Medical Big Data: Neurological Diseases Diagnosis Through Medical Data Analysis

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REVIEW

Medical Big Data: Neurological Diseases Diagnosis Through Medical Data Analysis

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Abstract Diagnosis of neurological diseases is a growing concern and one of the most difficult challenges for modern medicine. According to the World Health Organisation's recent report, neurological disorders, such as epilepsy, Alzheimer's disease and stroke to headache, affect up to one billion people worldwide. An estimated 6.8 million people die every year as a result of neurological disorders. Current diagnosis technologies (e.g. magnetic resonance imaging, electroencephalogram) produce huge quantity data (in size and dimension) for detection, monitoring and treatment of neurological diseases. In general, analysis of those medical big data is performed manually by experts to identify and understand the abnormalities. It is really difficult task for a person to accumulate, manage, analyse and assimilate such large volumes of data by visual inspection. As a result, the experts have been demanding computerised diagnosis systems, called "computer-aided diagnosis (CAD)" that can automatically detect the neurological abnormalities using the medical big data. This system improves consistency of diagnosis and increases the success of treatment, save lives and reduce cost and time. Recently, there are some research works performed in the development of the CAD systems for management of medical big data for diagnosis assessment. This paper explores the challenges of medical big data handing and also introduces the concept of the CAD system how it works. This paper also provides a survey of developed CAD methods in the area of neurological diseases diagnosis. This study will help the experts to have some idea and understanding how the CAD system can assist them in this point.

Keywords Medical big data analysis · Computer-aided diagnosis system · Neurological diseases diagnosis

1 Background

In the world of medicine, neurological disorders are the most challenging to diagnose, manage and monitor due to the complex nervous system. Diagnosis of neurological diseases and their treatments demand high precision, dedication and experience. Nowadays, modern technology and systems allow neurologists to provide proper neurological care. Neurological disorders are diseases of the body's nervous system. Structural, biochemical or electrical abnormalities in the brain, spinal cord or other nerves can result in a range of symptoms. There are more than 600 diseases of the nervous system, such as epilepsy, dementias, Alzheimer's disease and cerebrovascular diseases including stroke, multiple sclerosis, Parkinson's disease, migraine, neuroinfections, brain tumours and traumatic disorders of the nervous system such as brain trauma and autism. According to the World Health Organisation (WHO) report, more than 50 million people suffer from epilepsy [1]. It is estimated that 35.6 million people have dementia, with 7.7 million new cases every year; Alzheimer's disease is the most common cause of dementia and may contribute to 60–70 % of cases [2]. These disorders affect people in all countries, irrespective of age, sex, education or income. Neurological disorders are typically devastating to affected patients and their families,

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often depriving the patient's quality of life. A rapid and timely diagnosis of these diseases can save and significantly improve patients' life by applying appropriate procedures. Recently, varieties of advanced diagnosis technologies have been used to detect, manage and treat neurological disease, such as brain wave tests (Electroencephalography or EEG), computerised tomography (CT scan), magnetic resonance imaging (MRI scan), electromyography (EMG) and arteriogram (also called an angiogram), positron emission tomography (PET scan or PET imagery). These technologies are vital tools that help physicians confirm or rule out the presence of a neurological disorder or other medical conditions.

The produced huge amounts of medical data from these aforementioned technologies are an important source for diagnosis, therapy assessment and planning. In general, medical image data range anywhere from a few megabytes for a single study to hundreds of megabytes per study (e.g. thin-slice CT studies comprise of up to 2500+ scans per study) [3,4]. Such data require large storage capacities if stored for long term. Due to high volume, velocity and complexity of the medical data, it is really difficult for the experts to accumulate, manage, analyse and assimilate the large volumes of data for diagnosis, therapy assessment and planning. Integration of high quantity physiological data is the grand challenge for the experts to deliver clinical recommendations. Supporting medical experts or neurologists in the process of finding a correct diagnosis to a hypothesis in a timely manner is very desirable to improve a patient's outcome. In general, the analysis of those vast amounts of information is performed manually through visual inspection by neurologists/experts to identify and understand abnormalities from medical imaging and signal data [5]. The visual inspection of such huge data is not a satisfactory procedure for precise and reliable diagnosis as it is time-consuming, error prone and subject to fatigue. Thus, the medical analytics demand to develop automatic decision systems by utilising computational intelligence for fast, accurate and efficient diagnosis, prognosis, and treatment processes.

Recently, an advanced idea on automated CAD system is introduced for the experts/neurologists for detecting the neurological abnormalities from the medical big data. The algorithms of major CAD systems are developed by using techniques and theories of the pattern recognition field, and thus the CAD is involved as one of the pattern recognition fields [6]. The techniques of the CAD systems consist of data pre-processing, feature extraction and classification as discussed in Sect. 3. The CAD systems assist the experts in accurately interpreting medical big data, so that the accuracy and consistency of diagnosis can be improved and also reduce the analysis time. Many methods and frameworks on the CAD concept have been developed for analysis of medical image and signal processing as discussed in Sect. 4. The CAD system is cost-effective and efficient and can be used as a decision support system by the experts in the diagnosis and treatment of neurological disorders [6].

Section 2 of this paper provides brief information about current medical technologies in the neurological disease diagnosis and also discusses challenges in medical big data analysis. In Sect. 3, the CAD system is introduced and briefly described on how this method works for automatic diagnosis of neurological diseases. Section 4 provides a short review of the CAD system on the diagnosis of various neurological diseases, and Sect. 5 concludes the paper with the potentials of CAD systems in the future.

2 Current Medical Technologies for Medical Data Collections and Challenges in Medical Big Data Analysis

Currently, neurological diseases are diagnosed by using various medical techniques such as electroencephalography (EEG), computerised tomography (CT scan or CAT scan), magnetic resonance imaging (MRI scan), electromyography (EMG), positron emission tomography (PET scan or PET imagery), arteriogram (also called an angiogram) and single-photon emission-computed tomography (SPECT). These diagnostic tests help physicians confirm or rule out the presence of a neurological disorder or other medical conditions. In order to diagnose brain-related diseases such as epilepsy, certain seizure disorders, degenerative disorders, sleep disorders, autism, brain tumours and migraines, and EEG is used to record brain cell activity through the skull for studying the functional states of the brain to help physicians for detecting and monitoring brain abnormalities [7]. Variations or abnormalities in brain waves recommend different types of neurological disorders. To diagnose neurological conditions such as tumours, blood clots, degenerative disease and the location of strokes. To identify brain abnormalities, a CT or CAT scan is used to see the cross-sectional images of the body using X-rays and a computer [8]. Such tests are mainly used for swelling and lesions in certain areas, broken bones, heart disease and internal bleeding.

In finding brain and spinal cord abnormalities, MRI tests are valuable to investigate detailed images of body structures including tissues, organs, bones and nerves [9–11]. MRI tests help physicians to diagnose torn ligaments, tumours, circulation (blood flow) problems, eye disease, inflammation (e.g. arthritis) and infection. MRI scans are also used to detect and monitor degenerative disorders such as multiple sclerosis and can document brain injury from trauma. If the physicians need to investigate the brain in action (e.g. speaking or moving) and to pinpoint areas of the brain that become active and note how long they stay active, fMRI is a suitable diagnostic test. The fMRI test measures small changes in blood flow as a person completes tasks while in the MRI scanner [12]. The

fMRI imaging process is used to assess brain damage from head injury or degenerative disorders such as Alzheimer's disease and to identify and monitor other neurological disorders, including multiple sclerosis, stroke and brain tumours.

To follow-up to a CT or MRI scan, a PET test can be used to provide the physician with a greater understanding of specific areas of the brain including two- and three-dimensional pictures of brain activity. SPECT tests are also ordered as a follow-up to an MRI to diagnose tumours, infections, degenerative spinal disease and stress fractures. In order to detect abnormal electrical activity of muscle that can occur in many diseases and conditions such as amyotrophic lateral sclerosis (ALS, Lou Gehrig's disease), carpal tunnel syndrome, muscular dystrophy, neuropathy, sciatic nerve dysfunction, inflammation of muscles, an EMG scan is used to record the electrical activity of muscles [13]. For detecting different types of heart problems such as heart attack, coronary heart diseases and stroke, ECG is used to record the heart's electrical activity to understand how the heart works [14]. To detect blockage or narrowing of the vessels, arteriogram is used to have an X-ray of the arteries and veins. To investigate spinal nerve injury, herniated discs, fractures, back or leg pain and spinal tumours, myelograms are used. Ultrasounds are used to assess blood flow through various vessels, and transcranial doppler ultrasounds are used to view arteries and blood vessels in the neck and determine blood flow and risk of stroke.

These medical technologies produce huge quantities of complex and high dimension data that are an important source for diagnosing neurological diseases and treatment and therapy planning. The medical big data analysis has potential to be a valuable tool, but implementation can pose a challenge. It requires careful data analysis which can provide authentic, accurate and reliable information for good decision-making in disease diagnosis. In practice, most of the cases interpretations of that data are accomplished by experts/neurologists in visual manner [15]. It is very natural that clinicians are not always able to make optimal use of the acquired data due to the limitations of the human eye–brain system, limitations in training and experience and factors such as fatigue and distraction. The medical data interpretation by humans is limited owing to the non-systematic search patterns of humans, the presence of structure noise and the vast amounts of data. For handling the high volume of data with complexity, it is essential to use digital technologies to support medical data analysis. Hence, there is ever-increasing requirements to develop such CAD systems for the experts/neurologists that can automatically make an accurate assessment for the detection of different neurological problems.

3 Computer-Aided Diagnosis System for Automatic Diagnosis of Neurological Diseases

Recently, CAD is becoming very popular in medical and diagnostic imaging for automatic detecting abnormalities from medical big data sources. The basic concept of CAD was proposed by The University of Chicago, in the mid-1980s, whose idea was to provide a computer output as a "second opinion" to assist experts in interpreting medical data, so that the accuracy and consistency of diagnosis could be improved, and also the analysis time could be reduced [16–18]. The CAD system consists of three main steps [6] such as pre-processing, feature extraction and classification as shown in Fig. 1. In the pre-processing part, acquired medical data (e.g. medical image data or medical signal data) are processed for removing noises, which reduces the complexity and computation time of the CAD algorithms. The feature

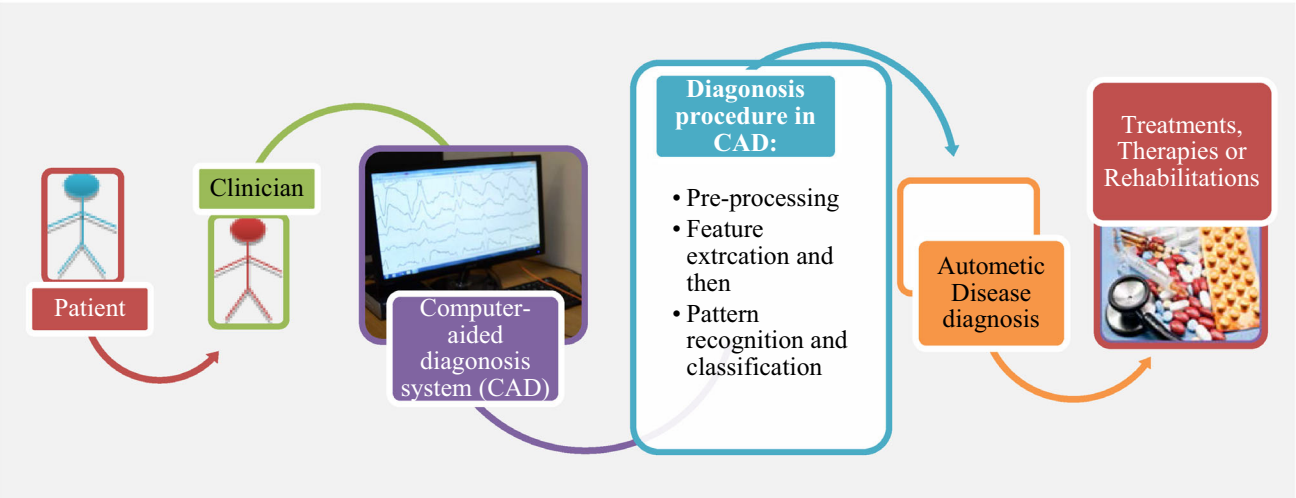

Fig. 1 Diagram of CAD system for automatic detecting abnormities from the medical big data

extraction part of the CAD system is one of the most important parts where the biomarkers of disease identification are extracted from the original source data. In the classification process for CAD systems, the extracted feature vector is used in the classifier model as input for assigning the candidate to one of the possible categories (e.g. healthy or normal) according to the output of a classifier. Generally, a CAD system can be two types. When CAD system involves in classifying all candidates into two categories such as abnormal and normal candidates, it is called two-class categorisation system. On the other hand, if a CAD system can classify unknown cases into several types of abnormalities, which are more than two, it is called a multi-class categorisation system. Many researchers are working to develop CAD schemes for detection and classification of various kinds of abnormalities from medical data.

Like pattern recognition, the performance of CAD systems is assessed by k-fold cross-validation test, bootstrap method, leave-one-out [19], etc. The free-response receiver operating characteristic (FROC) and ROC curves are used for evaluation of the overall performance of the CAD systems for various operating points. The FROC curve shows the relationship between the sensitivity and the number of false positives, which can be obtained by thresholding a certain parameter of the CAD system or the output of the classifier [6]. Recently, there has been a lot of research performed on the development of the CAD systems for detecting neurological problems such as epileptic seizures, dementia, Alzheimer's disease, autism, strokes, brain tumours, alcoholism related neurological disorders and sleeping disorders.

4 Research on Neurological Diseases Diagnosis Through the CAD System

Recently, a few automated computerised classification methods have been proposed to diagnose neurological diseases. They are sufficiently robust to handle data from different scanners for many applications. The numbers of developed CAD approaches are too large to review in a single article. Thus, in this section, we provide a brief review considering some of the essentials and recent researches of those for assisting neurologists in detection of neurological diseases.

4.1 Epilepsy and Epileptic Seizure Diagnosis

Epilepsy is one of the most common and devastating neurological diseases worldwide. Epilepsy is characterised by recurrent seizures [20,21]. Seizures are defined as sudden changes in the electrical functioning of the brain, resulting in altered behaviours, such as losing consciousness, jerky movements, temporary loss of breath and memory loss. The EEG is an important clinical tool which contains valuable

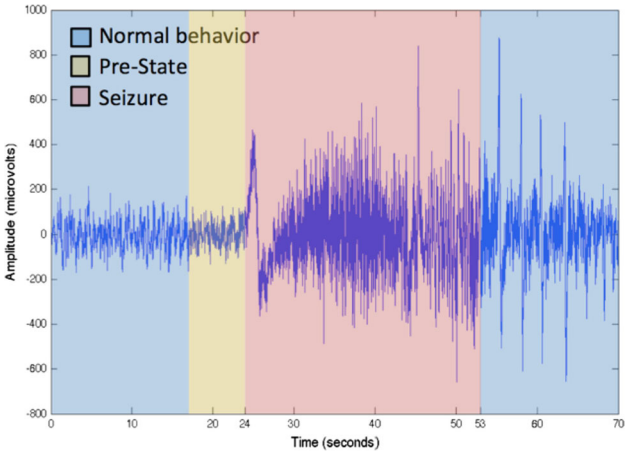

Fig. 2 An illustration of an EEG signal containing seizure [22]

information for understanding epilepsy [7,22]. Its chief manifestation is the epileptic seizure, which can encompass a discrete part of the brain partial or the complete cerebral mass generalised. Over the past few years, numerous epileptic seizure detection and prediction algorithms have developed from several countries throughout the world. Figure 2 shows an illustration of epileptic EEG signals during seizure activity. As can be seen in Fig. 2, the abnormal pattern of the signals significantly appears in the seizure period.

More recently, Shen et al. [23] introduced a method based on a cascade of wavelet-approximate entropy for feature extraction in the epileptic EEG signal classification. They tested three existing methods for classification: support vector machine (SVM), k-nearest neighbour (kNN) and radial basis function neural network (RBFNN), to determine which has the best performance in such as cascaded EEG analysis system. Acharjee and Shahnaj [24] used twelve Cohen class kernel functions to transform EEG data in order to facilitate the time frequency analysis. The transformed data formulated a feature vector consisting of modular energy and modular entropy, and the feature vector was fed to an artificial neural network (ANN) classifier. Siuly et al. [25] introduced a computerised approach based on simple random sampling (SRS) techniques and least square support vector machine (LS-SVM) to classify epileptic EEG signals. In another work, Siuly and Li [26] developed a new algorithm for feature extraction considering the variability of the observations within a time window called optimum allocation approach. Then, the extracted features were assessed by various multiclass least square support vector machine (MLS-SVM), classifying epileptic EEG signals; Aslan et al. [27] executed a study to check epileptic patients developing classification method. The classification process was performed into partial and primary generalised epilepsy by employing RBFNN and multilayer perceptron neural network (MLPNNs).

The experimental results demonstrated that the RBFNN model can be used as a decision support tool in clinical studies to validate the epilepsy. Li [28] proposed an approach based on multi-resolution analysis to automatically indicate the epileptic seizures or other abnormal events in EEG. Song and Liò [29] developed an EEG epilepsy detection scheme based on the entropy-based feature extraction and extreme learning machine. Subasi [30] applied a novel method of analysis of EEG signals using discrete wavelet transform and classification using ANN. Gular et al. [31] proposed an idea of a study for the assessment of accuracy of recurrent neural networks (RNN) employing Lyapunov exponents in detection seizure in the EEG signals. For the detection of epilepsy and seizure, Adeli et al. [32] developed a wavelet chaos methodology for analysis of EEGs and delta, theta, alpha, beta and gamma sub-bands of EEGs. Siuly et al. [5] introduced a clustering technique-based LS-SVM for EEG signal classification. Akin et al. [33] tried to find a new solution for diagnosing the epilepsy.

4.2 Dementia, Alzheimer's and Parkinson Diseases Diagnosis

Dementia refers to a group of neurodegenerative disorder diversity caused by the gradual neuronal dysfunction and death of brain cells. This disorder can be defined clinically as a syndrome that causes a decline in cognitive domain (i.e. attention, memory, executive function, visual–spatial ability and language) [34], which are common in the elderly. According to the American Academy of Neurology summary report, 10 % of people over the age of 65 and up to 50 % of people over 85 have dementia [35]. In 2011, it is estimated that nearly 300,000 people in Australia had dementia out of a total population of 23 million. This number is anticipated to increase to 900,000 by 2050 [36].

Dementia is classified into Alzheimer's disease (AD), Parkinson's disease (PD), dementia with lewy bodies, Creutzfeldt–Jakob disease, normal pressure hydrocephalus, vascular dementia, front temporal dementia [38,39]. AD is the most well-known and common type of dementia. Out of all the mentioned types of dementia, 2/3 of the demented patients suffer from AD. In this section, we provide a brief review in the developed CAD methods for detecting dementia AD and PD from medical image data and signal data. Figure 3 displays an image of PET scans showing a large area of normal activity in the brain of a normal person compared to reduced activity in the brain of a person who has dementia.

There is a large number of automatic computer assistance methods developed for identification of dementia. Koikkalainen et al. [40] completed an extensive study on various developed methods of CAD system for detecting dementias using only structural MRI data. An extensive set

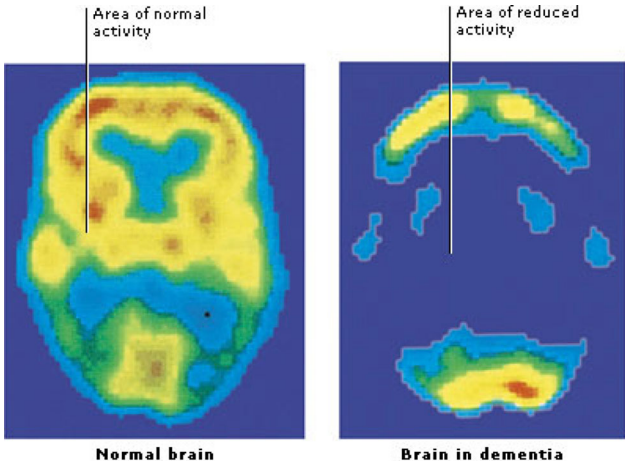

Fig. 3 An illustration image of brain activity in dementia [37]

of features was extracted quantifying volumetric and morphometric characteristics from MRI images, and vascular characteristics. The classification process was performed based on Disease State Index methodology. Hirata et al. [41] developed software based on the voxel-based specific region analysis for AD, which can automatically analyse 3D MRI data as a series of segmentation, anatomical standardisation and smoothing using a software and Z-score analysis. Li et al. [42] employed a SVM for characterisation of the hippocampal volume changes in AD and differentiation of AD patients from healthy control subjects. Kloppel et al. [43] developed a CAD method for diagnosis of AD from MRI scans obtained from two different centres and two different equipment [28] using linear support vector. In their method, MRI images were segmented into grey matter (GM), white matter and CSF using SPM. Colliot et al. [44] developed an automated segmentation method to aid distinguish between patients with AD, mild cognitive impairment (MCI) and elderly controls. Hamou et al. [45] proposed a computerised method based on cluster analysis and decision tree for analysing processing MRI image in the AD diagnosis.

Neural changes associated with dementia can also be detected through clinical biomarkers, such as EEG [34]. Numerous studies have been conducted on the CAD system to deal with EEG changes associated with dementia. The researchers developed CAD methods to identify the degree of severity of dementia, and some studies support the possibility for EEG to detect dementia in early stages [46–50]. For example, Henderson et al. [51] detected early dementia presence in EEGs with high sensitivity and specificity [46,51]. EEG may play an important role in detecting and classifying dementia because of its significant influence on dementia abnormalities in terms of rhythm activity. Joshi et al. [52] used neural network methods (NN) to classify AD by considering common risk factors. In that study, they also tested some other machine learning techniques such as DT, bagging, BF

tree, random forest tree and RBF networks. Can [53] introduced a parallel networks system which is bound together with a majority voting system in order to further increase the predictive accuracy of a PD data based on vocal recordings. In that study, an NN system with back-propagation together with a majority voting scheme was used for identification of the presence of PD. Khemphila and Boonjing [54] developed a CAD-based classification approach using multi-layer perceptron (MLP) with back-propagation learning algorithm where feature selection was performed on the basis of information with PD patients. David and Magnus [55] reported a number of methods such as MLP, SVM with the two kernel types and achieved a high precision level of the confusion matrix regarding the different measurement parameters (accuracy, sensitivity, specificity positive predictive value and negative predictive value). The SVM produces better results than the MLP.

4.3 Multiple Sclerosis Diagnosis

Multiple sclerosis (MS) is a chronic disease of the central nervous system, which is made up of the brain and spinal cord. It is an unpredictable condition that can be moderately involved in disabling. There are many possible causes of MS, including viruses, autoimmune disorders, environmental factors and genetic factors. MS affects an estimated 2.3 million people worldwide. Women are affected more than twice as often as men, according to the National MS Society.

There are a number of automated methods proposed for identifying MS lesions based on two- or three-dimensional (3-D) MRI images. Alfano et al. [56] developed an automated approach based on relaxometric and geometric features for classification of MS lesions from 3-D MRI images. Boudraa et al. [57] employed the FCM algorithm to 1.5 T two-dimensional (2-D) MRI images for classifying normal and abnormal brain structures. Leemput et al. [58] designed an automated method by using an intensity-based tissue classification and a stochastic model for detection of MS lesions from 3-D images. Zijdenbos et al. [59] developed a CAD framework for the pipeline analysis of MS lesions in MRI data. Khayati et al. [60,61] proposed an automated method for segmentation of MS lesions in brain MRI images using an adaptive mixture method and a Markov random field model in 3-D MRI images. Their proposed method was based on a Bayesian classifier to obtain and upgrade the class conditional probability density function and a prior probability of each class.

4.4 Autism Spectrum Disorder Diagnosis

Autistic spectrum disorder (ASD) is a neurodevelopmental conditions which affects the brain's growth and development characterised by impairments in reciprocal social interactions, communication skills and stereotyped behaviour [62]. ASD affects approximately 1 in 100 individuals [63,64] with recent estimates from the USA, suggesting that this figure could be even higher [65]. ASDs are composed of five disorders, namely, autism, pervasive development disorder not otherwise specified (PDD-NOS), Asperger's syndrome (AS), childhood disintegrative disorder (CDD) and Rett's disorder (RD) [66]. The diagnosis of ASD is not an easy process and generally requires certain behavioural and cognitive characteristics. Today, researchers are trying to find ASD diagnostic approaches through electrophysiological and neuroimaging techniques. Since EEG recording and analysis is one of the fundamental tools in diagnosing and identifying disorders in neurophysiology, researchers strive to use the EEG technique for diagnosing individuals with ASD. A group of studies has shown that EEG signals of individuals with ASD are relevant to age and intelligence quotient (IQ)-matched control subjects based on different conditions. The brains of children with autism have more connections than the brains of typically developing children do as displayed in Fig. 4 which was reported in two independent studies published in the Cell Press journal *Cell Reports* [67]. The brains of individuals with the most severe social symptoms are also the most hyper-connected.

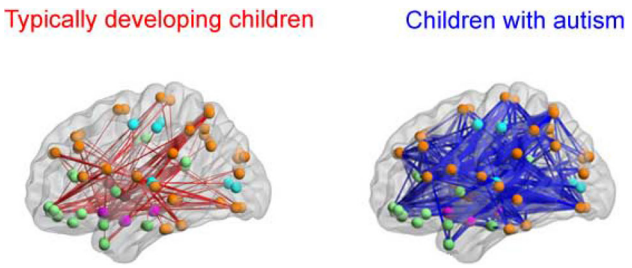

Fig. 4 An illustration of neural connections showing the difference between the typical brain and autistic brain [67]

Sudirman et al. [68] proposed a CAD method based on fast fourier transform (FFT) and power spectral density (PSD) to analyse the characteristics of the acquired EEG in the diagnosis of autistic children. Hoole et al. [69] achieved the results that the abnormalities in EEG alpha waves are related to the early age of autism. Listening to relaxing music helps increasing the alpha level and reduces the beta level in autistic children. Alhaddad et al. [70] developed a method to diagnose the autism where the extracted FFT features were used as input in the Fisher's linear discriminant analysis (FLDA) for the classification purpose. Sheikhani et al. [71] introduced a method based on Fourier methods to extract EEG features and k nearest neighbours (kNN) in classifying between normal and autistic children. Bosl et al. [72] proposed a classification method based on multiclass SVM and modified multiscale entropy for discovering differences between typically developing and high-risk group autism.

Razali et al. [73] applied Gaussian mixture model (GMM) to extract feature in frequency domain and MLP to classify the data. Further research was done by Duffy to differentiate between Asperger syndrome (ASP) and autism disorders which shows that Asperger diagnosis does not show symptoms of impairment in communication and does not have a lack of difficulty in language compared to autistic children.

4.5 Brain Tumour Diagnosis

A brain tumour is a collection, or mass, of abnormal cells in the brain. Many different types of brain tumours exist. Some brain tumours are noncancerous (benign), and some brain tumours are cancerous (malignant). Brain tumours can begin in the brain (primary brain tumours), or cancer can begin in other parts of body and spread to brain (secondary, or metastatic, brain tumours). According to the recent report, 1 in 50 people under the age of 60 die of a brain tumour.

The diagnosis of brain tumours is usually made individually using MRI imaging. Its accuracy may be limited by the presence of a typical cases or by a radiologist's insufficient clinical experience. A computerised method that is capable of providing objective information about an image may assist radiologists in the classification of brain tumours. A number of approaches have been used to segment and predict the grade and volume of the brain tumour. Vijayakumar et al. [74] proposed a computer-assisted method based on hierarchical multiresolution wavelet to perform segmentation of brain tumours on apparent diffusion coefficient (ADC) images. Kitajima et al. [75] developed an algorithm for differential diagnosis among pituitary adenoma, craniopharyngioma and Rathke's cleft cyst with MRI images. The results showed high performance in differentiation when they used the computer output. Papageorgiou and Spyridonos [76] developed a fuzzy cognitive map (FCM) to find the grade value of the tumour. Authors used the soft computing method of fuzzy cognitive maps to represent and model experts knowledge of the FCM grading model. Ibrahim et al. [77] used the image mosaicking method in evaluating the MRI brain abnormalities segmentation study. Fifty-seven mosaic images were formed by cutting various shapes and sizes of abnormalities and pasting it onto normal brain tissue. Karpagam and Gowri [78] proposed a computer assistance-based algorithm for detection of tumour growth by advanced diameter technique from MRI data. To find the volume of brain tumour, they proposed diameter and graph-based methods.

A various number of methods were introduced for detection of tumours through analysing EEG signal data. Habl et al. [79] proposed a CAD method to detect and characterise brain tumours. They removed location artefactual signals, applied a flexible independent component analysis (ICA) algorithm which does not rely on a priori assumption about unknown source distribution. The results demonstrated that tumour-related EEG signals can be isolated into single independent ICA components. Such signals where not observed in corresponding EEG trace of normal patients. Silipo et al. [80] developed a method for classifying brain tumours from EEG signals. The classification was performed using a nonlinear analysis. A high order hidden dynamic was detected in normal EEG records, confirming the very complex structure of the underlying system. Fadi et al. [81] presented an automated system to identify space occupying lesions on the brain using EEG signals where EEG features were extracted using wavelet transform for different tumour classes and classification by self-organising maps.

4.6 Stroke and Some Other Heart Problems Diagnosis

A stroke is the sudden death of brain cells in a localised area which happens when the blood flow to an area of the brain is interrupted by either a blood clot or a broken blood vessel. A stroke is a medical emergency that kills many brain cells per minute and causes permanent brain damage. Depending on the region of the brain affected, a stroke may cause paralysis, speech impairment, loss of memory and reasoning ability, coma or death. A stroke is also sometimes called a brain attack or a cerebrovascular accident (CVA). According to the World Heart Federation, every year 15 million people worldwide suffer a stroke. Nearly 6 million die, and another 5 million are left permanently disabled. Strokes are the second leading cause of disability, after dementia. Disability may include loss of vision and/or speech, paralysis and confusion. Besides strokes, there are several types of heart disease such as abnormal heart rhythms (arrhythmias), heart failure, heart valve disease, heart muscle disease and congenital heart disease. Various diagnosis tools such as CT scans, MRI scans and ECGs are used to diagnose and distinguish a stroke.

Devi and Misal [82] proposed a computerised algorithm based on wavelet transform (WT) in ECG for detection of heart valve disease. The extracted features by WT were evaluated by several machine learning methods such as traditional back-propagation network algorithm, the radial basis functions (RBF) network algorithm, SVM and adaptive neuro-fuzzy inference system classifiers. The test results showed that the performances of RBF networks are superior compared to others. Agarwal and Soliman [83] performed a review on the role of ECG in the stroke prediction. In that study, the authors discussed the prevalence, mechanisms and clinical applications of traditional and novel ECG markers in the prevention and treatment of strokes. They recommended that ECG is important for detecting several stroke risk factors/predictors including atrial fibrillation and left ventricular hypertrophy. They both are components of the Framingham Stroke risk score. Multiple other ECG traits such as cardiac electrical/structural remodelling-Q wave, QRS/QT duration, bundle blocks, P wave duration/amplitude/dispersion, and

other waveform angles and slopes appeared as potential predictors of strokes. Kallmünzer et al. [84] discussed common arrhythmias during and following a stroke event, and the hemodynamic changes associated with acute stroke.

4.7 Alcoholism Related-Disorders Diagnosis

Alcoholism also known as alcohol use disorder (AUD) is a broad term used for any drinking of alcohol that results in problems. According to the World Health Organisation (WHO) report in 2014, approximately 3.3 million people or 5.9 % of deaths worldwide are due to alcohol consumption (WHO Report, 2014) [85]. Globally, alcoholism is the world's fifth leading cause of death [86] and is the leading risk factor for premature death and disability [87]. Alcoholics experience a number of cognitive deficiencies such as learning and memory deficiencies, impairment of decision-making and problems with motor skills, as well as suffering behavioural changes that include anxiety and depression [88,89].

In the last few years, many methods have been developed in the literature for identifying alcoholism through EEG signals. Bajaj et al. [90] introduced a robust method that can automatically identify alcoholic EEG signals based on time–frequency (T–F) image information considering texture image for feature extraction and nonnegative least squares classifier (NNLS) for classification. Kannathal et al. [91] developed a feature extraction methodology based on correlation dimension (CD), largest lyapunov exponent (LLE), entropies and Hurst exponent (H) to extract characteristic features from the EEGs of alcoholics. These features are fed to the classifier for automated classification. Faust et al. [92] calculated the difference in the power distribution of EEG signals from healthy controls and people with alcoholism using different frequency domain parameters and classified the significant features using the ROC curve. They reported that Burg's method produced the most significant features for classification. Acharya et al. [93] used different nonlinear methods such as the largest lyapunov exponent (LLE), sample entropy (SampEn), approximate entropy (ApEn), and higher order spectra (HOS) to extract different features from EEG signals. Entropies provide a measure of regularity. They represent an index for the overall complexity and predictability of the time series. The HOS captures the subtle changes in the EEG signals effectively. These nonlinear features are then fed to the SVM classifier to classify the two classes. The novelty of this work is the use of the HOS for the automated classification of normal EEG signals and EEG signals from people with alcoholism. Faust et al. [94] used wavelet packet transform (WPT) (2007) to decompose EEG signals from healthy subjects and alcoholic subjects into different frequency sub-bands. Features were then extracted using relative energies, and the significant features were fed to the k-nearest neighbour (kNN) classifier. Parvinnia et al. [95] introduced significant discriminating features using fractal dimension (FD) and autoregressive (AR) features coupled with a weighted distance nearest neighbour (WDNN) classifier.

4.8 Sleep Disorders Diagnosis

The term "sleep disorder" refers to a range of conditions that result in abnormalities during sleep. The most common disorder is sleep apnoea. Apnoea means a temporary pause in breathing. Sleep apnoea occurs when the walls of the throat come together during sleep, blocking off the upper airway. Breathing stops for a period of time (generally between ten seconds and up to one minute) until the brain registers the lack of breathing or a drop in oxygen levels and then sends a small wake-up call [96]. The full name for this condition is obstructive sleep apnoea (OSA). Another rare form of breathing disturbance during sleep is called central sleep apnoea. It is caused by a disruption to the mechanisms that control the rate and depth of breathing. Obesity is one of the most common causes of sleep apnoea.

A number of algorithms have been proposed to tackle the problem of automatic OSA detection. Azarbarzin and Moussavi [97] developed a CAD method based on LDA where zero-crossing rate and peak frequency were calculated from snoring sound signals. Schlotthauer et al. [98] used empirical mode decomposition of pulse oximetry signals for automated OSAS screening. Varon et al. [99] proposed principal components of the QRS complexes as features for detecting OSA. Chen et al. [100] used a severity index of OSA with support vector machines for computer-assisted sleep apnoea identification. Single lead ECG signals had been used in this work. In other work, Chen et al. [101] implemented a kernel density estimator on features extracted from segmented RR intervals to perform classification of OSA.

5 Concluding Remarks

The dramatic impact of neurological disease pathologies in life quality is a growing concern. Modern technologies for diagnosing neurological diseases generate huge amounts of medical data such as medical images or electrical signals data. Interpreting those images or signals is the ultimate "big data" problem. Medical image analysis, signal processing and integration of physiological data face similar challenges in dealing with different big data sources. This paper provides an idea of how medical big data can be managed by computation intelligent system in neurological diseases diagnosis. A survey of recent reported CAD methods is also provided in this paper. The main goal behind this short review study is to assist the researchers or experts to provide an idea and understanding about CAD methods in the diagnosis of

neurological disorders. Neurologists expect that the CAD systems can assist them in diagnosing neurological diseases by providing useful information. Although there have been extensive studies into the development of various CAD systems for automatic screening diseases, the experts are still unable to use all of them in their decision-making process due to the lack of easily used online methods. Furthermore, sometimes inappropriate choice of feature extraction methods and classification methods in the CAD systems can make meaningless results to understand disease. In order to make robust CAD systems, an improvement of machine learning algorithms is also necessary for perfect classification work and diagnosis. In the literature, it has been observed that in most of the cases, the developed CAD systems are focused by offline manner while the experts require online CAD systems for real-time evaluation. Moreover, the best methods suffer from a trade-off between accuracy and efficiency. Therefore, the improvements in the CAD analytical systems are required to analyse the big data in a clinical setting. Thus, in order to generate even more accurate differential diagnostic systems, further research is required in the following directions: (1) developing efficient online CAD systems; (2) developing more general feature extraction methods; (3) developing robust classification methods; and (4) considering proper size of training and testing data set as large training data increase classification accuracy. Through addressing these concerns, the accurate CAD model can be developed for diagnosis of neurological abnormalities that will help the experts/neurologists with the timely diagnosis.

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