A smooth introduction to AI for clinicians

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Introduction

There is no single definition of artificial intelligence (AI), but the concept involves computer programs that perform functions that we associate with human intelligence, such as learning and problem solving [1,2]. AI, machine learning (ML), and deep learning (DL) are overlapping disciplines (see **Figure 1**). ML is a vast domain that involves computer science and statistics, in which a machine performs repeated iterations of models progressively improving performance of a specific task. It produces algorithms to analyze data and to learn descriptive and predictive models. Data are mostly in the form of tables with objects or individuals as rows and variables, either numerical or categorical, as columns. ML is roughly divided into supervised and unsupervised methods. Unsupervised learning occurs when the purpose is to identify groups within data according to commonalities, with no a priori knowledge of the number of groups or their significance. Supervised learning occurs when training data contain individuals represented as input–output pairs. Input comprises individual descriptors whereas output comprises outcomes of interest to be predicted—either a class for classification tasks or a numerical value for regression tasks. The supervised ML algorithm then learns predictive models that subsequently allow to map new inputs to outputs [3].

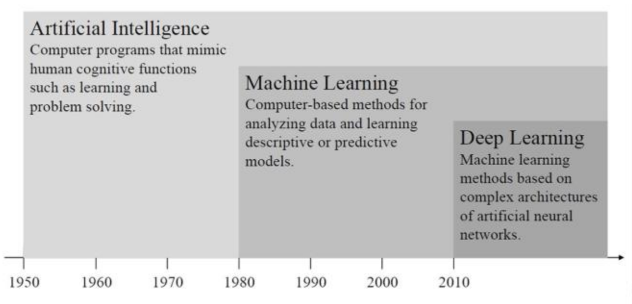

Figure 1. Timeline of Artificial Intelligence main concepts.

Artificial neural networks (ANN) are supervised ML models inspired by the neuroanatomy of brain. Each neuron is a computing unit and all neurons are connected to each other to build a network. Signals travel from the first (input), to the last (output) layer, possibly after going through multiple hidden layers (see **Figure 2**). Training an ANN consists of dividing the data into a training set that helps to define the architecture of the network and to find out the various weights between the nodes and then a test set to assess the capability of the ANN to predict the desired output. During training, weights of interneuron connections are adjusted to optimize classification. The competition for more performance has led to a progressive complexity of neural network architectures, resulting in the concept of DL [4].

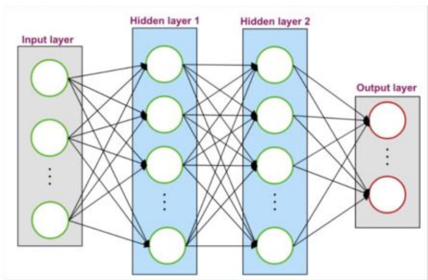

Figure 2. Overview of an artificial neural network (ANN) with one input layer, two hidden layers and one output layer. During training on a dataset of input-output pairs, weights of interneuron connections are adjusted to optimize classification. Once trained, such ANNs allow to map any new input (represented in the input layer) to a given output (represented in the output layer).

Deep neural network (DNN) models are characterized by the application of several consecutive filters which allow the automatic detection of relevant features of input data. For this reason, DNN are

considered as capable of learning data representation while including this learning in the global learning of the classification task. A variety of DNN architectures are included in DL-based methods [5]. However, the good performance obtained requires a huge amount of labeled training data. Researchers have addressed this issue by combining DL with reinforcement learning principles [6].
The limits to these techniques are overfitting and lack of explainability. The models obtained by DL often perform much better than any other at fitting the data, however they are intrinsically dependent on the training dataset. If the training population does not include enough diversity, or contains an unidentified bias, results may not be generalizable to real-life populations leading to problems in model validation. Moreover, DNN, like ANN, provide black-box models lacking explainability. Recent studies are oriented towards improving explainability of DNN models as it is a pre-requisite for their acceptability in many fields, particularly in the biomedical applications [7,8].

References

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