Neurodegenerative Diseases Monitoring (NDM) main Challenges, Tendencies, and Enabling Big Data Technologies: A Survey

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Abstract—**Evidence-based health monitoring has been recognized in the past few years as a very prominent solution to cope with continuous monitoring of chronic diseases such as neurodegenerative diseases for example: epilepsy. This has reduced the burden and cost for healthcare agencies and has led to efficient disease tracking, diagnosis, and intervention. Monitoring these diseases requires a long and continuous EEG signals recordings, pre-processing, analytics, and visualization. This will require a comprehensive solution to handle the complexity and time sensitivity of continuous monitoring. Several neurodegenerative disease monitoring (NDM) architectures have been proposed in the literature, however, they diverge on different aspects, such as the way they handle the monitoring processes, and the techniques they used to process, classify, and analyze the data. In this paper, we aim to bridge the gap between these existing NDM solutions. We provide first an overview of a standard NDM system, its main components, and requirements. We then survey and classify the exiting NDM solutions features, and characteristics. Afterwards, we provide a thorough evaluation of existing NDM solutions and we discuss the remaining key research challenges that have to be addressed. Finally, we propose and describe a generic NDM framework incorporating new technologies mainly the Cloud and Big Data to efficiently handle data intensive related processes. We aim by this work to serve researchers in this filed with useful information on NDM and provide direction for future research advancements.**

Keywords- Neurodegenerative Diseases Monitoring, Brain Informatics, Neuro Informatics, Big data, EEG, Seizure Detection

I. INTRODUCTION (HEADING 1)

In the last few decades, the number of people having neurodegenerative diseases grew immensely. These diseases are considered one of the main reasons for death worldwide. Neurodegenerative diseases are brain disorder like Alzheimer's disease (AD), Parkinson's disease (PD), or Epilepsy. These diseases have no cure and progress over time but can be controlled if detected in the early stages. This triggered the research interest to improve these patients' life and provide continuous healthcare assistance when needed without interfering with patient lifestyle by using smart monitoring systems. In the rest of the introduction section we will introduce the neurodegenerative diseases monitoring, and will identify the main related challenges.

A. NDM characteristics

Neurodegenerative diseases are defects in the central nervous system caused by progressive loss of neurons. The disorders could be in the form of dementia like Alzheimer's disease (AD) or motor skills disorder like Parkinson's disease (PD). These diseases increase predominantly in the aged population [1].

Example of these diseases is the epilepsy, which is a group of long-term epileptic seizures as a form of neurological disorders. The seizures are periods of shakings that can vary in time length.

In one hand, it is becoming very expensive and more complex to give appropriate medical care for patients with neurodegenerative diseases. Hospitalization and Long-term clinic stays for overseeing and change of the patients' medicine contribute to expense growth [1]. On the other hand, the amount of collected medical data has increased because of using computer based information systems. From 2005 till 2011, the number of office-based physicians and hospitals using electronic medical records (EMR) increased from 30% to 50% for physicians and 75% for hospitals. About 45% of hospitals in the United States participate in the health-information exchanges (HIEs). Eighty hospitals in the state of Indiana are connected to the HIE which has the information of 10 million patients which are used by 18000 physicians [2]. It is estimated that using technology in healthcare will reduce the healthcare cost for $300 billion to $450 billion, which is about 12% to 17% [2].

The increase of electronic medical data, urged the use of mobile health systems (M-health). M-health is defined in [3] as: "the application of mobile computing, wireless communications and network technologies to deliver or enhance diverse healthcare services and functions in which the patient has a freedom to be mobile, perhaps within a limited area". The Free Dictionary by Farlex defines patient monitoring (medicine) [4] as the nonstop or recurrent periodic measurement of physiological signs such as blood pressure, heart rate or respiration rate of a patient. There are a variety of terms relate to the use of ICT in patient monitoring, e.g. Tele-monitoring, remote patient monitoring, wireless patient monitoring and mobile patient monitoring [3].

Mobile patient monitoring is defined in [3] as: "the continuous or periodic measurement and analysis of a mobile patient's bio-signals from a distance by employing mobile computing, wireless communications and networking technologies".

Figure 1 illustrates the main components of NDM Systems. The Brain sensors collect the EEG signals from the brain. Sensors have different types, wired, wireless, wearable, or imbedded. In addition, sensors can support smart functionality such as signal preprocessing and filtering to save bandwidth and speed up the signals processing. The sensor-generated signals are transferred to the back-end server or a smart phone where they are processed, analyzed, visualized in order to serve the diagnoses purpose. Visualization of signals is represented in the form of reports or alarm signals. The diagnoses results and visualized reports are viewed by medical centers, physicians, or in case of emergency, an ambulance is called. The figure also shows the data storage component where the data along the process is stored in databases, Clusters, or distributed data centers.

B. *High-level motivations*

With the emergence of smart phones as inexpensive computational platforms allow monitoring some of the mental disorders, and also allow early detection of some of these problems [5]. They can provide activity recognition upon receiving this data. Moreover, to be able to monitor neurodegenerative diseases, we need to measure and evaluate EEG signals. Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain" [6]. Recently several neural recording microsystems with wireless transmission has been used as opposed to the wired ones. They are more practical for patients with neurological diseases as they offer movement freedom

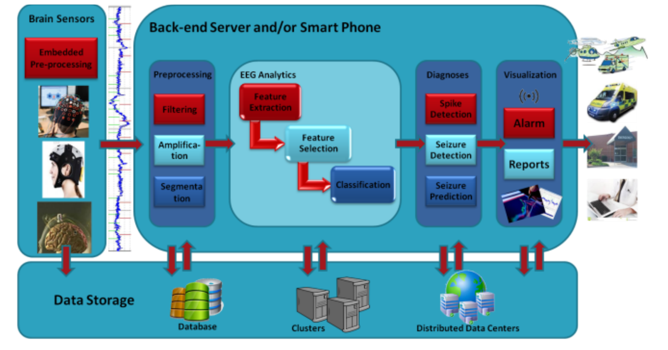

Figure 1 Neurodegenerative Diseases Monitoring (NDM) Systems

and reduce the infection risks caused by percutaneous plugs. These kinds of devices exhibit two main challenges that are: the limited battery power, and the variation in transmission rate. Therefore, some data size reduction algorithms must be implemented within these devices [7] to cope with these challenges and mitigate the induced risks of battery drainage, data transmission.

Other challenges facing the evolution of smart mobile health monitoring systems; the most significant of which is the volume of data to be transferred, processed, analyzed and stored. The following section highlights the importance of these challenges and envisions the application of big data technologies as proficient approach to overcome these challenges.

C. *NDM key challenges*

Neurodegenerative disease monitoring requires handling of long or continuous EEG signals recordings. The collected data has special characteristics mainly high volume and can be categorized as big data. Traditional techniques used for handling normal data sets are not anymore suitable for Big Data as it is dynamic, of continuous nature, voluminous, volatile, collected from varying sources, and it is of different types.

Big Data is referred to in [8] as "The tools, processes and procedures allowing an organization to create, manipulate, and manage very large data sets and storage facilities" and as "A collection of large and complex data sets which are difficult to process using common database management tools or traditional data processing applications".

Not only the size that defines big data, it is also characterized by complexity, diversity, veracity, and velocity. It is essential in Big Data context to answer new questions never been answered before. The challenges that face systems dealing with big data are: data collection, storage, search, analysis, and sharing. Big data has four dimensions, known as 4Vs: Volume, Variety, Velocity and Veracity. The main motivations behind adopting big data in healthcare are: increasing number of sensing technologies and tools for capturing health data, cost reduction in collecting such data, more people/patients become technology aware users, and more medical discoveries are added throughout time. In addition, to the previous drives, standard medical systems are moving towards using evidence-based healthcare and Electronic Health Records rather than paper-based healthcare [8].

The advantages of using big data technologies in healthcare systems are to provide prompt service to the patients, engage them into the monitoring process, and rely on evidence for health monitoring and disease diagnosis. It is eventually less costly especially, when taking the right decisions based on evidence data.

New technologies used in sensors will revolutionize the quality of Home Monitoring systems. These sensors generate different types of real-time data, which contributes to the healthcare data explosion. In 3 years, +1 billion smart phones will be used, 3 billion IP-enabled devices by 2015, by 2016, 4.9 million patients will use remote health monitoring devices, 3 million patients will use a remote monitoring device via smartphone hub, 142 million healthcare and medical application download [9]. Data size incurred huge increase in volume; healthcare cost grew to an unmanageable degree to be $2.9 trillion 2009, and expected to increase 25.0% in 2025 [9]. Using Big data in healthcare is expected to offer possible spending reduction of $300 billion annually in the US [9]. In the following sub-sections, we describe health Big Data characteristics and their related issues.

1. Data intensive related issues

- Health Data explosion and size

The health data increased exponentially because of converting existing data to digital format; such as personal medical records, radiology images, human genetics and population; and generating new forms of data such as 3D images, and sensor generated data. Worldwide healthcare data is expected to grow to 50 times, from 500 petabytes in 2012, to 25,000 petabytes in 2020 [9].

- Health Data variety

Health data is of large variety, traditionally, generated health data was generally unstructured like medical records generated in clinics and hospitals, or handwritten by doctors and nurses, hospital admission and discharge records, prescriptions, radiograph films, MRI, CT and other images. Structured data is generated by some laboratory instruments, or converted from paper medical records, or electronic accounting and billings [9]. Currently, health data are collected from social media, research, fitness devices and genetics, stored and analyzed by computing machines to produce meaningful and beneficial data.

- Data velocity

Speed at which the data is generated and speed at which it is collected, analyzed and viewed is increased due to the increase of volume and variety of data. Real-time data processing is required in health monitoring as it is vital and may compromise life of human such as in case of trauma monitoring, operating room, and bedside heart monitoring. Other types of data require medium speed handling such as daily blood pressure monitoring, and diabetic glucose measurements. The ability of handling such amount of data in real-time will make a huge leap in healthcare services protecting lives and avoiding outbreaks [9].

- Health Data accuracy (quality and completeness)

With the variation of heath data, different dissimilarity of data quality might be considered. Increasing the quality of the data is important because it may affect life and death of patients, and also may affects decision-making in terms of diagnosis, treatment, and prescription. However, quality of data is affected by the variety of data; as quality of data increase, the volume of data increases, so set of compromises need to be considered. Furthermore, completeness of the data and how trustworthy it is will definitely affect the big data analysis and clinical decision-making.

- Health Data transmission

The authors in [3] categorize the Wireless networking technologies used in mobile patient monitoring systems such as: the Wireless Wide Area Network (WWAN) which covers large geographic areas but has high latency and low bandwidth, and the Wireless local area network (WLAN) like WiFi that covers smaller areas with higher bandwidth and lower latency. GSM, which is a 2nd generation (2G) mobile network technology, can support some monitoring applications requiring low bandwidth. Higher data rates were provided using 2.5G wireless network technology like GPRS and 3G like UMTS, and lately the 4G providing the best data rates in WWAN technology. However, Long-term evolution (LTE) provides higher data rate potential; around 100 Mbps downlink; which will open the door for data-intensive mobile monitoring systems [3].

2. Energy consumption and network intermittence issues

Sensors as well as mobile devices have limited power capacity, battery drainage is affected by many factors such as the size of transmitted data, frequency of sensing, the network used, etc.

Network connecting sensors with the back end servers, mobile devices are subject of disconnection especially when a Wifi is used, therefore data can be lost, delayed, or corrupted.

3. Data and Application Integration issue

Integrating continuous sensed data, maybe from different sensors, with multitude of applications deployed on different devices (desktop, mobile, tablets) is very challenging. Many integration approaches can be used to incorporate the data and the application and this consider middleware, gateway, adapters, and Web services. The latters were proven to be an efficient way to allow a seamless integration of data and applications. It allow diverse systems and applications to interoperate regardless of their underlying platforms.

The remainder of this paper is organized as follows: the next 3 sections surveys existing work on automated EEG monitoring lifecycle starting with data acquisition, signal transmission, signal preprocessing, and finally signal analysis and classification. Section 6 provides a survey of related work on systems for health monitoring, systems for EEG monitoring of neurological disorders, and systems for EEG monitoring for Brain Computer Interaction. Section 7 discusses and compares existing EEG monitoring systems and highlights the main challenges of neurological diseases monitoring. Section 8 describes the principles of a comprehensive and smart monitoring framework for neurodegenerative diseases. Finally, section 9 concludes the paper and points to future research directions.

II. OVERVIEW OF NDM LIFECYCLE

It is important to understand the lifecycle of EEG signal acquisition, processing, and analysis. This section will review the current state of the art on automatic EEG-based monitoring. The analysis of brain signals in neuroscience encompasses 5 main phases: data acquisition, data transmission, data preprocessing, data analysis, and finally data interpretation and diagnoses [10]. The aforementioned phases comprise the EEG analysis lifecycle.

Phase 1. Data acquisition, it is the process where the EEG data is acquired from the scalp by sensor electrodes that measures electrical activity of the brain.

Phase 2. Data transmission, it is the process of transmitting the EEG signals using a protocol (e.g. Bluetooth) from the scalp to the server or the computing environment where it will be processed and analyzed.

Phase 3. Data preprocessing, it is the process of conducting some data treatments such as filtering data to remove the unwanted signal anomalies and noise to be ready for signal analysis phase.

Phase 4. Data analysis is the process of applying techniques to the EEG data in order to extract meaningful information and insights that will support diagnosis and decision-making.

Phase 5. Decision and diagnoses, which is the final stage where a professional automated decision is reached either by diagnosing neurodegenerative diseases or seizure detection.

Error! Reference source not found. illustrates the EEG analysis lifecycle where the above phases are sequentially enumerated.

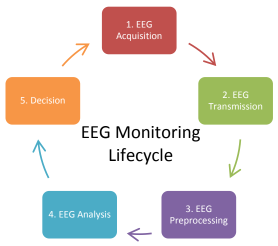

Figure 2 EEG Analysis Lifecycle

Architectural requirements

NDM systems deal with special data that can be described as intensive, sensitive, private, and time critical. Therefore, it should satisfy certain requirements regarding data collection, transfer, processing and analysis.
Noninvasive: collecting brain signals from a patient could be an uncomfortable process if the old fashion wired sensors with gel electrodes are used. The new smart wireless sensors are preferred for continuous monitoring process. The sensors should be noninvasive, lightweight, and have small size.
Accuracy: The signals collected should be accurate reflecting the correct patient's situation. Since the brain signal data is intensive, sensor should implement some smartness to allow preprocessing capabilities such as selecting which signal to transmit while maintaining high accuracy of data.
Performance: The monitoring system also should guarantee high performance and low response time as those criteria might make big differences in case of emergency situations, a few saved minutes may protect a life of a patient.
Confidentiality and security: should be guaranteed since patient's data is private and should not be divulgated to any non-authorized parties.
Heterogeneity and platform-independent: The system should support different patients using different monitoring tools and technologies.
Scalability: the system should be able to scale to support increasing number of clients and maybe monitoring varying vital signs.
Processing: distribution of processing and storage will be very important to cope with the huge data processing handled by the monitoring system.
Robustness: it is one of the important requirements for such systems to work under extreme conditions, support quick failure recovery process, and data loss recovery [11].

III. AUTOMATED EEG SIGNAL ANALYSIS

A. Brain Signal Acquisition

EEG sensors are electrodes that are either implanted in the brain as a small chip (invasive) or wearable and are placed on the scalp (noninvasive). Some of the wearable devices are wireless to provide patients the freedom of movement.

- Implantable devices

There are different examples of implantable EEG sensors discussed in literature. This section reviews some of the existing designs of neural implants. Authors in [12] describe a low-power analog-to-digital ADC architecture for neural implants that process extracellular potentials using signal processing. The system uses spike detector that reduces power consumption by differentiating a spike signal from noise signal using a threshold. The sampling rate is changed in an adaptive way when a spike is detected. When the value of the signal is above a certain threshold, it triggers a spike and the ADC works in full sampling rate. But when the signal value is lower than a threshold the sampling rate is reduced. The paper showed that by using this adaptive method the power consumption is reduced to 62% [12].

Another ADC suggested in [13] used a time-based algorithm; it is energy efficient but offer less speed and precision. The idea is using the operation of integrate-and-fire spiking neurons for ADC conversion [13]. Also, [14] offers a hybrid/cascaded seizure detection algorithm that works on implantable devices. The algorithm has better performance in terms of power consumption and accuracy. The technique is divided into two stages, the first stage is to use low power algorithm to detect the seizure candidates which then if detected are input to a second stage algorithm providing high accuracy. This reduces the power consumption by 80%. The paper proposes different algorithms for the first stage such as simple time-domain features like line-length or area for the first seizure detector because the signal amplitude change is the most common for seizure detection. For the second stage, the algorithms proposed are spectral entropy or a wavelet transform, for frequency-domain features to eliminate false detected in the first stage. This system is suitable for real-time implantable detectors and for wireless monitoring of seizure data.

The authors in [7] describe implantable circuit for raw brain activity acquisition that is capable of recording neural spikes and extracting features. The chip has low power consumption and can operate in several modes such as foreground self-calibration, adaptive threshold voltage, signal tracking and feature extraction using first-order PWL approximations. Simulations results showed that feature extraction capabilities reduced the bandwidth by approximately 90%.

Authors in [15] provide an implantable "Neuroprocessor" that is capable of processing the signal and detect spikes. The purpose of the algorithm is to decrease the amount of data so that it can be wirelessly transferred. The algorithm performs detection and alignment of signals. The proposed architecture is not applied in real scenarios.

- **Wearable devices**

The challenges for wearable devices are the power consumption, electronics with analog to digital converter and signal processing that requires low power consumption. It is very challenging to design a medical device that can be attached to the body for days, weeks or months [16]. In order to guarantee portability and comfort, the sensors should be attached to a "truly wearable device" like a cap, a headband, or a pair of sunglasses [17]. The challenging constraints are the battery life, weight, and size [18]. The work of [18] represents a battery free EEG signal acquisition circuit "powered by a standard UHF RFID reader; and uses backscatter to transmit the data using a EPC Class 1 Gen2 protocol". This is designed for long-term data acquisition with no need to change the battery and with feature of low power consumption.

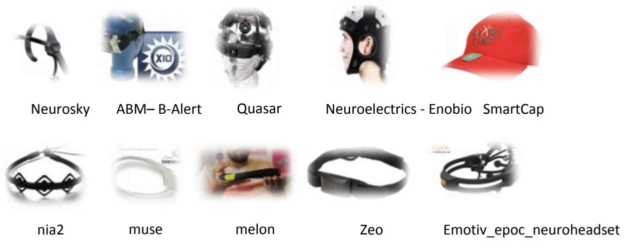

Figure 4 Examples of existing commercial wearable brain sensors

Commercial systems vary in number of electrodes and price; they used integrated headsets with dry electrodes. Neuroelectrics – Enobio, the Neural Impulse Actuator (NIA) is a brain–computer interface (BCI) device developed by OCZ Technology, Emotiv - Epoc , and N eurosky [16]. Figure 3 provides some examples of existing commercial wearable sensors.

B. *Brain Signal Acquisition*

The data acquired by the EEG sensor are transferred to a processing unit or a server. There are two main methods to perform the data transmission; wireless or using wires connected between the sensors and the server.

- **Wired**

Some of the EEG sensors are wired and usually heavy and cumbersome. They are not practical to be used by person who is not stretched and wants to lead normal life since they limit the patient's movements. In addition, to not being comfortable, the installation of such systems require experts assistance, consume time, and may have to be wet electrodes.

- **Wireless**

The other way of signal transmission is wireless transmission technology. There exist several protocols for wireless transmission like Radio Frequency (RF) and Bluetooth. The advantage of wireless communication is to provide the patient freedom of movement and allow leading normal style of life. Since, wireless transmission is embedded in many of everyday use products like cell phones and PDAs, it is more practical to use this kind of signal transmission in EEG monitoring systems [16].

C. *Brain Signal Preprocessing*

Before EEG data analysis, the raw EEG signals need to pass through preprocessing stage to filter to remove unwanted

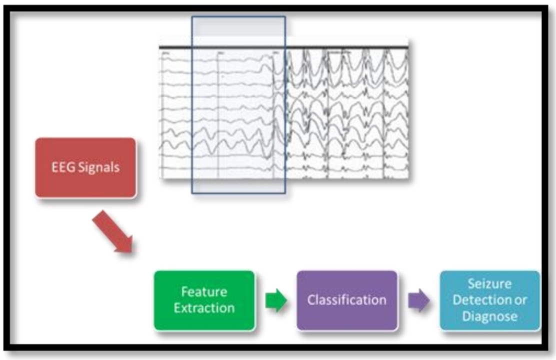

Figure 3 Brain Signal Analysis

signals DC component signals, signals caused by muscular activity, or signals caused by eye blinks or movements. These signals may lead to wrong analysis of EEG signals and wrong diagnoses [19]. There are many techniques such signal resampling, Filtering, Artifact Detection and Suppression, Artifact Rejection, Adaptive Filtering, Regression, and Blind Source Separation as described in [20], and [19]. Also, [21] provides segmentation methods for EEG signals based on frequency. Preprocessing stage also include signal cutting, amplitude scaling, and verification of expert marks.

D. *Brain Signal analysis*

The main objective of brain signal analysis is to assist neurologists to diagnose neurological disorders. Many efforts in the field of automatic EEG signal processing satisfy two main categories: seizure detection and seizure prediction. A thorough review about brain signal analysis is presented in the work of [22]. The authors classify the automatic EEG signal analysis into two main categories, spike detection and seizure analysis. The seizure analysis is grouped into seizure prediction, seizure detection and seizure origin localization. In order to do seizure analysis, the EEG signal has to go through a process of feature extraction, feature selection then classification. The following sections describe the types of signal analysis and methods used to perform signal analysis.

1. **Signal Analysis Type**

- ***Spike detection***

The authors in [22] classify spike detection algorithms into 9 categories: traditional techniques called mimetic techniques, morphological analysis, template matching algorithms, parametric approaches, independent component analysis, artificial neural networks, clustering techniques, data mining and other classification techniques, and knowledge-based rules [22].

- ***Seizure prediction***

Seizure prediction is important for warning medical caregivers before the occurrence of a seizure. It allows them to interfere and provide help to the subject under observation. Algorithms based on time-domain analysis, frequency-based, nonlinear dynamics and chaos, methods of delays, and some intelligent approaches are used for seizure prediction [22].

- ***Seizure detection***

On the other hand, seizure detection is used for diagnosing a neurodegenerative disease. The seizure detection process is a stage in which EEG recordings are analyzed using the algorithms of feature extraction, feature selection then classification. Subsequently, the question to be asked is what features best describe the spikes to be selected for the classification, and which machine learning algorithm is to be used [22].

2. **Signal Analysis Methods and Processes**

- ***Feature extraction***

The part of the EEG signal can be described by a collection of calculated features. These features can be statistical, frequency computed for typical and extended EEG bands, entropy-based, or obtained by interval or period analysis, or extracted after applying Wavelet Transform (WT) technique. The accuracy of features extracted is important and affect the end result of signal analysis process.

- ***Feature selection***

The features selection is sometimes done according to a physiological phenomenon like the fact that during an epileptic seizure many neurons fire synchronously. Feature like autocorrelation function can help measure the "synchronicity", the synchronization likelihood or the nearest neighbor phase synchronization. Other features are selected according to morphological characteristics of epileptic EEG recordings. Depending on the fact that epileptic seizures appear in EEG recordings as multiple spikes, an example for this feature is using the amplitude and duration to determine if the signal reveal a seizure or not. For measuring rhythmic discharges, recurrence of a waveform that is characterized with uniform morphology and duration [23], methods used are: fast Fourier transform based, frequency domain, time-frequency based or wavelet-based features usually used [22].

- ***Classification***

The classification methods varied from simple rule based or linear classifiers to ANNs that have a complex shaped decision boundary. Other classification methods have been used such as SVMs, k-nearest neighbor quadratic, logistic regression, naive Bayes, decision trees, Gaussian mixture model, mixture of expert model, and adaptive neuro-fuzzy inference systems [22].

IV. CLASSIFICATION OF EXISTING NDM SOLUTIONS

More patients now favor home healthcare for many reasons: it is less costly than hospital care, and more convenient and less mobility for patients to stay in their environment instead of recurrent visits to hospitals or clinics for checkups. Growing number of patients requiring home healthcare cause increase in the amount of health related data that need to be stored and processed. This issue requires good infrastructure systems to handle the complexity and time sensitivity of the health data [24].

Currently many m-health and e-health systems emerged and many research efforts are done to enhance healthcare services and optimize medical resources in order to reduce cost. Some of these systems are monitoring health bio-signals such as heart pulse, blood pressure and ECG. Other e-health systems monitor brain signals (EEG) for patients who suffer from neurodegenerative diseases. There is also much work done for analyzing the EEG signals starting from signal acquisition phase to diagnosis phase. However, Most of the existing e-health systems solutions do not discuss in details the end-to-end system in terms of data collection, transfer, storage and analysis [25].

Medical Cyber Physical Systems (MCPS) are kinds of systems that are commonly used in healthcare especially in remote health monitoring because they support handling real time data collected from sensors connected to human body and send this data using internet or mobile to the concerned entity without delay [24].

Neurodegenerative diseases monitoring related work are classified into four types of solutions: Systems monitoring general health diseases, solutions for monitoring neurodegenerative diseases, solutions based EEG analysis, and solution for brain computer interface where continuous monitoring of EEG signals were used.:

A. Frameworks, Architectures, and Solutions for e-health monitoring

This section reviews some of the existing framework solutions developed for e-health monitoring systems. These systems monitor general bio signals like blood pressure, heartbeat, and other health vital signs. The authors in [26] reviewed few smart health monitoring systems and categorized them with respect to their medical applications. Medical applications can be general multipurpose like ANGELA and LAURA, or for monitoring vital signs in a specific medical conditions like Alzheimer's, Parkinson, cardiac, diabetes, and dementia. Other systems use smart technology like smart vests or home [26]. Some of these systems are the ones that monitor patient movement and detect patient's posture; other systems monitor the eye movement for patient under coma in Intensive Care Unit (ICU). Most of these systems use cameras to monitor the movement, which is limited to the cameras area coverage [26]. This work also provide review for some of the existing remote monitoring systems that monitor vital signs and detect abnormalities then transmit the data in real-time to healthcare decision makers like doctors and medical centers. Some delays occur during the data transmission because of real-time data processing or the wireless transmission delay. However, most of these systems did not discuss data security and patient privacy [26].

The authors in [27] present a wireless sensor network, where sensors are used to collect vital signs of a patient being monitored. Wireless sensors provide freedom of movement for patients and reduce inconvenience to help them for better recovery conditions. The system uses multiple radio channels to allow monitoring more than one patient in a room. Also introduce relay hand-off algorithm to reduce data loss due to low battery life of sensors and weak signal strength [27].

Another example of solution is presented in [11] where a framework for health monitoring of chronic diseases is introduced. Patients' health data is collected and analyzed in real-time and medical assistance is provided for critical conditions. The data is collected using wearable biosensors and stored on the Cloud. The framework relies on Service Oriented Architecture (SOA) to facilitate relaying the information to the medial centers or physicians in charge of monitoring so that medical decisions made in timely manner. Sensors are used to measure one or more of health signs like blood pressure, blood sugar, body temperature, and oxygen saturation. These sensors are Non-intrusive in order not to infer a change to the patients' way of life. Data collection follows one of three methods: Continuous, on-demand, and periodic/regular [11].

ANGELAH in [28] is an integrated system that fulfills the following objectives: integrate a full system using bio-sensors for monitoring elders, ability to detect serious health conditions, and provide the rescue team in case of emergencies [28].

The authors in [29] review some of existing e-health systems that monitor general health issues such as ECG, and blood sugar. The wearable sensors collect the measurements from patient's body then they are transmitted through wireless or wired link to central unit such as Personal Digital Assistant PDA or a microcontroller board. The information is displayed to the user or to a medical center. The sensors used for such system are recommended to have the following specification: low weight and small size in order not to affect the patients' life, affordable, guarantee privacy of patient information, have minimal power consumption because of limited battery life, and less radiation concerns [29].

Another review provided in [3] describes the architecture of 6 existing systems like: 1) Yale-NASA Himalayan climbers monitoring system developed by NASA and Yale University. 2) The Advanced Health and Disaster Aid Network (AID-N) system developed by John Hopkins University, University of California, Harvard University and others. 3) Personalized Health Monitoring (PHM) system developed by the University of Technology. 4) A wireless-PDA based physiological monitoring system developed at the National Taiwan University in cooperation of National Taiwan University Hospital. 5) A wireless continence management system for the patients suffering from dementia developed by the Institute for Infocomm Research, Singapore in cooperation with other partners. And 6) MobiHealth patient monitoring system developed as a part of the MobiHealth project (supported by Commission of the European).

Some recommendations are proposed in [30] for creating a mobile health system that integrates Wireless body LAN network for health monitoring. Sensors communicate to a server that is connected to the Internet, these sensors have low power consumption, small size, and low weight, and noninvasive, wireless connectivity, and guarantee secure and reliable communication. Also, they consider robustness, and fault tolerance implementing retransmission of lost packets [30].

In addition, [24] describes framework for big data processing that take into account real time data and dynamic provisioning to help in healthcare decision-making. The limitation of existing traditional system are complexity algorithm to detect health abnormality which require large data and more processing time, configuring the system to adapt to current scenarios is not easy, and real time decisions is not supported by the system. Cyber Physical Systems (CPS) is the new paradigm to solve the aforementioned issues. It integrates computation, communication and control of health monitoring data in real world. They are typically used in military for critical missions [24]. The described infrastructure for big data analysis requires: data acquisition (large volume of real time data that need less delay and require simple query to process), data organization (large volumes stored into clusters and Apache Hadoop provides a way to process this data without moving it to local storage), and data processing (required to be distributed to reduce latency and accommodate statistical analysis) [24]. The framework has 3 Layers: component layer which provides messaging and distribution between the system and the application, services like "routing, protocol, data access and data distribution", process layer that implements message listener which receives the stream of data and process it. And application layer which is responsible for data analytics. However, this system does not refer to EEG signals.

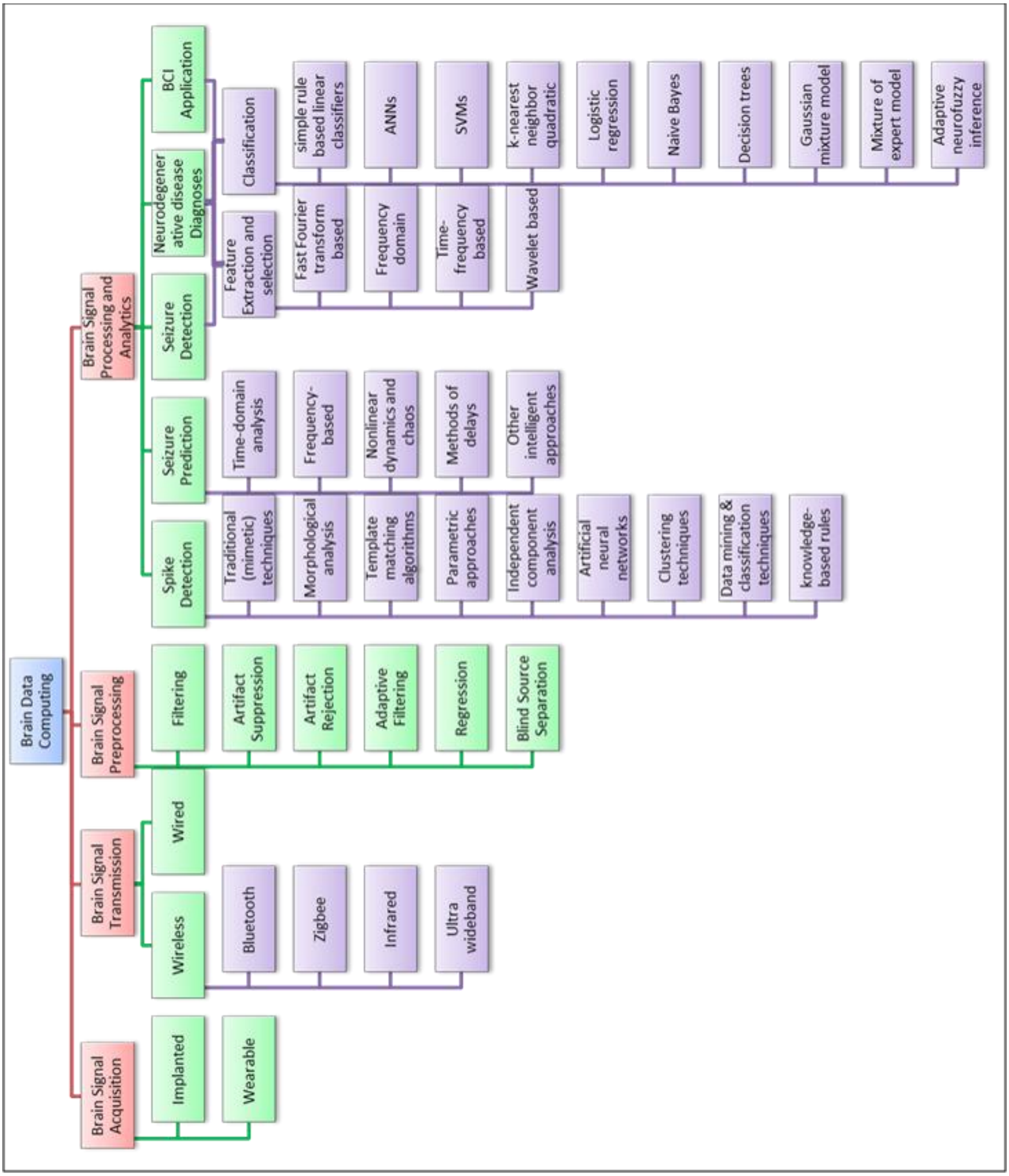

Figure 5 EEG-based Monitoring Techniques

B. Frameworks, Architectures, and Solutions for EEG-based monitoring

Lately, a lot of progress has been achieved in health monitoring techniques to improve the health system with accurate diagnoses and monitoring age related diseases such as dementia, Alzheimer's and Parkinson's [26]. EEG signals are used for diagnoses and monitoring patients with neurodegenerative diseases. The following section reviews some existing systems that use EEG signals to monitor neurodegenerative diseases.

Authors in [25] proposed a full end-to-end system for monitoring patients with neurological disorders is proposed. The system includes Brain Sensors (BS), Gateway, Home/Mobile SOA-based servers, Surveillance Center (SC), Big Data Technologies, Mining, Analysis and Visualization. The system is tested for Parkinson disease. In addition, the system proposes to apply advanced data mining techniques for analysis [25].

Another system is proposed in [31] integrates wireless biosensors placed around the body of the patient, data is received by a PDA held by the patient. The data is then forwarded to the physician or a medical center. The network has the capabilities of loss compensation and congestion reduction by developing interface chip that provides signal compression by extracting bio-signal feature parameter extraction. In addition, the system has different wireless loss recovery mechanisms [31].

A diagnosis-assisting tool named the neuronal activity topography (NAT) system is proposed in [32]. The system is used for Alzheimer's disease (AD) detection and other brain disorders. The system has 21- EEG channel electrodes connected to a server using Internet. The EEG recording is done over 5-minutes period. However, this system is designed as a check-up tool but not for mobile patients or periodic home based checkups. Also, it is still not in practical public use yet.

Health monitoring systems that monitors neurodegenerative diseases proposed in [33] is a pre-surgical investigation based health monitoring system that analysis body movement using multiple (in specific 3) tri-axis accelerometers that are attached to the patients' wrists and head to detect epileptic seizures. The output of these sensors is sent to long-term video electroencephalographic monitoring for data synchronization. With this collected data, a tonic–clonic (TC) seizures detector is proposed based on simple entropy. The evaluation shows 80% sensitivity with 95% specificity.

An Interactive MATLAB GUI is suggested in [34] which provides an EEG based analytical tool for monitoring, analyzing large volume dataset of EEG signals and continuous EEG signals. . The system GUI also supports different techniques like independent component analysis (ICA), time/frequency analysis (TFA), in addition to standard averaging methods [34].

C. Framework, Architecture, and Solutions for EEG-based diagnosis

This section reviews some of the existing systems on automatic EEG signal analysis for the purpose of seizure detection and neurodegenerative diseases diagnoses. An example of an offline automatic diagnoses system is provided in [13], they discuss an automatic diagnose for epileptic patients without the need for lengthy EEG data collection. Opposed to the traditional way of diagnosing epileptic patients by visually looking at the EEG long recordings, this is time consuming. They also suggest an automatic way to diagnose whether a patient is epileptic or not, by studying EEG signals between seizures which does not have the seizure activity signals (interictal). Power spectral feature, fractal dimensions, Hjorth parameters, and amplitude statistics are the features selected for this signal analysis algorithm. The EEG data is fed into Probabilistic Neural Network (PNN) and Leave-one-out cross-validation (LOO-CV) is applied on normal EEG data sets. This method proved 99.5% accuracy in determining if a person is normal or epileptic, and achieved 96.7% accuracy for seizure detection [13].

Another example of an offline automatic identification of epilepsy seizure is suggested in [35]. The authors use both multi-wavelet transform and Improved Approximate Entropy for feature extraction and artificial neural network for classification. Other algorithms are compared against this proposal, in terms of accuracy and sensitivity; the accuracy of this algorithm is 90% [35]. Another example of detecting epilepsy disorder is suggested in [36] and [37]. The authors propose a technique of detecting epilepsy disorder (telling if a person is epileptic) from Electroencephalogram (EEG) signals using discrete wavelet transform and the back propagation algorithm for classification using MATLAB software [36] and feed-forward Neural Network [37]. These experiments provide experimental verification that proved the detection of epilepsy within few seconds. This system use offline data acquisition. Another study provided by [38] proposed detecting epileptic seizures using multichannel EEG signals. Feature extraction used approximate entropy (ApEn) and statistic values for feature extraction, and support vector machine for classification with an accuracy of 98.91%. EEG Data is collected offline.

Another example of epilepsy diagnoses is provided in [39]. Since the traditional way of epilepsy diagnoses is to look at lengthy EEG data recordings, which is time consuming; this paper proposes a neural-network-based automated epileptic EEG detection system that uses approximate entropy (ApEn) as input feature. ApEn is a parameter that helps in predicting the amplitude of signals based on previous amplitude values. This value decreases during an epileptic seizure. This fact is used for the proposed system resulted in up to 100% accuracy rate. This method is good for real time detection of epilepsy. The EEG signal of normal subjects is obtained using intracranial electrodes [39].

The authors in [40] review the work done for automatic diagnosis of epilepsy, the Alzheimer's disease, and Attention Deficit Hyperactivity disorder. The author concluded that neural computing, chaos theory, and wavelets improve the accuracy of diagnoses of neurodegenerative diseases [40]. Finally, authors in [41] provide diagnosing Alzheimer disease and Mild Cognitive Impairment (MCI) using EEG signal features like Granger causality (in particular, full-frequency directed transfer function) and stochastic event synchrony. Classification used is leave-one-out cross validation technique [41].

D. Frameworks, Architectures, and Solutions for EEG-based Monitoring in Brain Computer Interface Systems

Brain Computer Interface (BCI) is new research area targeting the field of EEG analysis and continuous EEG monitoring but for the purpose of translating the brain activity into commands for a computer or robot rather than detecting neurodegenerative disorders or seizures. In [42] a review of different classification algorithms to make pattern recognition for the EEG signals in BCI Systems is presented. In this paper, classifier algorithms are categorized into: linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and combinations of classifiers. Authors recommend fuzzy classier for BCI purposes [42].

A full framework is proposed in [43] for a remote brain machine interfaces (RMBI) system that uses wearable headband with dry electrodes EEG nano-sensors with Bluetooth functionality. Signals collected by a smart phone and sent to an Internet connected laptop to analyze the signals and generate control commands for robots. One of the limitations of such BCI systems is the wireless transfer rate. Authors of [44] suggest a method to increase the bit rate of transferring EEG signals wirelessly; the algorithm uses signal processing and machine learning and the system target brain computer interface.

A discussion of Brain Computer Interface system is proposed in [45]. The system described, consists of four modules: Operator, source, signal processing, and application. In this survey work, group of researchers recommended SVMs as classification method with “common spatial patterns”, however others recommended machine-learning techniques with “a statistical analysis of a calibration measurement” for system training [45].

Figure 5 provides a comprehensive classification of EEG-based monitoring techniques as described in the above sections.

V. EVALUATION OF EXITING NDM SOLUTIONS

From the above study it is clearly identified that EEG based monitoring systems and other systems that monitor bio-signals require real-time transmission, and high quality signals excluding artifacts that might reduce operation’s delay. Choosing the right technique for preprocessing and analysis of EEG signals is very challenging, as it will highly contribute to the delay reduction and the quality of decision-making.

This section provides a review of some existing EEG-based neurodegenerative disease monitoring systems. It is divided into three subsections. The first subsection discusses the criteria for comparing some of the reviewed systems, the second subsection summarizes some of the main features and characteristics of the studied systems (see Table 1), and the third section identifies some key challenges that face the neurodegenerative disease monitoring systems.

A. Criteria and comparison

There are wide ranges of neurodegenerative disease monitoring systems presented in literature. This section discuss and compare some of these systems with respect to important criteria such as monitoring purpose, type of sensors, transfer protocol, and techniques used for EEG signal analysis.

- Monitoring type/purpose

Many algorithms for EEG signal analysis have been proposed in the literature. These algorithms are referred to as Automated EEG signal analysis. The proposed EEG signal processing methods intend to identify different patterns in EEG recordings that occur during an epileptic seizure. They can serve the following monitoring purposes: seizure prediction [25] [41], seizure detection [32] [33] [14] [7] [13] [39] [46], and disease diagnoses [40].

- Sensor Type

Data acquisition is an essential part of smart health monitoring systems. Collections of sensors are used to obtain health related data specifically EEG signals. These sensors have to satisfy certain criteria such as low weight and size, portability, global connectivity, and reliability. Connectivity is crucial for enabling remote monitoring and handling emergency conditions. Electrodes are EEG signal sensors that are used to collect EEG activity from the scalp. There are two main categories of these sensors: implanted in the brain as a small chip (invasive) [14] [7] or wearable and are placed on the scalp (noninvasive) [31] [43] [33] [34].

- Transmission Protocol

Systems investigated in this review are also classified according to network technologies used for transmission of EEG signals from the sensors placed on the scalp to the processing server. Transmission of EEG signals are done either wirelessly or wired. Wireless transmission is noninvasive and guarantees mobility, freedom, and wellbeing of patients. The table below provides more detail about the transmission protocols used by the systems under investigation.

- Signal Analytics and processing methods

After raw EEG signals are collected, different methods are applied to analyze and extract meaningful information from the EEG recording. As mentioned earlier, data goes through three main stages, preprocessing, feature extraction and classification. Table1 below shows a summary of existing work done in the area of EEG signal processing and analysis.

B. Comparative evaluation

Table 1 shows a number of automated EEG signal analysis systems found in the literature. In Table 1, all systems are listed with their monitoring objective, EEG sensor type, and transmission protocol. The systems under investigation/review can be categorized as two main groups: complete framework for monitoring patients with neurodegenerative diseases, or system designed for automatic EEG signal analysis (diseases diagnoses and seizure detection). The complete framework refers to an end-to-end system handling the overall cycle from EEG data acquisition to decision making based on signal analysis. The second class of work includes systems that tackle EEG signal analysis rather than patient's monitoring. The purpose of this review is to survey the current literature for EEG signal related topics such as data acquisition, data transmission, data analysis, and decision-making (diagnoses, or seizure detection). However, literature does not provide a detailed description of a complete integrated smart solution for neurodegenerative disease monitoring system.

Table 1 reviews some existing work related to EEG signal monitoring and analysis. The different systems are compared

Table 1 Classification of existing work related to EEG signal analysis

Reference	Monitoring type (e.g. Prediction, Detection)	Feature Extraction Techniques	Classification techniques	Sensor type	Transmission Protocol
[25]	Prediction	Not specified	Not specified	Wearable/implantable	Wireless
[31]	Not specified	Multi-scale Wavelet	Support Vector Machine	Wearable	Wireless
[43]	BCI Detection (commands) Continuous Monitoring	Not specified	Not specified	Wearable headband	Wireless (Bluetooth)
[33]	Detection	Acceleration norm entropy	Quadratic discriminant analysis	Wearable	Wired (offline)
[32]	Detection, non mobile Alzheimer's disease (AD)	NINDS-ADRDA criteria and neuroimaging diagnostic procedure (SPECT)	Not Applicable	Offline data acquisition	Offline data acquisition
[34]	Modeling EEG signals during surgical procedure	Time/frequency analysis & independent component analysis	Not Applicable	Wearable	Wired
[14]	Seizure detection	Time-domain feature & frequency domain spectral Entropy	Not Applicable	Implantable	Wireless
[7]	Spike detection	Piecewise-Linear (PWL) approximations for spike feature extraction	Not Applicable	Implantable	Wireless
[13]	Seizure detection	Power spectral feature, fractal dimensions, Hjorth parameters, and amplitude statistics	Probabilistic Neural Network (PNN)	Offline data acquisition	Offline data acquisition
[40]	Diagnosis of neurological disorders (Epilepsy, AD, HYPERACTIVITY DISORDER)	Wavelet Transform	Radial basis Function neural network	Offline data acquisition	Offline data acquisition
[36]	Detecting epilepsy disorder	Discrete wavelet transform	Feed-forward Neural Network	Offline data acquisition	Offline data acquisition
[37]	Detecting epilepsy disorder	Discrete wavelet transform	Back Propagation Neural Network	Offline data acquisition	Offline data acquisition
[39]	Real time detection of epilepsy	Approximate entropy (ApEn)	Elman and probabilistic neural networks	EEG signal of normal subjects are obtained using intracranial electrodes.	Not specified
[35]	Identification of epilepsy seizure	Multi-wavelet transform & Improved approximate entropy	Artificial neural network	Offline data acquisition	Offline data acquisition
[38]	Detecting epileptic seizures	Approximate entropy (ApEn) & statistic values	Support Vector Machines	Offline data acquisition	Offline data acquisition
[41]	Prediction of MCI & AD	Granger causality (in particular, full-frequency directed transfer function) and stochastic event synchrony	Leave-one-out cross validation	Offline data acquisition	Offline data acquisition
[47]	Detecting Epilepsy Seizure	Wavelet Transform	Support Vector Machines	Offline data acquisition	Offline data acquisition

with respect to monitoring type whether it is prediction or detection, feature extraction and classification method, sensor type, and EEG signal transmission protocol.

There are different algorithms used for EEG signal analysis, each approach gives different accuracy rate when evaluated using different experimental scenarios, and different datasets. Experiments show that using neural networks classification approach gives very high accuracy for seizure detection for example, 96.7% in the work of [13], 96% in work of [37], and as high as 100% in the work of [39]. However, using neural networks approach requires heavy processing power, and high training time. Other systems use SVM for classification, which also gives high accuracy as 90% in [47] and 98.91% in [38]. Using SVM might not give as high accuracy as neural networks approach, but SVM requires less training time and requires less prediction time, which makes it more suitable for real time monitoring. Other works experienced other classifications techniques such as quadratic discriminant analysis [33] and leave-one-out cross validation [41] and most of them generally provide lower classification accuracy, and higher processing time.

C. Discussion of the remaining Key challenges of NDM

Monitoring neurodegenerative diseases mainly aims to enhance the patients' style of living and reduce healthcare cost. A complete smart neurodegenerative disease monitoring system should satisfy the following requirements: 1) EEG signals collection using wireless noninvasive electrodes, 2) data transfer from sensors to a PDA or smart phone for basic preprocessing and filtering, 3) disseminate the data to a distributed system to detect or even predict any signal abnormalities, and 4) send real time notification to the medical assistance representative. There are many challenges that face this kind of system. The traditional techniques used for data transmission, analysis and storage will not be suitable for such systems. Continuous EEG monitoring generate humongous amount of data that cannot be transmitted wirelessly without data loss or delay. Therefore, in the next section we propose a generic NDM framework considering a set of requirements characterizing a smart neurodegenerative disease monitoring solution and how these requirements can be fulfilled using Big data, and Cloud technologies.

VI. TOWARDS A SMART NDM FRAMEWORK ENABLED EMERGING TECHNOLOGIES: BIG DATA, AND THE CLOUD

To address the above-mentioned NDM challenges, we propose in this section a generic framework providing an end-to-end monitoring solution starting from data acquisition, processing, then analytics, and finally visualization. The framework relies on advances in information and communication technology, advances in non-invasive sensing technologies, revolution in mobile and pervasive technologies, and availability of variety of Cloud infrastructures, platforms and software as services, as well as Big Data technologies. The framework is a service-oriented solution in which everything is exposed as a service (e.g. sensing as a service, data as a service, and monitoring as a service). The silent benefits of the end-to-end framework are enumerated hereafter:

- Handles efficiently key processes of continuous NDM from data acquisition, to its visualization.
- Solves issues related to the continuous data acquisition, processing, analytics, and visualization using Big Data technologies.
- Uses mobile technologies to allow the integration the above data operations from mobile devices anywhere anytime.
- Uses Cloud services (e.g. SaaS, PaaS, IaaS) to handle storage, processing, and visualization of big data in a scalable, flexible, and cost effective way.
- Implements some intelligent features to cope with the data variety, volume, and veracity such as pre-processing, filtering, profiling, and compression.
- Ensures quality of collected data, its consistency, and accuracy.

The application of the above mechanisms requires full integration of different technologies, systems, and communication infrastructures. These technologies include sensing technologies operating various devices (e.g., sensors, actuators), pervasive computing technologies, and wireless/mobile networking technologies.

A. Generic NDM framework

While considering the aforementioned technologies, we propose a framework, which is composed by a set of building blocks that collaborate and interact between each other to achieve end-to-end monitoring of brain related diseases. **Error! Reference source not found.**, illustrates a conceptual view of a multi-layer framework including the following components: brain data sensing and acquisition, storage and processing, analytics, and visualization. These blocks are integrated seamlessly to constitute an end-to-end infrastructure whose entities collaborate through standard protocols to achieve smart, efficient monitoring, and visualization of brain data. In addition, two towers illustrate important technologies and features that should be applied/used at each layer of the framework and are: 1) big data and cloud technologies and 2) Security, QoS, and Management. Big data technologies can be used at the all phases of the monitoring lifecycle where data is involved and this from data acquisition, processing, to analytics, then visualization. Also, Security and QoS should be supported at different levels of the framework since patient's data is confidential and should be of high quality.

B. Components description

We provide in this section, a brief description of each module's role and how they contribute together the monitoring activities. Smartness can be incorporated at each stage of the end-to-end solution and smart features can characterize each data related process of **Error! Reference source not found.**.

Figure 6 End-to-end Framework for neurodegenerative disease monitoring and visualization

1. Sensing and Smart Data Acquisition: Sensing as a Service

Data acquisition in the first process of NDM during which a data is collected from sensors, these sensing devices measure continuously different neurological data and make them available via Web services. Different sensing technologies might be used to monitor the patient's brain signals. Examples of these sensing devices include EEG neuroheadset [48], and EMOTIV [49]. Most of these devices generally have an interface (API) that allows accessing the collected data.

Streams of EEG data collection from sensors induce a set of challenges including for instance the significance of collected data, its consistency, and its accuracy. Therefore, a set of mechanisms should be put in place to insure that data collection mechanism is smart enough to implement pre-processing techniques of data collection in an effective way. Event-driven mechanism could be developed within sensors to proactively and intelligently collect data only in pre-programmed situations, for instance: (1) only when needed, (2) when a specific situation occurs, or (3) when unexpected event happen. Data collection approach should be accurate, reliable and effective in collecting only meaningful data that can be used for disease identification or diagnosis of medical disorder or pattern of health. Besides, the data gathering services can be easily integrated with other healthcare systems; which allows high interoperability and dynamic integration between heterogeneous systems.

Mobile devices can be used to collect sensory data and relay it to the appropriate server and/or system. These applications should be small and lightweight as possible so that it is not physically intrusive and employs low power requirements and power efficiencies for operations over significant time periods between charges. Transmitting sensory data to mobile devices might be unnecessarily expensive. In fact, some of these data might be inaccurate, outdated, and/or without any added value. For example, an EEG collected signals might be irrelevant if it reports the same signal structure over a period of time, given that an EEG signal is continuous and relatively require a considerable bandwidth to be transmitted over the network. Consequently, the mobile application needs to develop intelligent agents to decide on the following is central:

- Which data to retrieve?
- Which data the mobile application decide to share with back end?
- Which operations (e.g. store data, sync data, etc.) to be processed locally on the mobile device?
- Which operation to be processed remotely on the back end server or Cloud?
- How to assess the cost of an operation? (In terms of Battery, CPU, Memory, Network, security, availability, etc.)

2. Data Storage and Processing based Big data and Cloud

Continuous sensing of neurological signals based EEG will generate a massive amount of data. Managing this data requires intelligence and processing capabilities that might integrate different technologies and data oriented techniques. The application of these techniques relies heavily on the availability of resources needed to store and process this data, the accuracy and the consistency of collected data itself, the battery status, and the network availability.

In this context, Cloud and Big data technologies match well the required resources and approach for storage and processing. Advanced and distributed data storage are made possible through the Cloud data centers, high powerful Cloud processing servers, and distributed cluster processing. Big data technologies can also be used to handle data processing. Apache Hadoop project [50], is a one of the widely used open source frameworks for handling parallel distributed processing of Big Data. It offers a simple programming model enabling big data processing across thousands of clusters of commodity hardware. Thus, ensure computation intensive, scalability, and data accuracy.

3. Data Analytics using Big Data and Cloud

There are varying numbers of analytics algorithms and methods used to support distributed and parallel data processing for big data based MapReduce. Data analytics is used to medically extract relevant information from large quantities of data. Mining large amount of long-term period, for different neurodegenerative diseases, and from large populations of patients will help analyzing these data and developing treatment patterns to best manage or even control the onset and the progression of these diseases. Hadoop ecosystem provides a set of tools such as Mahout [51], Cassandra [52] implementing advanced big data analytics algorithms to efficiently. For example Mahout is a scalable machine-learning library implementing algorithms for clustering, and classification, which is implemented and redesigned from scratch using the map/reduce paradigm.

4. Data Visualization driven Big Data and Cloud

Collected sensory data will definitely add value to all concerned parties including patients, physicians, as well as surveillance entity in order to visualize and analyze these data for various purposes. Visualization serves for: 1) validation of collected data, 2) support physician to make appropriate decisions, 3) report on continuous updates about health status of monitored patient, and 4) observe the collected data to prepare for any intervention in case of a critical situation. The data can be presented using different views including summary of monitoring results, graphs, pattern of readings, and even report on discrepancies of measures and generation of automatic preventive actions that might be suggested. The visualization views can be personalized per patient and per type of disease. Also, access rights can be granted to only authorized users.

Visualization raises numerous challenges that are related to the volume, the speed, and the dynamicity of collected data especially if the number of monitored vital signs per patient is varying. This requires a smart visualization that considers the following.

- Pre-processing and formatting of sensory data,
- Optimized display,
- Summarization of data, and meaningful representation
- Smart data visualization,
- On demand visualization, and
- Web-based visualization.

Big data new visualization tools and software can be deployed to help streamline the visual presentation of collected and analyzed brain data. 3D view model can be used to allow inspecting the location of the brain where seizures are detected.

VII. Conclusion

Neurodegenerative disease monitoring is a very hot research area involving different disciplines including signal processing, classification, analytics, and visualization techniques. It provided many benefits to all involved stakeholders. For patients, it will allow early detection and prevention, noninvasiveness, and involvement. For physicians, it will provide them with up-to-date data for better diagnosis and treatment. For healthcare organization it will provide a low-cost, and less involvement, as it is a patient-centric solution. This work tried to comprehensively review the current research on neurodegenerative disease monitoring systems. Several NDM solutions were surveyed, classified, compared and evaluated to identify the remaining key research challenges. A generic NDM framework has been proposed and features emerging technologies including Cloud and Big data to efficiently acquire, process, analyze, and visualize data generated form monitoring. As future work, we are working currently on developing an NDM architecture that addresses the research challenges identified in this paper and apply the new technologies proposed in this work mainly Cloud and Big data technologies to handle for example distribution of processing, advanced analytics, and adaptive visualization.

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