Insights into Data through Model Behaviour: An Explainability-driven Strategy for Data Auditing for Responsible Computer Vision Applications

Alexander Wong\textsuperscript{1,2,3,*}, Adam Dorfman\textsuperscript{3}, Paul McInnis\textsuperscript{3}, and Hayden Gunraj\textsuperscript{1}
\textsuperscript{1}Department of Systems Design Engineering, University of Waterloo
\textsuperscript{2}Waterloo Artificial Intelligence Institute
\textsuperscript{3}DarwinAI Corp.

Abstract

In this study, we take a departure and explore an explainability-driven strategy to data auditing, where actionable insights into the data at hand are discovered through the eyes of quantitative explainability on the behaviour of a dummy model prototype when exposed to data. We demonstrate this strategy by auditing two popular medical benchmark datasets, and discover hidden data quality issues that lead deep learning models to make predictions for the wrong reasons. The actionable insights gained from this explainability driven data auditing strategy is then leveraged to address the discovered issues to enable the creation of high-performing deep learning models with appropriate prediction behaviour. The hope is that such an explainability-driven strategy can be complimentary to data-driven strategies to facilitate for more responsible development of machine learning algorithms for computer vision applications.

1. Introduction

The rise of open source benchmark datasets \cite{10, 6, 3, 13, 16, 11, 14} has led to significant progress in machine learning for computer vision. A common assumption made when leveraging benchmark datasets is that they are curated in a way that is free of data quality issues. Therefore, such datasets are often used ‘as is’ and sight unseen in practice to train new models, relying on scalar performance metrics to judge a model’s efficacy. However, data auditing in recent studies \cite{2, 9, 12} have unveiled hidden biases and data quality issues in well-known benchmark datasets, which can negatively affect real-world performance of models trained on such datasets.

Most data auditing strategies consider only data characteristics and not model behaviour, and thus such strategies are subjective, based largely on human intuition, and can leave hidden issues that affect model behaviour negatively. In this study, we take a different approach and explore an explainability-driven strategy to data auditing, where actionable insights into data are discovered through the eyes of explainability based on a model’s behaviour.

This paper is organized as follows. Section describes the underlying methodology behind explainability-driven strategy to data for the development of responsible computer vision applications auditing. Section 2 describes the experiments conducted on two popular medical benchmark datasets. Section 3 presents the results in terms of the hidden data quality issues that were discovered during the auditing process, as well as actionable insights and steps taken as a result of such insights. Finally, conclusions are drawn in Section 4.

2. Methodology

In this study, we aim to explore the efficacy of an explainability-driven strategy to data auditing for the development of responsible computer vision applications, which is a conceptual departure from the direction taken by existing data-driven strategies in research literature. More specifically, explainability-driven data auditing is conducted as follows (see Figure 1). First, a dummy model prototype is constructed and trained with the data under investigation. Second, the data is fed back into the trained dummy model prototype and a quantitative explainability technique is leveraged to identify the critical factors driving the behaviour of the prototype across the data. Third, the identified critical factors are studied to discover hidden data quality issues. An unique aspect of this explainability-driven strategy to data auditing is that hidden data quality issues are discovered based on prediction behaviour through the eyes of explainability, and as such has the potential to compliment data-driven strategies to uncover hidden issues not identified based on considering just data characteristics alone.
Figure 1. Overview of the explainability-driven data auditing workflow. A dummy model prototype is trained using the data under investigation. A quantitative explainability technique is used to identify critical factors in the data that drives the prediction behaviour of the prototype. The critical factors are audited to discover hidden data quality issues.

3. Experiments

We demonstrate this strategy by auditing two popular benchmark datasets (OSIC Pulmonary Fibrosis Progression dataset [8] and CNCB COVID-19 CT dataset [17]) on dummy deep CNN regression and classification model prototypes, respectively. For explainability we leverage GSInquire [7], which was demonstrated to better reflect a model’s decision-making process when compared to state-of-the-art approaches, and one of the only approaches that can be used on deep learning regression models. In particular, the OSIC dataset is part of a popular Kaggle challenge, with the winning solution [1] using the data largely ‘as is’ without considering the CT modality used. These are good use cases given the importance of responsible computer vision in healthcare.

4. Results and Discussion

In this section, we will discuss the hidden data quality issues that were discovered using the proposed explainability-driven strategy for data auditing, as well as the steps taken to address these issues based on the actionable insights gained from the data auditing strategy.

4.1. Hidden Data Quality Issues Discovery

The explainability-driven data auditing led to the discovery of several hidden data quality issues that caused the dummy model prototypes to make predictions for the wrong reasons, even if performance is high based on scalar metrics. These include: 1) incorrect calibration metadata led to data dynamic range being erroneously used by the model prototype to make predictions, 2) synthetic padding (Fig. 3a) introduced during data curation being used to erroneously guide predictions, 3) circular artifacts (Fig. 3b) being used by the model to erroneously guide predictions, and 4) patient tables (Fig. 3c) being used by the model to make predictions.

4.2. Actionable Insights

The discovered data quality issues led to the following actionable insights: 1) incorrect calibration data removal, 2-3) domain-specific artifact mitigation, and 4) automatic table removal (see Figure 2). By taking the above actions on the data set to address the discovered data quality issues uncovered via the aforementioned explainability-driven strategy for data auditing, the resulting deep learning models not only achieved significantly higher performance [15, 5], but also led to models that made predictions based on the right visual cues.

For example, in the case of the OSIC Pulmonary Fibrosis Progression dataset, addressing the discovered data quality issues led to the creation of a deep CNN regression model [15] with state-of-the-art performance above the winning solutions in the OSIC Kaggle Challenge [1] that learned to leverage relevant visual anomalies such as honeycombing in the lungs (see Fig. 4 for example CT images from the OSIC Pulmonary Fibrosis Progression dataset and corresponding identified critical factors). In the case of CNCB COVID-19 CT dataset, addressing the discovered data quality issues led to the creation of deep CNN classification models [5, 4] with state-of-the-art performance (exceeding 98% accuracy) that learned to leverage relevant visual anomalies in the lungs such as ground-glass opacities and bilateral bilateral patchy opacities.
5. Conclusions

In this study, an explainability-driven strategy for data auditing was explored and conducted on two different popular medical benchmark datasets. The proposed data auditing strategy led to the discovery of critical hidden data quality issues that led to incorrect prediction behaviour of deep learning models, and the actionable insights gained was leveraged to addressing these issues and enable the creation of deep learning models that not only had higher performance but also made predictions based on the right reasons. The hope is this explainability-driven strategy can compliment data-driven strategies to facilitate for more responsible machine learning-driven computer vision development.

References

[1] OSIC pulmonary fibrosis progression 1st place solution. https://github.com/artkulak/osic-pulmonary-fibrosis-progression, 2020.

[2] Chris Dulhanty and Alexander Wong. Auditing Imagenet: Towards a model-driven framework for annotating demographic attributes of large-scale image datasets. 2019.

[3] Mark Everingham, Luc Van Gool, Christopher K. I. Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (VOC) challenge. IJCV, 2010.
Figure 4. Example CT images from the OSIC Pulmonary Fibrosis Progression dataset, with the highlighted areas corresponding to the critical factors used by a state-of-the-art deep CNN regression model for predicting fibrosis progression, as identified via quantitative explainability. It can be observed that, by addressing the discovered data quality issues identified via explainability-driven data auditing, the model is able to learn to leverage relevant visual anomalies such as honeycombing in the lungs.

[4] Hayden Gunraj, Ali Sabri, David Koff, and Alexander Wong. Covid-net ct-2: Enhanced deep neural networks for detection of covid-19 from chest ct images through bigger, more diverse learning, 2021. 2

[5] Hayden Gunraj, Linda Wang, and Alexander Wong. Covidnet-ct: A tailored deep convolutional neural network design for detection of covid-19 cases from chest ct images. Frontiers in Medicine, 7:1025, 2020. 2

[6] Tsung-Yi Lin, Michael Maire, Serge Belongie, Lubomir Bourdev, Ross Girshick, James Hays, Pietro Perona, Deva Ramanan, C. Lawrence Zitnick, and Piotr Dollár. (Microsoft COCO: Common objects in context. 2015. 1

[7] Zhong Qiu Lin, Mohammad Javad Shafiee, Stanislav Bochkarev, Michael St. Jules, Xiao Yu Wang, and Alexander Wong. Do explanations reflect decisions? a machine-centric strategy to quantify the performance of explainability algorithms. 2019. 2

[8] OSIC. OSIC pulmonary fibrosis progression. 2020. 2

[9] Vinay Uday Prabhu and Abeba Birhane. Large image datasets: A pyrrhic win for computer vision? 2020. 1

[10] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. Imagenet large scale visual recognition challenge. 2015. 1

[11] Linda Wang, Zhong Qiu Lin, and Alexander Wong. Covidnet: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific Reports, 2020. 1

[12] Tianlu Wang, Jieyu Zhao, Mark Yatskar, Kai-Wei Chang, and Vicente Ordonez. Balanced datasets are not enough: Estimating and mitigating gender bias in deep image representations. 2019. 1

[13] Xiaosong Wang, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M. Summers. ChestX-Ray8: hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Jul 2017. 1

[14] Alexander Wong, Zhong Qiu Lin, Linda Wang, Audrey G. Chung, Beiyi Shen, Almas Abbasi, Mahsa Hoshmand-Kochi, and Timothy Q. Duong. Towards computer-aided severity assessment via training and validation of deep neural networks for geographic extent and opacity extent scoring of chest x-rays for sars-cov-2 lung disease severity. Scientific Reports, 2021. 1

[15] Alexander Wong, Jack Lu, Adam Dorfman, Paul McInnis, Mahmoud Famouri, Daniel Manary, James Ren Hou Lee, and Michael Lynch. Fibrosis-net: A tailored deep convolutional neural network design for prediction of pulmonary fibrosis progression from chest ct images, 2021. 2

[16] Jiancheng Yang, Rui Shi, and Bingbing Ni. Medmnist classification decathlon: A lightweight automl benchmark for medical image analysis. arXiv preprint arXiv:2010.14925, 2020. 1

[17] Kang Zhang, Xiaohong Liu, Jun Shen, Zhihuan Li, Ye Sang, Xingwang Wu, Yunfei Zha, Wenhua Liang, Chengdi Wang, Ke Wang, Linsen Ye, Ming Gao, Zhongguo Zhou, Liang Li, Jin Wang, Zehong Yang, Huimin Cai, Jie Xu, Lei Yang, Wenjia Cai, Wenqin Xu, Shaoxi Wu, Wei Zhang, Shanping Jiang, Lianghong Zheng, Xuan Zhang, Li Wang, Liu Lu, Jiaming Li, Haiping Yin, Winston Wang, Oulan Li, Charlotte Zhang, Liang Liang, Tao Wu, Ruiyun Deng, Kang Wei, Yong Zhou, Ting Chen, Johnson Yu-Nam Lau, Manson Fok, Jianxing He, Tianxin Lin, Weimin Li, and Guangyu Wang. Clinically applicable ai system for accurate diagnosis, quantitative measurements, and prognosis of COVID-19 pneumonia using computed tomography. Cell, 18(6):1423–1433, 2020. 2