Use case of no code machine learning tools for medical image classification.

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Abstract

AI tools are making paradigm changes in the field of medical imaging. Currently, the development of AI tools and their validation for clinical use is heterogeneously distributed with the end-users (i.e. the physicians or radiologists) adopting the software solution. As we are all progressing towards democratization of AI, no code tools offer a versatile and convenient; but largely under-utilized method for medical imaging tasks.

Purpose: As a proof-of-concept study, we attempted to evaluate whether no-code machine learning (ML) tools like teachable machine could perform a basic medical image classification task.

Methods: We selected 85 cases from our imaging database whose planar whole body Iodine-131 diagnostic scans were labelled into 2 classes as “No evidence of disease” (NED) and “abnormal for training and testing the model.

Results: The model generated could accurately classify all NED cases (100%) and abnormal cases with 93% accuracy.

Conclusion: We propose that no-code ML tools can perform simple medical image tasks easily. Validation on multiple source larger datasets may allow early adoption of this technology by imaging specialists.

Introduction

The computer-aided diagnosis and detection systems in medical imaging have been in use for many decades. The explosion of AI tools in medical imaging has bought a paradigm shift in the clinical management. The incorporation of AI has made certain workflows convenient and faster; but such technologies are not available widely. However, recently with introduction of low code or no code machine learning (ML), there seems to be a huge potential for easy implementation of machine learning models by end users like imaging specialists. But such tools seem to be under-utilized especially in the field of medical imaging for reasons discussed later. These tools were introduced largely for democratizing AI which have led to very interesting and creative implementation of such tools mostly in the domain of education, arts and technology.

No code ML tools are usually based on transfer learning methods. Transfer learning involves a pretrained feature extractor from a larger neural network architecture, and fine-tuning for the smaller subset of data locally.

Medical imaging classification tasks constitute one of the areas where automation is helpful. We tried to use Teachable machine as a proof of concept to test the hypothesis of medical image classification. Teachable machine is a browser-based tool for creating machine learning models easily without the need of any coding. It is built on top of Tensorflow.js allows working of such models in the browser without

downloading any libraries. Teachable machine uses transfer learning method by off-loading pretrained feature extractor from MobileNet on user's device [1–2]. There are two layers of hyperparameters in teachable machine which are used for training the small subset of data in the browser. Teachable machine then combines the data from the pretrained feature extractor and the 2-layer model to generate a joint model for prediction. The program runs locally on user's device without the need for files leaving the user's device for processing or analysis.

Our aim was to evaluate whether easily available ML tools like teachable machine can be used for a simple planar medical image classification as a proof of concept.

Methods

Planar whole- body images were chosen for simplicity for their fewer features and resemblance to the base architecture trained set of images. We randomly selected 85 whole body Iodine-131 planar scans from our institutional database in past 10 months. Those planar images with suspicion of contamination, poor count rate statistics and artefactual uptake were excluded.

Image acquisition parameters

The low dose Iodine-131 Whole body diagnostic scans in 85 patients with differentiated thyroid carcinoma were analysed. All scans were acquired on Siemens SymbiaEcam SPECT dual head gamma camera with high energy parallel hole collimator attachment, 48 hours after oral administration of 1- 1.5 mCi Iodine-131 capsule. Planar imaging was carried out in 1024 x 256 matrix in sweep mode with scan speed of 4 cm/min.

Image processing and classification

Both anterior and posterior projection images were used. The images were then classified into only 2 categories for simple use case analysis; as NED (No evidence of disease) and abnormal by a nuclear medicine physician having 8 years of experience for ground truth. Therefore, our 2 class labels (Figure 1) were:

- (1) No evidence of disease ("NED") and
- (2) "abnormal"

All images were anonymized and were transformed into squares of 250 x 250 px without cropping; using an online converter due to the requirement by teachable machine.

Eg.

Figure 1: binary classification of planar images

Teachable machine parameters:

We kept the default parameters teachable machine as: epoch= 50; batch size= 32; learning rate= 0.001. The 2 class labels were created as described above.

A total of 170 anterior and posterior images from 85 cases were analysed. However, due to an ill-defined focus of tracer uptake in lower neck region, 1 anterior image was discarded. Therefore 69 unambiguous images of NED were eventually considered with 100 abnormal images.

All images were then added to their respective classes (Figure 2) for training in teachable machine.

Figure 2: Overview of teachable machine in chrome browser

Results

The detailed results were collected from the "under the hood" section in teachable machine(Figures 3-6). The generated model accurately classified all the NED cases and abnormal cases with 93% accuracy.

Figure 3: Accuracy per class

Figure 4: Confusion Matrix

The confusion matrix allows visualization of performance of the model. One case of 15 abnormal scans was erroneously predicted as NED by the model (Figure 4). However, it could correctly predict all 11 NED scans.

Figure 5: Accuracy per epoch

The training and the test set accuracy show a converging trend (Figure 5); suggesting acceptable prediction by the model.

Figure 6: Loss per epoch.

The training set shows sustained loss after 20 epochs (Figure 6). Therefore, 20 to 30 epochs could be enough to avoid over-fitting.

The generated model could be availed by requesting the author. This model can be downloaded and loaded/imported on browsers compatible with teachable machine site for testing and fine tuning.

Discussion

We chose simple planar whole body image datasets for their resemblance to the natural images on which MobileNet is trained. We also performed simple image classification task with only 2 classes for testing the proof of concept that a simple browser-based tool can be used for medical image classification. The above results support our claim and demonstrate the feasibility that no code ML tools can be effectively used for simple medical image classification task.

The underlying assumption of teachable machine is that closely related images will yield similar embedding vectors. Therefore, it can theoretically classify images which were not used for training earlier.

Transfer learning has been extensively used for medical image tasks[4-5]with many open questionsregarding the performance of the models, feature reuse, etc. Maithra et al have demonstrated that there were no incremental performance benefits with large pretrained models on medical images like ResNet and Inception-v3 when compared against smaller basic convolution neural networks. While the neural network architectures and the methods used for the medical image tasks are still in exploratory phase, we want to emphasize on the applications of no code ML tools which are readily available with minimal requirements. This technology offers a huge untapped potential of incorporatingcustomizable AI in workflows of end users faster than the standard approach of waiting for a costly single use end proprietary or commercial software solution.

Medical images are complex standardized datasets with multiple variables like the type of medical images like 2D versus 3D, cross section, regional versus whole body image, high resolution vs low resolution, etc. Therefore, ideally neural networks trained from scratch on specific imaging modalities seem to be a safe bet to develop such models. However, with mounting evidence of usefulness of transfer learning as well as the availability of no-code ML, this approach can be explored further on larger datasets with multiple classes.

As outcomes based on only measurements could be biased by underlying drifts, a model trained on a large dataset from multiple sources will probably be better [6].

We would like to summarize the advantages and disadvantages of this method as following.

Advantages	Disadvantages
Quickly produce a working model	Many variables and assumptions probably leading to some bias
Minimal infrastructure or technical requirements	Prone to misinterpretation
Lower investment costs	Unknown influence of pretrained network
Preserved data confidentiality because of local training and implementation	

Table 1: Advantages and disadvantages of no-code ML programs

No code ML tools are easy to use and with increasing awareness as well as AI literacy, there would be wider adoption and demand of such tools.The incorporation of such tools to customize workflows of end users will lead to quicker reporting, recognise patterns, complement research work and ultimately help in patient management.

Conclusion

We successfully trained a no code web-tool like teachable machine to classify planer whole body images (low dose Iodine-131 scans) as NED or abnormal. This is only a proof of concept that these web tools can be used by physicians and radiologists to integrate in their daily workflows with minimal support.

Such tools can help in democratizing AI and accelerate transformation in medical imaging. However, larger dataset and validation is required to implement such tools in clinical practise.

Declarations

Compliance with Ethical Standards:

Funding:

The authors did not receive support from any organization for the submitted work.

Conflicts of Interest:

Both author and co-author declare that they have no conflicts of interest.

Research involving human participants:

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent:

All patients had signed a consent for usage of their data anonymously as well as their publication. After thorough discussion with various members of Institutional review Board, a waiver of Ethics Committee approval was suggested for this study.

Disclaimer:

We have only used teachable machine for a proof of concept. We neither endorse nor have received any incentives to promote the usage of this tool.

Data availability:

The model generated during the current study are available from the corresponding author on reasonable request.

References

1. Balasubramaniam K. Have you taught your machine yet? [Internet]. Medium. 2019. Available from: <https://towardsdatascience.com/have-you-taught-your-machine-yet-45540b7e646b>.
2. Choudhury A. This is how i created an object detection model in less than 5 minutes [Internet]. Analytics India Magazine. 2020. Available from: <https://analyticsindiamag.com/this-is-how-i-created-an-object-detection-model-in-less-than-5-minutes/>.

3. Raghu M, Zhang C, Kleinberg J, Bengio S, Transfusion: Understanding transfer learning for medical imaging. In Advances in neural information processing systems. 2019. p. 3347–3357.
 4. Chang J, Yu J, Han T, Chang H, Park E. A method for classifying medical images using transfer learning: A pilot study on histopathology of breast cancer. In: 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom). 2017. p. 1–4.
 5. Hassan M, Ali S, Alquhayz H, Safdar K. Developing intelligent medical image modality classification system using deep transfer learning and LDA. Sci Rep. 2020 Dec;10(1):12868.
 6. Ghassemi M, Naumann T, Schulam P, Beam AL, Chen IY, Ranganath R. Pr
 1. Balasubramaniam K. Have you taught your machine yet? [Internet]. Medium. 2019. Available from: <https://towardsdatascience.com/have-you-taught-your-machine-yet-45540b7e646b>
 2. Choudhury A. This is how i created an object detection model in less than 5 minutes [Internet]. Analytics India Magazine. 2020. Available from: <https://analyticsindiamag.com/this-is-how-i-created-an-object-detection-model-in-less-than-5-minutes/>
 3. Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. Transfusion: Understanding transfer learning for medical imaging. In Advances in neural information processing systems. 2019. p. 3347-3357.
 4. Chang J, Yu J, Han T, Chang H, Park E. A method for classifying medical images using transfer learning: A pilot study on histopathology of breast cancer. In: 2017 IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom). 2017. p. 1–4.
 5. Hassan M, Ali S, Alquhayz H, Safdar K. Developing intelligent medical image modality classification system using deep transfer learning and LDA. Sci Rep. 2020 Dec;10(1):12868.
 6. Ghassemi M, Naumann T, Schulam P, Beam AL, Chen IY, Ranganath R. Practical guidance on artificial intelligence for health-care data. Lancet Digit Health. 2019 Aug;1(4):e157–9.
- actical guidance on artificial intelligence for health-care data. Lancet Digit Health. 2019 Aug;1(4):e157–9.

Figures

Figure 1

binary classification of planar images

Figure 2

Overview of teachable machine in chrome browser

Accuracy per class

CLASS	ACCURACY	# SAMPLES
NED	1.00	11
abnormal	0.93	15

Figure 3

Accuracy per class

Confusion Matrix

Figure 4

Confusion Matrix

Figure 5

Accuracy per epoch

Figure 6

Loss per epoch.