Deep Learning for Health Informatics: Recent Trends and Future Directions

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***Abstract*—Health informatics has emerged as a growing domain of interest among researchers world-wide owing to its major implications on society. Applications of machine learning in healthcare range from disease prediction to patient-level personalized services. The prevalence of big data in healthcare has paved the way for applications based on deep learning techniques in the past few years. This paper reviews recent trends and applications of deep learning applied to the healthcare domain. We highlight recent research work, identify challenges and suggest possible future directions that could be pursued further in this domain.**

I. Introduction

The healthcare domain is of strategic national importance owing to its broad spectrum of reach to individuals and communities. The last decade has witnessed unforeseen advances in artificial intelligence techniques applied to numerous domains. Healthcare is amongst the primary focus of machine learning researchers and industry experts owing to the high volume and veracity of data. Conventional machine learning approaches were able to handle learning tasks in the healthcare domain when applications were restricted to small datasets. However, the healthcare domain is increasingly being characterized by big datasets from hospital management systems. This has provided a natural choice for application of deep learning approaches on healthcare datasets, which may be sparse, heterogeneous or often high-dimensional. Applications range from supervised learning tasks (disease prediction model) to unsupervised tasks (data clustering, outlier detection for trend analysis).

Figure 1 shows a count of the recent research papers and patents published in this domain over the past few years. The plot has been generated using the search terms "machine learning" and "health informatics" to search for patents and research papers from Google Patents and Scopus respectively. The graph is evidently indicative of a progressive trend for research in this domain.

Several reviews have appeared in literature surveying data analytics in healthcare [25], [5], [44], [48]. These have covered applications, techniques, algorithms and dataset evaluations. However, a recent review of deep learning techniques and trends applied to health informatics is not available to the best of our knowledge. In this paper, we seek to review applications published in this domain broadly over the last few years, and also enumerate challenges and future directions.

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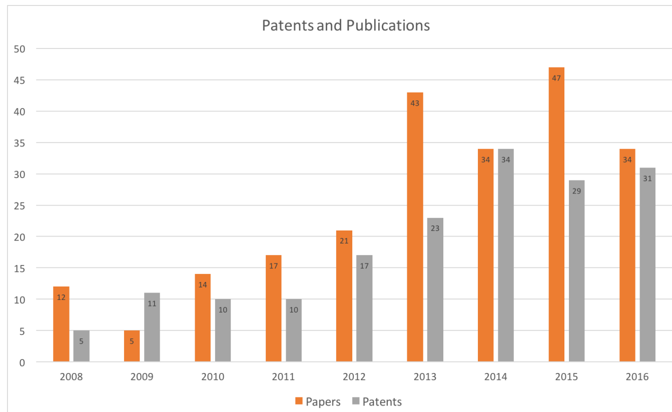

Fig. 1. Recent patents and research publications on machine learning in health informatics

Figure 2 summarizes major applications of deep learning architectures applied to the health informatics domain. As is evident, several applications have been developed using convolutional neural networks, deep belief nets, Boltzmann machines, stacked and de-noising autoencoders which we briefly explain in Section II. The list is only indicative of the major applications and the actual scope is much broader. We enumerate some of them in Section III, followed by the challenges identified in Section IV. Conclusions and future work are presented in Section V.

II. Deep Learning Architectures

In this section, we explain the technical aspects of various deep learning architectures.

- Convolution Neural Network (CNN): CNNs are a type of deep neural network whose design is inspired from the functioning of the human brain, however it must be noted that the human brain is just an inspiration for the connectivity patters[62] and the objective is replicate the efficiency. CNNs are multi layer network consisting of several hidden layers constituting convolution, pooling and fully connected layers in addition to the input and output layers. There may be hundreds of such layers in complex CNN architectures. Since the organization of neurons is similar to those in the receptive field of the visual cortex, the architecture possibly is able to exploit and represent visual data such as images, 3D models etc very well. Owing to

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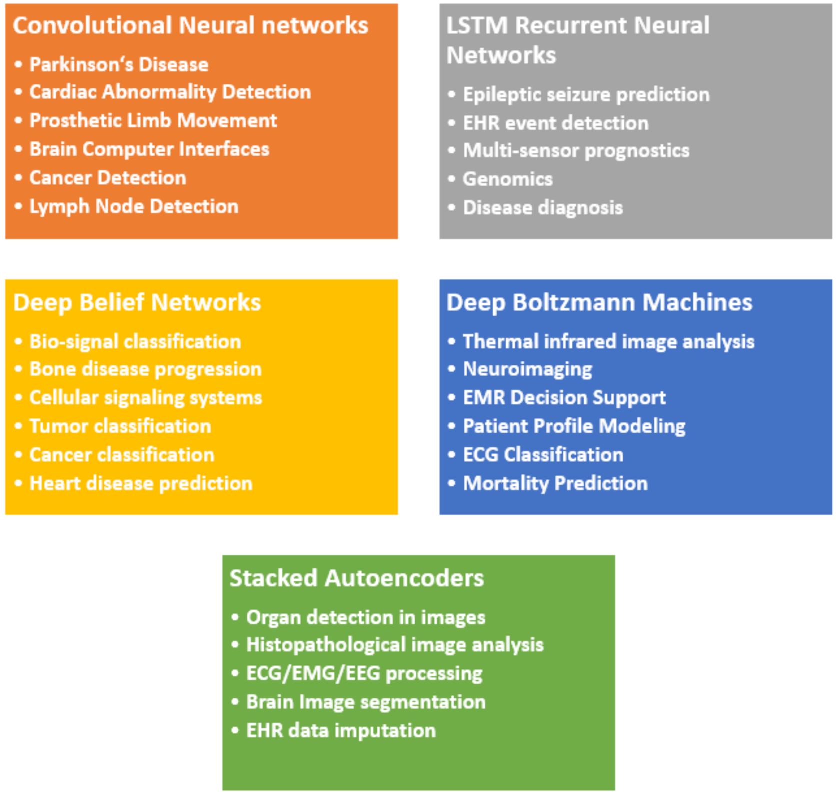

Fig. 2. Applications of deep learning in health informatics

such strengths, the research community has shown significant interest towards utilizing CNN especially for medical image analysis.

- Recurrent Neural Network (RNN): While CNNs work on structured inputs, RNNs can work on arbitrary inputs. This is made possible by the directed cycle of connections among units which can be unfolded. Due to their dynamic nature, RNNs come in many variants, where Recursive, Fully Recurrent, Bi-directional are popular architectures.
- Deep Belief Network (DBN): DBNs are a class of deep neural networks where each hidden layer is connected while there is no connection within a hidden layer. The training procedure is effectively greedy in nature.
- Deep Boltzman Machine (DBM): DBM is a kind of binary pairwise Markov Random Field. While due to their ability of train in both the directions, they are likely to perform better than CNNs and DBNs. However, training a DBM is computationally very expensive, therefore limiting their functionality to small datasets only.
- Stacked Autoencoders: As the name implies, the stacked autoencoders is an arrangement of layers of sparse autoencoders which can be trained in a greedy manner. Here noise is added to the input, while it is expected that the network would learn to differentiate amongst the true and noisy signals. Such an architecture becomes even more pertinent in case of medical datasets, where noise is inherently present and it is not only expensive but subjective to clean such datasets.

III. Deep Learning for Healthcare

This section discusses recent works on various applications of deep learning in the healthcare domain. These include disease prediction, which can be individual-based (predicting the onset of a specific disease for an individual based on the past health records) or community-based, which includes prediction of diseases or epidemics in communities. We also investigate data visualization applications, assistive technology solutions and works to enhance the security and privacy of health records which are based on deep learning methods.

A. Disease Prediction

Machine learning has been instrumental in disease prediction and pattern analysis of health informatics data. In the past few years, deep learning has surpassed all benchmarks especially where analyzing patterns in raw data or images is required. The problem of predicting diseases based on a patient's attribute falls directly under the scope of deep learning methodologies where the objective is to learn and replicate the decision making capability of a medical practitioner as accurately as possible. The advancements in deep learning have allowed for prediction of future diseases a patient can develop based upon Electronic Health Record (EHR) [38]. We primarily focus on diseases, data for which can be readily obtained from digital healthcare systems [10].

Several diseases have been attempted to be modeled for detection using machine learning techniques [65]. Deep Learning techniques primarily have found application in diagnosis of brain disorders [70] and various forms of cancers [54], especially due to the requirement of a large amount of labelled data. The basic pipeline of deep learning for medical diagnosis involves preprocessing and conversion of the raw data in the form of a data matrix, which is usually of the dimension of the number of samples *times* the number of features. The feature vectors usually comprise of correlation matrices among different areas in an image [27], or the images themselves in a meaningfully stacked order.

Alternatively, [41] propose a deep learning architecture where they predict the disease based on questions asked from the user. They report 10-15% improvement over traditional machine learning methods. Miotto et al. [38] develop *DeepPatient*, an unsupervised deep feature learning network which does disease classification and patient disease tagging. They train their network on data from 1.2 million patients, and employ pre-processing techniques to retain patient records with at least one diagnosed condition. This resulted in a dataset of 76,000 patients from which multiple clinical descriptors were derived. Their results demonstrate that the approach holds promise in applying deep networks for these tasks.

There are other similar works in literature as well. Ranganath et al. [47] develop a deep learning model for survival prediction for individuals based on their risk of developing Coronary Heart Disease (CHD). They used a dataset of around 313,000 patients and used a numerical evaluation metric, the Framingham CHD risk score, to determine if the patient would develop CHD. Their results outperform baseline results and also conclude that diagnosis results are vital in arriving at their evaluation metric, in comparison to medication, lab tests or vital recordings data. The work employed Deep Exponential Families (DEF), which is a generative hierarchical approach based on multi-layer probability models. An alternative approach was proposed by Choi et al. [13], where a RNN model based on reverse-time evaluation of descriptors was employed, to model the manner in which a physician inspected patient EHR. Further, Bayesian bi-partite models have also been employed for clinical disease tagging by Halpern et al. [22], while CNNs and LSTMs have been employed for disease prediction from lab test results in the work by Razavian et al. [49].

Depending on the size of the dataset, suitable deep learning approaches may be chosen to be configured to operate in batch mode where the model incrementally learns over subsets of the dataset. The model chosen also depends on the objectives to be attained, as well as the size of the dataset available, both in terms of number of samples as well as the number of descriptors or features. These works clearly indicate that deep learning methods hold promise for tasks such as disease prediction, and detecting trends and patterns in patient EHRs and clinical datasets.

B. Data visualization applications

A lot of healthcare data is in the form of images, which arise from various diagnostic procedures such as Magnetic Resonance Imaging (MRI), radiography, ultrasound, thermography, tomography, functional near-infrared spectroscopy (fNIRS), among others. These data are vital to clinicians primarily by means of data visualization techniques, and hence learning algorithms also tend to focus along those directions.

It is evident that these datasets are high-dimensional and not amenable to application of conventional machine learning methods for their processing. Deep learning approaches play a very significant role in enabling analysis and visualization of such data [51]. They have been applied for MRI [20], fMRI [64], [30], ultrasound [28], [11], X-ray [4] and several other modalities. The techniques have been used to aid clinicians in effective visualization and diagnosis of diseases such as diabetic retinopathy [67] and melanoma [3].

Another perspective to data visualization applications in the healthcare domain is the development of executive level summary information systems that mine large health databases to extract information that is relevant to future decision making. Such systems have been presented in [21], [66], [57], as well as dashboards [16]. These find applications in healthcare policy making, drug warehouse inventory management systems as well as trend detection and emergency response systems.

C. Assistive technology solutions

Assistive technology is an area of research in itself, but with the advent of wearable technologies and Internet of Things (IoT), there is a rising interest in providing personalized experience by utilizing data from EHRs and Health Informatics solutions [61]. Machine learning for assistive technologies constitute applications such as Brain Computer Interfaces (BCI) [59], neural prosthesis [43], rehabilitative devices [36] and others which aid persons with disabilities by the use of biomedical signal processing and artificial intelligence via machine learning.

Assistive technologies primarily rely on biosignals as inputs which may include ElectroEncelphaloGram (EEG) [55], ElectroOculoGram (EOG), surface ElectroMyoGram (sEMG) [56], ElectroCardioGram (ECG) [29], Galvanic Skin Response (GSR) [42] among others.

More recent developments have focused on using multi-sensor fusion approaches [34] and deep learning [33], [32] to develop assistive technology. This is essentially motivated by the relatively improved scalability of these learning architectures as opposed to the traditional feature extraction and classification pipeline. These have also been shown to offer more reliable and robust solutions [17]. Deep learning has enabled real time analysis [69] and is progressing towards addressing missing values problem [8]. Such applications are critical in developing resilient technology solutions for seamless integration of data from various sensors and digital healthcare systems.

D. Security and Privacy of Health Records

Security of health records is an important and challenging problem [18]. Healthcare data is available on cloud, mobile devices and other platforms in the form of EHR [60], Personal Health Records (PHR) etc. A recent study in United Kingdom [45] shows that a majority of individuals are concerned about the privacy of their health records. Moreover, the increasing sophistication of attacks and criticality of data mandates for more robust and intelligent techniques.

Authors in [2], [53] provide a comprehensive survey of various algorithms and techniques used for privacy and security of EHRs while Martnez-Prez et. al. [35] analyze regulations for security in mobile health apps. The primary aim of such techniques have often been to restrict unauthorized access in the form of stringent policies and encryption techniques [15], [58]. Another approach for ensuring privacy is to tweak the architecture itself so that it can use inputs from multiple sources without compromising the sensitive information. Research is actively progressing in this area with techniques where training occurs in parallel for data from multiple sources and a joint output is obtained by sharing only the key parameters of the model instead of the data [52]. Security may further be enhanced by obtaining a bound over the privacy-loss with novel deep architectures specifically tuned for this purpose [1].

IV. Challenges for Machine Learning in Healthcare

Though there are several research directions being pursued in the applications of machine learning for health informatics, there are several challenges faced in implementing and realizing ubiquity in these applications [6]. This section aims to highlight some of the challenges faced in this regard.

One of the perspectives of analyzing challenges is from a machine learning standpoint. This includes the limitations faced by conventional machine learning techniques in their application to health informatics. A primary problem stems from the lack of training samples for the learning model. For example, the conventional disease detection model, using a Support Vector Machine (SVM) classifier for instance, would fail to generalize well on the dataset as the number of positive samples is relatively much lower than those compared to negative samples. This issue also arises in the case of multi-intent classification for assistive technology development. Solutions to this involve use of alternative classifiers [19], or data augmentation and imputation methods [50], [7], [31].

Data pre-processing for applying learning algorithms also presents a significant challenge. Representation of appropriate feature spaces for data and feature engineering are often major application-specific challenges. The anonymization of patient data is also important, which has been explored in [53].

Another problem that arises is the number of dimensions of data available for analysis. This may be too high (biosignals, medical imaging data, genomics [46]) or too low (localized patient datasets). In both these cases, robust learning is a challenge. There are several feature generation, selection and reduction methods available in machine learning that can be used in to address this problem [40]. Datasets can also often be sparse as the relevant attributes may not have been captured [41].

There is also a concern regarding the reliability of the results arrived at by the machine learning techniques on healthcare datasets. This has led to the evolution of the interactive machine learning modality for healthcare, where the learning pipeline is not fully automated, but rather involves human interference to validate the model at specified intervals [24], [26], [68]. it can generally be infered from research in this direction that the decision to partially or completely automate the workflow for decision making is application-specific, and that there are restrictions with existing machine learning methods as well.

The compliance of health information systems that enable health informatics with health standards is also an important challenge [14]. Complaince to EHR standards such as HL7, ICD-10 [37], SNOMED CT, DICOM [12], RxNorm and several others ensures uniformity in the available data making data analytics inter-operable and reliable [63]. Privacy of health records has already been discussed as an area of critical importance. With the data analytics platforms accessing these data for mining information, effots to secure them need infusion of intelligence. Authors in [9] study impact of various machine learning techniques for detection of suspicious activities on EHR data. Miotto et al. [38] have used EHR to predict liver cancer, diabetes, and heart failure using deep learning approaches They also use denoising autoencoders to capture dependencies in EHRs [39]. We conclude that research in security of EHR data must progress at a greater pace than the advancement of machine learning algorithms in healthcare. This argument is primarily due to the fact that without effective security measures, the analysis of data may not be adopted by industries and hence the benefits may never reach the individual users. Therefore, advanced algorithms for anomaly detection [23] should be explored for healthcare data.

V. Conclusions

The paper presented recent trends in applications based on deep learning in the health informatics domain, including those for disease prediction, data visualization, assistive technology development and EHR based applications. Based on the recently emerging trends, it is certain that deep learning methodologies hold significant promise in developing intelligent applications for healthcare and health informatics domains owing to the prevailing nature of data. Evolving deep learning network architectures that have low computational, memory and power footprint are desired for emerging applications, which not only process data from healthcare systems, but also from a wide variety of devices and sensors that endow an individual and an implicit connected environment. The evolving Internet of Things (IoT) and healthcare integrated applications appear to be the primary consumers of evolving trends in deep learning.

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