Wireless Body Area Networks Using Machine Learning

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ABSTRACT

The purpose of this work is to employ machine learning methods and algorithms to find pathloss in Wireless Body Area Network(WBAN).The Wireless Networks used on the human body faces many challenges when the sensor placed node positions are in a moving state and losses are also occurred due to the environmental conditions. This study covers the most prevalent pathlosses that occur when sending bio-signals using machine learning. Using the provided methodologies, the various combinations of inputs are used to produce an accurate result. These machine learning algorithms are implemented by running it on Python IDLE(Integrated Development and Learning Environment).This strategy used is to achieve the goal of finding path loss in WBAN.

Keyword: *Convolutional Neural Network Algorithm(CNN), Support Vector Machine Algorithm(SVM), Logistic Regression Algorithm , Decision tree Algorithm , Random forest Algorithm*

1. INTRODUCTION

The Wireless Body Area Network (WBAN) has become a challenging one in current era for constantly monitoring the patient's health. They operate under a good condition if in an idle state. The problem occurs only when the network is in an unstable state due to various effects caused by changing the postures of body. Inorder WBAN to work in a good state, path losses during the transmission of bio signals can be detected. Path loss is caused by a variety of factors including energy absorption, reflection, diffraction, body shadowing, and body position. Classification of datasets will help to overcome these problems. This is done by using machine learning technique which will train the models. The path loss that occurs while monitoring a patient can be detected only when the patient is in a moving state. These are classified as lossless state and path loss state. Path Loss in Wireless Body Area Network(WBAN) is occurred when the body is in certain positions such as standing, walking, running, jumping states etc.... The advantages of the proposed method over the existing methods are highlighted below. Here We have used five algorithms to train our model and the one with more accuracy is chosen to be the best among the other algorithms.

2. LITERATURE SURVEY

Path loss models for distant WBAN (Wireless Body Area Network) have been established, but an advanced model is needed to detect the path loss in complex environments more effectively and easily. In this system there are three key methods are used. They are Grounded multi-dimensional retrogression using an artificial neural network (ANN), grounded friction analysis with a Gaussian process, and backed point selection with a principle element analysis (PCA). Multiple attributes such as distance, antenna height, and others are included in the estimated path loss dataset. Diverse methods like as Support Vector Machine Algorithm (SVM), Artificial Neural Network Algorithm (ANN), Arbitrary timber, and K-Nearest Neighbour (KNN) Algorithm have been used to create path loss models in this system. ANN models provide more accurate path loss detection than the methodological approaches. Machine learning techniques including feature extraction, Artificial Neural Network (ANN), and Gaussian method are used to predict path loss. The trials and testing were created to evaluate if applying a combination of ANN-MLP and Gaussian Process, data reduction might provide the similar losses in path, and in prediciting precision and also provide a dependable position in the retrogression problem. The four-point model's complexity was decreased using the PCA technique, resulting in a more general solution with one point and a considerable reduction in training phase. When compared to the four-variable prototype, one variable prototype in ANN and Gaussian process takes nearly 10, 1 during the training period. The statistics model integrates traction from GP to generate a shade effect by implying friction from GP. The system's expected result is the concerted path loss and shadowing model, appropriately predicts observed losses in the path that has a content fault of ,whereas the conventional direct long distant and long shadowing model has a content error of under 12. The case design of a very efficient wireless detector system would benefit from the proposed strategy.

2.1 MINIATURIZED SENSORS IN WBAN

Abbass Nasser, Guillaume Andrieux, Nour Charara(2021).The document explains the architectural constraints of the available WBAN network and illustrates the technologies, problems, and many features of WBAN. Usage of Power, WBAN control, and tolerance of malfunctions are all included into the WBAN system's framework. This WBAN network mainly focuses on monitoring remotely the older or ill people, which also includes other factors such as reliability, recurrence, regularity, throughput, connectivity. This article uses the most recent LPWAN wireless technologies, which are used as a way out for WBAN healthcare monitoring. The authors highlight the key problems with WBAN systems, such as the challenge of minimising energy consumption, the coexistence of wireless technologies, and others, along with a list of the basic characteristics of WBAN systems and circumstances of potential WBAN operations. This study explores how wireless technologies are changing Internet of Things (IoT) healthcare systems and outlines a potential route for enhancing Quality of Service by utilising the advanced technologies. From the standpoint of protecting confidential information, the authors of examine the capabilities of WBAN, its technologies, and a more comprehensive understanding of WBAN. Various types of tiny Wireless sensor are presented and analyzed.

2.2 CHRONIC HEART DISEASE IDENTIFICATION USING WBAN

H. M. Ramalingam, M. Pallikonda Rajasekaran, and H.R. Nagesh (2020) Several ways for implementing wireless sensors and high-performance computing interfaces have been presented. A new method for identifying chronic heart diseases was presented in this paper. A data transmission with no loss can be used for treating heart disease. This also describes the different MAC protocols in use, as well as the benefits and challenges. In this paper, the authors have used a variety of wearable bio sensors and physiological signal devices to construct a healthcare monitoring system which allows patients to monitor their health condition. Security and proper data transmissions are considered for the construction of wireless sensor network used in healthcare operations. There was a diverse operation particular comparison of the performance of Wireless detector networks in mortal health monitoring, exertion monitoring, connection in sports, and handicap support. The use of distributed computing in wireless sensor networks to access the patient's physiological indications is also taken into consideration. Patient monitoring through a new framework folds higher computing. Multiple sensors cloud designs for health care applications were used, along with different analyses. The use of different load balancing in grid and cloud computing was tested with, and several platforms to accomplish the same were also explained. A java-based application was presented to make the use of computer resources in a protein sequencing investigation. In this researchfor Wireless Sensor Network(WSN) implementation Java-based parallel processing framework was considered as a better choice.

2.3 AUTHENTICATION SYSTEM USING WBAN

PandiVijiyakumar, Mohammad S. Obaidat (2020).The authentication method for WBANs that gives long-term security is based on the use of bilinear pairing. This is robust to impersonation attacks. It can also reduce the amount of computation needed on the client side. Users' location privacy, however, it is not secured.It is mainly based on participant session keys, which expire after a set amount of time to protect unborn transmissions. There is still no way to remove the illegal users. in their location privacy protection model. T A generates location data and sends it to the user via the wireless network once the user has used the location service. Shen et al. proposed a cloud-assisted lightweight certificateless authentication approach for WBANs that maintains user privacy. However, patients' personal privacy is not secured. The authentication method proposed in this research differs from previously published identification and location privacy maintaining schemes in five ways. To begin, the suggested approach protects patients and doctors true identities from other network users in a computationally efficient manner. Second, when sensitive information is exchanged between the patient and the doctor, the security of the information is protected. Moreover, a minimal harmful user cancellation technique is offered to cancel problematic users in the WBAN system. Fourth, protection of the privacy is enhanced in the provided sensitive information. The location privacy of the patients is secured from unauthorized network entities.

3. PROPOSED METHODOLOGY

The methodology for path loss classification and detection is a step-by-step procedure. Reading data from the dataset is the initial stage. Then the pre-processing is completed in the Python IDLE. As the datasets are unlabelled, clustering and grouping is done. Training is given to the available datasets. They are divided into two categories: no path loss and path loss. After that, the loss prototypes are given a number of samples with more attributes and trained for experimental analysis. This procedure used a number of algorithms. In WBAN, the general algorithm for path loss classification and detection is illustrated in Figure 1.

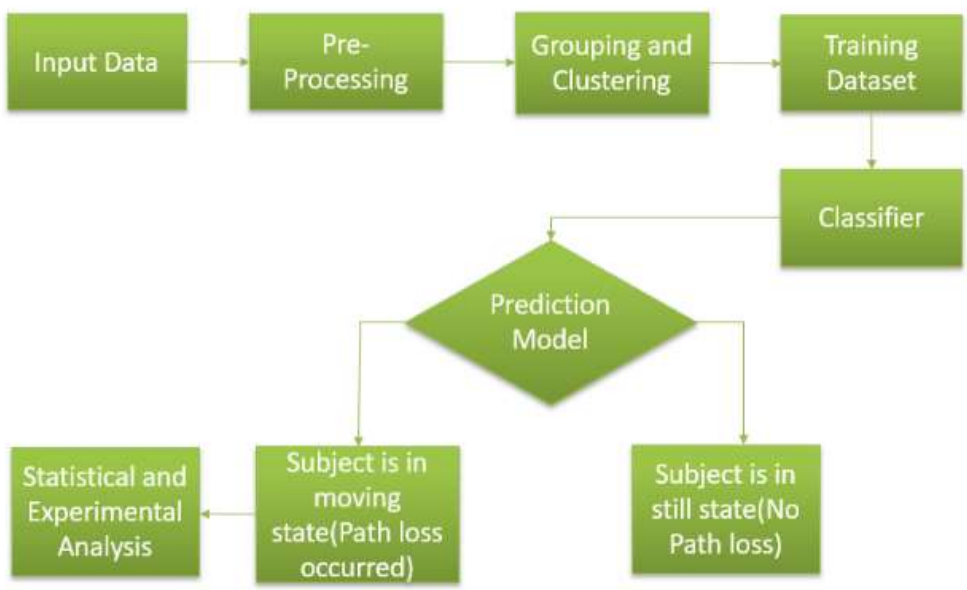

Fig-1 Proposed workflow

Wireless Body Area Network works under a balanced condition if in a still state. If any dynamic condition occurs in the system, it results in Path loss. These Path losses may occur due to natural conditions or caused due to any movements in the subject. In this proposed system, python IDLE is used for the detection and classification of path losses. At first level, the Received Signal Strength Indicator values (RSSI) in the dataset are unlabelled hence grouping and clustering is done. The RSSI values are compared with the preloaded datasets and path loss is detected as a result. The dataset serves as the training set for the algorithm that will be used to identify events as they happen. In this dataset, the RSSI values at various positions on the human subjects like left leg, right leg, chest, centre waist, left arm & foot, right arm & foot are present.

	chest	left leg	right leg	left foot	right foot	center waist	left arm	right arm	left hand	right foot.1	cluster
0	-47	-59	-51	-63	-64	-50	-48	-39	-43	-57	1
1	-47	-59	-50	-66	-70	-50	-48	-37	-47	-54	0
2	-47	-60	-50	-61	-60	-50	-43	-37	-47	-54	1
3	-47	-65	-49	-61	-60	-68	-43	-36	-42	-54	1
4	-47	-65	-55	-66	-64	-68	-43	-37	-46	-63	0
5	-47	-60	-55	-64	-71	-68	-43	-37	-46	-63	0
6	-46	-59	-53	-64	-71	-56	-43	-38	-46	-63	0
7	-46	-59	-51	-63	-63	-56	-43	-38	-43	-67	0
8	-46	-72	-51	-63	-63	-56	-43	-38	-43	-67	0
9	-42	-65	-52	-68	-63	-46	-43	-37	-47	-67	0
10	-42	-65	-52	-61	-71	-46	-43	-38	-41	-63	0
11	-42	-59	-52	-64	-62	-46	-42	-38	-41	-63	1
12	-39	-59	-49	-64	-62	-65	-42	-36	-46	-63	1
13	-39	-59	-46	-60	-63	-65	-42	-38	-41	-59	1
14	-39	-79	-46	-63	-71	-65	-41	-38	-41	-59	0
15	-46	-61	-54	-63	-71	-58	-41	-34	-43	-59	0

Fig-2 Clustered dataset

The above dataset given in Figure.2 is clustered dataset used for detection of Path Loss.

3.1 CLASSIFIED DATASET

There is no path loss under usual conditions. We notice some path loss in the subject as it is moving. The dataset for classification is shown below (Figure 3). The website from which the datasets are taken, is given below: Kaggle.com/dataset/guanslong/wban-rssi-dataset.

	chest	left leg	right leg	left foot	right foot	center waist	left arm	right arm	left hand	right foot.1
0	-47	-59	-51	-63	-64	-50	-48	-39	-43	-57
1	-47	-59	-50	-66	-70	-50	-48	-37	-47	-54
2	-47	-60	-50	-61	-60	-50	-43	-37	-47	-54
3	-47	-65	-49	-61	-60	-68	-43	-36	-42	-54
4	-47	-65	-55	-66	-64	-68	-43	-37	-46	-63
5	-47	-60	-55	-64	-71	-68	-43	-37	-46	-63
6	-46	-59	-53	-64	-71	-56	-43	-38	-46	-63
7	-46	-59	-51	-63	-63	-56	-43	-38	-43	-67
8	-46	-72	-51	-63	-63	-56	-43	-38	-43	-67
9	-42	-65	-52	-63	-63	-46	-43	-37	-47	-67
10	-42	-65	-52	-61	-71	-46	-43	-38	-41	-63
11	-42	-59	-52	-64	-62	-46	-42	-38	-41	-63
12	-39	-59	-49	-64	-62	-65	-42	-36	-46	-63
13	-39	-59	-46	-60	-63	-65	-42	-38	-41	-59
14	-39	-79	-46	-63	-71	-65	-41	-38	-41	-59
15	-46	-61	-54	-63	-71	-58	-41	-34	-43	-59

Fig-3 Classification Dataset

3.2 CLASSIFICATION ALGORITHM

SVM (Support Vector Machine), is a prominent and efficient analyzer. Either linear data or non-linear data can be classified using SVM. SVM continues to perform properly now because of its ability to detect path loss signals over other techniques.

4. EXPERIMENTAL RESULTS

The main objective of this project are the identification and characterization of wireless body area network problems. The results of the same are examined below. Datasets from sensors attached to various body parts of human body were used to construct machine learning algorithms for loss identification and prediction. The most precise application's result is also shown here. The total number of loss and lossless values given in the dataset are depicted .

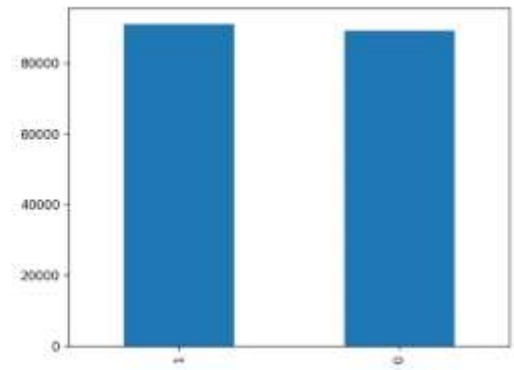

Fig-4 Classification and detection dataset range

Since, we have features without labels, we use K-means Cluster algorithm, a unsupervised learning algorithm because we don't know which values are loss and lossless. After grouping, the count of values as zeros and ones are shown in the above figure 4

4.1 PARAMETER DISTRIBUTION

The distribution of data in different parts of body are depicted using displot and its values are shown as histogram plot in the below figure 5. Sensors can be placed in any or all of these positions as wearable or in-plant sensors.

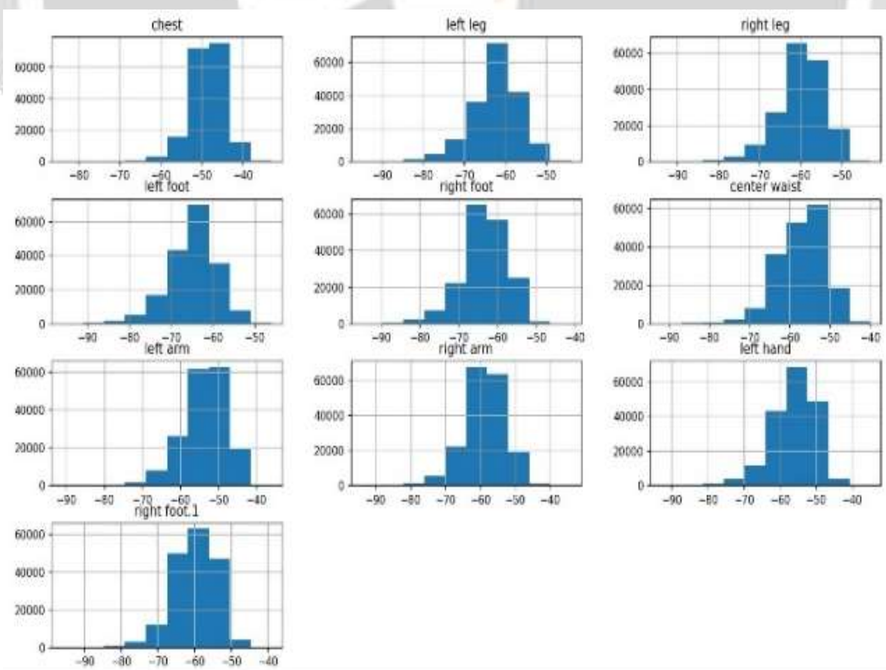

Fig-5 Attributes distribution Chart

4.2 DISPLOT WITH ATTRIBUTES

The increased and decreased values for each attributes (Different positions of sensor) are displayed below,

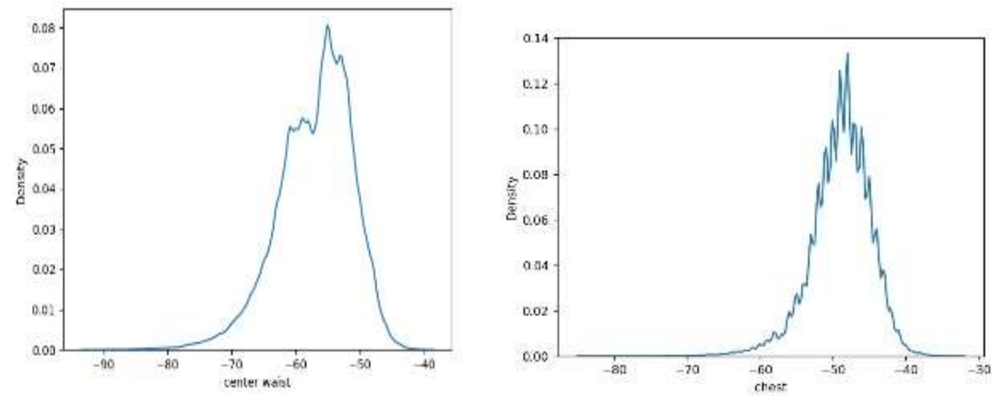

Fig-6 Centre waist and Chest

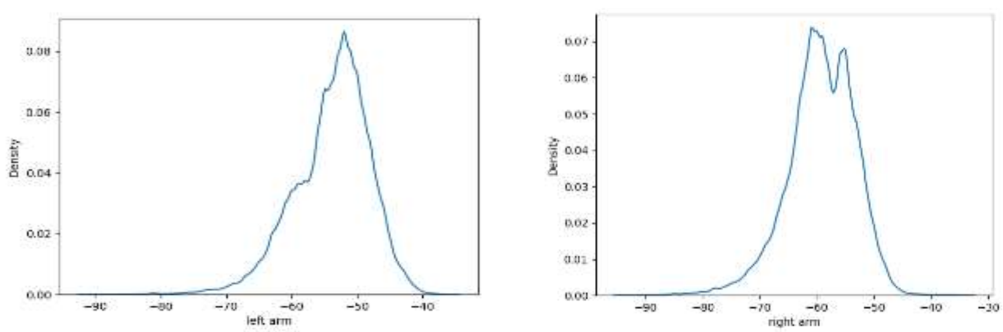

Fig-7 Left Arm and Right Arm

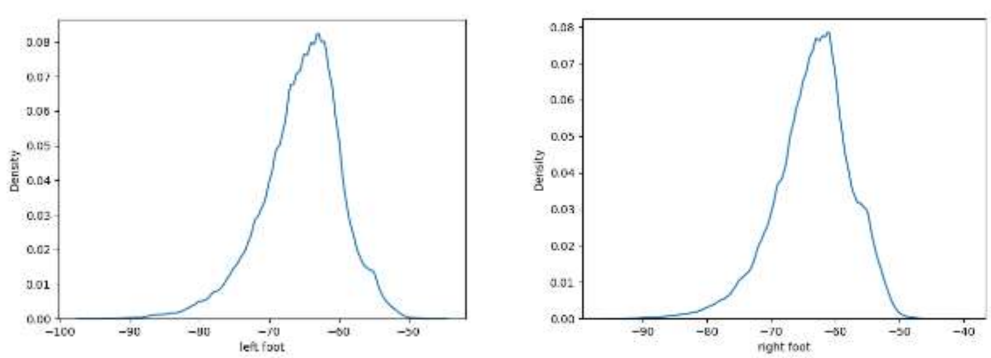

Fig-8 Left Foot and Right Foot

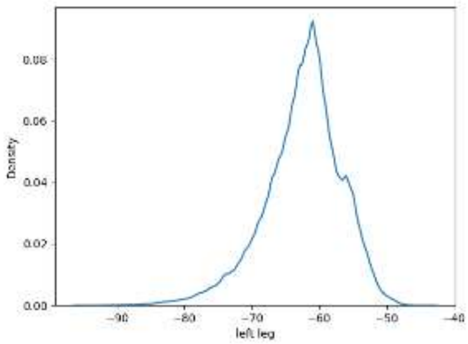

Fig-9 Left Leg and Right Leg

4.3 DATA LOSS AND ACCURACY

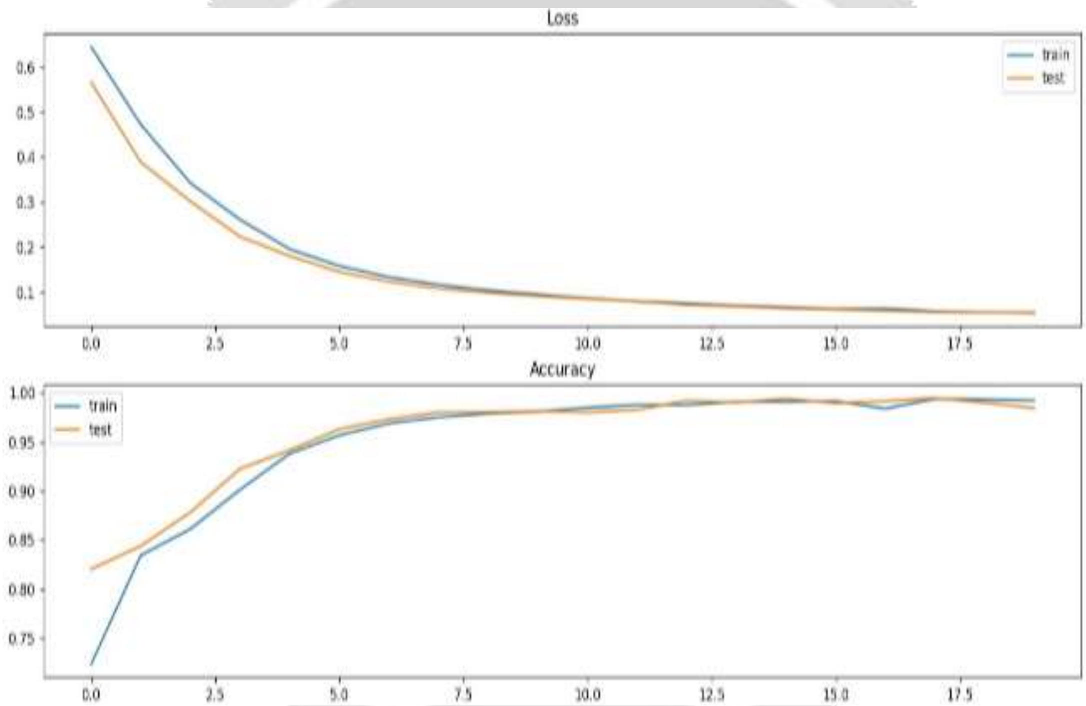

Fig-10 Data Loss and Accuracy

The above figure 10 shows the Data Loss and Accuracy calculated using CNN Algorithm for train and test data values. Different Algorithms are employed to train the dataset. The algorithm with more precise output is identified. Logistic Regression, Support Vector Machine Algorithm, Decision Tree Algorithm, Random Forest Algorithm and CNN(Convolution Neural Network) are the algorithms used for detection.

4.4 CONFUSION MATRIX FOR VARIOUS ALGORITHMS

The Confusion matrix is a matrix utilized to assess how well categorized models perform for a specific set of test data. It can only be decisive if the true values for test data are known.

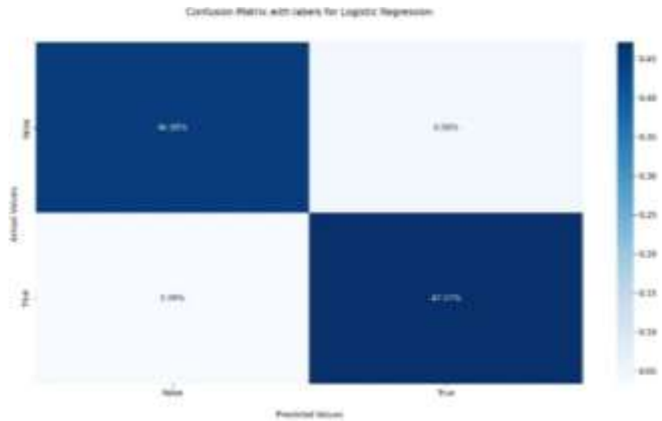

Fig-11 Logistic Regression model

The score of Logistic Regression,

```
Accuracy of Logistic Regression:  0.9204797867614394
              precision    recall  f1-score   support

           0       0.93      0.91      0.92     17844
           1       0.91      0.93      0.92     18172

    accuracy                           0.92     36016
   macro avg       0.92      0.92      0.92     36016
weighted avg       0.92      0.92      0.92     36016
```

The above figure 11 shows that Confusion Matrix has predicted the True Positive(TP), True Negative(TN), False Positive(FP), False Negative(FN) values which can estimate Loss value.

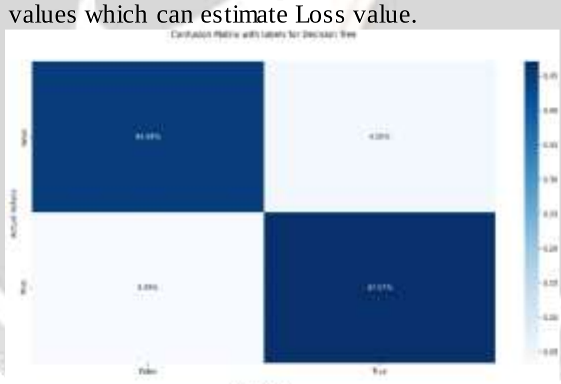

Fig-12 Decision Tree Model

The score of Decision Tree Classifier,

```
Accuracy of Decision Tree:  0.9255330964015993
              precision    recall  f1-score   support

           0       0.93      0.91      0.92     17844
           1       0.91      0.93      0.92     18172

    accuracy                           0.92     36016
   macro avg       0.92      0.92      0.92     36016
weighted avg       0.92      0.92      0.92     36016
```

Figure 12 illustrates the precision and the f1-score of Decision Tree Algorithm

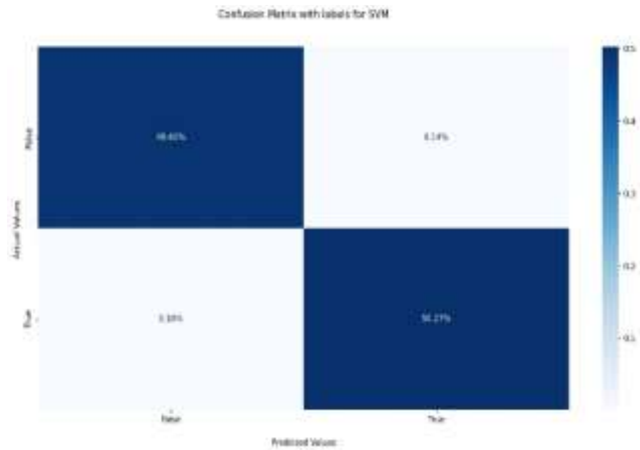

Fig-13 SVM Model

The score of Support Vector Machine(SVM) algorithm,

Accuracy of SVM: 0.9967514438027544

	precision	recall	f1-score	support
0	1.00	1.00	1.00	17844
1	1.00	1.00	1.00	18172
accuracy			1.00	36016
macro avg	1.00	1.00	1.00	36016
weighted avg	1.00	1.00	1.00	36016

Figure 13 illustrates the precision and the f1-score of Support Vector Machine Algorithm

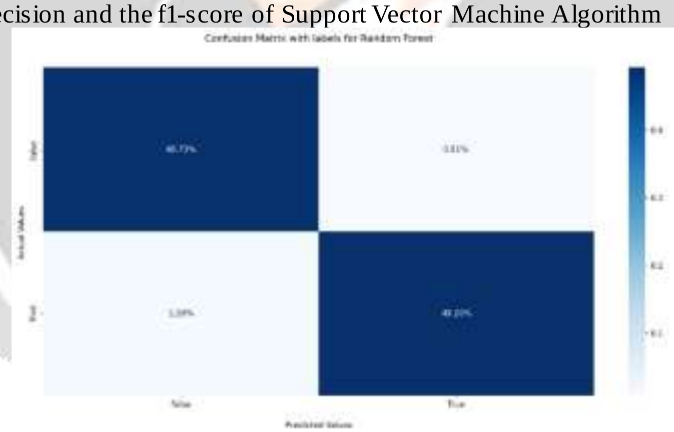

Fig-14 Random Forest Classifier Model

The score of Random Forest Algorithm,

Accuracy of Random Forest: 0.9792869835628609

	precision	recall	f1-score	support
0	0.97	0.98	0.98	17844
1	0.98	0.98	0.98	18172
accuracy			0.98	36016
macro avg	0.98	0.98	0.98	36016
weighted avg	0.98	0.98	0.98	36016

Figure 14 illustrates the precision and f1-score of Random Forest Algorithm

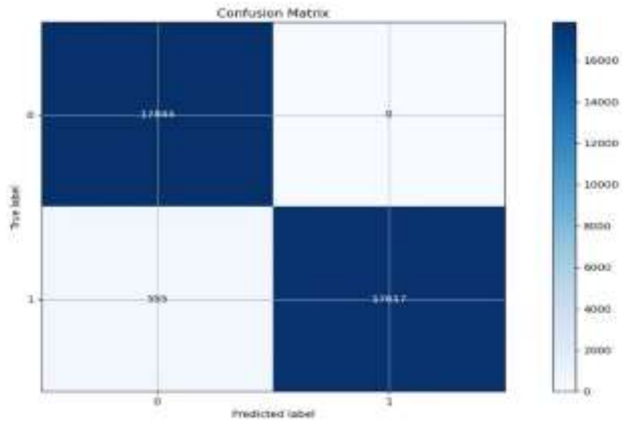

Fig-15 CNN

The score of CNN model,

```
Accuracy of CNN:  0.9869224788982675
              precision    recall  f1-score   support

           0       0.97      1.00      0.99     17844
           1       1.00      0.97      0.99     18172

    accuracy                           0.99     36016
   macro avg       0.99      0.99      0.99     36016
weighted avg       0.99      0.99      0.99     36016
```

Figure 15 illustrates the precision and f1-score of CNN Algorithm

```
The accuracy score of Logistic Regression : 0.9204797867614394 %
The accuracy score of Decision Tree : 0.9255330964015993 %
The accuracy score of SVM : 0.9967514438027544 %
The accuracy score of Random Forest : 0.9792869835628609 %
The accuracy score of CNN : 0.9775655264326966 %
>>>
```

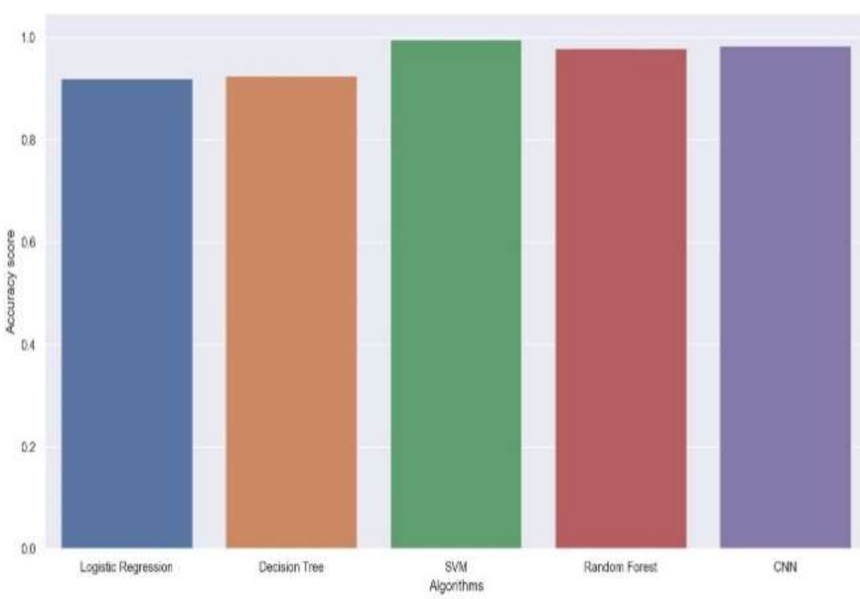

Fig-16 Algorithms Comparison

Classifier	Accuracy	Precision	Recall	F1 Score	Sensitivity	Specificity
Logistic Regression	92.04%	0.91	0.93	0.92	0.9137	0.9274
Decision Tree	92.55%	0.91	0.93	0.92	0.9079	0.9328
Random Forest	97.92%	0.97	0.98	0.98	0.9836	0.9750
SVM	99.67%	1.00	1.00	1.00	0.9971	0.9964
CNN	98.69%	1.00	0.97	0.99	1.0000	0.9694

Fig-17 Parameter Analysis

From the above table, SVM has better accuracy, precision, recall, sensitivity, specificity in PathLoss Detection in WBAN compared to the other models as it is able to detect all the path loss occured in bio- signals in an effective manner.Whereas in other models, path loss is not detected in complex cases. The Labelling process decides whether the algorithms are accurate. A comparison is made based on the score of all the algorithms used, SVM(Support Vector Machine) has achieved the highest score of 0.9967 and hence it is considered to the best one.

5. CONCLUSION

In this paper pathloss occurred while transmitting the bio-signals is detected using various Machine learning algorithms. The accuracy for pathloss detection is detected using various algorithms and the efficient one is used. The diagnosis process may perform better when using original data, and extending the size of dataset will also improve the precision of the classifiers which are being used. In the scope of WBAN systems, which involve prompt evaluation for real-time management, the precision and the time taken for training is the most important factor to consider when determining the optimum machine learning method. For effective medical diagnosis and convenience, WBAN will require advancements in energy conservation and control, versatile reflectors and more durable materials that comply with high frequency range, low Resonance equipment, and bandwidth functioning.

6. REFERENCES

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