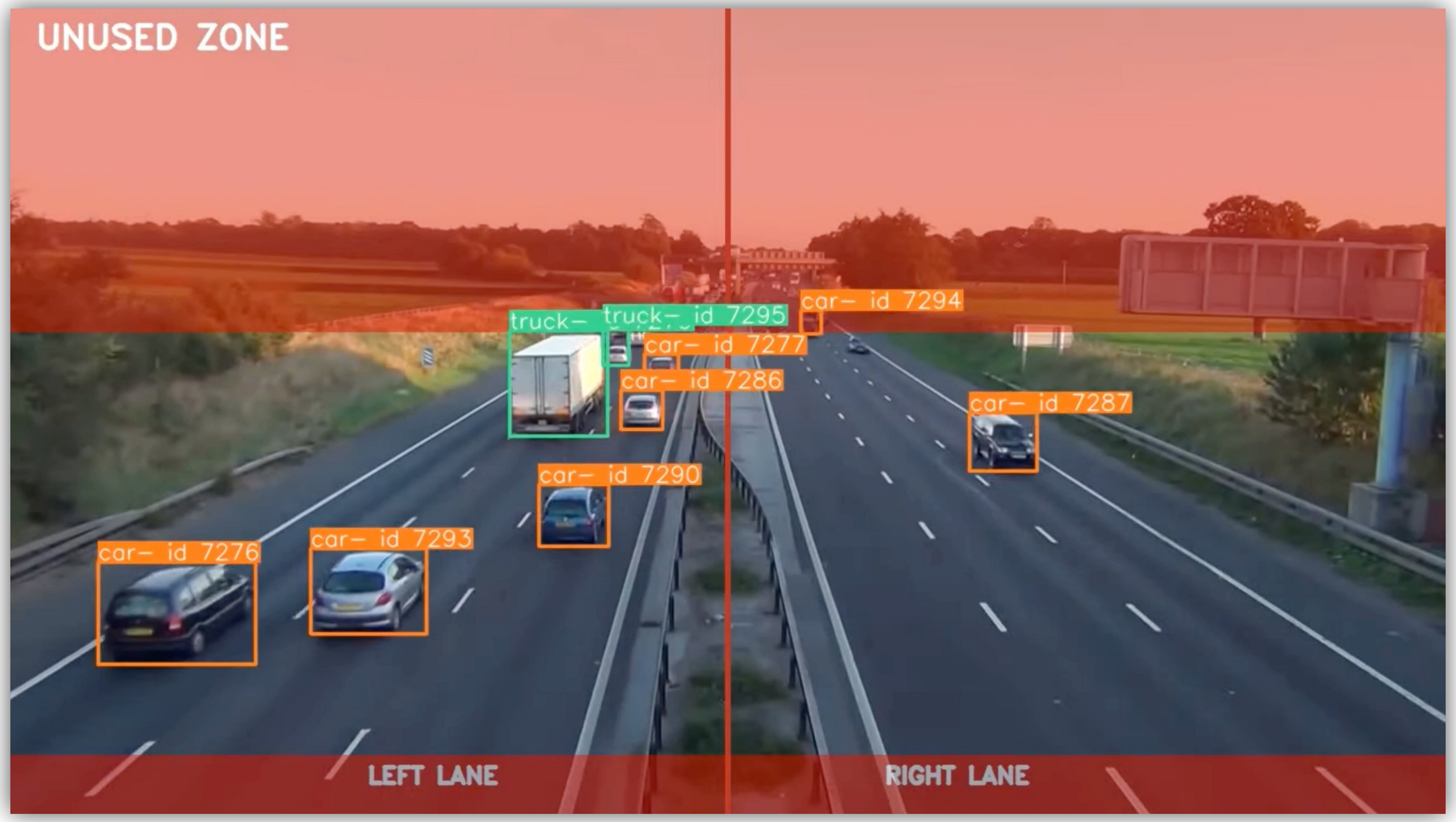
Yolo-v5 Object Detection on a custom dataset. Shanchen P. et al; PLOS ONE. (2020, August 16). https://doi.org/10.1371/journal.pone.0217647



A novel YOLOv3-arch model for identifying cholelithiasis and classifying gallstones on CT images. Pang, S et al. *PLOS ONE*, (2019, June 19). https://doi.org/10.1371/journal.pone.0217647

Methods – model training

- Traffic surveillance, self driving cars



Vehicle tracking / Traffic monitoring yolov5+deepsort. Công Nhã Dương (Director). (2022, January 21). https://www.youtube.com/watch?v=TCc3Agqb8Tg

Methods – model training

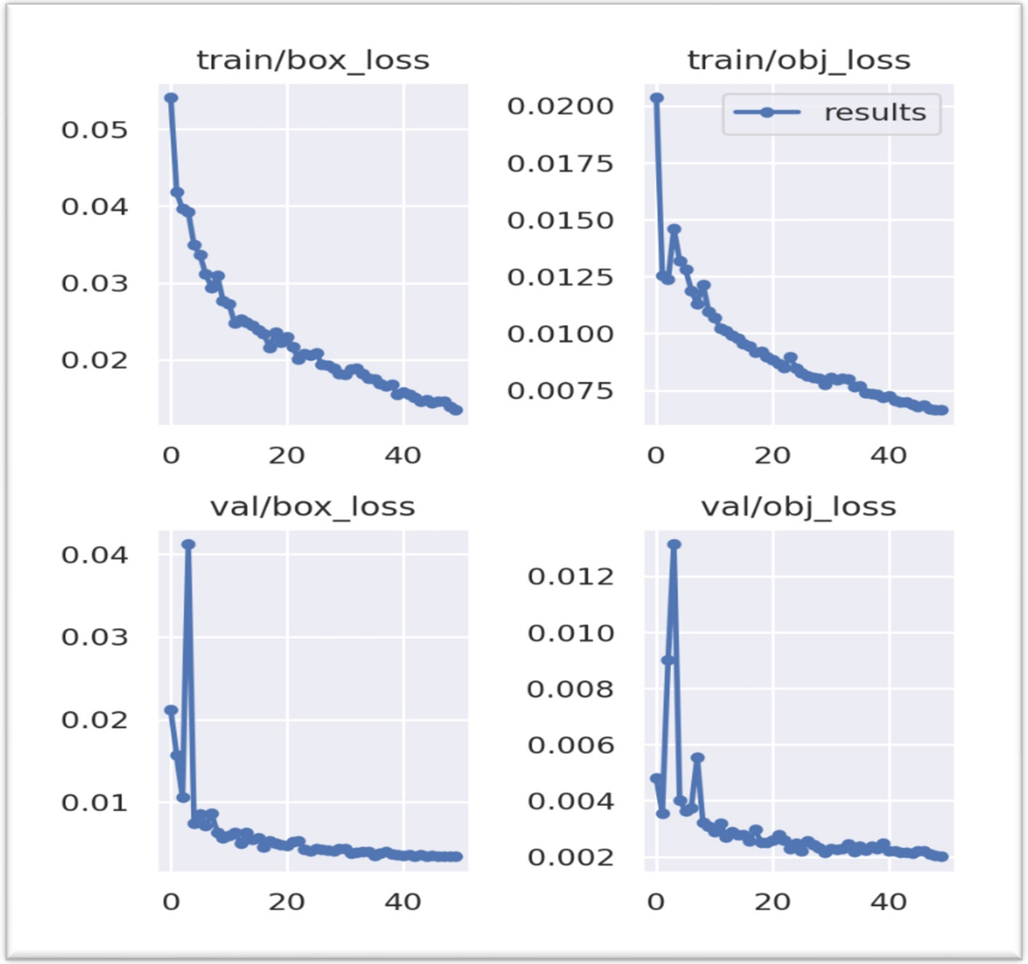
- YOLOv5* with default parameters
- Graphics Processing Units (GPUs) provided by Google Colab Pro+
- Model trained using transverse planes
- 50 to 100 epochs (iterations)
- 300 minutes approx. for training completion for each body areas

* Open source: Jocher, G. (2020). *YOLOv5 by Ultralytics* (7.0) [Python] - Github. https://github.com/ultralytics/yolov5

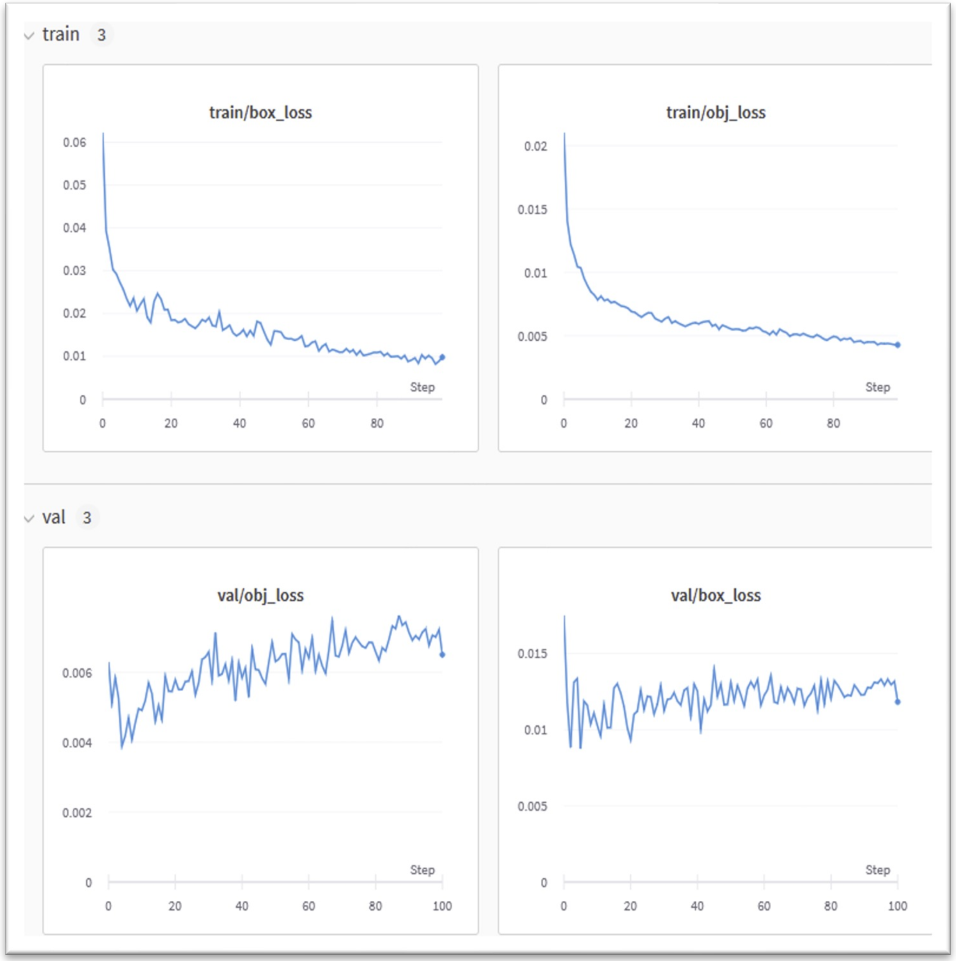
Results – training and validating

Body area	Model convergence	Model precision	Model recall / sensitivity	Image confidence score (approx.)
Head (26)	**Excellent**	**1**	**1**	**0.95**
Thorax (26)	Average	< 1	< 1	0.85
Abdomen (30)	Average	< 1	< 1	0.8
Pelvis (29)	Poor	<1	< 1	< 0.5
Spine (16)	Poor	<1	< 1	< 0.5

Results - performance metrics



HEAD: convergence



SPINE: NO convergence

Results - HEAD

Cineloop: Head CT scan

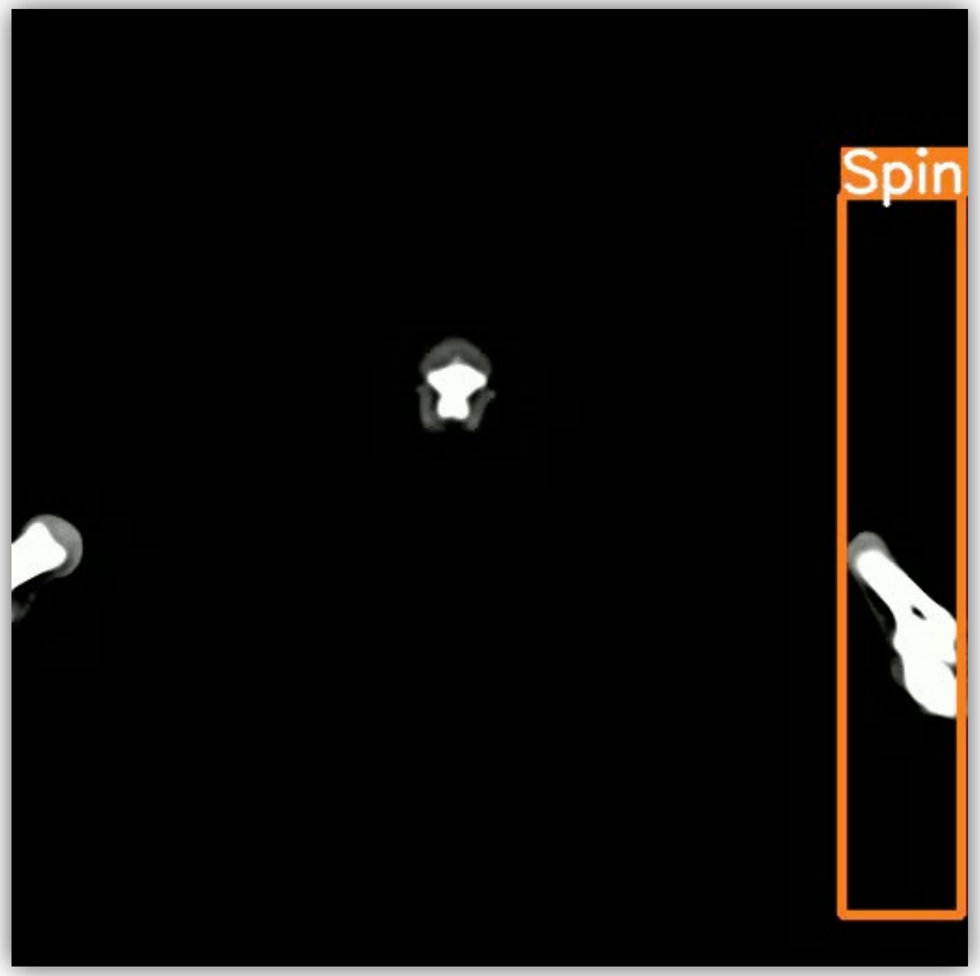
Transverse plane

Data: Test partition

Class label: HEAD

Confidence score: 0.95

Results – SPINE – performance metrics



Cineloop: Spine CT scan

Transverse plane

Data: Test partition

Class label: SPINE

Confidence score: < 0.5

Discussion / Conclusion

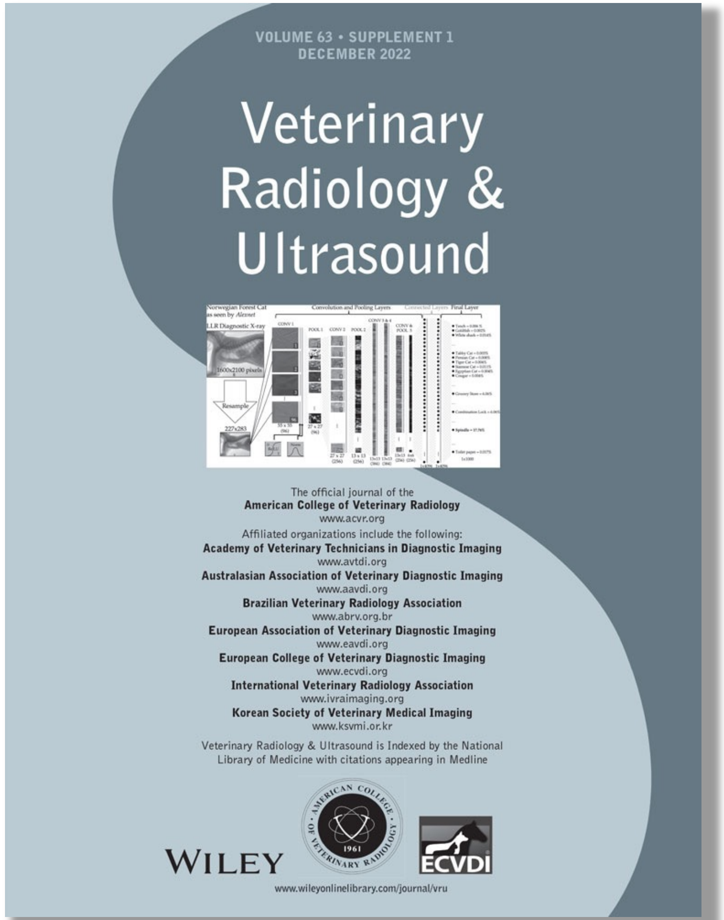
- Confirmed feasibility of training AI model using VetCT dataset
  - Excellent results for the Head
  - Still learnings for other body areas!

- Limitations
  - Overlapping body areas, the neural network requires more complexity
  - Small dataset only including normal
  - Data labelling is time consuming and should find ways to automate this

Discussion / Conclusion

- Future directions
  - This is a prototype, a proof of concept!
  - Evaluate the effect of pre & post contrast studies
  - Experiment with other object detection model such as **U-Net**
  - Use semi-supervised/unsupervised learning methods
  - Assess generalisability of the tool

Bibliography



Radiology: Artificial Intelligence

EDITORIAL

Checklist for Artificial Intelligence in Medical Imaging (CLAIM): A Guide for Authors and Reviewers

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Conflicts of interest are listed at the end of this article.

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The advent of deep neural networks as a new artificial intelligence (AI) technique has engendered a large number of medical applications, particularly in medical imaging. Such applications of AI must remain grounded in the fundamental tenets of science and scientific publication (1). Scientific results must be reproducible, and a scientific publication must describe the authors' work in sufficient detail to enable readers to determine the rigor, quality, and generalizability of the work, and potentially to reproduce the work's results. A number of valuable manuscript checklists have come into widespread use, including the Standards for Reporting of Diagnostic Accuracy Studies (STARD) (2–5), Strengthening the Reporting of Observational studies in Epidemiology (STROBE) (6), and Consolidated Standards of Reporting Trials (CONSORT) (7,8). A radiomics quality score has been proposed to assess the quality of radiomics studies (9).

Peer-reviewed medical journals have an opportunity to connect innovations in AI to clinical practice through rigorous validation (10). Various guidelines for reporting evaluation of machine learning models have been proposed (11–14). We have sought to codify these into a checklist in a format concordant with the EQUATOR Network guidelines (15,16) that also incorporates general manuscript review criteria (17,18).

To aid authors and reviewers of AI manuscripts in medical imaging, we propose CLAIM, the Checklist for AI in Medical Imaging (see Table and downloadable Word document [supplement]). CLAIM is modeled after the STARD guideline and has been extended to address applications of AI in medical imaging that include classification, image reconstruction, text analysis, and workflow optimization. The elements described here should be viewed as a "best practice" to guide authors in presenting their research. The text below amplifies the checklist with greater detail.

Manuscript Title and Abstract

Item 1. Indicate the use of the AI techniques—such as "deep learning" or "random forests"—in the article's title and/or abstract; use judgment regarding the level of specificity.

Item 2. The abstract should present a structured summary of the study's design, methods, results, and conclusions; it should be understandable without reading the entire manuscript. Provide an overview of the study population (number of patients or examinations, number of images, age and sex distribution). Indicate if the study is prospective or retrospective, and summarize the statistical analysis that was performed. When presenting the results, be sure to include *P* values for any comparisons. Indicate whether the software, data, and/or resulting model are available publicly.

The Introduction

Item 3. Address an important clinical, scientific, or operational issue. Describe the study's rationale, goals, and anticipated impact. Summarize related literature and highlight how the investigation builds upon and differs from that work. Guide readers to understand the context for the study, the underlying science, the assumptions underlying the methodology, and the nuances of the study.

Item 4. Define clearly the clinical or scientific question to be answered; avoid vague statements or descriptions of a process. Limit the chance of post hoc data dredging by specifying the study's hypothesis a priori. Identify a compelling problem to address. The study's objectives and hypothesis will guide sample size calculations and whether the hypothesis will be supported or not.

The Methods Section

Describe the study's methodology in a sufficiently clear and complete manner to enable readers to reproduce the steps described. If a thorough description exceeds the journal's word limits, summarize the work in the Methods section and provide full details in a supplement.

Study Design

Item 5. Indicate if the study is retrospective or prospective. Evaluate predictive models in a prospective setting, if possible.

Item 6. Define the study's goal, such as model creation, exploratory study, feasibility study, or noninferiority trial. For classification systems, state the intended use, such as diagnosis, screening, staging, monitoring, surveillance, prediction, or prognosis (2). Indicate the proposed role of the AI algorithm relative to other approaches, such as triage, replacement, or add-on (2). Describe the type of predictive modeling to be performed, the target of predictions, and how it will solve the clinical or scientific question.

Data

Item 7. State the source of data and indicate how well the data match the intended use of the model. Describe the targeted application of the predictive model to allow

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Veterinary Radiology and Ultrasound. Special issue. Volume 63, Issue S1. (2022, December 1). https://onlinelibrary.wiley.com/toc/17408261/2022/63/S1

Checklist for Artificial Intelligence in Medical Imaging (CLAIM): A Guide for Authors and Reviewers. Mongan, J., Moy, L., & Kahn, C. E. (2020). *Radiology. Artificial Intelligence*, *2*(2) https://doi.org/10.1148/ryai.2020200029

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