The promise of quantitative phase imaging and machine learning in medical diagnostics: a review

Yaw Ansong Jnr

Biomedical Engineering Department, University of New Haven, West Haven, CT, USA

Correspondence to: Yaw Ansong Jnr. Biomedical Engineering Department, University of New Haven, 300 Boston Post Road, West Haven, CT, USA. Email: yanso2@unh.newhaven.edu.

Abstract: Quantitative phase imaging (QPI) is a method of phase-contrast microscopy which quantifies the phase shift that occurs when light passes through an optically dense object. Machine learning relies on patterns and inference to study algorithms and statistical models with the goal of performing tasks without explicit instructions. QPI provides an enormous amount of information about cells. In the past, however, applying information obtained from QPI based cell profiling into practical translational solutions has been challenging due to limited access to analytical tools capable of making full sense of this data. Recent advances in Artificial intelligence and machine learning, however, suggest opportunities in applying QPI to medical diagnostics. This paper discusses how Artificial Intelligence, Machine Learning, and Quantitative Phase Imaging can be used in medical diagnostics.

Keywords: Artificial intelligence (AI); quantitative phase imaging (QPI); biology; computational; deep learning; machine learning

Introduction

Quantitative phase imaging (QPI) is a method of phase-contrast microscopy which quantifies the phase shift that occurs when light passes through an optically dense object (1,2). Unlike other conventional phase-contrast methods, QPI creates a phase shift image independent of the bright field image. The method is very useful in providing quantitative information about cells such as the morphology and cell dry mass (3). This method can, therefore, provide enormous information about cells. In the past, however, applying information obtained from QPI based cell profiling into practical translational solutions has been challenging due to limited access to analytical tools capable of making full sense of this data (4). Recent advances in Artificial intelligence and machine learning (5) suggest opportunities in applying QPI to medical diagnostics (6). The goal of this paper is to discuss artificial intelligence (AI), machine learning, QPI and how these techniques can be combined in medical diagnostics.

AI

AI can be described as machines (or computers) that mimic "cognitive" functions usually associated with the human mind, for example; "learning" and "problem-solving" (7). A more comprehensive definition of AI is "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation." (8). It is very common for tasks previously thought to be unachievable by machines to be removed from the definition of AI once machines achieve that task. This is known as the AI effect (9). AI involve the use of algorithms.

Machine learning

Machine Learning, seen as a sub-set of artificial intelligence (10), relies on patterns and inference to study algorithms and statistical models with the goal of performing tasks without explicit instructions (11).

In machine learning, the algorithm basically learns the associations of predictive data using examples in data (10). Using exploratory data analysis through unsupervised learning is known as data mining (12).

Deep learning

Deep learning, a machine learning method based on artificial neural networks, involves feeding an algorithm with large data sets with the goal of discovering the representations needed for classification or detection (13). It may be supervised or unsupervised.

Supervised learning

Supervised Learning, is the machine learning task of mapping input to an output based on input-output pairs (7). The outputs of interest in supervised learning are typically defined by a human supervisor. The goal of learning associations is to be able to predict future outputs based on input after the algorithm has been trained to make predictions.

Unsupervised learning

Unsupervised learning, unlike supervised learning, learns associations in a dataset without any external definition of associations of interest. It, therefore, identifies previously undiscovered associations instead of relying on known ones (10).

Quantitative phase imaging and deep learning in cell diagnostics

The diverse properties of cells in the body changes based on pathophysiological conditions (14). It is a known fact for example that various parasitic infections and diseases alter red blood cell properties (15). Alterations in the deformability of red blood cells have for example been documented in cases of malaria, sickle cell anemia, diabetes, just to name a few (16). Complete blood count, the universally accepted method for hematological examination of red cell properties, is population-based and fails to focus on individual red cell properties (4). Profiling individual red cells can, therefore, be a game-changer in screening diseases based on individual red blood cells (17). QPI, a method that uses the differences in intracellular refractive index distribution as an imaging contrast for label-free

imaging (18), can serve as a viable method for profiling individual cells. The challenge, however, is that the data will be accompanied by variations in each cell, a challenge which hitherto would mean difficulty in analyzing the resultant data due to lack of proper analytics tools. With the improvement in computing power and deep learning however, we can increasingly make sense of this massive data. For example, QPI and machine learning have been combined to help in the diagnosis of malaria infections (19), sickle cell (20), and sperm cell analysis (21). It is therefore proposed that, in the future, QPI can be combined with machine learning in order to provide novel diagnostic solutions.

Ethical considerations

It is obvious that large amounts of data sets will be needed in order to these train machine learning algorithms. It is essential that biases in the patient selection are avoided in order to ensure that samples used are representative enough. It is also important to ensure that data used in AI research are ethically sourced and not weaponized to attack vulnerable populations.

Final thoughts

There is great promise in combining QPI with machine learning and it can potentially lead to affordable, groundbreaking diagnostic solutions.

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Footnote

Conflicts of Interest: The author has completed the ICMJE uniform disclosure form (available at http://dx.doi.org/10.21037/jmai.2019.10.05). The author has no 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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