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Designing a model to detect and separate data anomalies caused by sensors and medical wearables using LSTM neural network algorithm

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Abstract

Predicting abnormalities of wearable medical devices plays a very important role in saving the lives and health of patients. This importance has opened new horizons for researchers with the development of newer algorithms. The long-term memory algorithm (LSTM) is one of the most important methods that are a special type of recurrent neural network (RNN) that has a high ability in this field and greatly increases the accuracy of correct and incorrect prediction of these abnormalities. In the current research, by using this algorithm and taking into account different parameters, the anomalies related to the sensors of the research field were determined. The results showed that there are influential parameters in the construction of this architecture, which include 3 very important factors: the number of neurons in the LSTM layer, the batch size, and the activation function. Also, the LSTM architecture together with the Dropout layer, with parameters Batch size = N = 128 and Tanh activation function shows a better performance and the lowest amount of error (MAPE) as well as the amount of the calculated mean square error (RMSE) in determining the anomaly. have sensors in the medical field. Investigations related to the results of 16 repetitions of optimization also showed that the process of reducing errors in the correct and incorrect identification of anomalies in the training phase has reached its lowest level with the increase in the number of tests, which shows the optimality and appropriateness of the work process. Therefore, this algorithm has a very good ability to identify errors in sensors and medical wearables, and it will be of great help in identifying the possible failure of sensors, and critical conditions of the patient, informing and finally helping patients in time.

Keywords: anomaly, medical sensors, medical wearables, neural networks, LSTM algorithm
2020 MSC: 78M32, 92B20

1 Introduction

Today, the use of wearable technologies in the field of health monitoring and treatment has created a revolution in the field of medicine. A wearable medical device is a device that is independent, non-invasive and has a specific therapeutic function such as monitoring or support over a long period of time. The term wearable means that the device is either worn by the patient or placed on the body. In this decade, the use of wearable medical equipment

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has grown tremendously. These devices fall into three main categories: wearable monitoring devices, wearable rehabilitation devices, and wearable medical assistive devices. Wearable monitoring devices help manage the treatment of chronic diseases and monitor vital signs such as heart rate, oxygen saturation, body temperature, etc. These devices non-invasively measure vital parameters with the help of their sensors and offer facilities such as data analysis, communicating and interacting with the patient and sending feedback to users. The use of wearable systems can reduce the pressure on the healthcare systems of today's societies, increasing costs and increasing the prevalence of chronic diseases that require long-term care [3, 4].

Therefore, the emergence of wearable medical devices allows continuous and real-time monitoring of vital signs such as: heart rate (HR), pulse, oxygen saturation (SpO2), respiratory rate (RR), body temperature (BT), electrocardiogram (ECG), electromyogram (EMG), blood pressure (BP), blood glucose levels (BGL), etc. Apart from monitoring, wearable medical equipment and related sensors are also used to collect and analyze various physiological parameters of people. The advantage of such a system is that it can be used anywhere and anytime [9].

The use of wearable medical devices, apart from their use to monitor vital signs, has also expanded to monitor patients with chronic diseases and cognitive disorders such as Parkinson's, diabetes, Alzheimer's, asthma and epilepsy. These devices have proven to be valuable and effective assets for both patients and health care providers, as they help reduce problems such as the growing number of patients in hospitals, increased waiting times for treatment, and overstaying of patients in health care facilities. , the need for the presence of the required number of nurses and doctors has had a positive effect and reduced health care costs.

But despite the numerous and significant advantages and possibilities that this technology offers to the field of treatment and medicine, these equipments are associated with a range of challenges and disadvantages, from poor reliability to high sensitivity to security attacks after deployment. Body wireless sensor network sensors are subject to hardware and software problems, such as parts failure, sensor calibration, battery discharge, or moving and changing the location of the sensor. Sensor data itself can be both unreliable and inaccurate. This is due to cases where there are limitations in hardware resources such as reduced processing power, memory limitations, lack of energy resources and transmission range. At the time of aggregating sensor data and transferring them to storage servers, there is a possibility of various types of irregularities such as interference, noise, incorrect placement of sensors, sweating of patients, reduction or depletion of energy sources. There is also the possibility of penetration risks and cyber attacks such as malware attacks, injection attacks, modifications or replays. All these challenges have a direct impact on the way of data transfer and storage and the accuracy, accuracy, accessibility of patient data. Therefore, the occurrence of these problems and defects can lead to unexpected results, false alarms, faulty diagnoses, and ultimately to a decrease in public trust in these systems.

As a result, it has become a very important concern to distinguish between critical patient conditions and sensor errors to minimize false alarms. Therefore, both the critical conditions of the patient and the occurrence of errors in the sensors lead to abnormality in the received data. Therefore, solving this important challenge requires that each of them be identified with the highest possible accuracy [15]. Therefore, this study tries to achieve this goal by using an anomaly detection mechanism to identify and extract unusual patterns and correlations in the data and distinguish between sick people and defective sensors. The main question that this study seeks to find the appropriate answer to is:

- How to detect the error in sensors and medical wearables, and based on that, separate the failure of the sensor from the critical condition of the patient and notify?

2 Theoretical foundations and background

2.1 Wearable systems

The ever-increasing growth in the communication, telecommunication and computer industries has confronted the world with a new revolution every day. With the development of information technology in the field of medicine, a huge change has taken place in the system of providing healthcare services. Wearable systems have been developed for patient monitoring, treatment follow-up, remote treatment, which, along with strategic nursing systems, surgical robots and many other systems, behind the scenes of their design, have a common goal, which in short is to facilitate It is treatment [18].

Wearable technologies or wearable devices are electronic computers that can easily be worn as an accessory or a part of a person's clothing that is integrated with his accessories and has the ability to store and process vital data and transfer data between different devices [26]. Basically, wearable technologies are one of the growing technologies, the development of which in the health field has advantages such as reducing many costs, the possibility of continuous monitoring of the patient through sensors, no need for communication wires and prevention of mobility, quick location of certain patients such as patients It has Parkinson's, Alzheimer's, etc. [24]. In 2021, the wearable medical device market was estimated at $18.9 billion and is expected to reach $60.6 billion by 2027. Various drivers influence the expansion of this market, ranging from lifestyle-related diseases (such as high blood pressure, etc.), to the growing demand for home healthcare and the need for better treatment and outcomes. Sciencesoft, 2023).

2.2 Classification of wearable health care devices (HWDs)

As can be seen in Figure 2, there are different types of wearable devices that can be classified into three main categories. These three main groups include non-invasive wearables that include skin-based wearables, wearables based on biological fluids (including saliva, sweat and tears) and wearable applications for drug delivery systems [8].

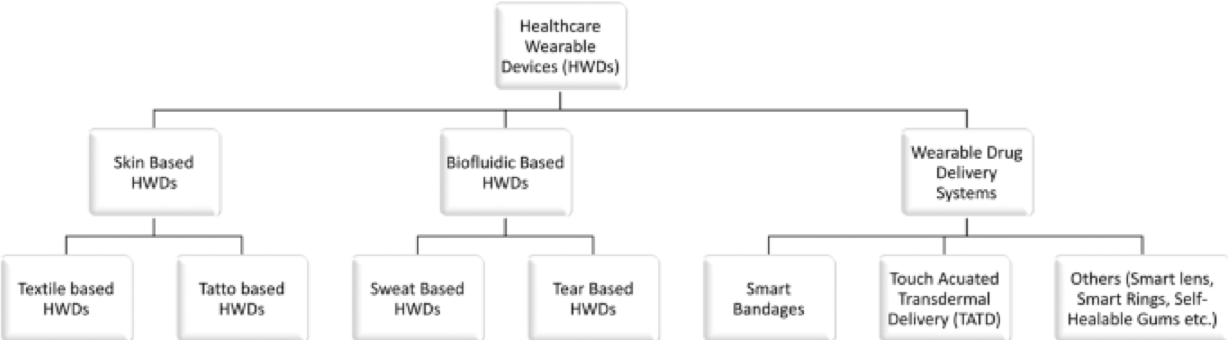

Figure 1: Classification of wearable health care devices [8]

2.3 Sensors and their importance in medicine and industry

Today, sensors are widely used in industry, daily life, and especially medicine. Wearable or implanted medical devices, such as insulin sensors, have been used for decades to non-invasively collect electrical, thermal and optical signals generated by the human body [13].

Numerous sensors indicating vibration, temperature and noise are used in nuclear power plants, gas turbines and continuous nuclear reactors [11]. Numerous other examples of complex sensor-based systems operating on data received from sensors are well documented. These observations show that ultimately, the proper functioning of these systems strongly depends on the reliability of the sensor data. For example, Figure 2 shows a multisensor-based non-invasive continuous glucometer that uses multiple sensors to measure blood glucose levels [6].

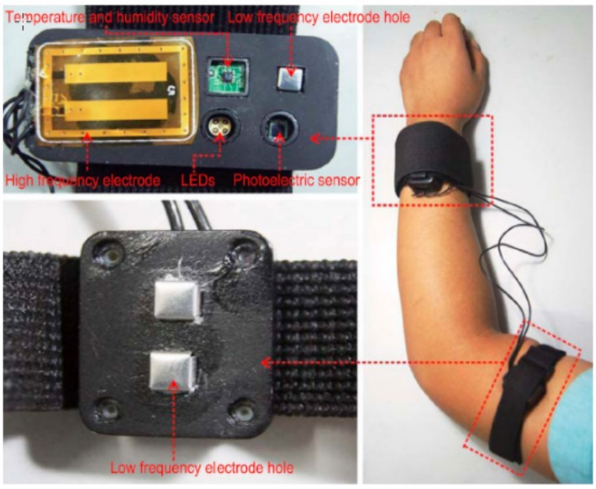

Figure 2: A non-invasive continuous glucometer based on multiple sensors

Unfortunately, sensors often fail. These failures can be caused by a variety of reasons, such as physical damage (both intentional and unintentional), manufacturing defects, software errors, uncontrolled environmental conditions, improper calibration or configuration, improper human-computer interaction (HCI), and even hacking. used for malicious purposes [30, 25]. When these failures occur, they lead to anomalies appearing in the data, making it unreliable forever, or at least for a certain period of time. When data with anomalies are fed upstream to high-level processing steps, this often leads to system misbehavior with unpredictable and even dangerous consequences, such as insulin overdose in patients or shutdown of nuclear power plants.

Today, with the widespread use of sensors and the consequences of their failure becoming significant, timely detection of abnormalities is also very important. The classification of anomalies is also of high priority, as it helps to identify the root cause of the failure and take appropriate preventive measures.

2.4 Main features of wearable technologies

In a general classification, the main features of a wearable sensor can be divided into two main categories: functional features and physical features. In the physical characteristics of a wearable system, in addition to beauty and good shape, the light weight, compatibility with the body and the hiddenness of this system are also mentioned, because people pay more attention to these system components when accepting these systems. Similarly, from a functional point of view, things such as being multi-functional, having the ability to use programs required by patients, being responsive at any time and place, and always being available are among the functional features that are of great importance to its users [31, 19].

2.5 Challenges and future prospects of wearable health care devices

Wearable health care devices have greatly modified the field of health care. As discussed, they have proven to be effective in monitoring many physiological parameters. However, there is still much room for improvement in these devices due to limitations that include stability, sensitivity, privacy, energy source, and limited applications for psychiatric disorders.

Since most wearables interact with the epidermis, the data received from the sensors in these devices may suffer from distortion and noise. Among the reasons for creating noise in them, we can mention things such as the continuous movement of the body and hair on the skin, which leads to minimal adhesion between the skin and the wearable. It has been observed that wearable healthcare devices are finding wide applications for monitoring purposes. Therefore, more efforts are needed to make them suitable for diagnostic purposes. This is because most diagnostic techniques involve the use of samples such as blood, urine, and saliva, and these devices have limited integration with these samples. Therefore, more efforts are needed to integrate them with platforms that can support the use of biological samples and can be used by the end user. In addition, the use of artificial intelligence algorithms such as the supervised learning regression algorithm can also be used to track the behavior of multiple parameters for prediction and pre-notifications [12] Similarly, user security is also important and since these devices contain protected health information (PHI), privacy is required regardless of the type of disease [2]. Therefore, for this purpose, a secure communication protocol in wearable health care devices is necessary to ensure the security and privacy of users.

In addition, one of the major limitations that hinders the use of wearable devices is their continuous power supply [29]. Batteries used in wearables have limited space because they must be coordinated with the design of the wearables. To overcome this limitation, efficient energy harvesting with better power management is required. Self-powered sensors, such as piezoelectric nanogenerator (PENG) and triboelectric nanogenerator (TENG), are small energy harvesters. These automatic sensors include the conversion of one form of energy into another, such as the conversion of mechanical energy into electrical energy, and ensure the convenience and miniaturization of HWDs134. It has also been observed that wearable healthcare devices find many applications for monitoring physiological diseases such as cardiovascular diseases, muscle disorders, blood levels and glucose. However, limited applications of wearable healthcare devices are available for mental illnesses, for example, PD, AD and other mental disorders. Therefore, increasing the use of these devices for mental illnesses could be beneficial in the near future.

2.6 Abnormalities as outliers

Basically, invalid data differs from valid data by the fact that they contain a certain amount of unusual values that are considered inconsistent observations and do not match the expected behavior [7]. Statistically, anomalies can be called as outliers when distributing data or its characteristics [27]. Therefore, in the context of data validation, failure localization and identification is equivalent to outlier detection and classification. In a general classification, abnormalities can be classified into the following three categories [16]:

1- **Point abnormality**. These points are individual data points that are considered abnormal with respect to the rest of the data. These types of anomalies refer to data points that are presented without contextual aspects such as time. Figure 3 shows an example of a point anomaly in a two-dimensional data set, where points $o1$ and $o2$, and all points inside the $O3$ region are considered outliers [5].

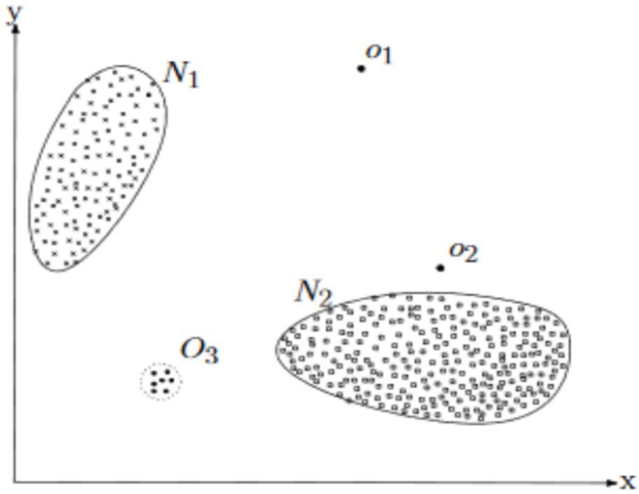

Figure 3: An example of a point anomaly

As can be seen in Figure 3, most of the observation data points are located in the $N1$ and $N2$ regions. These data can be considered normal in these areas. In contrast, points $o1$ and $o2$ and region $O3$ are abnormal. They are far enough away from the normal areas that it throws them off.

2- **Background abnormality**: This abnormality is also called conditional abnormality. These are individual data points that are unusual in a particular context. Here the context is defined by the structure of the dataset and is problem specific. Each data point is defined by attributes that define the neighborhood (context) of the point, and behavioral attributes that describe its non-textual properties. When dealing with time series data, an outlier is defined as a data point that must have both a contextual anomaly and a behavioral anomaly. In other words, it must have unusualvalues that appear in an unusual context. Figure 4 [5] shows an example of background anomaly in one-dimensional time series data of temperature throughout the year:

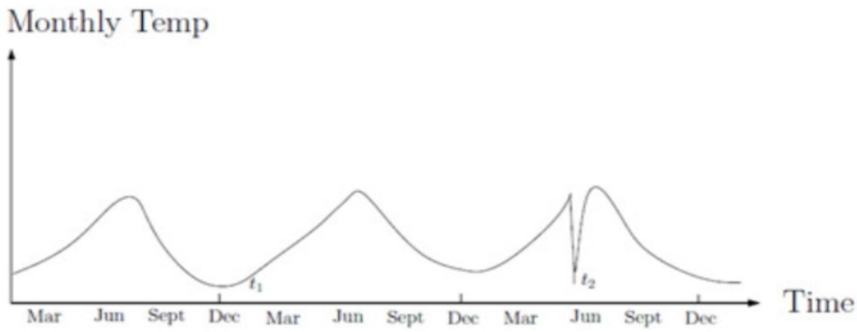

Figure 4: An example of background anomaly, $t2$.

According to Figure 4, points $t1$ and $t2$ have almost the same low values. On the one hand, $t1$ is considered normal because it remains within the climate norm for the period from December to March. On the other hand, $t2$ is further away, as such low temperatures are not expected in June. Clearly, the temporal context (months in this example) affects the normality of the data.

3- **Collective abnormality**: This type of abnormality refers to a set of related data points that are abnormal with respect to the entire data set. Two points are worth noting here: first, individual data points in such an anomaly set may not be anomalies per se, while only their coexistence appears as anomalies. Second, this type of anomaly can appear both in the data with context and in the data without context. Figure 5 [5] shows an example of collective anomaly in the data of an ECG sensor:

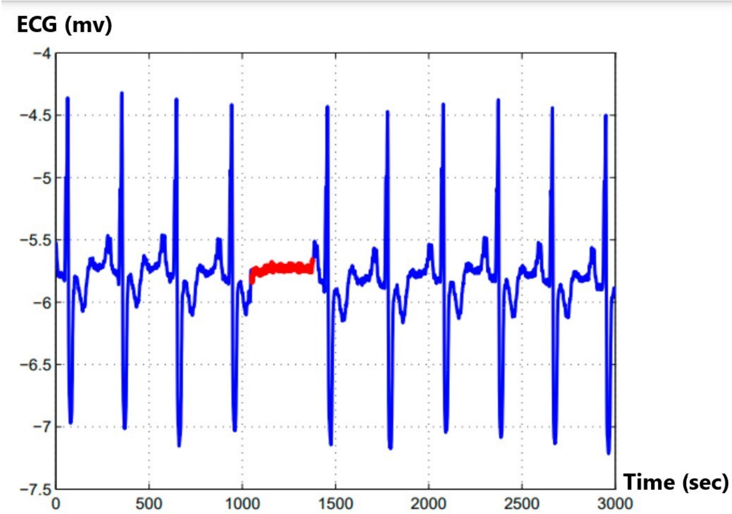

Figure 5: Example of mass anomaly, 1000-1500 s

In Figure 5, any single data point in the near-zero segment between 1000 and 1500 seconds is not an anomaly in itself, and as can be seen in the graph, the periodic fluctuation curve crosses the zero value several times. However, if the number of subsequent low-value points is large enough, they appear as a group from the same abnormality (in this case premature atrial contraction, PAC). Collective anomalies have been investigated for sequential data [28], graph data [14], spatial data [23].

2.7 Abnormality in sensor data

Basically, timely validation of raw sensor readings is very important to prevent invalid data from damaging the system, and it should be acknowledged that both detection and classification of invalid data are equally important. While the former protects the system from being damaged by invalid sensor data readings, the latter allows the nature of the error to be understood and allows appropriate corrections and improvements to be made in the sensor system to prevent future reoccurrence [22]. The task of detecting and classifying outlier observations, especially when it is related to sensor data, is multifaceted and challenging and can be caused by the following factors [5]:

1. The boundary between normal and abnormal behavior is not precise. In some cases abnormal observations may be very close to normal, and vice versa, which makes it very difficult to define an area with any possible normal behavior.

2. When anomalies originate from malicious actions, they appear as normal sensor data, making it very difficult to define normal behavior.

3. A defined concept of normal behavior that was valid enough at one point in time may not be valid later. In many domains, normal behavior changes dynamically as the system collects new data. Therefore, it is often not impractical to use a technique from one particular domain in another domain.

4. When using machine learning (ML)-based anomaly detection methods, labeled data for training and validating models is often a major issue.

5. Data are often mixed with noise that closely resembles real anomalies. Therefore, it becomes very difficult to detect and remove such noises.

2.8 Classification of abnormality diagnosis and classification methods

Throughout history, many scientists and researchers have dedicated their time to the problem of anomaly detection and classification in sensor data. One of the easiest ways to diagnose sensor failure is to use multiple sensors of the same type, then compare the readings and decide by majority vote which one is damaged. It goes without saying that this redundancy method cannot classify the anomaly, and sometimes it fails to detect the anomaly, for example, if an environmental factor, such as noise, affects the values of all sensors.

Obviously, more advanced and general methods were needed to serve the complex systems based on sensors that appeared from the beginning of the 19th century. Researchers have formulated the problem of outlier detection and classification by adopting concepts from various disciplines, such as statistics, information theory, spectral theory, ML, and data mining [5]. These formulations were based on the model of normal data patterns and creating an outlier score for each new data sample. The following types of models have been suggested [1]:

1. Models based on extreme values. These models use boundary values to define the range of normal data. Outliers are data points that exceed these boundaries. Data points can be univariate or multivariate.

2. Models based on clustering. These models create clusters of data points that co-occur. Outliers are data points that appear far from clusters.

3. Distance-based models. These models use the distribution of the total distance from each data point to its k nearest neighbors. For an outlier, this distance is significantly larger than for other data points.

4. Density-based models. These models use the local density of data points. Outliers have a low density.

5. Models based on probability. Similar to clustering-based models, these models create clusters of data points. However, instead of using the distance to determine the outlier score, it is determined by probabilistic fitting of a data point.

3 Research methodology

3.1 Research method and data collection

The research method used in this study is the use of quantitative research methods and the use of mathematical models, during which, while examining the theoretical foundations, researches and methods carried out regarding the diagnosis and determination of data anomalies in medical equipment and sensors will be reviewed. The proposed algorithm in this research is LSTM networks, which are an advanced example of recurrent neural networks (RNN) designed to avoid the long-term dependence problem in RNNs. In this study, data collection and research information will be a combination of library and field methods. In the library method of data collection, in order to model and optimize the process, the desired model will be obtained by studying scientific texts, studying theses and other domestic and foreign researches and related articles. The literature and theoretical foundations of the research will also be collected by studying books, domestic and foreign publications and topics related to the diagnosis of data anomalies in the context of medical Internet of Things, focusing on the case study of sensor equipment and medical wearables of heart and lung and diabetic patients using plugging. became. In this study, the proposed algorithms related to the subject are collected and analyzed. Also, due to the applicability of this research, part of the information will be collected from the websites of leading domestic and foreign technology companies, and sometimes conducting interviews and sending emails to them.

In the field method of data collection, considering that the history of using wearable medical equipment in the country is developing, for the training of the algorithm, at first, reliable medical datasets in the field of bioinformatics, such as Physionet, were used, and if necessary, after the training of the algorithm, The datasets of medical centers and nursing homes are used. In the end, by summarizing, an optimal algorithm is presented with the aim of solving the challenges and shortcomings of the previous methods and models, as well as increasing the accuracy and reliability for detecting and analyzing abnormalities in the field of sensors and medical wearables, which performs better compared to other researches.

3.2 Data description and analysis method

In this study, data analysis will be as follows:

1. Determining datasets of wearable medical devices
   These datasets include vital sign data such as heart rate (HR), pulse, oxygen saturation (SpO2), respiratory rate (RR), body temperature (BT), electrocardiogram (ECG), electromyogram (EMG), blood pressure (BP) and Blood glucose levels (BGL).

2. Creating the data transfer layer using the software programming interface
   At this stage, the inputs are the raw data collected by this interface layer from the origin of the data center of the vendors.

3. Gathering and storing data
   Data collection from sensors is done either on the server or on the cloud.

4. Sensor data pre-processing
   In this step, the creation of a unified and homogeneous data infrastructure is done from non-homogeneous data obtained from sensors of different wearable medical devices.

5. Data evaluation
   This stage consists of two activities: Anomaly Acquisition and Anomaly Detection.

6. Analyzing sensor data anomalies
   This stage includes separating the abnormality into the critical condition of the patient or failure and defects in the wearable medical device.

7. Evaluation of the algorithm, if the evaluation is confirmed, the data is used for training and learning the LSTM algorithm, and otherwise, step 6 is repeated. This processing leads to the creation of an input matrix of sensor events for each activity. The input data is fed into the LSTM network in order to predict each activity to the corresponding class. Then the modeling and simulation of the proposed method, based on the LSTM algorithm, using machine learning libraries and using the Python language, the implementation and the results of this research are analyzed and evaluated in the prepared artificial intelligence software.

3.3 LSTM neural network algorithm

LSTM deep neural network consists of layers of neurons. The input data is fed through the network to create a release prediction. Deep neural networks, like recurrent neural networks (RNN), have recurrent connections; Therefore, the previous activity state of the neuron from the previous time step is used as part of the data to formulate the input, but unlike the recurrent neural networks, the LSTM deep neural network has a unique feature that makes it The problems that exist in the training and scaling of the traditional recurrent neural network should be avoided [17]. The challenge we face in traditional recurrent neural network is how to train it effectively. Numerous experiments have shown that the recurrent neural network suffers from gradient decay and may also suffer from overfitting problems, which LSTM deep neural networks can overcome. The LSTM neural network, like the RNN network, is placed in a chain.

We can show the structure of the proposed deep neural network as described in Figure 6.

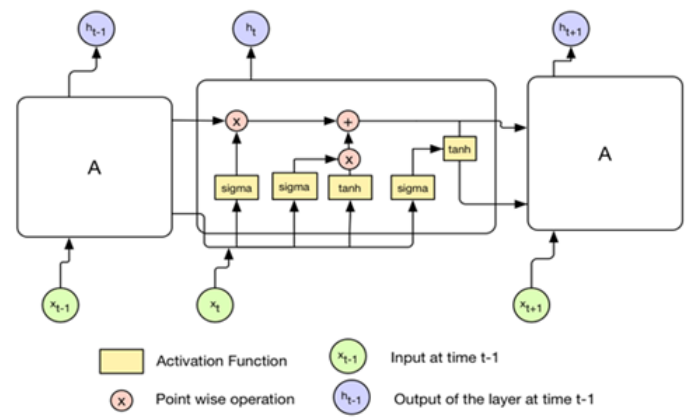

Figure 6: Variables and conceptual model of the research

where in:
Xt: input vector; Ht: output vector; Ct: cell state vector; Ft: forgetting gate vector. Weight to remember the old information; It: input gate vector. Weighting of new information; Ot: output gate vector. They are exit candidates.

Unlike the traditional recurrent neural network that only calculates the balanced sum of input signals and then passes through an activation function, each LSTM unit uses a memory in time. In LSTM deep neural networks, there are three gates through which the network controls the data flow within itself. The output or activation of the LSTM unit is the output gate that controls the amount of content that is presented through the memory. The output gate is calculated through the expression where is the sigmoid activation function. is also an Orib matrix. The memory cell is also updated by forgetting the current memory and adding the new memory content, where the new memory content is obtained through the expression. The amount of current memory that must be forgotten is controlled by the forget gate and the amount of new memory content that must be added to the memory cell is controlled by the update gate (or sometimes known as input gate). Therefore, in this algorithm, these actions and relationships are performed with the following calculations:

$$\hat{C}_t = \tanh\left(W_C[h_{t-1}, X_t] + b_C\right) \tag{3.1}$$

$$C_t = \Gamma_f \cdot C_{t-1} + \Gamma_u \hat{C}_t \tag{3.2}$$

$$\Gamma_f = \sigma\left(W_f[h_{t-1}, X_t] + b_f\right) \tag{3.3}$$

$$\Gamma_u = \sigma\left(W_u[h_{t-1}, X_t] + b_u\right) \tag{3.4}$$

$$\Gamma_o = \sigma\left(W_o[h_{t-1}, X_t] + b_o\right) \tag{3.5}$$

$$h_t = \Gamma_o \tanh(C_t). \tag{3.6}$$

The method that is usually used to train this type of network is the backpropagation method with gradient reduction [20], which has a high computational volume. Basically, in education, some important educational parameters such as: size (number of layers and number of neurons in each layer); There are learning rates and initial weights that must be considered for the deep neural network. In addition to the number of neurons in each LSTM layer, there are other parameters in building the optimal LSTM architecture, such as batch size and activation function, which are very important and They are effective. For example, a small number of neurons causes more errors and a lack of convergence of the network, and conversely, increasing the number of neurons will lead to overfitting [17]. Basically, searching in the parameter space to find the optimal parameters may not be possible due to the time and computational cost. There are several ways to increase the speed of calculations, among which we can point to a method such as classification (gradient calculation on several training samples at once instead of calculation for individual samples) [10].

4 Research findings

Examining the researches related to the subject using LSTM deep neural model shows that two Chinese (architectural) layers Dropout Layer and Dense Layer are generally used. One of the most effective ways to prevent overfit is to use dropout in neural networks; However, in LSTM networks, the use of both methods can be seen. Basically, every LSTM network is like this, it is a highly nonlinear layer, which is like a dense layer, but with the following differences:

- It does not receive all the data at once and moves step by step on the input.
- It receives input from the previous step, but the connections are dense.
- It has a gate that makes it have memory power.

Basically, what Dropout does is that during training, based on a probability that we specify, the output of a number of neurons is zero. Therefore, by doing this, we will practically face a reduced network (a different network) which, when faced with data, is forced to discover and use more powerful features without relying on other neurons. In this approach, in each repetition of this operation, which is repeated randomly, a different number of neurons are eliminated in this way. Therefore, in this study, the second architecture is used.

To implement the desired algorithm, it has been done using the powerful and reliable Physionet medical library. The data set for the collected events in question has 20,956 processes. Basically, the inputs of the algorithm are a history file, which is assumed to be possible to record events sequentially, so that each event refers to an activity and is related to a specific process instance. The table below shows a small part of the history of events.

To implement the model, the data is divided into two parts: training data (70 percent) and test data (30 percent). The selection of different parameters is considered based on the results of the research as described in the table below.

After running the model many times (16 times) using different permutations of the number of neurons and batch size and using two activation functions Relu and Tanh, the values related to the average absolute value of error (MAPE) and also the amount The root mean square error (RMSE) is calculated. By examining the results of the model implementation in this part, it can be seen that the combination of $N = 128$ and Bach size $= 64$ with Tanh activation

Table 1: An example of the history of events

RESP	HR	Event	time	Event ID
34	94	A	7.13.1995 18:10	100001
21	101	B	7.13.1995 18: 11	100002
19	99	C	7.13.1995 18: 12	100003
24	97	D	7.13.1995 18: 13	100004

Table 2: Various functions and parameters used in the implementation of the model

Mathematical relationship / values	Description	Functions and parameters
$g(z) = \max(0, z)$	Rectifier function	Functions
$g(z) = e^z - e^{-z}/ez + e - z$	Hyperbolic tangent	
64 , 128, 256	number of neutrons (N)	parameters
32 , 64, 128	Batch Size	
Adam	optimizer	
Mean Square Error	Loss	

function (Table 4) has the best prediction accuracy and the error obtained with the mentioned parameters, the results are much better is showing.

Table 3: LSTM model execution error by considering the Dropout layer by different Relu parameters

Number of neurons			Error type	Rule activation function	
256	128	64			
1.89 %	2.92 %	2.97 %	MAPE	32	size
1.74 %	2.42 %	2.67 %	RMSE		
2.31 %	2.89 %	2.80 %	MAPE	64	
2.39 %	2.21 %	2.74 %	RMSE		
3.11 %	2.04 %	2.30%	MAPE	128	
2.78 %	2.21 %	2.55 %	RMSE		

Table 4: LSTM model execution error by considering the Dropout layer by different Tanh parameters

Number of neurons			Error type	Rule activation function	
256	128	64			
2.23 %	2.30 %	2.21 %	MAPE	32	size
2.29 %	2.42 %	2.67 %	RMSE		
2.09 %	1.39 %	2.37 %	MAPE	64	
2.55 %	1.62 %	2.79 %	RMSE		
2.51 %	2.72 %	3.36 %	MAPE	128	
2.80 %	2.41 %	2.49 %	RMSE		

Therefore, on this basis, in the following figures, respectively, the graphs related to the accuracy of the model in correctly and incorrectly identifying the anomalies of the medical sensors according to the training data of HR and RESP show how the models were able to properly identify the correct and incorrect data. Separate the false from each other. Therefore, it can be stated that this algorithm has a very good ability to identify the errors in sensors and medical wearables, and therefore, by detecting them in time, we can quickly identify the failure of the sensors and, knowing the critical conditions of the patient, inform or help the patient. Presented on time.

In the continuation of the results of repeating 16 times of optimization, the error reduction process in the training phase is shown in the form of the following diagram.

5 Conclusion and suggestions

Various sensor-based systems are widely used in our daily life. These systems are highly dependent on the validity of the data they receive from the underlying sensors. Abnormal sensor data can cause unpredictable system behavior

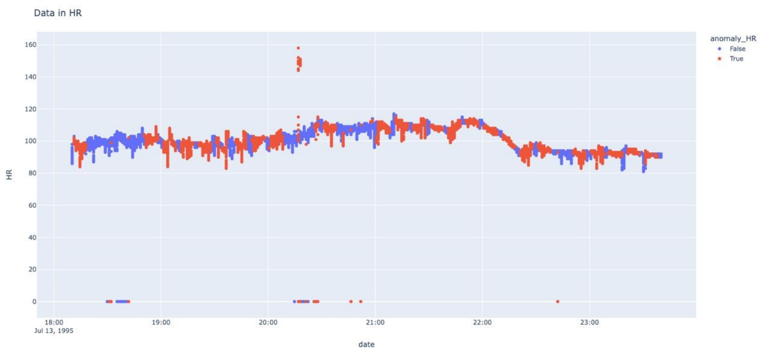

Figure 7: Correct and incorrect identification diagram of HR abnormalities

Figure 8: Correct and incorrect identification diagram of RESP anomalies

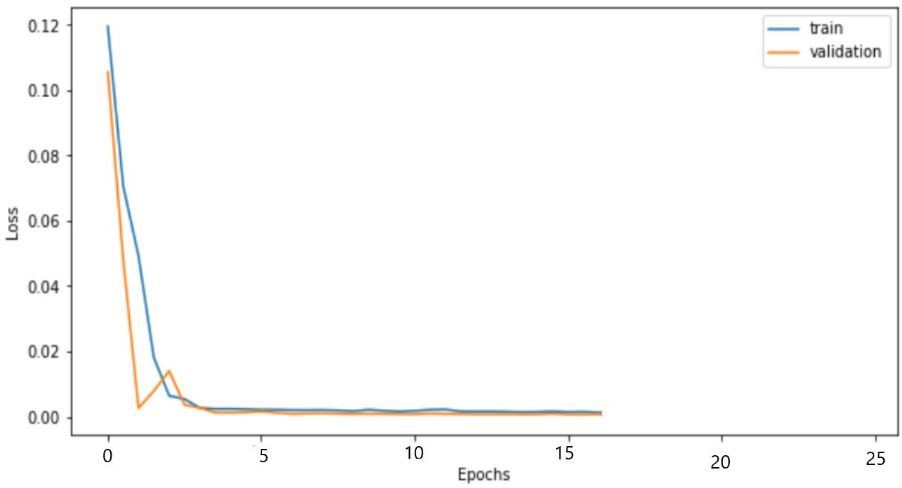

Figure 9: The error reduction process for the training phase in the selected LSTM model

and have dangerous consequences. Therefore, it is very important to provide sensor-based systems with mechanisms that detect anomalies and identify their types automatically. For years, scientists and researchers have conducted research in the field of data validation and have proposed many solutions to identify anomalies. Basically, invalid data differs from valid data by the fact that they contain a certain amount of abnormal values that are considered inconsistent observations and do not match the expected behavior. Statistically, anomalies can be considered as outliers when Named data distribution or characteristics. There are different types of anomalies that can be divided into three main groups of point, collective and background anomalies.

One of the research trends that has quickly gained popularity in sensor anomaly detection is the LSTM algorithm. LSTM networks are especially effective in classifying raw time series data in different domains. In these models, one of the most important factors that is very effective in predicting abnormalities is the selection of appropriate input variables, and if a model is trained using appropriate data, it can perform well in predicting abnormalities of wearable medical devices. have

Deep learning is a type of machine learning algorithm that includes several layers of information processing that gives the algorithm the ability to be most synchronized with the data. The most important advantage of deep learning algorithms such as persistent short-term memory algorithm (LSTM) compared to the traditional neural network model is the automatic extraction of suitable features from the raw inputs that are used for the learning process of the model. The LSTM method, which is a special type of recurrent neural network (RNN), has the ability to learn long-term dependencies over time; In this research, a standard architecture with different parameters has been used to select the optimal algorithm for determining anomalies; The studies conducted showed that there are influential parameters in the construction of this architecture, which include 3 very important factors: the number of neurons in the LSTM layer, the batch size, and the activation function; For this reason, in the first stage of evaluation, by using different combinations of the mentioned parameters, the optimal values for this architecture were obtained, and finally, in the last stage of evaluation, it was determined that the LSTM architecture together with the Dropout layer, with 64 parameters Batch $size = N = 128$ and function Tanh activation shows better performance and has the lowest mean absolute value error (MAPE) as well as the calculated root mean square error (RMSE) in determining anomalies of sensors in the medical field. Investigations related to the results of 16 repetitions of optimization also showed that the process of reducing errors in the correct and incorrect identification of anomalies in the training phase has reached its lowest level with the increase in the number of tests, which shows the optimality and appropriateness of the work process. Therefore, this algorithm has a very good ability to identify errors in sensors and medical wearables, and it will be of great help in identifying the possible failure of sensors, critical conditions of the patient, informing and finally helping patients in time.

Since only one architecture was used in this study, it is suggested that in future studies, using other architectures of recurrent neural networks such as GRU, on the determination and identification of abnormalities in sensors in the medical field, more detailed investigations It should be done to identify the weak points or strengths of these architectures in order to make a final decision about the best evaluation method.

References

[1] C.C. Aggarwal, *Data Mining: The Textbook*, Yorktown Heights, Springer, New York, 2015.

[2] R. Alharbi and H. Almagwashi, *The privacy requirments for wearable IoT devices in healthcare domain*, Proc. Int. Conf. Future. Internet Things Cloud Work, 2019.

[3] G. Appelboom, E. Camacho, M.E. Abraham, S.S. Bruce, E.L. Dumont, B.E. Zacharia, R. D'Amico, J., Slomian, J.Y. Reginster, O.Bruyère, and E.S. Connolly, *Smart wearable body sensors for patient self-assessment and monitoring*, Arch Public Health **72** (2022), no. 1, 28.

[4] M. Chan, D. Estéve, J.Y. Fourniols, C. Escriba, and E. Campo, *Smart wearable systems: Current status and future challenges*, Artific. Intell. Med. **56** (2012), no. 3, 137–156.

[5] V. Chandola, A. Banerjee, and V. Kumar, *Anomaly detection: A survey*, ACM Comput. Surv. **41** (2019), no. 3, 15.

[6] Z. Geng, F. Tang, Y. Ding, S. Li, and X. Wang, *Noninvasive continuous glucose monitoring using a multisensor-based glucometer and time series analysis*, Sci. Rep. **7** (2017), no. 1, 12650.

[7] M.A. Hayes and M.A. Capretz, *Contextual anomaly detection in big sensor data*, IEEE Int. Cong. Big Data, 2014, pp. 64–71.

[8] S.M.A. Iqbal, I. Mahgoub, E. Du, M.A. Leavitt, and W. Asghar, *Advances in healthcare wearable devices*, NPJ Flex. Electron. **5** (2021), no. 9.

[9] S. Jithin, P. Pawan, K. Khushi, P. Sandeep, L. Feng, A. Misa, J. Lawrence, and K. Santosh, *Anomaly detection framework for wearables data: A perspective review on data concepts, data analysis algorithms and prospects*, Sensors **22** (2022), no. 3, 756.

[10] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F.E. Alsaadi, *A survey of deep neural network architectures and their applications*, Neurocomputing **234** (2017), 11–26.

[11] R. Luo, M. Misra, and D.M. Himmelblau, *Sensor fault detection via multiscaleanalysis and dynamic PCA*, Ind. Engin. Chem. Res. **38** (1999), no. 4, 1489–1495.

[12] B. Mohanta, P. Das, and S. Patnaik, *Healthcare 5.0: A paradigm shift in digital healthcare system using artificial intelligence, IoT and 5G communication*, Proc. Int. Conf. Appl. Mach. Learn, 2019.

[13] A. Mosenia, S. Sur-Kolay, A. Raghunathan, and N.K. Jha, *Wearable medical sensor-based system design: A survey*, IEEE Trans. Multi-Scale Comput. Syst. **3** (2017), no. 2, 124–138.

[14] C.C. Noble and D.J. Cook, *Graph-based anomaly detection*, Proc. 9th ACM SIGKDD Int. Conf. Knowledge Discov. Data Mining, ACM Press, 2017, pp. 631–636.

[15] S. Osman, G. Alexey, and M. Ahmed, *Anomaly detection in medical wireless sensor networks using SVM and linear regression models*, IEEE. Med. **8** (2015), 34–48.

[16] J.D. Parmar and J.T. Patel, *Anomaly Detection in Data Mining: A Review*, Int. J. **7** (2017), no. 4.

[17] S. Pourzaker Arabani and H. Ebrahimpour Komleh, *The optimization of forecasting ATMs cash demand of Iran banking network using LSTM deep recursive neural network*, J. Oper. Res. Appl. **16** (2019), no. 3, 69–88.

[18] S. Rezaei and A.A. Safai, *A systematic review of wearable technologies and their applications in health*, Inf. Biomed. J. Med. Inf. Res. Center **3** (2015), no. 3, 242–233.

[19] E. Sazonov and M.R. Neuman, *Wearable Sensors: Fundamentals, Implementation and Applications*, Elsevier, 2014.

[20] J. Schmidhuber, *Deep learning in neural networks: An overview*, Neural Network **61** (2015), 85–117.

[21] Science Soft, *IT consulting and software development services*, Wearable Medical Devices, 2021, `https://www.scnsoft.com/healthcare/medical-devices/wearable`.

[22] M.V. Shcherbakov, A. Brebels, N.L. Shcherbakova, V.A. Kamaev, O.M. Gerget, and D. Devyatykh, *Outlier detection and classification in sensor data streams for proactive decision support systems*, J. Phys.: Conf. Ser. **803** (2017), no. 1, 012143.

[23] S. Shekhar, C.T. Lu, and P. Zhang, *Detecting graph-based spatial outliers: algorithms and applications (a summary of results)*, Proc. 7th ACM SIGKDD Int. Conf. Knowledge Discov. Data Min., ACM Press, New York, NY, USA, 2001, pp. 371–376.

[24] E.H. Shortliffe and J.J. Cimino, *Biomedical Informatics: Computer Applications in Health Care and Biomedicine (Health Informatics)*, 4th ed., New York, USA, Springer, 2018.

[25] A.K. Sikder, G. Petracca, H. Aksu, T. Jaeger, and A.S. Uluagac, *A survey on sensor-based threats to Internet-of-Things (IoT) devices and applications*, arXiv 2018, arXiv:1802.02041.

[26] B.G. Silverman and J.A. Ichalkaranje, *Intelligent Paradigms for Healthcare Enterprises: Systems Thinking (Studies in Fuzziness and Soft Computing)*, Springer, 2005.

[27] M. Stoecklin, *Anomaly detection by finding feature distribution outliers*, Proc. ACM CoNEXT Conf., 2006, pp. 32–33.

[28] P. Sun, S. Chawla, and B. Arunasalam, *Mining for outliers in sequential databases*, SIAM Int. Conf. Data Mining, 2016.

[29] A. Tarar, U. Mohammad, and S.K. Srivastava, *Wearable skin sensors and their challenges: A review of transdermal, optical, and mechanical sensors*, Biosensors **10** (2020), 56.

[30] M. Van Der Meulen, *On the use of smart sensors, common cause failure and the need for diversity*, 6th Int. Symp. Program. Electron. Syst. Safety Related Appl., 2004.

[31] X. Zhu and A. Cahan, *Wearable technologies and telehealth in care management for chronic illness*, C. Weaver, M. Ball, G. Kim, J. Kiel, (eds) Healthcare Information Management Systems, Health Informatics. Springer, Cham, 2016, pp. 375–98.