Review on Heart Disease Diagnosis Using Deep Learning Methods

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Developments for automation and advanced computing in the area of medical data processing has outcome with different new learning techniques. Deep learning has evolved as an advanced approach in machine learning applied to different old and new area of applications. Deep learning approaches have evolved as supervised, semi-supervised and un-supervised mode applied for different real time applications. The approach has shown a significant usage for image processing, computer vision, medical diagnosis, robotic and control operation application. Among various usage of machine learning approaches for automation, medical diagnosis has been observed as a new upcoming application. The criticality of data processing, response time, and accuracy in decision, tends the learning system more complex in usage for medical diagnosis. This paper outlines the developments made in the area of medical diagnosis and deep learning application for heart disease diagnosis. The application, database and the learning system used in the automation process is reviewed and outlined the evolution of deep learning approach for medical data analysis.

Keywords: Deep learning approach, Heart disease diagnosis, Diagnosis and decision.

1. INTRODUCTION

A heart disease is observed to be a very primary cause of death in various countries [WHO [2018]]. Heart disease directly or indirectly impact on various other diseases. Electronic health record system (EHR) [Wong K K L [2013]] is one of the monitoring systems used in monitoring of health. For the diagnosis of heart diseases the observation has biological representation of risk factors for different parameters which makes the detection process more complex and critical in use. In the surveillance [MacNeill [2003] citeNkips] of health recorded of a patient, EHR has a greater usage in detection of critical effects at an early stage [E. O. Olaniyi and Adnan [2015]]. Mining of large dataset has evolved as an useful way for numerous health monitoring usage [Anthimopoulos M [2016]] such as the medical image processing [Miao S [2015]], health representation of patient [Vardhana M [2018]], tools in liver and lung cancer diagnosis [K. J. Xia [2018],Lecun Y [2015]] etc. The difficult environment of actual medical dataset demands for a proper organization because a forecasting error would lead to severe consequences. Therefore, medical observations are cautiously applied in developing the diagnostic statistics and precisely categorizing infection using machine learning and numerical processing's. Due to this reason, new mechanism of classification approaches like 'Decision Trees' (DT), 'Naive Bayes' approach [Xiao Z [2017]], and 'K-Nearest Neighbor' (KNN) approach [Jiang Z [2013]] for classification were proposed. Multiple SVM type decision system for detecting the 'Coronary artery disease' is outlined in [Zheng M [2011]]. An automatic analysis method was presented for the classification of heart diseases using 'Support Vector Machines' (SVM) for categorization of heart rhythms [Krizhevsky A [2012]]. In recent development, 'Neural Network' (NN) [Szegedy C [2015]] offered exceptional outcome for information forecast and processing a variety of categorization issues in learning system. Deep learning (DL) is an extended area of machine learning using neural network which stimulated by means of organization and execution of human brain to investigate and learn network, which replicates a brain operation for classifying a given observation based on learned data. Notion of deep learning is derivative of artificial neural network, with the multi-layer deep learning architectures. Functional units of a deep learning system are trained with descriptive features by constructing a hidden mechanism and developing a huge training process to improve accuracy of classification. A brief outline of the Deep learning approach is presented in following section.

2. DEEP LEARNING APPROACH

Deep learning approach have a important function in healthcare field for information detection and diseases categorization, such as heart disease, brain disease, by means of observed medical information [Simonyan K [2014]], that illustrates numerous types of medical usage used in deep learning structure, as well defines limitations in usage of analytical models using neural networks developed for precisely defining the diagnosis of heart disease [He K [2016]]. In Recent development in DL, 'convolutional neural networks' (CNN) is developed for detecting diverse classes of ECG signals [Caffe [1999]], and customized 'deep convolutional neural network' is proposed in categorizing the ECG information as normal or abnormal class [Tensorflow [1999]]. 'Recurrent neural network' (RNN) is also used for forecasting of potential ailment by strong patient information in heart disease diagnosis [Pytorch [1999]] developing temporal relativity between data in the database for Heart disease diagnosis [Poudel R P K [2016]]. A new learning using 'Long short-term memory networks' (LSTM) in detecting threat for cardiovascular disorder is outlined in [Bai W [2017]]. A 'gated recurrent unit' (GRU) for vascular disorderness is outlined in [CDC [2013]]. [Oktay O [2017]] Outlined 'bidirectional neural network' models, such as the 'bidirectional LSTM' (BiLSTM) and 'bidirectional GRU' (BiGRU), giving more optimal outcome as they can overcome the constraint of data flexibility in input. It is outlined in numerous usages like Natural Language Processing (NLP) [Chang Y [2018]] and unified tagging solution [Kotu L P [2015]]. Supplementary usage for heart disease recognition using sequence labeling for EHR based on Bidirectional RNN is outlined in [Gan Y [2016]], and a classification method for arrhythmia's using Bidirectional LSTM is presented in [Ghaemmaghami H [2017]]. An optimal 'recurrent convolutional neural network' (RCNN) used for risk evaluation using large information database is outlined in [Gao X [2017]]. The main issue in the healthcare study is the short of available information for performing precise analytical models. The massive disproportion of dataset allocation is one more difficulty in health investigation and mainly in heart disease categorization. To rise the flexibility and accuracy of machine learning performance, ensemble-learning have been outlined for improved analysis. 'AdaBoost ensemble classifier' used in heart beat categorization [Madani A [2018]], and 'cardiovascular disease' recognition by means of hybrid architectures [Isensee F [2018], Rohé M M [2017]] are few of such applications. Ensemble neural networks is presented in 'phonocardiogram recordings' developed by a 'feed-forward neural network' [Gao Z [2017]]. One more useful way presented to undertake the joint handling of class inequality in learning under deficiency of data is by balancing the data by means of new under-sampling method using noise filter [Zhen X [2017]], or by means of re-sampling approach with time varying parameter to solve the group inequality issue [Gao Z Zhao S [2017]]. The evolution of Machine learning approach has developed the usage of Artificial Intelligence (AI) in the area of automation. Neural Networks (NN) as a part of Machine learning domain evolved the Deep Learning (DL) concept in machine learning. From its commencement, DL has been developing great distraction, illustrating exceptional achievement in approximately all relevance area. Figure 1 illustrates the subset modeling in AI.

DL use deep architectures or hierarchical architectures for learning to estimate model metrics to perform a specified operation. Weight metrics is the computing parameter in neural network modeling. DL is defined by different layers of input and output, which formulate a non-linear hierarchical model for classification. Current developments in the area of DL representation learning engage a order of details or notion, wherein high-level details are presented commencing the lower-level and low-level details presented from high-level data. The DL method is presented

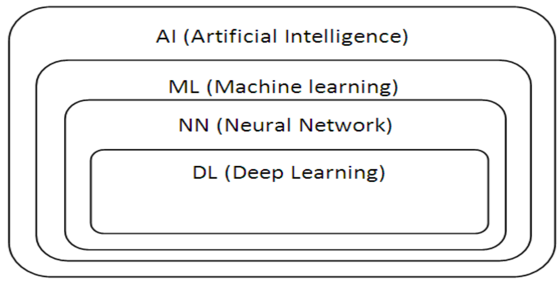

Figure 1. Subset modeling in artificial intelligence and machine learning

as a general learning method which is capable of solving approximately all types of issues in diverse relevance area. By other means, DL is not a task oriented [E. J. Benjamin and Delling [2018]]. Deep learning method is represented as: Supervised, semi-supervised and unsupervised. There is one more group of training method termed 'Reinforcement Learning' (RL) or 'Deep RL' (DRL) frequently presented in the extent of semi-supervised or unsupervised methods. Figure 2 illustrate the representation of the deep learning scheme.

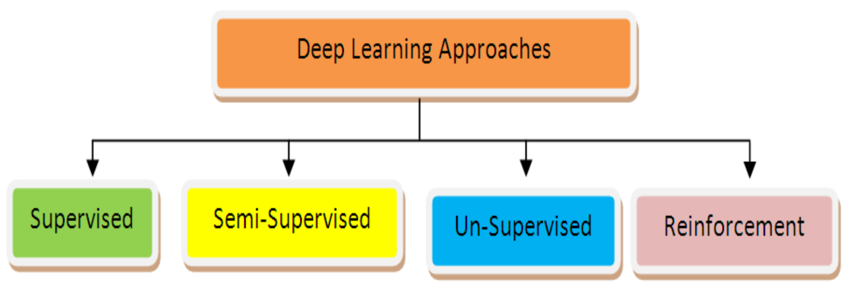

Figure 2. Deep learning approaches classification

2.1 Supervised Learning

Deep Supervised learning is developed using labeled information. For a supervised DL method, the process is given with a set of inputs and equivalent result. Following successful training, the learning method predicts the appropriate result based on trained information. Various supervised learning approaches were developed for deep learning such as the 'Deep Neural Networks' (DNN), 'Convolutional Neural Networks' (CNN), 'Recurrent Neural Networks' (RNN), 'Long Short Term Memory' (LSTM), and 'Gated Recurrent Units' (GRU).

2.2 Semi-supervised Learning

Semi-supervised learning is developed using partially labeled information. In many usages, 'Generative Adversarial Networks' (GAN) is applied as semi-supervised method in learning approach. In addition, RNN, LSTM and GRU, were also developed with semi-supervised learning approach.

2.3 Unsupervised Learning

Unsupervised learning is developed as the method with no labeled information. In this approach, the method learns the inner depiction or significant features to find out unidentified associations or arrangement in the input information. Frequently clustering, dimensional minimization, and productive methods were stated for unsupervised learning methods. Number of methods for deep learning approach which were superior for grouping with dimensional reduction, such as the 'Auto-Encoders' (AE), 'Restricted Boltzmann Machines' (RBM), and 'GAN' approach. Additionally, methods like LSTM and RL were as well applied in unsupervised learning in numerous relevance fields.

3. DEEP LEARNING IN IMAGE INTERFACE

Deep learning approaches were used in various applications among which imaging application is predominate. Various feature definitions such as the color, shape, textures were used in defining the content of an image in learning system. The accuracy of learning is dependent on the features passed to the learning system with the method used in learning approach [Xu L [2017]]. Recurrent neural network is a profound application in this domain as outlined in [Nues and hugo C. [2013]]. The learning system has a significant usage in the application of image processing which gives a optimal performance in term of time of decision and accuracy of the system [Khamparia A [2019]]. Deep learning approach has illustrated beneficial usage in many applications. The development has shown a greater performance under the large data processing where the information's are to be retrieved or decision is to be made based on the input information. The processing algorithms were developed using a learning approach [Albuquerque V H C D [2018]] and perform classifications for a decision. Many of applications for real time interface were observed listed in the following sections.

3.1 Image Mining

In many image processing applications deep learning has shown a great advantage in faster and accurate retrieval. Different format of learning method using neural network is presented such as the 'Convolutional Neural Network' (CNN) for Recognition which shows a performance up to 99.35% of precision as compared to conventional approach [WHO [2017b]]. In many a approach the supervised semantic preserving Deep Hashing (SSPDH) approach was developed in [KementrianKesehatan [2013]] for the security approach using fingerprint selection. The approach illustrated a performance of 70% enhancement. Image processing tools such as the Google face book, and Microsoft has used the learning approach for facial image processing [Y. Zheng and Zhao [2014]]. The learning approach in detection of age group is outline in [D. R. Chowdhury and Samanta [2011]] using image processing approaches using deep learning approach.

3.2 Medical Image Processing

Computer interfacing in data handling and processing has a greater impact in examination of medical image processing for the diagnosis of various medical data in images or signal representation. [G. Subbalakshmi and Rao [2011]] process on Magnetic Resonance Imaging (MRI) samples for Alzheimer diseases detection. Various heterogeneous modeling [J. Nahar and Chen [2013]] were developed in the detection of medical samples in classification and decision making in the area of diagnosis and decision making. In [Jaffer F A [2009]] Optical Coherence Tomography (OCT) is presented using deep learning for defect detection. This approach is used for image processing to outcome with learning approach for retinal image processing using CNN approach.

4. HEART DISEASE DIAGNOSIS

Heart diseases are major issue in medical domain which has a significant mortality every year and it is a rapidly increasing issue. The unregulated lifestyle outcome with the issue of heart diseases among majority of population. The early diagnosis would prevent or slow the impact of heart disease and decrease the mortality factor. In early detection of heart disease, diagnosis of heart images, signals are used, which are tend to be automated for early and faster detection of medical issues in heart diseases. Advanced learning approaches were proposed in the development of automation scheme for pre detection of heart issues. The advanced learning approach has shown a major development in better presentation of diseases diagnosis compared to traditional approaches. Researchers have outcome with scheme by means of 'conventional neural network' and machine learning approach however, the outcome are less accurate in performance. Using conventional neural network, 'deeper neural network' (DNN) were projected in [Z. Xing and Keogh [2010]]. The 'neural network' is developed as a 'supervised learning algorithm' which performs the categorization process. The DNN representation implement a dual sorting to identify HD present ("1") or HD absent ("0"). The 'National Heart, Lung, and Blood Institute' (NHLBI) explain angina as the general indication of HD [NHLBI [1999]]. Angina is a chest pain or discomfort occurring when a region of heart muscle don't obtain sufficient oxygen-rich blood [N. A. Sundar and Chandra [2012]]. HD is also stated as 'coronary artery disease' or 'ischemic heart disease'. A quiet HD shows no symptoms of heart disorder. In this case the disease is not detected until the patient has a heart failure, heart attack, or an arrhythmia. In earlier work, a number of machine learning algorithms used in HD detection is presented. [Chaurasia and Pal [2014]] Outline artificial neural network (ANN) in HD detection and the total analytical accurateness obtained was 75%, processed with one hidden layer. [Aditya A. Shinde [2017]] outline Naïve Bayes in HD detection and the performance is improved to 82.31%. [Nabel and Braunwald [2012]] Outline method of processing efficiency for diagnosis of heart disease to obtained accuracy about 86.77%. [Jain and Bhandare [2011]] Outlined the approach with one hidden layer obtaining an accuracy of 85%. HD analysis reduces the analysis time of experts and improves the precision of analysis. In [F. Amato and Havel [2013]] to improve the performance in detection a new feature representation for HD is presented. A new learning approach to obtain improved metrics in accuracy, sensitivity, and specificity for HD detection is outlined. The examination of learning method is applied to increase the performance metrics of conventional feature-oriented methods. The 'deep neural network' (DNN) for HD detection can be trained with hierarchical feature from actual information automatically, minimizing manual errors in feature selection. [N. Larasati and Oktarina [2017]] Presented a back propagation neural network (BPNN) to identify heart disease by means of allocation information ratio 60:40 by means of 6 hidden nodes. This illustrated BPNN as optimally efficient and precise in analysis of heart disease, obtaining a precision of about 85%. [Y. Lei and McLaren [2014]] Outlined a multi-layered 'feed-forward neural network' and 'back-propagation neural network' using three hidden layers with 18 terminals to identify heart disease. The precision obtained by the presented method is 92%.

5. CARDIAC DATA PROCESSING

The rapid expansion of artificial intelligence , deep learning, with the evolution in new technologies have outcome with new advanced approach for processing on medical data using image processing, signal processing and machine learning approach. The complexity in medical image processing is many fold as the content of medical features are highly variant in nature, and representation of these feature builds a large overhead on the processing system. advanced clustering approaches and dimension reduction techniques has reduce the burden of these overhead to certain extend, however the selection of feature coefficient and accuracy of retrieval is a major bottleneck in deep learning methods.
The processing of medical data is represented and processed using different processing methodology where the process of sample region, method used has an impact on the retrieval performance. Table 1 illustrates recent development in the area of heart disease diagnosis with the achieved performance processing on different regions with variation in learning methods.

There are also various approaches of processing measured parameters for automation in heart diagnosis. [S. Nurmaini [2018]] Proposed to process on cine-MRI using time series region selection with specific application for feature representation. [P.-T. De Boer and Rubinstein [2005]] Applied the shape matching approach in deriving the deformation in registration process in different patient data. In [Ronaghan [1999]] a state space modeling of elastic behavior of carotid artery wall in heart is proposed. The variation in the elastic behavior is recorded in representation of heart condition. [WHO [2017a]] Proposed a new approach of measuring the volume of heart

Reference	Database	Approach	Accuracy
[Poudel R P K [2016]]	PRETERM	RFCN	0.93
[Bai W [2017]]	UK Bio Bank	Semi Supervised	0.92
[CDC [2013]]	ACDC	FCN	0.95
[Oktay O [2017]]	UK Digital	ACNN	0.93
[Chang Y [2018]]	ACDC	FCN	0.90

Table I: Classification Method Analysis for Different Dataset

chamber in the heart movement. A segmentation approach of heart movement is proposed in [Heart$_disease_fact_sheet$[2015]]by the monitoring of carotid IM borders following cardiac cycle. An implicit framework (UE-LUPI) for deep learning approach to derive strain observation in heart using ultrasound elastography is presented in [Gao Z Zhao S [2017]]. [Baumgartner C F [2017]] improved the measurement by extended the approach on three dimension (3D) speckle tracking echocardiogram (STE). The performance of retrieval accuracy and decision making is tabulated in table 2 with different learning approaches with retrieval accuracy

Reference	Database	Approach	Accuracy
[Kotu L P [2015]]	Test Case	KNN	0.94
[Gan Y [2016]]	Test Case	Region Based	0.80
[Ghaemmaghami H [2017]]	Test Case	TDNN	0.95
[Gao X [2017]]	Tsinghua Hospital	Improved CNN	0.92
[Madani A [2018]]	Test Case	CNN	0.97

Table II: Classification Accuracy Observation

6. DATA REPRESENTATION

The processing efficiency of any learning system depends on the data representation and the features describing the input. The accuracy of learning is effective with the learning features, where consideration of large feature details results in more accuracy, the processing overhead in high. Higher overhead leads to slower decision making and demands large resources. In addition the complexity of the retrieval performance also increases with the increase in details representation. Hence, feature representation, selection and processing are very critical in deep learning system. A standard heart diseases diagnosis dataset used universally in the heart disease diagnosis is the ‘UCI Machine Learning Repository Heart Disease Dataset’ [Jansoi [2018]] which contain a total of 76 attributes with 14 subsets defining “age, sex, chest pain (cp), trestbps, chol, fasting blood sugar (fbs), restecg, thalach, exang, oldpeak, slope, ca, thal”. The parameters are collected by Cleveland Clinic foundation, with 303 participants of which 241 males and 62 females’ samples are presented. A brief outline of the database parameter is presented in table 3 below. In the process of classification classifiers such as the decision tree, SVM machine learning and discriminate modeling based on Bayesian approach, ensemble learning [M. Shouman and Stocker [2011]] are used in decision making in heart disease diagnosis. Majorly 13 attributes are used in the process of decision making system.

Variable	Attribute Description	Variable	Attribute Description
Age	Year	Htn	Hypertension
Sex	1=Male 0= Female	Tpeakbp	Peak exercise blood pressure (part 2)
CP	Chest pain rating: 1= typical angina 2= atypical angina 3= non anginal pain 4= asymptomatic	Restecg	Resting ECG 0= Normal, 1= ST T wave abnormality (¿0.05 mV), 2= Left ventricular hypertrophy
Tpeakbps	Peak exercise blood pressure (part 1)	Tresrbp	Blood pressure at rest (mm Hg)
Chol	Serum cholesterol (mg/dl)	Exang	Exercise induced angina 1=yes, 0=no
Ekgmo	Month of exercise ECG reading	Lvf	Left ventricular failure
Ekgday	Day of exercise ECG reading	Oldpeak	Exercise induced ST depression
Ekgyr	Year of exercise ECG reading	Cmo	Cardiac cath: month
Dummy	Dummy variable	Cday	Cardiac cath: day
Xhypo	1=yes, 0=no	Cyr	Cardiac cath: year
Prop	Beta blocker used during exercise ECG 1= yes, 0= no	Nitr	Nitrates used during exercise ECG 1= yes, 0= no
Thaldur	Exercise test duration (min)	Thalach	Maximum heart rate achieved
Xhypo	1= yes, 0= no	Thalrest	Resting heart rate
Pro	Calcium channel blocker used during exercise ECG 1= yes, 0= no	Diag	Heart disease diagnosis: Angiographic 0(¡50 % diameter) 1(¿50 % diameter)

Table III: Database Parameters [Jansoi [2018]]

7. CLASSIFICATION ALGORITHM

The classification process is the approach of deriving class label for a given test sample from a large database based on the features used for learning and recurrent matching process in deriving the decision. The classification performance is dependent on the classifier model, trained information's, and the distance metric computation in making a decision. Confusion matrix among the classified sample compared with the existing values formulate the positive and negative parameters, which defines the system performance in terms of accuracy, recall, sensitivity, specificity, structural similarity index etc. recent developments in the diagnosis of medical data processing for heart disease diagnosis has outcome with various classifier models which are applied for computer aided detection on clinical data. Approaches such as decision tree model, support vector machine, fuzzy system, principal component analysis, particle swarm optimization, k-star algorithm, Bayesian approach, Neuro fuzzy logic [Marateb and Goudarzi [2015],Schmidhuber [2015],Miao and Miao [2018],D. J. Newman and Merz [2018]] have evolved. The performance of thee classifier models are depended on the learning method, feature used and the classifier algorithm used. Deep learning approach based on neural network has an advantage of deeper learning which gives a better classification among different variation of feature values. The metric of performance for different learning methods for heart disease diagnosis is outlined in table 4 below.

Reference	Approach	Accuracy
[Kips J G [2008]]	RFCN	75%
[E. O. Olaniyi and Adnan [2015]]	Data Mining Naïve Bayes Method	82.31%
[Lecun Y [2015]]	Likelihood approach Weighted associative classifier	84%
[Lecun Y [2015]]	Naïve Bayes	78%
[Xiao Z [2017]]	Naïve Bayes	82.13%
[Xiao Z [2017]]	J48 decision tree	84.35%
[Krizhevsky A [2012]]	Ensemble machine learning	80.14%
[Krizhevsky A [2012]]	Deep neural network learning model	83.67%

Table IV: Performance Metric Evaluation for Learning Method in Heart Disease Diagnosis

8. CONCLUSION

The development in the area of deep learning for the diagnosis of heart diseases is reviewed and developed approaches with their approach of processing are outlined. The development of deep learning has a greater benefit of providing reliable and accurate diagnoses in automated decision for faster and accurate diagnosis in medical data processing. In development of learning method, objective of developing new approaches for error free diagnosis is primal. The developments in recent past shows the need of further need of improvement in the area of feature representation, dimensional reduction and minimal processing overhead to achieve the objective of faster and accurate processing. In the need of new approach for classification performance, new techniques with minimal complexity but higher gain in decision making is needed. The existing approaches are further to be optimized with complexity reduction and feature mapping in making deep learning system more efficient and reliable in heart disease diagnosis.

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