International Journal of Multidisciplinary Engineering in Current Research

ISSN: 2456-4265, Volume 5, Issue 7, July 2020, http://ijmec.com/

Deep Learning Approaches for Some Health Care Challenges: An Analytical Review

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Abstract

Over the past couple of decades, Artificial Intelligence (AI), and more specifically Deep Learning (DL) became a reality of our daily lives and also seen quick adoption in the healthcare system as a tool to prevent, diagnose, treat, monitor and decision-making. Deep Learning technology is intended to address challenges in the health care system to create and deliver personalized and precise solutions to various health care problems. This review paper presents some of the latest advancements in Deep Learning Based Health Care Solutions and Approaches from a wide variety of algorithms often cited in research literature. Some of the recent advances in various healthcare areas electronic health record, biological system, Sensor Signals and medical image have been extensively investigated and critically analyzed. Out of this study, some key issues with available research are presented. This paper concludes with some interesting future potential research directions.

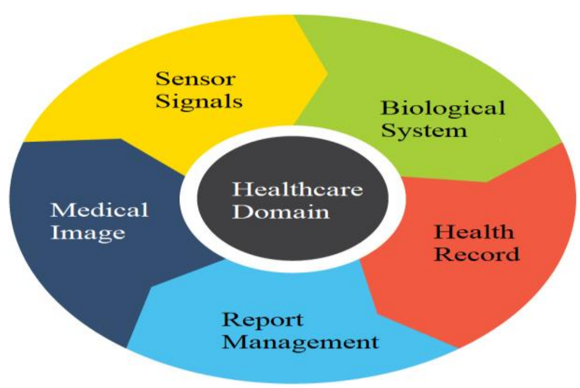
Keywords: Deep Learning, Neural Networks, CNN, RNN, Machine Learning, Healthcare,

Introduction

In the recent years, new data capturing and monitoring technologies in healthcare system produced humongous and complex amount of data which allow researchers to provide improved solution for various healthcare challenges. Usage and analysis of the healthcare data is going to play a very vital role in personalized care. To analyze humongous health data, the application of Deep Learning have become more attractive given the complexity of the data, available frameworks and computing resources.

After careful analysis from the wide variety of algorithms cited in the literature, this paper focuses on some potential and well performed Deep Learning methods for various healthcare domains. The structure of the health data and the desired results determine the Deep Learning technique to be implemented.

Many number of research studies have highlighted the capabilities of deep learning approaches, which caters to multiple domains of healthcare systems including Biological System, Health Record and Report Management, Medical Image and Physiological Signals and Sensors.



Over the years, many applications and methods were developed to cater to multiple Healthcare challenges using RNN and CNN. In this review, following deep learning architectures are focused with respect to

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Healthcare Domain., Convolutional Neural Network (CNN) [1], Deep Belief Networks (DBN) [2], Auto-Encoder (AE) [3], Recurrent Neural Network (RNN) [4], Deep Boltzmann Machine (DBM) [5], Generative Adversarial Network (GAN) [6] and Restricted Boltzmann Machines (RBMs) [7].

Deep Learning is far better compared to traditional machine learning, as Deep Learning approaches can learn from huge raw health data, and also has many internal hidden layers which allow to learn abstractions based on inputs [8]. The key success lies on the deep learning approach which can learn from the humongous health data through general learning method [8].

The main contributions of this review are summarized as below:

- In depth study and analysis of Deep Learning based recent advances in various healthcare aspects.
- Summarize experimental results of methods cited in research literature publications.
- Describe present research issues of various healthcare aspects and present some interesting potential future research directions.

The rest of this paper is organized as follows: At first, various deep learning methods from the available literature are presented and then described and discussed some experimental comparisons of the presented methods. Finally, some of the research issues are presented with future directions at the conclusion.

Some recent methods in the literature

In [10] proposed a combined CNN and LSTM for prostate cancer identification with Gleason score of 7. The model assesses the correlation between histopathology images and genomic data with disease recurrence in prostate tumors to identify prognostic biomarkers within tissue by modeling the spatial relationship from automatically created patches as a sequence within the tissue. Their experiments show that integrating image features with genomic pathway scores, are more strongly correlated with patients recurrence of disease compared to standard clinical markers and engineered image texture features.

In [11] proposed a multiclassifier effective framework to detect mitotic cells in breast histopathology images using DBN step by step enhancement of segmentation and classification. They have successfully implemented a framework that resulted in better performance with high sensitivity make it more realistic in clinical applications.

In [12] at a high level, denoise small cytoplasmic RNA sequence (scRNA-seq) datasets was generated. The deep count auto encoder network (DCA) takes the count distribution, dispersion, and sparsity of the data into account using a negative binomial noise model with or without zero inflation. The technique was capable of capturing nonlinear gene-gene dependencies.

[13] Presented an approach for gene multi-function discovery which is called stacked denoising AE for

multilabel learning. The method can capture intermediate representations robust to partial corruption of the input pattern and generate low-dimensional codes superior to conditional dimension reduction tools.

In [14] described a CNN framework which is composed of four layers: input layer, one-side convolution layer, max-pooling layer and softmax prediction layer for phenotyping from patients' EHRs. Every patient's record was represented as a temporal matrix with time on one dimension and event on the other dimension. Different temporal fusion mechanisms are also investigated to explore temporal smoothness of patient EHRs in the proposed framework.

In [15] to solve challenges relating to EHR, they proposed a deep-learning model that uses a bidirectional long short-term memory (BiLSTM) conditional random field network to recognize entities and a BiLSTM-Attention network to extract relations from the dataset. They built three multi-task learning (MTL) models, called HardMTL, RegMTL, and LearnMTL, respectively.

In [16] they designed multitask learning methods to simultaneously identify types of Chinese clinical entities from free text in EHRs. In this approach used two features namely Character embedding and segmentation to diagnosis, test, symptom, body part, and treatment simultaneously.

In [17] presented an approach to generate a general-purpose patient representation from EHR data that facilitates clinical predictive modeling using unsupervised deep feature learning method. This technique consists of a three-layer stack of denoising autoencoders to capture hierarchical regularities and dependencies in the aggregated EHRs.

In [18] investigated the task of relationships classification on clinical narratives. In this paper, a relation classification model is proposed by adopting a CRF model. To address the problem of word sparsity, they applied auto encoder and sparsity limitation for features optimization.

In [19] Described unsupervised feature learning for computational phenotype discovery from noisy and irregular longitudinal EMR data. Introduced differential time warping function that brings no stationary clinical data sufficiently close to stationarity to allow modeling with a Gaussian process.

In [20] presents a convolutional neural network method for the automatic segmentation of MR brain images into a number of tissue classes. The network model uses multiple patch sizes and multiple convolution kernel sizes to acquire multi-scale information about each voxel to ensure accurate segmentation details as well as spatial consistency in the images. The segmentation method is applied to five different data sets

In [21] described a modified DBN technique to minimize the computation load from 3D ultrasound data by converting the sagittal plane detection problem into a symmetry plane and axis searching problem. Feature extraction requires neuroimaging, which contains features for diagnosing diseases.

In [22] a deep generative shape model-driven method was designed that can automatically track the motion of the heart, a complex and highly deformable organ, on cine MRI images. This heart shape model was established by training a three-layered deep Boltzmann machine (DBM) in order to characterize both local and global heart shape variations. Frame-by-frame heart motion tracking was achieved by iteratively mapping the obtained heart contour for each frame to the next frame as a reliable initialization, and performing a level-set evolution.

In [23] proposed a restricted Boltzmann machine Model as a basic building block to initialize the weight parameters of each layer of the Network Model. This paper adopted an explicit control of the weight-sparsity level of each hidden layer of the Network Model to circumvent the paucity of input samples available to train the Model.

In [24] described conditional variational autoencoders which learn the reconstruction and encoding distribution of healthy images and also have the ability to integrate certain prior knowledge about the data (condition). Experiments on different 2D and 3D datasets show that the approach is suitable for the detection of pathologies and deliver reasonable Dice coefficients.

In [25] proposed an algorithm that overcomes the problem of intensity inhomogeneity in the sonogram, and in combination with the deep learning approach for high efficiency tumor classification. A classifier is established by extracting features in the multilayer training of stacked denoising autoencoder (SDAE).

In [26] an approach designed and developed for automatic sleep stage classification. This method can capture the sleep information hidden inside electro encephalo graphy (EEG) signals and automatically

International Journal of Multidisciplinary Engineering in Current Research

ISSN: 2456-4265, Volume 5, Issue 7, July 2020, http://ijmec.com/

extract features from raw data. A new model fast discriminative complex-valued convolutional neural network (FDCCNN) is proposed to extract features from raw EEG data and classify sleep stages. This method combines complex-valued back propagation and the Fisher criterion. Also they proposed a speed-up algorithm to reduce computational workload and gain improvements.

In [27] paper described use of deep recurrent neural networks to build recognition models that are capable of capturing long-range dependencies in variable-length input sequences. They presented unidirectional, bidirectional, and cascaded architectures based on long short-term memory and evaluate their effectiveness on miscellaneous benchmark datasets.

In [28] the usage of fuzzy logic with RNN to create a recurrent fuzzy neural network increases adaptability and the bottleneck of regression problem to handle driving fatigue for preventing road accidents. This paper also analyzes brain dynamics in a simulated car driving task in a virtual-reality environment.

In [29] to detect automatic emotion recognition with non-stationary EEG signals they proposed a deep learning network with a stack of three autoencoders and two softmax classifiers for valence and arousal state classifications. To alleviate overfitting problem, principal component analysis (PCA) is applied to extract the most important components of initial input.

Analytical Review

According to the in depth analysis, the deep presented research methods that are consistent on accuracy on some standard datasets. All the presented Research Models consumes High computational resources when compared to traditional neural networks and also these approaches comparatively slow training process without GPU's.

Based on systematic study some of the approaches used for Risk prediction of chronic congestive heart failure observed significant prediction accuracy increase by using the % of training data.

According the analysis in the approach [23] a hybrid methodology with a combination of multiple techniques to identify tumor from image data enormously improved.

According to the research results [14], [20] and [26] on some standard data sets have failed in scenarios that consist of simultaneous multiple critical QoS attributes.

In depth study of [14], [20] and [26] describes exploiting on deep features and take the advantage of hybrid framework to address some of the challenging QoS parameters.

Research Challenges

Despite rapid considerable advancements that are emerged in Deep Learning based Healthcare systems, the mentioned methods from research literature are still unable to handle the real-world challenges efficiently.

Studies on references from literature revealed that deep learning based methods are still not reliable for real-world applications as they are lacking in intelligent situation understanding with real time speed.

It is understood that despite decades of research still have the problems to simultaneously handle challenging scenarios which significantly consists of multiple attributes need to worked at the same time.

Some Deep Learning approaches perform well with specific scenarios and Standard Data Sets.While applied to other cases, however, they may not produce satisfying results.

Though some of the methods presented performs well in a specific challenging scenarios but they are not robust enough to handle the diversity of situations.
Based on the review it is understood that maintaining accuracy in numerous situations, robustness and

International Journal of Multidisciplinary Engineering in Current Research

ISSN: 2456-4265, Volume 5, Issue 7, July 2020, http://ijmec.com/

computational efficiency all at once is an existing research challenge.

Based on thorough analysis computational complexity and memory usage is the biggest research challenge in Deep Learning Based Healthcare solutions even to address single challenging Scenario.

All these issues restrict further development of the Healthcare research and its applications in real-world, real-time systems. Recently, attempts to deal with some of these issues have been made,for example, the Benchmark new data sets provides a large set of testing use cases, standard baseline evaluation tools, new methods of evaluation, Optimization of QoS inputs, privacy, deployment etc. This is likely to advance the further studies and developments of Healthcare techniques.

Conclusion and Future Directions

There is a great potential for the deep learning models and their applications in healthcare systems in view of the humongous size and complexity of health data.

According to the study, the following observations have been made:

- A Deep Learning architecture which is capable of integration of various types of health data simultaneously is needed to handle some real-world situations.
- Multiple complementary features exploitation from different efficient Deep Learning based methods may improve robustness of the model.
- Build more effective systems by improving the network structure of the model which work with different types of health data Improving prediction, detection efficiency in handling simultaneously challenging attributes.
- To handle success rate, robustness and efficiency need more exploitation on integrating multiple Deep Learning network architectures and the efficient combination of different methods.
- Work towards more intelligent methods to reduce the computational complexity that is a necessity in real-time applications to achieve real time performance.
- Introduce Deep Learning methods to more healthcare and medical fields to improve services, operations, equipment, and software.

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