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Using machine learning for healthcare challenges and opportunities

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A B S T R A C T

Machine learning (ML) and its applications in healthcare have gained a lot of attention. When enhanced computational power is combined with big data, there is an opportunity to use ML algorithms to improve health care. Supervised learning is the type of ML that can be implemented to predict labeled data based on algorithms such as linear or logistic regression, support vector machine, decision tree, LASSO regression, K Nearest Neighbor, and Naive Bayes classifier. Unsupervised ML models can identify data patterns in datasets that do not contain information about the outcome. Such models can be used for fraud or anomaly detection. Examples of clinical applications of ML include the formulation of various clinical decision support systems. An important public health application of ML is the identification and prediction of populations at high risk for developing certain adverse health outcomes and the development of public health interventions targeted to these populations. Various concepts related to ML need to be integrated into the medical curriculum so that health professionals can effectively guide and interpret research in this area.

1. Introduction

Machine learning (ML) is an old concept that has recently gained a lot of attention due to the explosion of data generation processes in healthcare. According to one report, approximately 86% of healthcare organizations use some form of ML solutions, and more than 80% of healthcare organization leaders have an artificial intelligence (AI) plan [1,2]. ML is an important discipline in the larger field of AI. ML is defined as "the ability of a machine to mimic intelligent human behavior " [3]. An algorithm is trained to learn from data and then make decisions based on similar characteristics or variables from new data [4] The intersection of various disciplines, especially mathematics, statistics, and computer science, is an important essence of the data science required to implement various ML models [5] Despite the power of human intelligence, humans tend to make mistakes because of their limited short-term memory [6]. When the tremendous growth in data is combined with the increasing ability of computers to process and use the data to formulate various machine learning algorithms, there is an opportunity to use machine learning to help humans make decisions by taking into account a significant amount of contextual information.6 Recently, ML has been used in a variety of medical disciplines that include heart failure management, clinical decision support in clinical medicine, and medical imaging [7–9].

Compared with traditional hypothesis-driven statistical analysis, ML focuses on the predictive accuracy of a model.10 Epidemiologic methods have traditionally driven the process of data generation in health care. Although the methods of ML allow for new ways to answer various questions, the lack of effective integration between the two disciplines is a major challenge, especially when data scientists and epidemiologists communicate as a team [10]. It has also been argued that although many different terminologies are used in these disciplines, different words are used for overlapping or nearly the same concepts.10 Because epidemiologists and statisticians have long used such concepts in hypothesis-driven research, it is fairly easy for them to understand these concepts if they are sensitized to the fact that ML only applies these concepts with a new framework in mind. In addition, other healthcare professionals such as clinicians, public health physicians, pathologists, and radiologists are more familiar with hypothesis-driven research than with ML algorithms. Therefore, it is necessary to convey the conceptual parallelism between the two different but closely related disciplines.

With this narrative review, we aim to provide an overview of several relevant ML concepts and the scope of their potential implementation in healthcare. Emphasis is placed on explaining the classification of ML models and the details of the various algorithms that can be used. This methodological review provides an overview of different relevant ML algorithms to make an informed decision.

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1.1. Type of machine learning models

ML models are divided into supervised learning, unsupervised learning, and reinforcement learning, depending on the problem we are trying to solve [10–12].

1. Supervised Learning

Supervised ML models are used in situations when the outcome of interest is specified, and data is explicitly labeled for the outcome [11]. For example, the outcome may be the presence or absence of a disease like diabetes or hypertension. One requirement for these models is that since we are training the model based on the outcome labels in the data, we need to be sure that those labels are correct. Any bias in outcome assessment will also affect the performance of the formulated model and, therefore, make the prediction less generalizable to the population outside the dataset on which the model is trained. The process of formulating a supervised ML model is explicitly defined and matured since these models are being used quite frequently. In order to formulate a supervised ML model, the first step is to come up with a problem statement followed by identification of the needed data that is relevant to the problem of our interest [13]. Processing of the data is an important step that must be undertaken that may involve data wrangling, limiting the data to needed variables, and removing other variables [14]. One popular method is choosing a random sample of the data, choosing an algorithm, training the model, and evaluating the model made [13]. There are several types of algorithms that we can choose. One way is to train the model using several relevant algorithms and check the performance of these models using confusion matrix and receiver operating curve (ROC) [15]. Coming up with a final model is an iterative process. An algorithm is selected with the best possible combination of parameters to ensure the maximum possible predictive ability for the model.16 Some methods papers have suggested default values for different parameters to minimize hyperparameter tuning time and computational effort [16].

1.2. Different algorithms used for supervised machine learning

The algorithms used in supervised learning can be broadly divided into regression and classification algorithms based on the prediction of a quantitative or categorical variable [17,18].

a regression algorithms

1.2.1. Linear regression

Linear regression is one of the most used algorithms developed to predict a quantitative variable using one or more independent variables with the assumption that the independent variables and the outcome variables have a linear regression with each other [19]. Because of its wide use, this algorithm is widely understood, and therefore it is easy for health professionals to interpret it compared to other ML algorithms.

1.2.2. Support Vector Machine Regression

Sometimes quantitative dependent variable does not have a linear relationship with the predictors. In such a case, support vector machine regression is one suitable option to predict the outcome variable [20]. Advantages of using Support Vector Machine Regression include its ability to accurately predict without compromising generalizability and its ability to be robust to outliers. This model is unsuitable for a few situations, like dealing with a large dataset [20]. Similarly, when there are many variables, and the sample size is lesser than the number of variables, this model might not be suitable [20].

1.2.3. Decision Tree Regression

Decision Tree Regression is a model used to predict a quantitative variable by asking several questions in the form of true and false. The model predicts when it is confident to make a correct prediction at an appropriate point [21]. One important strength of this algorithm is its intuitive interpretation because it is near to how human beings think and predict an outcome by asking many questions [21]. This is a non-parametric method meaning that this model does not have a strict assumption about the distribution of the outcome variable [21].

1.2.4. Least Absolute Shrinkage and Selection Operator regression

Least Absolute Shrinkage and Selection Operator (LASSO) regression penalizes the coefficients that do not contribute significantly to the prediction of the outcome variables [22]. As a result, some coefficients may become zero and therefore only the variables that better predict the outcome variables are selected [22].

b Classification algorithms

1.2.5. Logistic regression

Logistic regression is a commonly used classification algorithm that predicts a categorical outcome in situations where the outcome has two levels [23]. A disadvantage of logistic regression is that interactions must be added manually [24]. Multinomial logistic regression predicts categorical variables with more than two levels [24].

1.2.6. K Nearest Neighbors

This simple prediction algorithm is known for its ease of implementation and interpretation [18,25]. This model does not require the setting of many parameters [25]. This algorithm slows down as the number of predictor variables increases [25]. The result is categorized based on the majority vote of the neighboring data points near the point of interest. For this purpose, the Euclidean, Manhattan, and Minkowski distances are used.

1.2.7. Naïve Bayes classifier

This classifier is used based on Bayes' theorem [26]. This algorithm is well suited for predicting outcomes with more than two levels [27]. In situations where the assumption of independence holds, less training data is required than in logistic regression [27]. Although independence of the predictor variables is assumed, in most cases the variables are not independent in the real world.

1.2.8. Decision tree classification

The decision tree can be used to predict a categorical variable and uses an approach called recursive partitioning, which further divides the decision space into smaller and smaller areas and then labels this space [28]. An important strength of the decision tree is its ability to easily adapt to a clinical context and its better interpretability compared to other algorithms. In a clinical setting, this algorithm makes the prediction and tells the decision maker the exact reason for that prediction. It is also well suited to classify unknown data sets [28]. As the number of variables increases, it becomes difficult to interpret the decision tree [28]. These models are often biased toward splits on variables with multiple levels [28]. The decision tree is quite sensitive to small changes in the training data [28].

2. Unsupervised Learning

The outcome is not specified in unsupervised ML, and the data is not labeled. The algorithm has to identify and infer patterns from data without an outcome variable [29]. Different methods can be used for unsupervised learning. Clustering is one method in which data is split into groups through an algorithm [29]. One needs to be cautious about making decisions based on clusters because cluster analysis overestimates similarity between groups [29]. Unsupervised ML techniques can be used to identify an unusual pattern in the data and detect an anomaly that can be a possible fraud [29]. When there are many features, dimensionality reduction can be used to reduce the features in the dataset [29].

3. Reinforcement Learning

Reinforcement learning is one type and a practical application of ML. A sequence of models is made to make some decisions [12]. The system takes some action and gets feedback based on that action. The decisions and resulting actions are modified based on the received feedback. The process starts with trial and error, and this artificially intelligent system learns from the feedback received. The feedback is incorporated as subsequent decisions and actions are modified until the system gives favorable feedback. When different machine learning algorithms are combined and organized in a creative way to make different decisions, get regular feedback, modify the decisions, and experiment on a range of decision space until the final decisions are optimized based on the outcome [12]. In healthcare, the decision is not linear, and that requires considering a multitude of factors before making a decision [30]. Reinforcement learning can be used to design a decision support system to provide treatment recommendations to the physicians [30]. There are several challenges when adopting reinforcement learning to healthcare, like evaluating the decision made by this system and choosing the reward to modify the decision and action [30]. This model also requires understanding the disease dynamics and contextually establishing the causal relationships between the relevant factor and the outcome [30].

1.3. Application of ML in different areas of healthcare

1. Clinical Decision Support Systems in Healthcare

There are several examples of ML methods and algorithms used to formulate a clinical decision support system (CDSS) to assist clinicians. One example is the use of an ensemble model of four different models, i. e., a neural network, a gradient boosted decision tree, a support vector machine, and logistic regression to stratify the mortality risk of patients with infection COVID 19 [31]. Similarly, a CDSS has been formulated to reduce prescribing errors by helping to prioritize prescription checks [32,33]. A similar support system can also be formulated to help the pharmaceutical industry select a candidate molecule for research that is more likely to pass through regulatory processes and reach the market as a drug [34]. Maternal health initiatives can use a CDSS to predict ectopic pregnancies [35]. CDSSs have been developed to use imaging data such as positron emission tomography and computed tomography to predict lung cancer so that it can be treated in a timely manner [36]. Many other examples include CDSS assisting in the treatment of periodontal disease, early detection of circular RNAs, detection of shock conditions, and assisting in self-referral decisions for back pain [37–39]. A deep-learning algorithm has been used to detect diabetic retinopathy in patients with diabetes [40].

A common concern when implementing ML algorithms is whether such an implementation can be as good as expert opinion. One research group formulated a deep neural network algorithm and mimicked the diagnostic skills of experienced dermatologists to detect skin cancer [41]. A similar study reported that a nested neural network algorithm performed comparably to an experienced radiologist in predicting disease based on chest x-rays.

2. Use of machine learning in Public Health

Population-level healthcare outcomes can be predicted by ML algorithms using large data sets [42]. ML algorithms are advantageous when there are large data sets and a non-linear relationship between the outcome and other independent variables. Several ML algorithms are reproducible, and the true essence of these algorithms lies in the underlying authentic and high-quality data. Predictive models are not new in health care, an example being the Framingham health score formulated in 1967 [43]. Although parametric statistics have been used in the past to predict various population-level outcomes, there is a recent need and interest in using various ML algorithms to predict these outcomes [44]. Although the theoretical knowledge and principles used in formulating ML models have been around for some time, there has been a recent explosion in the process of generating a large amount of variable data at high velocity in various public health organizations [45]. In addition, the improved ability to process data through various hardware and cloud solutions has enhanced our ability to effectively use complex algorithms for Big Data [46]. Examples of the use of ML to improve population health include the prediction of childhood lead poisoning, the occurrence of suicidal ideation, the detection of diabetic retinopathy, the management of public health emergencies, and the incidence of yellow fever [44,47,48]. A review of population health prediction through ML found that the most used algorithms to predict public health outcomes were neural networks, support vector machines, and single tree-based models [44]. The same review found that ML algorithms were commonly used to predict communicable and noncommunicable diseases but were less likely to predict outcomes not related to disease [44] cardiovascular disease was the most predicted outcome. Behaviors such as health care utilization were also predicted using various ML models [44]. ML algorithms used to predict population-level health outcomes used structured data from electronic medical records and other similar sources [44]. Although unstructured data from multiple publicly available data sources can be quite useful in predicting various health outcomes, this is not commonly practiced by public health practitioners.

1.4. Machine learning in the medical curriculum

With all advancements in the field ML, the increasing use of various ML algorithms, and the ever-increasing demand for better utilization of data in healthcare, the next generation of healthcare providers will need to know the concepts, potential and terms necessary to understand ML. Knowledge of ML algorithms and relevant terminology will help to understand and interpret relevant literature or lead research involving ML algorithms. There is a need to educate public health professionals, epidemiologists, clinicians, pathologists, radiologists, and other health care professionals the various ML terminologies. Given the conceptual interaction between data science and epidemiology, it is equally important to train public health data scientists who have good epidemiologic acumen. It is recommended that some of these data science and ML -related concepts be incorporated into the medical curriculum in the long term [49].

1.5. Challenges in implementing ML models in health care

Numerous challenges that arise in the application of ML algorithms in healthcare need to be explored and discussed by experts [50]. Any machine learning model depends on high-quality data that are representative of the population to which the model's results are to be generalized. Thus, if we intend to integrate ML models into health care, formulating effective data management at all levels becomes an essential requirement. In addition, pipelines for data processing and ML with user-friendly front ends for the products must be formulated. These pipelines can transform the raw data into datasets that can be used to train various ML models. The relevant stakeholders need to formulate an effective data governance strategy to leverage the generated data.

Another critical challenge is that prediction based on ML usually does not provide reasons for the prediction unless models such as decision trees are used that allow intuitive interpretation [50,51]. In situations where the ML model is used to predict a health outcome, the legal procedures are not optimized in case of a potential error. This point can be quite challenging in practice, given the complexity of legal procedures in different countries.

1.6. Ethics and machine learning

As in any other area of research or clinical practice, it is necessary that ethical principles be central to any decision-making framework. It is expected and indeed observed that new ethical dilemmas will arise with the advent of new technologies [52]. Experts have argued that ethical dilemmas related to ML algorithms can be categorized in the areas of accountability, equity of resource allocation, and personal integrity [52]. One of the fundamental guiding principles of any ethical framework is "Do No Harm," so at a minimum, a predictive ML algorithm must not be harmful [53]. It is critical to ensure algorithmic fairness when generalizing the results of such an algorithm [54]. Low- and middle-income countries are particularly vulnerable to bias due to generalizations based on such algorithms. This is due to the lack of legal protection, the prevalence of bias against some minority groups, and the lack of technical capacity [54]. Given these complex ethical dilemmas, there is a need to research and develop ethical guidelines to propose solutions to these dilemmas. Similarly, we have seen that the algorithms of ML tend to reinforce inequalities presented in the underlying data [50,55]. These inequalities may be based on gender, ethnicity, or racial groups [50]. There is a need to conduct methodological research to ensure that ML models do not reinforce these inequalities.

2. Conclusion and recommendations

Hypothesis-driven research that uses epidemiologic and statistical knowledge has long been practiced in health care. The recent generation of large amounts of variable data, combined with the improved computational power of high-speed physical and virtual machines, has allowed us to develop several predictive ML algorithms. These algorithms have enabled us to formulate several clinical decision support systems and predict population-based health parameters. With the increasing demand for ML algorithms in health research and their application in clinical practice, health professionals must receive the necessary training to understand the various terminologies. It is equally important that data scientists understand the conceptual parallels between data science and various epidemiological concepts. Finally, it is important to ensure that the ethical principle of "do no harm" is observed when generalizing findings from these ML algorithms.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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