Medical Image Quality Assurance using Deep Learning

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Abstract

This is a great paper and it has a concise abstract.

Keywords: quality control, quality assurance, deep learning, web interface.

1. Introduction

Discovery of new knowledge in medicine is sometimes accomplished by large, multi-center imaging studies. The success of these studies depends on the quality of images and the resulting measurements, regardless of the size of the study. Many studies rely on in-house procedures that combine automatically generated scores with manually guided checks, such as visual inspection. Currently these procedures are often implemented by combining several software systems that are not designed to support Quality Assurance (QA) or Quality Control (QC) processes. Our Medical Image Quality Assurance (MIQA) system represents a design that facilitates collaboration and sharing. It incorporates a state-of-the-art deep learning component to improve the effectiveness of QC efforts unique to the needs of multi-center studies. The usefulness of this unique QC system is being tested by National Consortium on Alcohol and Neurodevelopment in Adolescence (NCANDA) project. NCANDA uses magnetic resonance images (MRIs) of the brain, so we focus on deep learning using head MRIs in this paper.

Add here description of MIQA web application. I would like to mention that we use MRIQC (Esteban et al., 2017), but we should implement that soon, ideally before the paper deadline.

As far as we know, this is the first attempt at assessing image quality of 3D images. Previous studies used photographs (Bosse et al., 2017; Bianco et al., 2018; Hosu et al., 2020), retinal fundus images (Yu et al., 2017), linguistic descriptions of images (Hou et al., 2014), or tried to improve image quality by e.g. reducing noise (Higaki et al., 2019).

We use data from PREDICT-HD study (Paulsen et al., 2014), which has manually assesed quality for 9475 structural (T_1, T_2, PD) brain MRIs.

This is where the content of your paper goes. Some random notes:

- You should use LaTeX(?).
- JMLR/PMLR uses natbib for references. For simplicity, here, `\cite` defaults to parenthetical citations, i.e. `\citep`. You can of course also use `\citet` for textual citations.
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Table 1: An Example Table

Dataset	**Result**
Data1	0.12345
Data2	0.67890
Data3	0.54321
Data4	0.09876

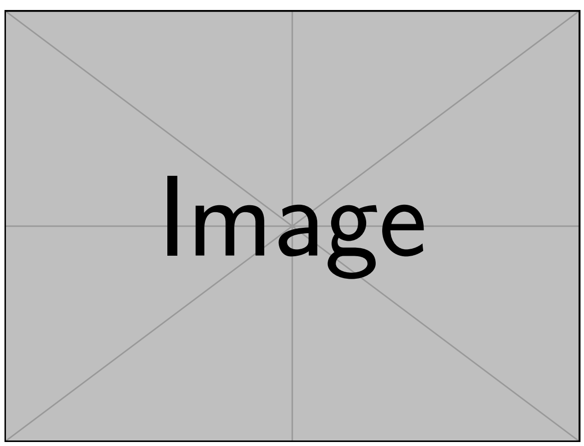

Figure 1: Example Image

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Algorithm 1: Computing Net Activation

Input: $x_1, \ldots, x_n, w_1, \ldots, w_n$
Output: y, the net activation
$y \leftarrow 0$;
for $i \leftarrow 1$ **to** n **do**
  $y \leftarrow y + w_i * x_i$;
end

References

Simone Bianco, Luigi Celona, Paolo Napoletano, and Raimondo Schettini. On the use of deep learning for blind image quality assessment. *Signal, Image and Video Processing*, 12(2):355–362, 2018.

Sebastian Bosse, Dominique Maniry, Klaus-Robert Müller, Thomas Wiegand, and Wojciech Samek. Deep neural networks for no-reference and full-reference image quality assessment. *IEEE Transactions on image processing*, 27(1):206–219, 2017.

Oscar Esteban, Daniel Birman, Marie Schaer, Oluwasanmi O Koyejo, Russell A Poldrack, and Krzysztof J Gorgolewski. Mriqc: Advancing the automatic prediction of image quality in mri from unseen sites. *PloS one*, 12(9):e0184661, 2017.

Toru Higaki, Yuko Nakamura, Fuminari Tatsugami, Takeshi Nakaura, and Kazuo Awai. Improvement of image quality at ct and mri using deep learning. *Japanese journal of radiology*, 37(1):73–80, 2019.

Vlad Hosu, Hanhe Lin, Tamas Sziranyi, and Dietmar Saupe. Koniq-10k: An ecologically valid database for deep learning of blind image quality assessment. *IEEE Transactions on Image Processing*, 29:4041–4056, 2020.

Weilong Hou, Xinbo Gao, Dacheng Tao, and Xuelong Li. Blind image quality assessment via deep learning. *IEEE transactions on neural networks and learning systems*, 26(6): 1275–1286, 2014.

Jane S Paulsen, Jeffrey D Long, Hans J Johnson, Elizabeth H Aylward, Christopher A Ross, Janet K Williams, Martha A Nance, Cheryl J Erwin, Holly K Westervelt, Deborah Lynn Harrington, et al. Clinical and biomarker changes in premanifest huntington disease show trial feasibility: a decade of the predict-hd study. *Frontiers in aging neuroscience*, 6:78, 2014.

FengLi Yu, Jing Sun, Annan Li, Jun Cheng, Cheng Wan, and Jiang Liu. Image quality classification for dr screening using deep learning. In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 664–667. IEEE, 2017.