Role of Data Analytics in Bio Cyber Physical Systems

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Abstract Data science has proved its versatility in all dynamics of the field known to mankind, making decision making faster, and accurate over the past two decades. Coupled with IoT devices and their setups, these have been forerunners in terms of data generation and accurate prognosis. According to advisory firm International Data Corporation (IDC), the number of IoT devices is forecasted to reach 41.6 Billion by 2025, and the data generated from these devices is expected to be 79.4 Zettabytes. One broad sector which has emerged as a gold mine for data generation is the Bio Cyber Physical Systems. Bio Cyber Physical Systems are based on the incorporation of computational elements with biological processes of the human body. The following chapter aims to discuss a new design, implementation of a system based on Bio-CPS, focused primarily on health wearable technologies equipped with state-of-the-art sensors, couple their data with machine learning algorithms to detect real-time health complications primarily in a diabetic person and use of long short-term memory (LSTM) for prediction of such health complications.

Keywords Bio cyber physical systems · Health wearable technologies · LSTM neural network

1 Introduction

The human civilization has been subject to revolutionary changes over the course of its long evolving journey. The pace of changes brought about into the life of people has exponentially increased in the twenty-first century with the advent of technology in cyberworld. People have adapted to these changes in a positive and fast paced response. The most remarkable changes in the twenty-first century is 1. The introduction of Windows XP in the year 2001, this OS single handedly changed the user interface era by bringing in a plethora of changes and making it extremely user friendly for people, 2. In the year 2004, Facebook was founded and brought the

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world more closer than ever, coining in the term “social media” and revolutionizing messaging, in 2007, Steve Jobs introduced the world to iPhone, which led to the start of the smartphone era which subsequently has led to changes in almost all aspects of digital technology and later in the year 2009 Fitbit entered the market with an activity tracker. From the year 2010 onwards, most tech giants have invested in improving and coming up with more better specs in that have a big appeal to the customers. One such sector has been the wearable devices sector, with advancement in the field of IoT, semiconductors and the data science playing at the very center of all these revolutionary technologies, it is safe to say that wearable tech is bringing upon a new age of technological revolution. “Bio Cyber Physical System” is the term being used to describe the integration of health wearable tech with the human body and its association with data science. People from all backgrounds have shown interest in these miniature wrist devices which help them keep check on their health without any need for frequent consultations from the doctor. The scope of these wearable devices can easily be expanded to people already suffering from diseases and in turn warn them of severe complications from these diseases or help in mobilizing paramedical forces when the person is in grave danger and the individuals collected data accurately helping in a better diagnosis. In this paper, we propose a system comprising of wearable devices equipped primarily with PPG sensors, EDA sensors, and the data collected from these sensors in detecting diabetic seizures, heart attack, breathlessness and fainting of a person using a multi-channel CNN so as to warn the paramedic services instantly. Later we discuss the possibility of using LSTM model so as to predict future attacks based on the persons activity.

2 Cyber Physical Systems

Cyber physical systems can be defined as an integrated environment of cyber world with the physical components and their processes in various fields such as chemical, mechanical, electrical, and many more. The elements belonging to the cyber division in general interact and coordinate with sensors, which return data from based upon the indications from the physical components. According to the data perceived and real-time decision making by the system, the actuators modify the physical and cyber environment accordingly.

Cyber physical systems are slowly emerging onto the market and are poised to play a vital role over the next decade. The reason for its slow emergence is attributed to the fact that its base concept, and architectural flow is closely related to IoT and industrial IoT. There is a hairline difference between the two terminologies, and leading industry experts have been unable to come up with a distinctive difference between the two.

2.1 CPS and IoT

IoT is defined as the interconnection of various devices equipped with sensors and connected to each other over a network, exchanging data, monitoring the performance of devices and in turn optimizing their processes so as to efficiently run the entire network and generate profits for the users and the industry.

When it comes to find the factor that leads to the difference between IoT and CPS, it can be basically said that CPS concerns itself more with the physical entity and its processes [1].

So, in short, IoT is all about interconnectivity between "Things" over the internet whereas CPS is the amalgamation of physical processes with computer networks.

2.2 Concept Map of Cyber Physical Systems

The above concept map gives a clear idea of the main application sectors of CPS. Each sector of application requires a robust design methodology and security so as to protect the network from foreign attacks. Design methodology revolves around six important factors, specification, modeling, scalability, complexity, validation, and verification [2] (Fig. 1).

For the CPS to be efficient and reliable, there needs to be a feedback system which analyzes and relays back info real time for decisions that are based on the predictions of the model and adapt rapidly to the diverse changes that are occurring in the domain in which it has been implemented. Involving humans and nature into the loop helps the system to accurately identify more setbacks and other thought processes that might not have been detected by the system in the first place. The concept map also

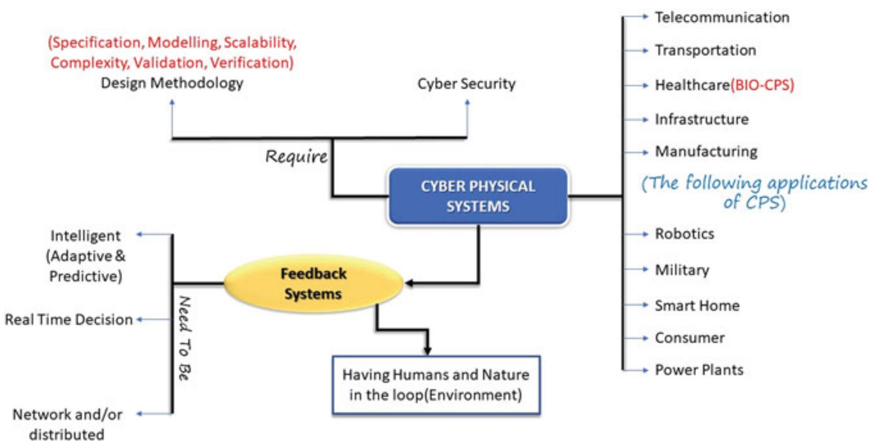

Fig. 1 Concept map of cyber physical systems

points out the main applications of cyber physical systems at the moment. Out of the 10 applications pointed out currently military, healthcare and smart home drive more than 60% of the market. In terms of research military sector leads followed by healthcare division. Healthcare division expands the scope of research with more people coming forward willingly for free medical benefits in return for providing their data to companies which helps in the research and development of such sensors. More people using these devices increases the size of the dataset available for research making the decision making more accurate and increases the chance of a successful diagnosis in the future. The healthcare divisions association with cyber physical systems opens a completely new domain of applications and research, and thus, this domain is termed as 'Bio Cyber Physical Systems' [3].

2.3 Bio Cyber Physical Systems

Biological systems when integrated with CPS lead to the concept of Bio-CPS. At the moment, the most relevant way of integrating CPS to biological processes is available through the healthcare sector. Advancements in the field of surgery, medicine, health monitoring devices have opened a new array of doors for machines to integrate and change the way people used to see the healthcare sector. Many pivotal changes have been brought into robotic surgeries since the first performed in 1985. With a high successful rate and no chances of human error, the medical industry is pushing for such automated technology to perform minimal invasive surgeries. Although there is still a lot to be achieved and understood to make this a reality, the one area where Bio-CPS is taking great leap and stride is health wearables. Health wearables are mostly non-intrusive except a few (pacemakers, etc.).

Robert Bosch in collaboration with IISc Bengaluru has opened up a Bio-CPS research center where they are developing an approach to understand gut biology (cyber-gut) [4].

3 Health Wearables

Health wearables devices have been long used in the medical industry. Monitoring of patients' pulse rate, glucose levels, ECG monitoring have been done since the 1970s–80s, now these devices have been made smaller over time, which makes them portable and also easy to use. According to a survey, the market for wearable devices which monitor vital health aspects reach USD 980 million growing at 21.7% CAGR by the end of 2020. This survey excludes the surge in demand caused by the coronavirus pandemic. In all, the global medical wearable market was at a staggering USD 12.788 billion dollars in 2019 and is forecasted to increase by 19.73% by 2025 standing at a value of USD 37.67 billion. The consumer usage of wearable trackers skyrocketed from 9% in 2014 to 33% in 2018 [5, 6].

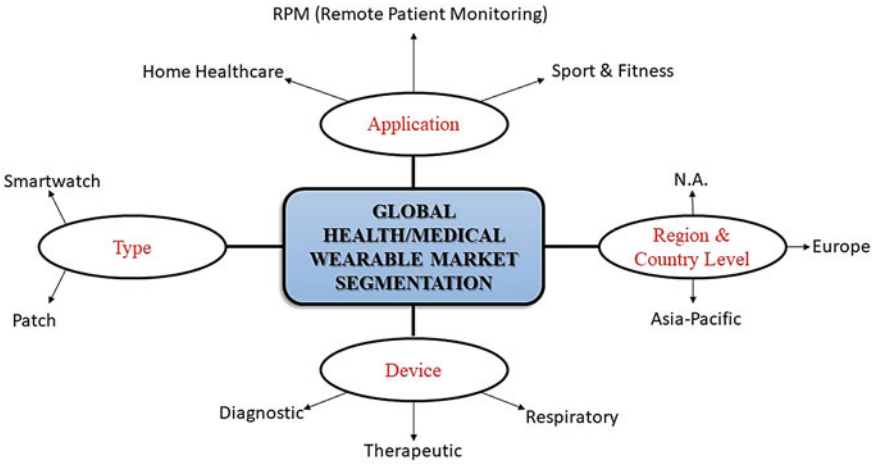

Fig. 2 Segmentation of global health market

The worldwide medical wearable market can be broadly classified into four main segments that are applications, devices, region, and type (Fig. 2).

At the moment, the two primary types of wearable are attributed to Smartwatch/smart band and patch. The Smartwatch/smart band being the most popular of the two as it serves a dual purpose of health monitoring and functionalities of a basic watch. Few more watches also come with inbuilt Wi-Fi, GPS trackers as well as the options to control basic phone activities from the watch. Smart patches are basically designed to deal with details of a person at molecular levels. These patches basically derive data out of the persons sweat. Some patches even have the capability to derive data out of the blood, such as detection of tumor cells.

When it comes to the type of devices, it is basically down to three segments, respiratory, therapeutic, and diagnostic. Smart wearables these days are able to monitor the volume of oxygen in blood and relate it with the heartbeat to give near accurate results for patients suffering from respiratory problems. Diagnostic devices are meant for people suffering from a particular disease and need to maintain record of their activities so as to aid them in their treatment.

The application of wearables can be categorized into RPM, home healthcare, and sports and fitness. Out of these three, the most crucial is remote patient monitoring. This particular monitoring is meant for people suffering from a chronic disease such as kidney failures, heart problems are implanted with a pacemaker or cancer, where the person is undergoing treatment from the confines of his house. RPM allows the devices to send data to the concerned doctor so as to continuously monitor the patient's health. Home healthcare is for people who are in their mid30s-50s and instead of regular consultations and check-ups with a doctor they can keep a tab on their basic health by looking up at their daily activity meter and ECG reports.

North America, Europe, and Asia–Pacific regions are driving the current business on health wearables. North America is leading the demand in consumption of these devices by users followed by Europe and Asia Pacific region. The production of these wearables is at a peak in Asia Pacific region with most tech companies outsourcing.

The increase in the demands of such wearable devices so as to remotely monitor and diagnose include the following reasons: (i) An ageing population; (ii) Improved supply factors; (iii) Better R&D; (iv) Enhanced Functionality, (v) Better integration with IoT system and solutions.

There are various wearable devices out in the medical market and are generally of the following type: (i) Devices which can be integrated into daily life apparels so as to make it the least intrusive or the one which can be worn as a fashion statement as well (this helps in making the patient feel mentally comfortable and also hides the fact that the patient is ill); (ii) Medical implantable devices such as pacemakers, devices to monitor glucose levels (basically needed for patients with extreme health complications and need to be under constant observance); (iii) Sensors placed strategically at specific parts of the body to communicate with an overall body system.

3.1 Fitness Trackers/Smart Watches

As discusses earlier in the paper, the market is dominated by the fitness tracker and watches which offer a plethora of options and functionalities along with the basic features. Smart watches have an edge over fitness trackers because of the functionalities they provide, such as, ECG monitoring, calorie burning according to a specific exercise, manual control of apps linked with the phone, answering calls and reading important texts, and many more [7].

3.2 Types of Sensors

Health wearable devices collect the data through the various sensors and self-input from the users. Wearable devices such as a watch or a wrist band have sensors embedded immaculately across its body. There are various data read by these sensors that ultimately lead to the display of basic health status. Sensors generally found in wearable devices are GPS, accelerometer, gyroscope, pedometer, inertial measurement unit (IMU), piezoresistive or piezoelectric sensor, photoplethysmography (PPG) sensor, and many more. Recently, Samsung's galaxy watch was approved for ECG readings which is recorded by its miniaturized ECG sensor in South Korea.

Each sensor gathers a particular list of feature data that are later on combined together to give readable data to the common user. For example, an ECG sensor gathers data from features such as ECG Peaks, ECG average amplitude, ECG resting, ECG differ mean. Similarly, blood volume pulse feature gathers BVP peaks, average amplitude, and difference mean. The accelerometer in total gathers 15 features, i.e., mean, standard deviation, correlation, kurtosis, and crest factor on each of its 3 axes

(x, y and z). Every sensor gives out near accurate data based on its feature recording and calculations.

The photoplethysmography sensor is perhaps the most vital sensor when it comes to health monitoring. The non-invasive technology is possible through a photodetector and light source. The sensor measures the volumetric variations of blood circulation in the nerves and veins with the help of the photodetector placed at the surface of the skin. The sensor uses a visible infrared light to check the volume of the blood in the nerves, it also is able to determine the oxygen levels in the blood by comparing the color of the blood. Blood color is attributed to hemoglobin which binds with the oxygen, darker blood signifies deoxygenated blood [8]. In total, two information are gathered by the PPG sensor: (1) Heart rate estimation, (2) Pulse oximetry readings. Furthermore, PPGs second derivation wave constitutes vital health information that later on analysis and extensive research may help researchers and physicians in evaluating and further diagnosing cardiovascular diseases such as arterial stiffness and atherosclerosis.

3.3 Activity Log

Data collected by the device is never enough to provide accurate health analysis and decisions, user input is equally important and needs to be near accurate. The two main data that needs to be provided by the user is calorie logging and his/her body composition. Calorie logging is critical for a person suffering from any long-term disease and especially having impact on his/her metabolism. Calorie logging ultimately decides the effect that the person is having, such as weight gain, sleepiness, exhaustion or whether the calorie intake needs to be increased if the stats prove otherwise. Body composition refers to the weight, height, and gender of a person. These three factors help in calculating the body mass index (BMI), which is a primary index of a determining a person's level of fitness [9].

3.4 Advanced Sensors

A company named "Empatica" has manufactured an unobtrusive device which works on the principles of electrical signals. The device is termed as the electrodermal activity sensor and uses skin conductivity to detect a calm or distress condition from the obtained physiological EDA signals. Their research shows that when the results are solely based on the EDA signal processing, the reports come out with a successful accuracy rate of 89% in distinguishing stressful conditions from calm conditions. This capability of EDA sensors can be made to calculate changes in the sympathetic nervous system in the future. The ability to detect a person in stress can be used to predict whether the person is having seizures or strokes if the results are combined with the patients' medical records [10].

Researchers at University of Michigan have developed a wrist wearable prototype that has the capability to scan for circulating tumor cells (CTCs) in the blood and examining them. This can lead to early detection of tumors and cancer in a person. Researchers have also come up with an inventive way of detecting Alzheimer's in a person by examining their GAIT. Gait is the pattern in which a particular person walks, the pressure that is applied on his foot and his posture while walking. Alzheimer brings a distinctive change in a person's GAIT. Researchers have compared the walking pattern of a person along with the pressure sensors attached in the sole of their shoes to determine whether a person has an onset of Alzheimer or not [11].

3.5 Data Gathering

The wearable devices have a microcontroller placed where the onboard processing of various signals take place and are displayed to the user. The microcontroller gathers input and translates them into decision favorable for the subject wearing it. For a particular individual where constant monitoring and check-ups are necessary, the data can be relayed back to the servers of the hospital where a physician can keep track of his or her records. Due to security concerns, most of the wearable tech companies usually ask for the permission of the individual for storing and analyzing the data for research purposes. Data is generally stored on the individuals' phone which can be received by Bluetooth, Wi-Fi, NFC and is stored in the cloud.

4 Diabetes

Diabetes mellitus is defined as a condition when your blood sugar level is higher than the usual limit. The earliest evidence of diabetes dates back to 1552 B.C. when an Egyptian physician documented symptoms of diabetes. The early prescriptions given to patients in the 1700s and 1800s were to exercise a lot and have to keep fast at regular intervals. There are three main types of diabetes, type 1, type 2, and gestational diabetes. Type 2 diabetes is the most common occurring diabetes with almost 90–95% of the diabetic patients coming under this category. It generally affects people of age 40 and above but recent studies and statistics also show that it is also affecting younger adults and in some cases children as well. Of all the cases in the world type 1 diabetes accounts only for 5% of them and is considered a deadly disease as it reduces the lifespan of an individual by 50% or more. The smaller number of cases in type 1 makes it more difficult for researchers and doctors to find a diagnosis that actually benefits the patient in the long term.

4.1 Complications of Diabetes

Diabetic patients have been steadily on the increase across the world. They are soon going to reach alarming levels that can basically be termed as a health epidemic. Nearly 18 million people lose their life because of cardiovascular diseases and its complications in which diabetes plays a major part of the blame. Around 1.7 billion adults and 115 million children around the world are overweight and 312 million of them are obese. The population with diabetes is around 246 million and is to top 380 million by 2025. 80% of the diabetic people belong to developing countries where health infrastructure is poor, and the treatment provided is not unilateral across the region. India leads the global top ten in terms of the highest number of people with diabetes with a current figure of 40.9 million. There are growing number of cases of type 2 diabetes at a younger age and some even among children who are yet to hit puberty. This scenario is generally common in developing and developed countries. In developing countries, the people diagnosed with diabetes mostly belong to the younger adults, who are in the middle of their productive lives whereas in developed countries this generally affects people post the age of retirement. Diabetes can shorten a person's life by almost 12–14 years and leads to a medical budget two to five times more than that of a regular medical budget. Diabetes is basically attributed to change in a person's lifestyle. Around the clock job, irregular eating habits and other drastic changes are generally the main reasons behind it [12].

Diabetes leads to many complications in the human body and a person not following his diet and prescriptions properly risks a higher chance of death with respect to the other patients. Thus, proper sleep time and daily exercise routine is very important for people suffering from diabetes. High blood sugar can lead to health complications such as heart attacks, heat strokes, seizures, kidney and nerve damage, and many more. Strokes and seizures are the most prevalent among the diabetic patients.

In the coming sections, we will be discussing on the complex problems that the diabetes patient mostly suffers from such as heart attack, seizures, fainting, sun strokes, and the ability of the sensors combined with power of neural networks in-order to detect them in real time and the possibility of predicting such attacks beforehand.

5 Case Studies of Diabetic Complications

Firstly, we will discuss the major life-threatening complications that arise and what data is required from the sensor for the neural network model to recognize the complication accurately. It can be argued that all the sensors with their data can provide far accurate results for a particular complication, but we need to keep in mind not to burden the model with unnecessary data that might delay the response in case of medical emergencies. Of all the data collected by the wearable devices into the system, the most important data is input by the user itself. The calorie logging is extremely important in case of people with diabetes, and food intake regulation is the key to a proper diagnosis.

5.1 Heart-Attack

Diabetes as we know is due to high blood sugar level in the blood. High glucose level in the blood of a diabetic patient eventually degenerates the blood vessel and heart muscles making the particular person more susceptible to heart attack. Failure of a quick response from the medics will ultimately prove the heart attack to be fatal. In this case, notifying health authorities and mobilizing them based on the reading of one particular sensor might turn out to be a false alarm or a malfunction of the device, to increase the certainty of the information being relayed from the watch we take into consideration of the readings from the PPG or ECG sensor, fall detection sensor, accelerometer, and GPS. The GPS sensor will come into effect once it has been established that the person has suffered a heart attack and needs to relay the coordinates to the medical responders. PPG sensor alone is not enough to determine a heart attack, in a circumstance where a person has been frightened all of a sudden, the heart rate tends to shoot up altogether or a scenario might occur where the person has removed the device or the PPG sensor has suffered a malfunction. In this case, we take into consideration the data from the fall sensor. A detection of fall accompanied with irregular or no heartbeat can prove as a strong result to ascertain the heart attack. The above two results can also be accompanied with the accelerometer in case a person on a particular path comes to an abrupt halt. To make the device fool proof, developers can add a prompt on the device which can ask for false alarm from the user. In case the user is not able to verify the false alarm within a particular time interval, the system can be sure that the particular person is having a heart attack (Fig. 3).

5.2 Seizures and Strokes

Both seizures and strokes are correlated in a way to diabetic patients. Recent study has also showed that onset of seizures in late part of life can increasingly lead to a chance of having a stroke. Both stroke and seizures have an effect in the brain and ultimately the nervous system. A stroke occurs when the blood circulation to the brain is stopped suddenly and stroke occurs when there is a surge of electrical activity in the brain.

Diabetic seizures are often caused by extremely low level of blood sugar and can lead to partial or complete paralysis if not taken care of immediately. Now, when a person suffers a seizure, the most notable changes that occur biologically are in the heart rate, respiration rate, and most importantly in the biochemical composition of

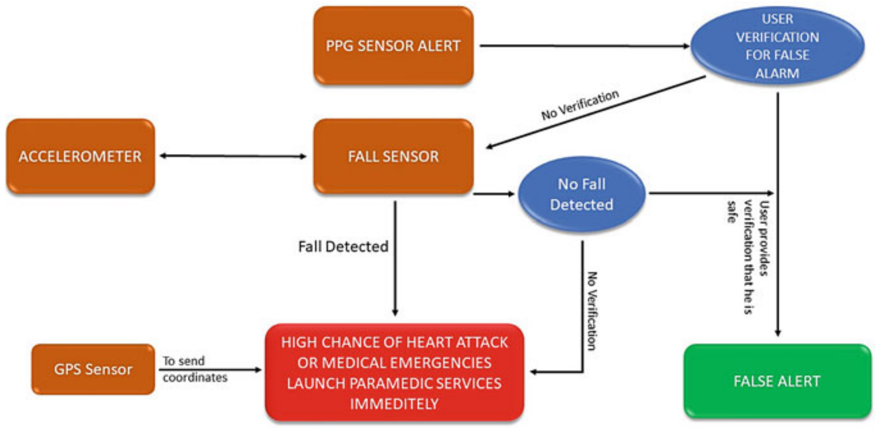

Fig. 3 Flowchart for real-time analysis of a heart attack

a person, i.e., the person starts to sweat profusely. In case of such complications, the data at disposal from the PPG sensor, electrodermal activity sensor, and most importantly the self-input of the persons calorie intake and calories burned by him on that particular day. Most diabetic seizures are attributed to the carelessness of the diabetic patient in following his diet. Electrodermal sensor reading will provide the readings from the sweat of a person. Moreover, electrodermal sensors can also be made to calculate glucose level in blood by analyzing the sweat. In the paper ‘Correlation Between Sweat Glucose and Blood Glucose in Subjects with Diabetes’ the authors using perfusion method were able to analyze the sweat from the forearms and come to a conclusion from 23 different studies on seven individuals that if sweat is harvested properly by a sensor from a forearm, it can accurately reflect blood glucose levels [13].

In case of a stroke, the chances of a diabetic person of facing this complication increases by 1.5 times, diabetes has the tendency to weaken the biomechanics of a person at all levels. The persons immunity, sustainability, and stamina drop as he/she gets old. The person is more susceptible to stroke who is residing in a hot and humid climate, has a stressful job and most importantly does not follow his diet. Calorie maintenance is of the utmost priority in these scenarios.

Since both the complications have initial common factors and sensors at play, we can categorize the data into one portfolio to detect both the complications. However, the final result will play a major deciding factor in alerting the paramedical forces. By final result, we refer to heartbeat monitoring as in case of a stroke the heartbeat is most likely to falter rapidly and need of professional help and guidance. More importantly, user confirmation itself is going to be vital (Fig. 4).

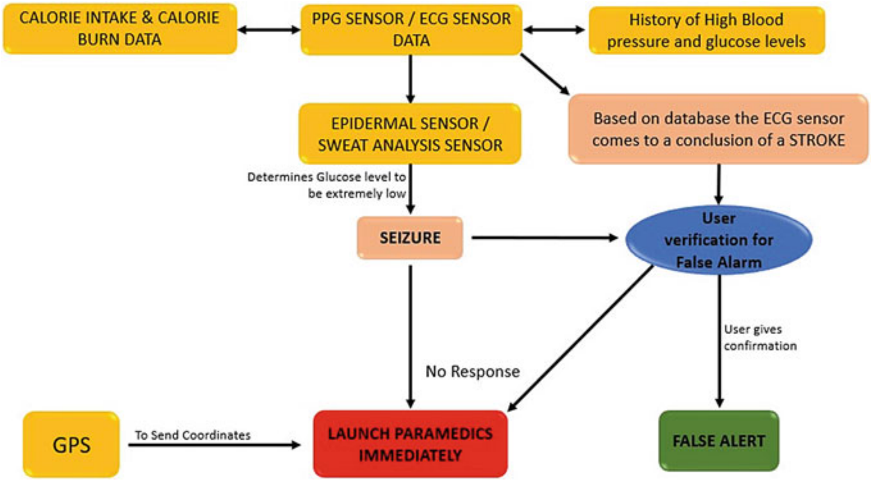

Fig. 4 Flowchart for real-time analysis of seizure or stroke

6 Role of Neural Networks in the Case Scenarios

Machine learning has played a vital role so far in altering the relationship in positive ways between producers and consumers. It has constantly shown strong and progressive potential for the past sixty years. Machine learning, which is a type of artificial intelligence has been in existence since the late 1950s, when Arthur Samuel wrote a progressive learning program in 1959 which made the computer get better at the game of checkers the longer it played. Over the years, machine learning has progressed and brought in numerous changes and new terminologies and concepts across the globe. Deep learning is one of them. Deep learning can be described as a broader part of machine learning dealing with artificial neural networks. Over the past 10 years, deep learning has progressed at a pace unimaginable, marking its dominance in major IT sector firms. Being used in Netflix to suggest you shows on the pattern of your watch to self-driving autonomous cars deep learning has marked its dominance everywhere. The primary difference between machine learning and deep learning is between their data dependencies and subsequent performances. Deep learning cannot perform well on a relatively small amount of data whereas machine learning with their traditional handcrafted algorithms are able to perform satisfactorily in this situation (Fig. 5).

More data dependency of deep learning implies the fact that it needs more high-end hardware for feature learning and training itself as compared to machine learning. It also tries to learn and analyze high level features from a data set and thus takes immense time to train. Neural networks are an integral part of Deep learning. Modeled on the neurological system of the human brain, the neural networks work primarily on the principal of multiple nodes and multi-layer perceptron (MLP). Neural networks are categorized into 3 types: (i) Feed-forward neural network, (ii) Recurrent neural network, (iii) Convolutional neural network.

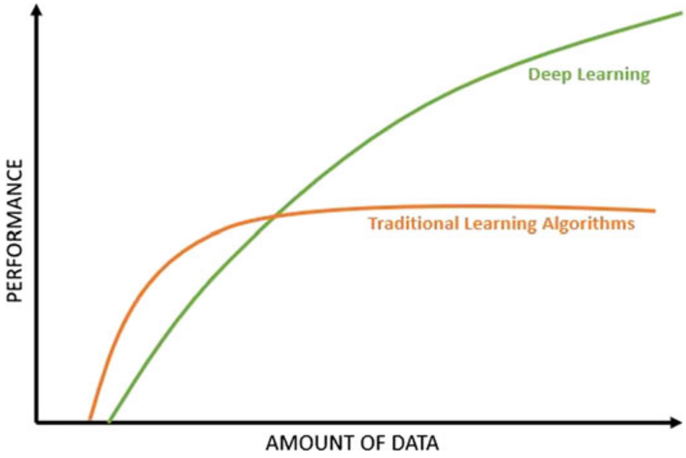

Fig. 5 Data dependency graph

6.1 Convolutional Neural Network

For the above health complications, we will be taking help of convolutional neural network. Convolutional neural networks with their unique convolutional layers provide an edge over recurrent neural networks, feed-forward neural network, and other traditional machine learning algorithms. Figure 6 shows the various layers available in a basic CNN architecture, which according to complexity can be modified and more layers can be subsequently added [14]. When it comes to RNN, each input is evaluated on a single layer and the output is then presented based upon that layer whereas in CNN multiple layers are used to process the data and bring out a more accurate result. Within each convolutional layer the input is transformed before being passed to the next layer.

CNN makes use of filters in between convolutional layers to filter the data, i.e., CNN transforms data with the help of filters. A convolution unit receives its input from

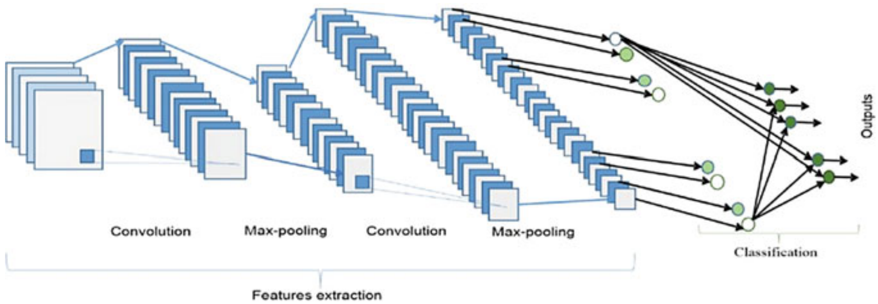

Fig. 6 A basic convolutional neural network architecture

multiple units from the previous layer which together create a proximity. Therefore, the input units (that form a small neighborhood) share their weights. The entire feature extraction process is advantageous for the following reasons: (i) They decrease the number of units in the CNN because of many-to-one mapping architecture which results in lower chances of overfitting the model due to less parameters to learn and in turn making the model less complex than a fully connected network; ii. They consider the context/shared information in the small neighborhoods. This particular feature is valuable in case scenarios where the application of text, speech recognition, data mining, and many more, as related information is generally carried in neighboring units.

CNNs are great at interpreting visual data and data that does not come in a sequence.

In this particular chapter, we will be focusing on multi-channel CNN and the reason for which this model will perfectly work for the given scenarios.

Multi-channel convolutional neural networks basically is a *combination of multiple convolutional networks connected in parallel*, that read data from a source using varying kernel sizes as displayed in Fig. 7 [15].

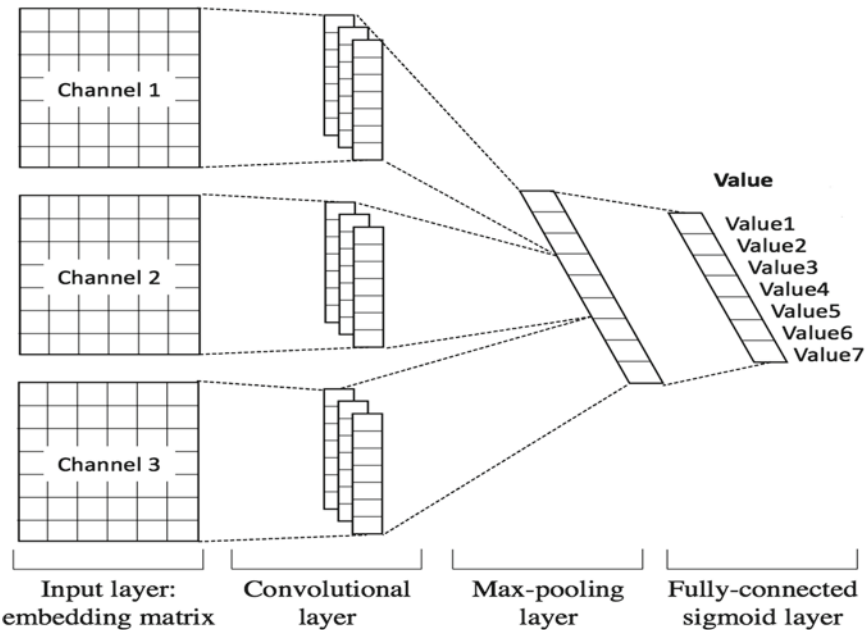

Fig. 7 A basic representation of a multi-channel neural network

7 Multi-channel CNN

As mentioned above, the combination of multiple neural networks in parallel connections will play a very important factor for the case scenarios that we will be dealing with. The detailed flowchart in Sect. 5.1 and 5.2 clearly depicts that at one particular time our proposed architecture would be dealing with a minimum of three or a maximum of 5 different bio-signals at a time. Each bio-signal has a corresponding set of features as well.

The above-mentioned Fig. 8 shows namely a few sensors and various features that are recorded off them. It may also be noted that the number of features may vary upon different sensors, more complex, and advanced the sensor the more features it has to offer. As it is obvious that each and every sensor producing so much data might not be feasible for a regular convolutional neural network to handle and might lead to mixed results not in favor of the physicians and patients alike. Thus, this is the reason for which multi-channel convolutional network is proposed as a model. Separate channels for different bio-signals will help to keep the initial feature learning using CNN discrete from each other thus preventing mixture of information and analysis between individual layers.

Multi-channel CNNs have proved their mettle in different related works as well. In the paper, 'Multi-Channel Convolutional Neural Networks Architecture Feeding for Effective EEG Mental Tasks Classification' the authors aimed to classify mental tasks based on EEG signal processing and its analysis. They put up their multi-channel CNN against various other multi-channel architectures. The result stood in favor of the multi-channel CNN with an astonishing 5% generalization rate [16]. In another research article, 'A Multichannel Convolutional Neural Network Architecture for the Detection of the State of Mind Using Physiological Signals from Wearable Devices' authors used bio-signals from the body to determine the state of mind of a person and ultimately the persons wellbeing. In their research, the model performed effective results based on the classification of the different state of minds for a particular subject. The model achieved an average recall and precision of 97.238% and 97.652%, respectively [17].

It is important to note that despite the fact that the model suiting this situation perfectly, it will still take an enormous amount of data to train upon in-order for it to give out satisfactory results and even more exposure and inputs from various

ECG	ACCELEROMETER	BLOOD VOLUME PULSE	CALORIE COUNT
ECG peak	Mean	BVP Peak	Calorie Intake
Average Amplitude	Standard Deviation	Average Amplitude	Calorie Burnt
ECG resting	Correlation	Mean Difference	Time period between intake
Mean Difference	Kurtosis		
	Crest Factor		

Fig. 8 Features of a few sensors

researchers to make it extremely accurate. Since this is a medical situation in which the model is being applied and lives are at stake, the model would need extensive research, collaboration with plenty patients and third-party members and a dataset with *billions* of data.

8 Complication Prediction Through LSTM

The multi-channel CNN model was used to bring out real-time decision based upon the data collected from the sensors in-order to administer paramedical services on time. It might also be possible to predict such attacks beforehand using a neural network and ultimately be able to save yourselves from the life-threatening complications by getting yourself assessed and taking the proper steps based upon your physician.

LSTM neural networks can be a suitable option for it. *Long short-term memory* neural networks are a special type of recurrent neural network. The problem that used to persist in recurrent neural networks has been easily dealt with in LSTMs, i.e., *long-term dependency problem.* Although in theory, an RNN should not be troubled with long-term dependency, but in practicality it falls short of its expectations. LSTMs were specially engineered to get rid of this problem in recurrent neural networks. The default behavior of a long-short-term memory neural network is to remember information that was analyzed earlier for a longer period of time.

This specialty of LSTM serves as a perfect model for predicting health complications. Basically, this model remembers the analyzed data of the past and also keeps on analyzing the data in real time. Combining both these data, it has a fair enough chance to predict such attacks beforehand. As seen above in Fig. 9 [18], the LSTM repeating module contains 4 interactive layers as compared to the one in the chain RNN repeating module.

In the research paper 'An Effective LSTM Recurrent Network to Detect Arrhythmia on Imbalanced ECG Dataset' the authors use the LSTM network to disentangle timing features in ECG signal to help cardiologists to succinctly diagnose ECG signals. This setup of theirs is very similar to what is proposed in this section. ECG signals need to be remembered by the model for a long duration so as to compare and analyze the older data with the present data and give out satisfactory results. In the above-mentioned paper, the model achieved an accuracy, recall, precision, specificity, and $F1$ score greater than 90%, thus implicating that the LSTM network has immense capability [19].

9 Conclusion

The chapter describes in detail the basic needs for integrating data analytics in Bio-CPS in an effective manner in-order to predict a major complication in a patient and

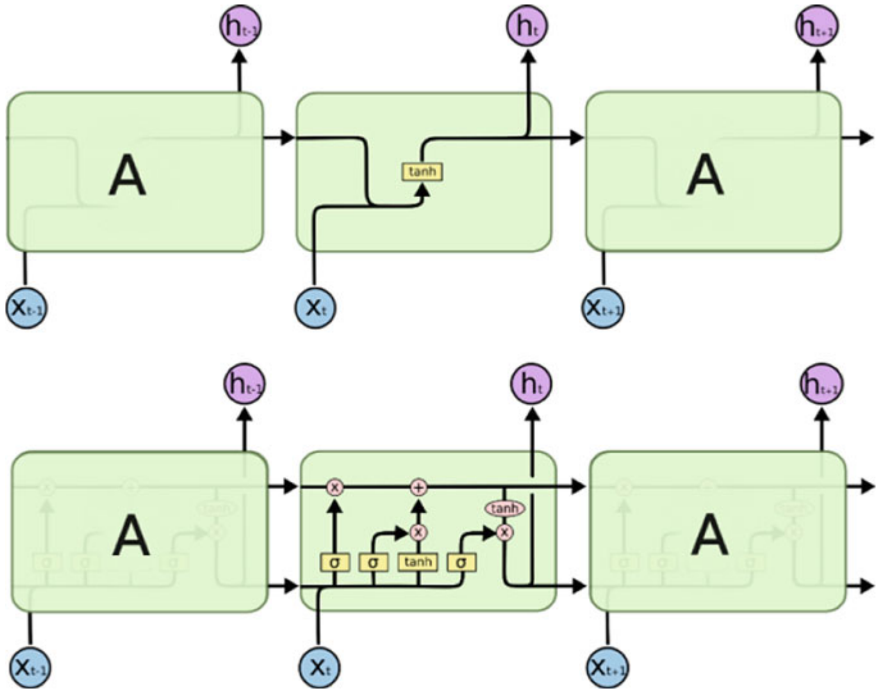

Fig. 9 1st chain structure-repeating module in a standard RNN. 2nd chain structure—repeating module in a LSTM

alert services instantly. The multi-channel convolutional neural network proves to be an extremely efficient model for the situations described above, similar models have brought effective results to other researchers as well. Over the time, with more efficient collection of data and a larger database, the model will cement itself to be near accurate for real-time analysis. With the increase in database, the long-short term memory model will be able to accurately predict complications beforehand.

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