International Journal of Early Childhood Special Education (INT-JECS)
DOI:10.9756/INTJECSE/V14I7.60 ISSN: 1308-5581 Vol 14, Issue 07 2022

An Analysis Of The Literature On The Use Of Deep Learning To Generate Medical Reports For Chest X-Rays Automatically

Running Title: An Analysis Of The Literature

Shailendra Kumar Diwakar[1] , Pushpendra Kumar Rajput[2], Piyush Pandey[3], Maruf Ahmad[4], Meghna Guha[5] Fauzia Khan[6], Himanshu Mishra[7*], Bhawna Solanki[8*]

[1]Assistant Professor, Department of Paramedical & Health Sciences, Faculty of Medicine, Parul University, Gujarat,India.

[2]Assistant Professor, Department of Paramedical Sciences, Swami Vivekanand Subharti University (UP) India.

[3]Assistant Professor, Motherhood University, Roorkee (UK), India.

[4]Assistant Professor, Integral University, Lucknow, (UP), India.

[5]Assistant Professor,Royal Global University,Guwahati,Assam,India.

[6]Assistant Professor, Integral University, Lucknow, (UP), India.

[7]*Himanshu Mishra, Assistant Professor, Medical Radio-Imaging Technology, Uttaranchal PG college of Biomedical sciences & Hospital, (UK), India

[8]*Bhawna Solanki Assistant Professor, Department of Radio-Diagnosis, Santosh Deemed to be University NCR, India.

* All authors contributed equally to the study.

***Corresponding Author:-**Himanshu Mishra, Bhawna Solanki

*Himanshu Mishra, Assistant Professor, Medical Radio-Imaging Technology, Uttaranchal PG college of Biomedical sciences & Hospital, (UK), India

* Bhawna Solanki Assistant Professor, Department of Radio-Diagnosis, Santosh Deemed to be University NCR, India.

Overview

Medical imaging is used in radiology to identify and treat disorders. A radiologist's job is to diagnose illnesses from radiographic images and write a report outlining each vision they look at. Radiomics is the study of obtaining numerous features from radiographic pictures. The characteristics are used to find diseases automatically. Despite their significant expertise in radionics, radiologists frequently review images with various variations in one sitting and create a templated report describing anomalies, including results and an impressions section (Liu et al., 2019). In addition, the process can be time-consuming and prone to human mistakes, particularly in nations with a high population density (Jing et al., 2018). Artificial intelligence may readily be used to automate this process of creating medical reports from radiographic pictures (AI)

As well as Machine Learning (ML) methods. However, different security laws and restrictions frequently make it difficult for machine learning researchers to access medical information. However, several datasets have been made publicly available recently and over the past few years. Large medical datasets become available, opening the door for AI, ML, and Deep Learning (DL) models to automate and create insights for medical professionals and patients. Health and medical information typically come in various formats, including text reports like electronic health records, patient report outcomes, medical imaging reports, and visual data like MRI, X-ray, and brain scans. After the data were cleared and de-identified, several medical and health datasets were accessible. In order to further the use of AI in healthcare, datasets like the MIMIC Chest X-ray dataset (Johnson et al., 2019), Chexpert (Irvin et al., 2019, p. 201), and other publically available EMR datasets have recently been made available. The amount of data accessible and the developments in AI, ML, and DL are believed to make these techniques particularly helpful in automating various difficult and expensive medical activities. Therefore, it seems that the DL community has expectations about how to solve specific automation or inference challenges in the medical industry generally and in medical image-based diagnostics specifically (Litjens et al., 2017). However, creating meaningful DL models is not an easy effort since many features and parameters need to be trained semi-supervised when dealing with medical imaging (Lundervold & Lundervold, 2019). Creating radiologist reports from MRI, X-ray, or brain scans is one issue that deep learning has encountered and advanced in automating. Medical personnel in radiology typically manually create medical reports from, for instance, chest x-rays or with the help of those above essential computer-aided technologies. Therefore, automating that process can reduce the time and money spent by medical professionals examining x-rays and producing reports. DL has made significant progress in resolving computer vision issues, like creating captions for images. Early research in this area only used statistical computer vision methods and image processing (Kulkarni et al., 2011; Kuznetsova et al., 2012). With the launch of the MS COCO dataset, DL models began to play a significant role in image-based text creation issues to develop a model that would produce captions from images (Lin et al., 2015; Chen et al., 2015).

Deep learning improves semantic segmentation problems (Fang et al., 2015). The DL encoder-decoder paradigm for producing captions and insightful text descriptions from images emerged as a result (Long et al., 2015). According to S. Liu et al. (2018), this field of research has been divided into three primary model architectures: CNN-CNN, CNN-RNN, and Reinforcement Learning. However, the CNN-RNN model came to dominate research in this field, giving rise to well-known models like Show & Tell (Vinyals et al., 2015), in which the authors used a deep CNN trained on vision using semantic segmentation in combination with an RNN decoder to produce language correspondence for images. The performance took off with the inclusion of attention models in DL models for images (Mnih, Heess, Graves, & Kavukcuoglu, 2014). The "Show & Tell" method was improved thanks to the incorporation of attention models by including an attention mechanism that results in longer descriptions (Xu et al., 2016).

In contrast to how human attention functions, attention models learn latent alignments between images and matching words from scratch instead of explicitly using object detectors. This enables the model to develop beyond object detection and to focus on intangible ideas. However, in this paper, we based our model on the "Show, Attend and Tell" (Xu et al., 2016) due to its robustness and the thorough evaluation carried out by the authors. Research in text generation from images, mainly based on attention models, has been advancing rapidly (You et al., 2016; Krause et al., 2017; Rennie et al., 2017).

In contrast to typical picture captioning assignments, where evaluation primarily hinges on comparing the readability of the generated text to a ground truth often provided by a person, medical reports also consider the report's clinical accuracy and adherence to accepted medical practices. Olatunji et al. (2019).'s study of the issue of accurate clinical reports, particularly in radiology, revealed "a very high disparity between what radiologists visually observe and what they clinically describe" using a set of 1000 chest x-ray examinations and the related reports. They also cited the problem that sophisticated medical natural language processing methods cannot produce labels of a high caliber. The fact that "current evaluation measures are borrowed directly from general image captioning" is mentioned (Pavlopulos et al., 2019, p.). This does not eliminate the need for typical NLP assessment methods to examine the generated reports' credibility and clinical correctness. However, it does call for the addition of additional evaluation techniques. The readability of the generated text is typically evaluated using similarity metrics in contrast to the ground truth provided by humans. The similarity metrics ROUGE, BLEU, and CIDer are all n-gram-based. They do not account for context when calculating precision, recall, and the F1 scores. A recently created metric that considers context is called BERT Score. Clinical accuracy has been examined, with the vital contribution of their study being highlighted (G. Liu et al., 2019).

Funding: There was no outside support for this study.
Conflicts of Interest: There are no conflicts of interest declared by the authors.

Ethics approval and consent to participate

This evaluation does not require ethical approval because no patient data will be collected. Plagiarism, confidentiality, malfeasance, data falsification and/or falsification, double publishing and/or submission, and duplication are among the ethical problems examined in this study.

Acknowledgments

First and foremost, I want to express my gratitude to God for allowing me the opportunity to conduct and complete this research project for my academic achievement. I'd want to thank and show gratitude to my mentor for encouraging and guiding me during the process of writing this post. who had devoted their valuable time to guide me, either directly or indirectly, during the journey I'd want to express my heartfelt gratitude to all of my friends for their unwavering support and aid in completing this study. Finally, I'd like to express my gratitude to my family for their love, patience, and support throughout the study process.

References

DOI:10.9756/INTJECSE/V14I7.60 ISSN: 1308-5581 Vol 14, Issue 07 2022

1. Ebeid, I. A. A Literature Review On The Automatic Generation of Chest X-Ray Medical Reports using Deep Learning.
2. Jing, B., Xie, P., & Xing, E. (2018). On the Automatic Generation of Medical Imaging Reports. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) , 2577–2586. https://doi.org/10.18653/v1/P18-1240.
3. Liu, G., Hsu, T.-M. H., McDermott, M., Boag, W., Weng, W.-H., Szolovits, P., & Ghassemi, M.(2019). Clinically Accurate Chest X-Ray Report Generation. ArXiv Preprint ArXiv:1904.02633 .
4. Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. Zeitschrift Für Medizinische Physik , 29 (2), 102–127. https://doi.org/10.1016/j.zemedi.2018.11.002
5. Olatunji, T., Yao, L., Covington, B., Rhodes, A., & Upton, A. (2019). Caveats in Generating Medical Imaging Labels from Radiology Reports. ArXiv Preprint ArXiv:1905.02283 . Pavlopoulos, J., Kougia, V., & Androutsopoulos, I. (2019). A Survey on Biomedical Image Captioning. Proceedings of the Second Workshop on Shortcomings in Vision and Language . https://doi.org/10.18653/v1/w19-1803
6. Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. Annual Review of Biomedical Engineering , 19 , 221–248.
7. Xu, K., Ba, J., Kiros, R., Cho, K., Courville, A., Salakhutdinov, R., Zemel, R., & Bengio, Y. (2016). Show, Attend and Tell: Neural Image Caption Generation with Visual Attention.ArXiv:1502.03044 [Cs] . http://arxiv.org/abs/1502.03044.
8. You, Q., Jin, H., Wang, Z., Fang, C., & Luo, J. (2016). Image Captioning with Semantic Attention. ArXiv:1603.03925 [Cs] . http://arxiv.org/abs/1603.03925