Gastroenterology needs its own ImageNet

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In a period spanning less than a decade, deep learning with Convolutional Neural Networks (CNNs) has become the standard for Artificial Intelligence (AI) applications. While most of the key concepts were introduced decades ago, the two driving forces behind its success have only started building momentum at the dawn of this century: (I) an exponential increase in computational power and (II) the growing availability of large sets of labeled data. These two developments reached critical mass first in speech recognition (1), and later in computer vision, with the introduction of AlexNet (2): the first deep learning architecture to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) (3).

Ever since these first breakthroughs, the graphical processing units (GPUs) required for deep learning have been dropping in price and increasing in power, rendering the availability of data the limiting factor for deep learning. Especially in the medical domain, this is hampering the progress of AI, as medical data is hard to acquire and expensive to label. Moreover, additional challenges arise when building medical datasets, such as patient privacy, data uniformity over different medical centers and a considerable inter-observer variability among different medical experts, who provide the ground truth for training AI algorithms. Finally, data ownership is a rising topic of interest now that the first AI algorithms hit the market and start yielding commercial profit, while their development is completely fueled by patient data.

To deal with the scarcity of high-quality, labeled datasets, transfer learning has been first explored as an interesting solution for CNNs by Oquab *et al.* (4), and in 2016 some early successes in the medical domain were reported by Shin *et al.* (5) and Tajbakhsh *et al.* (6). This technique effectively alleviates the need for large, task-specific datasets to train deep neural networks by introducing a so-called pretraining stage, in which the network is trained on a large dataset from a different domain (for example natural images), for which an abundance of data is available. Then, during a second training stage, the target data (for example endoscopic images of neoplastic lesions) are used to fine-tune the model to the task at hand. In this fashion, the knowledge (i.e., network weights) that the network has learned from the large dataset is transferred to a different domain. The success behind this approach can be explained by the observation that a lot of visual features are useful for a variety of different image types. For example, visual features such as color/intensity transitions, edges, lines and basic shapes appear in both natural images (e.g., birds, cars and buildings) and in e.g., ophthalmology scans or stained histology slides. Moreover, the depth of the employed neural networks facilitates complex hierarchical patterns that are useful for a broad variety of tasks.

For the abovementioned reasons, nearly all methods proposed for AI-based medical image analysis exploit a form of transfer learning. To this end, ImageNet is by far the most popular dataset for pretraining purposes and it is used for a wide variety of tasks: from classification of pulmonary tuberculosis in chest radiography (7) to whole-slide pathology image analysis to detect of lymph node metastases in women with breast cancer (8). Also in endoscopy, ImageNet pretraining is used ubiquitously: for polyp localization (9) and staging (10), classification for invasion depth of esophageal squamous cell carcinoma (11) and the detection of early neoplasms in Barrett's esophagus (12-14).

While transfer learning using ImageNet as basis is widely employed, its efficiency can be questioned. The ImageNet dataset (15) consists of 1.2 million images of a thousand different categories, including "tree", "tool" and "tractor", but also more sophisticated categories such

as "membranophone", "face powder" and "mongoose"—not to mention the 120 dog breeds that have been added as categories for fine-grained classification[1]. Although ImageNet pretraining has proven to be an efficient tool for medical image analysis with AI, it is at least unsettling that a complete understanding of the inner workings driving this success is lacking. Moreover, disturbing results have been reported on fooling neural networks that were trained using ImageNet (16). Therefore, it is not surprising that ImageNet pretraining is questioned by He *et al.* in a recent publication (17) and there's an increasing interest in domain-specific pretraining (18,19). The reasoning behind this approach is twofold: (I) from a logical point of view, pretraining with images that are more similar to the target domain is more intuitive than pretraining with images of cats, dogs and trees, and, more importantly, (II) it leads to better and more robust results that are less prone to the natural variation exhibited by the images in the target domain (e.g., endoscopic imagery).

In an attempt to demonstrate the effectiveness of domain-specific pretraining in endoscopy, our consortium[2] has constructed a set of 494,355 retrospectively collected endoscopic images and have roughly categorized a subset of 3,743 images into five classes (i.e., "stomach", "duodenum", "esophagus", "colon" and "other"). Our first experiments indicate that even with a small proportion of the images labeled and a very modest number of categories, an improvement is shown for the detection of early Barrett's dysplasia (20). Moreover, further experiments demonstrated that this dataset also offers a suitable basis for an AI algorithm to grade the informativeness of endoscopic video frames (21). We hypothesize that this dataset, which we have titled GastroNet, serves as a better pretraining dataset for endoscopic imaging problems than the widely employed ImageNet and we are currently setting up the experiments that aim to test this hypothesis.

From our experiments, a number of first observations can be made: (I) domain-specific pretraining can lead to improved results of AI algorithms within endoscopy, (II) the power harnessed by such a domain-specific dataset is not only limited by the number of labeled samples, but also by the number of classes, as this forces the neural network to forge complex hierarchical structures with high discriminative power and (III) partially labeled, poorly structured, heterogenous data can be beneficial for pretraining deep neural networks. Especially the latter observation is interesting, since most medical data satisfies these conditions. However, dealing with this data to unlock its potential comes with substantial technical challenges and introduces numerous research questions regarding the design of deep neural networks and how they are trained. How to deal with missing labels, exploit variability in the data and combine different types of data during the training phase, just to name a few.

Over the past 5 years, AI-assisted endoscopy has grown from a curiosity into a valuable asset that will shape the future of gastroenterology. About a decade ago, the first outlines of this field became slowly visible by retrospective experiments on small, homogeneous datasets (22-24), recently, large clinical, prospective studies on real-time endoscopic video demonstrate that the field has matured (25,26). To maintain this momentum, and to make the next step into clinical application, additional parameters become important, such as, for example, robustness against small variations over different imaging devices and interpretability of the AI predictions. In this next development stage, data will play an increasingly important role, for both training algorithms and validating their clinical performance. Given the costly acquisition of high-quality labeled datasets, we anticipate that retrospectively collected, largely unlabeled data will fuel further progress of the field. In particular, the abundance of unlabeled endoscopic image data will facilitate domain specific pre-training, leading to a domain-native neural network that is more robust against the natural variations within endoscopic imagery.

Acknowledgments

Footnote

Provenance and Peer Review: This article was commissioned by the Guest Editors (Michael F. Byrne and Brandon J. Teng) for the series "Artificial Intelligence and Gastrointestinal Cancer" published in *Journal of Medical*

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[1] A very interesting video can be found online about what ImageNet pretrained neural networks "see" when the neuron excitations are amplified during a clip of a grocery trip, and it's a lot of animals and in particular—not surprisingly—dogs.

[2] The University Medical Centers (UMC) Amsterdam, the Catharina Hospital Eindhoven and Eindhoven University of Technology.

Artificial Intelligence. The article did not undergo external peer review.

Conflicts of Interest: The author has completed the ICMJE uniform disclosure form (available at http://dx.doi.org/10.21037/jmai.2019.11.03). The series "Artificial Intelligence and Gastrointestinal Cancer Column" was commissioned by the editorial office without any funding or sponsorship. The author has no other conflicts of interest to declare.

Ethical Statement: The author is accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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