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Machine Learning Architecture in Soft Sensor for Manufacturing Control and Monitoring System Based on Data Classification

Dr. N. Shanthi
Life Science and Mathematics
Pachaiyappa's College, Affiliated to University of Madras
https://orcid.org/0000-0002-1261-2499
prithishanthi@gmail.com

Shreyas J
Computer Science & Communication Engineering
Crrencia Technologies Pvt. Ltd.
Orchid Id-0000-0002-3427-4486
shreyasj.email@gmail.com

Article History	***Abstract***
Received: 15 July 2021 Revised: 20 September 2021 Accepted: 22 November 2021	Deep learning, a feature representation method that was just recently developed for data with complex structures, has a lot of potential for soft sensing of industrial processes. However, with the unprocessed observed input data, most deep networks primarily concentrate on hierarchical feature learning.This research propose novel technique in soft sensor for manufacturing industry based on controlling and monitoring using machine learning techniques. Here the data has been collected as IoT based monitored data and processed for noise removal, normalization. The processed data classified for detection of faults using probalistic convolutional neural network. the control system is carried out using weighted auto-encoderbelief network (WAEBN). The experimental analysis has been carried out in terms of QoS, measurement accuracy, RMSE, MAE, prediction performance. Keywords: soft sensor, manufacturing industry, controlling, monitoring, machine learning.

1. Introduction:

Because of the complexity of several characteristics and the difficulty in measuring them, developing intelligent systems for monitoring the environment continues to be difficult [1].Aside from air quality monitoring, one of the most important parts of environmental monitoring is water quality. Health and a high quality of life depend on having access to safe drinking water [2].First-principle methods as well as data-driven models are two major types into which soft sensors can generally be divided. Accurate process first principle models are frequently hard to come by and take a lot of time.Data-driven methodologies are now available and usable in real-world industrial production thanks to the quick development of computer science as well as data technology [3]. As a result, during past few decades, process modelling has drawn increasing interest.In addition to other data-driven techniques, neural networks (NNs) have been frequently used to construct soft sensors because they are good at simulating the nonlinear relationship between the quality and auxiliary variables.

2. Literature review:

In order to provide practical and affordable alternatives to expensive or impractical physical measurement sensors, soft sensors are a virtual sensing technique that builds an inferential model to estimate various parameters of interest based on other measured parameters that are currently available [4].To do its duty, soft sensor technology needs computing on the back end. As a result, it leverages powerful servers (cloud computing) for a variety of applications [5]. A centralised pool of storage and processing resources is offered by cloud computing [6].Although it has a broad perspective of the network [7], it is unsuitable for applications that require a real-time response with minimal lag and maximum quality of service (QoS) [8]. It still lacks enough computational and storage capabilities [9].To enable live data analytics in IoT applications, these two approaches (edge-cloud processing) can be combined with efficient machine learning algorithms [10].

3. Proposed method:

This research propose novel technique in novel technique in soft sensor for manufacturing industry based on controlling and monitoring using machine learning techniques. here the data has been collected as IoT based monitored data and processed for noise removal, normalization. The processed data classified for detection of faults using probalistic convolutional neural network. the control system is carried out using weighted auto-encoder belief network (WAEBN). The proposed architecture is shown in figure-1.

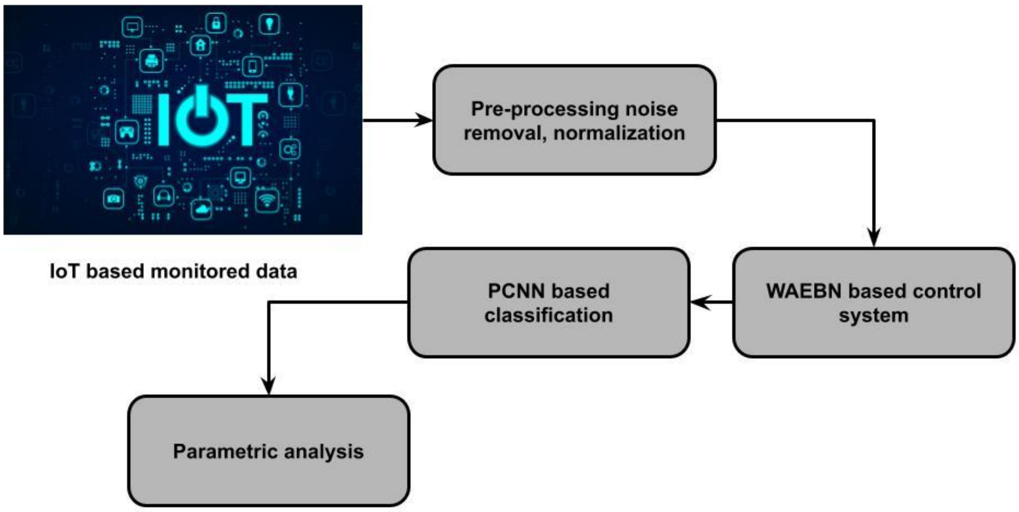

Figure 1: Overall architecture

3.1 Probabilistic convolutional neural network (PCNN) in monitored data classification:

For each training instance I in training set, there is one hidden node in a PNN. Input vector of instance I is the centre point yi that is connected to each hidden node hi. The spread factor, si, of a hidden node also controls the size of its particular field. This parameter can be set in a variety of ways. For each instance I si is equal to the fraction f of distance to its closest neighbour by eq. (1).

$$g(x, y_i, s_i) = \exp(-D^2(x, y_i)2s_i^{\ 2})$$

$$\mathrm{radbas}(n) = e^{-n^2} \qquad (1)$$

Every component of n is changed in Eq. In the Radial Basis Layer's output vector, a, the corresponding element of 1 and is produced. The representation of i-th element of an is eq. (2)

$$\mathrm{a_i} = \mathrm{radbas}(\|\mathbf{W}_\mathrm{i} - \mathbf{p}\|.*_\mathbf{i}) \qquad (2)$$

where bi is i-th element of bias vector b and Wi is vector formed from i-th row of W. A multilayer perceptron with a specific architecture for identifying two-dimensional picture information is the convolution neural network algorithm. always has more layers, including input, convolution, sample, and output layers. A deep network architecture also allows for numerous convolution layers and sample layers.Finally, an activation function produces a narrow Sx + 1 times n times feature map.

3.2 Weighted auto-encoder belief network (WAEBN):

The backpropagation-based gradient descent approach calculates the objective function of reconstruction loss for traditional training of AE using just original training data. Data from a generic neighbourhood distribution is generated using DA method to train this AE, which enhances the learnt network's capacity for generalisation. On raw as well as virtual training data, the reconstruction error can be reduced to train this DA-AE as eq. (3):

$$J(W,\tilde{W},b,\tilde{b}) = \frac{1}{2N}\sum_{i=1}^{N}\left\|\tilde{x}_{r(i)} - x_{r(i)}\right\|^2 + \frac{1}{2(N-1)}\sum_{i=1}^{N-1}\left\|\tilde{x}_{v(i)} - x_{v(i)}\right\|^2 \qquad (3)$$

The output layer then decodes hidden feature variable vector h to produce reconstructed input vector as eq. (4)

$$\tilde{z} = \tilde{f}(\tilde{W}h + \tilde{b}) \qquad (4)$$

where W, b, and f stand for the output layer's weight matrix, bias vector, and activation function, respectively by eq. (5).

$$J(W,\tilde{W},b,\tilde{b}) = \frac{1}{2N}\sum_{i=1}^{N}\|\tilde{z}_i - z_i\|^2 = \frac{1}{2N}\sum_{i=1}^{N}\left\|g\left(z_i, W, b, \tilde{W}, \tilde{b}\right) - z_i\right\|^2 \qquad (5)$$

With reference to input layer data and quality data, the decoder's parameter sets and activation function can be divided into two portions since it has two parts. In other words, its characteristics can be broken down into eq. (6)

$$\tilde{W} = \begin{bmatrix}\tilde{W}_z\\ \tilde{W}_y\end{bmatrix}, \tilde{b} = \begin{bmatrix}\tilde{b}_z\\ \tilde{b}_y\end{bmatrix}, \tilde{f} = \begin{bmatrix}\tilde{f}_z\\ \tilde{f}_y\end{bmatrix} \qquad (6)$$

As a result, the QAE's reconstructed input and quality data is expressed as eq. (7)- (9)

$$\begin{bmatrix}\tilde{z}\\ \tilde{y}\end{bmatrix} = \tilde{f}(f(z)) = \begin{bmatrix}\tilde{f}_z\left(f(z,W,b), \tilde{W}_z, \tilde{b}_z\right)\\ \tilde{f}_y\left(f(z,W,b), \tilde{W}_y, \tilde{b}_y\right)\end{bmatrix} \qquad (7)$$

$$J(W,\tilde{W},b,\tilde{b}) = \frac{1}{2N}\left(\sum_{i=1}^{N} \| \left(\begin{bmatrix}\tilde{z}_i\\ \tilde{y}_i\end{bmatrix} - \begin{bmatrix}z_i\\ y_i\end{bmatrix} \|^2\right)\right) \qquad (8)$$

$$= \frac{1}{2N}\sum_{i=1}^{N}\left(\|\tilde{z}_i - z_i\|^2 + \|\tilde{y}_i - y_i\|^2\right) \qquad (9)$$

4. Performance analysis:

The aforementioned strategy has been developed using Python 3.7 in a prototype software system to evaluate and confirm the possible contribution of the suggested approach for upcoming real-world applications. A computer with an Intel i7 processor (Intel(R) Core(TM) i7-3770 CPU @3.40 GHz 3.80 GHz, Intel, Santa Clara, CA, USA), and eight (8) gigabytes of RAM memory were the resources required to integrate the aforementioned system (Samsung, Seoul, Korea). Microsoft Windows 10 served as the platform for hosting and testing the suggested system.

Table-1 comparative analysis for various fault situation for proposed and existing technique

Techniques	Computational rate	QoS	RMSE	MAE	Prediction performance	Measurement accuracy
CNN	55	51	56	45	53	55
RBF	52	55	58	48	58	62
PCNN_WAEBN	48	59	61	51	62	65

The above table-1 shows comparative analysis for various fault situation for proposed and existing technique. Here the fault situation has been detected by Virtual sensor based datasets of automation industry. The parametric analysis has been carried out in terms of QoS, measurement accuracy, RMSE, MAE, prediction performance and computational time.

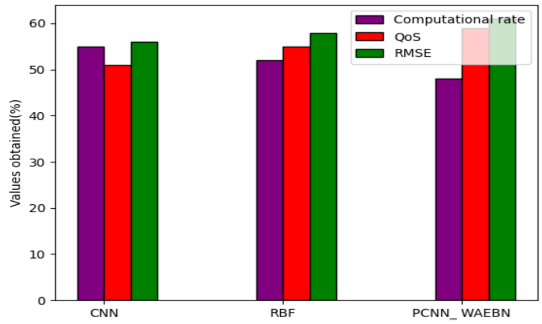

Figure 2: Comparison of existing and proposed method

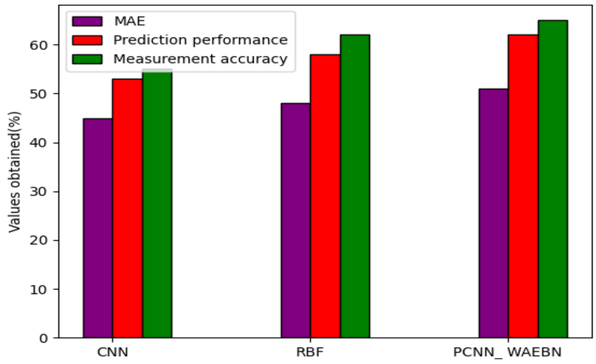

Figure 3: comparison of proposed methods

The above figure 2,3 shows comparative analysis for various virtual sensor based dataset from automation industry. The dataset collected from cloud are based on spindle fault detection based data, gear fault detection based data and bearing fault detection based data. For spindle fault detection data, the proposed technique obtained computational time of 48%, QoS of 59%, RMSE of 61%, MAE of 51 %, Prediction Performance of 62%, Measurement accuracy of 65%.

5. Conclusion:

This research propose novel technique in soft sensor for manufacturing industry based on controlling and monitoring using machine learning techniques. The processed data classified for detection of faults using probalistic convolutional neural network and weighted auto-encoder belief network (WAEBN) based controlling system. Here the aim is to design novel technique in automation of manufacturing industry where the dynamic soft sensors are used in feature representation and classification of the data. The data has been collected from cloud storage and create the virtual sensors dataset based on spindle fault detection, gear fault detection and bearing fault detection in automation industry. Proposed technique attained computational time of 48%, QoS of 59%, RMSE of 61%, MAE of 51 %, Prediction Performance of 62%, Measurement accuracy of 65%. Future research will concentrate on developing multistep forecasts for industrial processes and modelling with an erratic sample rate.

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