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Construction of Data Driven Decomposition Based Soft Sensors with Auto Encoder Deep Neural Network for IoT Healthcare Applications

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Abstract

The architecture of IoT healthcare is motivated towards the data-driven realization and patient-centric health models, whereas the personalized assistance is provided by deploying the advanced sensors. According to the procedures in surgery, in the emergency unit, the patients are monitored till they are stable physically and then shifted to ward for further recovery and evaluation. Normally evaluation done in ward doesn't suggest continuous parameters monitoring for physiological condition and thus relapse of patients are common. In real-time healthcare applications, the vital parameters will be estimated through dedicated sensors, that are still luxurious at the present situation and highly sensitive to harsh conditions of environment. Furthermore, for real-time monitoring, delay is usually present in the sensors. Because of these issues, data-driven soft sensors are highly attractive alternatives. This research is motivated towards this fact and Auto Encoder Deep Neural Network (AutoEncDeepNN) is proposed depending on Health Framework in the internet assisting the patients with trigger-based sensor activation model to manage master and slave sensors. The advantage of the proposed method is that the hidden information are mined automatically from the sensors and high representative features are generated by multiple layer's iteration. This goal is consistently achieved and thus the proposed model outperforms few standard approaches which are considered like Hierarchical Extreme Learning Machine (HELM), Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM). It is found that the proposed AutoEncDeepNN method achieves 94.72% of accuracy, 41.96% of RMSE, 34.16% of RAE and 48.68% of MAE in 74.64 ms.

Keywords: Neural network, soft sensors, Healthcare, Activation model, Auto encoder

1. Introduction

Nowadays, there is a rapid growth in the healthcare industry in which the revenue and employment are the major contributors [1]. Before few years, the disease diagnosis and human abnormalities were probable after the physical examination in hospitals. Many patients are recommended to stay in hospitals till the they recover or during the period of treatment. Because of this cost of healthcare is increased and also the healthcare facility is strained in the rural areas and the places that are remotely located. The advancement in the technology is attained in the current rear and various diseases are diagnosed by monitoring health through small size devices like smart watches [2]. E.g., many clinical analysis like blood pressure measuring, monitoring the level of blood glucose, level of pO_2 etc was done in home with no help from the professional of healthcare. Additionally, remote area's healthcare centres are communicated with the clinical data through advanced telecommunication services [4]. The communication services are associated with the quickly growing approaches like big data analysis, Internet of things (IoT), machine learning, mobile computing, wireless sensing and cloud computing to improve the healthcare facility's accessibility [5]. Independence is not only enhanced by IoT and human interaction with the external environment are also diversified. Aided with the futuristic protocol and algorithms, IoT became the main global communication contributor. Huge number of devices, home appliances, wireless sensors and electronic instruments are connected to the Internet by this IoT. Automobiles, healthcare, home and agriculture are areas uses the IoT application [6]. IoT's growing popularity is because of benefits of increasing accuracy, cost efficiency and capability of predicting future in the acceptable manner. Additionally, knowledge gains in software and applications present with the mobile and computer technique upgradation, wireless technology's easy availability, and the improved digital economy have added with the rapid revolution of IoT [7]. Integration of IoT devices with other physical equipment are for monitoring and exchanging information by various protocols of communication like Bluetooth, Zigbee, IEEE 802.11 (Wi-Fi) etc. In the application of healthcare equipment, either the sensors may be inserted or wearable on the patient body for collecting physiological information like temperature, pressure rate, electrocardiograph (ECG), electroencephalograph (EEG) etc from the body of patients. In addition, the information about the environment like as temperature, humidity, date, and time are also recorded and it will helpful in taking necessary and precise inferences on the patient's health conditions. The storage of data and accessibility also act as a significant factor in the IoT system as large data amount obtained or recorded from different sources like e-mail, phones, sensors, software applications. The above-mentioned devices obtain data that will be accessible by the doctors, caregivers, and authorized parties. The data sharing among the healthcare providers by cloud/server permits rapid disease diagnosis of patients and provides treatment if it is needed [8]. The cooperation among the patients, users and communication module is sustained for efficient and secured transmission. Soft sensors are studied extensively and employed in the healthcare units processing over the past 20 years. Characteristically, these predictive models depend on massive data amounts accessible in the process of healthcare and are mostly accountable for some variable's online predictions which plays a crucial role in control of quality and also in production safety, because of measuring hardware instruments are inaccessible or expensive [9]. Generally, two kinds of soft sensors are principle models (white-box models) and data-driven models (black-box models). First-principle models are based on a prior mechanical knowledge and because of this there is an unavailability in complex healthcare process and it is difficult to analyse creating the mechanical knowledge slightly hard-won. Alternatively, the data-driven models complements to provide empirical models depending on the historical data collected in the process of healthcare application [10]. complements to provide empirical models depending on the historical data collected in the process of healthcare application [10]. A difficult problem of soft sensors is in the real scenario of healthcare; the processes are strongly characterized by variables of correlated process. Typically, the number of such process variables are higher than its real dimension, and it is denoted as data rich with poor information. The contribution of this work are as follows,

- Auto Encoder Deep Neural Network (AutoEncDeepNN) based Internet of Health Framework is constructed for the patient's assistance with trigger-based sensor activation model for managing master and slave sensors

- To design the process of making decision in IoT environment is reinforced by three layers like user layer, network layer and application layer

The organization of paper is as follows: In section 1 the background of soft sensors, Healthcare in Internet of Things and the application of neural network in soft sensors are discussed along with contribution. In section 2 the existing traditional methods for data driven soft sensors are discussed. Section 3 explains the proposed AutoEncDeepNN architecture with data collection, pre-processing and Trigger-based soft sensor activation model. In section 4 experimental analysis are done three existing methods and graphs are obtained. Finally, the paper ends with section 5 conclusion and future work.

2. Related works

In [11] new data-driven soft sensor technology depending on a multilayer perceptron (MLP) neural network having a double least absolute shrinkage and selection operator (dLASSO) technique, called dLASSO-MLP, which is established with a two-step process. At first, the construction of MLP model is performed by dataset processing and the integration of sLASSO algorithm and this model was happened secondly for solving the two redundant problems which are redundancy of input variable and the model structure. This method not only chooses the input variables which are highly sensitive to the model and MLP structure are also simplified by the redundant hidden node's deletion for avoiding overfitting of model. Deep layer wise supervised pretraining framework is presented in [12] to extract quality-relevant feature and to model soft sensors, that are dependent on Stacked Supervised Encoder-Decoder (SSED). The hierarchical quality-relevant features are learnt successively in SSED through supervised encoder-decoder (SED) model's number. For every SED, the previous hidden layer features are assisted as new inputs for generating the high-level features which are learnt by the prediction of data quality constraint as best value at the SED output layer. The structure of deep learning and its consistent training algorithm for soft sensor known as probabilistic sequential network is presented in [13]. This model merges supervised dynamic modelling technique and unsupervised feature extraction for improving the performance of prediction. Gaussian-Bernoulli restricted Boltzmann machine and the RNN structure forms the basis for this model. The semi supervised deep learning model for the development of soft sensor dependent on Hierarchical Extreme Learning Machine (HELM) is proposed in [14]. Auto encoder as deep network is employed for extraction of unsupervised feature with all the process samples. Later, extreme machine learning is used to perform regression by adding the variable quality. In the meantime, the various methods of regularization are presented for semi-supervised model training. For healthcare soft sensing an augmented multidimensional Convolutional Neural Network (CNN) is presented in [15]. For the entire data information process, fine-grained data is used for obtaining coarse-grained data and deep features are extracted by using CNN. Data's physical meaning is analysed for designing multidimensional convolution structure focussing various information process details. The partial missing data problem is highlighted in this framework. The memory gates equipped Long Short-Term Memory (LSTM) neural networks are presented in [16] for learning dependencies of time in series of data and it is proved to perform well than other network types in the prediction of water level in the urban drainage system. In the usage of soft sensing, usually the neural network receives antecedent observations as input in the current value predicted.

From the existing methods it is observed that the when the deep learning can be applied to monitor the signals may have involved in reducing power and considerable amount of increases the accuracy but the extracting more features from the data involves in increases the response time with increased errors. The aforementioned shortcomings of the literature motivated the formulation of the proposed AutoEncDeepNN method discussed in the forthcoming section.

3. System model

The system model of Internet on Health (IoH) system with layered architecture is comprised in this section. In this architecture the process of making decision in IoT environment is reinforced by three layers like user layer, network layer and application layer as given in figure 1

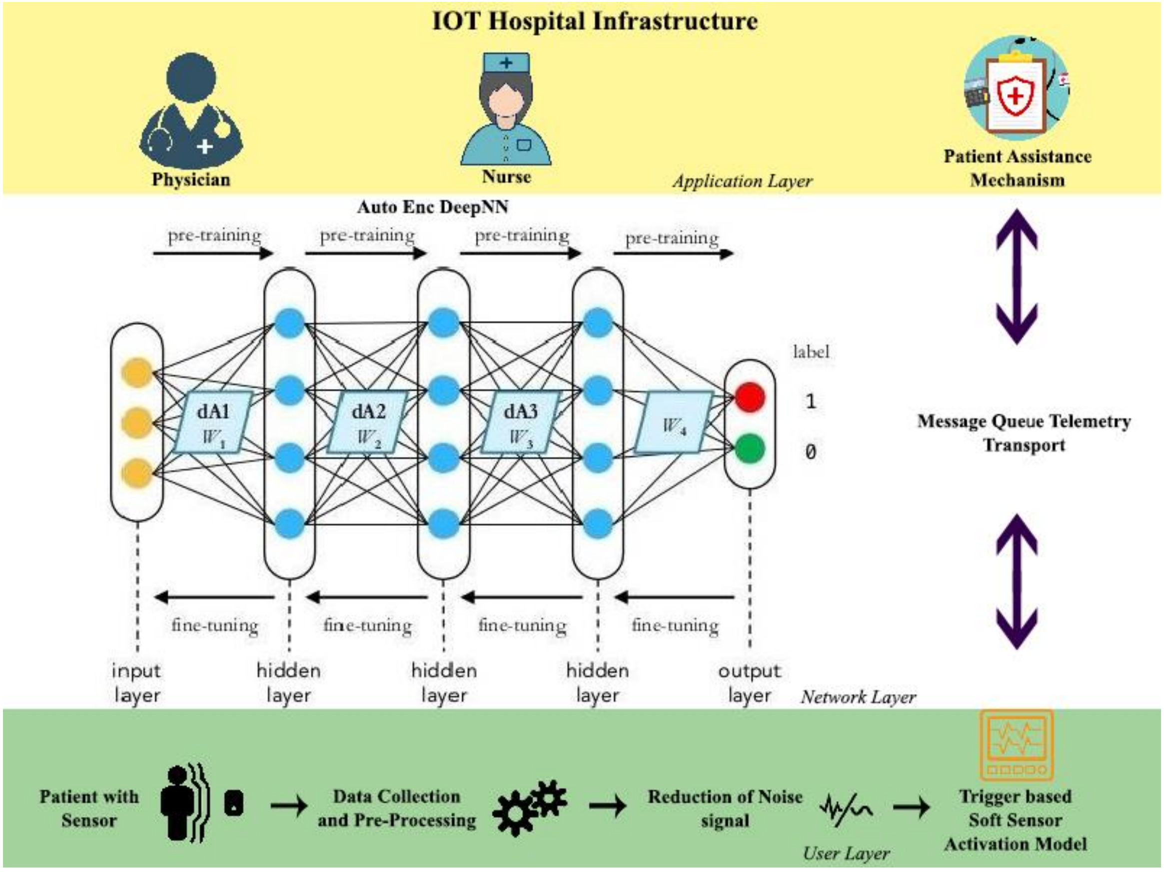

Figure-1 System architecture for data driven soft-sensors in IoT healthcare applications

4. Data collection and pre-processing

Acquiring processed data is the first step taken in the data-driven soft sensor design. This paper illustrates the primary study to design soft sensors in the application of various approaches to synthetic data; thus, for application of these techniques in real time system, real data processing is essential, and it is discussed in this paper. For the successful development of soft sensor, pre- processing of data set is needed for the elimination of missing and redundant values, outliers and signal noise. Thus, the noise of the signal must be suitably handled for soft sensors for estimating accurate values in various conditions. Previous to building this model and prediction, Weighted Moving Average (WMA) method is used for reducing the noise in the signal, because it computed quickly, and it is simply utilized as contrasted with other approaches. Every data point in WMA presented in the sample window is the multiplication of various weight depending on its position [17] and it is presented in Equation (1)

$$F(t) = \frac{\sum_{i=1}^{n} w(i)A(t-i)}{\sum_{i=1}^{n} w(i)} \quad (1)$$

where at time t, smoothed signal occurrence is given by Ft, weight to be given to the actual occurrence for the t – i time is represented as Wi, actual occurrence for the t − i time is Ai and total number of window lengths in the prediction is denoted by n.

5. Trigger-based soft sensor activation model

The sensors deployed are partitioned into two groups called master sensor and slave sensor. A mechanism of trigger-based activation is utilized to handle these sensors for achieving enhanced energy efficiency. Primarily, the master sensors are active, and if it is needed then only the slave sensors become active. Sleep mode is adopted by slave sensors because of the non-active message obtained from the master sensor. Message Queue Telemetry Transport (MQTT) subscribe/ publish method is used for this purpose for awaking the slave sensor if it is needed. Gait sensor are equipped by patients here and this sensor are regarded as master sensors to each and every sensors. The patient's movement was tracked by this gait sensor which is used to trigger further the slave sensors when the motion of patient is happen. The slave sensor set are registered as designated in equations (2), (3),(4)and (5):

$$Z_{IG},\ Z_{EG}, Z_{R1}, Z_{R2}, Z_{R3}, \ldots Z_{Rn} \tag{2}$$

$$A_{IG}, A_{EG}, A_{R1}, A_{R2}, A_{R3}, \ldots A_{Rn} \tag{3}$$

$$BL_{IG}, BL_{EG}; BL_{R1}; BL_{R2}; BL_{R3}, \ldots BL_{LR} \tag{4}$$

$$B_{O1}, B_{O2}, B_{O3}, \ldots; B_{OM}, M_H; , M_T \tag{5}$$

where zenith sensor is represented by Z, placement of internal sensor is given by IG, placement of external sensor is given by EG, the room numbers (1 to n) are represented as Rj, the auditory sensor is denoted by A , Bluetooth sensor boards are represented by BL, binary sensor is given by B, the openable device sensors (1 to n) denoted by Oj, medical sensor for heartbeat is represented by M_H and the medical sensor for body temperature is represented by M_T.

6. Construction of AutoEncDeepNN

The training sample X is provided, first the input $X \in R^{d0}$ is encoded by the auto coder into the $Y \in R^{d1}$ hidden representation through the mapping fc as designated in equation (6):

$$Y = fc(X) = S_c\,(W^T 1\ X + b_1) \tag{6}$$

where the encoder's activation function is denoted by S_c, and its input is known as hidden layer's activation. The parameter set with a weight matrix $W1 \in R^{d0 \cdot d1}$ is represented by W1 and b1 and a $b1 \in r^{d1}$ is the bias vector [18] as represented in figure-2.

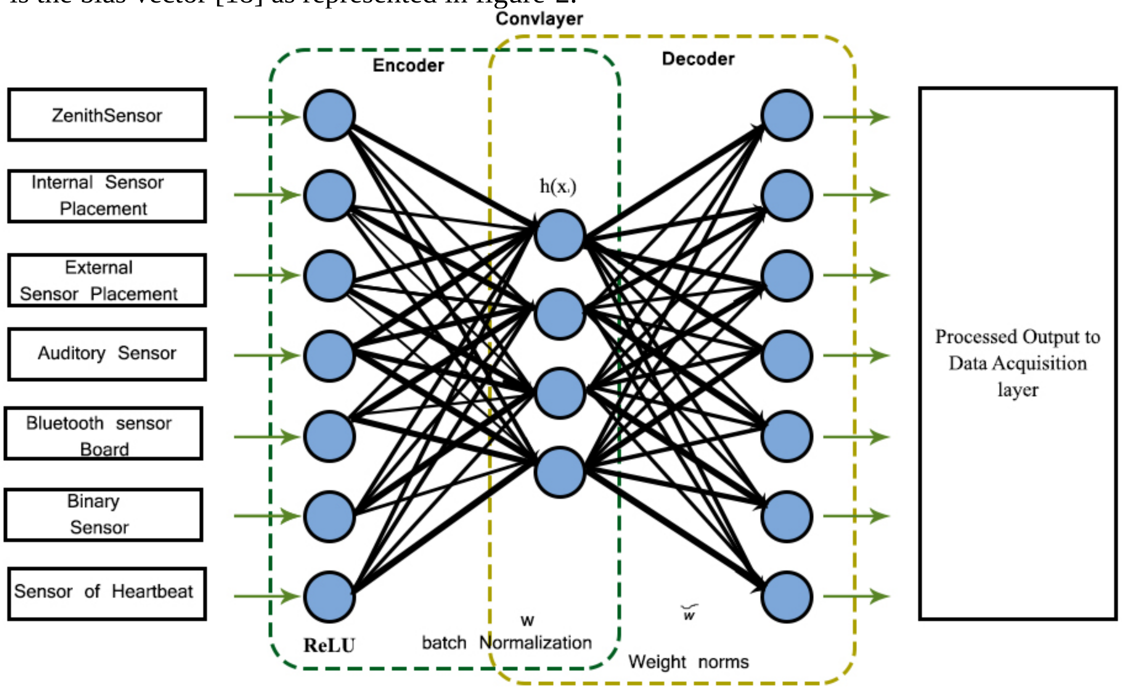

Figure 2 Overall architecture of Auto Encoder Deep Neural Network (AutoEncDeepNN)

In the second step, the hidden layer Y 's representation to the output layer $Z \in R^{d0}$ is mapped by the decoder through the fd mapping function as designated in equation (7):

$$Y = fd(Y) = S_d\,(W^T 2\ Y + b_2) \tag{7}$$

where the encoder's activation function is represented by S_d, and its input is known as activation of the hidden layer. The parameter set with a weight matrix $W2 \in R^{d0 \cdot d1}$ is given by W2 and b2 and a $b2 \in r^{d1}$

is the bias vector. The parameters are learnt by back-propagation by the loss function Ω (X, Z) minimization as designated in equation (8):

$$\Omega(X, Z) = \Omega(X,Z)+0.5\mu(W^T 1+ W^T 2) \quad (8)$$

where reconstruction error is represented by Ω(X, Z) and the cost of weight decay is s. For minimizing reconstruction errors, original input is needed to be represented as probable on features of hidden layer. The original input's feature information is learnt by the hidden layer in this way to the maximum extent. The feature concatenation mathematically defined, and it is defined in equation (9):

$$z^l = H_l([z^0, z^1, \dots, z^{l-1}]) \quad (9)$$

where, a function of non-linear composite transformation is given by H_l containing batch normalization (BN), subsequently with ReLU function and a 3 x 3 conv layer. $z^0, z^1, \dots, z^{l-1}$denotes the concatenated feature map related to layers 0 to l which makes implementation easier. For the purpose of down-sampling, AutoEncDeepNN are created in the architecture of the network and are separated by transition layers which contain BN followed by 1x1 conv layer and at last an average 2x2 pooling layer. Thus, every subsequent layer access every feature maps of the preceding layers. Every layer adds the feature maps to the global state where the feature maps provided as input at l^{th} layers $(FM)^1$ is given by as indicated in equation (10):

$$(FM)^1 = k^0 + k(l-1) \quad (10)$$

Here, in the input layer, channels are given by k^0. For enhancing the efficiency of computation, 1x1 conv layer is used prior to each 3x3 convlayer which reduces the input feature maps that are usually high compared to the output feature maps k [19]. 1x1 conv layer called bottleneck layer is used which produced 4k feature maps. activation function converts that outputs that are non-normalized to binary outputs either as 1 or 0.

But, the minimum norm least-squares avoided tuning those parameters. In the training process in equation (11) with fixed $\mathbf{w}_i$ and bi was identical for estimating the least square solution $\hat{\beta}$ of $H\beta = T$

$$\left\|H(w_1, \dots, w_M, b_1, \dots, b_M)\hat{\beta} - T\right\| = min_\beta \|H(w_1, \dots, w_M, b_1, \dots, b_M), \beta - T\| \quad (11)$$

with the smallest value $\hat{\beta} = H \dagger T$

where, $H \dagger$ was Moore-Penrose generalized inverse of matrix H. Basic significant properties of this solution are less training error, unique solution and smallest weight norms. Results of various variables obtained by wrapper method is based on the feature ranking model used. The R environment's fscaret package was utilized for avoiding the problem. Three steps are involved in performance of variable ranking they are training the model, extraction of variable ranking and scaling the variable ranking as per the error of generalization. The last variable ranking is acquired by the multiplication of raw variablle importance and minimal error fraction acquired from actual error of model by model.

7. AutoEncDeepNN based Internet of Health

İnput: sensed data from soft-sensors
Output: processed data

```
Initialize the sensed data (S)
If
While S=1,2...n
Compute input [S1]←n
For n=1:S=0
S[n1,l]
End for
İnitiate ReLU function (zl)
For
I = (zl) − k(m − t)
Neurons [Nu]←input [Nu]
Nu←zl
```

End for
End while
End if

8. Patient assistance mechanism by soft-sensors

The Data Distribution Layer acts as a messaging broker, data messages redirected between the components of data production and data consumption in the another two layers. The Application Layer is divided into two portions they are user application and External applications. The system users (desktop and mobile) are accessible with the applications are represented by user application. Typical legal applications are incorporated in the external application for supporting the process of institution and the system of hospital information like Electronic Health Records, Enterprise Resource Planning (ERP), Consent Management platform, Public Health Agency systems, among others. Data exchange to one another in the application layer is performed by direct interfaces or by messaging broker.

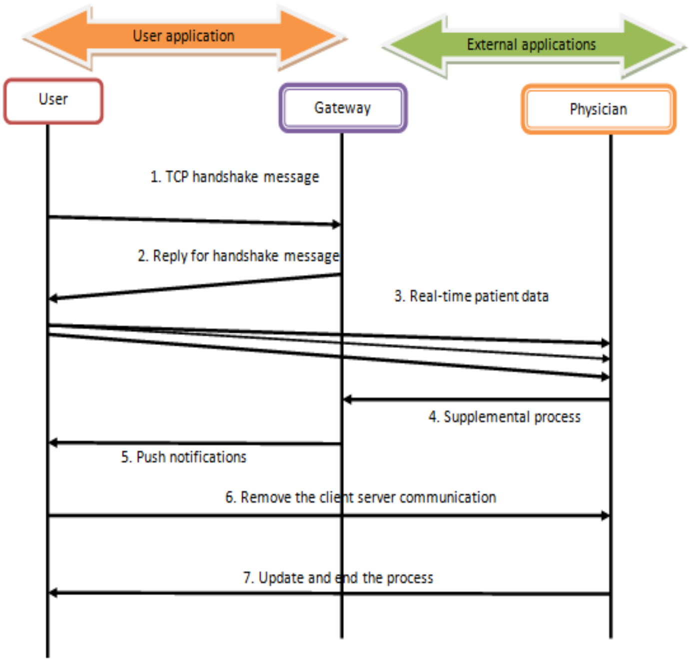

Figure 3 Data transfer process from user to application layer

Figure-3 shows the access of network by patient and physicians once the vitals signals are processed by AutoEncDeepNN. Monitoring patient in the remote areas are focussed in this system, followed from discharge of ICU to wards. Thus, the Web Service's virtual resources are nurses or physician the may interpret the data of sensor and patients group which are below surveillance. From the provided time, a single person from the medical staff able for accessing the gateway device. This technique is complied with Transmission Control Protocol (TCP)'s handshake message initiation by user with accesing the gateway and hence the isolation action among several clients utilizing the same system. The reply message is done by the authorized users by gateway and which is followed by sendint the real time patient data and supplemental process. Once receiving the supplemental message the push messages are forward to concern user.Then the client server communication in removed form the data unit which tends to end the entire process.

9. Performance analysis

The experimental analysis is performed and the parameters utilized in the analysis are accuracy, response time, Root Mean Square Error (RMSE), Relative Absolute Error (RAE) and Mean Absolute Error (MAE). These parameters are contrasted with three existing methods such as Hierarchical Extreme Learning Machine (HELM), Convolutional Neural Network (CNN) and Long Short-Term

Memory (LSTM) with the Auto Encoder Deep Neural Network (AutoEncDeepNN) proposed. The final tuning parameters of soft sensors for IoT-based patient assistance mechanism is represented in table-1.

Table 1 Final tuning parameters of soft sensors for IoT-based patient assistance mechanism.

Name of activity	Triggered sensor	Tuning Parameters	values
sleep	binary	Transfer Function	Tanh
walk	motion	ReLU	257*218
medicine	binary	Activation layer	32
Conversation	audio	Neuron size	1673
faint	zenith	Sigma	36
dream	binary	Number of Hidden Layers	785
pain	zenith	Transfer function Sigmoid	9

- **Accuracy**

The capability of prediction in the machine learning technique projected is indicated by accuracy. The classifier capacity is computed by True positive (TP) and true negative (TN) for calculating the lack and data error. The false prediction amount obtained in this model is recognized by False positive (FP) and false negative (FN) and the expression for accuracy is represented in equation (12):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (12)$$

Table 2. represents the comparison of accuracy between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method.

Table 2. Accuracy Comparison

	Soft sensor model			
Number of epochs	**HELM [14]**	**CNN [15]**	**LSTM [16]**	**AutoEncDeepNN [proposed]**
100	91.3	91.5	91.6	91.9
200	92.6	92.8	93	93.5
300	93.4	93.6	93.8	94.6
400	94.5	94.6	94.9	95.8
500	95.8	95.9	96.2	97.8

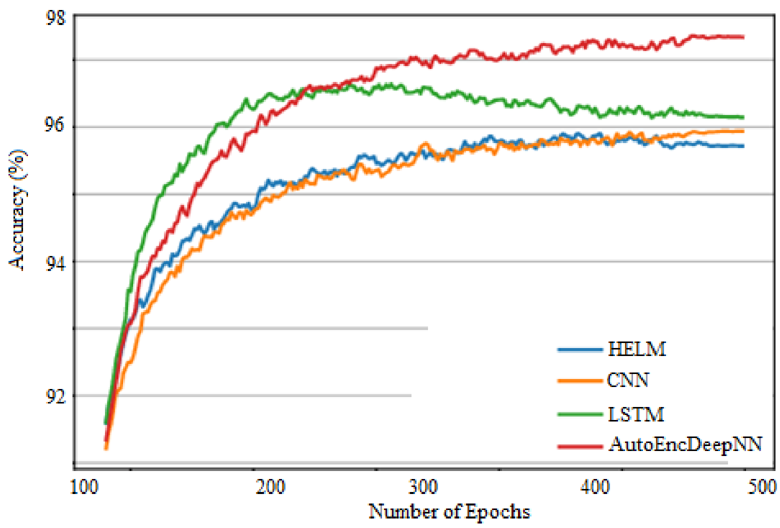

Figure 4 Comparison of accuracy

The figure 4 indicates the accuracy comparison between existing HELM, CNN, LSTM methods and AutoEncDeepNN method proposed where X axis shows the number of epochs used for analysis and the accuracy values obtained in percentage is represented in Y axis. As compared to existing HELM, CNN and LSTM methods achieve 93.52%, 93.68% and 93.90% while the proposed AutoEncDeepNN method achieves 94.72% which is 1.2% better than HELM,1.16% better than CNN and 1.22% better than LSTM.

- *Response time*

The mean of time taken by every classification algorithm in the ten folds overall number of correct classifications to the number of instances in the dataset is expressed as response time. Officially, $S(i)$ is the test set including instance $xi =< vi, yi>$, then the response time is as given in equation (13):

$$\mathrm{RT}=\frac{1}{n}\sum_{vi,yi}\mu(I)vi,yi \tag{13}$$

Table 3. represents the comparison of response time between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method.

Table 3. Comparison for response time

	Soft sensor model			
Number of epochs	**HELM [14]**	**CNN [15]**	**LSTM [16]**	**AutoEncDeepNN [proposed]**
100	69.9	70	70.5	70.9
200	70.2	70.6	70.8	72.6
300	71.5	71.6	72.9	73.8
400	71.6	72.8	73.6	75.9
500	72	75.9	79.9	80

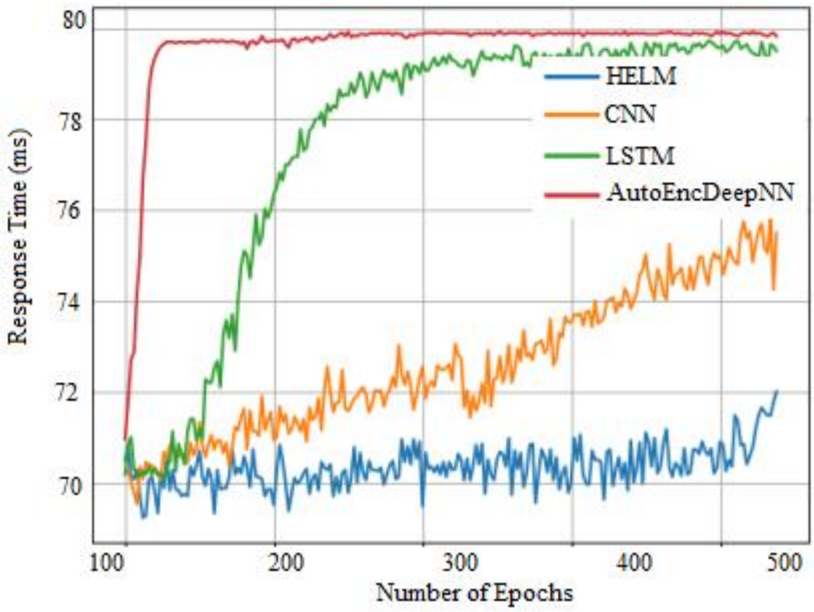

Figure 5 Comparison of response time

The figure 5 presents the response time comparison between existing HELM, CNN, LSTM methods and AutoEncDeepNN method proposed where X axis shows the number of epochs utilized for analysis and response time values acquired in milliseconds is represented in Y axis. In this comparison, existing HELM, CNN and LSTM methods achieve 71.04%, 72.18% and 73.54% while the proposed AutoEncDeepNN method achieves 74.64% which is 3.6% better than HELM,2.54% better than CNN and 1.1% better than LSTM.

- *Root Mean Square Error (RMSE)*

The variation exists between the predicted values of the model, or an estimator and the observed values are frequently measured by root mean square value (RMSE) and it is expressed in equation (14):

$$\text{RMSE} = \sqrt{\sum_{t}^{T}(y'(t) - y(t)} \quad (14)$$

Table 4. represents the Root Mean Square Error comparison between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method.

Table 4. Comparison for Root Mean Square Error

	Soft sensor model			
Number of epochs	**HELM [14]**	**CNN [15]**	**LSTM [16]**	**AutoEncDeepNN [proposed]**
100	42.1	41.5	40.6	40.1
200	42.9	42.4	41.9	40.8
300	43.6	42.6	42.9	41.2
400	45.8	44.1	43.5	42.6
500	49.6	49.3	48	45.1

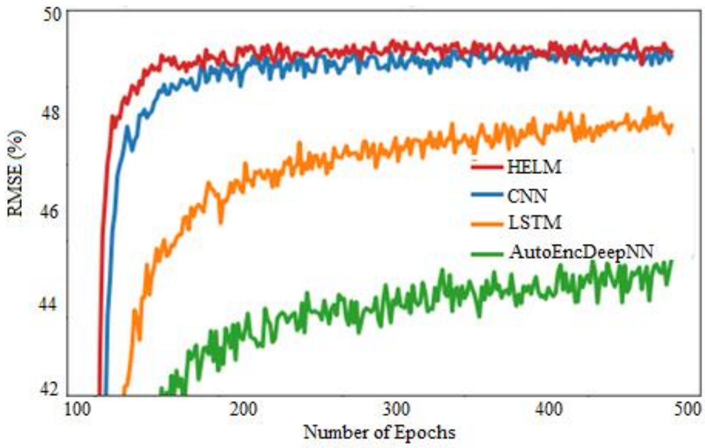

Figure 6 Root Mean Square Error Comparison

The figure 6 represents the Root Mean Square Error comparison between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method where X axis shows the number of epochs utilized for analysis and Root Mean Square Error values obtained in percentage in Y axis. In this comparison, existing HELM, CNN and LSTM methods achieve 44.8%, 43.98% and 43.38% while the proposed AutoEncDeepNN method achieves 41.96% which is 3.16% better than HELM, 2.02% better than CNN and 2.62% better than LSTM.

- *Relative Absolute Error (RAE)*

The ratio of mean error to the produced error obtained by the trivial or naïve model is Relative Absolute Error and it is represented in equation (15):

$$\text{RAE} = \frac{\sum_{i=1}^{n}(pi - Ai)^2}{\sum_{i=1}^{n} Ai} \quad (15)$$

Table 5. presents the Relative Absolute Error comparison between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method proposed.

Table 5. Relative Absolute Error Comparison

	Soft sensor model			
Number of epochs	**HELM [14]**	**CNN [15]**	**LSTM [16]**	**AutoEncDeepNN [proposed]**
100	35.5	33.2	32.5	30.2
200	38.2	35.6	34.5	32.5
300	40.5	38.4	36.4	34.1
400	44.5	43.5	42.4	35.6
500	57.8	54.2	48.6	38.4

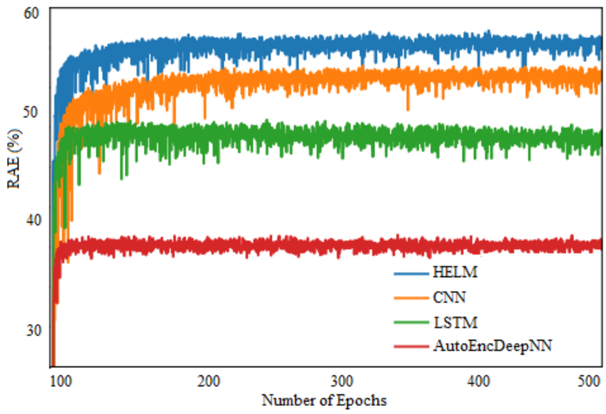

Figure 7 Comparison of Relative Absolute Error

The figure 7 represents the Relative Absolute Error comparison between existing HELM, CNN, LSTM methods and AutoEncDeepNN method proposed where X axis shows the number of epochs utilized for analysis and Relative Absolute Error values acquired in percentage is represented in Y axis. In this comparison, existing HELM, CNN and LSTM methods achieve 43.3%, 40.98% and 38.88% while the proposed AutoEncDeepNN method achieves 34.16% which is 9.26% better than HELM, 6.82% better than CNN and 4.72% better than LSTM.

- *Mean Absolute Error (MAE)*

The error measured between the paired observation with the expression of same phenomenon is defined by Mean Absolute Error (MAE). Examples of *Y* versus *X* incorporates comparisons of predicted value versus observed values, subsequent time versus initial time, and one technique of measurement versus an alternative technique of measurement as given in equation (16):

$$\text{MAE}= \sum_{i=1}^{n}(yi - xi) \tag{16}$$

Table 6. represents the Mean Absolute Error comparison between existing HELM, CNN, LSTM methods and AutoEncDeepNN method proposed.

Table 6. Comparison for Mean Absolute Error

	Soft sensor model			
Number of epochs	**HELM [14]**	**CNN [15]**	**LSTM [16]**	**AutoEncDeepNN [proposed]**
100	48.6	48.2	47.9	47.7
200	49.2	48.6	48.1	47.9
300	50.4	49.2	48.6	48.1
400	52.6	50.4	49.2	48.8
500	55.9	54	52	50.9

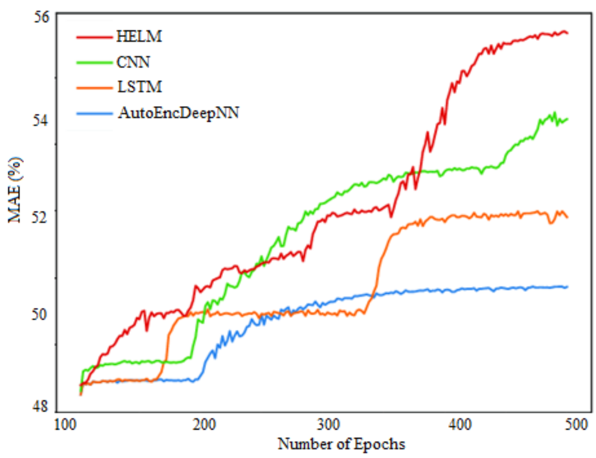

Figure 8 Comparison of Mean Absolute Error

The figure 8 represents the Mean Absolute Error comparison between existing HELM, CNN, LSTM methods and AutoEncDeepNN method proposed where X axis shows the number of epochs utilized for analysis and the Mean Absolute Error values obtained in percentage is indicated in Y axis. In this comparison, existing HELM, CNN and LSTM methods achieve 51.34%, 50.08% and 49.16% while the proposed AutoEncDeepNN method achieves 48.68% which is 3.34% better than HELM, 2.6% better than CNN and 1.52% better than LSTM.
Table 7 presents the overall comparison for various parameters between existing HELM, CNN, LSTM methods and proposed AutoEncDeepNN method.

Table 7. Overall comparison of existing and proposed methods

Parameters	HELM [14]	CNN [15]	LSTM [16]	AutoEncDeepNN [proposed]
Accuracy (%)	93.52	93.68	93.90	94.72
Response Time (ms)	71.04	72.18	73.54	74.64
RMSE (%)	44.8	43.98	43.38	41.96
RAE (%)	43.3	40.98	38.88	34.16
MAE (%)	51.34	50.08	49.16	48.68

10. Conclusion

This research develops a soft sensor model dependent on Auto Encoder Deep Neural Network (AutoEncDeepNN) with data pre-processing method and Trigger-based soft sensor activation model for data selection of input variable. The enhanced AutoEncDeepNN presents feedforward and local feedback networks, that is trained for obtaining better generalization and overfitting is avoided to some extent. The method of data pre-processing efficiently saves the structure of neighbourhood and the dataset's global mutual distance and the original dataset's real character is reflected, that is utilized for removing the abnormal condition of working data, noises, and input variables with data redundancy obtained from AutoEncDeepNN. This analysis is done by comparing with three standard approaches which are considered like HELM, CNN and LSTM. It is found that the proposed AutoEncDeepNN method achieves 94.72% of accuracy, 41.96% of RMSE, 34.16% of RAE and 48.68%of MAE in 74.64 ms. This great performance demonstrates that the soft sensor model based on AutoEncDeepNN with data pre-processing and activation model provides a powerful and promising method for complex healthcare applications. The future work concentrates on including pilot-scale binary distillation process for activation model which expects to improve the sensing speed.

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