Baselines for automatic medical image reporting

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Abstract

Despite the high number of deep learning models presented in the last few years for automatically annotating medical images, clear baselines models are still missing. Furthermore, though there are only two datasets publicly available for the task, there is neither a shared and commonly adopted procedure for preprocessing the raw data nor an unanimous way in which the intermediate tasks have been defined. The work here presented tries to fill this gap by clearly characterizing the datasets, defining the learning task and providing some baselines that can be especially helpful when trying to replicate the results in languages with less resources than those available in English.
Key words: computer vision, natural language generation, image classification

1 Introduction

The demand for image-based medical examinations has been rising for the past years and has nowadays become so high as to make it impossible for radiology departments to report on the acquired images in a timely manner[1]. A short turnaround of written reports from radiologists to clinicians is a key factor from several points of view: it enables an early planning of a correct treatment, increasing the likelihood of healthier clinical courses, it reduces costs and, more in general, it improves the patient experience[2]. For the previous reasons several approaches for automatizing this important step are being proposed.

The task of automatic medical image reporting (AMIR) consists in the generation of a narrative text, expressed in natural language, describing the diagnostic content of one or more medical images given as input data to a computer program. It is an inherently multi-modal task involving images and texts, whose solution requires a successful combination of computer vision (CV) and Natural Language Processing (NLP) algorithms [1, 2]. Any algorithm tackling the previous task can be roughly described as implemented with a pipeline of two computational steps: the first step processes the input image and maps its visual content onto a feature space accessed in the second step for generating a verbal description of an appropriate surface form, with correct lexicon and grammar, a task normally referred to as Natural Language Generation (NLG). The current state of the art performance is held by deep learning (DL) models [3], usually based on a convolutional neural network (CNN), acting as the visual encoder, and a recurrent neural network, acting as the decoder generating text. Recently, large language models (or surrogate smaller versions) have been introduced improving upon previous results [4] However, as noted also in other works [2], this initial set of works is hardly comparable: baselines are not assessed, very complex systems are compared between

[1] Radiology Review, A national review of radiology reporting within the NHS in England, CareQuality Commission, July 2018. https://l.cnr.it/nhseng18

[2] American College of Radiology, Qualified Clinical Data Registry, January 2022. https://l.cnr.it/acrqdr22

each other without establishing how well they perform with respect to a baseline measurerement, the image encoding steps are not uniformly defined. It is not even clear whether or not images are needed to seed the generation of text [5]. Even if reviews list up to eight datasets available for the task [6], basically only two datasets are actually usable and, indeed, used. This makes replicating the results very difficult, especially when trying to build an analogous system for languages other than English.

2 Approach

The work will try and provide sound criteria for assessing a baseline and comparing different approaches, with a specific attention to choosing methods and pre-processing steps that are language-agnostic and that can be used also when dealing with non-English texts and with low-resource languages.

In all the available datasets the images are associated to multiple labels and are extremely unbalanced. Many works with important contributions either do not specify which labels are selected and how (e.g, [7]) or seem to arbitrary select a subset of them. Preliminary experiments prove that such choices have a deep impact on performance of the CNN encoder. This work will try and select quantitative criteria for selecting and encoding labels, and for partitoning the images in the training and test splits.

In all the datasets the most frequent class is the *"normal"* one, i.e. most of the images do not show any suspicious area. Preliminary experiments show that normal images can be classified by the CNN with high accuracy. This work will establish whether or not separating normal images from the rest leads to better text generation. Image labels are encoded either with random vector embeddings or with pre-trained word embeddings. However, a detailed study on which is the best choice is missing. This point will be included in the experimentations, as well as other details that are found missing or overlooked in the literature.

The goal of the work is thus to provide baseline models with the full specification of the procedures used for pre-processing data, training the models and evaluating their output in order to have results that are fully reproducible and replicable.

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