



ATHENS UNIVERSITY
OF ECONOMICS
AND BUSINESS

AUEB NLP Group at ImageCLEFmedical Caption 2023

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You can find out more on our work here: nlp.cs.aueb.gr/















- Diagnostic Captioning
- Task #1: Concept Detection
 - Task Breakdown
 - Methods
- Task #2: Caption Prediction
 - Task Breakdown
 - Methods
- Results & Future Work













Diagnostic Captioning



- Challenging research problem → Helpful <u>only</u> as an <u>assistive</u> tool, <u>not a replacement</u> of the medical staff.
- More experienced clinicians → improve throughput and accuracy.
- Less experienced clinicians → consider the generated medical report & reduce the possibility of a clinical error.

Suggested DL-based pipeline for the diagnosis of a given medical image:

Medical Images Generated report from DL system Doctor considers the

Doctor considers the generated report































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Task #1: Concept Detection



Goal: given a radiology image; predict relevant biomedical concepts → multi-class, multi-label classification task.



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Desired answer from our Diagnostic Captioning deep learning system: C0041618;C0238207;C0030797; C0022646;C0006736;C0549186



This image is associated with the following biomedical concepts: Ultrasonography, Ectopic kidney, Pelvis, Kidney, Calculi, Obstructed









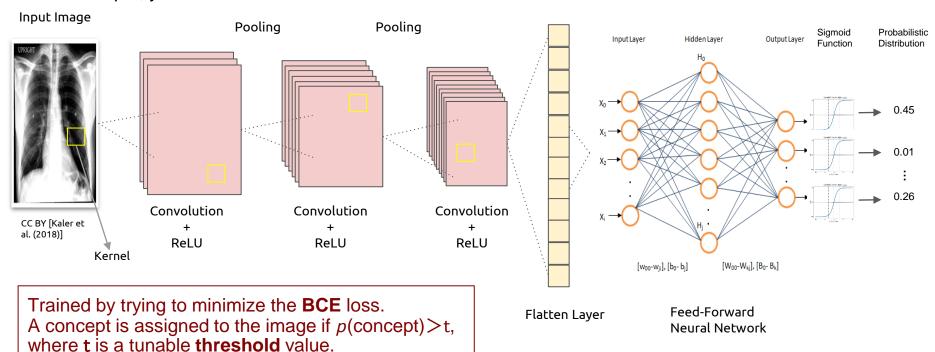




System #1: CNN + FFNN



- CNN: in charge of encoding the image into numeric vectors. FFNN: responsible for yielding a
 probability distribution over the medical concepts.
- Simple, yet effective idea.











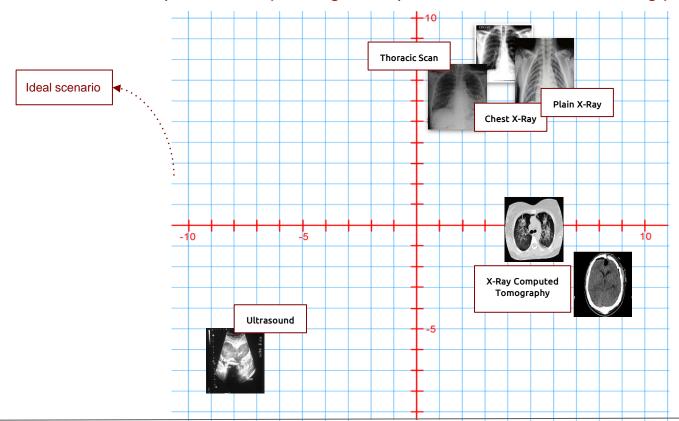




System #2: Contrastive Learning-based Tagger



Goal: Train a multi-modal model w.r.t a contrastive objective; bring representations of true pairings closer in the vector space, while pushing the representations of mismatching pairs far away.











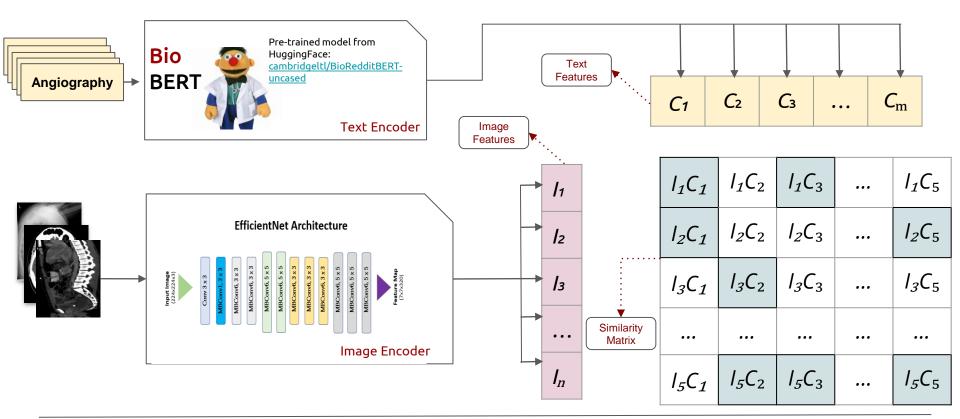




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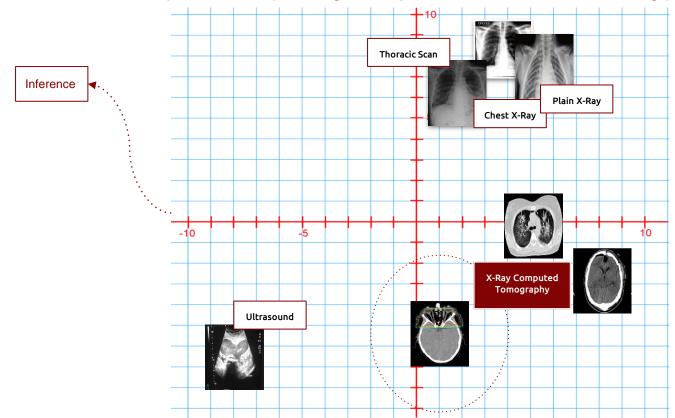




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Task #1: Caption Prediction



Goal: given a radiology image; generate a draft diagnostic report → open-ended generation task.



Generate caption...



Chest X-ray showing bilateral clavicular hypoplasia.



Generate caption...



Abdominopelvic ultrasound scan showed ectopic kidneys at the hemi-pelvis, fused in their upper poles, normal size and texture of the kidneys with normal corticomedullary differentiation, no stones or obstructive changes.









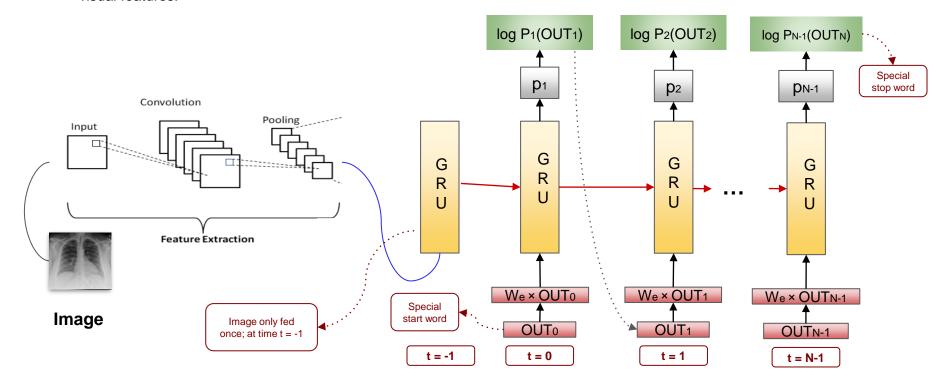




System #1: CNN-RNN (Show&Tell)



- Well-known Image Captioning architecture SotA before the introduction of Transformers.
- **CNN**: in charge of encoding the image and extracting visual features. **RNN**: generates the diagnostic caption based on the visual features.









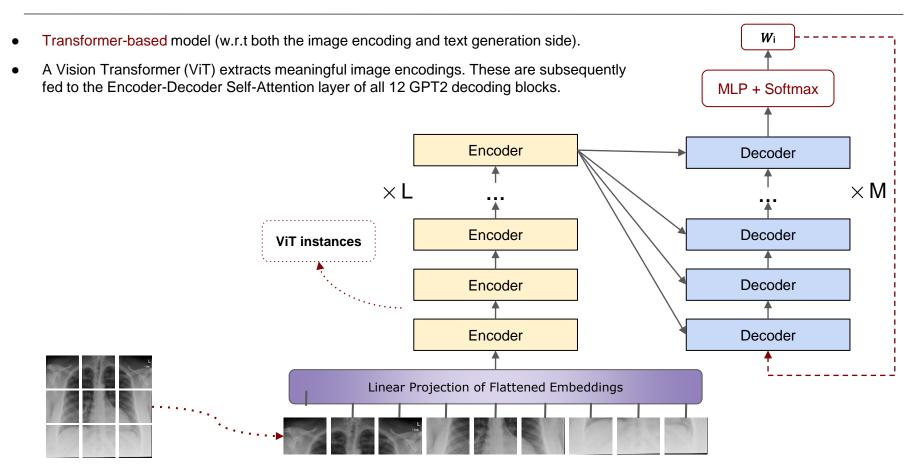






System #2: ViT-GPT2













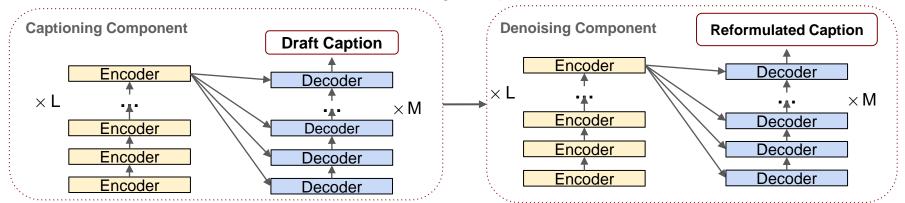




System #3: 2xE-D: Captioning Model + Seq2Seq denoiser



2xE-D: two Encoder-Decoder architectures running in sequential order.



Experimented with two pre-trained denoising models, BART and T5. BART is a denoising autoencoder model. It is trained by reconstructing text that has been distorted by an arbitrary noise function.

We fine-tuned BART towards the goal of correcting our model's common grammatical, syntactical and also diagnostic mistakes.

By feeding it (draft generated caption, ground truth caption) pairs, enabling it to learn common mistake patterns in the corpus generated from the initial captioning model.



ClinicalBAR T (or ClefBART)



Further pre-trained a BART-large instance on a held-out set of the ImageCLEFmedical dataset → following the original text corruption processes.

Then applied as a denoising component to the draft diagnostic captions derived from our captioning systems.















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Results & Future Work



- In this year's ImageCLEFmedical competition (Caption Task), the AUEB NLP Group ranked 1st in the Concept Detection and 3rd in the Caption Prediction sub-tasks, according to the competition's primary evaluation metrics.

 - Our best performing Caption Prediction system was a BART (<u>Caption Prediction System #3</u>) instance applied on top of our CNN-RNN (<u>Caption Prediction System #1</u>) captioning component, namely BART@CNN-RNN.

Ensemble: combination (Union or Intersection) of two or more instances predictions'.

Future Work:

- Explore instruction-tuning techniques in conjunction with state-of-the-art LLMs in order to enhance the accuracy and interpretability of the generated diagnostic captions.
- Experiment with few-shot, as well as prominent in-context learning techniques, as restricted data is a common problem, especially in the biomedical domain.



Scan for our paper











Thanks for attending! Any questions?

You can find out more on our work here: nlp.cs.aueb.gr/



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Additional optional slides













Input

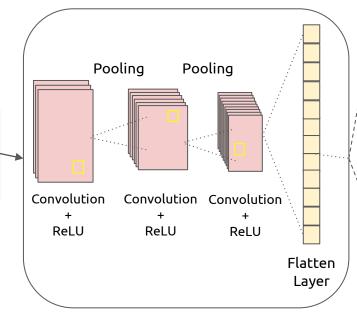
Image

(Tagging) System #2: CNN+FFNN-based Multi-task Classifier



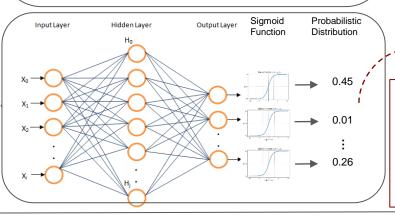
Motivation: There are four main medical modalities in the dataset: X-Ray, Computed Tomography, MRI and Ultrasonography which almost never occur concurrently.

Shared backbone



Input Layer Hidden Layer Output Layer Softmax Function Distribution $X_0 \longrightarrow X_1 \longrightarrow X_2 \longrightarrow X_2 \longrightarrow X_2 \longrightarrow X_1 \longrightarrow X_2 \longrightarrow X_2 \longrightarrow X_1 \longrightarrow X_2 \longrightarrow X_2 \longrightarrow X_3 \longrightarrow X_4 \longrightarrow X_4 \longrightarrow X_4 \longrightarrow X_4 \longrightarrow X_4 \longrightarrow X_4 \longrightarrow X_5 \longrightarrow X_5 \longrightarrow X_6 \longrightarrow X_$

Task-specific Layers



Task-specific Predictions

> Modality Tag

Trained by trying to minimize the **CCE** loss.

The concept that corresponds to the maximum prob value is assigned to the image.



Modalityspecific Tag

A concept is assigned to the image if p(concept) >t, where **t** is a tunable **threshold** value.









