NeuralDynamicsLab at ImageCLEFmedical 2022

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Research Question

To what extent Deep Neural Networks are capable of **automatically** generating a diagnostic text from a set of medical images but also how much their interpretation of these medical images can assist medical professionals **reduce their amount of clinical errors**, as well as help them **increase their productivity by ameliorating the quality and speed** in producing medical diagnoses, which is associated to an **increased throughput** of medical imaging departments.

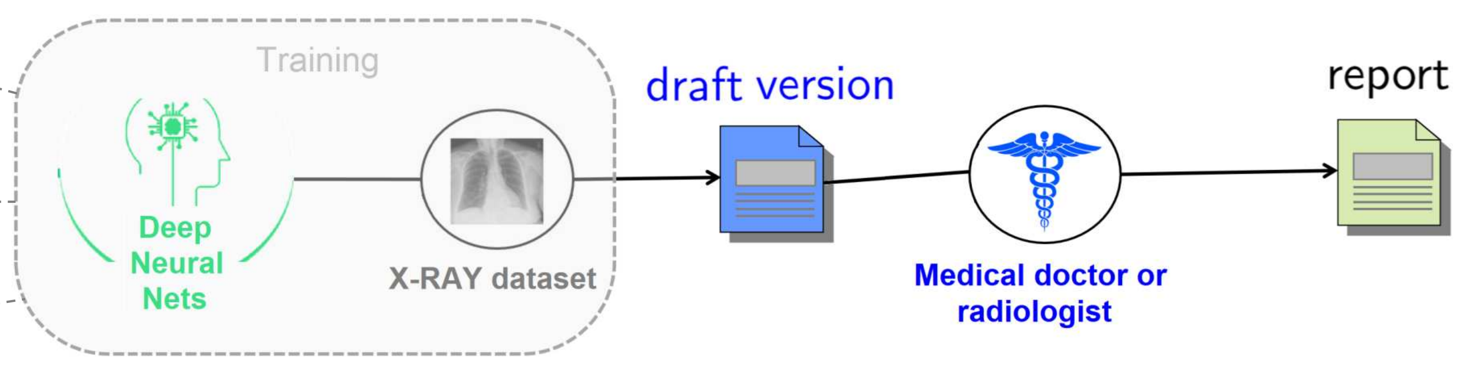
Data

90920 medical images; 80% training set, 10% validation set, 10% development set

Proposed Method

Image encoders: State-of-the-art CNN architectures, pretrained on ImageNet for classification, which have been obtained through `torchvision` models' library to perform inference; in order to encode the medical images into **descriptive dense numerical representations**. **They are shared for both subtasks.**

AlexNet | ResNet 50 101
DenseNet 121 161 | VGG 13 16
EfficientNet B3 B5



Concept Prediction

8374 tags of concepts assigned to the medical images. Each image in the training, validation, or development set is assigned **5 tags on average** based on a reduced subset of the Unified Medical Language System 2020 AB release.

In all baselines we use pre-trained encoders and train Perceptron heads initialized using Glorot, apart from the latter two, where we fully fine-tune a DenseNet161 and use the tags of the visually most similar image respectively.

Backbone Network	Training Regime	Learning Rate	Test F_1
DenseNet161	Adam optimizer and gradient clipping	constant 10^{-3}	0.43601
DenseNet161	Adam optimizer and gradient clipping[1]	constant 10^{-3}	0.43567
DenseNet161	AdamW optimizer and gradient clipping	constant $5 \cdot 10^{-4}$	0.43558
DenseNet161	Adam optimizer without gradient clipping	constant $5 \cdot 10^{-4}$	0.43539
DenseNet variants	Ensemble of best-performing DenseNets	per weak learner	0.43496
Various networks	Ensemble of diverse configurations[2]	per weak learner	0.43404
Various networks	Ensemble of diverse configurations[2]	per weak learner	0.43130
Various networks	Ensemble of diverse configurations[2]	per weak learner	0.42957
DenseNet161	Full fine-tuning with AdamW optimizer	cyclical	0.31687
VGG-16	Nearest Neighbor baseline (1-NN)	–	0.25061

[1] Model training occurred in 80% of the data; apart from the best performing DenseNet161 where we merge the training, validation, development sets and train in all the provided data (all 90920 medical images).
[2] Configuration search involves optimizers, learning rates, number of epochs, batch sizes, weight decay.

Caption Generation

Training set: 72736 captions, 70879 unique captions, average length 108 words,
Validation set: 9092 captions, 8984 unique captions, average length 107 words, and
Development set: 9092 captions, 8977 unique captions, average length 108 words

In (1+k)-NN we keep the caption of the visually most similar image as is and pass the remaining k ones to Pegasus summarizer; then concatenate. In k-NN with RAG we pass the captions of all k most similar images to RAG-token; then concatenate all of them with RAG-token's generation.

Backbone Network	Training Regime	Neighbors	Length	BLEU
AlexNet	(1+k)-NN retriever with Pegasus	k = 9	15 tokens	0.29166
AlexNet	(1+k)-NN retriever with Pegasus	k = 4	15 tokens	0.28343
AlexNet	(1+k)-NN retriever with Pegasus	k = 3	15 tokens	0.27855
AlexNet	(1+k)-NN retriever with Pegasus	k = 2	15 tokens	0.27007
AlexNet	(1+k)-NN retriever with Pegasus	k = 4	5 tokens	0.25521
AlexNet	(1+k)-NN retriever with Pegasus	k = 3	5 tokens	0.25334
AlexNet	k-NN retriever with RAG-token	k = 1	–	0.25127
VGG-16	k-NN retriever with RAG-token	k = 1	–	0.23958
AlexNet	k-NN retriever with RAG-token	k = 1	–	0.24064
VGG-16	Nearest Neighbor baseline	k = 1	–	0.22757