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A Deep learning approach for trust-untrust nodes classification problem in WBAN

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ABSTRACT

The enormous growth in demand for WBAN services has resulted in a new set of security challenges. The capabilities of WBAN are developing to meet these needs. The complexity, heterogeneity, and instability of the mobile context make it difficult to complete these duties successfully. A more secure and flexible WBAN setting can be attained using a trust-untrust nodes classification, which is one method to satisfy the security needs of the WBAN. Considering this, we present a novel Deep Learning (DL) approach for classifying WBAN nodes using spatial attention based iterative DBN (SA-IDBN). Z-score normalization is used to remove repetitive entries from the input data. Then, Linear Discriminate Analysis (LDA) is employed to retrieve the features from the normalized data. In terms of accuracy, latency, recall, and f-measure, the suggested method's performance is examined and contrasted with some other current approaches. Regarding the classification of WBAN nodes, the results are more favorable for the suggested method than for the ones already in use.

Keywords: WBAN, Trust-Untrust Nodes, Deep Learning (DL), Linear Discriminant Analysis (LDA).

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1. Introduction

Sensors are crucial in the current telecommunications environment, and sensor nodes can link to any location on Earth. Wireless sensor networks constitute wireless communications systems (WSNs). Wireless sensor networks (WSN) can cover a larger geographical area than wireless body area networks (WBAN). WBANs are presently utilized for real-time patient monitoring in the healthcare industry. The development of WBAN networks has enabled the human body to detect, monitor, and control numerous vital signs, such as temperature and humidity. The WBAN comprises many sensor nodes, each serving a particular function [1]. The majority of WBAN deployments take place via various use cases. They are mainly employed for long-term monitoring of patients' biological signals or telehomecare, also known as remote diagnostics. They treat various medical conditions like diabetes, dementia, falls, asthma, and sterility that require quick intervention and careful assessment. Fig.1 depicts the deep learning strategy utilizing WBAN. WBAN video display units the fitness fame of sufferers in actual time and responds to emergency conditions as quickly as viable [2]. A crucial piece of technology is wireless body area networks (WBANs), which evaluate several dangerous diseases and perform continuous health checks on patients. A WBAN offers a variety of therapeutic and non-restorative uses while operating near, on, or inside a human body [3]. Sensor data is gathered using a smartphone and any other devices or controllers. The most crucial element of WBAN is energy efficiency. As a result of their tiny size, sensors use less energy than more extensive devices, yet signal transmission uses more energy. The energy-efficient technique was developed in earlier works [4] to prevent problems with energy exhaust.

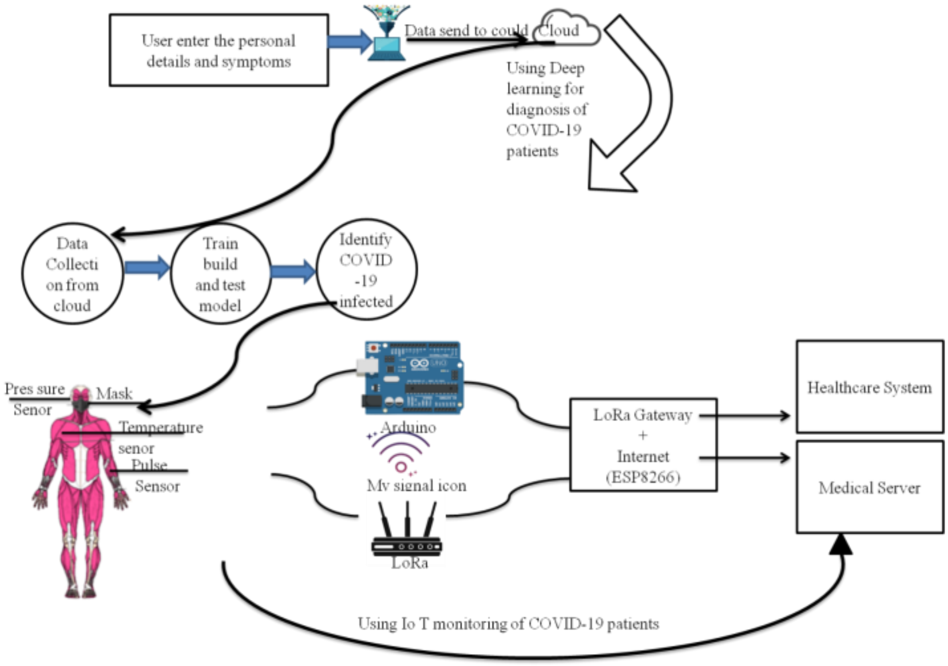

Figure 1. Deep learning approach based on WBAN

Quality of Service (QoS) is also impacted when more retransmissions are needed. QoS requirements may fluctuate depending on the kind of traffic (emergency versus non-emergency). Diverse QoS standards (data transfer rate, delay, and packet delay) could be challenging in WBAN due to the severe resource constraints on devices and the unstable networks connecting them [4]. The patient's body is covered in Wireless Physiological Area Networks (WBANs), a class of biosensing used to gather vital body data like heart rate, oxygen levels, respiratory rate, etc. A wireless body biosensor network can be created by the biosensors connecting wirelessly. The body might have biosensors either inside or outside of it. Another way to link the biosensors in these networks to the body is through wearable technology. Several examples of communication technologies [5] include Bluetooth low-power Bluetooth (BLE), ultra-wideband, and radio frequency identification (RFID). Following are the paper's main contributions:

· We use a variety of preprocessing techniques, including Z-score normalization.
· To extract features, we added linear discriminate analysis (LDA).
· To achieve superior performance in node categorization, we deployed SA-IDBN.

The following sections comprise the paper: Section II provides an overview of previous research, Section III provides a more detailed explanation of the suggested methodology, and Section IV presents the findings and a conclusion. The section v conclusion was described.

2. Related work

The Reference cited in [6] proposes a new medical strategy for the early detection of stroke and other maladies requiring immediate medical attention. Radiofrequency identification (RFID), ultra-wideband Bluetooth (BLE), and Bluetooth low energy (BLE) are examples of communication technologies (RFID). The experimental results demonstrate that the proposed method outperforms more conventional models with an accuracy of 88.47%, indicating its suitability for disease detection, particularly in the case of stroke-related issues. Reference [7] suggests a lightweight cloud-assisted authentication technique based on physical unclonable functions (PUFs) in multi-hop body domain networks to enhance data transmission security and human mobility. This authentication system reduces data transmission's resource consumption and storage burden. Both standards directly impact clustering and routing, so Reference [8] improves the unified sensor node clustering. The initial

routes are determined using tree clustering techniques for improved load balancing. The K-nearest neighbors (K-NN) technique can be used to group sensor nodes more equitably.
A biometrics iris fusion-based trusted anonymized secured routing protocol is suggested to maintain the WBAN unlinkability and secrecy. Reference [9] suggested an IoTs-based infrastructure for medical and healthcare with regulated access to achieve that objective. Through simulations, the effectiveness of the proposed algorithm is compared to that of the most recent technique. Through speedy cluster building, little information loss, and execution time for data distribution, simulation results show the value of the proposed solutions. To address this security issue, reference [10] proposed a deep learning-based IoT solution for privacy protection and data analysis. User data is collected, and sensitive data is isolated and stored separately. Without identifying information, health-related data are analyzed in the cloud using convolutional neural networks (CNN). A secure access control module based on user attributes is introduced for IoT-Healthcare systems. The proposed research establishes a connection between quality and consumer trust. The proposed CNN classifier meets the accuracy, recall, and F1 score specifications. The reference [11] addresses the security issues of WBAN and proposes a system based on IoT and deep learning for data analysis and privacy protection. Sensitive information is gathered distinct from user information. Health-related data can be viewed in the cloud using convolutional neural networks without access to the user's confidential information (CNN).

The IoT-Healthcare system was thus augmented with a secure access control module based on user attributes. With the aid of the proposed work, a connection between quality and user confidence was discovered. The proposed CNN classifier succeeded in terms of F1 score, recall, and precision. Focusing on applications concentrated on remote monitoring of chronically ill patients and the elderly, Reference [12] offers some insight into the scientific foundation of WBSN and highlights recent advancements in the field. A thorough investigation of the architecture, difficulties, healthcare applications, and requirements of WBANs is necessary to realize the scientific idea of WBAN. Data gathering, fusion, risk assessment, and decision-making are included after explaining the WBAN's key features. Reference [13] improved the security of the information collected by storing data using blockchain technology.

Additionally, our approach recommends a storage architecture based on blocks for WBAN. Blockchain storage, however, creates new issues, such as its limited storage capacity and the vulnerability of the stored content to unauthorized intruders. The problems were addressed in this work, and the privacy of WBAN users was protected by developing a sequential aggregate signature mechanism with a designated verification. By using this technique, it is ensured that nobody other can access the user's data. Reference [14] presented a wireless body area networks (WBAN)-based compact embedded healthcare industry model tailored to the sector to lower management costs and increase power consumption in mobile e-health services. An optimal learning algorithm is implemented to reduce the cost of maintaining the embedded system and to convert and administer EHRs more efficiently.

3. Proposed Methodology

One of the gifted technologies with a wide range of applications for the e-health care industry is WBAN employing machine learning. The proposed deep learning model's primary duties include gathering from the cloud information on vital bodily indicators like temperature, respiratory function, and oxygen levels in order to classify the user (patient) into one of two groups: 1) COVID; 2) the common cold. The third stage of the proposed iot-based WBAN approach calls for ongoing surveillance of COVID-19 afflicted people. To determine trusted and untrusted nodes, lansif, decision trees, support vector machines, and k nearest neighbors are utilized. Figure 2 depicts a diagram of the WBAN constructed using deep learning techniques. This study examines 50 sensor nodes, each with a data throughput of 512 bytes per second. The sensor nodes transmit each 512-byte payload with a latency of 100 milliseconds between each data cycle of two consecutive sequences. A battery for uninterrupted data transmission and reception fuels each sensor component. Each sensor node battery has an initial energy capacity of one thousand joules [15-20].

RSA needs a key with a 1024-bit size in order to be used securely. However, WBAN's limited computational power, connection speed, and memory necessitate RSA modification. Simply decreasing the key size will reduce security levels; however, to get over these issues, adding numerous pre-processing layers with quick computation times will increase the number of total combinations for generated hypertext by RSA. Z-score normalization involves changing each value in a dataset so that the standard deviation is 1 and the mean of all the values is 0. This was referred to as it [21-23].

$$x_i = \frac{x_{i-\mu}}{\sigma} \times \propto \qquad (1)$$

Fisher Linear Discriminant Analysis (FLDA), or Linear Discriminant Analysis (LOA) or LDA, is a prominent feature extraction technique for face images. For classification problems, the LOA dimension reduction method is utilized. The strategy seeks to determine the projection direction of images from various sources. At least two divisions exist. It performs the following calculations to determine the projection matrix's weights. The ratio of the intra-class scatter matrix to the inter-class scatter matrix is maximized for image projection. Unlike the PCA-based approach, LOA considers class membership when reducing dimensionality. The main goal of LOA is to achieve good class mean separation while maintaining limited variance around these means in the projection direction. Like PCA, LDA uses a linear combination of initial data to generate its features [24-36].

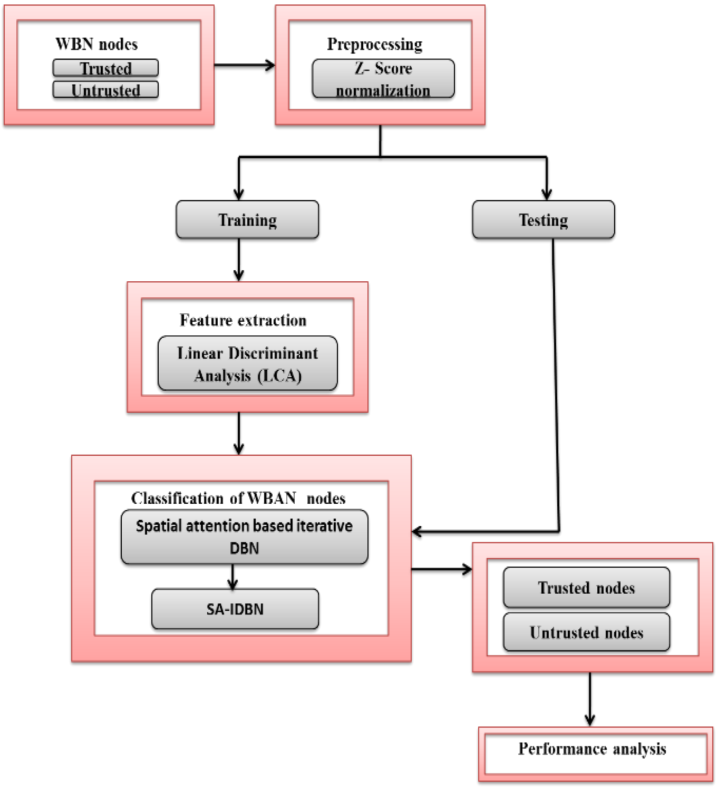

Figure 2. Block Diagram of Trust Node Classification Problem in WBAN

LOA is appropriate for graphical representation of the data sets since it efficiently reduces the data onto a low dimensional space (2).

$$W_{opt} = arg \max_{w} \left| \frac{W^T S_B W}{W^T S_W W} \right| \qquad (2)$$

An optimal discrimination projection matrix W0P1 is what LOA is trying to solve in “Eq (3)-(5)”.The following are the fundamental LOA steps:

a) Determine the scatter matrix within each class, where S_W represented in “Eq (3)”.

$$S_W = \sum_{i=1}^{C} (x_i - \mu_{ki})\ (x_i - \mu_{ki})^T \qquad (3)$$

b) Determine the s_B between-class scatter matrix as

$$S_B = \sum_{i=1}^{C} n_i(\mu_i - \mu)\ (\mu_i - \mu)^T \qquad (4)$$

c) Determine the projection matrix's eigenvectors

$$W = \mathrm{Eigen}\ (S_T - 1S_B) \tag{5}$$

d) Compare the projection matrices of each training image to the test image using a similarity metric. The result is the training image, which closely resembles the test image.
S_W is the internal scatter matrix, while $S_a + S_r$ equals the scatter matrix between classes. Using the general scatter matrix
The data c, x, and k stand for the number of samples in the whole collection of images, the feature vector for a sample, and the class of images that sample x; belongs to. The number of samples in picture class I, denoted by the symbol n, equals the mean feature vector of class I. The intra-personal scatter matrix, often referred to as the within-class scatter matrix, illustrates changes in a person's appearance brought on by different lighting and facial expressions. The extra-personal scatter matrix, also known as the between-class scatter matrix, depicts changes in appearance brought on by different identities.

3.1 Spatial attention

The effectiveness of attention mechanisms in many visual activities may be attributed to their ability to highlight key information while filtering out distractions. High-level characteristics must be refined until they're as sharp as the details below E_x, we apply 2 × 2 convolution with stride 2 to E_1 , marked as $\widetilde{E}_x$={$\widetilde{E}_{xi}$ }$_{j=1}^{s}$. The 1 × 1 convolution is applied to $E_x$to obtain$\widetilde{E}_x$={$\widetilde{E}_{xi}$ }$_{j=1}^{s}$. One possible expression of this is as continues to follow:

$$\tilde{E}_x = \phi_{vy} * E_x \tag{6}$$

Where $\phi_{vy} \epsilon R^{2\times2\times n\times s}$ and $\phi_{vx} \epsilon R^{2\times2\times n\times s}$ represent convolutional kernels of 2×2 and 1×1, respectively, $\widetilde{E}_y$ and $\widetilde{E}_x$ are then added to capture spatial information, followed by two convolutional layers, one with a 3×3 kernel and the other with a 1 1 kernel. Using a sigmoidal procedure, the spatial feature map is normalized to the interval [0, 1]. The entire procedure appears as follows:

$$N_t\left(\tilde{E}_y, \tilde{E}_x\right) = \delta(\Psi_2 * \sigma\left(\Psi_1 * \left(\tilde{E}_y + \tilde{E}_x\right)\right)) \tag{7}$$

Where $\Psi_1 \in R^{3\times3\times s\times s}$and $\Psi_2 \in \mathrm{R}^{1\times1\times s\times1}$denote the 3×3 and 1×1 convolutional kernels, respectively.

3.2 Iterative DBN for classifying WBAN nodes

The categorization labels are often hand-labeled, and the DBN is trained to derive a strong feature representation for subsequent applications. Once the networks have been trained, their effectiveness is determined mainly by the expertise of the humans assigned the labels. However, it might be challenging to get these labels, or they can be prohibitively costly if you do. Additionally, even after successful training, DBN performance is still constrained due to the inherent error-proneness of human or automated labeling techniques. In this part, the DBNs are trained recursively to model the distribution of classifying WBAN nodes with little a priori information to solve this challenge. The suggested model's performance relies on the previous knowledge labels. To begin, we use a single verification system to classify WBAN nodes. To train DBN, we provide a window containing every pixel. If a window goes beyond the picture's visible area, the missing pixels are created by reflecting the visible ones. The last DBN layer's output is understood to represent the likelihood of classifying WBAN nodes. When DBN is applied this way, the classifying WBAN node characteristics are retrieved at a probability threshold of 0.5. DBN is retrained for division using a brand new training set, and the resulting binary images are used to re-label all pixels within the original images. The DBN is trained this way until it has reached an acceptable level of verification accuracy on a validation dataset. As DBN progresses through training iterations, inaccurate pixel classifications are empirically rectified to boost quality. Algorithm 1 describes in depth the DBN model suggested in this paper.

Algorithm 1: Iterative DBN for classifying WBAN nodes

Input: The learning algorithm as well as the validation data, in addition to the unprocessed hand vein image $f\ (x, y)$.
Output: The F(x, y) picture of a segmented hand vein;

Step 1: Dissecting the veins of a hand along a single baseline.
Step 2: This binary data is then used to identify each pixel as either a 0 for background pixels or a 1 for vein pixels, and when constructing the learning set, A, patches centred on data represent positive examples, whereas patches centred on surrounding pixels serve as negative class.

Step 3: Deep learning network training using random reduction.
Step 4: We feed C pictures into DBN to generate probability maps, and then we use a threshold of 0.5 to extract the vein structure.
Step 5: Recognisability on a validation data is determined by applying a based algorithm to the resulting binary images. Once the highest level of confirmation accuracy has just been achieved on a testing dataset, iteration should cease and Step 7 should be performed; otherwise, iteration should continue to Step 6.
Step 6: DBN is used to extract a probability map P(x, y) from an input picture, which is then used to relabel each pixel and produce a training set. Selecting patches with a high probability of belonging to the vein as tested cases (P(x, y)>0.6)) and selecting patches with a high probability of belonging towards the background as test instances (P(x, y)>0.4) are used to construct the training set.
Step 7: DBN is used to the input picture $f\ (x, y)$ to produce an improved data, and the binaries result is the data $F.(x, y)$. the expression $F(x, y)$ is returned.
Return $F(x, y)$;

The output in the sequence is dependent on certain inputs according to spatial attention based iterative DBN. However, in exchange for a higher computational cost, a more accurate and efficient model is produced.

4. Result and discussion

The main station will receive the signals gathered from the base station's nodes. With the aid of Network Simulator-2, several parameters for this experimental setup were obtained. This simulation took 200 seconds and involved 100 nodes. “Fig 3” shows the comparative analysis of accuracy. The term accuracy describes how closely a measured value resembles the real (or "true") value. A correct reading for the weight would be as close to 100g as feasible, for instance, if you were to weigh a conventional 100g weight on a scale. The new method obtained 96%, outperforming the outcomes for the ANSIF 60%, SVM 72%, DTA 85%, and KNN 65% existing methods. It shows that the suggested system performs excellently.

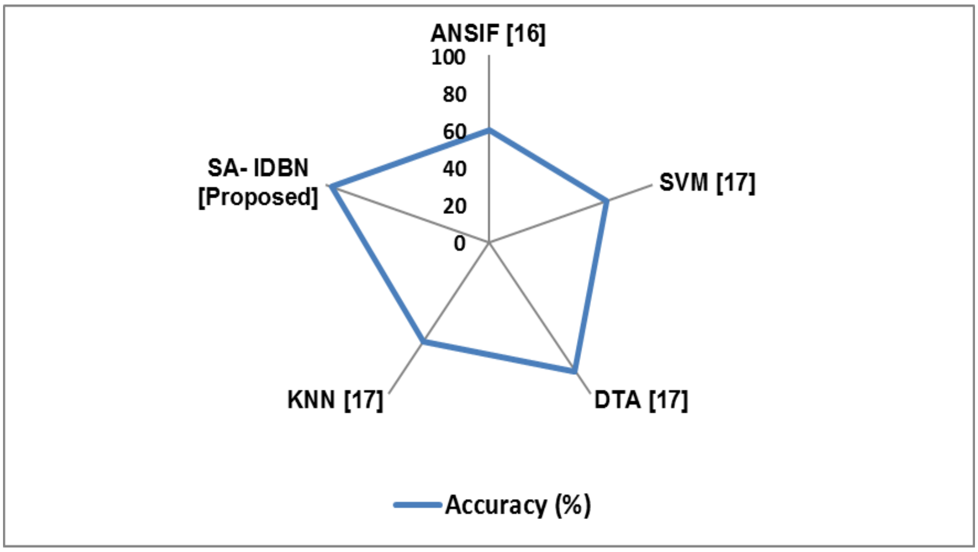

Figure 3. Comparative analysis of accuracy

Data latency, defined in milliseconds, is the amount of time it takes for data to be transported between its original source and its destination. Satellite, cable, and some Wi-Fi internet connections are all impacted by internet latency and network latency. Fig 4 illustrates the comparison of latancy. The comparative study of latency is shown in Fig. 4. The results for the new approach were 60%, exceeding those for the previous ANSIF 90%, SVM 64%, DTA 85%, and KNN 72% methods. Latency demonstrates the lack of success of the proposed technology.

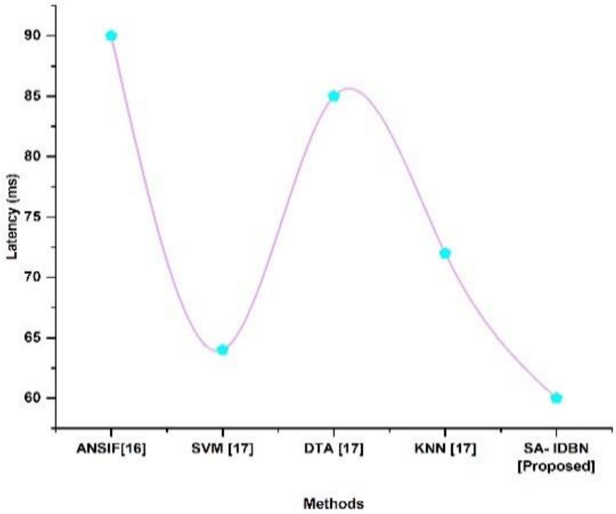

Figure 4. Comparative examination of latency

In psychology, recall refers to the process of bringing back memories of past experiences without the aid of a specific stimulus. Recall is calculated as the proportion of malicious nodes in the network that have been verified as being malicious to all malicious nodes. In Fig. 5, the comparative analysis of recall is displayed. With results of 99%, the new methodology surpassed the previous ANSIF 56%, SVM 79%, DTA 85%, and KNN 72% approaches. Recall demonstrates the more efficacy of the suggested technology.

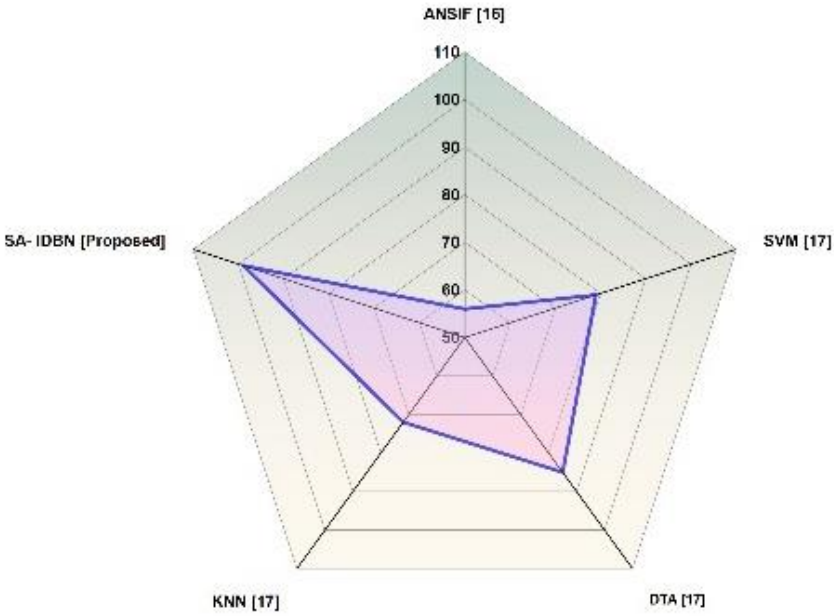

Figure 5. Comparative analysis of recall

F-measure is a frequent assessment metric utilized in records retrieval structures such as search engines and computer getting-to-know models, mainly those utilized for herbal language processing. It is viable to alter the F-score to give precision greater weight than recall and vice versa. It can be challenging to determine what a decent result actually is when using the F1 score, a metric that is frequently employed for classification machine learning models. The comparative study of the f-measure is shown in Fig. 6. The new strategy outperformed the old ANSIF 56%, SVM 69%, DTA 85%, and KNN 72% methods with outcomes of 90%. The effectiveness of the suggested technique is shown by f-measure.

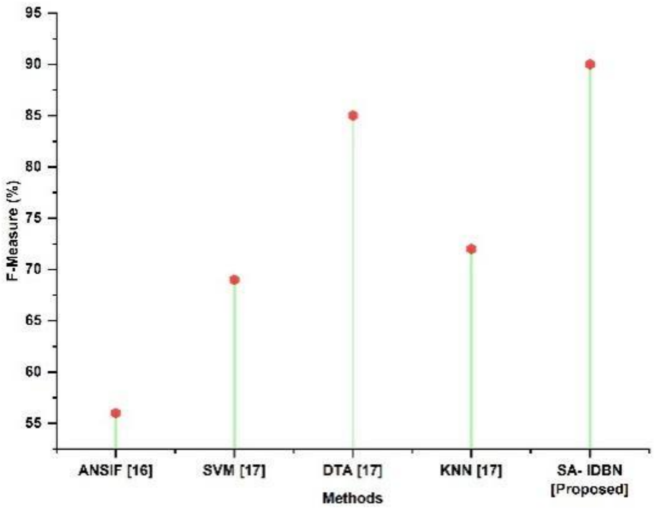

Figure 6. Comparative analysis of F-measure

5. Conclusion

This study aims to detect malicious nodes and achieve energy-efficient data transmission in WBAN. In terms of precision, latency, F-measure, and recall, untrusted sensor nodes degrade the overall efficacy of WBAN networks. DBLSTM enhances the classification rate of the proposed classification system for trusted sensor nodes. In this study, the classifier achieved high levels of F-measure, precision, latency, and recall. Deep learning requires highly complex data models and massive quantities of data to be effective, so training is costly. In the future, robust classification methods incorporating channel characteristics in various environments will be studied more deeply. The classification will be utilized to enhance the comprehension of human motion in order to establish communication within WBAN systems.

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Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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