PEOPLE'S DEMOCRATIC REPUBLIC OF ALGERIA

MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH

MOHAMED BOUDIAF UNIVERSITY - M'SILA

FACULTY: MATHEMATICS AND COMPUTING SCIENCE

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1985

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Université Mohamed Boudiaf - M'sila

DOMAIN: MATHEMATICS AND COMPUTING SCIENCE

SECTOR: COMPUTING SCIENCE

OPTION: IDO

Thesis presented for obtaining

academic master's degree

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Subject

ANOMALY DIAGNOSIS IN WIRELESS BODY AREA NETWORKS

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University year: 2023/2024

DEDICATIONS

I would like to dedicate this thesis to my parents, whose unwavering support, encouragement, and love have been my driving force.

May God bless them.

My precious brothers, sisters, and family who've been there for me throughout my entire journey.

Finally, a special dedicate to my partner at work "Lina"

All of my friends and colleague.

Cheyma Chenih

DEDICATIONS

I dedicate this humble work to my generous parents,

who supported me during my studies.

May God bless them.

To my siblings and all my generous family and friends.

And to my precious colleague "Cheyma".

Lakhneche Fatima Lina

THANKS

First and foremost, we express our heartfelt thanks to God Almighty for granting us the will, strength, and courage to overcome all obstacles and complete this work.

We wish to express our sincere gratitude to our supervisor,

Dr. Bahache Mohamed, for his invaluable advice and guidance.

Our appreciation also extends to the jury for their time and effort in evaluating our work.

Lastly, we thank all the teachers in the Faculty of Mathematics and Computer for their dedication and support throughout our years of study.

Thank you all.

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ABBREVIATIONS LIST

IEEE	Institute of Electrical and Electronics Engineers
IOT	Internet of Things
MAD	Median Absolute Deviation
MM	Markov Model
SVM	Support vector machine
WBAN	Wireless Body Area Network
WSN	Wireless sensor networks
SVM	Support Vector Machine
MV	Majority Voting
KNN	K-Nearest Neighbor
SOM	Self organizing map
ROC	Receiver operating characteristic
ECG	Electrocardiogram
RMSE	Root Mean Square Error
LPU	Local Processing Unit
HR	Heart rate
SpO2	Oxygenation ratio
TP	True Positives
TN	True Negatives
FP	False Positives
FN	False Negatives

General introduction

In recent decades, data from the U.S. Census Bureau shows that rising life expectancy worldwide has led to an increase in the elderly population. Globally, the percentage of elderly individuals grew from 6.9% in 2015 to an anticipated 12% by 2025. In Europe, this demographic is projected to rise from 14.08% to 19.37% over the same period, while in the United States, it is expected to increase from 15.5% in 2015 to 24.3% by 2025. Cardiovascular diseases are the leading cause of death worldwide, with heart disease causing approximately 17 million deaths in 2019. Access to healthcare can mitigate several diseases, including Parkinson's disease, kidney problems, Alzheimer's disease, and others.

Furthermore, the COVID-19 pandemic, which has persisted since 2019, has claimed many lives globally. In the first year of the pandemic, many hospitals and health centers were overwhelmed, and many individuals avoided these facilities for other essential treatments. In this context, the importance of integrating Wireless Body Area Networks (WBANs) and the Internet of Things (IoT) becomes even more significant. This integrated system would enhance treatment and disease management.

However, designing a WBAN is a highly delicate endeavor that involves numerous challenges. These range from developing small and lightweight mobile devices that do not excessively interfere with patients' lifestyles or compromise their health, to ensuring the secure and reliable operation of the network.

Many techniques used to detect faults have been proposed for WBANs, these techniques may be classified as machine learning and statistics.

This dissertation is organized into four chapters dealing with relevant topics. After the general introduction, Chapter one introduces Body Sensor Networks (WBANs), and we give a general outline of WBANs, their architectures, application areas, topologies, and the communication technologies they use. In the second chapter considered as background in which we present the essential theoretical concepts used to detect faults in WBANs .In the third is devoted to previous work on techniques used for fault detection in WBANs, the fourth chapter is reserved to the experimentation.

CHAPTER 1

Wireless body area network basics

CHAPTER 1
WIRELESS BODY AREA NETWORK BASICS

1. Introduction

Over the years, the dynamic field of WBANs has gained much interest, mainly due to new and exciting developments in microelectronics and wireless communications. The criteria for adopting such a technology must are strict, including reliability, energy efficiency, and low device complexity this requires the design of new protocols specifically intended for WBANs to set them apart from the typical sensor networks widely known as general-purpose. Consequently, substantial research efforts as well as a standardization process have been underway recently. In this chapter, we provide an overview of WBANs covering their architecture and application areas, communication technologies, and challenges facing such network.

2. Sensor definition

Sensors are devices that convert physical events or conditions into quantifiable signals, they detect and measure various phenomena in the environment. Sensors are critical components in systems that monitor and control conditions in numerous industries and applications. They can be classified according to the type of physical quantity they measure, such as temperature, pressure, humidity, light intensity, sound level, and chemical composition. Sensor characteristics include sensitivity, accuracy, and resolution.
The figure 1.1, presents the essential components of a sensor node, these components are: sensing module, communication module, processing module and energy module.

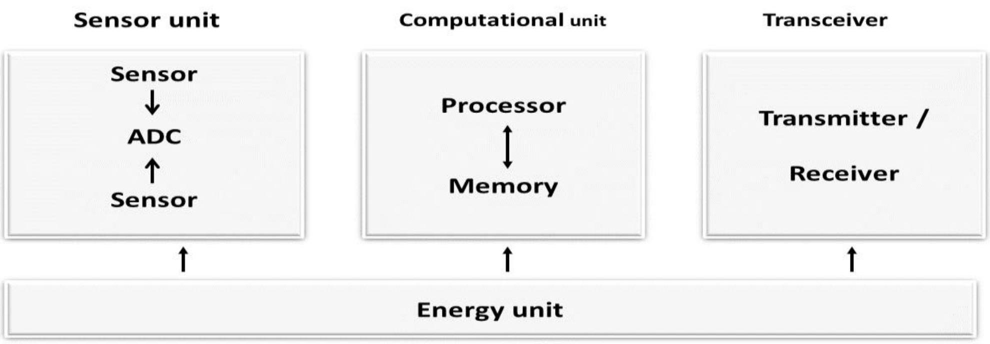


Figure 1.1: Sensor Node Architecture. [1]

3. WSN defenition

Wireless sensor networks (WSN) typically consist of thousands of sensor nodes, each of which is capable of sensing, processing, and transmitting environmental information and used to monitor specific physical phenomena or detect and track specific objects in an area of interest. Since sensor nodes are limited batter power, energy-efficient information processing is crucial for extended network operation.

as shown in figure 2.1 :

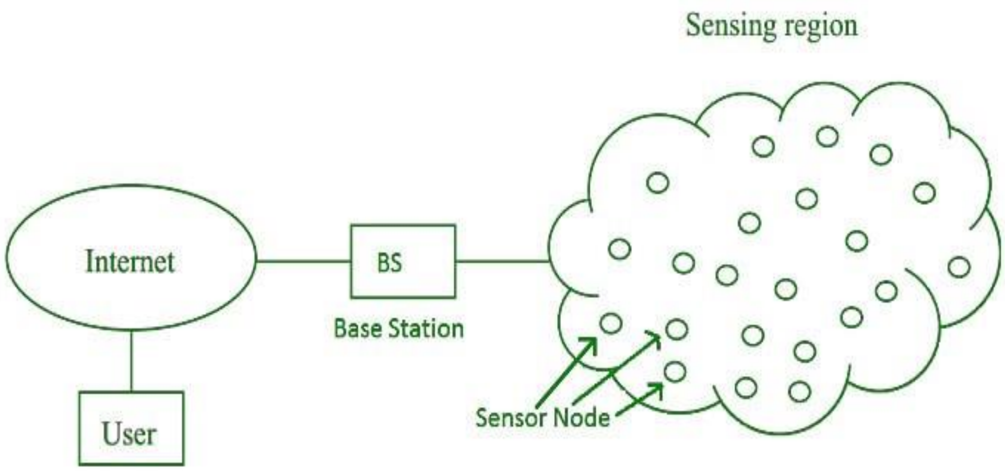


Figure 2.1: Wireless sensor networks (WSN). [2]

4. Wireless body area network (WBAN) definition

Wireless body area network (WBAN) is a network system designed to connect wearable health sensors directly attached to or near a patient’s body, enabling communication and data transfer. These networks are used in healthcare to ensure effective monitoring of physiological parameters such as blood pressure, heart rate, respiratory rate and body temperature. WBANs facilitate fast data transfer, allowing the health care worker to monitor patients' health conditions and make timely decisions regarding medical intervention. WBAN plays a role in improving healthcare delivery by providing treatment to patients and enabling rapid intervention strategies.
as shown in figure 3.1:

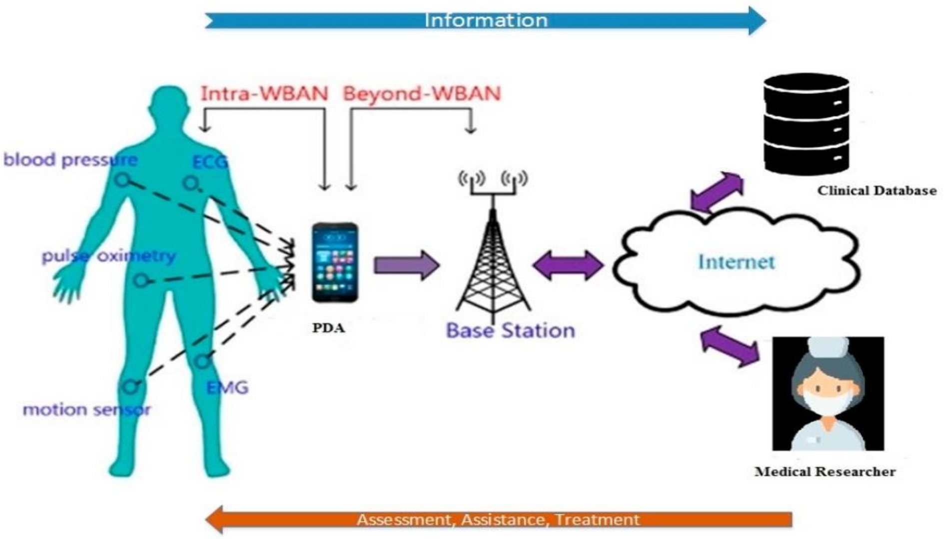


Figure 3.1: wireless body area network. [2]

5. Body sensor functions

The following table shows some body sensor functions:

Sensor	Description
ECG	The heart's electrical activity
Blood pressure	The force applied by the circulation of blood on the walls of the blood vessels
Body temperature	An indicator of the body's ability to create and release heat
Respiration rate	Number of inhale and exhale movements per unit time
Oxygen level	Indicates the oxygen that is flowing in the patient's blood
Heart rate	The frequency of the cardiac cycle
Blood sugar	Measures the amount of sugar (type, source, energy) in the blood

Table 1.1: Various medical sensors deployed on the human body. [3]

6. Body sensor network architecture

The design of body sensors can be categorized into three levels as shown in figure 4.1:

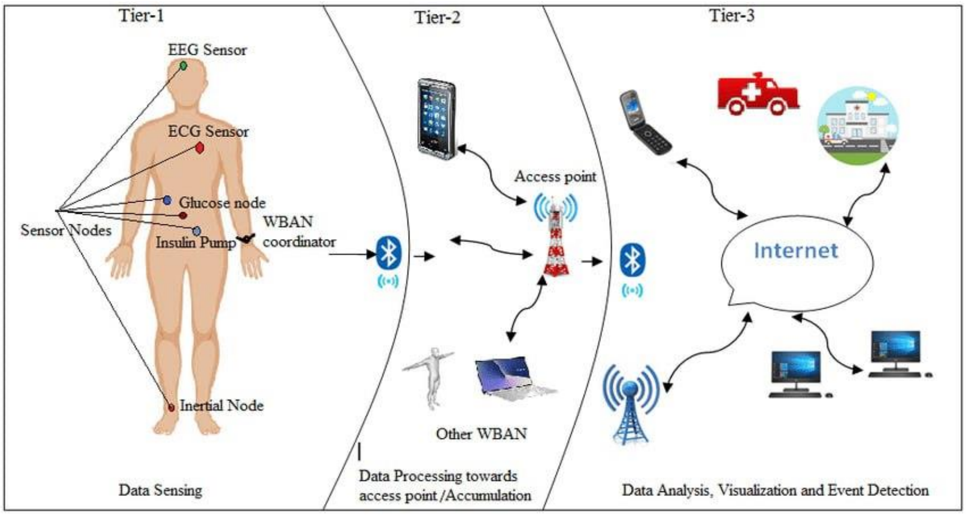


Figure 4.1: Architecture of Wireless Body Sensor Networks. [4]

Tier-1: Medical sensor nodes are implanted on or in the human body along with the sinkhole located at this level**.** [2]

Tier- 2: Sensor nodes transmit the data to the sinkhole, and the data are then transmitted to the BS by aggregating and processing the data. [2]

Tier-3: After the data are received by the BS, they are transmitted to the medical centre through the Internet infrastructure for remote monitoring and treatment. In general, in the architecture of this type of network, each sensor monitors the individual's health by receiving the sensory information from the patient's body, then sending the data to sink node before transfer to the BS to call for medical. [2]

7. Wireless Communication Technologies

In the area of short-range wireless networks, various types of short-range wireless technologies can be utilized at different stages. Within this section, we will provide an overview of the most prevalent technologies, including Bluetooth [5], ZigBee [5], WIFI [5], and IEEE 802.15.6[5], all of which can be implemented for the deployment of WBAN:

7.1. Bluetooth

Bluetooth is a wireless communications technology that uses short UHF radio waves in the ISM band between 2.4 and 2.485 GHz. It is operated by the Bluetooth Specialist Group (SIG), which has more than 35,000 member companies in the fields of telecommunications, computers, networking and electronics.[5]

7.2. ZigBee

ZigBee is a wireless communications standard designed for low power, low data rate, and Near Field communications. It is based on IEEE 802.15.4 and is used in a variety of applications such as home use, industrial control, and medical data collection. [5]

7.3. WIFI

WiFi is a networking technology that uses radio waves to create a high-speed Internet connection. It is based on IEEE 802.11 standards and is widely used in local area network equipment and Internet devices. [5]

7.4. IEEE 802.15.6

IEEE 802.15.6 is an international wireless communication standard that has been specifically designed for Wireless Body Area Networks (WBAN). It supports both in-body and on-body communication and has been optimized for low-power, short-range devices. It is used in a variety of applications, including medical and non-medical applications. [5]

8. Difference between WSNs and WBANs

Wireless Sensor Networks (WSNs) and Wireless Body Area Networks (WBANs) share certain similarities but also exhibit notable differences. The following table (2) will delineate the key distinctions between these two networks.

WSNs	**WBANs**
Cover the environment	Cover the human body
Large number of nodes	Fewer sensor nodes
Multiple dedicated sensors	Single multitasking sensors
Lower accuracy	Robust and accurate
Resistant to noise	Predictable environment
Failure reversible	Failure irreversible
Fixed structure	Variable structure
Low level security	High security
Accessible power supply	Inaccessible power source
High power demand	Lower power availability
Wireless solutions available	Lower power wireless
Data loss less of an issue	Sensitive to data loss

Table 2.1: Difference between WSNs and WBANs. [6]

9. WBAN applications

WBAN applications are increasingly recognized for their potential across various fields, including the medical domain and beyond.

9.1. In medical applications

WBANs play a pivotal role in enhancing healthcare delivery, facilitating investigative monitoring, and improving patient care. They enable remote patient monitoring, timely health status updates, emergency communication, and notification systems, ultimately leading to improved doctor-patient interactions.[7]

9.2. In non-medical applications

WBANs are utilized in various sectors such as sports, military, and entertainment.

- **In sport**

  WBANs are utilized in various sectors such as sports, military, and entertainment. [7]
- **In the military**

  WBANs are employed for communication between troops on the battlefield and data relay to enhance situational awareness and coordination.[7]
- **In entertainment**

  WBANs can monitor performers' vital signs or enhance interactive experiences through physiological data tracking. [7]

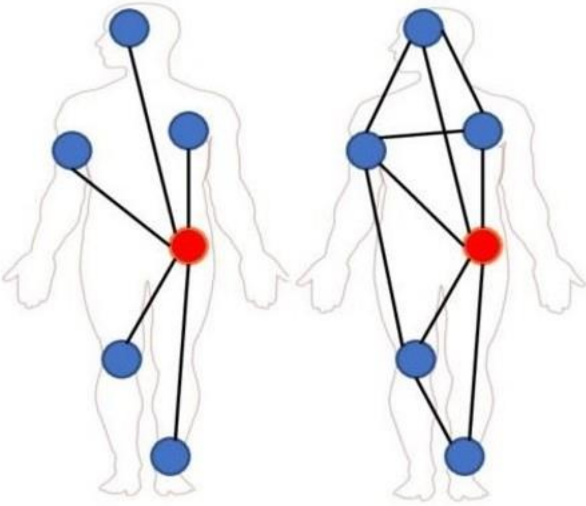
10. WBAN topologies

There are two topologies that we have identified thus far:

The first is the star topology, which involves all nodes on the network sending data to a central collector unit.

The second is the hybrid mesh-star method, which establishes communication among the coordinating units of each group. In the event of problems in one node, the other nodes are notified immediately. This topology also incorporates collector units and bridges to facilitate connections to broader networks.

The structure of a mesh-star composite topology involves nodes connected to a central node. Another characteristic of these networks is their hierarchical structure. This network is designed to continuously receive large amounts of data, which microprocessors must then extract and process in order to extract the necessary data and properties.



Star topology(a) mesh topology (b)

Figure 5.1: Topology structure in WBAN. [8]

11. WBAN challenges

The technical challenges that need to be addressed in Wireless Body Area Networks (WBANs) primarily revolve around security and privacy concerns. These challenges are crucial for ensuring the confidentiality, integrity, and privacy of patients' health records. Additionally, wins face other challenging techniques, which are as follows:

11.1. Challenges related to the Mac layer

Since wireless sensor networks are always monitoring the human body, and they must send sensitive and important data of the human body to the medical teams at any moment, so it is useful to establish a system able to classify the sensed data, and to distinguish between the faulty and abnormal data, also there are concerns about the delay in sending vital and important information.

In order to reduce the dela in critical information sending, it is recommended to use quality control services that can prioritize essential and sensitive information and send it with the least delay. Using the technique of sending sensitive information directly is another method to reduce the delay, which is recommended. [9]

11.2. Challenges related to the Network layer

WBAN body sensor network traffic by itself can cause energy consumption and create bottlenecks if proper routing protocols are not utilized. For this purpose, to reduce energy consumption and distribute traffic in a balanced way, it is recommended to use router protocols that have load-balancing capabilities. Furthermore, using quality and weight control and prioritizing network traffic can eliminate the bottleneck. [9]

11.3. Challenges related to the transportation layer

It is necessary to have a highly reliable transport mechanism to be able to provide vital and essential information instantly and quickly in the case of data loss since, in WBAN, correct data delivery is very sensitive, and the loss of, destruction of, and damage to vital body information during sending can increase the risk of death. In order to reduce energy consumption, this system can use a periodic or periodical system for recording and reporting unnecessary information. [9]

11.4. Application layer challenges

As this layer is responsible for communicating with the user in the form of an interface at the highest level, having an intelligent mechanism that can send rich and meaningful information in medical environments seems crucial. For this purpose, it is possible to use intelligent methods of artificial intelligence and machine learning algorithms in this layer to use more valuable information to produce knowledge and experience.[9]

12. Conclusion

In this chapter, we have introduced wireless body sensor networks. After a general definition of sensors and wireless sensor networks (WSN), we discussed the body sensor network architecture and wireless communication technologies, comparing WBAN and WSN.

Finally, we identified some of the challenges and problems that the proposed technology may face. In the next chapter, we will discuss fault detection and some of the algorithms that detect errors and false alarms in WBANs.

CHAPTER 2

Background

CHAPTER 2
BACKGROUND

1. Introduction

In this chapter, we will present few technics that have commonly used to detect faults in WBANs, when it happens. These technics are: Decision tree, SVM, LR …

2. Machine learning

2.1. Decision Tree

2.1.1. Definition

Decision tree is a supervised classification model, created through algorithmic methods that determine ways to split a data set based on various criteria. It is one of the most widely used and practical methods in supervised learning. A decision tree is a tree-like graph whose nodes represent where we select attributes and ask questions. Edges represent answers to questions and leaves represent actual outputs or class labels, which are used for nonlinear decisions with simple linear decision surfaces[11]. Decision Trees have O(Nlog(N)Pk) complexity.[12]

Let's look at the basic components of the decision trees:

1. **Root Node:** It represents the entire population or sample, and this further gets divided into two or more homogeneous sets.
2. **Leaf/ Terminal Node:** Nodes do not split is called Leaf or Terminal node.
3. **Decision Node:** When a sub-node splits into further sub-nodes, then it is called a decision node.
4. **Branch / Sub-Tree:** A subsection of the entire tree is called a branch or sub-tree.
5. **Parent and Child Node:** A node, which is divided into sub-nodes, is called the parent node of sub-nodes, whereas sub-nodes are the child of the parent node.
6. **Splitting:** It is a process of dividing a node into two or more sub-nodes.
7. **Pruning:** Pruning is when we selectively remove branches from a tree. The goal is to remove unwanted branches, improve the tree's structure, and direct new, healthy growth.

See Figure 1.3:

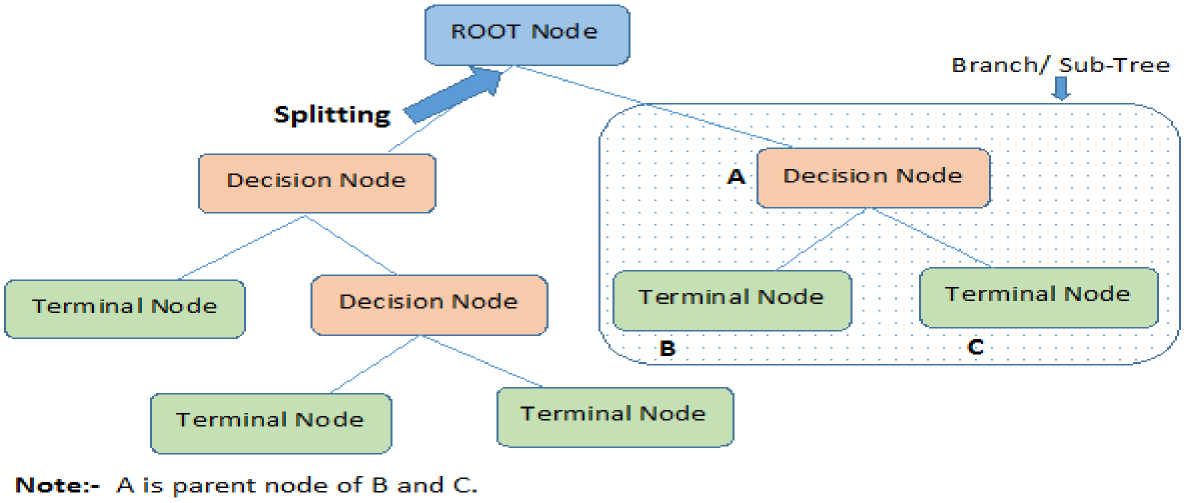


Figure 1.3: decision tree [11]

To construct a decision tree two notions are used: entropy and information gain as given by the following equations[13]:

Calculated using probabilities (p(i)) of each class (i) in the data:

$$Entropy = -\sum_{i=1}^{n} \mathrm{Pi} * \log(Pi) \qquad (9)$$

Gini Impurity (Classification):

$$\text{Gini Impurity } = 1 - \sum_{i=1}^{n} Pi^2 \qquad (10)$$

2.1.2. Algorithm steps [11]

- Step-1**:** Begin the tree with the root node, says S, which contains the complete dataset.
- Step-2: Find the best attribute in the dataset using Attribute, Selection, Measure (ASM).
- Step-3: Divide the S into subsets that contains possible values for the best attributes.
- Step-4: Generate the decision tree node, which contains the best attribute.
- Step-5: Recursively make new decision trees using the subsets of the dataset created
- Step-6: Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

2.2. Linear Regression

2.2.1. Definition

Linear regression is one of the easiest and most popular Machine Learning algorithms. It is a statistical method that is used for predictive analysis. it makes predictions for continuous/real or numeric variables such as **sales, salary, age, product price,** etc.[14]

Linear regression algorithm shows a linear relationship between a dependent (y) and one or more independent (y) variables as shown by the equation(), hence called as linear regression. Since linear regression shows the linear relationship, which means it finds how the value of the dependent variable is changing according to the value of the independent variable.[14]

Linear regression can be further divided into two types of the algorithm:

- Simple,Linear,Regression:

  If a single independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Simple Linear Regression.[14]

Multiple,Linear,regression:
If more than one independent variable is used to predict the value of a numerical dependent variable, then such a Linear Regression algorithm is called Multiple Linear Regression[14]. the time complexity of this linear regression is :O($m^w n$) [15].

The linear regression model provides a sloped straight line representing the relationship between the variables. See Figure 2.3:

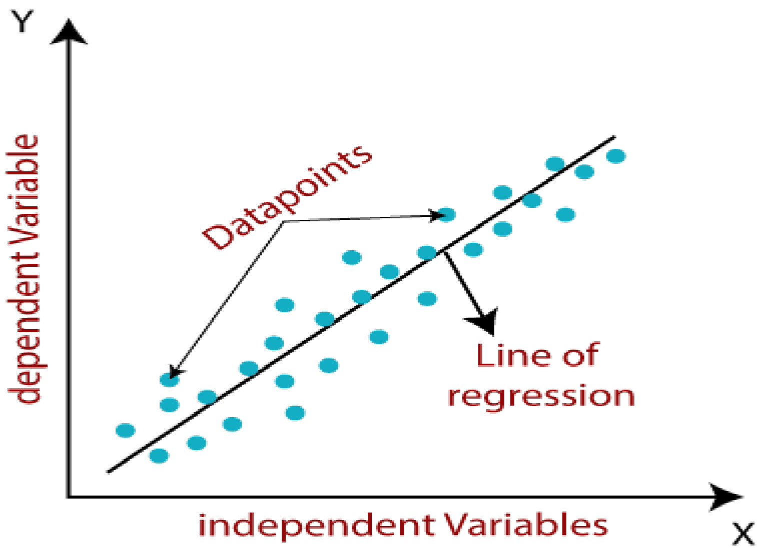


Figure 2.3: Linear Regression. [14]

Mathematically, we can represent a linear regression as:

- y= a_0+a_1x+ z
- Y= Dependent Variable (Target Variable)
- X= Independent Variable (predictor Variable)
- a0= intercept of the line (Gives an additional degree of freedom)

- a1 = Linear regression coefficient (scale factor to each input value).
- z = random error.[14]

2.3. Support vector machine algorithm (svm)

2.3.1. Definition

Support Vector Machine (SVM) is a supervised machine learning algorithm used for both classification and regression. Though we say regression problems as well it's best suited for classification. The main objective of the SVM algorithm is to find the optimal hyperplane in an N-dimensional space that can separate the data points in different classes in the feature space. The hyperplane tries that the margin between the closest points of different classes should be as maximum as possible [16]. The complexity of SVM: $O(n^2)$.[17]

As shown by the Figure 3.3:

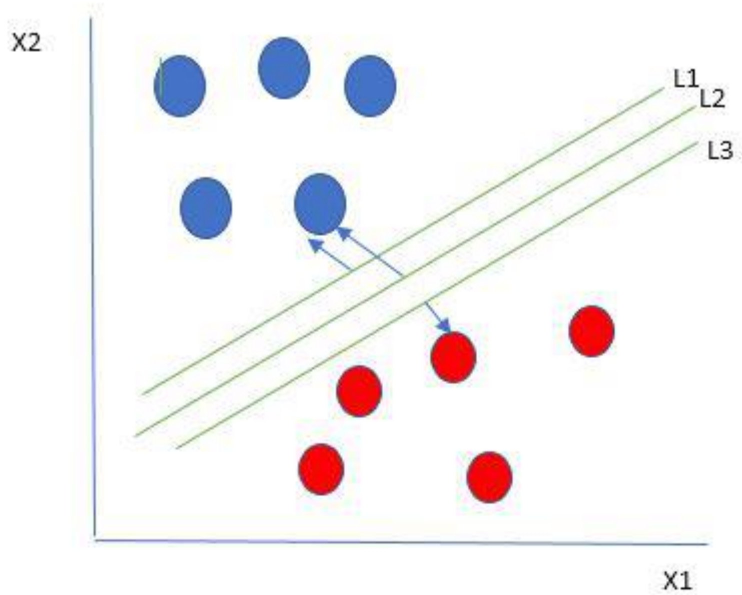


Figure 3.3: Support vector machine algorithm (svm). [16]

SVM Formulation (Linear Case):

Decision Function: The SVM aims to find a hyperplane represented by the equation:

$$W^T x + b = 0 \quad \ldots\ldots\ldots\ldots \quad (11)$$

W: Weight vector, defining the hyperplane's orientation in the feature space.

X: Input data point (vector).

b: Bias term, shifting the hyperplane.

T: Transpose operator [16].

2.3.2. Algorithm steps

Based on the search results, the key steps in the Support Vector Machine (SVM) algorithm are:

- Step-1: Understand the Problem.
- Step-2: Prepare the Data.
- Step-3: Split the Data.
- Step-4: Choose the Kernel Function.
- Step-5: Train the SVM Model.
- Step-6: Tune Hyperparameters.
- Step-7: Evaluate the Model.
- Step-8: Make Predictions.
- Step-9: Interpret the Results.

The key aspects of the SVM algorithm are finding the optimal hyperplane that maximizes the margin between the classes, and the use of kernel functions to handle non-linear decision boundaries [16].

2.4. K-Nearest Neighbor (KNN) Algorithm

2.4.1. Definition

KNN is one of the most basic yet essential classification algorithms in machine learning. It belongs to the supervised learning domain and finds intense application in pattern recognition, data mining, and intrusion detection [18]. The formul is:

$$distance(x, Xi) = \sqrt{\sum_{j=1}^{d} (xj - Xij)^2} \,\ldots\ldots\ldots \,(12)$$

KNN Algorithm working visualization. see Figure 4.3:

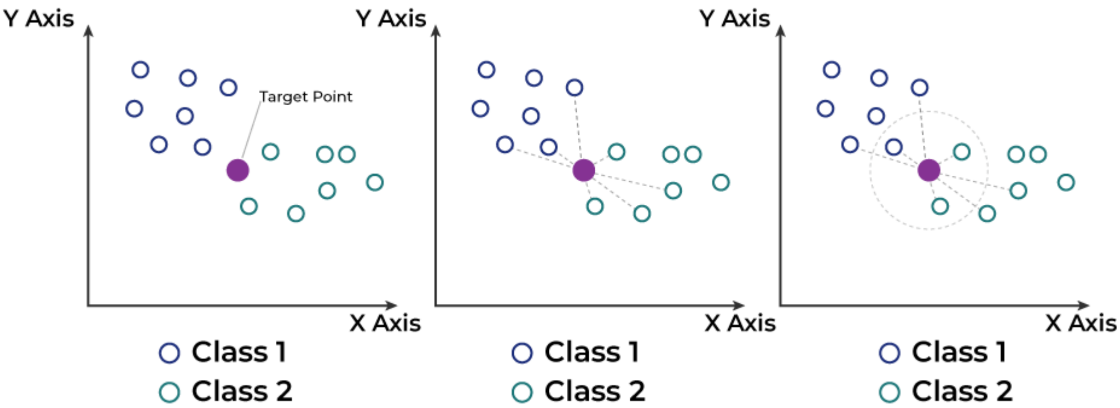


Figure 4.3: KNN Algorithm working.[18]

2.4.2. Algorithm steps

• Step-1: Selecting the optimal value of K. [18]

• Step-2: Calculating distance. [18]

• Step-3: Finding Nearest Neighbours. [18]

• Step-4: Voting for Classification or Taking Average for Regression. [18]

After presenting few technics of ML, now we move to present two technics: MV and Median Absolute Deviation. The complexity of K Nearest Neighbors (KNN): O(knd).[17]

3. Statistic

3.1. Majority Voting Algorithm

3.1.1. Definition

The Boyer-Moore voting algorithm is one of the popular optimal algorithms which is used to find the majority element among the given elements that have more than N/ 2 occurrences.

This works perfectly fine for finding the majority element which takes 2 traversals over the given elements, which works in O(N) time complexity and O(1) space complexity. [19]

3.1.2. Algorithm steps[19]

• Step-1:

1. Find a candidate with the majority –Initialize a variable say i, votes = 0, candidate =-1.
2. Traverse through the array using for loop.
3. If votes = 0, choose the candidate = arr[i], make votes=1.
4. else if the current element is the same as the candidate increment votes.
5. else decrement votes.

• Step-2:

1. Check if the candidate has more than N/2 votes.
2. Initialize a variable count =0 and increment count if it is the same as the candidate.
3. If the count is >N/2, return the candidate.
4. else return -1.

3.2. Median Absolute Deviation

3.2.1. Definition

The median absolute deviation (MAD) is a robust measure of how spread out a set of data is the variance and standard deviation are also measures of spread, but they are more affected by extremely high or extremely low values and non-normality.

If your data is normal, the standard deviation is usually the best choice for assessing spread.[20]

The formul is:

$$MAD = med(|Xi - median(X)|) \ldots\ldots\ldots\ldots\ldots \quad (13)$$

3.2.2. Algorithm steps

• Step-1: Find the median. [20]

• Step-2: Subtract the median from each x-value using the formula $|y_i$ – median|. [20]

• Step-3: find the median of the absolute differences. [20]

4. Conclusion

This chapter is considered as a background, where we present a plethora of technics used to detect faults in Wireless Body Area Networks, the next Chapter, represent the state of the art for the fault detection in WBAN's.

CHAPTER 3

Related Works

CHAPTER 3
RELATED WORKS

1. Introduction

In this chapter we focus on the techniques used to detect faults in WBANs, these techniques may be classified as machine learning and statistics, concerning the machine learning both support vector machine and decision tree are gathered with linear regression, also the statistics is used in this literature.

2. Machine Learning techniques

2.1. Support vector machine (SVM) with Linear regression

Machine learning's vast toolbox of methods remains a key player in diagnosing faults within WBANs, citing the work of the authors in [21], the paper proposes a machine learning approach for anomaly detection in WBANs. This approach utilizes Support Vector Machines (SVMs) as the initial step, this supervised machine learning method used for binary classification that uses training data to build a classification model. The SVM then uses this model to classify each instance in the test set using attribute data.

The main concept is to construct a linear hyperplane (a decision boundary) to separate instances of one class from the other class. The separation between the classes is optimized by obtaining the separating hyperplane which is defined as the plane having the greatest distance (margin) to the nearest training data points of any class defined by the following equation:

$$w^T x_i + w_0 = 0 \quad \ldots\ldots (1)$$

The main concept behind linear SVMs is to maximize the distance between two parallel hyperplane (boundary) which are defined by support vectors:

The first hyperplane vector:

$$w^T x_i + w_0 = 1 \quad \ldots\ldots (2)$$

The second hyperplane vector:

$$w^T x_i + w_0 = -1 \quad \ldots\ldots (3)$$

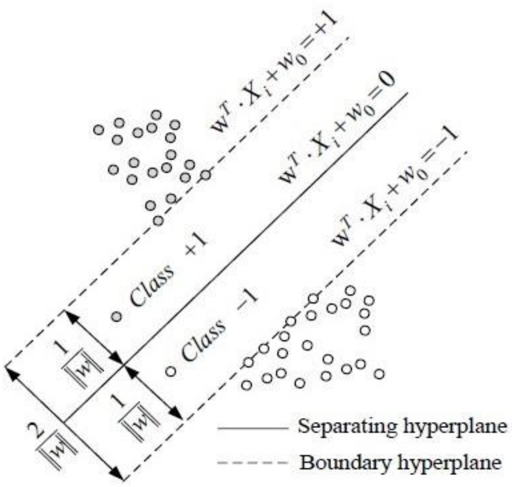


Figure 1.2: Linear SVM and data separation. [21]

In the event of an anomalous measurement being identified, the authors proposed applying linear regression as a predictive technique is a statistical modeling method used to predict the current value of monitored attribute, after that they use Euclidean distance and threshold (10% of estimated value) to compare between the measured value x_{ik} and the estimated value (perfect value)

$\hat{x}_{ik}$.

If $| x_{ik} - \hat{x}_{ik} | \geq 0.1$, then the measured value considered faulty and replaced by estimated value with linear regression.

Algorithm: detection algorithm [21]

for each received X_i record during T **do**
    Classify X_i using SVM
    if Class(X) == "ABNORMAL" **then**
        for each x_{ik} **do**
            $\hat{x}_{ik} = \Sigma_{j=1, j \neq k}^{n} a_i . x_{ij}$
            Ctr+= $((| x_{ik} - \hat{x}_{ik} | \geq 0.1 \times \hat{x}_{ik}) ? 1 : 0$
        end for
        if (Ctr $\geq$ K) **then**
            Raise alarm for healthcare
        end if
    end if
end for

2.2. Decision tree with linear regression

In this article [22] , the authors focus on anomaly detection in medical wireless sensor and They propose a new technique based on machine learning to detect data as normal or abnormal in the collected measurements for physiological parameters are represented by data matrix X = (X_{ij} / i is the time , j is the monitored parameter) where they use firstly the decision tree (J48) , this supervised learning algorithm used to classify records (line) and to reduce temporal complexity , the attributes are represented by nonterminal nodes and terminal nodes represent the decision result.

To build the nodes of the tree from the root to the leaves the Gain ratio (GR) for each attribute is calculated by equation 4:

$$GR(x\ ,x_k) = \frac{IG(x\ ,x_k)}{SI(x\ ,x_k)} \quad \ldots\ldots. (4)$$

$$\text{Entropy (X)} = \sum_{i=1}^{c} \alpha_i \log_2 \alpha_i \quad \ldots\ldots (5)$$

The information Gain IG (X, X_k) in equation 5 of an attribute is given by:

$$IG(X, X_k) = H(X) - \sum_{x_{ik} \epsilon X} \frac{|x_{ik}|}{|X|} H(x_{ik}) \quad \ldots\ldots. (6)$$

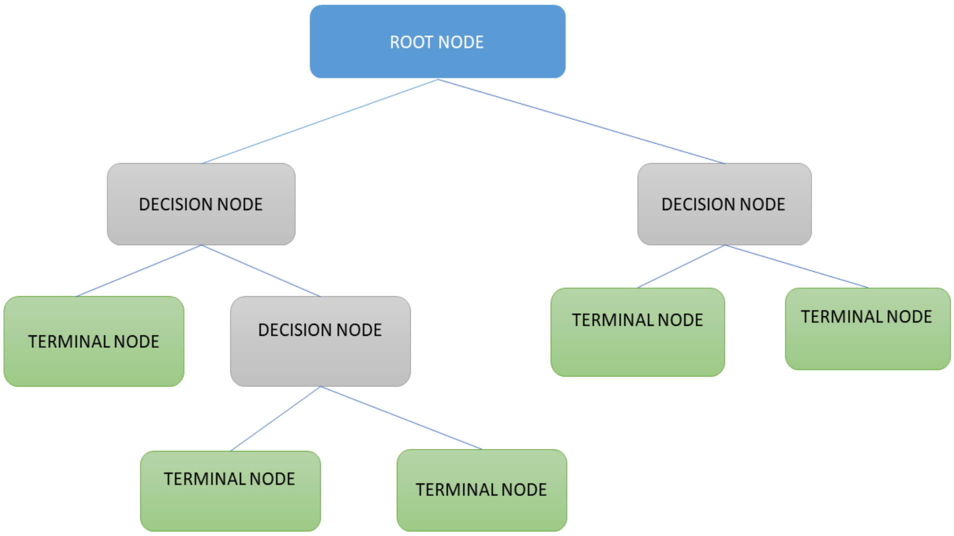


Figure 2.2: Decision tree

When an abnormal record is detected, the authors use linear regression (LR) algorithm to predict current measurements for each parameter, is a statical method which models a dependent variable (Y_{ik}) using a vector of independent variables (X_{ik}) called regressors.

The model Itself is represented by:

$$y_{ik} = C_0 + C_1 x_{i1} + C_2 x_{i2} + \cdots + C_n x_{in} \quad \ldots\ldots (7)$$

After that they use Euclidean distance and threshold to compare between the measured value x_{ik} and the estimated value (perfect value) $\hat{x}_{ik}$.

If $| x_{ik} - \hat{x}_{ik} | \geq 0.1$, then the measured value considered faulty and replaced by estimated value with linear regression. But, if at least two readings are higher than the threshold, we trigger an alarm for response caregiver emergency team to react.

Algorithm: detection algorithm [22]

1: **for each** received R_i record during T **do**

2: Classify R_i using J48

3: if Class(R_i) == "ABNORMAL" **then**

4: **for each** x_{ik} **do**

5: $\hat{x}_{ik} = \Sigma_{j=1, j\neq k}^{n} C_j . x_{ij}$

6: Ctr+= (($| x_{ik} - \hat{x}_{ik} | \geq 0.1 \times \hat{x}_{ik}$) ? 1 : 0

7: **end for**

8: **if** (Ctr ≥ K) **then**

9: Raise alarm for healthcare

10: **end if**

11: **end if**

12: **end for**

2.3. Under Bayesian Network Model

In this paper the authors [24], they utilize a Bayesian network-based method for fault detection in BSNs. They formalize a Bayesian network model to represent the body sensor network and propose a method to identify faulty sensor readings. They conduct a theoretical analysis of the fault detection rate, false alarm rate, and error probability after applying the fault diagnosis algorithm, and present an approximate algorithm for determining the discrete decision threshold.

Their experiments experiments demonstrate that the simulation results align with theoretical predictions, and the number of errors can be reduced by 60% using our fault diagnosis method by applying algorithm.

Algorithm: detection algorithm

Input: A probability distribution set of a Bayesian network and a discrete threshold set **Θ**

Output: The optimal threshold $\boldsymbol{\delta_{op}}$

1: $\delta_{op} = 0$;

2: min = 1 ;

3: **for each** $\delta \in \Theta$ **do**

4: **if** μ (P / ϱ) < min **then**

5: min = μ (P / ϱ);

6: $\delta_{op} = \delta$;

7: **end if**

8: **end for**

9: **return** δ_{op};

3. Statistical techniques

3.1. Median absolute deviation (MAD) with Majority voting (MV)

The approach described utilizes the Median Absolute Deviation (MAD) for anomaly detection, the authors [23] using a distance-based measure, where a data point is considered an outlier if a fraction or less of the total points fall within a certain distance (radius). Distance-based outlier detection calculates the distance or similarity between every pair of points, and points with distances longer than a specific threshold are considered outliers.

$$MAD = median\ (|Xi - median(X)|) \ldots\ldots (8)$$

In the context of a Wireless Body Area Network (WBAN), sensed values are compared against predicted values for a subject attribute at a given time t serves as the input for the anomaly detection. The MAD is used to determine if a data point falls within a dynamic range, based on a sliding window method. If a point is outside this range, a majority-voting (MV) algorithm is triggered to vote on sensor values (0 for normal, 1 for anomalous).

Each sensor monitors specific attributes and if the residual falls within the range, the patient is considered healthy, and a simple classifier labels the physiological attribute.

The MV algorithm aggregates votes for each physiological parameter measured by different sensors. If the votes for anomalous values exceed the average number of physiological parameters, it determines if the sensor value is faulty. This process aims to detect faulty measurements and minimize false alarms.

Looks the figure 3.2 bellow:

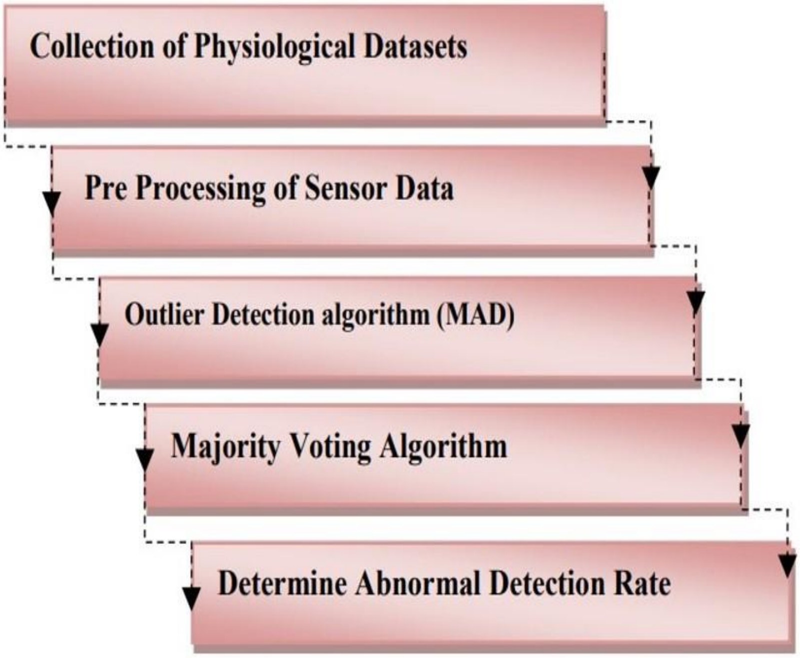


Figure 3.2: Method of the proposed work.[23]

3.2. Markov Model (MM)

The authors in [25] present a novel approach using a Markov chain-based model is defined as a model built from random variables that evolve over time, where the future state depends only on the current state and is independent of past states. The model consists of countable states with transitions between them, forming a Markov chain. This model used for centralized anomaly detection in Wireless Body Area Networks (WBANs) utilized in healthcare monitoring. This model focuses on distinguishing faults from abnormal physiological changes by analyzing the number of deviated attributes. By leveraging the Root Mean Square Error (RMSE) between forecasted and measured values, the system effectively detects changes and achieves high detection accuracy with low false alarms. Additionally, the system optimizes energy consumption by transmitting only deviated measurements to a Local Processing Unit (LPU) for analysis, contributing to enhanced efficiency and accuracy in remote healthcare monitoring.

Algorithm: detection algorithm

1: Collect Markov Model training data

2: Derive lower and upper bound of Tukey box

3: Replace X_t by s_i

4: Calculate N , N_i , $N_{i,j}$ and $T_{i,j}$

5: Calculate $q_i = N_i / N$ and $P_{i,j} = N_{i,j} / T_i$

6: Set the size of SW_i and threshold h

7: Replace new X_t by state s_i

8: **for each** $SW_j \in$ Testing **do**

9: $P(SW_j) = q_i \prod_{t=1}^{w} P_{t-1,t}$

10: **if** $P(SW_j) \leq$ h **then**

11: Raise an alarm for spatio-temporal analysis

12: **end if**

13: **end for**

4. Conclusion

In this chapter, we examined machine learning and statistical techniques for fault detection in WBANs. Methods like SVM, decision trees, Bayesian networks, MAD, and Markov models enhance anomaly detection accuracy and reliability. These approaches ensure robust health monitoring by effectively identifying and correcting faulty measurements.

CHAPTER 4

WBANs Implementation

CHAPTER 4
WBANs IMPLEMENTATION

1. Introduction

In this chapter, we will present the working environment and tools used in our analysis, including WEKA and the PhysioNet database, followed by a useful comparison between few technics used in this literature.

2. Working environment and tools

2.1 Weka

WEKA - an open-source software provides tools for data preprocessing, implementation of several Machine Learning algorithms, and visualization tools so that you can develop machine learning techniques and apply them to real-world data mining problems, see Figure 1.4.[26]

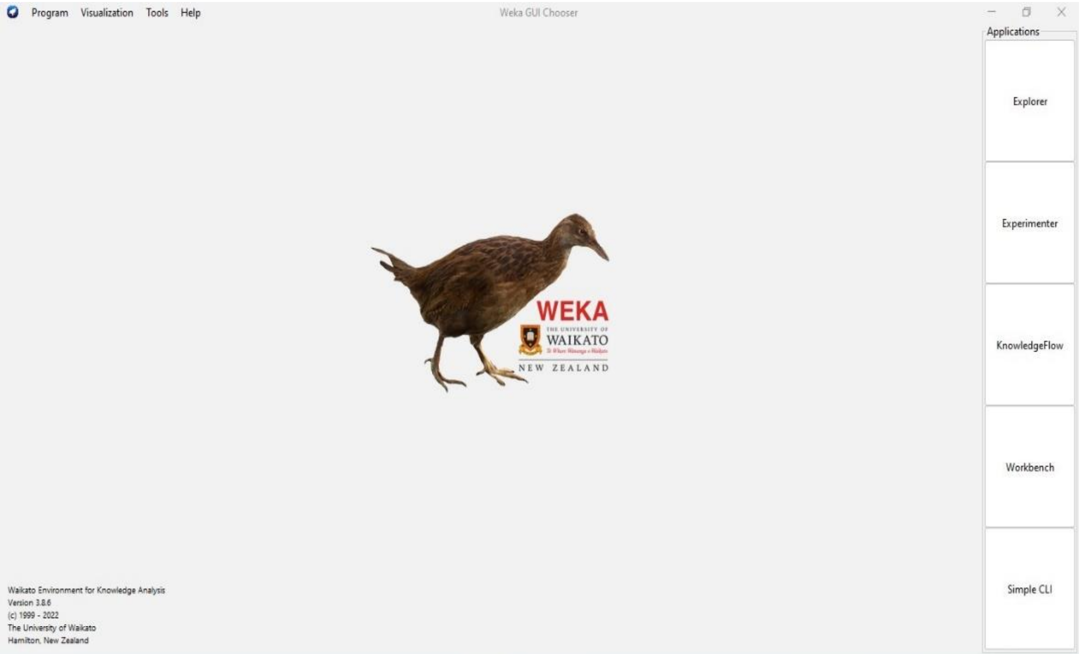


Figure 1.4: Weka GUI chooser with Explorer window open with Student dataset.[27]

2.2 Using Weka Tools

The Weka workbench contains a collection of visualization tools and algorithms for data analysis and predictive modeling, together with graphical user interfaces for easy access to this functionality. It is freely available software. It is portable & platform independent because it is fully implemented in the Java programming language and thus runs on almost any modern computing platform.

Weka has several standard data mining tasks, data preprocessing, clustering, classification, association, visualization, and feature selection. see the figure 2.4.[28]

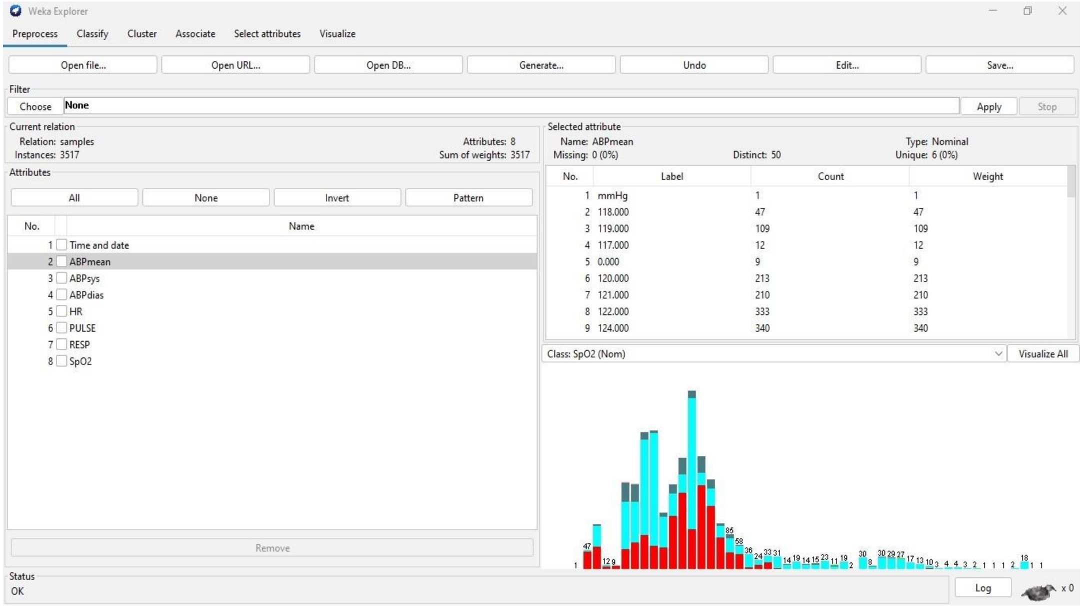
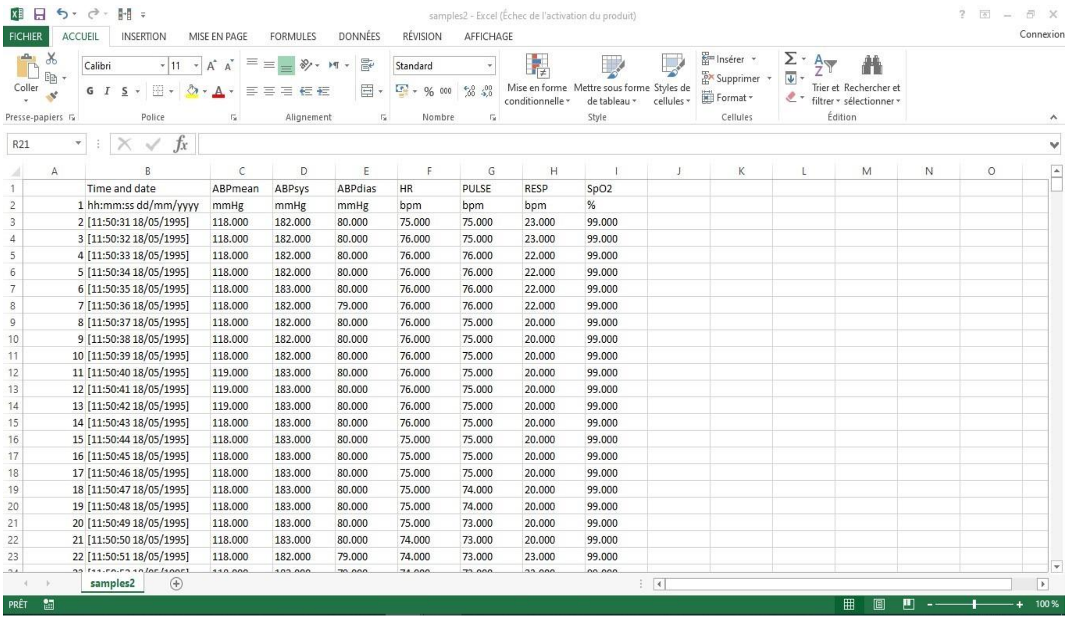


Figure 2.4: Weka with Explorer window open with Student dataset.

3. Data sete

The dataset used in our research has been obtained from PhysioNetan online database of recorded physiological signals. We will be using the dataset, which contains 121 records and each recording contains total of attributes: Time and date, ABPmean, ABPsys, ABPdias, HR, PULSE, RESP, SpO2. See Figure 3.4.



	A	B	C	D	E	F	G	H	I
1		Time and date	ABPmean	ABPsys	ABPdias	HR	PULSE	RESP	SpO2
2	1	hh:mm:ss dd/mm/yyyy	mmHg	mmHg	mmHg	bpm	bpm	bpm	%
3	2	[11:50:31 18/05/1995]	118.000	182.000	80.000	75.000	75.000	23.000	99.000
4	3	[11:50:32 18/05/1995]	118.000	182.000	80.000	76.000	75.000	23.000	99.000
5	4	[11:50:33 18/05/1995]	118.000	182.000	80.000	76.000	76.000	22.000	99.000
6	5	[11:50:34 18/05/1995]	118.000	182.000	80.000	76.000	76.000	22.000	99.000
7	6	[11:50:35 18/05/1995]	118.000	183.000	80.000	76.000	76.000	22.000	99.000
8	7	[11:50:36 18/05/1995]	118.000	182.000	79.000	76.000	76.000	22.000	99.000
9	8	[11:50:37 18/05/1995]	118.000	182.000	80.000	76.000	75.000	20.000	99.000
10	9	[11:50:38 18/05/1995]	118.000	182.000	80.000	76.000	75.000	20.000	99.000
11	10	[11:50:39 18/05/1995]	118.000	182.000	80.000	76.000	75.000	20.000	99.000
12	11	[11:50:40 18/05/1995]	119.000	183.000	80.000	76.000	75.000	20.000	99.000
13	12	[11:50:41 18/05/1995]	119.000	183.000	80.000	76.000	75.000	20.000	99.000
14	13	[11:50:42 18/05/1995]	119.000	183.000	80.000	76.000	75.000	20.000	99.000
15	14	[11:50:43 18/05/1995]	118.000	183.000	80.000	76.000	75.000	20.000	99.000
16	15	[11:50:44 18/05/1995]	118.000	183.000	80.000	75.000	75.000	20.000	99.000
17	16	[11:50:45 18/05/1995]	118.000	183.000	80.000	75.000	75.000	20.000	99.000
18	17	[11:50:46 18/05/1995]	118.000	183.000	80.000	75.000	75.000	20.000	99.000
19	18	[11:50:47 18/05/1995]	118.000	183.000	80.000	75.000	74.000	20.000	99.000
20	19	[11:50:48 18/05/1995]	118.000	183.000	80.000	75.000	74.000	20.000	99.000
21	20	[11:50:49 18/05/1995]	118.000	183.000	80.000	75.000	73.000	20.000	99.000
22	21	[11:50:50 18/05/1995]	118.000	183.000	80.000	74.000	73.000	20.000	99.000
23	22	[11:50:51 18/05/1995]	118.000	182.000	79.000	74.000	73.000	23.000	99.000

Figure 3.4: Data base

3.1. PhysioNet

PhysioNet tutorials are intended to provide hands-on introductions to the data and software available from this resource. This index lists currently available PhysioNet tutorials by category, as well as reference manuals, workshop materials, and links to other tutorials likely to be of interest to PhysioNet visitors, see Figure 4.4.[29]

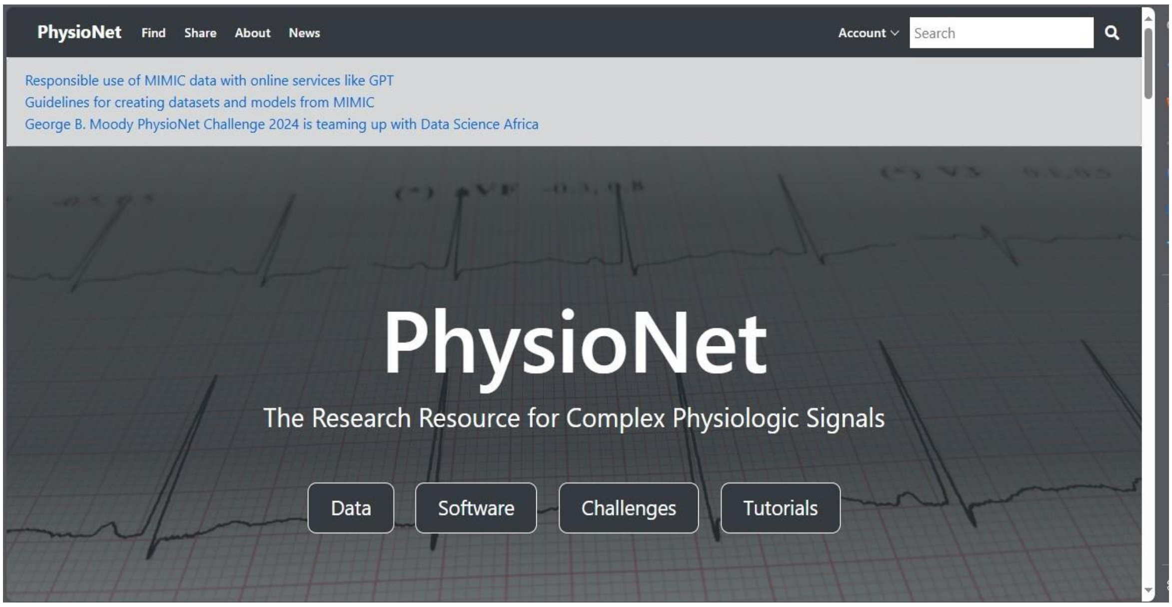


Figure 4.4: PhysioNet website.[29]

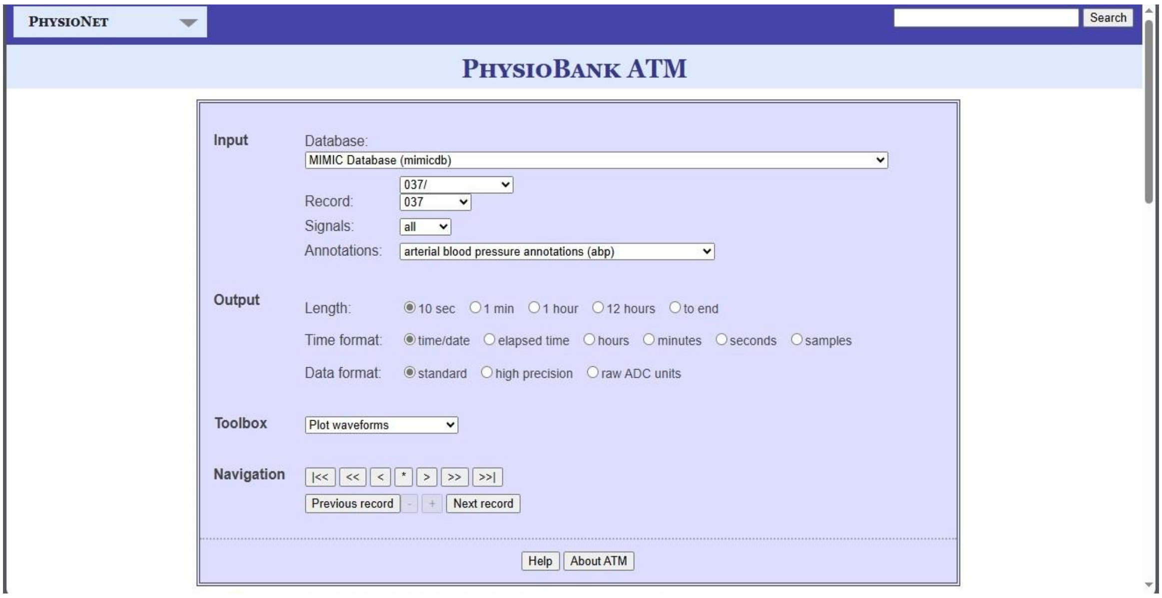


Figure 5.4: PhysioBANK ATM window. [30]

3.2. MIMIC-II

The MIMIC-II (Multiparameter Intelligent Monitoring in Intensive Care) Databases contain physiologic signals and vital signs time series captured from patient monitors, and comprehensive clinical data obtained from hospital medical information systems, for tens of thousands of Intensive Care Unit (ICU) patients. Data were collected between 2001 and 2008 from a variety of ICUs (medical, surgical, coronary care, and neonatal) in a single tertiary teaching hospital. The MIMIC-II Clinical Database contains clinical data from bedside workstations as well as hospital archives. The MIMIC II

Waveform Database includes records of continuous high-resolution physiologic waveforms and minute-by-minute numeric time series (trends) of physiologic measurements. Many, but not all, of the Waveform Database records are matched to corresponding Clinical Database records, see Figure 6.4.[31]

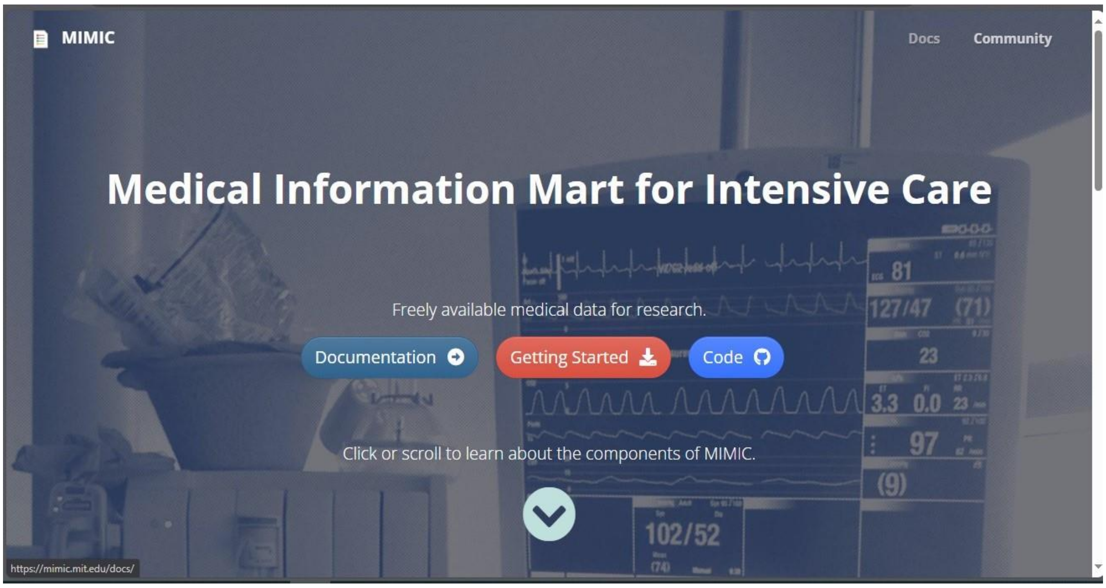


Figure 6.4: Medical Information Mart for Intensive Care web site.[30]

4. Evaluation

We have used weka and we have selected MIMIC II data base from physionet ATM BANC data sete that contains seven physiologie si forals (Time and date Nominal, ABPmean, ABPsys, ABPdias, HR, PULSE, RESP, SpO2) our evaluation.

4.1. Tools

4.1.1. <u>J48 Classifier</u>

J48 is a machine learning decision tree classification algorithm based on Iterative Dichotomiser 3. It is very helpful in examine the data categorically and continuously.[32]

4.1.2. Self organing map (SOM)

The Self Organizing Map is one of the most popular neural models. It belongs to the category of the competitive learning network. The SOM is based on unsupervised learning, which means that is no human intervention is needed during the training and those little needs to be known about characterized by the input data. We could, for example, use the SOM for clustering membership of the input data. The SOM can be used to detect features inherent to the problem and thus has also been called SOFM the Self Origination Feature Map.SOM also represents the clustering concept by grouping similar data together.[33]

4.1.3. Instance-based k-nearest neighbors classifier (IBK)

IBK is a k-nearest-neighbour classifier that uses the same distance metric. The number of nearest neighbours can be specified explicitly in the object editor or determined automatically using leave-one-out cross-validation focus to an upper limit given by the specified value.[34]

4.1.4. BayesNet

Bayes Nets or Bayesian networks are graphical representation for probabilistic relationships among a set of random variables. Given a finite set X= {X1…Xn} of discrete random variables where each variable Xi may take values from a finite set represented by Val (Xi).[34]

4.2.The specific domain

sPo2	75–100 mm Hg [35]
Heart rate	Is 60 to 100 (bpm)[36]
RESP	8-16 breaths per minute[37]
ABPmean	120/80 mm Hg [38]

Table 4.1: The specific domain.

4.3. The variation

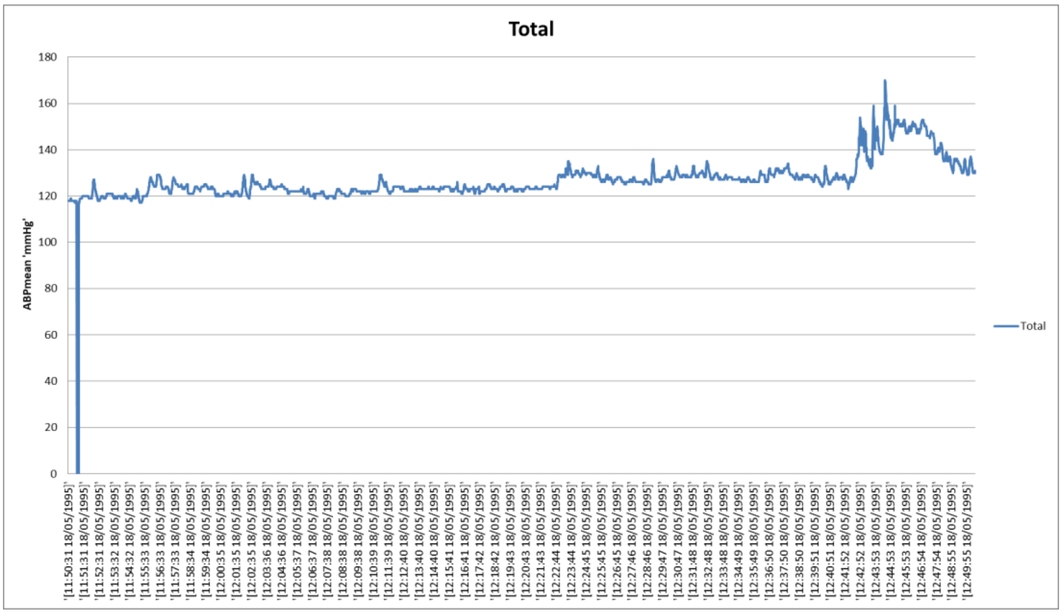


Figure 7.4: Pulmonary artery pressure.

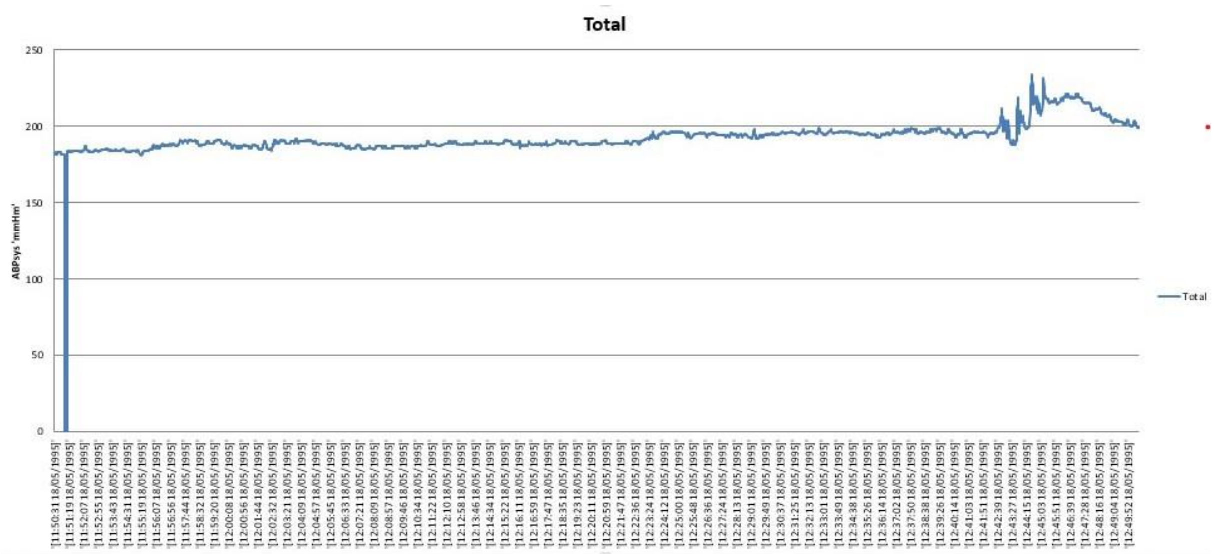


Figure 8.4: Systolic Arterial Blood Pressure.

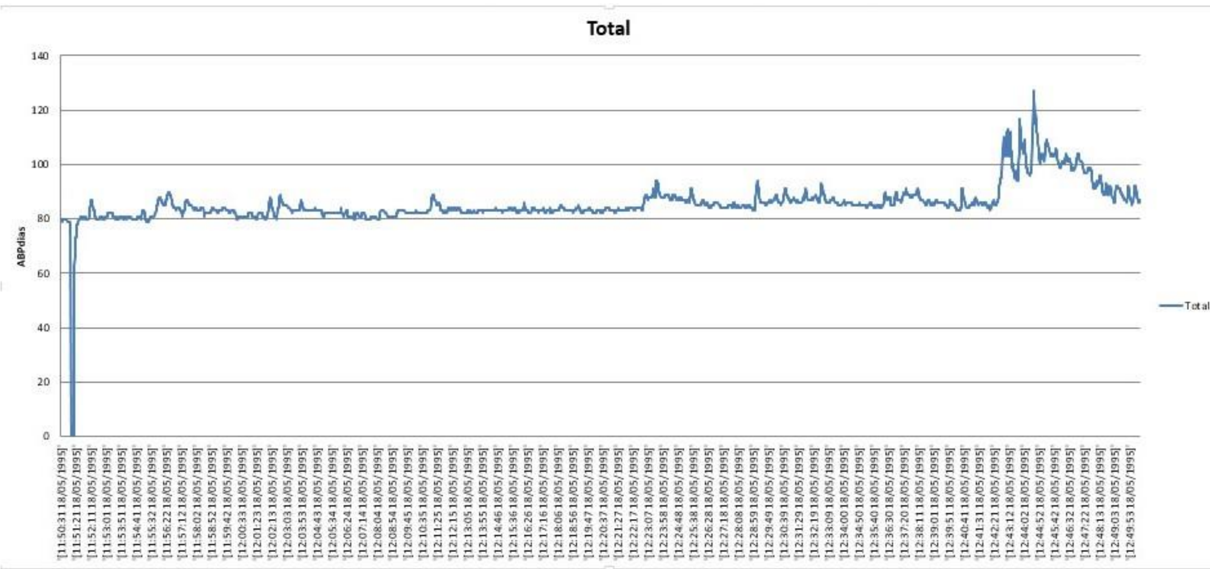


Figure 9.4: **S**tands for Diastolic Arterial Blood Pressure.

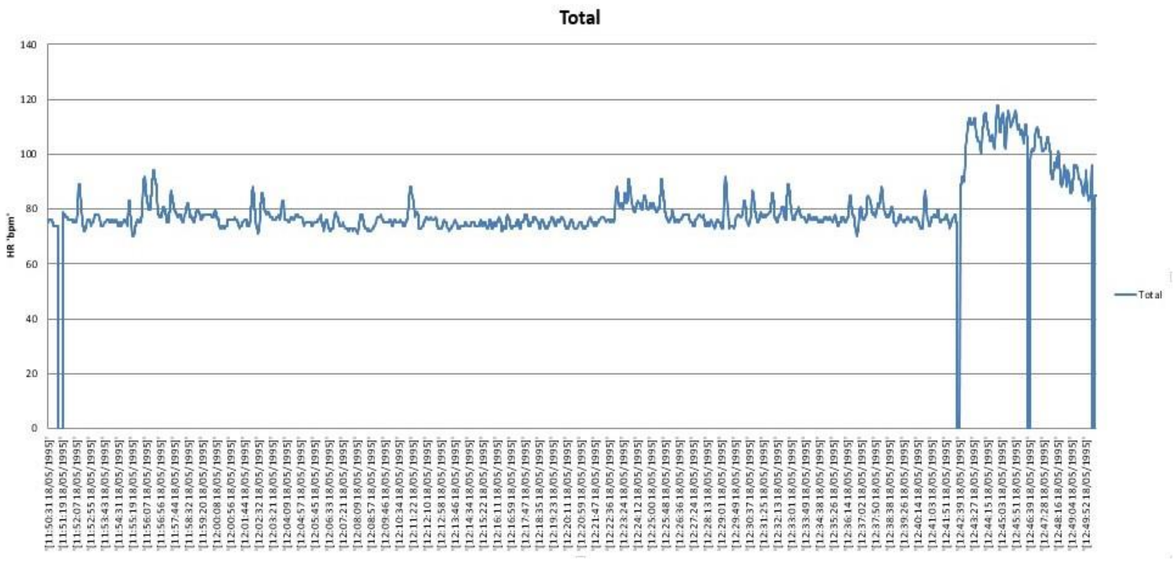


Figure 10.4: Heart rate.

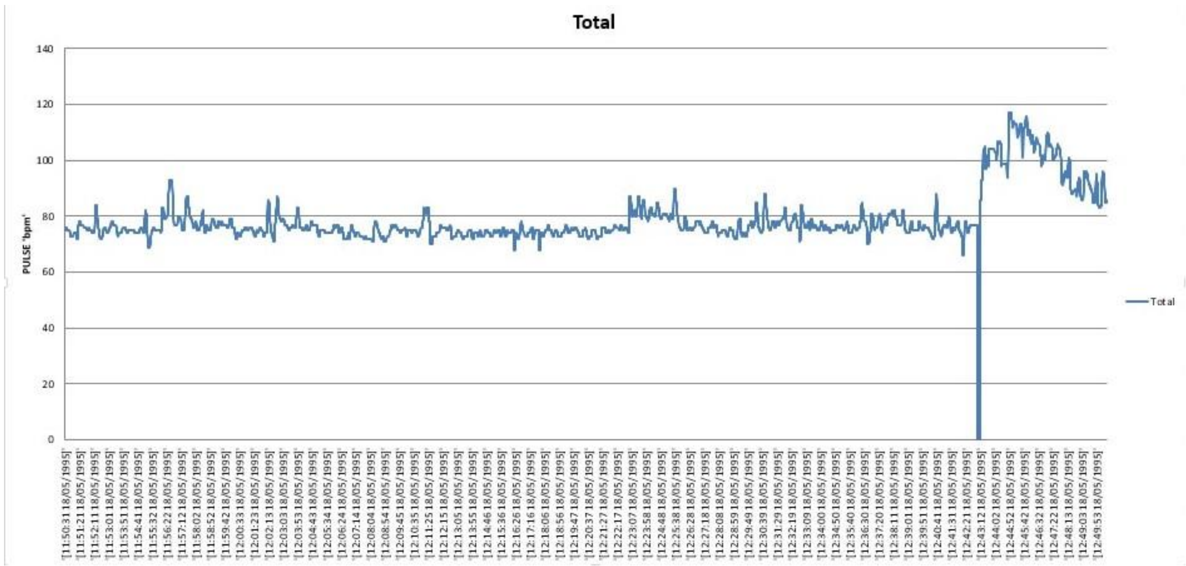


Figure 11.4: Pulse rate

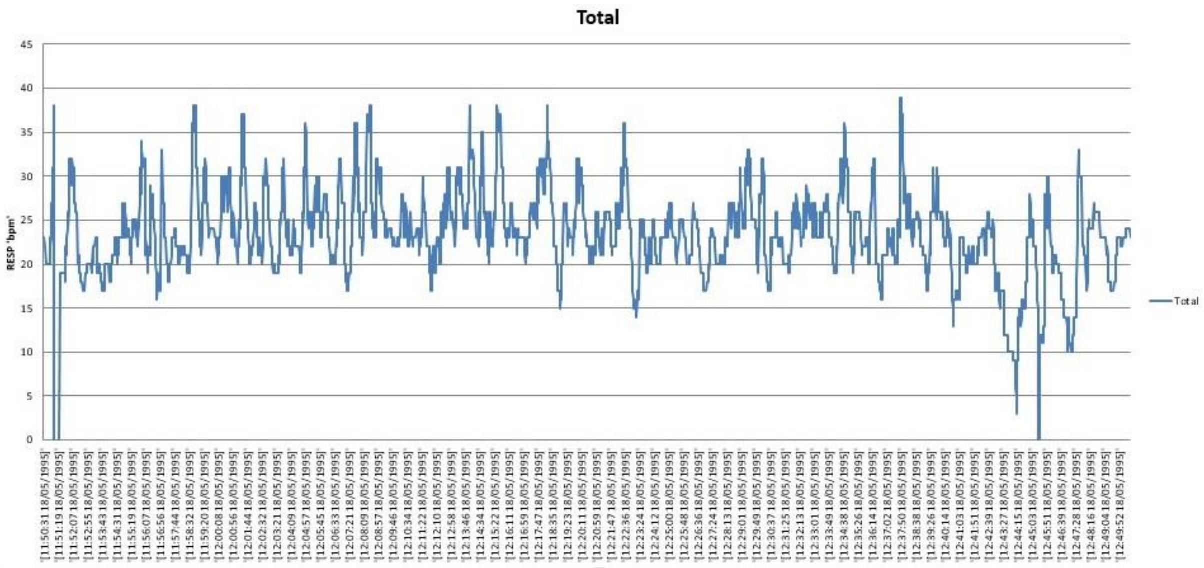


Figure 12.4: Respiration rate

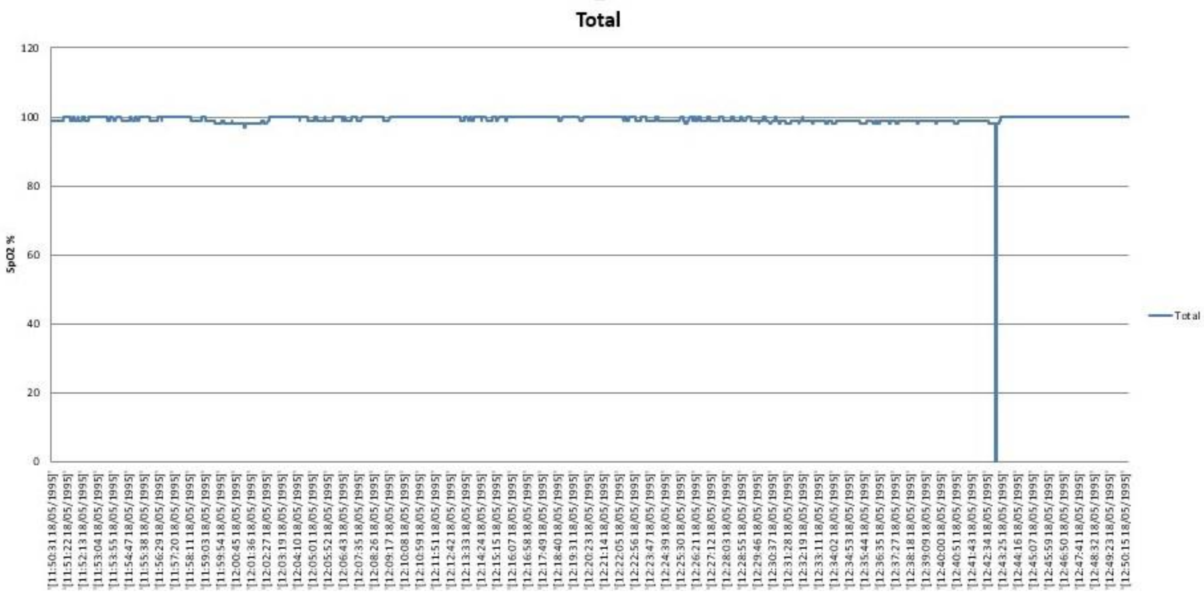


Figure 13.4: Oxygenation ratio

5. The comparison

For comparison, we have used the following evaluation metrics.

5.1. Accuracy

Accuracy detection is a used as evaluation metric. It is calculated according to the following equation:

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad \dots\dots\dots (14)$$

• TP (True Positives): Number of instances correctly classified as positive.

• TN (True Negatives): Number of instances correctly classified as negative.

• FP (False Positives): Number of instances incorrectly classified as positive (Type I error).

• FN (False Negatives): Number of instances incorrectly classified as negative (Type II error), see Figure 14.4.[39]

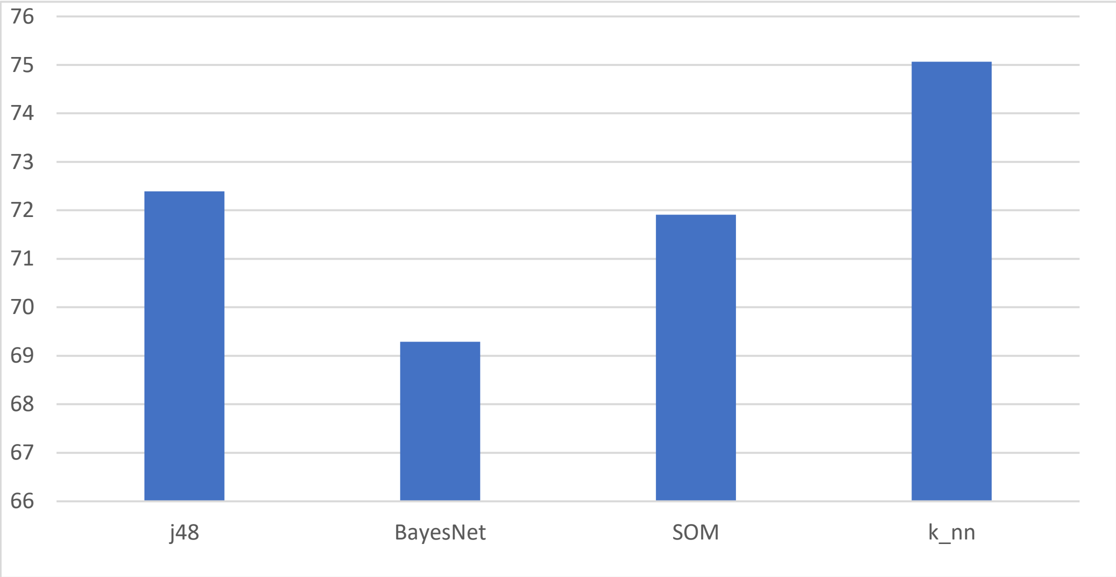


Figure 14.4: Detection accuracy compared to 4 relevant alternative approaches in the literature.

5.2. Kappa statistics

The Kappa statistic is a widely used evaluation n metric for classification tasks that provides a more robust measure of performance compared to accuracy alone. It is particularly useful when dealing with imbalanced datasets or multi-class problems. See Figure 15.4. [40][41]

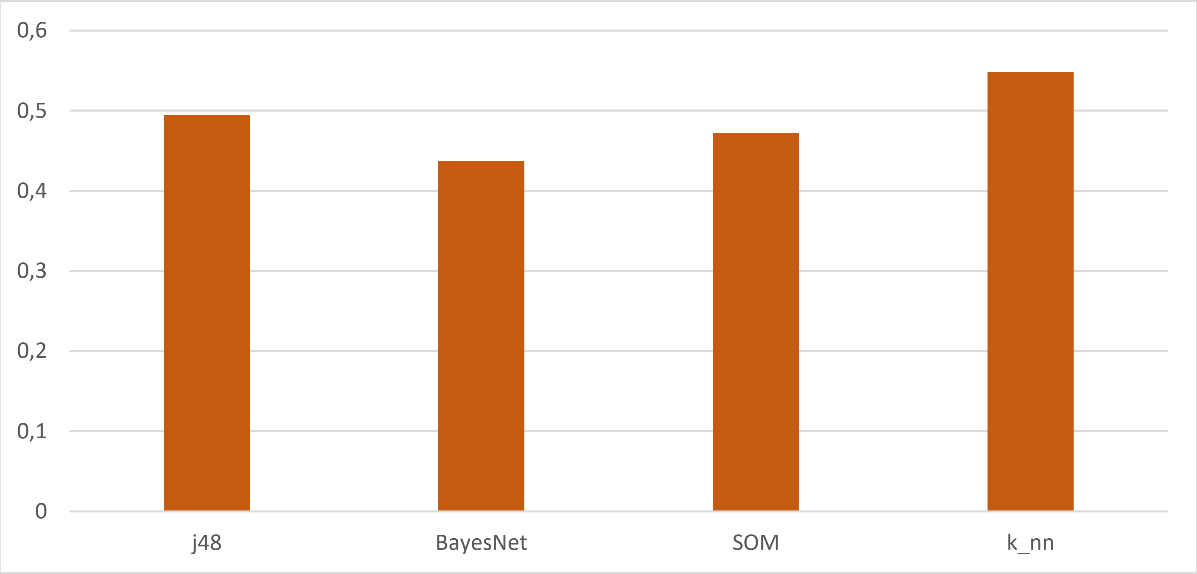


Figure 15.4: Kappa statistics compared to 4 relevant alternative approaches in the literature.

5.3. Mean absolute error

Mean absolute error (MAE) is the average of the absolute difference between actual and predicted values [42]. the following equation:

$$\text{MAE} = \frac{\sum_{i=1}^{n} |\text{pvi} - \text{avi}|}{\text{n}} \quad \ldots\ldots\ldots (15)$$

See the figure 16.4

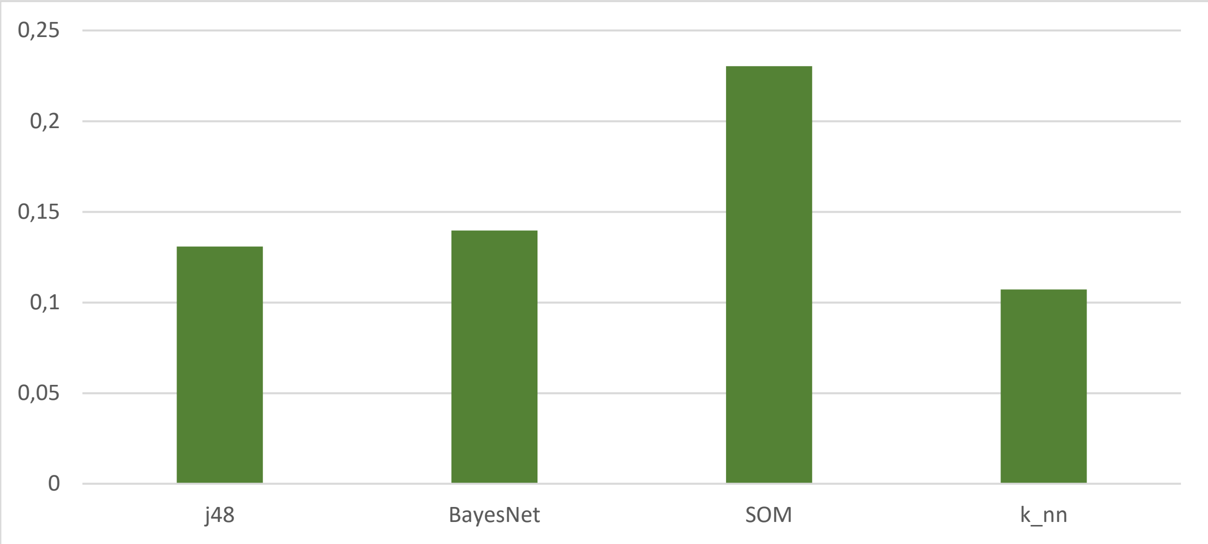


Figure 16.4: Mean absolute error compared to relevant alternative approaches in the literature.

6. Receiver operating characteristic (ROC)

ROC curve is a performance measurement for the classification problems at various threshold settings. ROC is a probability curve and AUC represents the degree or measure of separability. It tells how much the model is capable of distinguishing between classes. [43]

The TPR (also called sensitivity or recall) is the proportion of actual positives that are correctly identified as such.

The FPR (also called fall-out) is the proportion of actual negatives that are incorrectly classified as positive

It is calculated as:

$$TPR = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \qquad (16)$$

$$FRP = \frac{\mathrm{FP}}{\mathrm{FP+TN}} \qquad (17)$$

- TP = True Positives
- FN = False Negatives

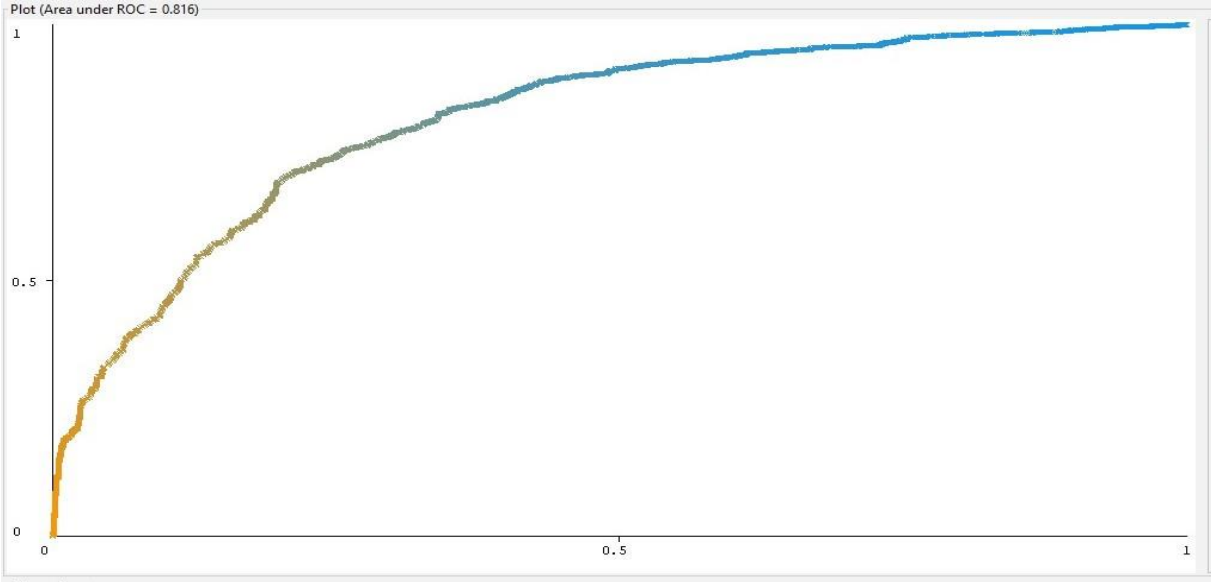


Figure 17.4: Dicition tree(ROC)

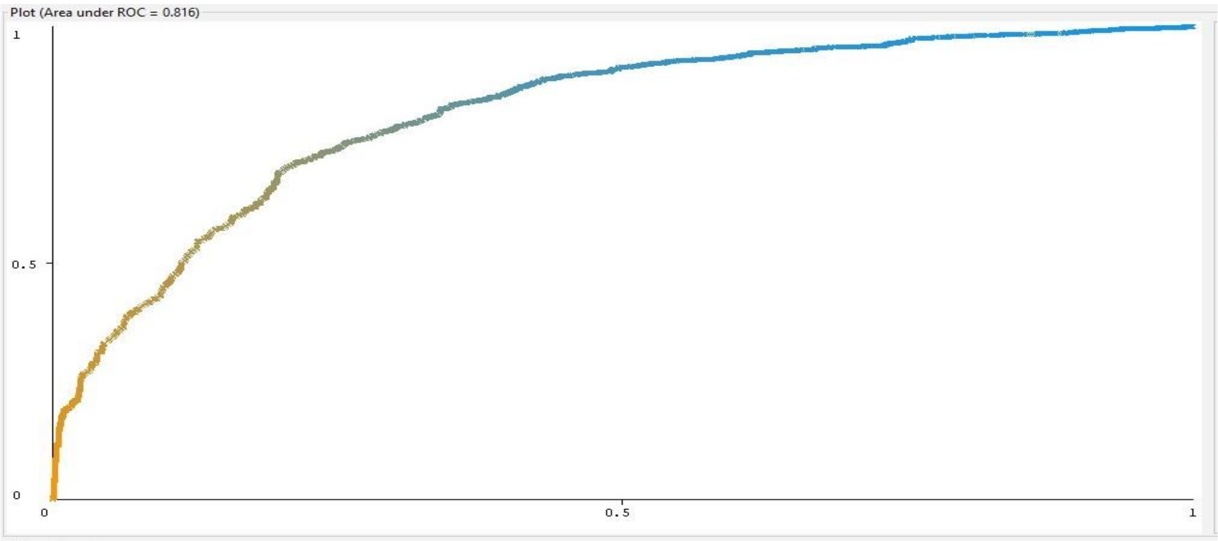


Figure 18.4: Bayse (ROC)

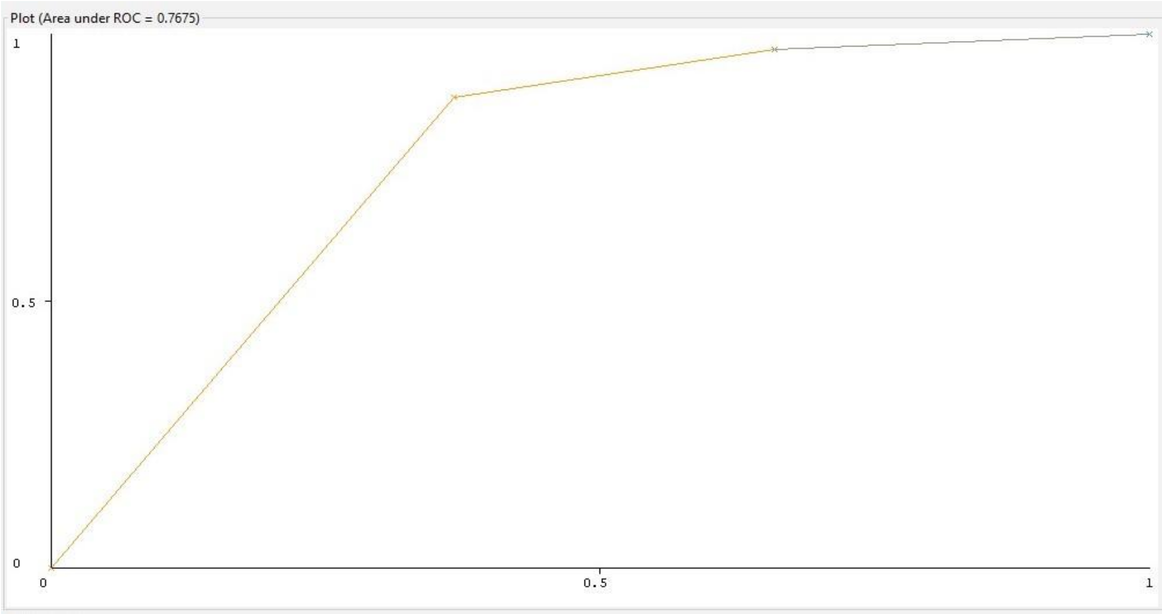


Figure 19.4: Support vector machine (SVM OR SOM) (ROC)

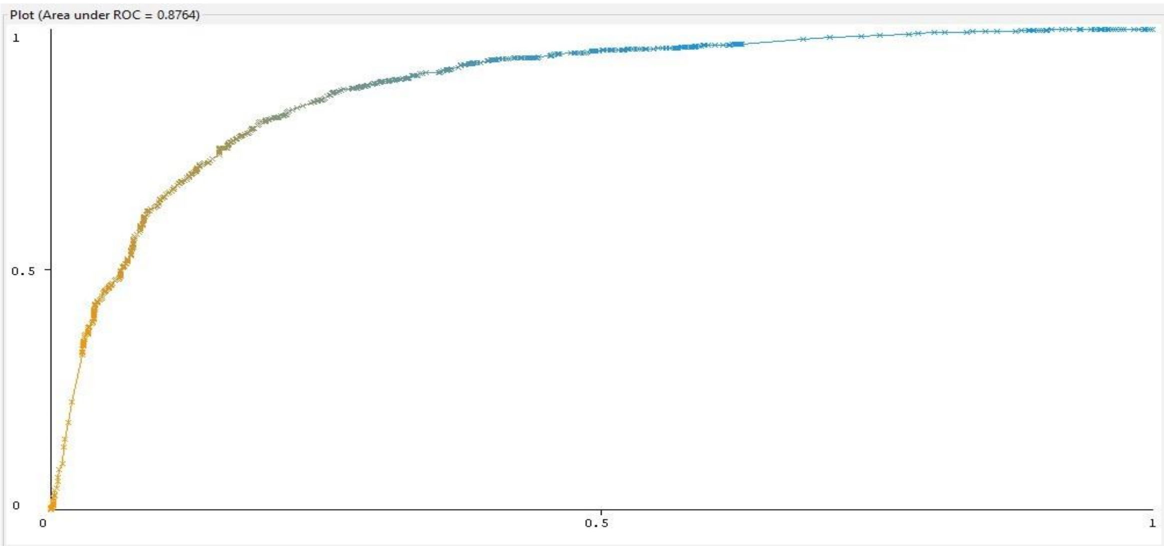


Figure 20.4: 4.K_NN (IBK) (ROC)

7. Conclusion

In order to choose the best algorithm from the given results, the results have shown that the best method is Knn.

In this chapter, we compared several machine learning algorithms. The results showed that in terms of accuracy, Knn achieved 75.064%, Kappa statistics 54.82%, SOM 23.03%, and ROC 0.8764%.

GENERAL CONCLUSION

With the advancement of technology and the increasing use of telecommunications networks, the miniaturisation of these devices led to the development of WBAN devices that play a role in all fields, especially in the field of health and human health monitoring. WBAN devices are currently receiving a lot of attention and one of the most important priorities is to correct fault detection and ensure that the information or signals reach the concerned parties correctly and without errors.First, the thesis begins with a comprehensive introduction, outlining the specific problem and desired outcome of the research. In Chapter 1, we gave an overview of WBANs, including body sensor network architecture and operation, Communication Technologies and applications of WBANs and WBAN challenges, as well as WBAN issues.In Chapter two, considered as background in which we present the essential theoretical concepts.

In the third,we talked about the previous work, the algorithms used and the results obtained.

In the fourth chapter, we conducted a comparative analysis of various machine learning algorithms. We identified the algorithm that yielded the best results in terms of accuracy and ROC (Receiver Operating Characteristic) …

Leveraging the PhysioNet database, we utilized WEKA to connect the algorithms to the data.

The transmission process requires high speed and zero tolerance for errors. Any malfunction or error can have detrimental consequences for human health. Sensor data should be transmitted seamlessly to healthcare professionals or relevant parties, enabling prompt intervention without delay. Conversely, communication failures can leave patients in danger without the necessary notifications reaching the concerned authorities, potentially leading to a deterioration in their health.

BIBLIOGRAPHY

[1] "Nitin Gupta ",researchgate.Sensor node architecture | Download Scientific Diagram (researchgate.net)

[2] "*Wireless Sensor Network (WSN)*", 17 Mar, 2023, Accessed on: April. 03, 2024. [Online]. Available: https://www.geeksforgeeks.org/wireless-sensor-network-wsn/

[3] YAGHOUBI, Mohammad, AHMED, Khandakar, et MIAO, Yuan. "Wireless body area network (WBAN): a survey on architecture, technologies, energy consumption, and security challenges", *Journal of Sensor and Actuator Networks*, 2022, vol. 11, no 4, p. 67.

[4] ZHONG, Lisha, HE, Shuling, LIN, Jinzhao, *et al.* Technological requirements and challenges in wireless body area networks for health monitoring: A comprehensive survey. *Sensors*, 2022, vol. 22, no 9, p. 3539.

[5] "*Reinforcement Learning Based Energy Management in Wireless Body Area Network: A Survey*", - Scientific Figure on ResearchGate. , Accessed on: May. 22, 2024. [Online]. Available : https://www.researchgate.net/figure/3-Tier-wireless-body-area-network-architecture_fig1_340694475

[6] AREFIN, Md Taslim, ALI, Mohammad Hanif, HAQUE, AKM Fazlul, *et al.* Wireless body area network: An overview and various applications. *Journal of Computer and Communications*, 2017, vol. 5, no 07, p. 53.

[7] Directional MAC Approach for Wireless Body Area Networks - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Difference-between-WSNs-and-WBANs_tbl2_221844022 [accessed 22 May, 2024]

[8] TOBÓN, Diana P., FALK, Tiago H., et MAIER, Martin. Context awareness in WBANs: a survey on medical and non-medical applications. *IEEE Wireless Communications*, 2013, vol. 20, no 4, p. 30-37.

[9] B. Latré, B. Braem, I. Moerman, C. Blondia, and P. Demeester, "A survey on wireless body area networks," Wireless networks, vol. 17, no. 1, pp. 1-18, 2011.

[10] Yaghoubi, Mohammad, Khandakar Ahmed, and Yuan Miao. 2022. "Wireless Body Area Network (WBAN): A Survey on Architecture, Technologies, Energy Consumption, and

Security Challenges" *Journal of Sensor and Actuator Networks* 11, no. 4: 6.

[11] “Tree Algorithm overview explained”. Accessed on: April. 08, 2024. [Online]. Available: https://towardsmachinelearning.org/decision-tree-algorithm/

[12] “Nitin Gupta”, researchgate. Sensor node architecture | Download Scientific Diagram (researchgate.net)

[13] Vrutti Tanna,(Jan 31 , 2020),UNDERSTANDING THE MATHEMATICS BEHIND THE DECISION TREE ALGORITHM (PART – I),Understanding the mathematics behind the decision tree algorithm (Part - I) - Data Science Prophet

[14] Studocu. (n.d.). “*Linear Regression in Machine Learning*”. Studocu. Available : https://www.studocu.com/in/document/chandigarh-college-of-engineering-and-technology/mca/machine-learning-notes/42473882

[15] ”What is the Time Complexity of Linear Regression? **“,**datascience.stackexchange. 2024 Mar 26 at 19:01. machine learning - What is the Time Complexity of Linear Regression? - Data Science Stack Exchange

[16] “*Support Vector Machine (SVM) Algorithm*” 10 Jun, 2023, Accessed on: April. 10, 2024. [Online]. Available: https://www.geeksforgeeks.org/support-vector-machine-algorithm/

[17] “Computational Complexity of ML Models “,Paritosh Kumar. Dec 14, 2019. Computational Complexity of ML Models | by Paritosh Kumar | Analytics Vidhya | Medium

[18] “*K-Nearest Neighbor (KNN) Algorithm*” (25 Jan, 2024). Accessed on: April. 12, 2024. [Online]. Available : https://www.geeksforgeeks.org/k-nearest-neighbours/

[19] “*Boyer-Moore Majority Voting Algorithm for Searching elements having more than K Occurrences*” (27 Sep, 2022). Accessed on: April. 14, 2024. [Online]. Available : https://www.geeksforgeeks.org/boyer-moore-majority-voting-algorithm/

[20] A Fast Majority Vote Algorithm J Strother Moore, The University of Texas at Austin,

[21] SALEM, Osman, GUERASSIMOV, Alexey, MEHAOUA, Ahmed, *et al.* Anomaly detection in medical wireless sensor networks using SVM and linear regression models. *International Journal of E-Health and Medical Communications (IJEHMC)*, 2014, vol. 5, no 1, p. 20-45.

[22] SALEM, Osman, GUERASSIMOV, Alexey, MEHAOUA, Ahmed, *et al.* Sensor fault and patient anomaly detection and classification in medical wireless sensor networks. In: *2013*

IEEE international conference on communications (ICC). IEEE, 2013. p. 4373-4378.

[23] ADERIBIGBE, Temilola et CHI, Hongmei. A quick outlier detection in wireless body area networks. In: *Proceedings of the Practice and Experience in Advanced Research Computing 2017 on Sustainability, Success and Impact*. 2017. p. 1-3.

[24] ZHANG, Haibin, LIU, Jiajia, et LI, Rong. Fault detection for medical body sensor networks under Bayesian network model. In: *2015 11th International Conference on Mobile Ad-hoc and Sensor Networks (MSN)*. IEEE, 2015. p. 37-42.

[25] SALEM, Osman, ALSUBHI, Khalid, MEHAOUA, Ahmed, *et al.* Markov models for anomaly detection in wireless body area networks for secure health monitoring. *IEEE Journal on Selected Areas in Communications*, 2020, vol. 39, no 2, p. 526-540.

[26] "*Weka - Quick Guide*". Accessed on: April. 16, 2024. [Online]. Available: https://www.tutorialspoint.com/weka/weka_quick_guide.htm

[27] Weka 3 - Data Mining with Open Source Machine Learning Software in Java (waikato.github.io).

[28] Aher, S. B., & Lobo, L. M. R. J. (2011, March), "*Data mining in educational system using weka*". In International conference on emerging technology trends (ICETT) (Vol. 3, pp. 20-25). Foundation of Computer Science.

[29] "*PhysioNet tutorials*". Accessed on: April. 17, 2024. [Online]. Available: https://physionet.org/about/tutorial/

[30] "*PhysioBank*". Accessed on: April. 18, 2024. [Online]. Available: https://archive.physionet.org/physiobank/

[31] "*MIMIC II Databases*". Accessed on: April. 19, 2024. [Online]. Available: https://archive.physionet.org/mimic2/

[32] "*Building a Machine Learning Model Using J48 Classifier*" (06 Mar, 2023). Accessed on: April. 21, 2024. [Online]. Available : https://www.geeksforgeeks.org/building-a-machine-learning-model-using-j48-classifier/

[33] Amir Ali, "*Self-Organizing Map(SOM) with Practical Implementation*", The Art of Data Scicne | Medium". [Online]. Available: https://medium.com/machine-learning-researcher/self-organizing-map-som-c296561e2117

[34] Ms S. Vijayarani1, Ms M. Muthulakshmi, "Comparative Analysis of Bayes and Lazy Classification Algorithms"," *International Journal of Advanced Research in Computer and Communication Engineering*", Vol. 2, Issue 8,2013.

[35] "*Is My Blood Oxygen Level Normal*? ""Written By: Kimberly Holland","Edited By:Alex Marceau","Medically Reviewed By:Danielle Hildreth, RN, CPT". Jun 29, 2023 Blood Oxygen Levels: What Is a Normal Level? (healthline.com)

[36] "*Normal Resting Heart Rate By Age", Deb Hipp ,Ardeshir Hashmi, M.D., F.A.C.P. ,Mar 28, 2024, 1:55pm.* Normal Heart Rate By Age (Chart) – Forbes Health

[37] سرعة التنفس (Respiration rate) | الطبي (altibbi.com)

[38] HIGH BLOOD PRESSURE What Is High Blood Pressure? April 25, 2024 High Blood Pressure - What Is High Blood Pressure? | NHLBI, NIH

[39] "*Confusion Matrix in Machine Learning*" 13 May, 2024, Accessed on: 19 May, 2024. [Online]. Available: https://www.geeksforgeeks.org/confusion-matrix-machine-learning/

[40] "*Cohen's Kappa Score*" 13 Nov, 2022, Accessed on: 19 May, 2024. [Online]. Available: https://bootcamp.uxdesign.cc/cohens-kappa-score-33a0710b2fe0

[41] "Cohen's Kappa - Testing with Kolena" 31 May, 2024, Accessed on: 01 Jun, 2024. [Online]. Available: https://docs.kolena.com/metrics/cohens-kappa/#:~:text=Cohen's%20Kappa%20is%20a%20statistical,classifier%20based%20on%20class%20frequencies.

[42] "*What are RMSE and MAE?*" 14 May, 2021, Accessed on: 22 May, 2024. [Online]. Available: https://towardsdatascience.com/what-are-rmse-and-mae-e405ce230383

[43] "*Understanding AUC - ROC Curve*" 26 Jun, 2018, Accessed on: 22 May, 2024. [Online]. Available: https://towardsdatascience.com/understanding-auc-roc-curve-68b2303cc9c5

ملخص:

يركز هذا العمل بشكل أساسي على اكتشاف الأعطال في شبكات الجسم اللاسلكية (WBANs) كما يسلط الضوء على الأهمية البالغة لضمان وصول المعلومات والإشارات من أجهزة شبكات الجسم اللاسلكية إلى الأطراف المعنية بدقة ودون أخطاء، خاصة في سياق مراقبة الصحة.
بالإضافة إلى ذلك، يهدف هذا العمل إلى معالجة التحديات المتعلقة باكتشاف الأعطال في شبكات الجسم اللاسلكية من خلال إجراء تحليل مقارن لمختلف خوارزميات التعلم الآلي والأساليب الإحصائية.

الكلمات المفتاحية: شبكات الجسم اللاسلكية، اكتشاف الأعطال، خوارزميات التعلم الآلي، الأساليب الإحصائية.

Abstract:

The primary focus of this work is on fault detection in Wireless Body Area Networks (WBANs). It emphasizes the critical importance of ensuring that information and signals from WBAN devices are accurately and reliably transmitted, particularly in the context of health monitoring.
Additionally, this work aims to address the challenges related to fault detection in WBANs by conducting a comparative analysis of various machine learning algorithms (ML) and statistics.

Keywords: Wireless Body Area Networks, fault detection, machine learning algorithms, statistics.

Résumé :

L'objectif principal de ce travail est la détection des pannes dans les réseaux de capteurs corporels sans fil (WBANs). Il souligne l'importance cruciale de garantir que les informations et les signaux provenant des dispositifs WBAN soient transmis de manière précise et fiable, en particulier dans le contexte de la surveillance de la santé.
De plus, ce travail vise à relever les défis liés à la détection des pannes dans les WBANs en effectuant une analyse comparative de divers algorithmes d'apprentissage automatique (ML) et des méthodes statistiques.

Mots-clés : Réseaux de capteurs corporels sans fil, détection des pannes, algorithmes d'apprentissage automatique, statistiques.