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Applying Machine Learning to the Health Industry

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Abstract

Recent developments in ML and AI have made great leaps in several areas, including the prediction and identification of health emergencies, disease populations, disease states, and immune responses. The use of ML-based techniques is rapidly expanding in healthcare settings, despite ongoing skepticism about their practical use and interpretation of outcomes. Here, with examples, we give a concise introduction to learning algorithms and methodologies based on machine learning, covering topics such as supervised, unsupervised, and reinforcement learning. The second part of the article is devoted to the use of ML in many areas of medicine, such as neuroimaging, genetics, EHRs, and radiology. Additionally, we offer recommendations for future uses of ML and quickly go over the hazards and difficulties of applying it to healthcare, including system privacy and ethical considerations.

Key words: Machine Learning, Health Industry, Deep Learning, Electronic Health Records

Introduction

The application of machine learning began in the 1950s when Alan Turing suggested the first artificially intelligent system capable of learning [1]. Since its inception, machine learning has found usage in a wide range of applications, including face detection for security services [2], reducing risk and boosting efficiency in public transportation [3, 4], and more recently in several facets of biotechnology and healthcare [5–10] Anticipated developments in healthcare and medicine mirror the transformative impact of artificial intelligence and machine learning on commercial operations and everyday life. Alarming progress has been made in this area, which holds the potential to alleviate a portion of the burden of physicians while simultaneously enhancing precision, predictability, and the quality of care provided. Thus far, advances in medical machine learning have predominantly aided analysts and physicians in the identification of healthcare trends and the development of malady prediction models. In large medical organizations, the implementation of machine learning-based techniques has benefited robotics-assisted procedures [9, 13], organs [6–8], bones [12], and the organization of electronic health records [11]. The application of machine learning has now made it possible to speed up hospital reaction and testing in the fight against COVID-19. In spite of the epidemic, hospitals have used GE's clinical deep learning system to coordinate care, disseminate information, and keep tabs on everything from patients to beds to rooms to ventilators to electronic health records and even staff [14]. Additionally, researchers have using AI to detect SARS-CoV2 genetic sequences, develop vaccines, and track their efficacy [15].

With the introduction of numerous new innovations annually, the healthcare business is quickly adjusting to the current technological environment. Improving diagnostic speed, accuracy, and simplicity are all goals of the profession that can only be achieved with the help of AI and machine learning-based methods and applications. This review aims to shed light on the pros and cons of healthcare-related machine learning-based techniques. As new machine learning technologies engulf the healthcare industry, we want to provide a brief overview of the various ML techniques and highlight the domains where these approaches are primarily applied. We talk about how common they are and the possibilities for their further development in healthcare. Additionally, we cover the difficulties and dangers that arise from their implementation from an ethical and logistical standpoint.

Overview of Machine Learning

Machine learning, deep learning, and AI are often thought to mean the same thing, but in reality, they all refer to distinct algorithms and learning processes. Anything a machine can learn to do tasks normally performed by a human brain is considered to be part of artificial intelligence (AI) [16]. Although AI is most commonly associated with autonomous vehicles and robotics, it is also present in many commonplace applications, such as targeted online ads and search engines. Artificial intelligence (AI) has advanced tremendously in recent years, finding use in a wide variety of contexts thanks to its superior processing abilities, accuracy, problem-solving capacity, and decision-making abilities [17]. In order to guarantee accurate learning, statistically valid populations, and fair forecasts, the data collected is typically divided into two sets, a training set and a test set, while developing AI systems. Training algorithms makes use of sets of data points that describe them (features) and the predictions that go along with them (in supervised learning), as the name implies. For the express purpose

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of evaluating the algorithm's performance, the testing data set is completely novel to it. There will be no bias in the algorithm's testing on the training dataset if this step is done [18]. Algorithms are introduced into healthcare settings once they successfully complete the training and testing phases. While artificial intelligence (AI) has numerous potential uses, we focus on just two of these areas—machine learning and deep learning—to give you a taste of what this technology has to offer.

To answer issues without specialist programming, machine learning incorporates several algorithmic models and statistical methodologies [19]. Due to the fact that many ML models only have one layer of processing, a lot of work is done on the data and features before they are even fed into the algorithm [20]. In order for these machine learning algorithms to prevent over-fitting or under-fitting the training dataset and provide accurate predictions without the additional layers, extensive data pretreatment is necessary. Deep learning, a more advanced branch of machine learning that uses stacked artificial neural networks, improves accuracy and specificity while decreasing interpretability [21]. One definition of the neural network approach is a multilayer network that facilitates communication between the simulated neurons (or units) in successive layers [22]. Through the use of these multilayer linkages, these networks are able to process input autonomously, learning, discerning, and deducing from it until they reach the desired specialized outputs [21].

Learning Approaches

A variety of learning techniques form the basis of most algorithms used in machine learning and artificial intelligence. Supervised learning, which makes use of previously produced instances or outputs, is one method for training algorithms that perform classification and prediction. The training set includes characteristics and matching predictions or outcomes, which is a significant difference for this learning approach. To put it simply, supervised learning relies on the characteristics of the training set to build a model that can accurately predict the outcomes of the training set. Then, using the learnt model, predictions are made using the new features of the testing set [20]. Decision trees, support vector machines, artificial neural networks, and random forests are a few examples of ML algorithms that employ supervised learning techniques. By starting with a single node and identifying all of the potential consequences of that choice, decision tree algorithms provide a decision assistance tool. From that selection and subsequent ones, the tree builds up to the ultimate output [23]. By determining the best fit for the data and the widest margin hyperplane to partition it, Support Vector Machines (SVMs) employ supervised learning to categorize features in two-group situations [16, 24]. Every neuron in an input layer is linked to every neuron in the layer below and above it in an Artificial Neural Network (ANN) [25]. ANNs also have one or more hidden layers and an output layer. Disease prediction[26], hospital outcome identification[14], and picture detection[27] are only a few examples of the many healthcare applications of supervised machine learning techniques.

Data evaluation and application clustering frequently make use of unsupervised learning, a subset of AI-based learning approaches. Data analysis, stratification, and reduction are the usual applications of unsupervised machine learning rather than prediction. Unsupervised clustering approaches often employ algorithms to independently cluster data sets that have not been labelled or classed. Although most machine learning approaches begin with data preprocessing and feature extraction before input, this method goes a step further by allowing feature extraction and investigating data clustering possibilities via the identification of underlying relationships or features and subsequent grouping of similar data sets [18]. The k-Means algorithm, DBNs, and CNNs are all examples of unsupervised learning techniques. As a clustering technique, the k-Means algorithm is the most popular unsupervised learning algorithm for finding the mean across groups in unlabeled datasets and then creating new groups according to that mean [18]. Unsupervised learning is the norm in Deep Belief Networks (DBNs), which are multi-layer networks with intra-level connections that are good for data retrieval. DBNs often include several hidden layers that are responsible for detecting features and discovering correlations in the data [28, 29]. Anomaly detection, picture recognition, and identification are all made easier with the help of Convolutional Neural Networks (CNNs), which are multilayer networks that depend on feature recognition and identification [25]. Despite their usefulness and speed, unsupervised algorithms are only partially popular in healthcare, despite their prevalence in clustering owing to the absence of predefined outputs and data homogeneity.

Another approach to learning that falls somewhere in the middle is reinforcement learning. Learning based on reward sequences, analogous to conditioning in psychology, helps shape an approach to dealing with a specific problem area. Some have compared reinforcement learning to the learning processes shown by animals and humans because of its emphasis on environmental input and its goal of maximizing the error criterion [30]. The implementation goal often dictates the choice of learning techniques, which is less complex than algorithm selection given the varieties of learning approaches. Recurrent Neural Networks (RNNs) are a popular type of neural network that employ reinforcement learning. Redundant Neural Networks (RNNs) are a type of neural network in which each artificial neuron is linked; with RNNs, inputs can be received at a later time, and outputs from one phase can be used as input for the next stage. It has applications in music composition, rhythm learning, translation, voice recognition, and time series prediction [25]. There is great promise for reinforcement learning to make substantial advances in healthcare, despite the fact that its current applications are limited owing to its requirements for structure, heterogeneous data, reward specification and implementation, and large computing resources.

There are many different kinds of machine learning and deep learning techniques; thus, it is critical to choose one that works for healthcare applications and put it into practice. A number of aspects should be taken into account, such as the features count [28], the sample size [31, 32], and the data distributions [33], all of which can significantly impact the learning and prediction processes.

Medical Machine Learning

When it comes to machine learning, the healthcare industry has long been at the front. The use of artificial intelligence (AI) has the potential to improve neuroimaging [37], decision-making [11], case triage and diagnosis [26], picture scanning and segmentation [34], and illness risk prediction [35, 36]. A concise synopsis of recent developments in AI applications to selected areas of health research is presented here. The mentioned applications require more readily available digital data for ML-based techniques and their clear integration of learning approaches with clinical trials and applications. In this review, we focused on machine learning's applications in three specific areas: genetic engineering, medical imaging, and EHRs. These domains also include the "big data" of healthcare, which includes both structured and unstructured information, and they have demonstrated great potential for therapeutic use.

Table1: List of primary references.

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Healthcare Area	Type of Machine Learning Model	Description	Applied or Experiment	References
EHRs	SVM, DT	Using EHRs for predicting diagnoses	Applied	Liang *et al*. 2014 [26]
	RNN	Predicting post-stroke pneumonia using deep neural network approaches	Experiment	Ge *et al*., 2019 [35]
	LSTM, CNN	Deep EHR: Chronic Disease Prediction Using Medical Notes	Experiment	Liu, Zhang & Razavian 2018 [40]
	ML	**SRML-Mortality Predictor:** A hybrid machine learning framework to predict mortality in paralytic ileus patients using Electronic Health Records (EHRs)	Experiment	Ahmad *et al*., 2020 [41]
Medical Imaging	CNN	Dermatologist-level classification of skin cancer with deep neural networks	Experiment	Esteva *et al*. 2017 [7]
	CNN	**Chexnet:** Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep--Learning	Applied	Rajpurkar *et al*., 2017; Tsai & Tao, 2019 [8]
	CNN	International evaluation of an AI system for breast cancer screening	Experiment	McKinney *et al*. 2020 [49]
	Deep CNN	Deep-learning algorithm predicts diabetic retinopathy progression in individual patients	Experiment	Arcadu *et al*. 2019 [56]
	DBN	Structural MRI classification for Alzheimer's disease detection using deep belief network	Experiment	Faturrahman *et al*., 2017 [37]
	Decision tree prediction	Machine learning approaches for integrating clinical and imaging features in late-life depression classification and response	Experiment	Patel *et al*., 2015 [27]
Genetic Engineering & Genomics	RT	Application of machine learning models to predict tacrolimus stable dose in renal transplant recipients	Experiment	Tang et al. 2017 [10]
	ML	Artificial intelligence predicts the immunogenic landscape of SARS-CoV-2 leading to universal blueprints for vaccine designs	Applied	Malone et al. 2020 [15]
	Deep CNN, Deep FFs	Off-target predictions in CRISPR-Cas9 gene editing using deep learning	Applied	Lin & Wong 2018 [76]
	RNNs	Deep HF: Optimized CRISPR guide RNA design for two high-fidelity Cas9 variants by deep learning	Applied	Wang et al., 2019 [82]
	Random Forest	CUNE: Unlocking HDR-mediated nucleotide editing by identifying high- efficiency target sites using machine learning	Applied	O'Brien et al., 2019 [81]
	CNNs	ToxDL: deep learning using primary structure and domain embeddings for assessing protein toxicity	Applied	Pan et al., 2020 [79]

EHR: Electronic Health Records, SVM: Support Vector Machine, LSTM: Long Short-Term Memory Neural Network, CNN: Convolutional Neural Network, MLP: Multi-Layer perceptron Neural Network,

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RNN: Recurrent Neural network, DBN: Deep Belief Network, ANN: Artificial Neural Network, ML: Machine Learning. Applied is defined as an algorithm or application that is currently available on a public or private platform to healthcare professionals. It also refers to applications that are currently applied in medical practices such as clinics, hospitals, etc. An experiment is defined as an algorithm or application that has been used in a research study.

Specifically, we will be searching for publications published between June 2020 and December 2020 in electronic libraries and journal databases. The following databases were utilized: Pubmed, OneFile, Nature, Sage Journals, Science Direct, PsycNet, and Gale. Machine learning and artificial intelligence in healthcare: past, present, and future was the focus of this anthology of essays and papers. Some of the search phrases that were used were: AI medical imaging, electronic health records, machine learning in genomics, big data and machine learning, electronic health records problems, and medical applications of AI. To make sure the search results were comprehensive, we utilized variations of these phrases. No specific year or journal was used to narrow the searches (Table 1).

Electronic Health Records (EHRs)

Lockheed initially offered electronic health records (EHRs) in the 1960s [38]. These systems were formerly called as clinical information systems. There have been several reconstructions of the systems since then in an effort to establish a common system for the whole industry. Nearly 87% of office-based practices nationwide have used EHRs by 2015 [39], thanks to billions of dollars funded by the US federal government in 2009 to promote EHR deployment in all practices and boost work quality and efficiency. Deep learning applications, such as drug refills and using patient history for diagnosis prediction, have greatly benefited from BIG data acquired from EHR systems with structured feature data [11]. Thanks to this, doctors are better able to make accurate diagnoses and provide effective treatments, while patients benefit from much improved data organization, accessibility, and overall care quality. Researchers now have easier access to more health records because to feature standardization across databases.

Researchers have created deep learning models to use electronic health records (EHRs) for the purpose of diagnosing and predicting clinical diseases, due to the critical role that prediction plays in treatment provision. A deep learning method for illness onset prediction, including heart failure, renal failure, and stroke, was recently created by Liu, Zhang, and Razavian. The program makes use of LSTM networks (reinforcement learning) and CNNs (supervised learning). This method differentiated itself from previous prediction models by combining structured data from EHR with unstructured data found in progress and diagnostic notes. According to Liu and colleagues, these algorithms are very versatile and resilient since adding unstructured input to the model significantly improved all the baseline accuracy measurements [40]. Ge and colleagues developed a model to anticipate the onset of post-stroke pneumonia between 7 and 14 days, utilizing deep neural network methodologies in a separate investigation. Area under the ROC curve (AUC) values of 92.8% for 7-day predictions and 90.5% for 14-day predictions were returned by the model, indicating that it was a very accurate model for predicting pneumonia after a stroke [35]. The prediction of death in intensive care unit patients has also made use of a number of ML-based models. When it comes to paralytic ileus (PI), a partial blockage of the intestine that prevents food from passing through, eventually leading to a buildup and total blockage of the intestines, one model developed by Ahmad and colleagues utilizing EHRs has demonstrated remarkable capacity to predict death in these individuals. The Statistically Robust Machine Learning-based death Predictor method had an accuracy rate of 81.30% when it came to forecasting death in PI patients [41]. In order to help patients and practitioners make more informed decisions about clinical care, EHR prediction algorithms can provide expected mortality.

Diagnostic Imaging for Healthcare

By capitalizing on digital data and standardized data formats such as DICOM, machine learning-based methods have achieved remarkable progress in medical imaging. These approaches have been applied to various imaging modalities, such as CT, MRI, X-ray, PET, ultrasound, and more. Tumors[42,43], lesions[44], fractures[45,46], and tears[47,48] may all be detected with the use of ML-based models.

A deep learning method was recently developed and used by McKinney and colleagues to identify early-stage cancers using mammograms. These screen approaches based on deep learning can detect and localize tumors early in the course of breast cancer, enabling a higher rate of resection, as compared to more conventional methods of tumor identification. The AUC score for the deep learning-based method was 11.5% higher than that of seasoned radiologists in a head-to-head comparison [49]. Wang and colleagues [50], Amrane and

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colleagues [51], and Ahmad and colleagues [52] are among the several studies that have used ML-based techniques for breast cancer diagnosis, with varying degrees of effectiveness.

Just recently, Esteva and colleagues employed convolutional neural networks (unsupervised learning) to categorize 2032 distinct skin illnesses based on dermoscopy photos. Confirming the results' accuracy, an objective comparison was conducted with 21 board-certified dermatologists, and CNN categorization was found to be "on par" with theirs [7]. This method has the potential to bring about early diagnosis and convenience of use when combined with the typical consumer mobile platform. At the same time, research has used ML-based methods to measure the development of retinal disorders [51-54]. One research that used a deep learning CNN to identify diabetic retinopathy (DR) aneurysms that lead to vision loss was conducted by Arcadu and colleagues [55]. Despite not being intentionally built to do so, the CNN was also capable of detecting tiny, low-contrast microaneurysms [55, 56]. Even though it affects around 60% of people with type 1 diabetes, diabetic retinopathy is hard to see in its early stages [57]. The use of convolutional neural networks (CNNs) to make early predictions may help patients avoid or postpone permanent eyesight loss. While X-rays have been useful for decades in diagnosing lung illness and chest anomalies, a trained radiologist should still do a thorough examination. In an effort to replicate the detection capabilities of trained radiologists, Rajpurkar and colleagues recently performed a retrospective study to investigate the capabilities of a 121-layer convolutional neural network to analyze a set of chest x-rays involving different thoracic diseases and detect abnormalities [8]. Compared to the radiologists, CNN achieved an 81% success rate in identifying patients, which is 2% better. Despite its retrospective application, this study, along with CNNs developed by Tsai and Tao [58], Asif and colleagues [59], Liang and colleagues [60], and Lee and colleagues [61], shows that these approaches can aid healthcare professionals greatly in examining and diagnosing illnesses, which is a huge relief.

Additionally, ML-based methods have been used to forecast and identify the advancement of neurodegenerative diseases such as Alzheimer's [37, 62], Parkinson's [63, 64], severe mental disorders such as psychosis [65, 66], depression [27, 67], post-traumatic stress disorder [68] and developmental disorders such as autism [69, 70] and attention deficit hyperactivity disorder [71, 72]. One research that used structural MRI scans to predict the course of Alzheimer's disease (AD) used a higher-level model that used DBNs (unsupervised learning) and achieved a 91.76% accuracy, 90.59% sensitivity, and 92.96% specificity [37]. Even while

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Alzheimer's disease currently has no known treatment, detecting it early can help put measures in place to slow the progression of symptoms and deterioration. Patel and colleagues created a model to forecast the diagnosis and response to depression treatment using decision tree models and feature-rich data sets including functional magnetic resonance imaging (MRI), cognitive behavior scores, and age. According to [27], the model achieved a diagnostic accuracy of 87.27% and a treatment response accuracy of 89.47%. Using the results of this predictive diagnosis, doctors can better pinpoint depressed individuals and craft individualized treatment regimens. Given the present state of machine learning (ML) in medical imaging, its clear benefits in prediction and diagnosis in terms of sensitivity, specificity, accuracy, and classification make its usage worthwhile for the advancement of the medical industry.

Risk and Challenges

There are new risks, difficulties, and reasons to be skeptical about healthcare applications based on machine learning, but there are also exciting new prospects. In this section, we will go over the primary aspects of risk, such as the likelihood of prediction mistake and its consequences, the security and privacy vulnerabilities of the systems, and the fact that there isn't enough data to get consistent findings. There are a number of obstacles, such as questions of ethics, the potential erosion of the human touch in healthcare, and difficulties in translating theoretical concepts into action at the bedside. The biggest risk of machine learning algorithms is their reliance on probabilistic distributions, which increases the possibility of incorrect diagnosis and prognosis. Predictions made by ML-based algorithms should so be approached with a healthy grain of skepticism. Although error and chance are inherent in all aspects of health care, the seriousness of ML-based systems causing a human fatality is a matter of great concern. The use of these machine learning-based techniques should only be used after they have been rigorously approved by many bodies, both legally and institutionally [73, 74]. In very delicate situations, such as when diagnosing depression or breast cancer, human interaction and supervision by a trained healthcare professional can help prevent incorrect results. Current healthcare workers' participation in these methods' creation and implementation has the potential to boost adaptation rates while calming fears of a reduction in human job chances or the workforce as a whole [75].

Another concern associated with applying ML and deep learning algorithms to healthcare is the availability of high-quality training and testing data with enough samples to ensure very repeatable and reliable predictions. It is crucial to have high-quality data since methods based on machine learning and deep learning 'learn' from it. The learning networks and methods rely on massive volumes of feature-rich data, which is not easily accessible and could only be a small subset of the population. Data obtained is also incomplete, diverse, and has many more attributes than samples in a variety of healthcare domains. The development and interpretation of ML-based techniques should give careful thought to these problems. Open science and the emerging trend of sharing research data might make these challenges more manageable. Also, before implementing ML-based solutions in healthcare, it's important to think about the privacy and ethical implications. We create and execute numerous ML-based ways employing cloud-based technologies with the idea that these approaches demand large-scale, readily expandable data storage and very high computational power.

The area of genetic engineering has been the site of heated ethical discussion, providing valuable lessons for researchers attempting to apply ML-based techniques to healthcare. The use of genetic engineering to produce permanent genetic improvements and therapies is a topic of ongoing debate. Potentially game-changing treatments for devastating diseases may be found by identifying and modifying deleterious genetic abnormalities, such the HTT mutation that causes Huntington's disease [76]. On the other hand, for populations that cannot afford it, the creation of therapies that change the genome of the individual and their descendants can exacerbate the socioeconomic gap [77]. A set of standards for the creation of AI machines has now emerged. To help private companies create and use AI in an ethical manner, Singapore put out a Model AI Governance Framework in 2019 [78]. Also, in an effort to "maintain American leadership in artificial intelligence" [79], the US administration has issued an executive order regulating the development of AI. Ethical research and development are the goals of these stringent rules and laws. The results' interpretation and clinical applicability pose a significant hurdle to ML applications in healthcare. The complex architecture of ML-based techniques, especially deep learning-based methods, makes it very difficult to disentangle and identify the original characteristics' contribution to the prediction. Adaptability of ML-based techniques in healthcare has been greatly hindered by a lack of transparency, which may not be a big problem in other ML applications (like online searches). In healthcare, it is well-known that the approach to a problem is just as crucial as the problem itself. Finding and measuring the fundamental data elements needed for prediction has to happen in a methodical way. One way to increase the acceptance rates of ML-based initiatives is to have doctors and other healthcare workers participate in their creation, testing, and deployment. Furthermore, ML-based approaches provide a one-of-a-kind chance to boost engagement, even though there is reasonable concern about the possibility of a diminished personal interaction between a patient and PCP as a result of growing adoption of these methods. Research shows that the traditional doctor-patient connection is under decline, and 25% of Americans do not have a primary care physician (PCP) [80]. Here, ML can provide novel chances to boost involvement in areas where patients debate possible diagnosis findings and to enhance the efficacy of outreach efforts. Patients may be able to work with their primary care physicians to establish healthy lifestyle habits with the aid of early prediction made possible by ML-based methods. At last, a poll that specifically targeted doctors indicated that 56% of doctors were spending just 16 minutes or less with each patient, and 5% spent less than 9 minutes [81]. Improved patient satisfaction and results can result from doctors spending less time on administrative tasks and more time building relationships with their patients through the use of AI techniques in diagnosis and symptom monitoring.

Conclusion

In summary, Even if the overview shows how far machine learning has come, there is still room for massive improvements in the road. A lot of the new machine learning developments in healthcare are geared on helping doctors and specialists treat patients better, faster, and more precisely. Improving data collecting, storage, and dissemination methods or inventing algorithms to handle unstructured data can overcome the problems associated with ML algorithm development. Reduced health inequalities and easier access to services for low-income countries and people may be possible outcomes of future applications that usher in cheaper medical imaging and more reasonably priced medical tests. The use of genetic modification to treat genetic diseases and mutations, optimization of medicine selection and dose, and improvement in predicting customized therapeutic response are all areas where scientists anticipate progress [82]. The use of ML has the potential to revolutionize patient care by enhancing the function of doctors. While the challenges and risks of future ML applications are addressed, current ML algorithms can provide a firm groundwork for advancements and healthcare ML.

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