Journal of Ambient Intelligence and Humanized Computing
https://doi.org/10.1007/s12652-021-03237-2

ORIGINAL RESEARCH

An approach to detect human body movement using different channel models and machine learning techniques

Monica Kaushik[1] · **Sindhu Hak Gupta**[1] · **Vipin Balyan**[2]

Received: 7 May 2020 / Accepted: 25 March 2021

Abstract
Worldwide, 16.7 million people die each year due to cardiovascular disease. These statistics raise demand of devices like sensor-based pacemakers (PM) which are not just doing heart rate augmentation but also capable to transmit information via wireless link to on body sensor and support remote monitoring of such patients. As per the world health organization WHO reports there are more than 3 million functioning PMs and about 600,000 pacemakers are implanted each year in world. On an average, 70–80% of PMs are implanted in aged patients around 65 years or older. In addition to continuous monitoring of cardiovascular parameters, detection of physical movement of such patients may be helpful to assess their well-being. This paper has been formulated with an aim to highlight an approach which may be used to detect the physical movement of the patient using information signal received from implanted PM. The transmitted signal will experience a pathloss offered by wireless human body channel, which will affect the link quality parameters namely Signal to Noise Ratio (SNR) and Bit Error Rate (BER) and received signal strength indicator (RSSI). In the current work mathematical model has been formulated considering in body and on body channel propagation conditions and received power, received energy, pathloss, SNR, BER, bit rate, energy per bit and RSSI have been evaluated using IEEE802.15.6 channel models CM2 and CM3. Data set has been created and human body movement has been detected using Machine Learning (ML) techniques. Prediction accuracy of Multilayer Perceptron (MLP), k-Nearest Neighbours (kNN) and Random Forest have been compared. The analysis performed depicts that human body movement can be detected using different channel models and ML techniques such as MLP, kNN and Random Forest with an accuracy of 65.3%, 72.8% and 93.4% respectively. The critical comparison of the result indicates that the performance of Random Forest is better than MLP and kNN. This approach will be helpful in remote detection of human body movement of patients.

Keywords Bit error rate (BER) · Random Forest · Signal to noise ratio (SNR) · Received signal strength indicator (RSSI) · Wireless Body Area Network (WBAN)

1 Introduction

The number of cardiovascular disease (CVD) patients are increasing rapidly across globe. CVD is one of the leading factor for cause of death and approximately shares 30% of overall death (Mishra et al. 2019). To avoid sudden death or life-threatening situation, early detection of abnormality in cardiac functions is required. (Wu et al. 2020; Che et al. 2020). Continuous monitoring of cardiac activity may help in the prevention of severe heart conditions as timely detection and further medical advice can be offered by experts in advance (Mandala et al. 2017; Snegalatha et al. 2019). The concept of continuous monitoring may be beneficial for those patients who require or went through by-pass surgery as they are on high risk of neurological problems like stroke (Martin et al. 2006). In both cases body movement tracking in addition to heart monitoring may help in the early diagnosis of any cardiac or neurological disorder (Chen et al. 2010; Arora et al. 2020). Traditionally, a person must be appointed for regular measure of physiological parameters (blood pressure, heart rate etc.) and to monitor the patient's

✉ Sindhu Hak Gupta
shak@amity.edu

[1] Department of Electronics and Communication Engineering, ASET, Amity University Uttar Pradesh, Sector 125, Noida, India

[2] Department of Electrical, Electronics and Computer Engineering, Cape Peninsula University of Technology, Cape Town, South Africa

activity which is expensive and not practicable for most of the patients. These requirements and issues accelerate the growth of wireless health monitoring systems (Andreu et al. 2015). The advancement of wireless wearable systems also called on body systems improve the patient's care and quality of life (Merli et al. 2011). For heart patients, sensor-based implantable pacemakers also called in body devices helps not only in monitoring of cardiovascular parameters but also able to communicate information to the receiver which may be an on-body sensor (Shi et al. 2011). Typical approaches include optical, infrared (IR), inertial and wearable sensor systems (Cavallari et al. 2014). Among above mentioned technologies, IR signals are not able to penetrate through obstacles (Zhang et al. 2010), inertial sensors require complex calibration process and face fluctuation offset (Liu et al. 2007), while performance of optical based motion capture system is effective as it provides high accuracy, but this system is very expensive and needs long procedure of calibration. Regular monitoring systems generally restricted to the lab-based environment which may not be feasible for real time remote monitoring of patients (Betke et al. 2002).

On the other hand, wearable sensor technology offers an advantageous solution for monitoring of patient as it provides mobility to the patients, real- time feedback, low power and high data rate etc. The network formed by wearable sensors is called Wireless Body Area Network (WBAN) (Patel et al. 2012). Sensors might be deployed inside the body, on the body and off the body, accordingly the network are called in body, on body and off body. These sensors sense the health parameters like pulse rate, hemodynamic status etc. and direct the sensed signal to sink node (Gupta and Devarajan 2020). The collected information may be examined by concern medical expert for appropriate advice (Kaushik et al. 2020). For WBAN different pathloss channel models (CM) have been defined by the IEEE 802.15.6 standard. CM1 formulates the pathloss for implant to implant communication, CM2 evaluates the pathloss which is occurred for implant to body surface, CM3 and CM4 express pathloss for body surface to body surface and for body surface to external respectively. Federal Communication Commission (FCC) has assigned diverse operating frequency bands for them. For CM1 and CM2 402–405 MHz bands have been allotted and the operating range for CM3 and CM4 consists 13 MHz, 50 MHz,400, 600, 900 MHz, 3.1–10.6 GHz bands (Yazdandoost et al. 2009).

Table 1 represents a state of art of human body movement detection techniques focusing on approach and limitations.

WBAN has immense potential to classify human body activities and is very efficient to analyze them (Cuesta-Vargas et al. 2010). The basic requirement for an efficient human movement tracking system is an accurate classification or prediction of activities and reliability because incorrect data may lead to critical issues in diagnosis or treatment (Rose and Christina 1997). The recent development

Table 1 State of art of human body movement detection

References	Approach	Detection methods	Features
Camurri et al. (2003)	External sensors have been used to capture human body movement	Vision based system	High end processors and high data rate required
Zhang et al. (2010)	Based on RSS (Received Signal Strength)	Infrared sensor-based systems	Line of Sight (LOS) mandatory
Bilro et al. (2011)	Optical communication properties have been used to detect any motion activity	Optical fibre sensor-based systems	High Accuracy but calibration dependent Expensive
Buke et al. (2015)	Accelerometer, Gyroscope and Compass has been used to measure coordinates of moving object	Inertial sensor system	Complex calibration process High Power consumption
Thakur et al. (2020)	Sensors present inside the smartphone has been used to analyse to human body movement	Smart Phone Senor based system	Difficult to always carry smartphone and standardized testing procedures
Gupta et al. (2020)	Recognition of Human body movement using antenna parameters by applying deep learning	Antenna based system	Data base created using scattering parameters of antenna
Current work	Human body movement detection using CM2 and CM3 pathloss models, data set comprising parameters like pathloss, SNR, BER, RSSI has been created and classified human body movement by using machine learning techniques MLP, kNN and Random Forest	Machine Learning Techniques based System	An approach which highlights that already deployed monitoring device like pacemaker can aid in detection of human body movements

in the field of WBAN motivated researchers to investigate the application of machine learning methods in human body movement detection. The models in machine learning are data-driven, self-adaptive and nonlinear. This can give a better result from the classification point of view. Some of the popular algorithms used in classifications are Artificial Neural Networks (ANN), Support vector machine (SVM), kNN, decision tree, Naive Bayes and Random Forest (Negra et al. 2018).

The main objective of the current work is the detection of human body movement with the help of machine learning using channel characteristics and link quality parameters (pathloss, SNR, BER, energy per bit, RSSI and bit rate) of proposed WBAN.

Rest of the paper has been structured as follows, In Sect. 2 related work has been discussed. Section 3 describes the system model. Machine learning techniques have been explained in Sect. 4. Section 5 highlights the outcomes of the proposed work. Section 6highlights the conclusion of the work.

2 Related work

Over the past few years overwhelming research on the human activity recognition system has been carried out relevant to healthcare applications using wearable sensor technology (Lara et al. 2012). Analysis of daily activities of patients may help in early diagnosis of any life-threatening medical issue (Malasinghe et al. 2019). Thus monitoring, tracking and accurate classification of daily physical activities of the patient are required. The complex nature of human body movements makes activity classification a challenging task (Alinia et al. 2015). Several researchers focused on human activity identification using wearable sensors, camera or radio technologies. A system called MercuryLive based on wearable sensor technology has been presented by Chen et al. (2010) where wearable sensors are used to monitor the motor fluctuation of a patient remotely. Liu et al. (2007) carried out a comparative analysis of the sensor-based wearable system consisting of gyroscopes and two-axis accelerometers with an optical motion analysis system and stated that wearable sensor system could be used in analysis of human body movement. In this Cuesta-Vargas et al. (2010) study human motion using inertial sensors has been carried out and observe that human motion can be analysed utilizing inertial sensors, but the performance may be influenced by location and task. In Kwapisz et al. (2011) smartphone-based human activity recognition system has been examined considering common daily activity of human (sitting, walking, standing, jogging and climbing stairs). In Thakur et al. (2020) Machine Learning and Deep Learning techniques have been applied on the data obtained from smartphone sensors to distinguish between various human activities in Seiffert et al. (2017) concept of Activity Assessment Chain (AAC) has been introduced for human movement using wearable sensors. In Archasantisuk et al. (2015) authors used radio signal strength (RSS) to detect physical movement in WBAN with collection of radio signal strength (RSS) of each movement individually. Accurate classification of human body movement in WBAN is still a challenging task. In last few years, various approaches have been proposed to achieve accuracy in human body movement classification and machine learning is one of them.

The models used in machine learning are data driven, self-adaptive and nonlinear. This can give good result from the classification point of view (Solomatine 2003). Generally supervised learning or un-supervised learning has been used for classification purpose. In order to classify daily human activity like jump, walk etc. (Jagannath et al. 2019) presents a comparative analysis of discrete cosine transform (DCT), the Principal Component Analysis (PCA) and multi-class SVM. Authors stated that performance of SVM is best among them. Authors in Negra et al. (2018) examined possibility of human activity classification from channel gain measures by using supervised learning for on body scenario only. Random Forest algorithm has been used in Casale et al. (2011) to classify daily activities using motion sensors. Existing literature reveals that human body movement classification methods for wearable networks have been investigated exhaustively. From the Table 2 of related work,

Table 2 Related work

References	Approach	Metrics analyzed	Machine learning technique
Negra et al. (2018)	On body	Path-gain, SNR and BER	Decision tree, random forest, SVM
Kwapis et al (2011)	Off body	Time domain analysis	Logistic regression, MLP, Straw Man
Archasantisuk et al. (2015)	On body	RSS	Neural network, decision tree
Jagannath et al. (2019)	On body	Time domain analysis	DCT, PCA, SVM
Current work	(In + on) body	Pathloss, received power, received energy, bit rate, energy per bit, SNR, BER, RSSI	Random forest, kNN, MLP

it is observed that existing work has been carried out mainly for on body WBAN. For implanted networks tracking and human body movement recognition still need to be explored. The current work presents a novel approach to detect human body movement considering in body and on body WBAN.

The main contributions of this work are:

- A WBAN is modeled to detect the human body movement (sit, stand and walk) aided by the implanted pacemaker which transmits the detected cardiovascular parameters of the patient to on body sensor.
- Received power, received energy and link quality parameters (pathloss, SNR and BER, RSSI, Bit Rate, Energy per bit) of the proposed model have been analyzed using IEEE 802.15.6 CM2 and CM3 models and data base has been created with evaluated channel characteristic parameters.
- Machine learning techniques like MLP, kNN and Random Forest have been applied and their accuracy has been critically compared for detection of human body movement (sit, walk, stand).

3 System model

For this work a scenario has been considered where it is assumed that a patient is being monitored after pacemaker has been implanted inside his body. In order to observe post-surgery issues like stroke predictions or associated reactions, regular monitoring of patient is necessary. For the considered scenario, it has been assumed that a sensor node A′ has been implanted in the pulmonary artery (PA) of patient to monitor cardiovascular parameters of the patient. Apart from sensing desired cardiovascular parameters, implanted sensor will also aid in detecting human body movement. The sensors which are implanted inside the human body will sense the data and transmit them to on body sensor nodes A and B which have been placed on body near the heart and ankle respectively. The purpose of these nodes is to assure that signals are transmitted properly to sink node and further hand held device. Node B is acting as a sink node and the information will be transmitted to it via node A. Multiple nodes are considered in order to ensure the link quality of the wireless communication. Sink node B forwards the information to a cloud server which after required data analytics aids medical experts. The focus of the work is to emphasize that the PM apart from doing the regular functioning which has been attributed to it can aid in human body movement detection.

Figure 1 depicts the layout for the proposed model where the distance from node A′ to node A and node A to node B is denoted by $d_{A'A}$ and $d_{A,B}$ respectively. The in body sensor node A′ will sense the signal and further transmit it wirelessly to on body sensor node A. While the transmission takes place the signal strength will be impacted by the wireless nature of in body. The pathloss incurred inside the human body can be computed using CM2 pathloss model defined by IEEE802.15.6. It has been assumed sensor are operating at 402–405 MHz band. Once the signal reaches at on body sensor node A placed on the heart from that the signal will be further transmitted to sink node B operating at 400–450 MHz band and placed at the ankle. Due to wireless nature of medium between node A and node B certain amount of pathloss will be incurred which will be computed using CM3 pathloss model define by IEEE802.15.6. The

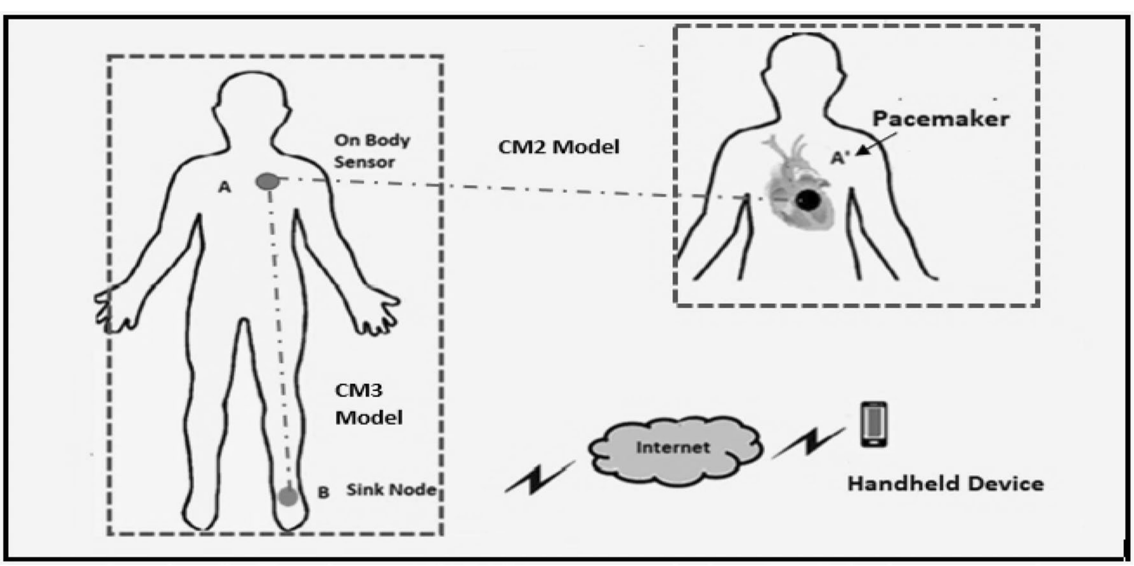

Fig. 1 WBAN architecture to monitor cardiovascular parameters

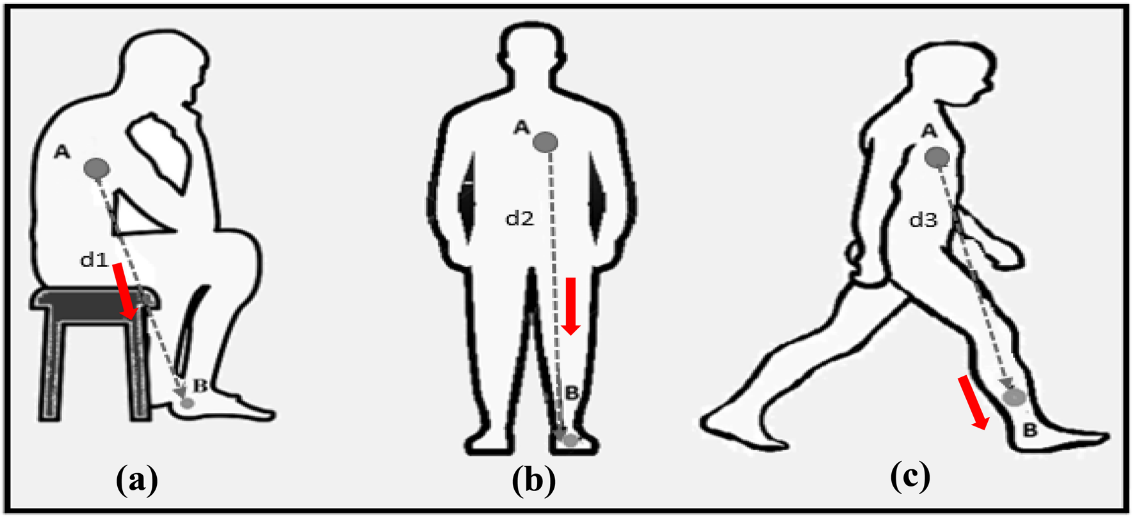

Fig. 2 Physical body movement **a** sit **b** stand **c** walk

equation for CM2 and CM3 pathloss model have been given further in (1) and (2).

The main idea behind this research is that when there is a certain amount of physical movement by a subject the distance between two nodes will vary. Since the pathloss is directly dependent on the distance between the communicating nodes, there will be variation in the pathloss. Net variation in the pathloss is calculated considering the pathloss which has occurred inside the body and pathloss which will occur on body. Net pathloss is calculated using (3).

In this analytical study three physical activities (sit, stand and walk) have been considered to analyse the quality of the transmitted signal and detection of human body movement as shown in Fig. 2. The distance variation with respect to physical movement sit, stand and walk between node A and node B is denoted by d1, d2, and d3 respectively. There are various communication link parameters which can be evaluated indirectly using pathloss, distance and other parameters. Evaluation of various link parameters have been carried out in the following section.

A data set has been created under the considered scenario with 100 different healthy human subjects who agreed for the on-body data collection. Heart related health issues tend to arise in middle age, keeping this fact in mind, the average age of subjects was taken around 45 years. Height, weight and body mass index (BMI) of some subjects have been shown in Table 3. BMI is significant as it exhibits the height-weight relationship and gives a more precise measure than body weight only. A sample data set of distance variation with respect to body movement is given in Table 4.

As mentioned in the earlier section for evaluating the pathloss which will incur inside the body has been calculated using CM2 model (Yazdandoost et al. 2009) and is given in (1),

Table 3 Sample height and weight of subjects

Subjects	Age	Height (cm)	Weight (kg)	BMI (kg/m^2)
F	49	162	78	29.7
F	39	154	48	20.2
F	42	162	60	22.9
F	37	156	77	31.6
F	43	164	63	23.4
M	41	178	78	24.6
M	34	181	76	23.2
M	38	182.8	75	22.4
M	39	185.9	78	22.6
M	39	187.3	88	25.1

Here *F* female and *M* male

Table 4 Sample data set

Subject	d1	d2	d3
1	86	104	108
2	90	108	112
3	94	112	116
4	98	112	114
5	102	110	118
6	104	121	122
7	109	120	123
8	110	121	128
9	113	128	130
10	116	130	132

Here d1, d2 and d3 are in cm

$$PL(d)_{A'A} = PL(d_0) + 10n\log_{10}\left({d_{A'A}}/{d_0}\right) + S \tag{1}$$

Here, $PL(d_0)$ is the pathloss at reference distance d_0 and $d_0 = 50$ mm. $d_{A',A}$ is the separation distance from the node A′ and the node A. S denotes the shadowing component.

Once the signal will reach on body, the pathloss between the node at the heart (A) and to the node at ankle (B) will be calculated using CM3 model (Yazdandoost et al. 2009) and given in (2)

$$PL(d)_{A,B} = a \times log_{10}(d_{A,B}) + b + N \tag{2}$$

Here, $d_{A,B}$ denotes the distance between nodes A and B, a, b are linear fitting coefficients and N is standard deviation.

Parameters used in pathloss computation for CM2 and CM3 channel models have been given in Table 5

As mentioned earlier, the total pathloss will be the summation of pathloss incurred inside human body and on body. From (1) and (2), the net pathloss experienced by the signal during propagation from node A′ to node B can be represented as,

$$PL_{TOTAL} = \left\{PL(d_0) + 10n\log_{10}\left({d_{A'A}}/{d_0}\right) + S\right\} + \left\{a \times \log_{10}(d_{A,B}) + b + N\right\} \tag{3}$$

For the considered scenario it is assumed that the signal will be transmitted at the power level P_t. Pathloss will impact the signal strength and received power will obviously be attenuated in comparison to the transmitted power. The received power will be calculated as (Rappaport 1996).

$$P_r = \frac{P_t}{PL_{TOTAL}} \tag{4}$$

Here P_t is the transmitted power and PL_{TOTAL} is the total pathloss experienced by the signal during travel from node A′ to node A (in body) and then node A to node B (on body).

Received power can be obtained by substituting values from (3) in (4) and is given in (5),

$$P_r = \frac{P_t}{\left\{PL(d_0) + 10n\log_{10}\left({d_{A'A}}/{d_0}\right) + S\right\} + \left\{a \times \log_{10}(d_{A,B}) + b + N\right\}} \tag{5}$$

Data rate (R_b) analysis is required to achieve successful transmission of data. Higher the data rate higher the energy consumption. Hence it is required to operate WBAN in permissible limit of data rate to achieve energy efficiency. Computation of data rate has been given in Proakis et al. (2014) and written as,

$$R_b \le Blog_2\left(1 + \frac{P_r}{N_o}\frac{1}{B}\right) \tag{6}$$

where, B is the bandwidth, N_0 is the noise power density.

By using (5) and (6) R_b has been computed and presented in (7) as,

$$R_b \le B\log_2\left[1 + \left(\frac{P_t}{\left\{PL(d_0) + 10nlog_{10}\left({d_{A'A}}/{d_0}\right) + S\right\} + \left\{a \times log_{10}(d_{A,B}) + b + N\right\}}\right)\frac{1}{N_o}\frac{1}{B}\right] \tag{7}$$

Energy received by the end node is one of the important factor to analyse the performance of the network. Received energy primarily depend upon transmitted power and transmission channel and calculated using (8),

$$E_{rec} = \left[\frac{P_t}{antilog\left(\frac{PL_{TOTAL} - b - N}{a}\right)}\right] \times t \tag{8}$$

Here t (assumed) = 1 ms and value of pathloss PL_{TOTAL} will be obtained by using (3).

Link quality is a very important optimization parameter for WBANs. Link quality has been evaluated using the parameters like RSSI, SNR, Energy per bit, BER etc. For the considered scenario these parameters can be evaluated as follows,

Received signal strength indicator (RSSI) signifies the quality of received signal at the receiving end. This

Table 5 Channel model parameters (Yazdandoost et al. 2009)

Description	Symbols	Values
Pathloss at reference distance (d_0)	PL (d_0) (dB)	47.14
Pathloss exponent	N	4.26
Shadowing component	S	7.85
Linear fitting coefficients	A	3
	B	34.6
Standard deviation	N	4.63

parameter plays a crucial role as it determines appropriate signal strength required for successful reception as expressed in Rappaport (1996) and given as,

$$RSSI = -\left(10 \times \alpha \times \log\left(d_{total}\right)\right) + \frac{P_t}{\left(d_{total}\right)^{\alpha}} \tag{9}$$

where α is the path loss exponent. α = 3.

SNR is a very important parameter to analyse the performance of the network. High SNR means good quality of the signal. $SNR_{A,\,B}$ for the considered scenario has been given in Soliman et al. (2012) and written as,

$$SNR_{A,B} = \frac{|h|^2 \times P_t}{PL_{Total} \times \sigma^2} \tag{10}$$

where h is complex normally distributed channel gain, which is taken unity for simplicity, P_t is the transmitted power and σ^2 is the noise variance.

Substituting values from (2) and (3) the computed $SNR_{A,\,B}$ is given as,

$$SNR_{A,B} = \frac{|h|^2 \times P_t}{\left[\left\{PL\left(d_0\right) + 10nlog_{10}\left({}^{d_{A,A'}}/{}_{d_0}\right) + S\right\} + \left\{a \times log_{10}\left(d_{A,B}\right) + b + N\right\}\right] \times \sigma^2} \tag{11}$$

Energy efficiency is most critical issue with WBANs. Hence calculation of energy per bit is very important parameter which helps in performance analysis of the network. Computation of energy per bit is given in Gallager (2008) and can be represented as,

$$E_b = \frac{SNR \times N_0}{R_b} \tag{12}$$

Substituting value of SNR from (11), E_b can be rewrite as:

$$E_b = \left(\frac{|h|^2 \times P_t / \left[\left\{PL\left(d_0\right) + 10n\log_{10}\left(d_{A,A'}/d_0\right) + S\right\} + \left\{a \times \log_{10}\left(d_{A,B}\right) + b + N\right\}\right] \times \sigma^2}{R_b} \right) \times N_0 \tag{13}$$

Further Bit error rate (BER) for the considered scenario has been calculated using (11) and expressed in Peng and Peng (2016),

$$BER = \left[\left\{PL\left(d_0\right) + 10n\ \log_{10}\left(d_{A,A'}/d_0\right) + S\right\} + \left\{a \times\ \log_{10}\left(d_{A,B}\right) +\ b + N\right\}\right]^{-k} \tag{14}$$

Here k is the specific subcarrier index.

Based on the parameters calculated with the help of above mentioned equations have been summarized in Table 3, a data set has been created which is further used in Machine learning for human body movements prediction. In next subsequent section machine learning algorithm has been discussed and further implemented on the data set for human body movement detection.

4 Human body movement detection based on machine learning techniques

In Machine Learning, a machine learns from its experience, takes decisions and make predictions (Ayodele 2010). Machine Learning is generally used to deal with classification, regression and clustering problems**.** The selection of learning approach and appropriate machine learning algorithm depends upon the available data types (Ali et al. 2019). In literature, to classify the human body movement variety of machine learning techniques have been developed like decision tree, Random Forest, SVM, kNN, ANN, and Naïve Bayes etc. In the current work human body movement detection has beesssn carried out with MLP, kNN and Random Forest using data set created by channel characteristics parameters. Details of which are explained below:

Multilayer Perceptron (MLP) MLP is a linear classifier with input, hidden and output layers. The layers are associated to each other in such a manner that each node of previous layer connects to the node present in the subsequent layer and assigned weight (Wahid et al. 2017). The output and expected result will be compared to compute error and trained in the perceptron by adjusting the connection weights accordingly. For MLP training backpropagation technique is applied. MLP may be useful in recognition of speech, image etc. (Simeone 2018).

k-Nearest Neighbours (kNN) kNN works on the assumption that similar things are near to each other. It classifies samples based on the distances (similarity function) from its k neighbours in the training data. Distance calculation in kNN is generally done by using the Euclidean distance (Ali et al. 2019). Application of kNN can be found in the classification of medical data, handwriting recognition, handwriting detection, image recognition etc. (Ray 2019).

Random Forest Random Forest algorithm is collection of tree predictors. It is a classification algorithm which works on supervised learning and depending upon input data set creates a forest with several trees. It maps complex nonlinear decision boundaries (Breiman 2001). It works on voting system and final decision is taken on the majority of votes. Generally, the accuracy of the result is directly related with number of trees. Higher accuracy can be achieved by increasing density of trees in the forest (Liaw et al. 2002). By reducing the correlation between trees, it realizes great reduction in variance which makes Random Forest more robust against noise. At the time of splitting it always considers only a subset of the available predictors to reduce correlation. Classification accuracy given in Casale et al. (2011) and presented as follows:

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{Total predictions made}} \tag{15}$$

A comparative flow chart of MLP, kNN and Random Forest is illustrated in Fig. 3.

The work has been performed using the cloud service provided by Google (Google Colaboratory). The model has been created using python library with 150 inputs and the number of outputs was one at a time to classify the human body movement like the object is sitting or standing or walking (Table 6).

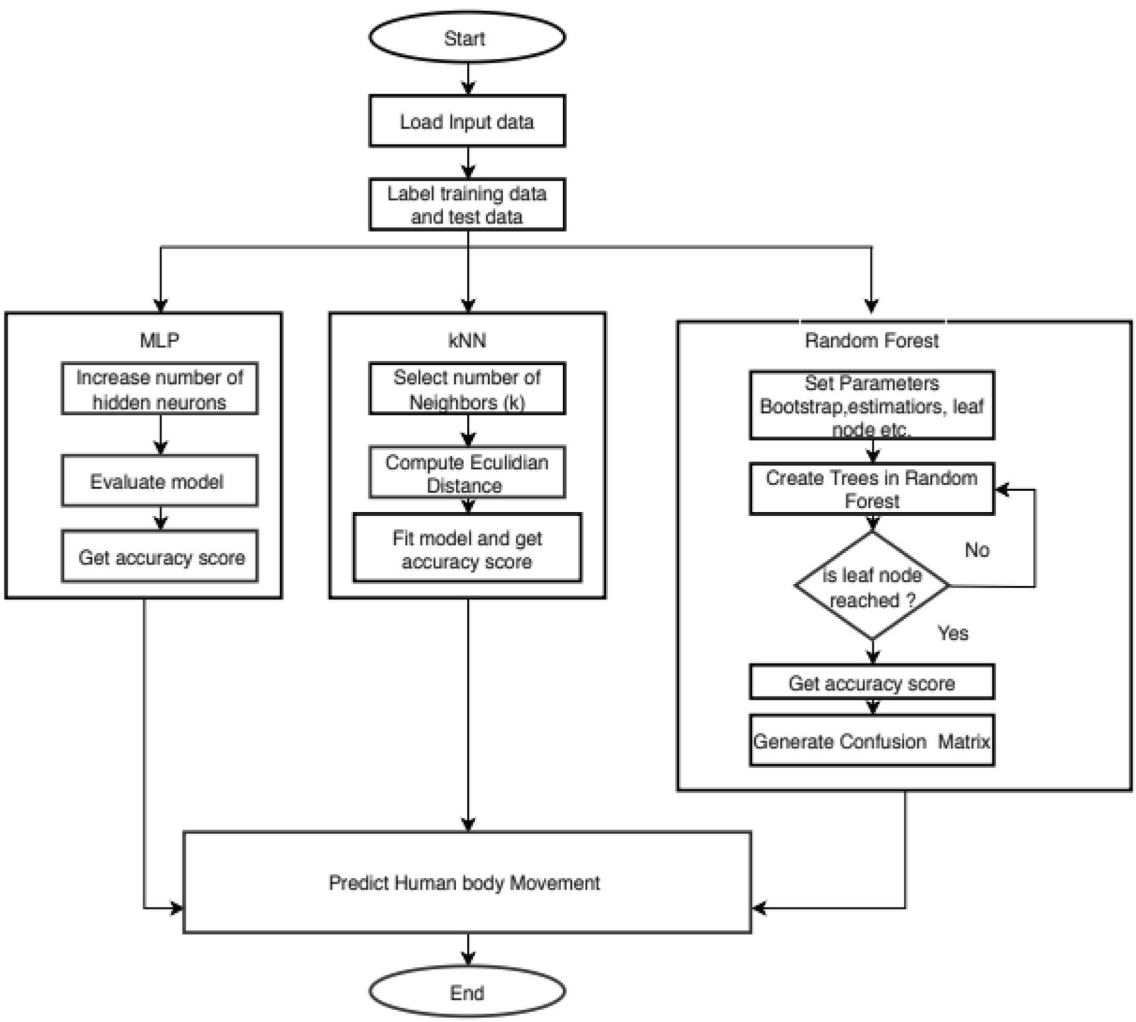

Fig. 3 A comparative flow chart of MLP, kNN and random forest algorithm

Table 6 Sample set for human body movement identification

Subject	Height (cm)	Movement	PL (dB)	SNR (dB)	BER ($\times 10^{-5}$)	P_r (dB)	Rb ($\times 10^{6}$) (bps)	RSSI(dB)	E_b ($\times 10^{-21}$) (J)	E_{rec} ($\times 10$^$^{-18}$) (J)
1	167	Sit	71.2725	26.46676	5.3938	− 141.2725	1.4989	− 89.1938	1.181	2.085
		Stand	71.3585	26.45628	5.4002	− 141.3585	1.4889	− 91.4765	1.182	2.029
		Walk	71.3756	26.45421	5.4015	− 141.3756	1.4879	− 91.5924	1.183	2.029
2	178	Sit	71.3585	26.45628	5.4002	− 141.3585	1.4998	− 91.4765	1.184	2.037
		Stand	71.4196	26.44885	5.4047	− 141.4196	1.4879	− 92.3754	1.183	1.965
		Walk	71.4234	26.44839	5.4051	− 141.4234	1.4869	− 92.4754	1.182	1.952
3	166	Sit	71.293	26.46426	5.3954	− 141.2930	1.4988	− 89.0938	1.181	2.053
		Stand	71.3585	26.45628	5.4002	− 141.3585	1.4879	− 91.3765	1.182	2.037
		Walk	71.3671	26.45524	5.4008	− 141.3671	1.4889	− 91.4265	1.183	1.946
4	175	Sit	71.288	26.46487	5.3949	− 141.2880	1.4998	− 90.0000	1.184	2.053
		Stand	71.3407	26.45845	5.3989	− 141.3407	1.4880	− 91.9337	1.183	1.965
		Walk	71.3628	26.45576	5.4006	− 141.3628	1.4878	− 92.1565	1.182	1.812
5	162	Sit	71.2725	26.46676	5.3938	− 141.2725	1.4987	− 89.7368	1.181	2.085
		Stand	71.3671	26.45524	5.4008	− 141.3671	1.4978	− 90.5110	1.182	1.939
		Walk	71.3839	26.45319	5.4021	− 141.3839	1.4973	− 90.1296	1.183	1.914
6	162	Sit	71.2286	26.47211	5.3905	− 141.2286	1.4997	− 89.1938	1.181	2.157
		Stand	71.3222	26.46071	5.3975	− 141.3222	1.4989	− 90.5210	1.182	2.007
		Walk	71.3407	26.45845	5.3989	− 141.3407	1.4984	− 90.5510	1.183	1.979
7	154	Sit	71.2511	26.46936	5.3922	− 141.2511	1.4999	− 88.1938	1.179	2.120
		Stand	71.3407	26.45845	5.3989	− 141.3407	1.4978	− 90.8815	1.181	1.979
		Walk	71.3585	26.45628	5.4002	− 141.3585	1.42975	− 90.5110	1.182	1.952
8	164	Sit	71.3127	26.46186	5.3968	− 141.3127	1.4987	− 90.2580	1.181	2.022
		Stand	71.3497	26.45736	5.3995	− 141.3497	1.4978	− 91.2418	1.182	1.965
		Walk	71.3839	26.45319	5.4021	− 141.3839	1.4973	− 91.5924	1.183	1.914
9	178	Sit	71.3222	26.46071	5.3975	− 141.3222	1.4998	− 90.5110	1.184	2.007
		Stand	71.3961	26.45171	5.4030	− 141.3961	1.4879	− 92.4836	1.183	1.939
		Walk	77.3971	26.45220	5.4040	− 141.3971	1.4869	− 92.0456	1.182	1.903
10	181	Sit	71.3452	26.45790	5.3992	− 141.3452	1.4998	− 91.1228	1.184	1.972
		Stand	71.3921	26.45219	5.4027	− 141.3921	1.4980	− 92.3754	1.183	1.902
		Walk	71.3981	26.45320	5.4050	− 141.3981	1.4978	− 92.3754	1.182	1.894
11	182.8	Sit	71.3497	26.45736	5.3995	− 141.3497	1.4998	− 91.2418	1.184	1.965
		Stand	71.4119	26.44978	5.4042	− 141.4119	1.4982	− 92.9073	1.183	1.933
		Walk	71.3981	26.45320	5.4050	− 141.3981	1.4979	− 92.4836	1.182	1.894
12	185.9	Sit	71.3628	26.45576	5.4006	− 141.3628	1.4968	− 91.5924	1.184	1.946
		Stand	71.4234	26.44839	5.4051	− 141.4234	1.4964	− 93.2163	1.183	1.857
		walk	71.4196	26.44885	5.4047	− 141.4196	1.4963	− 92.9073	1.182	1.863

Table 6 (continued)

Subject	Height (cm)	Movement	PL (dB)	SNR (dB)	BER ($\times 10^{-5}$)	P_r (dB)	Rb ($\times 10^6$) (bps)	RSSI(dB)	E_b ($\times 10^{-21}$) (J)	E_{rec} ($\times 10$^$^{-18}$) (J)
13	187.3	Sit	71.3756	26.45421	5.4015	−141.3756	1.4964	−91.9337	1.184	1.927
		Stand	71.4309	26.44748	5.4056	−141.4309	1.4962	−93.4183	1.183	1.847
		Walk	71.4309	26.44748	5.4056	−141.4309	1.4960	−93.0111	1.182	1.847
14	179.2	Sit	71.3407	26.45845	5.3989	−141.3407	1.4998	−91.0027	1.184	1.979
		Stand	71.3839	26.45319	5.4021	−141.3839	1.4980	−92.1565	1.183	1.914
		Walk	71.3961	26.45171	5.4030	−141.3961	1.4978	−92.2664	1.182	1.897
15	165	Sit	71.303	26.46304	5.3961	−141.3030	1.4998	−90.0000	1.181	2.037
		Stand	71.3585	26.45628	5.4002	−141.3585	1.4992	−91.4765	1.182	1.952
		Walk	71.3756	26.45421	5.4015	−141.3756	1.4990	−91.8209	1.183	1.927

Table 7 Simulation parameters

Parameters	Symbols	Values	References
Bandwidth	B	500 kHz	Yazdandoost et al. (2009)
Transmitted power	P_t	100 nw	Abbasi et al. (2016)
Noise variance	σ^2	− 171 dB	Abbasi et al. (2016)

5 Result and discussion

Performance of the proposed model has been evaluated in terms of pathloss, received power, received energy and link quality parameters (SNR, BER and RSSI, energy per bit). With these parameters human body movement detection has been carried out using machine learning techniques. Considering three human body movement (stand, sitting and walk) a data set has been created consisting of 300 readings of male and female subjects of the age group 45. IEEE 802.15.6 CM2 and CM3 pathloss models have been used to analyse the channel characteristics of proposed model. Simulation work has been carried out on MATLAB R2021a) and simulation parameters are listed in Table 7.

Figure 4 presents comparative plots of pathloss variation with distance. Figure 4a and b depicts pathloss comparison of combined channel with on body and in body respectively. There is a significant difference in pathloss computed for combined channel and individual channels (in body and on body) which indicates that combined pathloss dominates the signal quality. Further effect of human body movement on the pathloss with respect to distance has been depicted in Fig. 5. It is noticeable in Fig. 5a that with any physical movement of subject (sit, stand or walk) pathloss varies as distance get changed also when subject is walking pathloss is maximum in comparisons to other activities. In Fig. 5b normalized pathloss has been plotted with respect to distance to highlight the different human movement precisely.

In Fig. 6 SNR variation with respect to distance is presented. Figure 6a indicates that different human body movement affects the SNR values. The lowest SNR is received when subject is walking, it may be said that distance variation between communicating nodes is maximum when subject is walking and when subject is sitting best SNR value is obtained as shown in Fig. 6b with normalized output.

Figure 7 illustrates the relationship between SNR and pathloss. Figure 7a shows that higher the pathloss lower the SNR. Figure 7b exhibit normalized SNR where different human body movement may be recognized. Apart from SNR, BER is also one of the important parameters to examine the link quality as well as reliability of any channel model which is plotted in Fig. 8 with respect to SNR. Figure 8a indicates that during walking the BER is maximum. For more clarity normalized BER has been shown in Fig. 8b. Critical analysis of link quality parameters (pathloss, SNR

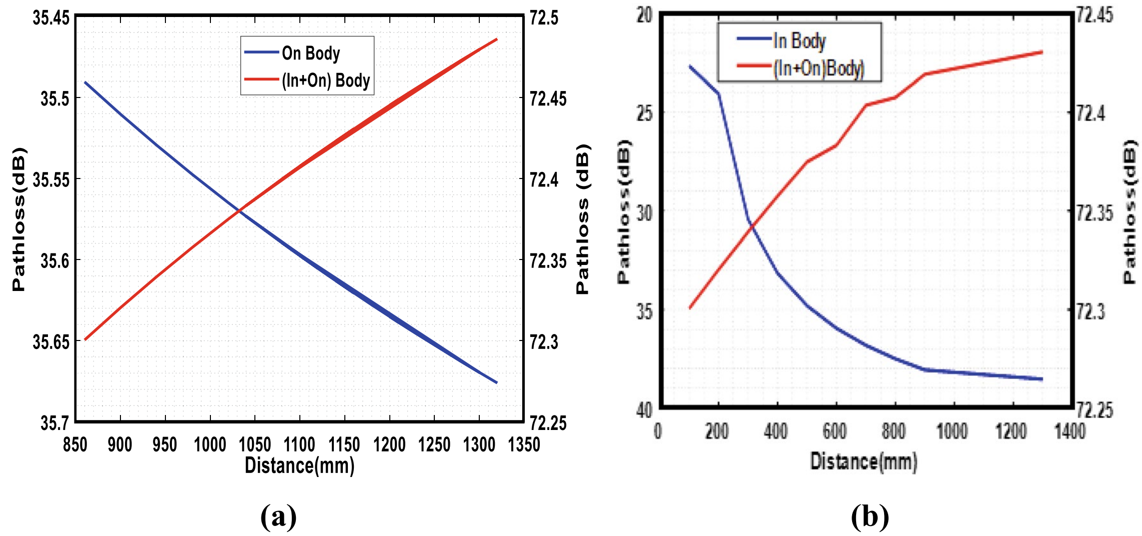

Fig. 4 Comparative plot of pathloss with distance **a** on body and (in body + on body) pathloss with distance **b** in body and (in body + on body) pathloss with distance

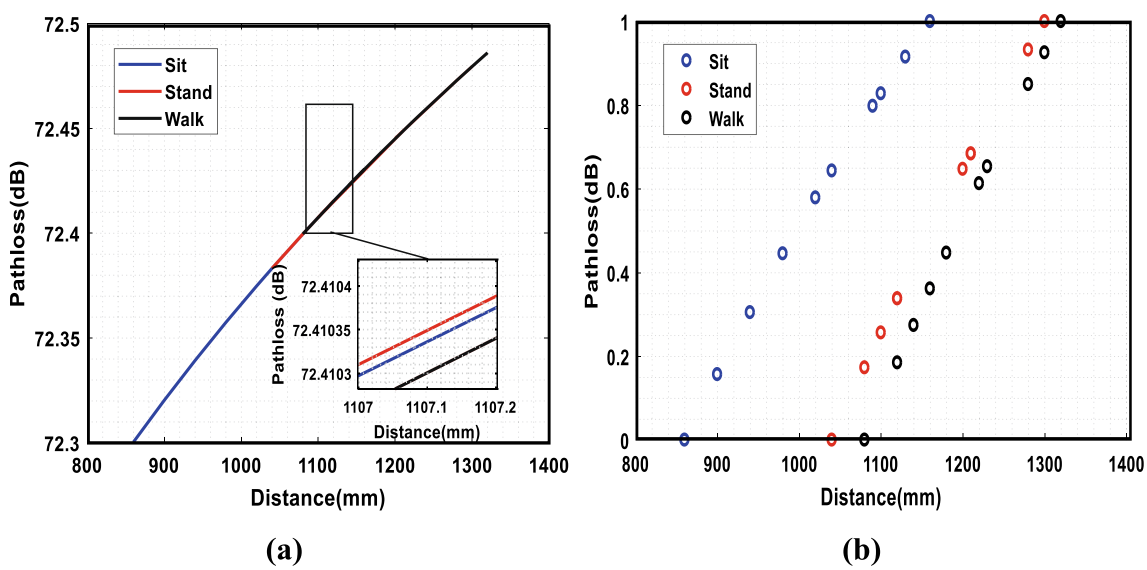

Fig. 5 Pathloss for different human body movement **a** pathloss with distance **b** normalized pathloss with distance

and BER) shows that human body movement affects the link quality which may be used to detect human body movement.

Figure 9 depicts the bit rate for different human body movements with respect to distance. Figure 9a shows that bit rate is impacted by increase in distance. Normalized plot of bit rate has been plotted in Fig. 9b which gives insight to differentiate human body movement.

Further human body movement detection using machine learning techniques (MLP, kNN and Random Forest algorithm) have been carried out. The Performance of Random Forest algorithm has been depicted in Fig. 10. Learning curves for loss and accuracy is shown in Fig. 10a which indicates that accuracy of Random Forest algorithm is 93.4% and loss is.049. Figure 10b illustrates plot of training and validation score. The gap between these two indicates that Random Forest fit the training data very well.

The confusion matrix is utilized to evaluate the performance of classifier. At the time of making predictions the confusion of classifier model is given by confusion matrix. In the matrix each sample is located mutually independent.

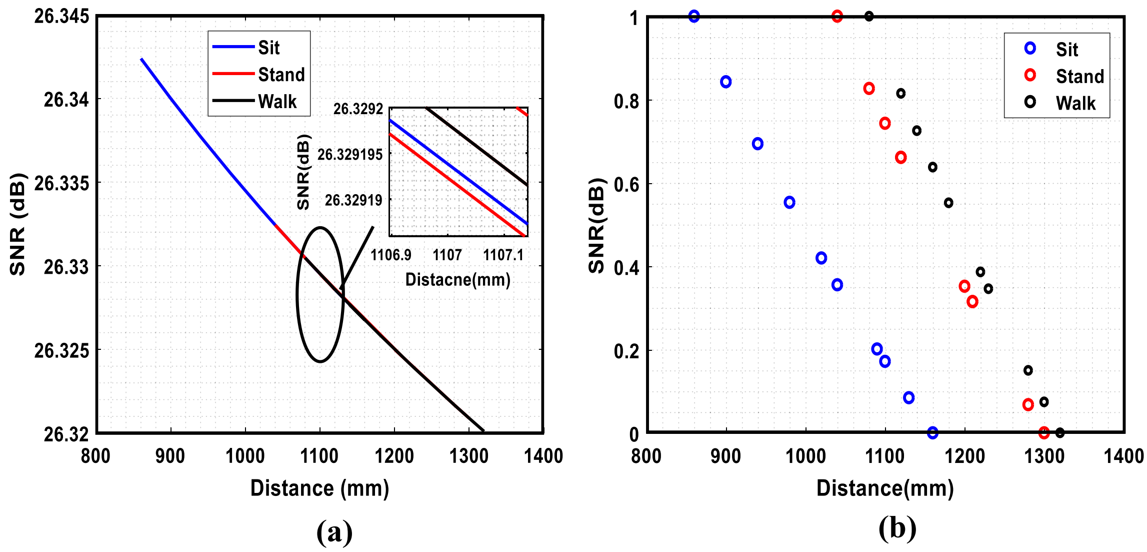

Fig. 6 SNR for different human body movement **a** SNR with distance **b** Normalized SNR with distance

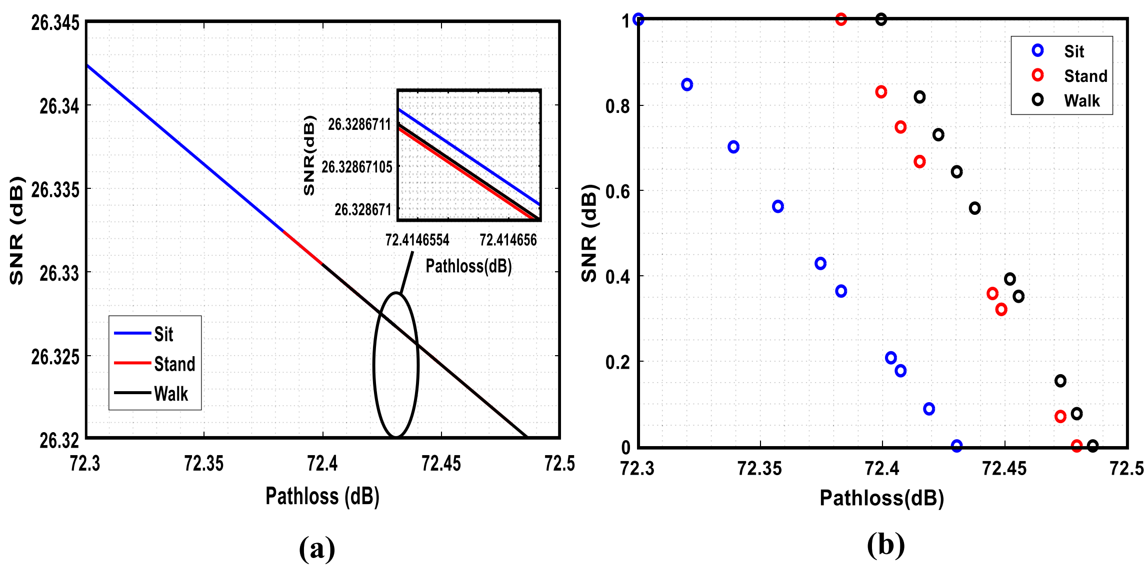

Fig. 7 SNR and pathloss relationship for different human body movement **a** SNR with pathloss **b** normalized SNR with pathloss

Original class is represented by rows and column represents the class as produced by classification model. The main diagonal values provide the correct predictions. For the sample set size of 160, 52 samples have been labelled under class "Sit" in Random Forest classifiers while for samples whose label is "stand" 51 samples classified correctly and 5 are misclassified and for label" Walk", 54 samples are correctly classified and six samples are incorrectly predicted. The accuracy of Random Forest classifiers is high in comparison to MLP and kNN. The results of this analysis show that Random Forest classifier performs better and gives high accuracy. The confusion matrix for different human body movement is presented in Table 8.

Further a comparative analysis of prediction accuracy of MLP, kNN and Random Forest algorithms has been carried out. The prediction accuracy obtained of MLP, kNN and Random Forest are 65.3%, 72.8%. and 93.4% respectively. A comparative chart of prediction accuracy and loss is shown in Fig. 11 which indicates that performance of Random Forest is best in comparison to MLP and kNN algorithms for the proposed model.

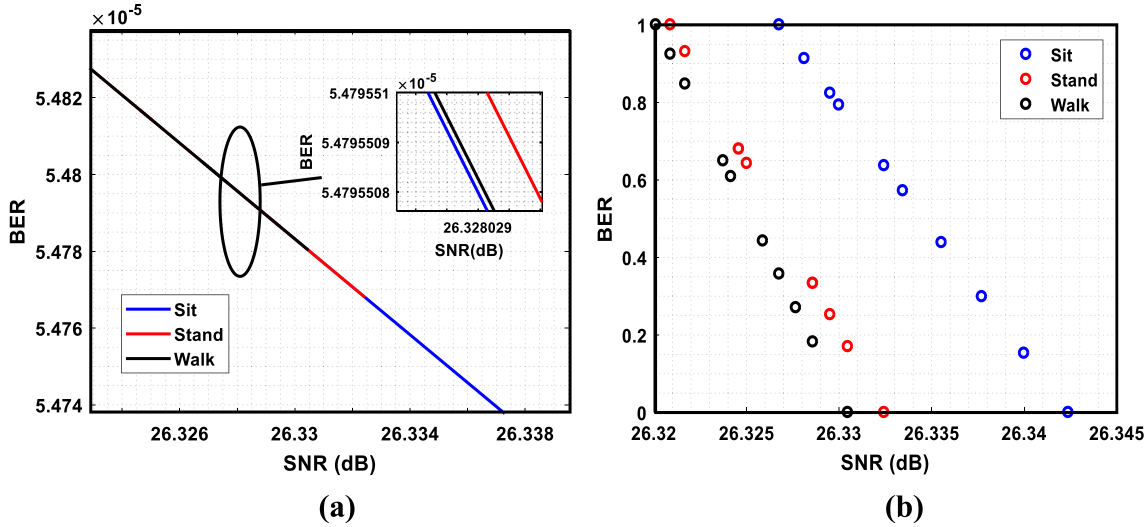

Fig. 8 Bit error rate analysis for different human body movement **a** BER vs SNR **b** bormalized BER with SNR

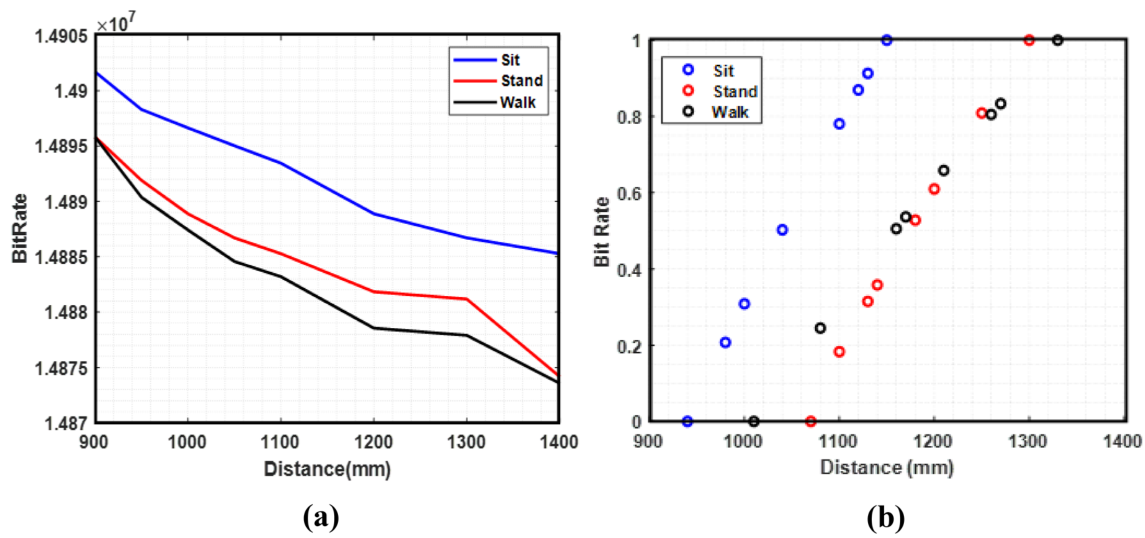

Fig. 9 **a** Bit rate w.r.t distance **b** normalized bit rate w.r.t distance

6 Conclusion

In the current work, the information signal received from implanted pacemaker has been analysed in terms of received power, received energy, pathloss, SNR, BER, bit rate, energy per bit and RSSI and detection of human body movement has been performed using Machine Learning techniques. For creation of data set three human body movements sit, stand and walk have been considered and evaluated for 160 subjects of the age group of 45. The data set comprises of various parameters like received power, received energy, pathloss, SNR, BER, bit rate, energy per bit and RSSI which have been evaluated using CM2 and CM3 models defined by IEEE 802.15.6. Further machine learning techniques have been applied to create the data set for human body movement using MLP, kNN and Random Forest. From the critical comparative analysis for Machine Learning algorithms it has been observed that movement of human body can be detected from the created data set with an accuracy of 65.3%, 72.8% and 93.4% for MLP, kNN and Random Forest respectively. Random Forest algorithm shows promising performance than MLP and kNN. The proposed model and approach will prove beneficial in the monitoring of human body movement of patient using an already deployed in body sensor device.

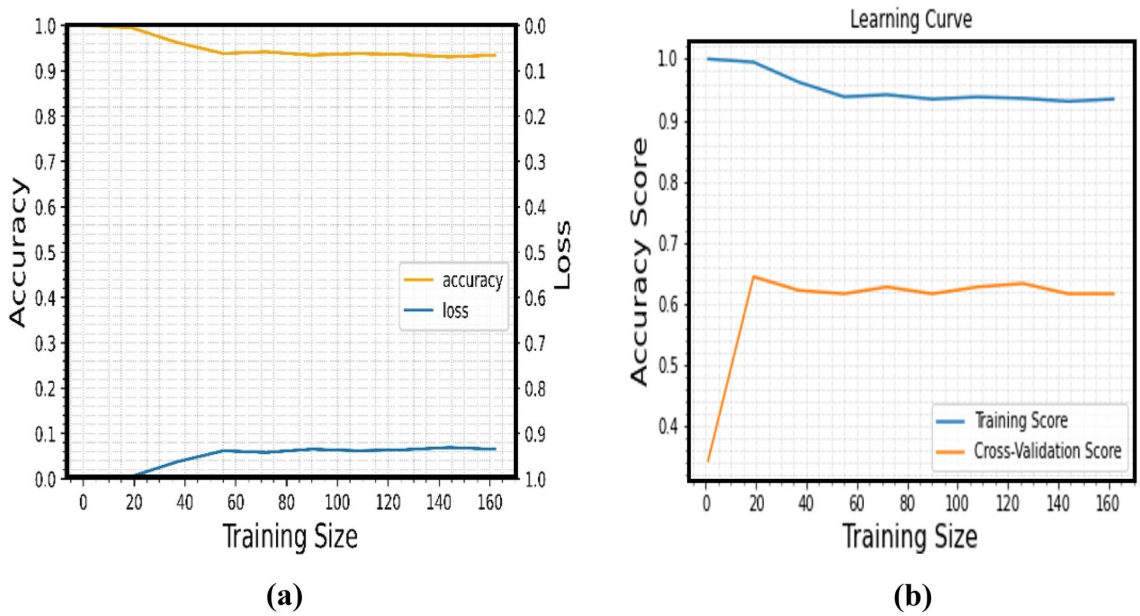

Fig. 10 Learning curve and loss curve **a** accuracy and loss curve **b** training and validation score

Fig. 11 Prediction accuracy comparison

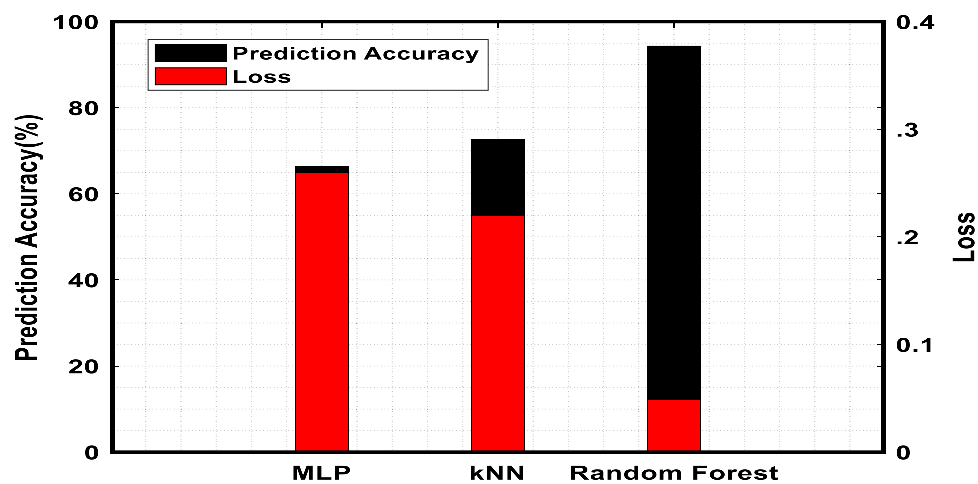

Table 8 Confusion matrix

Class	Sit	Stand	Walk
Sit	52	0	0
Stand	1	51	4
Walk	0	6	54

References

Abbasi QH et al (2016) Terahertz channel characterization inside the human skin for nano-scale body-centric networks. IEEE Trans Terahertz Sci Technol 6(3):427–434

Ali N, Neagu D, Trundle P (2019) Evaluation of k-nearest neighbour classifier performance for heterogeneous data sets. SN Appl Sci 1(12):1559

Andreu-Perez J, Leff DR, Ip HM, Yang GZ (2015) From wearable sensors to smart implants—toward pervasive and personalized healthcare. IEEE Trans Biomed Eng 62(12):2750–2762

Archasantisuk S, Aoyagi T (2015) The human movement identification using the radio signal strength in WBAN. In: 2015 9th International symposium on medical information and communication technology (ISMICT), pp 59–63

Arora N, Gupta SH, Kumar B (2020) An approach to investigate the best location for the central node placement for energy efficient WBAN. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-01847-w

Ayodele TO (2010) Introduction to machine learning. New advances in machine learning. IntechOpen, pp 1–9

Betke M, Gips J, Fleming P (2002) The camera mouse: visual tracking of body features to provide computer access for people with severe disabilities. IEEE Trans Neural Syst Rehabil Eng 10(1):1–10

Bilro L, Oliveira JG, Pinto JL, Nogueira RN (2011) A reliable low-cost wireless and wearable gait monitoring system based on a plastic optical fibre sensor. Meas Sci Technol 22(4):045801

Breiman L (2001) Random forests. Mach Learn 45(1):5–32

Buke A, Gaoli F, Yongcai W, Lei S, Zhiqi Y (2015) Healthcare algorithms by wearable inertial sensors: a survey. China Commu 12(4):1–12

Camurri A, Mazzarino B, Volpe G, Morasso P, Priano F, Re C (2003) Application of multimedia techniques in the physical rehabilitation of Parkinson's patients. J Vis Comput Anim 14(5):269–278

Casale P et al (2011) Human activity recognition from accelerometer data using a wearable device. In: Iberian conference on pattern recognition and image analysis, pp 289–296

Cavallari R, Martelli F, Rosini R, Buratti C, Verdone R (2014) A survey on wireless body area networks: technologies and design challenges. IEEE Commun Surv Tutor 16(3):1635–1657

Chen BR, Patel S, Buckley T, Rednic R, McClure DJ, Shih L, Tarsy D, Welsh M, Bonato P (2010) A web-based system for home monitoring of patients with Parkinson's disease using wearable sensors. IEEE Trans Biomed Eng 58(3):831–836

Che X, Abdelwahed YS, Wang X, Fang Y, Wang L (2020) Pacemaker implantation in patients with major depression, should it be of concern? A case report and literature review. BMC Cardiovasc Disord 20(1):1–5

Cuesta-Vargas AI et al (2010) The use of inertial sensors system for human motion analysis. Phys Ther Rev 15(6):462–473

Gallager R (2008) References. Principles of digital communication. Cambridge University Press, Cambridge

Gupta SH, Devarajan N (2020) Performance exploration of on-body WBAN using CM3A-IEEE 802.15. 6 channel model. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-019-01663-x

Gupta SH, Sharma A, Mohta M, Rajawat A (2020) Hand movement classification from measured scattering parameters using deep convolutional neural network. Measurement 151:107258

Jagannath J, Polosky N, Jagannath A, Restuccia F, Melodia T (2019) Machine learning for wireless communications in the Internet of Things: a comprehensive survey. Ad Hoc Netw 93:101913

Kaushik M, Gupta SH, Balyan V (2020) Power optimization of invivo sensor node operating at terahertz band using PSO. Optik 202:163530

Kwapisz JR, Weiss GM, Moore SA (2011) Activity recognition using cell phone accelerometers. ACM SIGKDD Explor Newsl 12(2):74–82

Lara OD, Labrador MA (2012) A survey on human activity recognition using wearable sensors. IEEE Commun Surv Tutor 15(3):1192–1209

Alinia et al. (2015) Impact of sensor misplacement on estimating metabolic equivalent of task with wearables. In: 2015 IEEE 12th international conference on wearable and implantable body sensor networks (BSN), pp 1–6

Liaw A, Wiener M (2002) Classification and regression by randomForest. R news 2(3):18–22

Liu T, Inoue Y, Shibata K, Zheng R (2007) Measurement of human lower limb orientations and ground reaction forces using wearable sensor systems. In: 2007 IEEE/ASME international conference on advanced intelligent mechatronics, pp 1–6

Malasinghe LP, Ramzan N, Dahal K (2019) Remote patient monitoring: a comprehensive study. J Ambient Intell Humaniz Comput 10(1):57–76

Mandala S, Di TC (2017) ECG parameters for malignant ventricular arrhythmias: a comprehensive review. J Med Biol Eng 37(4):441–453

Martin CG, Turkelson SL (2006) Nursing care of the patient undergoing coronary artery bypass grafting. J Cardiovasc Nurs 21(2):109–117

Merli F, Bolomey L, Gorostidi F, Barrandon Y, Meurville E, Skrivervik AK (2011) In vitro and in vivo operation of a wireless body sensor node. In: International conference on wireless mobile communication and healthcare, pp 103–110

Mishra R (2019) Determinants of cardiovascular disease and sequential decision-making for treatment among women: a Heckman's approach. SSM Popul Health 7:100365

Negra R, Jemili I, Zemmari A, Mosbah M, Belghith A (2018) WBAN path loss based approach for human activity recognition with machine learning techniques. In: 2018 14th international wireless communications and mobile computing conference (IWCMC), pp 470–475

Patel S, Park H, Bonato P, Chan L, Rodgers M (2012) A review of wearable sensors and systems with application in rehabilitation. J Neuroeng Rehabil 9(1):21

Peng Y, Peng L (2016) A cooperative transmission strategy for body-area networks in healthcare systems. IEEE Access 4:9155–9162

Proakis JG, Salehi M (2014) Digital communications, 5th edn. McGraw Hill Education

Rappaport TS (1996) Wireless communications: principles and practice, vol 2. Prentice Hall, New Jersey

Ray S (2019) A quick review of machine learning algorithms. In: 2019 international conference on machine learning, big data, cloud and parallel computing (COMITCon), pp 35–39

Rose DJ, Christina RW (1997) A multilevel approach to the study of motor control and learning. Allyn and Bacon

Seiffert M, Holstein F, Schlosser R, Schiller J (2017) Next generation cooperative wearables: generalized activity assessment computed fully distributed within a wireless body area network. IEEE Access 5:16793–16807

Shi WV, Zhou M (2011) Body sensors applied in pacemakers: a survey. IEEE Sens J 12(6):1817–1827. https://doi.org/10.1109/JSEN.2011.2177256

Simeone O (2018) A very brief introduction to machine learning with applications to communication systems. IEEE Trans Cogn Commun Netw 4(4):648–664

Snegalatha D, Anand J, Seetharaman B, John B (2019) Knowledge and attitude regarding permanent pacemaker and the quality of life of patients after permanent pacemaker implantation. Indian J Contin Nurs Educ 20(1):33

Soliman SS et al (2012) Exact analysis of dual-hop AF maximum end-to-end SNR relay selection. IEEE Trans Commun 60(8):2135–2145

Solomatine DP (2003) Applications of data-driven modelling and machine learning in control of water resources. Computational intelligence in control. IGI Global, pp 197–217

Thakur D, Biswas S (2020) Smartphone based human activity monitoring and recognition using ML and DL: a comprehensive survey. J Ambient Intell Humaniz Comput 11:1–12

Wahid F, Ghazali R, Fayaz M, Shah AS (2017) Statistical feature-based approach (sfba) for hourly energy consumption prediction using neural network. Networks 8:9

Wu JMT, Tsai MH, Xiao SH, Liaw YP (2020) A deep neural network electrocardiogram analysis framework for left ventricular hypertrophy prediction. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-020-01826-1

Yazdandoost KY, Sayrafian-Pour K (2009) Channel model for body area network (ban). In: IEEE P802. 15 working group for wireless personal area networks (WPANs). IEEE P802. 15-08-0780-10, pp 6.

Zhang D, Xia F, Yang Z, Yao L, Zhao W (2010) Localization technologies for indoor human tracking. In: 2010 5th international conference on future information technology. https://doi.org/10.1109/FUTURETECH.2010.5482731