Incorporating privileged information in the context of deep learning for medical imaging

Background and Motivation

Medical imaging techniques allow doctors to see inside the human body and it helps to diagnose a wide range of diseases. Over the last few years, Artificial Intelligence (AI) techniques have been exploited as a useful tool aiming to automate and improve image-based diagnosis of several diseases. Deep learning is a cutting-edge AI technique that is being recently used for faster and more accurate image-based diagnosis. It removes subjective analysis and mitigates the risk of human errors by ensuring standardisation and a numerical output which helps in making treatment decisions. It can also discover abnormalities in images which may not be spotted by medical experts with naked eyes. Unlike standard machine learning methods, deep learning techniques apply feature learning instead of feature engineering, therefore learns the representations needed for feature detection or classification from labelled training images.

In traditional deep learning systems, the model is trained based on input training data of medical images (e.g. MRI scan, X-ray or pathology image), and it is tested using another set of medical images. However, in real-world medical scenarios, there are some situations where you have an additional expert information about the same medical case which can play an important role in improving the diagnosis of diseases. This information is often obtained from another medical domain and therefore presented in a different format such as numerical features (e.g. blood test), text (e.g. clinical report) or another relevant imaging scan. This substantial information, so-called privileged information, is usually ignored by the existing deep learning image classification approaches, and they are not used to improve the predictive performance of the image classification task.

The idea of using privileged information in a supervised machine learning framework was first suggested by V. Vapnik and A. Vashist in [1,2], in which they manged to improve the performance of a Support Vector Machine (SVM) algorithm by incorporating the privileged information during the training course of a binary classification task. The problem of Learning Using Privileged Information (LUPI) has recently received big attention by the machine learning community because it lends itself to several practical applications. It is thought that privileged information is often available for almost every machine learning problem, however, not exploited in the learning process. Hence, several approaches have been presented [3,4,5] which aim to improve the predictive performance in various supervised machine learning models.

Proposed Research

In this PhD project we aim to design an algorithm that is specifically designed for incorporating expert medical knowledge (privileged information) into the learning course of image classification deep learning models. It is worth mentioning that the privileged information will only be available during the training phase along with the classification label of each image but will be absent during the testing phase. A similar problem has been investigated in [5] where the privileged information was given in the form of a segmentation mask and was incorporated into the training stage to improve the performance of Convolutional Neural Networks (CNNs). Another approach in [6] used a heteroscedastic dropout approach to incorporate images as privileged information in the learning phase of CNNs and Recurrent Neural Networks (RNNs).

Unlike the exiting approaches which are limited to integrating imaging data as privileged information, in this project we aim to incorporate various types and formats of privileged information (such as texts, images and numerical features), depending on the knowledge domain, to improve the performance of image classification deep learning models. The framework that is to be developed in this project will be applied and tested in the context of medical imaging practical problems.

Potential Impact

Medical imaging is used in a wide range of diseases. However, patients are often going through a series of other non-imaging investigations, such as clinical assessments and blood tests, to collect more evidence about their diagnosis. Current image classification methods rely only on the analysis of images and ignore such privileged knowledge that is provided by other complementary investigations. The development and adoption of the proposed technology will allow for more accurate and robust diagnosis because it takes into consideration all forms of investigations in one computer diagnostic framework.

The pressure on the NHS continues to rise with decreasing number of qualified staff and increasing number of patients and demands. The ultimate impact for the proposed research will be seen in adoption and widespread use of AI-based imaging diagnostic systems in clinical practice, which will help to improve patient care, therapies and reduce the workload on NHS.

References

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