Master's Thesis at the Pattern Recognition Lab, FAU Erlangen-Nuremberg

Master Thesis Short Proposal

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Deep-learning based detection of detector artifact

All medical imaging modalities are subjected to spurious findings, leading to missed or erroneous diagnoses. During x-ray image acquisition, due to either hardware failure or operator error [1], different types of artifacts such as defective lines, columns, dead pixel can appear. While it is critical to recognize these artifacts, artifacts on radiographic images are distracting and may compromise accurate diagnosis [2]. Therefore, to best assist physicists, radiologists, and radiology technologists, it is important that they become visually familiar with an expanded spectrum of artifact phenomena [3].

Motivated by the success of deep learning in tackling computer vision related tasks such as image processing problems and object detection [4, 5], especially in medical imaging [6], we aim to focus on *development of deep learning based algorithm to fully automate detection of radiographic x-ray image artifacts from flat-panel detector*.

Initially, existing neural network architectures, such as ResNets [7] and VGG [8, 9], will be used as baselines to benchmark the performance, following by proposing our algorithm that aims to address the problem of multi-label artifact identification from the radiographic x-ray image dataset internally collected by Siemens. Both the approaches 1.Two-staged approach of first binary decision of artifact presence and then artifact classification ;and 2. single-staged classification approach where new label 'normal' is introduced to signify images with no artifacts, will be tried out.

Existing classification tasks in medical image diagnostic assessment bear several challenges, one of which is imbalanced data [10]. Medical imaging data is non-uniformly distributed, meaning that each class does not have comparatively similar numbers of samples, which creates imbalanced datasets. A natural solution to address this problem is to augment the minority label classes using different augmentation techniques, and increase their number of samples.

The problem could also be tried to be solved using one-class classification. One-class classification aims to learn the classifier from only one class of data. Variational auto-encoder (VAE) has been widely used in it[11].

General workflow of thesis:

- Development of algorithm that indicate whether a given image is affected by an artifact, and also, if possible by which kind of artifact.
- Deal with unbalanced dataset, by generating artificial training data using data augmentation techniques and one-class classification
- Check if the algorithm developed for so called raw images (which are intensity linear), works also for post-processed images
- Perform assessment on detectors health based on artifact detected

The implementation should be done in Pytorch, Python.

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