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Artificial Intelligence-Based Classification of Trusted and Untrusted Sensor Nodes in WBAN Using Multi Layered Stacked Naïve Bayes Method for Resilient Infrastructure

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ABSTRACT

WBAN Magnetic Sensor Nodes can be classified based on artificial intelligence using the Multi-Layered Stacked Naïve Bayes Method for Resilient Infrastructure. As wireless body area networks (WBANs) hold considerable potential for monitoring, identifying, forecasting, and diagnosing disease in humans, this study is significant for the healthcare industry. WBAN data can be inaccurate and unreliable when collected by untrusted sensor nodes, leading to inaccurate diagnoses and treatments. WBAN networks can be improved by identifying untrusted sensor nodes in this study to address this issue. Sensor nodes are categorized using the MLSNB method based on their trust aspects. When compared to other methods currently in use, MLSNB performs better. It is possible, using the proposed methodology, to introduce high-quality, affordable, and easily accessible healthcare systems to the world's growing population, in particular to the elderly and persons living with old-age diseases.

1. INTRODUCTION

Human disease monitoring, identification, forecasting, and diagnosis have been made possible by wireless body area networks (WBANs). The potential applications of WBAN in the healthcare industry are described and defined throughout the paper. Privacy and security can be enhanced by WBANs, but their use is a concern. Using Artificial Intelligence-Based Classification on Sensor Nodes in WBAN, we propose a Multi-Layer Stacked Nave Bayes Method for Resilient Infrastructure to help overcome these issues. Patients can continue their daily routines while receiving medical care thanks to WBANs, which reduce foundation costs and pharmaceutical costs [1]. There is however a possibility that WBANs can fail to diagnose and treat patients accurately due to untrusted sensor nodes. WBAN networks can be made more efficient by identifying untrusted sensors. In this method, MLSNB is used to extract and categorize trust attributes from sensor nodes. MLSNB is the method that was used in this study and is described and explained in detail in this paper. Comparing MLSNB with other current methods, it also shows superior performance [2]. A min-max normalization technique was used to prepare the data. By using independent component analysis, we were able to extract features. For feature selection, we used a bi-objective genetic algorithm. To categories the nodes, we utilized Ensemble Naive Bayes. The paper improves healthcare services by identifying untrusted sensor nodes, the accuracy and reliability of the data collected by WBANs can be improved, which can lead to better diagnoses and treatments. This can ultimately lead to more efficient and effective healthcare systems that provide top-notch, affordably priced, and easily accessible health care services to the world's rising population, particularly those who are older and afflicted by ailments of old age [3]. In a multifaceted, dynamic, and connected setting like the Smart Home, where personal information is now more readily accessible from a distance, the renter is subject to privacy and security issues. A health care system can be installed in a smart home using wireless communication technologies, wearable sensor nodes, actuator nodes, and actuator nodes. A WBAN is the name of this technique. The architecture of WBAN is shown in Figure 1.

IoT improvements have made data detection, collection, and analysis processes more effective and efficient. IoMT, or "Internet of medical things," is a term that describes the usage of IoT and wireless body area networks in the healthcare industry. A variety of medical devices and software programmes with the ability to link to healthcare IT systems are referred to as IoMT [4]. WBAN evolves as a result of extensive research. A person's (outdoor) physical fitness, blood pressure, and risk of having a heart attack can all be analyzed by utilizing a sensor, cloud, and machine learning approach, as an example. Installing sensors (retina artificial arm chips) could give the blind individual their vision back. Research on heart problems, pneumonia, hypertension, Alzheimer's, Parkinson's, and other conditions can be done with WBAN. Although patients must stay in hospitals as part of traditional wellness programs, WBAN admits that these patients can continue with their regular daily routines. It reduces foundation costs and costs associated with pharmaceutical work [5]. Untrusted Nodes might have a negative effect on the performance of a WBAN network as a whole. Because of outside attackers, the WBAN network topology becomes one of untrusted sensor nodes. This paper makes the following contributions:

- To prepare the data, we utilized min-max normalization technique.
- To extract features, we utilized independent component analysis.
- For feature selection, we used a bi-objective genetic algorithm.
- To categories the nodes, we utilized Ensemble Naive Bayes.

Figure 1. Structure of WBAN

The remaining parts of the paper are provided below:

The related works are included in Section II. Section III provides specifics on the suggested technique along with the experimental data sets. A discussion of the result and analysis is provided in Section IV. The conclusion is presented in Section V. Healthcare is one of the industries that could benefit from this study. A wireless body area network (WBAN) holds considerable promise for monitoring, identifying, forecasting, and diagnosing human disease. Researchers found that WBAN networks can be improved to provide better healthcare through the use of the study's findings. The data collected by WBANs can be improved with better accuracy and reliability by identifying untrustworthy sensor nodes, which could lead to improved treatments and diagnoses. Throughout the introductory section of this paper, the objectives, methodology, and results of the study are outlined. WBAN networks can be improved by identifying untrusted sensor nodes as part of the study. Sensor nodes are classified into trusted and untrusted based on their trust aspects using the MLSNB method. Study results show that MLSNB performs better than other currently used methods. It is possible to use the study's findings to develop more efficient and effective healthcare systems that provide quality healthcare services at an affordable price to the world's growing population, especially those who are older and have chronic illnesses. Following is a breakdown of the remaining sections of the paper. This study presents a description of the experimental data sets and the proposed methodology in Section 2. In section 3, we present a methodology that we are proposing. Results and discussion are presented in Section 4. To conclude, Section 5 outlines directions for future research and provides a conclusion.

2. METHOD

A method to identify untrusted sensor nodes is proposed in this study to improve the performance of Wireless Body Area Networks (WBANs). Artificial Intelligence-Based Classification of Trusted and Untrusted Sensor Nodes in WBAN using Multilayer Stacked Na+ve Bayes Method for Resilient Infrastructure (MLSNB) is the proposed algorithm. Our MLSNB method was carried out according to the following steps, which will provide more information about how it works. The data was first normalized using the min-max method. By scaling data to a specific range, it helps machine learning algorithms perform better. In this step, Independent Component Analysis (ICA) was used to extract a trust aspect from sensor nodes. The ICA procedure separates multivariate signals into independent and non-overlapping signals that are non-Gaussian. ICA was used to categorize sensor nodes as trusted or untrusted. In order to categorize the sensor nodes as trusted or untrusted, the Bi-Objective Genetic Algorithm (BGA) was used to extract the trust aspects from the nodes. BGAs can be used to solve problems with multiple objectives. According to their features, BGA classified these sensors as trustworthy or untrustworthy. In order to categorize sensor nodes as trusted or untrusted, Ensemble Naive Bayes is used. Naive Bayes algorithms are used for performing classification tasks. Naive Bayes was improved in the present study using Ensemble Naive Bayes. Comparing the MLSNB method's performance with other methods currently in use in the field led to an evaluation of the method's performance. The MLSNB method results in a greater efficiency for WBAN networks than any other method, according to our study. Using Artificial Intelligence-Based Classification, the WBAN identifies trusted and untrusted sensor nodes using the Stacked Naive Bayes Method. In this process, data are prepared, features are extracted, features are selected, and classification is performed. Our results demonstrate the superiority of the MLSNB method over other methods currently being used when applied to experimental datasets.

Several predictive analysis methods have been evaluated in the study [6] for categorizing different limb movements. This study examined the Transmission and Reflection coefficients of an on-body Wireless Body Area Network antenna for each of its hand movements. Liu and Zhang [7] establishes an ensemble learning strategy to solve the Human activity reorganization (HAR) problem under WBAN to develop a lucrative HAR technique. Zhang and Yang [8] presented a fresh mutual key agreement and authentication system for WBAN. The suggested protocol is efficient and small since it only uses straightforward homogeneous cryptographic systems, including such simple XOR and a cryptographic hash function. Performance comparisons with the pertinent, existing protocols show that the proposed protocol is effective in reducing communication and processing complexity. This study [9] suggested innovative distributed system paradigms and wireless communication approaches that may make it easier to detect polysubstance use. Wearable biosensor readings from individuals who have consumed various medicines are combined with two separate offline data streams. This study [10] proposed that the Tunicate Swarm-Sail Fish Optimization algorithm (TS-SFO) is used to anticipate cardiac illness using extracted statistical data, and an enhanced Recurrent Neural Network (RNN) is proposed by changing specific parameters. The test results show that flexible design allows RNN hyper-parameters to be tweaked to a high prediction rate. They suggested a trusted and untrusted sensor nodes detection and classification mechanism to improve the efficacy of WBAN networks. The classifier used in this method is the adaptive neuro-fuzzy inference system (ANFIS). Features extraction and categorization modules make up the system as proposed. The sensor nodes' trust features are taken out and then using a genetic algorithm, these traits are optimized. Classification rate, packet delivery ratio, and latency are all used to evaluate the WBAN network's performance. This study [11] outlined in detail that sensor nodes operating in the healthcare industry can communicate in an energy-efficient manner that is link-aware. The suggested architecture is built on top of the (Remote Management and Control Protocol) RMCP routing system and is based on the DSDV routing protocol. This study [12] examined the results of altering the amount of body sensor data under different access modes, such as IEEE 802.15.4 Path loss variations and no path loss alterations, as well as TDMA and CSMA. This study [13] suggested a high-throughput, dependable, and power-efficient WBAN methodology. A fresh method of sending packets to the sink has been suggested. The suggested technique's simulation findings demonstrate that reducing energy usage lengthens the duration of network stability and boosts throughput. These studies [14, 15] examined the technology's suitability for usage in a medical setting as well as the support system needed. It is addressed how to support WBAN devices in various situations with an integrated system that uses Amazon web service (AWS) IoT services.

3. PROPOSED METHODOLOGY

To categorize nodes within WBAN networks into trustworthy or untrusted, this study used an MLSNB algorithm. Sensor trust information is extracted from sensors using MLSNB by using an objective genetic algorithm (BGA) based on independent components extracted from each sensor. Using trust versus untrust classifications, WBAN networks can operate more efficiently. A performance record over other methods led to the selection of MLSNB. With the help of ICA and BGA, MLSNBs can categorize and extract relevant features from sensor nodes. The MLSNB implementation was evaluated against other current methods to provide more detail. The performance of MLSNB approaches makes them attractive in WBAN networks. This approach, however, may have limitations or challenges. It is possible that MLSNB's scalability may be compromised due to its higher computing resource requirement. As well as having broader implications and applications, this research has broad implications The WBAN network improves healthcare services for the elderly in a growing global population. By improving the performance of these networks, healthcare facilities can provide more comprehensive healthcare services. As an additional application, the MLSNB method may be useful in other fields beyond healthcare, such as environmental monitoring or industrial automation. This method can be used for both testing, which determines how well each node in the WBAN network functions, and training, which generates the input pattern. Figure 2 illustrates the WBAN process flow.

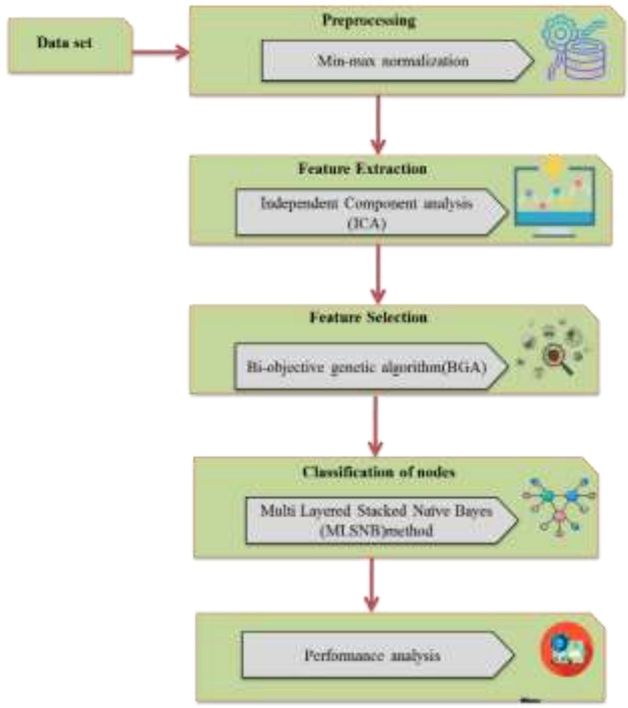

Figure 2. Block diagram of proposed methodology

The WBAN network responses, or acquired signal levels, for typical human movements were gathered in order to train the classifier in the human motion categorization system. Based on earlier research, a WBAN transmission network was created in the bandwidths of 403.5 MHz and 2.45 GHz [16-22]. Data preprocessing modifies the data's format to speed up and improve the efficiency of processes like data mining and machine learning. The approaches are often used early in the AI and machine learning continued development and utilized to ensure high quality output [23-28]. Here, the Min-Max normalization step of the WBAN preprocessing procedure was applied. The unique records are converted linearly on this technique of records normalization. The minimal and most cost from the records is retrieved, and every cost is changed the usage of the Eq. (1):

$$V' = \frac{Min\ A}{Max\ A - MIN\ A}(new\_\max(A) - new\_min(A) + new\_min(A) \tag{1}$$

3.1 Feature extraction using independent component analysis

A high order statistical unsupervised learning algorithm is called the ICA. The linear transformation is best estimated from the data itself since it may then be fine-tuned for the specifics of the input. In the case of regular transformations, the basis vectors do not adapt to new information but remain constant [29-38]. They can utilize a statistical latent variable model to define ICA. As random variables are combined linearly. s_1, ..., s_n that they observe, the model n random variables x_1, ..., x_n in (2):

$$x_i = a_i s_1 + a_2 s_2 + \cdots + a_{in} s_n \tag{2}$$

when there exist some real coefficients, a_{ij} and i, j=1, ..., N. The S_i are statistically independent of one another by definition. The basic ICA model is presented here. It is not feasible to directly witness the independent components s_i since they are latent variables. Additionally, it is believed that the mixing coefficients a_{ij} are unknown. We only have the random variable x_i to go on, so we must use x_i to estimate the independent components s_i as well as the mixing coefficients a_{ij}. Under a general set of assumptions, this is possible. The mixing model is expressed as follows in vector-matrix notation (3):

$$X = As = \sum_{i=1}^{n} a_i s_i \tag{3}$$

This model is viewed as a linear combination of basis vectors when it comes to image processing. Moreover, the basis vectors a_i is undoubtedly spatially, directionally, and spectrally localized. Finding a strong set of basis vectors is our aim to adequately depict iris patterns.

3.2 Feature selection using bi-objective genetic algorithm

To select the most beneficial and condensed feature subset, this research suggests using a bi-objective genetic algorithm (BGA) with a mutation pool. Figure 3 schematically depicts the suggested Bi-objective genetic algorithm (BGA)-based feature selection algorithm (FS). This suggested stochastic search-based feature selection technique is initially utilized to construct a subset of features from the dataset. Following the evaluation of these features, the non-dominated feature subset is selected.

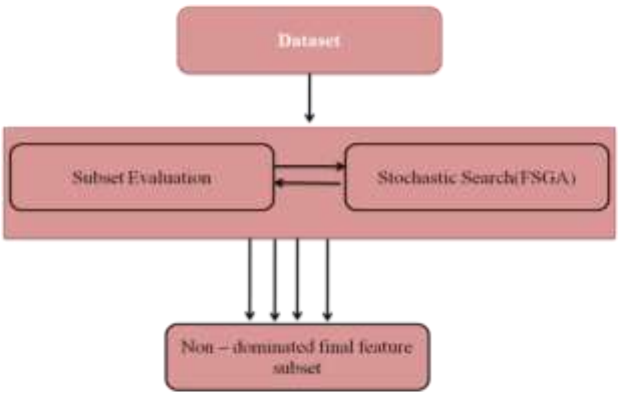

Figure 3. Diagram of one feature selector's flow

Due to the fact that GA is a population-based stochastic search technique, the initial population for the suggested feature selection is generated at random. P(n), where P is the expected population size and n is the total number of features in the dataset; together make up the dimension of the population set. The chromosomes were represented in this study as binary strings. The dataset's overall feature count is the same as the length of the string. For each gene, there are only two possible values, 1 and 0, which represent the presence or absence of the index feature in the current subset. Therefore, the following is a representation of chromosome c_1 of length K.

Every people have an equal chance of becoming a parent under the planned feature selection. To produce offspring from parent chromosomes, a single-point crossover technique is used. The application of mutation is mostly done to increase population variety. Multiple mutation strategies are used in the method, including bit flip mutation, leaping gene, Gaussian mutation, uniform and non-uniform mutation approach, and others. The mutation strategy that will be used at any given time for any current offspring is dynamically selected from the pool. By maximizing population member quality through the effective use of those individual mutual strategies, this mutation strategy was chosen. The suggested feature selection algorithm is listed below:

Algorithm 1: BGA-based Feature selection

Stage 1: Input: Data set
Stage 2: Begin
Stage 3: Generate Population (P) of size N
Stage 4: Analyze both fitness metrics for the entire population.
Stage 5: Make a global best calculation for each fitness function.
Stage 6: Repeat
Stage 7: For i=1 … N
Stage 8: First-parent=P_1
Stage 9: Choose a different parent P_j from the available list.
Stage 10: To create offspring, implement a single-point crossover between p_i and p_j.
Stage 11: Choose a mutation approach dynamically from the available options.
Stage 12: Mutate the progeny and
Stage 13: Create two fitness scores for the progeny.
Stage 14: If both of the fitness values of the children are ideal, then that is the situation
Replaces one of its parents, updating the list of the world's finest
Else If a child rules over a parent, then
Replacement of that parent by offspring
End if
Stage 16: End for
Stage 17 until the required number of generations have been created
Stage 18: Reintroduce a population member group that is not dominated as a remedy.
Stage 18: Close
Stage 20: Result: a set of non-dominated reductions

3.3 Multi layered stacked nave bayes (MLSNB)

This section illustrates the proposed Naive Bayes-based trust node classification method. The naive Bayesian model is straightforward along with the less complex model. The absence of repetitive parameter estimation shows that the naive Bayes model has simple functionality and is especially beneficial for very large data sets. One definition of the Bayesian Theorem is shown in (4) to (6):

$$\text{P (x |y)}=\frac{\text{p(y|x)} \times \text{p(x) p(y)}}{\text{p(y)}} \tag{4}$$

$$P\ (y|x) = p\ (y1\ |x) \times p\ (y2\ |x) \times \ldots \times\ p\ (y_n\ |x) \qquad (5)$$

where, $P(x)$ is the probability of class occurrence, $P(y)$ is the likelihood that instance y will occur, and $P(y|x)$ is the likelihood that instance y will occur given class x given in the (4). All parameters are freed by the naive Bayes classifier. The Naive Bayes classifier can be used to simplify the Bayesian theorem in cases where there are multiple features or parameters. In this study, rogue WBAN nodes were found using a Naive Bayesian classifier. The Naive Bays classifier have been denoted by the “Packet Error Rate” (PER) and “Packet Loss Rate” (PLR). The hostile node intentionally discards packets or spreads false packets. It served as the impetus behind our choice to combine PLR and PER we suggested using the trust model to assess a sensor node's dependability. If PER=a and PLR=b for a node n under a piece of evidence. It served as the impetus behind our choice to provide PLR and PER in the trust model we suggested to assess a sensor node's dependability.

$$\begin{gathered} Value = High\text{:}\ P(T = High \times P(PER = a \\ = High) \\ \times\ P\ (PLR\ =\ b|T\ =\ High) \\ value = Low\text{:}\ P(T = Low) \times\ P(PER = a|T \\ = Low) \times (PLR = b|T = Low) \\ Value =\ Moderate\text{:}\ P(T \\ = Moderate)\ \times\ P(PER\ = a|T \\ = Moderate) \\ \times P(P = b| = Moderate) \end{gathered} \qquad (6)$$

Trust worthiness is represented by the letter T. If the results of the calculation show that node n is malevolent, the expected value will be Low, followed by the predicted values and the forecast value. They used the Naive Bayes Classifier to classify the nodes' trustworthiness as high, moderate, and low. The trustee node with the highest trustworthiness value will subsequently be chosen by the coordination node. The coordination node will choose the trustee node with a moderate trustworthiness value if a high trustworthiness node is not present. Any trust node with a low trustworthiness rating will be permanently removed by the coordinator node and marked as hostile. In reaction to this, the coordinator node will then generate a notification.

4. RESULT AND DISCUSSION

With a data rate of 512 B per second for each sensor node, 50 sensor nodes are taken into account in this study. A sensor node transfers packets that are 512 bytes in size and have a transmission delay of 100 milliseconds between each cycle of data between two subsequent sequences. The battery inside each sensor node supplies energy for continuous data transmission and reception. A 1000 J initial energy is present in each battery in the sensor node. The sum of the numbers on the diagonal divided by the sample size into the test data represents the accurate classification rate. The ratio of precise predictions to all input samples is measured. There must be an equal amount of samples from each class for it to work effectively. The suggested method of categorization rate for the trust sensor node in WBAN is based on the performance of MLSNB being 94%, ANFIS being 77%, SVM being 84%, LSTM being 66% and DTA being 58%. Figure 4 shows a comparison of the packet delivery ratio (PDR). The PDR stands for the percentage of deliverable packets to those delivered from source nodes to destination nodes. The objective is for most data packets to be delivered to the destination. The suggested method of packet delivery ratio for the trust sensor node in WBAN is based on the performance of MLSNB being 97%, ANFIS being 66% SVM being 60%, LSTM being 85% and DTA being 77%.

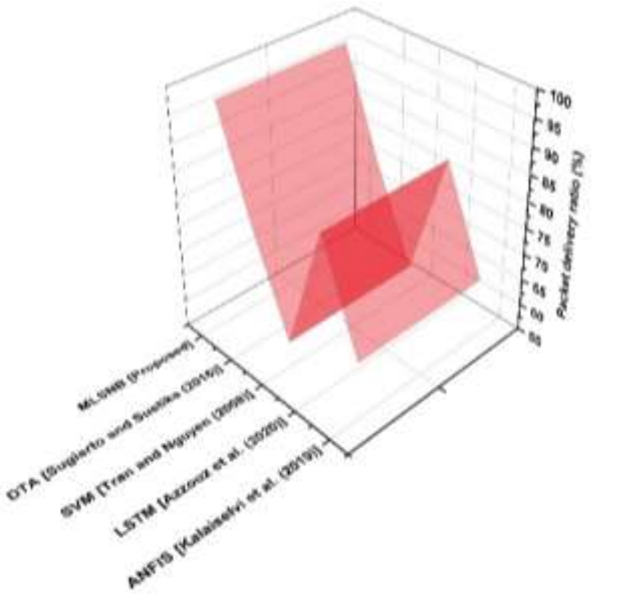

Figure 4. Comparative analysis of packet delivery ratio

The amount of time it takes for data to travel from its original source to its final destination is known as latency, and it is measured in milliseconds. Internet latency and network latency have an impact on all internet connections, including satellite, cable, and some WiFi connections. An investigation of delay in comparison may be shown in Figure 5. The suggested method of latency for the trust sensor node in WBAN is based on the performance of MLSNB being 55ms, ANFIS being 98 ms SVM being 85ms, LSTM being 74ms and DTA being 63ms.

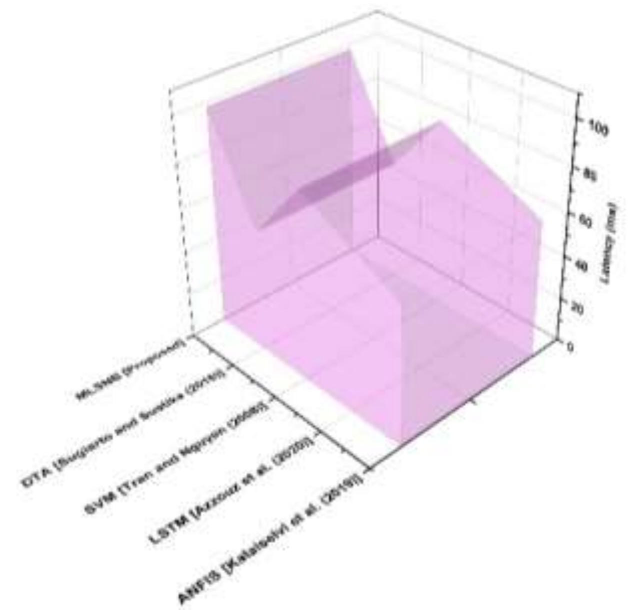

Figure 5. Comparative analysis of latency

5. CONCLUSIONS

A wireless body area network that tracks a patient's health consists of some nodes on or in the body. The providing of energy is a crucial problem in these networks, according to the nodes' inaccessibility. Harvesting energy from the surroundings where these nodes are located is one option for their energy supply. This paper suggested the Multi Layered Stacked Nave Bayes (MLSNB) approach to categorize trust nodes and untrust nodes in WBAN networks. We compared a few currently used methods, including ANIFS, SVM, TDA, and KNN. The performance of the proposed method is great when compared to the existing methods. Moreover, three parameters—categorization rate, packet delivery ratio, and latency—were assessed. Future sensor nodes will feature intelligence that will allow the sensors to decide where to convey the data they have collected in emergency situations.

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