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Treatment Policies For Chronic Illnesses And The Potential To Transform Health Care With Artificial Intelligence

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ABSTRACT:

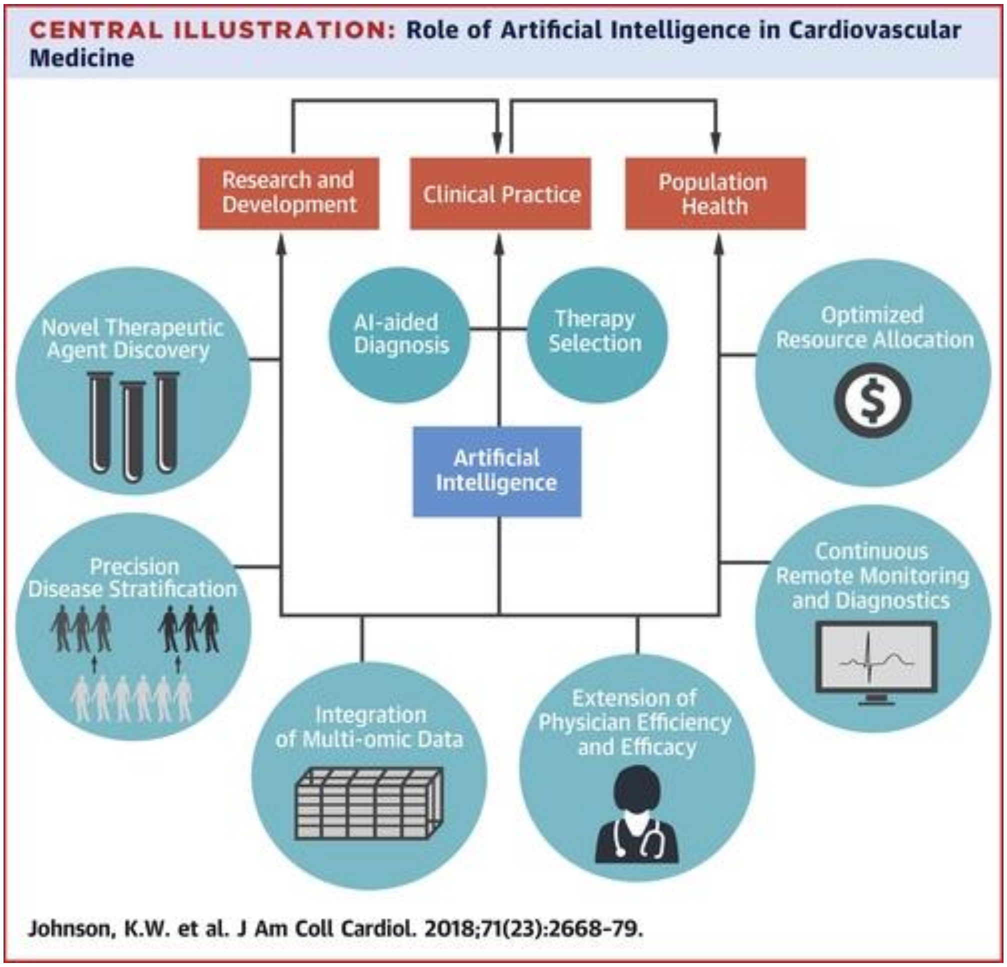
Artificial intelligence (AI) and machine learning (ML) are poised to influence almost every aspect of the human condition, and cardiology is no exception to this trend. This article guides for clinicians on relevant aspects of AI and ML, evaluates selected applications of these approaches in cardiology to date, and identifies How cardiovascular medicine can integrate artificial intelligence into the future [1]. Artificial intelligence approaches combined with the latest technologies, including medical devices, mobile computing, and sensor technology, have the potential to enable the creation and delivery of better managed services to deal with chronic diseases [3]. The widespread application of AI in healthcare was predicted half a century ago. For much of this period, this approach has produced expert systems and graphical models that attempt to automate expert reasoning processes. However, in the last decade, a completely different approach to artificial intelligence called deep learning has made breakthroughs and is now used on billions of digital devices for tasks. complex services such as speech recognition, image interpretation, and language translation [2].

Keywords:

Artificial intelligence, machine learning, cardiology, chronic diseases, image interpretation

Introduction:

The promise of artificial intelligence (AI) and machine learning (ML) in cardiology is to provide a set of tools to enhance and expand the effectiveness of cardiologists. This is necessary for several reasons. The clinical introduction of data-rich technologies such as whole-genome sequencing and mobile biometric data transfer will soon require cardiologists to interpret and manipulate information from multiple disciplines. different biomedical fields. At the same time, increasing external pressures in medicine demand greater operational efficiency from physicians and healthcare systems [1]. The potential of machine learning in cardiovascular imaging is being further explored as algorithms are created, with training on large datasets far beyond what traditional statistical reasoning can handle. Deep learning, when applied to large image repositories, recognizes complex relationships and embedding patterns of all image attributes, unlocking further connections to natural history and prognosis. heart disease states [6]. AI simulates these aspects of human intelligence through several tools. AI methods and techniques have been applied to medicine and general health over the past decades. Diagnosis, classification, therapy, and robotics, among other things, are common medical applications of AI [5]. However, in the last decade, a completely different approach to artificial intelligence called deep learning has made major breakthroughs and is now used on billions of digital devices for tasks. complex services such as speech recognition, image interpretation, and language translation. The goal of this perspective is to provide healthcare professionals with an intuitive understanding of the technology underlying deep learning. In an accompanying Viewpoint, Naylor1 describes several factors driving the adoption of this technology in medicine and healthcare [2]. The concept of computerized clinical decision support when it was a major topic for research in computer science. Two recent insights from JAMA have highlighted the promise of deep learning in medicine. These new methods of data analysis offer many benefits in the interpretation of large and complex data sets. Complex [7].



METHODS:

A literature review was performed using PubMed and related bibliographic resources. A literature review from 2010 to 2018 yielded 1849 relevant articles, of which we selected 141 for a detailed review [3].

Macular retinal images focused at 45° in color of 1273 patients as part of a screening program for intra-city diabetic retinopathy. A system involving preprocessing was used to normalize color and improve contrast, segment to detect possible lesions, and classify lesions using an artificial neural network. The system was trained using a subset of 500 patient images and evaluated by comparing its performance with a human scoring tool on a test set of 773 images. patient photo [4].

Why does cardio need artificial intelligence?

AI arises because more familiar algorithms can often be improved for real-world tasks. Take the case of logistic regression. To allow statistical inference such as estimates of coefficients and p-values, this model requires some strong assumptions (e.g. independence of observations and no multicollinearity between variables). When logistic regression is used for other purposes, the assumptions that allow statistical inference may not be relevant for the purpose and may hinder the performance of the model. In contrast, machine learning algorithms are often used without making many assumptions about the underlying data. Although this approach hinders traditional statistical reasoning, it results in algorithms that are often more accurate for prediction and classification. Therefore, cardiovascular medicine can benefit from the integration of AI and machine learning [1].

What will cardiovascular medicine gain from machine learning and artificial intelligence?

Cardiologists make data-driven patient care decisions, and they tend to have access to richer quantitative patient data than many other specialties. While there are some potential pitfalls, it's clear that the best way to make data-driven decisions is to apply techniques learned from AI. Therefore, cardiologists will need to integrate AI and machine learning into the clinic. Indeed, as the amount of data available at the patient level continues to grow, and as we continue to integrate new and complex biomedical data streams into the clinic, it is likely that AI will become essential to our patients. with clinical practice. This is likely to happen earlier, as evidenced by the rapid adoption of automated algorithms for computer vision in radiology and pathology [1].

unsupervised learning

Therefore, although we mainly focus on supervised machine learning, an equally important concept is unsupervised learning (Table 1). While supervised learning focuses on predicting outcomes and requires labeled cases, unsupervised learning focuses on discovering the underlying structure and relationships in the data set. Unsupervised learning does not require labeled observations. Like supervised learning, unsupervised machine learning methods coexist with more traditional statistical methods such as principal component analysis, mixed models, and various clustering methods. However, in recent years, new techniques that require less assumptions about the data set have emerged, such as advanced algorithms for matrices or tensor coefficients, data analysis. topology and deep learning [1].

A brief survey of supervised machine learning algorithms in cardiology

Finally, supervised machine learning is an attempt to model the relationship between independent and dependent variables (Table 1). In machine learning, you must choose a strategy (by choosing a particular algorithm) to explore these relationships. This section highlights several algorithms that can be used in the cardiovascular setting and provides a summary of supervised and unsupervised algorithms.

Table 1Brief Overview of 3 Common Supervised and Unsupervised Learning Algorithm Classes*

Example Algorithm Class	Advantages	Disadvantages	Example Application (Ref. #)
Supervised Learning Goals: Prediction of outcome, classification of observation, estimation of a parameter			
Regularized regression	Straightforward and automatic solution to high-dimensional problems Familiar interpretations for relationship of variables to outcomes	For groups of correlated features, arbitrary selection of single feature (LASSO)	Construction of a predictive model for acute myocardial infarction by using proteomic measurements and clinical variables (18)
Ensembles of decision trees	Often best “off-the-shelf” algorithm for prediction or classification Feature selection and variable importance assessment are built in	More useful for prediction than for descriptive analysis of dataset and variables Tendency to overfit data	Prediction of cardiovascular event risk (19)
Support vector machines	Transforms linear classifiers into nonlinear classifiers with the “kernel trick” Often makes highly accurate predictions	Performs nonprobabilistic classification by default Computation can be difficult in high-dimensional space	Prediction of in-stent restenosis from plasma metabolites (22)
Unsupervised Learning Goals: Discovery of hidden structure in a data, exploration of relationships between variables. Features discovered by unsupervised learning can often be incorporated into			

Table 1Brief Overview of 3 Common Supervised and Unsupervised Learning Algorithm Classes*

Example Algorithm Class	Advantages	Disadvantages	Example Application (Ref. #)
supervised learning models			
Deep learning algorithms	Current state-of-the art method for feature engineering; features are often used as input for supervised learning model Wide interest across industry and academia; rapidly developing software ecosystems	Computationally expensive to train Requires a large dataset to train the model Model interpretability can be difficult	Construction of predictive representations of patients in an unsupervised fashion from electronic health records (36)
Tensor factorization	Natural incorporation of multimodal and multidimensional data	Modest number of applications thus far in published cardiovascular reports Choice of factorization algorithm is crucial for results	Subtyping of congestive heart failure with preserved ejection fraction (34)
Topological data analysis	Interpretable clustering and discovery of variable relationships	Software ecosystem less mature than for other methods Commercial offerings require licensing agreement	Subtyping of type 2 diabetes mellitus from electronic medical records (35)

LASSO = least absolute shrinkage and selection operator.

∗ Deep learning was introduced as an unsupervised learning method; however, many of the most notable applications of deep learning are those that use features learned using deep neural networks as input to supervised learning models. In fact, the last neural network layer in a deep learning model is usually just a classifier layer, and in such a case, a deep learning model can be considered as an example of supervised learning.

Machine Learning:

Machine learning (ML) algorithms are characterized by the ability to learn over time without explicit programming. The main features of ML are that problem solving is often based on data classification. There has been a gradual shift from heuristic approaches to ML techniques. In the field of data mining, ML algorithms are used to uncover valuable knowledge from large databases such as electronic medical records, which may include latent patterns. ML can also be applied to areas where computer programs must automatically adapt to changing conditions. For example, ML algorithms are useful for learning from individual patient monitoring data and adjusting over time in an artificial pancreas system. ML is based on findings from AI, probability and statistics, computational complexity theory, control theory, information theory, philosophy, psychology, neurobiology, and more [5].

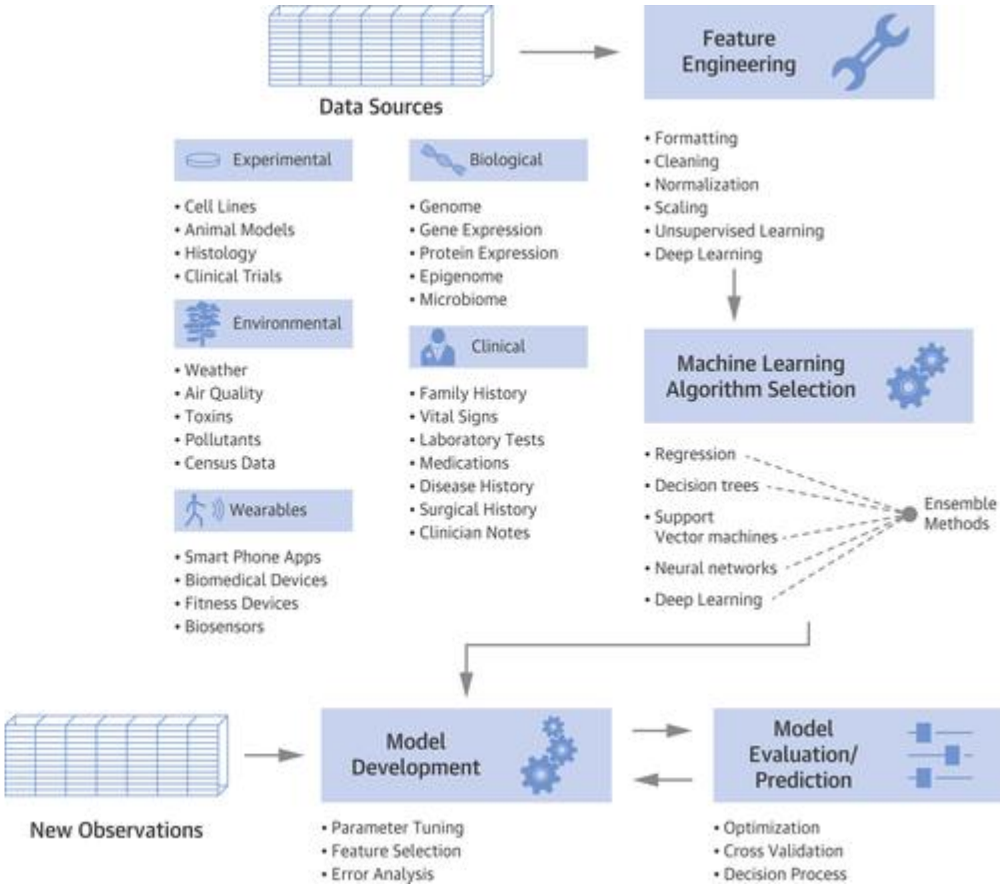


Figure 1

Overview of the Machine Learning Workflow

The central promise of machine learning is to combine data from a variety of sources (clinical measurements and observations, biological omics, experimental results, environmental information, wearable devices) into models. sensitive to describe and predict human diseases. The typical machine learning process begins with data collection, moves on to feature engineering, then algorithm selection and model development, and finally ends with model evaluation and application.

Deep learning in cardiology

Deep learning is a new branch of ML that is based on the behavior of neurons inside the human brain. It can be viewed and extended from ANN, it uses a hierarchical level of ANN to perform the classification process. Deep learning algorithms are particularly powerful in learning processes and provide a high level of intelligence to the systems that rely on them. In deep neural networks, depth refers to the factor by which multiple processing layers transform input data (be it images, speech, or text) into useful output for decision-making [5].

Unlike other areas of technology, deep learning in healthcare is still under development and its applications to date in cardiology are rather limited. The first commercial applications of deep learning were in computer vision or computer image analysis. Similarly, many of the first biomedical applications of AI were in image processing. Mined CNN to detect diabetic retinopathy from a database of 128,000 retinal images. These investigators obtained a sensitivity of 97.5% and specificity of 96.1% compared with the reference classification of 7 to 8 ophthalmologists. used CNN on 129,000 dermatological lesions to classify whether the lesion was benign seborrheic keratosis versus squamous cell carcinoma or benign mole versus malignant melanoma. This group found that their CNN performed as well as a group of 21 board-certified dermatologists. It is important to note that these 2 papers show a significant drawback of deep learning: a huge amount of data is needed to train a deep learning model due to the large number of parameters that need to be estimated. The cost and difficulty of obtaining biomedical data compared to other fields are factors that limit the application of AI in certain cases [1].

Results:

We propose a functional classification for diabetes management and artificial intelligence. In addition, a detailed analysis of each topic type was performed using relevant key findings. This approach reveals that the experiments and studies reviewed have yielded encouraging results [3].

The maximum sensitivity for detecting any retinopathy per patient was 95.1%, with a specificity of 46.3%. Specificity can be increased up to 78.9% but is accompanied by a decrease in sensitivity to 70.8%. In the setting of 94.8% sensitivity and 52.8% specificity, no cases of vision-threatening retinopathy were missed (retinopathy requiring immediate referral to ophthalmology or re-examination). within one year according to the criteria of the National Eye Research Institute). Clinical excellence). If the system is implemented with a sensitivity setting of 94.8%, more than half of the images without retinopathy will be correctly identified, reducing the need for reviewers to review images at 1 1/3 of the patients [4].

Conclusions:

We have obtained evidence of accelerating research activities aimed at developing artificial intelligence-based tools to predict and prevent diabetes-related complications. Our results indicate that AI methods are gradually being established a suitable for use in daily clinical practice, as well as for the self-management of diabetes. Thus, these methods provide powerful tools to improve patient's quality of life [3].

This system can be used when screening for diabetic retinopathy. At the sensitivity setting of 94.8%, the number of normal images that need to be reviewed by a human proofreader can be halved [4].

Diabetes must go through an adaptation process to integrate new diabetes management tools. Technology, particularly sensors and computer applications, has become a key tool in diabetes management for healthcare providers and patients. While modern diabetes care units should include diabetes technicians17 to manage the technology, doctors and nurses cannot ignore the basics to find better solutions for each. patient situation. Knowledge of insulin pumps and more recently of glucose sensors has gradually increased; However, understanding the performance of AI and smart applications is largely inadequate. This article provides a general overview of the basic concepts, definitions, and terms commonly used in AI-related applications, as well as a list of related AI publications for diabetes [5].

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