Data Science for Speech Therapy
Computer Vision and VFSS

Clinical sharing for continuous education

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Content

Data Science

- Recap
- Computer Vision
  - Image vs video
  - Reading images
  - Reading videos (image task)
  - Reading videos (action task)
  - Learning images (CNN)

Clinical Application

- Current practice
- Use cases
  1. hyoid bone detection
  2. pharyngeal phase
  3. PAS
  4. abnormal swallow
- Strategies to use CV

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Computer Vision

- Data types: more than just spreadsheet

- Visual Data Source
  - Images
  - Videos/ gifs

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Image vs Videos

	Image	Video
Spatial information *(where?)*	Yes	Yes
Temporal information *(when?)*	N.A.	Yes

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Image vs Videos

	Image	Video
Spatial information *(where?)*	Yes	Yes
Common Tasks	Image tasks • Image Classification • Image Detection • Image Generation	
Temporal information *(when?)*	N.A.	Yes
Unique Tasks	Nil	Action tasks • Action recognition

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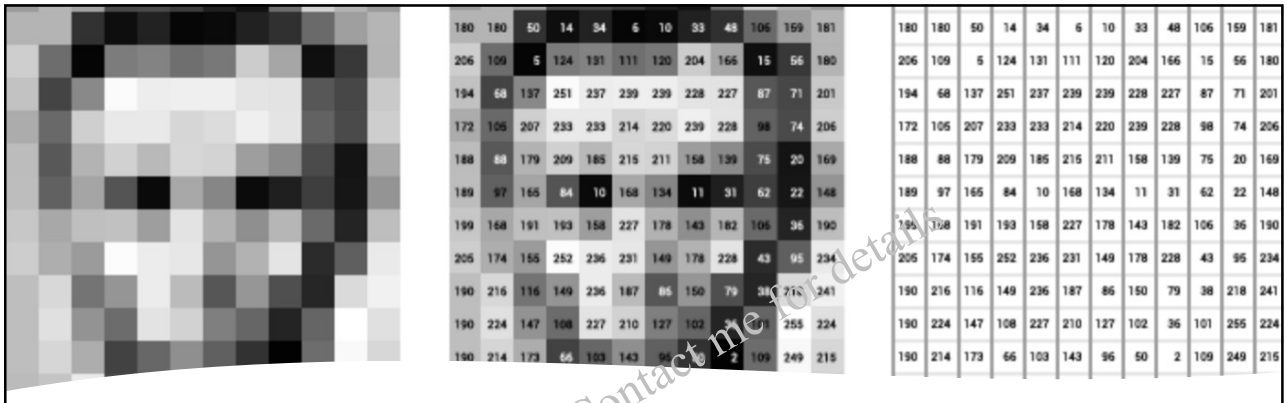

- Image is made of multiple pixels
- Each pixel has an intensity value from 0 (absent colour) – 255

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Importing Videos for image tasks

	Image	Video
Spatial information (where?)	*Yes*	**Yes**
Common Tasks		**Image tasks** • **Image Classification** • **Image Detection** • **Image Generation**
Temporal information (when?)	*N.A.*	*Yes*
Unique Tasks	*Nil*	*Action tasks* • *Action recognition*

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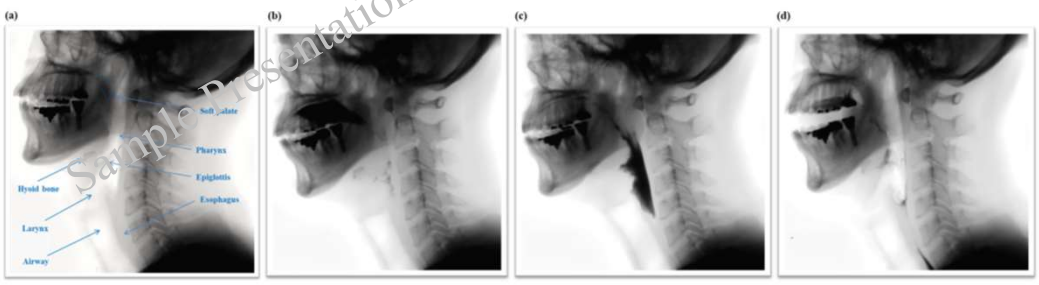
- Multiple image frames in sequence.
- Extract images frames from videos at fixed time intervals.



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Importing Videos for ACTION tasks

	Image	**Video**
Spatial information (where?)	*Yes*	Yes
Common Tasks	*Image tasks* • *Image Classification* • *Image Detection* • *Image Generation*	
Temporal information (when?)	*N.A.*	**Yes**
Unique Tasks	*Nil*	**Action tasks** • **Action recognition**

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Optical flow

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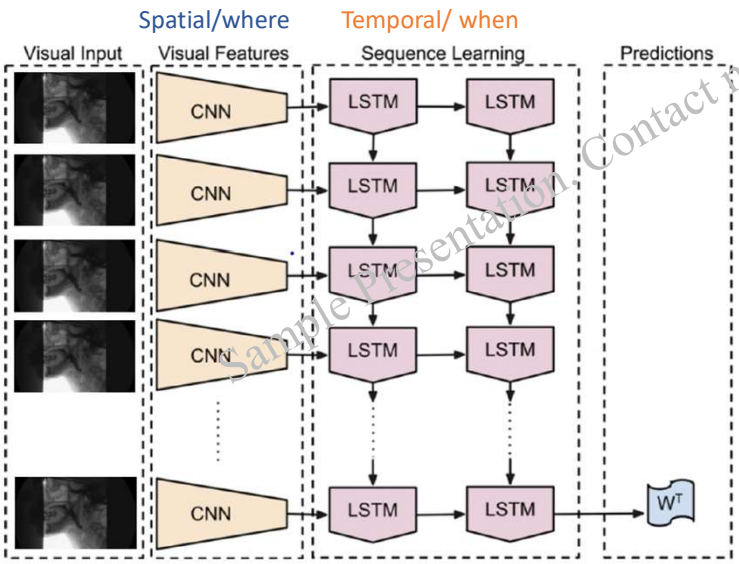
Layering the inputs



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Convolution Neural Network

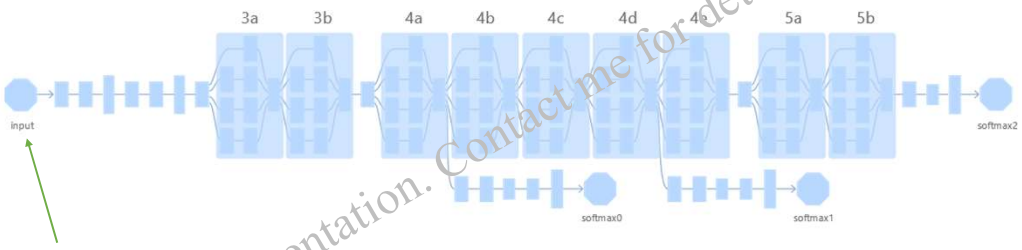

Image is fed into the model.

The image is read as a matrix of numbers (0-255)

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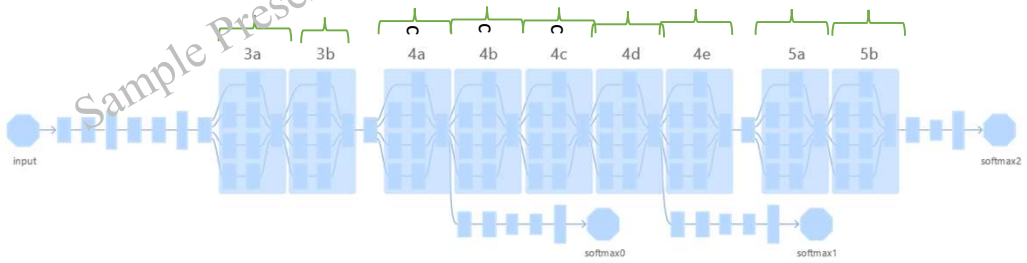
Convolution Neural Network

The image goes through multiple layers of mathematic transformation.

At each layer, the model learns new features of the image.



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Ethical AI

- Need to address blackbox medicine
- How does CNN learn? What is CNN learning?

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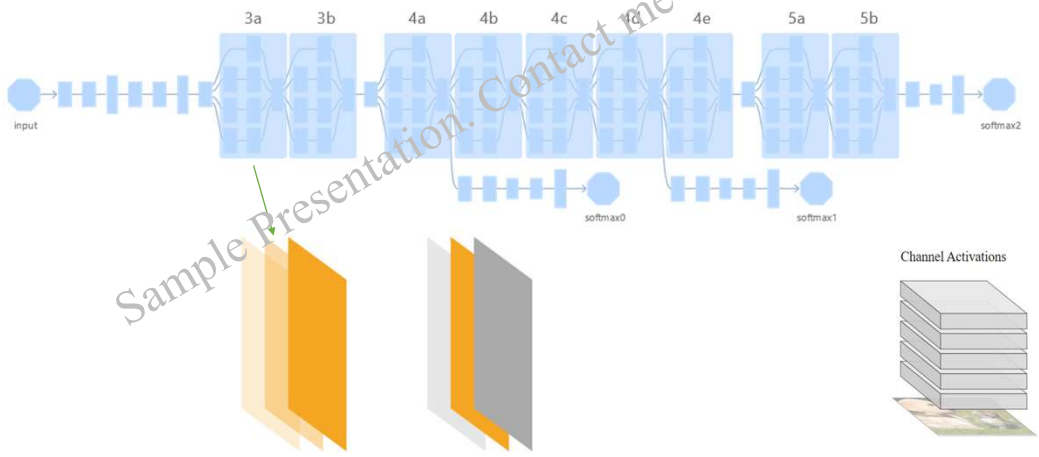
- Output of a layer is not a single image

- Volume of images representing all the different slices in that layer.



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Feature visualization

- Generate a image of what a specific slice in a specific layer is detecting.
- Creating "semantic dictionary"

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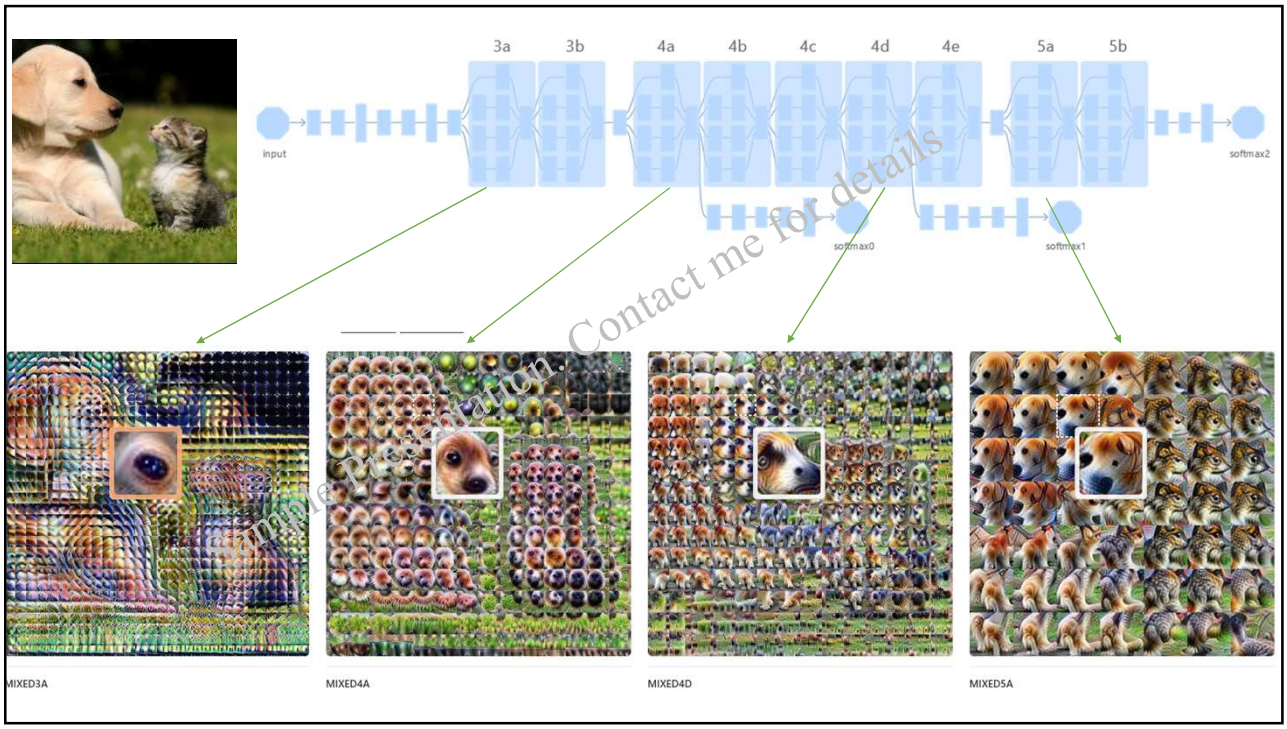

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Current clinical practice

- "Eye" power

- Subjectivity (e.g. extend of hyoid displacement)
- Time consuming

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Current research practice

- Splice VFSS videos
- Annotate area of interest *(demo)*

- Reduced inter and intra-rater reliability

- Some research in using computer assistance
- Still need to annotate inputs on a calibration frame.
- Lack of scalability to operationalize for front end clinical use.

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How modern CV/CNN can help

- Automaticity
- Better accuracy
- Scalability

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Automatic hyoid bone detection in fluoroscopic images using deep learning (2018)

- 265 patients
- 1434 swallows
- 48,000 image frames. (70% train: 30%test)

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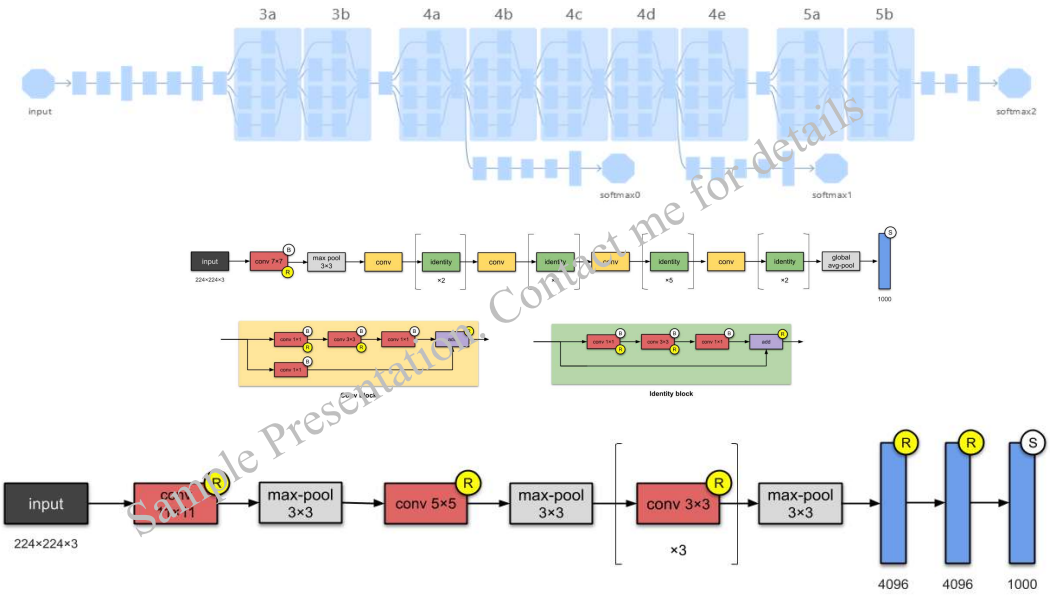

Different CNN architecture

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Clinical findings

Model	Mean average precision
YOLOv2	33.10%
Faster-RCNN + ZF	69.01%
SSD300-VGG	84.37%
SSD300-ResNet	81.92%
SSD500-VGG	89.14%
SSD500-ResNet	89.03%

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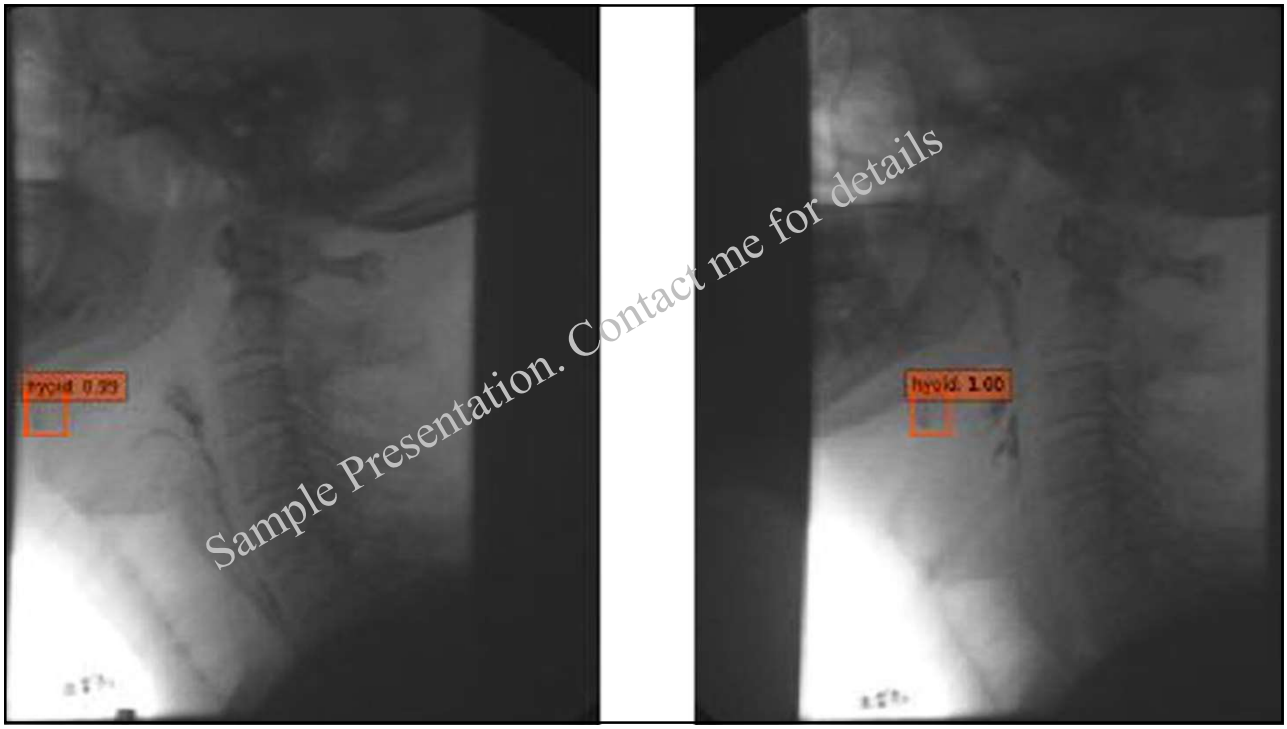

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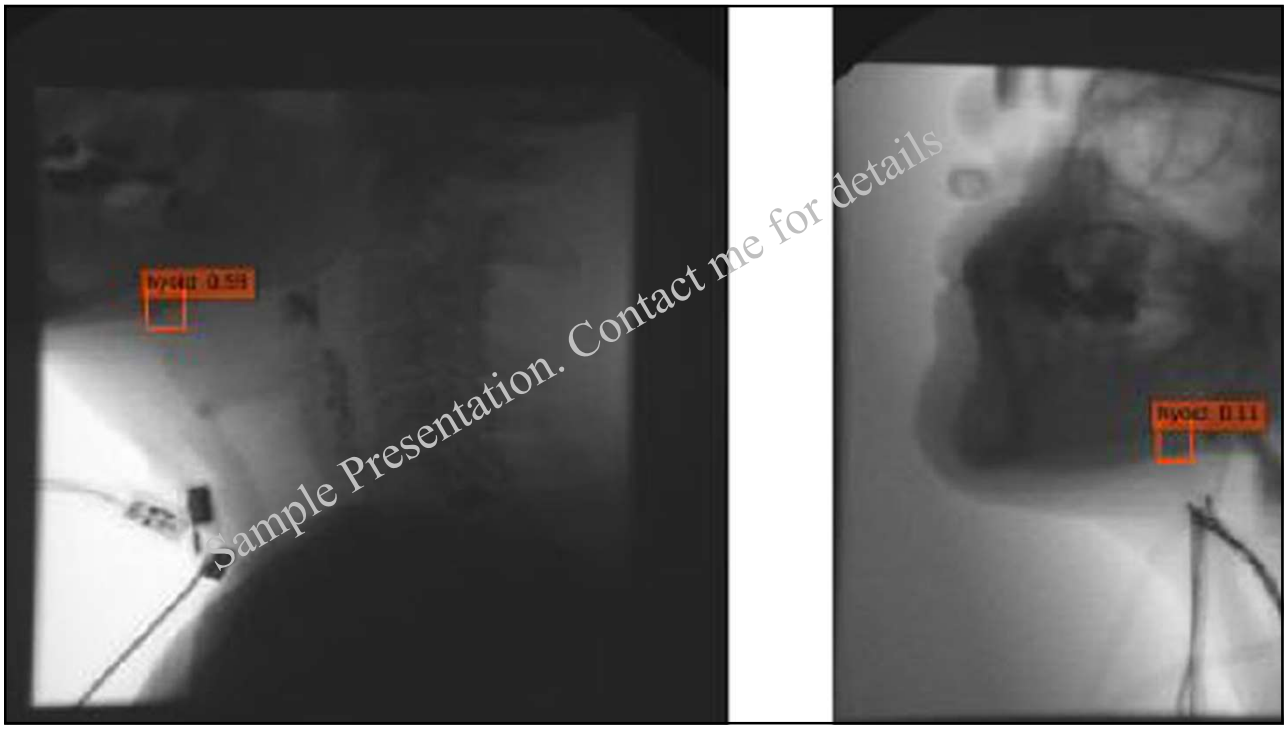

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Potential application

- automatic segmentation of hyoid bone areas
- determine hyoid displacement is disordered
- Is reduced airway protection or reduced UES 2' hyo-laryngeal excursion?

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ML findings

- Radiation dosage
- Model's ability to detect small objects vs computational time

- Unexpected detections
  - Colour boxes are detected hyoid bones

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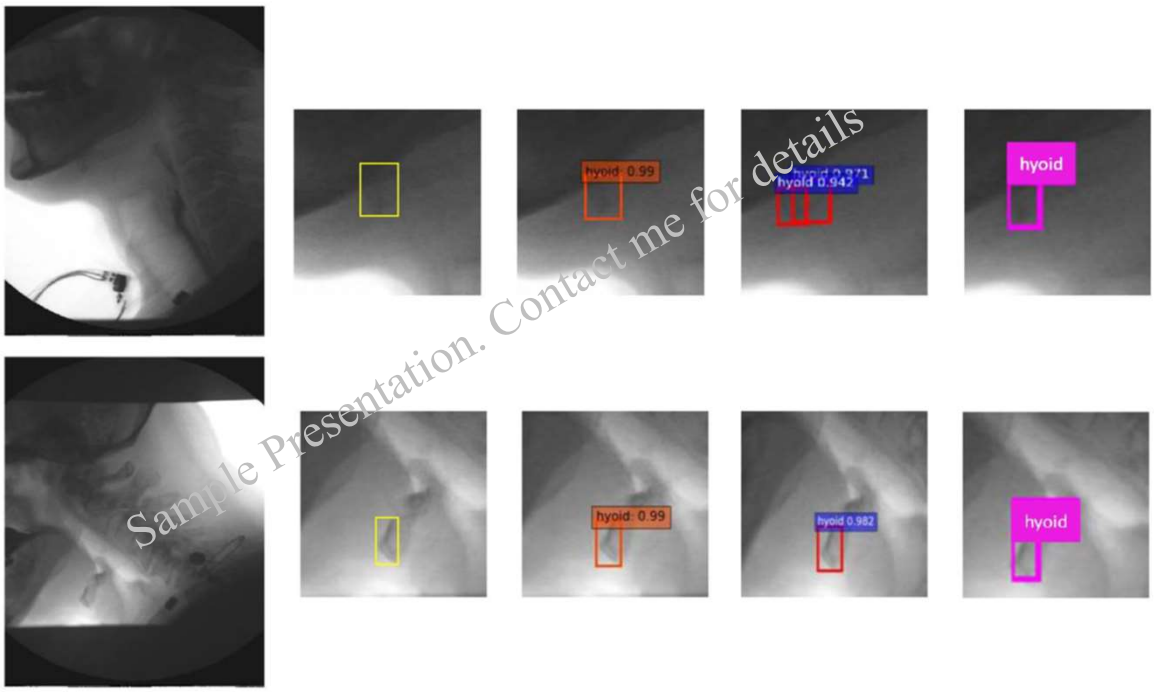

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Automatic Detection of the Pharyngeal Phase in VFSS Using Efficient Data Collection and 3D Convolutional Networks (2019)

- Pharyngeal phase <1s
  - Finding a needle in a haystack

- identifies the pharyngeal phase in VFSS
- without the need for spatial or temporal annotations.

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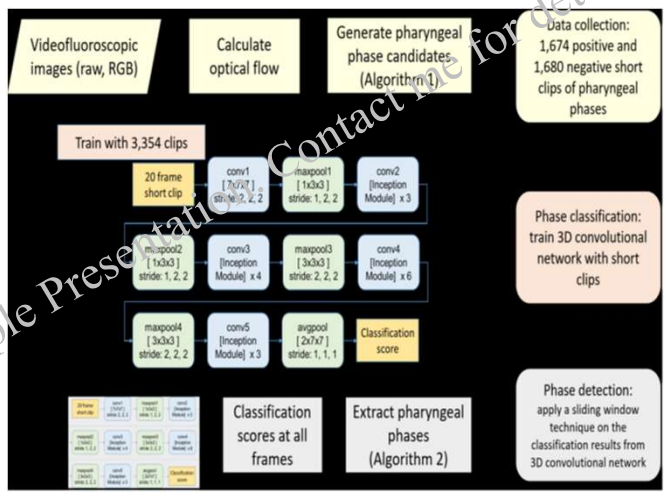
3 stage process



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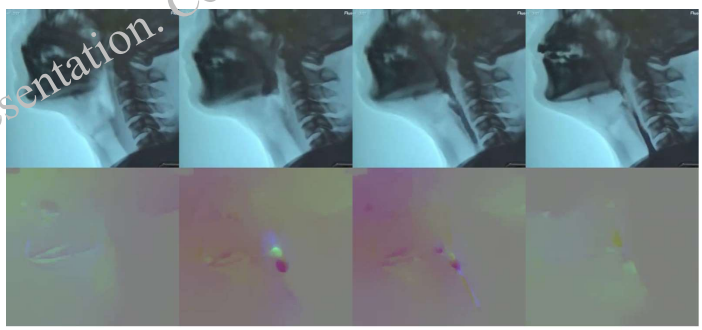
Phase 1

- Models used can be computational taxing
- Screen VFSS video for pharyngeal frames
- Optical flow to detect vertical placement of pixels



(a) Pharyngeal phase

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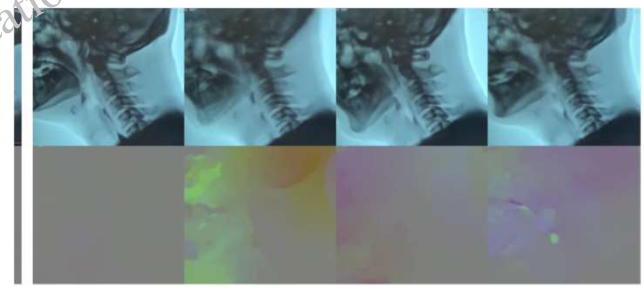
False positive

(a) Pharyngeal phase



(b) Head shaking

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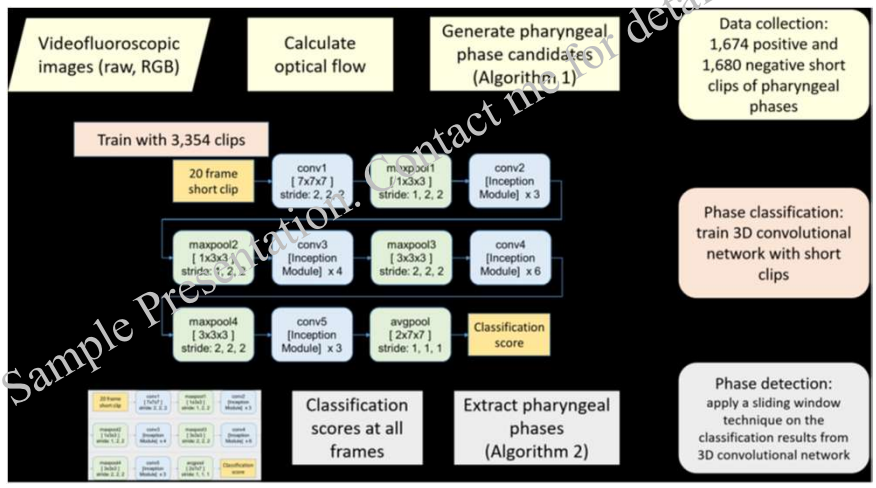
Phase 2-3



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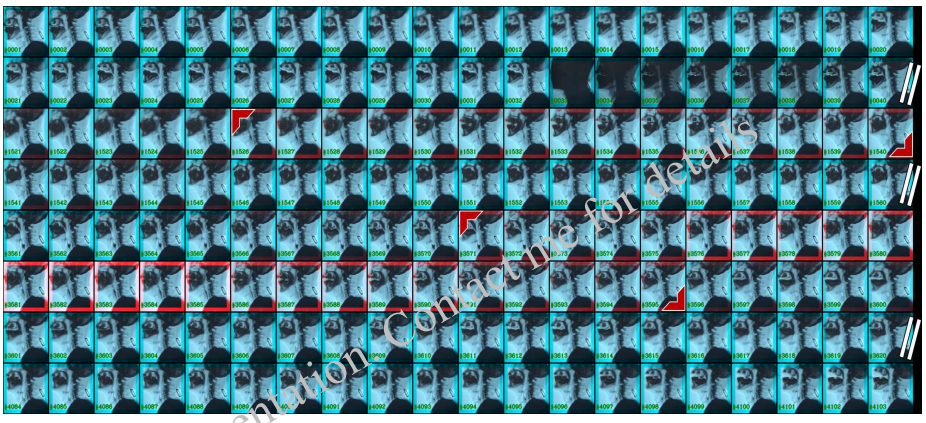

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- Detection Score (F1)
  - 45.73 to 84.25%
- Detection Time Error
  - 1.42s to 3.82s

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Others

- Deep learning based application for videofluoroscopic swallowing study (VFSS): A pilot study (2019)
  - PAS
- A deep learning approach to VFSS exam classification (2020)
  - Abnormal swallow

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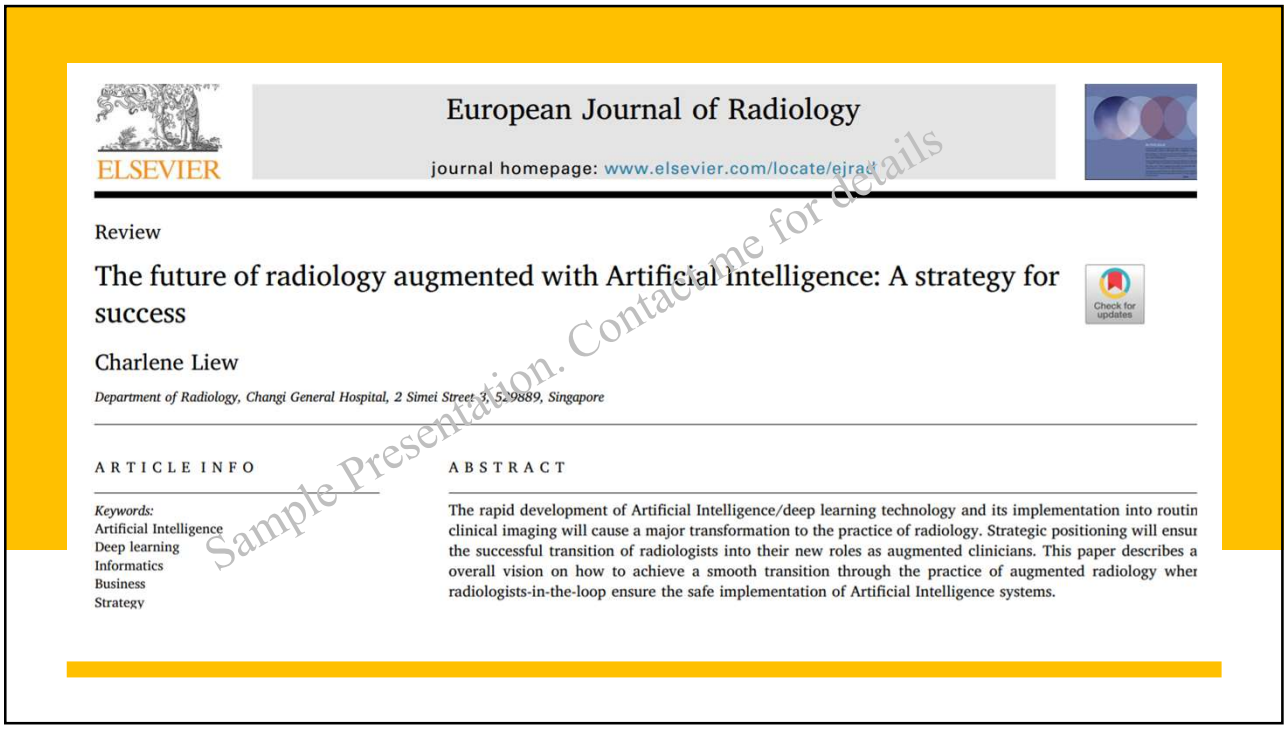

European Journal of Radiology

journal homepage: www.elsevier.com/locate/ejrad

Review

The future of radiology augmented with Artificial Intelligence: A strategy for success

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ARTICLE INFO

Keywords:
Artificial Intelligence
Deep learning
Informatics
Business
Strategy

ABSTRACT

The rapid development of Artificial Intelligence/deep learning technology and its implementation into routin clinical imaging will cause a major transformation to the practice of radiology. Strategic positioning will ensur the successful transition of radiologists into their new roles as augmented clinicians. This paper describes a overall vision on how to achieve a smooth transition through the practice of augmented radiology wher radiologists-in-the-loop ensure the safe implementation of Artificial Intelligence systems.

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The future of radiology augmented with Artificial Intelligence: A strategy for success (2018)

1. Current state and the need for a strategy
2. General use cases, potential impact and implementation strategy
3. Impact upon cost leadership, differentiation and focus
4. Defining roles, technical considerations and requirements for implementation
5. Organizational aspects of implementation
6. Special considerations, job displacement and risk mitigation
7. Safety, privacy, moral and ethical concerns

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