Chapter 5
Future of Big Data and Deep Learning for Wireless Body Area Networks

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Abstract Deep learning is an innovative set of algorithms in machine learning and requires minimum efforts of human engineering in extraction of features from data. It has the ability to find the optimum set of parameters for the network layers using a back-propagation algorithm, thereby modeling intricate structures in the data distribution. Further, deep learning architectures have resulted in tremendous performance on most recent machine learning challenges included working with sequential data such as text and time series data. In this connection, big data technology is an asset for modern businesses and is useful if powered by intelligent automation. Big data involves huge datasets that can be analyzed by machine learning such as deep learning algorithms to find insightful patterns and trends. With modern-day machine learning and big data technology, organizations can drive its long-term business value far more successful than ever before. Potential real-world applications of big data are not limited to healthcare, retail, financial services, and the automotive industry. In this way, the deep learning can have a great impact on analyzing the patient's data generated from wireless body area networks (WBANs). WBAN is the emerging technology in healthcare to assist in monitoring of vital signs of patients using biomedical sensors. The monitored data is transmitted to the medical doctor for an optimal treatment in a life-threatening situation. At the end of this book, open research issues in WBAN and big data have discussed.

List of Acronyms

BMS	Biomedical sensor
CAP	Contention-access period
CNN	Convolutional neural networks
CEP	Complex event processing
CGOC	Compliance, Governance and Oversight Council
CFP	Contention-free period
CS	Conventional server
CSMA/CA	Carrier-sense multiple access with collision avoidance

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DNN	Deep neural network
EAP	Exclusive access phase
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyography
IEEE	Institute of Electrical and Electronics Engineers
IP	Inactive period
GPU	Graphics processing unit
GSM	Global system for mobile
GST	Guaranteed time slot
HDFS	Hadoop Distributed File Systems
LOS	Line-of-sight
LSTM	Long short-term memory
MLP	Multilayer perceptron
MAC	Medium access control
NLOS	Non-line-of-sight
PHY	Physical layer
QoS	Quality of service
RAP	Random-access phase
RNN	Recurrent neural network
SPO2	Peripheral capillary oxygen saturation
TDMA	Time-division medium access
VC	Virtualized cloudlet
WBAN	Wireless body area networks
WHO	World Health Organization
WSN	Wireless sensor network
TG6	Task Group 6

5.1 Introduction

Machine learning is a modern-day technology that enables systems to learn from experience using statistical techniques, where it is difficult to explicitly program the computing tasks involved. It leverages data to create intelligent programs and has tremendous applications in almost any industry not limited to healthcare, banking, finance, agriculture, manufacturing, and automation. From content filtering on social networks and self-driving cars, it is gradually employed to handheld devices and consumer products. Specific goal of a machine learning system can be identifying biological cells in a microscopic image, converting speech to commands, translating text to a different language, or recommending the next movie to watch.

Recently, these applications are revolutionized by a class of algorithms based on neural networks, called deep learning. Advanced tools and techniques have dramatically transformed the conventional neural network algorithms to the point where they can outperform humans. Simple neural network design allowed 2–3 layers,

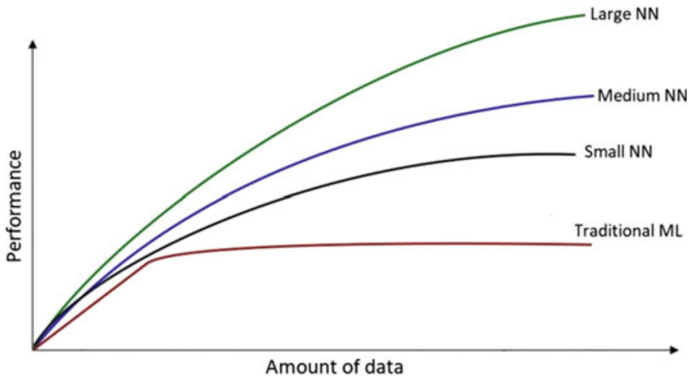


Fig. 5.1 Performance relationship of deep networks with the increase in amount of data original slide by Professor Andrew Ng

while deep networks may contain hundreds of layers. The successful design and applicability of a deep network is possible due to three main technologies. First, the availability of huge label datasets allows it to capture the actual distribution of the patterns. Second, together with high-performance GPUs and increased memory, it has made it possible to reduce training time of deep networks with huge data from months to hours. Last but not least, pretrained models can be retrained with smaller data sizes for new tasks, a technique known as transfer learning, which results in saving training time and effort yet not compromising performance. Figure 5.1 shows the performance relationship of deep networks with the increasing amount of data. It is clear that traditional machine learning can hardly benefit from the increase in data size.

Deep learning learns to extract features directly from images, text, and sound, at multiple layers of the networks, where complex features are defined across the layered hierarchy in terms of simple low-level features. It then also learns a function to map the features into a desired output and achieves higher accuracy with more data, entitling deep learning as an end-to-end learning algorithm. This is contrary to other machine learning algorithms that learn only a function that maps input features to a desired output. For the reason, machine learning workflow needs an explicit feature engineering or feature extraction step done by human engineers, resulting in features termed as handcrafted features. See Fig. 5.2.

The rest of the chapter is constructed as follows: Sect. 5.2 presents deep learning frameworks based on the feed-forward network model. Future of deep learning in big data is discussed in Sect. 5.3. Further, introduction of wireless body area network is presented in Sect. 5.4. Section 5.5 presents the existing applications and future applications of wireless body area network. Section 5.6 presents the existing challenges in routing protocols of wireless body area network. Working of superframe structures of IEEE 802.15.4 MAC and IEEE 802.15.6 MAC along with research challenges has been presented in Sect. 5.7. Further, introduction to big data is described in Sect. 5.8, and the applications of big data are presented in Sect. 5.9. Open research issues of WBAN and big data are presented in Sects. 5.10 and 5.11, respectively.

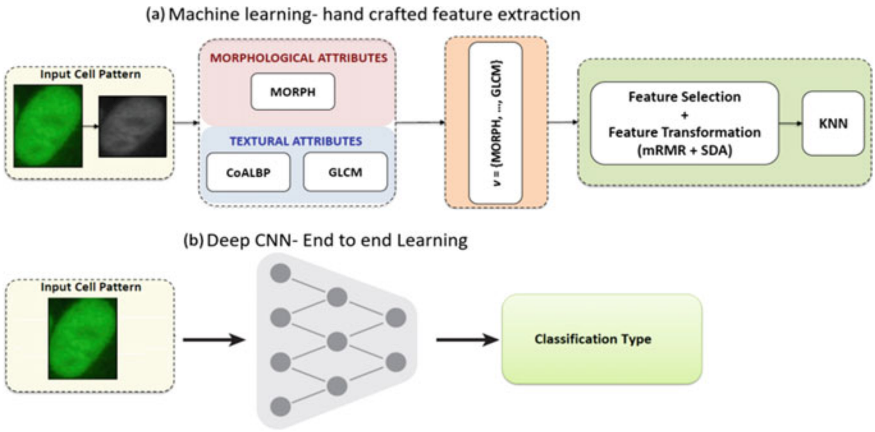


Fig. 5.2 **a** (Di Cataldo et al. 2014; Ul-Islam 2014) Traditional machine learning with feature engineering by a domain expert versus end-to-end deep convolution learning **b** Deep CNN-end to end learning

5.2 Feed-Forward Network Model

A deep neural network loosely mimics the human mind. It has layers with nodes or neurons which are interconnected from the previous layers that act as input activations. The layered construction utilizes the unknown data distribution and models to capture nonlinearity, resulting in better representation. It consists in an input layer, hidden layer(s), and an output layer(s). Modern-day neural nets can be classified into a number of types based on their design and application. Among are multilayer perceptions (MLPs), deep convolution neural nets (Lecun and Bottou, n.d.), recurrent neural nets (Schmidhuber 1997; El Hihi and Bengio 1996), and many others like autoencoders (El Hihi and Bengio 1996), generative adversarial networks (El Hihi and Bengio 1996), and residual networks (He et al. 2016). Figure 5.3 shows MLP with one input and output layers and with two hidden layers.

In a forward pass, the input layer accepts inputs presented to the model; subsequently, each layer linearly combines the weighted output from the previous layer, and at each node, an activation function is applied. Input x_i is the applied at the input layer, where at each node in the hidden layer the activation a is calculated as the weighted combination of the input variables, $a = \sigma(z)\ and\ where\ z = w^T x + b$, from the previous layer in the network.

Activation function characterizes the output of a neuron and introduces nonlinear transformation making the network capable of learning complex tasks. On contrary, its absence would limit the network nodes with simple linear transformations and never be able to model complex structures. Many kind of activation functions are commonly used in practice like the hyperbolic tangent function $tanh$, sigmoid function, ReLU (Taigman et al. 2014), and leaky ReLU functions, Fig. 5.4. Intuitively,

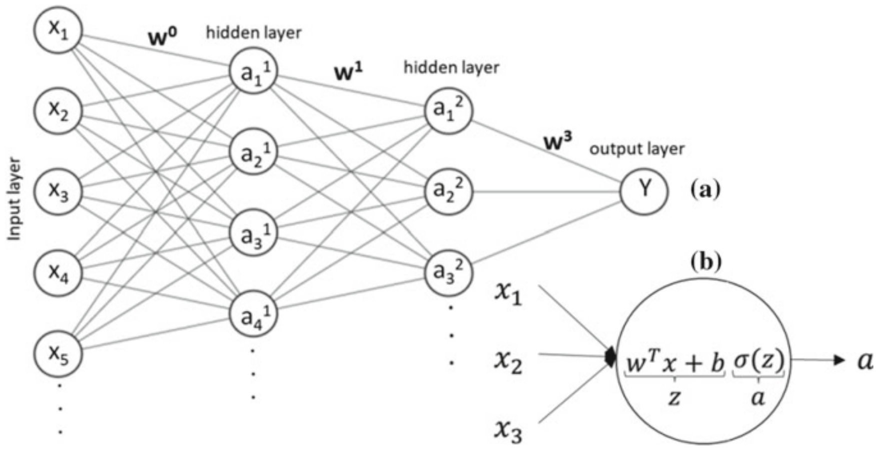


Fig. 5.3 **a** A feed-forward network (or MLP) with input layer, hidden layers, and output layer and **b** the computation at a single neuron with input and output activation

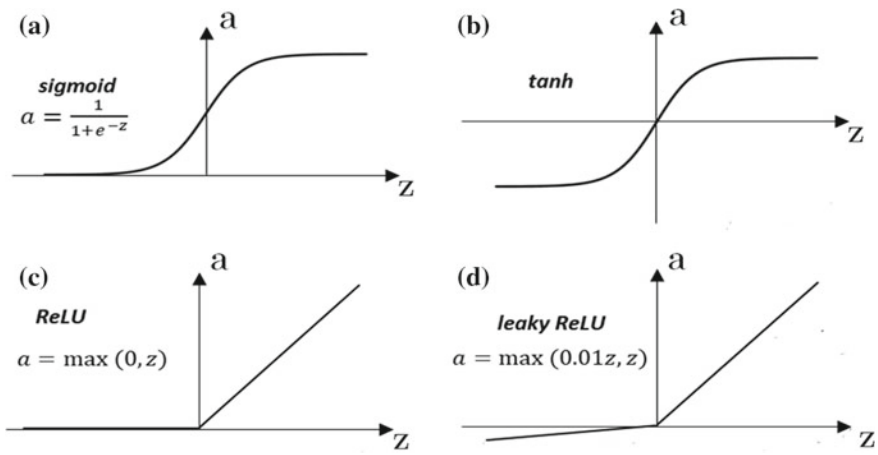


Fig. 5.4 Different activation functions are shown in **a** sigmoid, **b** tanh, **c** ReLU, and **d** leaky ReLU

each node in the network is responsible for detecting a particular feature. In case of $tanh$ function, a smaller value of z would give a higher gradient, suggesting further training of the node, and a larger z would seize such training. Calculation of these gradients and retraining of weights are part of a back-propagation step of the deep learning algorithm. A heuristic activation function ReLU has become quite popular, due to its fast computation; however, its updating of weights sometimes leaves a node as inactive. This problem is being resolved by utilizing, for example, a leaky ReLU (Maas and Hannun 2013) at the expense of additional computations. Figure 5.4 shows the different activation functions.

To make this all happen, a cost is always computed at the output layer, which is a measure of the difference between output value and actual ground truth value. A cost function is represented as $J(w, b) = \frac{1}{m}\sum_{i=n}^{m} L(y', y)$, where w are the weights, b is the bias, m is the number of training samples, y as actual and y' as the estimated output, and L is the loss function. The popular loss functions are cross-entropy loss, misclassification rate, or $L2$ loss also known as the mean squared error. The objective of the training process is to minimize this cost, using an optimization algorithm such as gradient descent algorithm which involves taking gradients of the activations and updating weights at network layers. This process is called back propagation. The final weights that minimize the loss function are considered to be the solution of the DNN model.

5.2.1 Deep Learning Frameworks

Among the types of deep neural nets is convolution neural network (CNN), which has attracted many researchers in the computer vision community (Multi-column deep neural network for traffic sign classification 2012; Taigman et al. 2014; Hadsell et al. 2014; Sainath et al. 2013). The algorithm works well where the inputs are images or if the data modalities are in the form of multiple arrays. Like MLP, CNN also contains an input layer, several hidden layers, and an output layer. The layers involve some operations on data termed as convolution, pooling, and the ReLU function. Convolution uses filters on image or multiarray to highlight certain features. Pooling involves nonlinear downsampling or reducing the parameters of the network. ReLU activation is applied for the purpose of faster training. Some top CNN architectures are AlexNet (Krizhevsky et al. 2012), VGG (Karen Simonyan 2014), Inception V3 (Szegedy et al. 2016), and ResNet (He et al. 2016), resulting in significant gains on the popular ImageNet dataset (Sutskever et al. 2011), with 1000 classes and 1.2 million labeled images. The trained models are useful to study, as they can be utilized to perform transfer learning, a technique that helps to reduce the training time on new tasks.

Whereas CNNs are winner algorithms for processing images and multiarray modalities like video, speech, and audio, recurrent neural net (RNN) has excelled on tasks that involve sequential data such as language modeling and translation, speech recognition, handwriting recognition, and other sequence problems. They can be used to identify the next character in a word (Sutskever et al. 2011) or the next word in a sentence or can be used for more complex task such as outputting the sentiment expressed in a paragraph. A sequence is simply a stream of data items, where the individual items are interdependent. For instance, the meaning of a sentence can be correctly understood once we put the entire workflow of conversation into context. Similarly, in stock market, a single tick will only tell the current price, but to model the movement and enable a buy–sell decision, more data readings are needed in the sequence. The construction of RNN is such that the hidden state of the previous time step and the input of the current time step are used to calculate the current output. Unlike the basic NN, RNN uses its internal memory to process somewhat arbitrary sequences of inputs. One of the famous algorithms is long short-term memory (LSTM) (Schmidhuber 1997) which is a widely class of RNNs.

5.3 Future of Deep Learning

The progress in deep learning and AI-based solutions will continue and is expected to accelerate in the coming future. Although this success is only seen in supervised learning-based solutions, the future holds reviving interests for the research community in unsupervised learning. This is plausible, as the human learning process is largely unsupervised, we model structures in the world by observation not by being taught by its names. To this end, potential future work in deep learning for computer vision can involve in combining different representations like CNN, RNN, and deep reinforcement learning. Initial advances in this regard have resulted in interesting applications like a computer learn to play video games. With increasingly massive data sizes and computational facilities, end-to-end deep learning-based algorithms and architectures are expected to see more successes in the near future.

5.4 Introduction to Wireless Body Area Networks

Wireless body area networks (WBANs) are the emerging technology and the most attractive field for the research community (Cavallari et al. 2014), academia (Quwaider and Jararweh 2015), and industry (Shu et al. 2015) to solve the health monitoring issues for patients in urban and rural areas. Further, the World Health Organization (WHO) (Latré et al. 2010a; Acampora et al. 2013; Murray et al. 2012) has issued various reports on the death rates that have been increased in millions annually due to various diseases. These diseases are cancer, heart attack, diabetic issues, stroke, respiratory, abnormality of blood sugar (Acampora et al. 2013). Further, WHO has categorized these death rates based on the income of countries which are low income, middle income, high income worldwide as shown in Fig. 5.5. Figure 5.5 depicts the increased number of death rates due to insufficient health resources to provide to patients on time (Latré et al. 2010a, b). The existing studies show that most of the deaths are home-based old aged people and also because of remotely monitoring of patients from remote areas which are away from routine health checkup. In addition, the existing hospitals cannot provide health services on time due to lack of manpower and resource-constraint environment of hospitals which are the costly practices. Thus, for long-term monitoring of health problems of patients and home-based old aged people, WBAN is the innovative technological and cheap solutions to

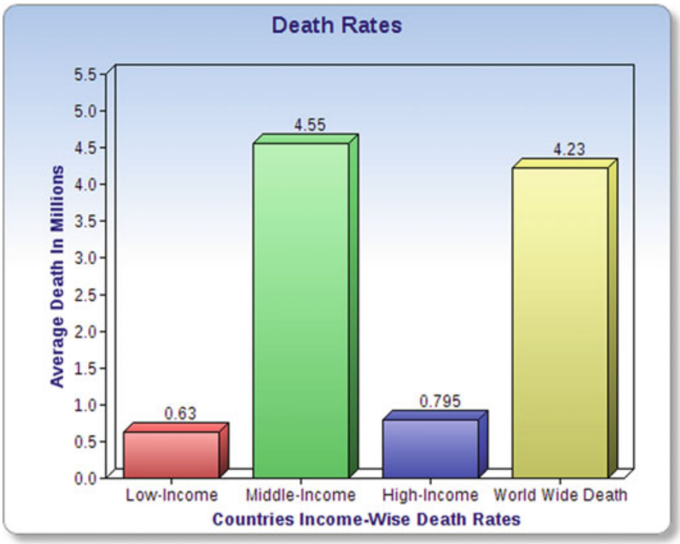


Fig. 5.5 WHO reports on average death rates in million

monitor vital signs of a patient. The monitored data is then forwarded toward medical doctors for an optimal treatment via GSM technology.

WBAN employs various biomedical sensors (BMSs) to monitor various vital signs of a patient. These BMSs are included to monitor respiratory rate, heartbeat rate, blood pressure, glucose level, temperature, ECG, EEG, EMG, and SPO2 (He et al. 2011) of patient. The monitored (sensory) data of a patient is transmitted to coordinator where all types of sensors are connected with coordinator as shown in Fig. 5.6. The coordinator is responsible for transmission of the sensory data to medical doctors. BMSs are connected with coordinator in the star or mesh topology based on the need of a patient. Figure 5.6 shows three methods of deployment of BMSs with a coordinator in the star topology. The first method is known as implantable, whereas different BMSs are inserted inside the patient's body to monitor various organs like lungs, kidney, and heart. The suitable example of the implantable sensors is capsule endoscope, as shown in Fig. 5.7a. Using wearable sensors is the second method to monitor vital signs like using of ECG, EEG, and EMG sensors which are sewed in the shirt of a patient or directly placed on the skin of a patient, as shown in Fig. 5.7b. The third method of deployment of sensors is different where different behavioral monitoring sensors are placed around the patient to monitor different physical activities. These physical activities are included monitoring of sleeping position and duration, postural movements of a patient like running, walking, dancing, and defective setting on sofa.

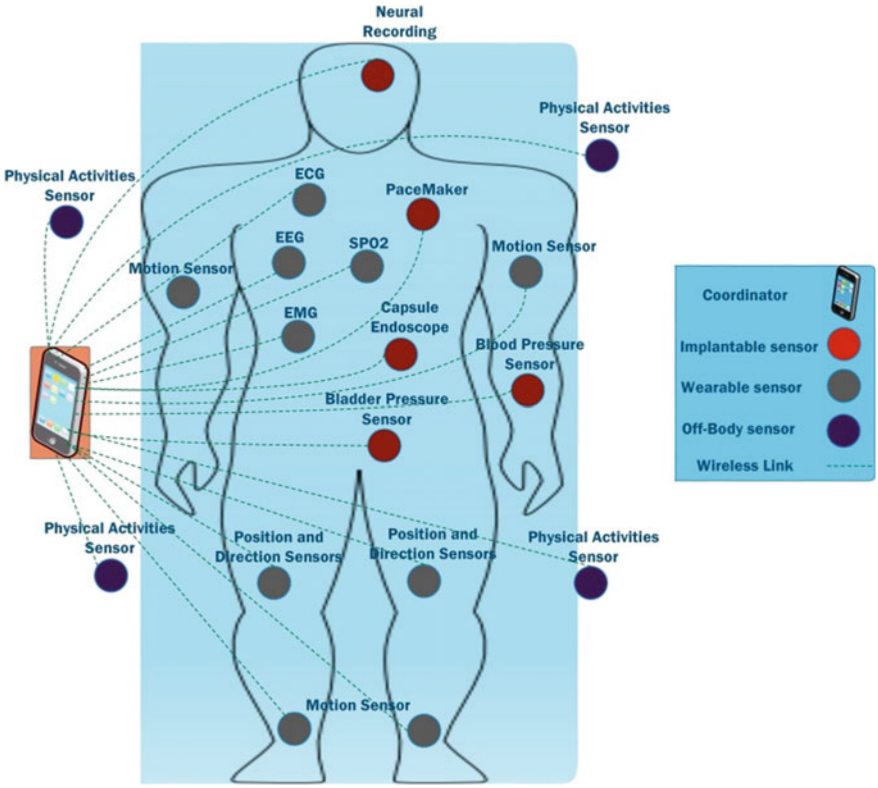
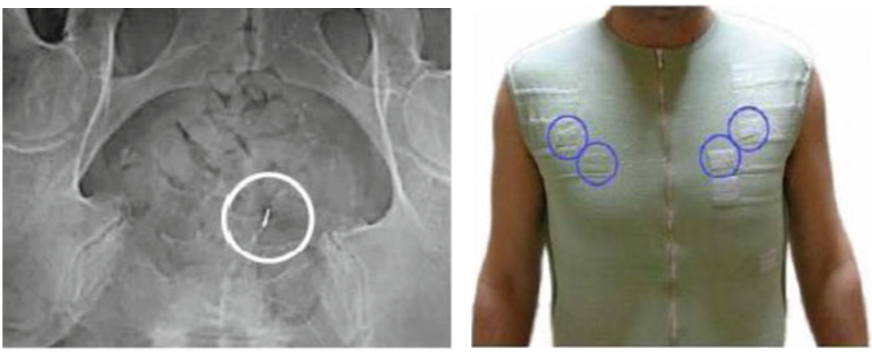


Fig. 5.6 Typical deployment of BMSs to monitor vital signs of patient



(a) Implantable BMS for Heart Monitoring in real time

(b) Wearable of BMSs

Fig. 5.7 Typical deployment of BMSs

5.5 Applications of Wireless Body Area Networks

Wireless body area network has wide applications in many fields including emergency services, consumer electronics, sports and fitness, lifestyle, defense, entertainment and gaming, personal healthcare, and medical (Applications of WBAN 2018), as shown in Fig. 5.8. In emergency services and defense, the deployed BMSs monitor vital signs of firefighters and soldiers, respectively, in their working environment. The aim of this monitoring is to inform the medical doctors if the person wounds or any emergency situation occurs. The sports and fitness, personal healthcare, and medical are together to monitor and maintain his/her health during sports activities, monitor home-based aged people health, and monitor different vital signs of serious patients in intensive care units (ICUs) and wards, respectively. The entertainment and gaming and consumer electronics are come in categories of enjoyable applications, whereas a person can open, forward, install, and delete game or songs, and similarly, a person can download, install, and remove an app, based on the mood, respectively. With these applications serving for humanity, it may be used widely.

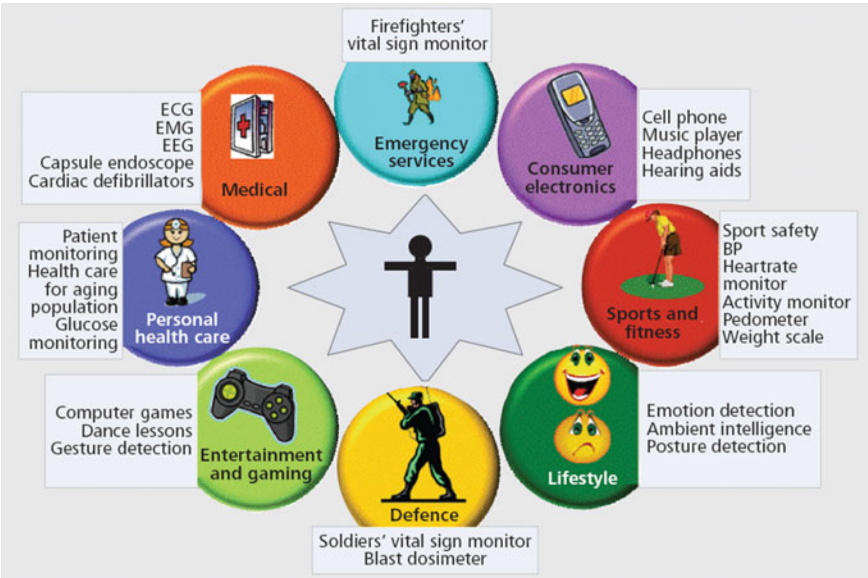


Fig. 5.8 Applications of wireless body area network (Applications of WBAN 2018)

5.5.1 Future Applications of Wireless Body Area Networks

The future of technological applications of WBAN is emerging toward driving assistance, electronic bill payment, security-based entrance to office, automatic operation in printing, and monitoring of health condition of patient (Future Applications of WBAN 2018), as shown in Fig. 5.9. In future, the driving person can adjust a seat of car if she feels uncomfortable with her driving seat. In this situation, she will apply force toward backside of seat for adjustment. In addition, the deployed BMSs will monitor different vital signs and will inform medical doctors if a person feels uncomfortable. In similar way, the person will not keep all transaction cards in his pocket but the embedded sensor in body will authenticate user and perform transactions. Furthermore, the outnumber of security guards will be reduced by company and the implanted sensors will authenticate users either he/she can enter to office or not. Printing of documents will be easy because bar code on the paper will recognize how much documents need to be printed. In this situation, the device will send printing information to the sewed sensors. The sewed sensor will forward the request of printing to the printing device.

Fig. 5.9 Future applications of wireless body area network (Future Applications of WBAN 2018)

5.5.2 *Use of Biomedical Sensors in Wireless Body Area Networks*

The biomedical sensor is made of two units that are radio transceiver and physiological-signal sensor (Chan et al. 2012). The function of the radio transceiver is to receive and transmit signals from sensor node and forward toward the destination node, while function of the physiological-signal sensor is to convert analog signal into digital form that has sensed from sensing environment. Further, the existing BMSs are respiration, blood pressure, accelerometer, heart rate, glucose, ECG, EEG, blood oxygen, EMG, pulse oximetry, pressure, gyroscope, and motion sensors used to monitor different vital signs of a patient. The functionality of some BMSs with their respective transfer rates (data rate) is presented in Table 5.1 in the following.

These BMSs help in monitoring vital signs and transmitting alert signals to the medical doctor if the condition of a patient is life threatening. Further, every BMS has different transfer rates in transmission of sensory data, and they need different quality of services (QoSs) due to their sensitive data. Therefore, they need to allocate

Table 5.1 Functionalities of BMSs in WBAN (Chakraborty et al. 2013; Al Ameen et al. 2012)

Name of BMS	Transfer rate	Use
Respiration	0.23–9.95 kbps	Respiration assists different organs to consume energy with the support of oxygen and glucose
Blood pressure	<9.99 bps	This sensor contains systolic and diastolic values which show either blood pressure level is normal or abnormal
Accelerometer	11 kbps	Assisting to show directions in 3D for calculating the desired energy for movements
Heartbeat	2.2 kbps	This sensor monitors beat of heart per minute showing low and high threshold values or normal ranges
ECG	142 kbps with 12 leads	Contains of different wires installed on chest to monitor heart rate
Temperature	122 bps	Monitors the patient’s body to show either it has coldness or hotness
Blood oxygen	15 kbps	Needs a certain amount of oxygen for smooth flow of blood in the body
Gyroscope	9 kbps	Monitors changes in body and sends an alert signal during emergency situation
Pressure	2.2 kbps	Normally, this sensor is placed on the shoulder of a patient to monitor sitting and falling position
Pulse oximetry	1.22–2.1 kbps	Assures delivery of certain level of oxygen in blood
EMG	318–580 kbps	Uses electrodes to monitor neuromuscular and is placed in the human body
EEG	30 kbps	Brain uses waves to recognize whether it is working in normal or in abnormal conditions

dedicated paths and channels for data transmission without collision, retransmission, and delay and consume minimum energy in transmission of data with higher data reliability. However, the research community needs to develop innovative solutions to transmit data without retransmission due to collision and delay. In addition, BMSs need to consume minimum energy in different decisions of path selection.

5.6 Existing Challenges in Wireless Body Area Networks

IEEE has defined two standards for wireless communication that are IEEE 802.15.4 (IEEE 802.15.4 2006) and IEEE 802.15.6 (Man et al. 2012). IEEE publicizes guidelines on MAC and PHY layers, while there are no guidelines provided about routing layer. Hence, it is the responsibilities of the research community to design and develop routing protocols which must be delay-aware, energy-efficient, and a highly reliable in path selections. Furthermore, IEEE 802.15.4 has designed and developed for wireless sensor networks (WSNs), while the Task Group 6 (TG6) has specially designed and developed IEEE 802.15.6 for wireless body area networks (WBANs). IEEE has published its first draft related to IEEE 802.15.6 WBAN in 2012. However, the research community and academia have been used IEEE 802.15.4 for WBAN before commencing of IEEE 802.15.6. IEEE 802.15.4 has provided all functionalities which are currently provided by IEEE 802.15.6. Numerous researches have been conducted for WBAN, and various routing protocols and MAC protocols have been suggested which are explained in the following.

5.6.1 Routing Protocols

The routing protocols assist to specify devices for communication with other devices and distribution of network information which enables to select a reliable path between devices. Normally, the sensory data of patient's body is classified into non-emergency and emergency data. The non-emergency data contains normal readings of vital signs like normal temperature and blood pressure, while emergency data contains abnormal reading of vital signs such as abnormal readings of heartbeat rate and respiratory rate. This sensory data is transmitted to the coordinator without priority, and the coordinator further transmits them without prioritization of emergency data. However, the existing classification of the patient's data is not sufficient because it does not distinguish between same types of emergency data if two different sensors transmit them to the coordinator at the same time. In addition, the coordinator is not able to resolve the conflict of allocation of path/channel on the priority if two sensors transmit data at the same time.

The selection of appropriate paths is based on the residual energy level of nodes, avoidance of the hot spot, and delay paths. Due to this, the research communities divide the routing protocols in WBAN into four groups (Bangash et al. 2014), as

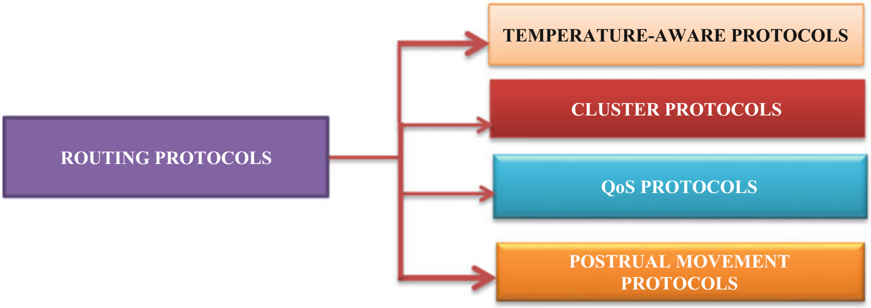


Fig. 5.10 Classification of routing protocols in WBAN

shown in Fig. 5.10. These are temperature-aware routing protocols, cluster routing protocols, QoS routing protocols, and postural movement protocols. Explanation of each routing protocol is presented in the following.

5.6.1.1 Temperature-Aware Routing Protocols

The monitoring of vital signs of the patient's body is with the support of BMSs. A BMS heats up during monitoring and transmission of sensory data of vital signs using multiple BMSs which burns skin and tissues. Causes of heat-up of BMS are using of high-frequency radio power, radiation of antenna, and the node's circuitry (Movassaghi et al. 2014). Numerous studies have suggested new design and development of routing protocols. Further, the researchers need to design and develop energy-efficient algorithms, selection of reliable paths with lowest temperature rise and shortest path to destination.

5.6.1.2 Cluster Routing Protocols

The large scale of communication area is divided into small area, known as cluster-based routing protocols. The aim of clustering is to provide optimal connectivity among nodes in WBAN. For example, the deployed BMS can communicate with other BMSs in one sitting position of person. In case of changing of sitting position of person, a BMS cannot communicate to other BMSs due to non-line-of-sight, and BMSs consume maximum energy by using higher power of antenna, which may cause other problems as mentioned in temperature-aware routing protocols.

5.6.1.3 Quality of Service (QoS)-Based Routing Protocols

The problems of QoS arises in communication network when outnumber of BMSs demand for dedicated and guaranteed bandwidth and network cannot fulfill requirements of the BMSs. In this situation, the congestion inside network has increased by dropping maximum amount of data which causes delay in retransmission of data and BMSs consumes a high amount of energy. The researchers need to design a reliable and efficient algorithms based on QoS.

5.6.1.4 Postural Movement-Based Routing Protocols

Postural means bringing change in the static object. In WBAN, the structure of the star or mesh topology has been frequently changed due to physical change in the body such as sit, lying down, stand, walk, defective sitting on the sofa, and the defective sleeping position. Due to effect of postural movement, BMSs cannot transmit data directly to the coordinator by consuming a high energy with the support of relay nodes. Existing researches have suggested to use line-of-sight (LOS), non-line-of-sight (NLOS) (Latré et al. 2010a), and store-and-forward (Quwaider and Biswas 2010) techniques. However, the patient's data needs reliable paths for data transmission without delay which can extend the network lifetime.

Another most important challenge is securing of sensory data in transmission. The asymmetric encryption techniques cannot be implemented due to resource-constraint setup of the tiny BMS. However, the existing academia needs to design a lightweight security protocols for better security and optimal utilization of the hardware sources of BMS. In concluding remarks, one should carefully design a routing protocol considering different pros and cons of the four routing protocols in WBAN.

5.7 MAC Protocols

As mentioned earlier, there are two standards used for WBAN containing IEEE 802.15.4 and IEEE 802.15.6. Each of them is explained in the following.

5.7.1 Superframe Structure of IEEE 802.15.4

There are two types of superframe structure of IEEE 802.15.4 presented. First form of superframe structure is known as non-beacon mode, and the second form of superframe structure is known as beacon-enabled mode (Ullah et al. 2010). In the non-beacon-enabled mode, the allocation of channels to BMSs is purely implemented on contention with access scheme unslotted CSMA/CA. The non-beacon mode is

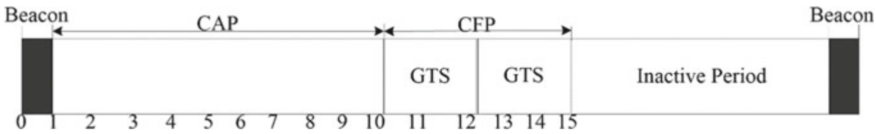


Fig. 5.11 Superframe structure of IEEE 802.15.4 (re-drawn)

specially designed for limited number of nodes and has no special consideration needed to take care of data in transmission.

The beacon-enabled-mode-based superframe of IEEE 802.15.4 (Ullah et al. 2010) is presented in Fig. 5.11 and comprises of beacon, contention-access period (CAP), contention-free period (CFP), and inactive period (IP). This superframe structure of IEEE 802.15.4 is implemented on the coordinator node in MAC layer of OSI model with sixteen channels/slots. Moreover, CAP is implemented on the scheduling access CSMA/CA scheme, while CFP is implemented on TDMA scheduling access scheme including guaranteed time slots (GTSs). The coordinator allocates CFP channels to those BMSs who got access in the CAP channels. However, the allocation of the CAP's channel is based on the contention. The IP is used for sleep period when a coordinator is free of allocation of slots.

At the beginning of superframe structure, the coordinator broadcasts a beacon frame to all BMSs in the network. This frame contains information about scanning of active and passive channels, calling of the next beacon interval, and time interval of the superframe duration. However, IEEE 802.15.4 (Touati and Tabish 2013) has the following drawbacks.

i. The superframe structure of IEEE 802.15.4 assigns sixteen channels which is not sufficient for large data produced by BMSs.
ii. Allocation of channels to BMSs is based on the contention.
iii. Allocation of the GTS CFP slots once a BMS gets access of channel in CAP.
iv. No priority has defined to allocate channel to emergency data.
v. Due to limited channels and round contention, a maximum number of collisions occur in CAP in which BMSs retransmit data with a higher delay and consume a maximum energy.
vi. Considered only emergency and non-emergency data.
vii. Gap in the research of WBAN for IEEE 802.15.4 is that it does not resolve the conflict of slot allocation if BMSs have same types of data.

Hence, the existing research community has suggested many superframe structures for MAC protocol in order to reduce collision, delay, retransmission of the lost packets, and energy consumption.

5.7.2 Superframe Structure of IEEE 802.15.6

In 2006, IEEE 802.11 had started new group that was Task Group 6 (TG6) (Al Ameen et al. 2012). TG6 was assigned a task to design low-power sensors for monitoring the health of patients. In 2012, the first draft was published for research community containing information of superframe structure of IEEE 802.15.6 MAC. Furthermore, the superframe structure of IEEE 802.15.6 comprises of beacon, exclusive access phase (EAP-I/II), random-access phase (RAP-I/II), type I/II, and contention-access period (CAP) (Rousselot and Decotignie 2009). At the beginning of communication, the coordinator transmits a beacon frame to all nodes in the network for communication convergence. EAP-I and EAP-II have designed to handle emergency traffic, while RAP-I, RAP-II, and CAP have designed to manage and handle non-emergency data of patient. Type I is associated with emergency data, while type II is associated with non-emergency data. Type indicates to coordinator which kinds of slots need to be occupied. The slotted ALOHA and CSMA/CA scheduling access schemes have implemented on IEEE 802.15.6. However, it has the same limitations as mentioned in IEEE 802.15.4 like high energy consumption, allocation of channels based on contention due to which retransmission becomes high with a higher delay, and not suitable for emergency data.

5.8 Introduction to Big Data

With the beginning of twenty-first century, the cloud computing is emerging technology for managing and allocation of resources online to different stack holders. Such stack holders are the government machinery, industry, and academia (Bates et al. 2014). Due to this importance, the big data has been introduced and merged in cloud computing to handle different input, output, and processed data of various devices for efficient utilization of resources online without buying costly equipment. Further, it has been reported in the Compliance, Governance and Oversight Council (CGOC) (Du et al. 2015) that each year volume of data becomes double and the existing infrastructure is not able to handle this huge amount of data locally. In the similar way, it has also been reported that huge amount of sensory data is produced from vital signs of a patient's body which needs efficient mechanisms to receive, process, and disseminate data toward the medical doctors. For this purpose, the existing studies in WBAN big data have numerous contributions toward an efficient design and development of mechanisms. The paper (Du et al. 2015) has included a mechanism who designed a framework in WBAN for big data for processing of sensory information of a patient, as shown in Fig. 5.12. At the beginning of first phase, a huge of amount data is collected from patient's body with the support of deployed BMSs containing clinical history from cloud servers. The load balancer unit extracts very relevant information from sensory data of patient's body about diseases based on information of clinical history. Further, distributed CEP is an emergent technology

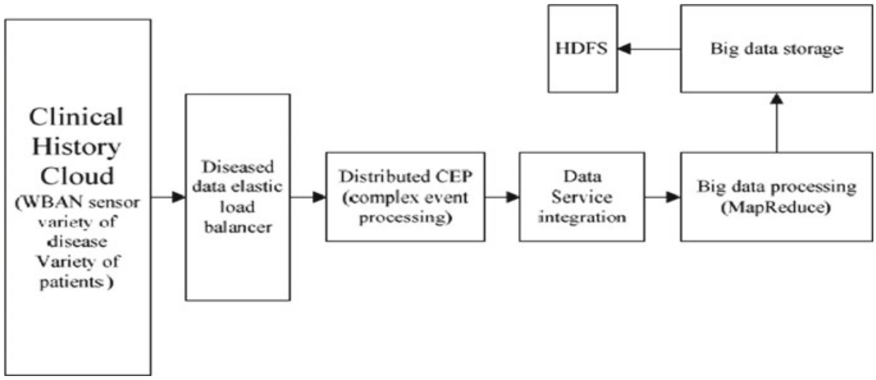


Fig. 5.12 Framework for WBAN big data (Du et al. 2015)

for WBAN in big data with functionalities to process data and identifies the actual disease(s). In this way, the data is transmitted using online data service integration. The big data processing unit removes detailed information using MapReduce feature provided by Google and finally stores data in the big data storage server. The final unit is Hadoop Distributed File System (HDFS) which splits data into different working subunits with attributes of key and values. However, the suggested WBAN big data model has many steps to extract the accurate information which creates overhead in terms of a higher delay for decision-making and consumes a maximum energy of BMSs by losing the life of patients. In addition, many WBANs have problems of frequency interference/overlapping which may not able to process the sensory data of patients and transmit to the medical doctor for optimal treatment. The authors of (Quwaider 2014) has designed conventional server (CS) and virtualized cloudlet (VC) to utilize efficiently online resources of big data for WBAN. Figure 5.13 shows collection of data using cloudlet in WBA. However, it has the same challenging issues as mentioned in (Du et al. 2015).

5.9 Applications of Big Data in WBAN

In this section, we will elaborate the applications of big data in WBAN which comprises of monitoring of vital signs and analysis, early detection of abnormal conditions of patient, and daily basis activity monitoring of a patient using BMSs (Lin et al. 2018).

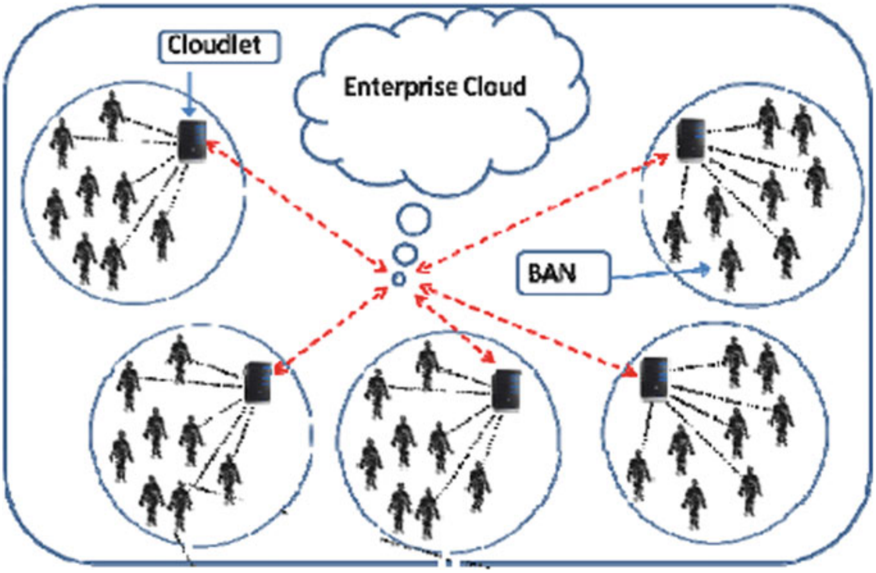


Fig. 5.13 WBAN with cloudlet-based data collection system (Quwaider 2014)

5.9.1 Monitoring of Vital Signs and Analysis

Big data plays a vital role in predication of accurate symptoms finding in patient's body using historical and clinical data information. With this predication, it improves primarily the quality of life. However, these predications are based on some certain parameters as mentioned in (Bates et al. 2014) that are management and childbirth, consumer behavior, clinical decision support, and support services. In addition, the symptoms of diseases need to be classified further for better understanding and early detection that can be performed with the support of ontology using protégé tool. Further, the existing tools which may assist to find symptoms in advance before alarming situation happens to the life of patient include Google Flu Trends and HealthMap. However, the research community needs to design and develop efficient mechanisms in early detection of abnormal conditions of patient.

5.9.2 Early Detection of Abnormal Conditions of Patient

Normally, the patient of chronic metabolic needs an adequate healthcare comparatively to other types of diseases. Due to this, different BMSs are used to monitor vital signs and periodically transmit results of sensory data to the physician. With this support, the physician can proclaim in advance the severity of patient and do precaution activities. The proclaiming practices need history and clinical data which need to be stored online and available every time. This can applicable only with the support of big data.

5.9.3 Daily Basis Activity Monitoring of a Patient Using BMSs

As mentioned earlier, Fig. 5.2 depicts how different BMSs can be deployed for monitoring of different vital signs of patient. Sometimes, physicians need to monitor the daily activities of patients and impact of these activities on their health. In addition, the physician needs sensory data of blood pressure, heart beat rate, respiratory rate, temperature, and blood glucose level.

5.10 Open Issues of WBAN

This section discusses open research issues of WBAN which comprise of routing protocols and MAC protocols.

5.10.1 Resource-Constraint Architecture of BMS

The sensor nodes have limited computational processing power, limited storage, and limited battery backup. These are challenging problems in WBAN and WSN. It has been noticed that the manufactures should need to improve the design of BMSs and include new features like harvesting for energy consumption in replacement of existing architecture.

5.10.2 Hotspot Paths

During monitoring of vital signs and data dissemination activities sometimes heat-up BMSs due to radio frequency, radiation of BMSs and circuitry design of BMSs. With this heat-up, the deployed BMSs burn skins and tissues of patient.

5.10.3 QoS in WBAN

The sensory data of patient's body is divided into critical, delay-sensitive, reliability-sensitive, and ordinary data. This data does not accept delay in transmission toward the coordinator and must allocate guaranteed QoS.

5.10.4 Path Loss in WBAN

Deployed BMSs are directly (line-of-sight) connected with coordinator for data transmission. Due to postural movement, the topology structure changes frequently and BMSs loss paths for data transmission.

5.10.5 Data Protection in WBAN

The sensory data of patient's body is important to secure in transmission from eavesdroppers in the resource-constraint environment of BMS.

5.10.6 Step-Down in Energy Consumption

Due to periodically monitoring of vital signs and transmission of results consume maximum energy of BMSs. However, the research community needs to design harvesting-based energy-efficient architecture of BMSs.

5.10.7 Channel Access Allocation and Its Complexity

The existing techniques for channel allocation are contention and predefined. However, this is expensive practices and the delay-sensitive data of the patient's body does not accept delay in allocation of channels and transmission.

5.10.8 Permission- and Preemption-Based Channel Assignment

The protocols should be efficiently designed and developed to allocate channels based on permission and preemption according to the sensitivity of patient's data.

5.11 Open Issues of Big Data

This section discusses the vital research issues of big data, which are data management which is elaborated in the following.

5.11.1 Varieties of Data

On daily basis, every IoT-enabled device generates millions of data. Now, how to extract the important and the most relevant information from unstructured of off-line and streaming data quickly?

5.11.2 Increased Amount of Data Storage

How to design and develop efficient methods to recognize the important and relevant data from large amount of unstructured data?

5.11.3 Integration of Data from Different Sources

The research community needs to design new protocols to combine relevant data from same objects and integrate them for further use.

5.11.4 Allocation of Channel, Processing, and Management of Data

Need to improve the design of the existing communication models for off-line and online streaming of data for efficient allocation of resources, process, and manage them for accurate retrieval of information on time.

5.11.5 Cost-Effective Business Model

The future models for businesses should be user-friendly for available resources with minimum cost.

5.11.6 Delay-Aware Models for Quick Solutions

The research community should design efficient delay-aware models in terms of quick responses to customers on time.

5.11.7 Automation in Allocation of Services

The new business models should replace services provided by human with machine learning and big data analysts.

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