Improved Fault Diagnosis in Wireless Sensor Networks using Deep Learning Technique

G.Kiruthiga, P.MayilVel Kumar, K.M.Murugesan,T.Yawanika

ABSTRACT---In recent times, Wireless Sensor Network (WSN) has increased its attention due to its positive impact on surveillance in its surrounding environment. Numerous researches have been report since decades, however, the studies on diagnosing the network fault in critical conditions have received little attention. This could be another area of interest in WSN to increase its overall lifespan and network scalability. However, owing to ad-hoc characteristics of sensor nodes, the scalability of network reduces and this makes the network administrator to poorly observe the conditions of the network. The other major limitations associated with the fault diagnosis in WSN includes: short communication range, limited energy resource, limited processing power, low bandwidth, storage in sensor node, conditionally independent transmission of signals, high power in transmission and signal acquisition and faulty sensory reading under harsh operating condition. The present study considers improving the lifetime and scalability of sensor nodes using passive fault diagnosis using a deep learning approach named Conventional Neural Network. This method effectively classifies the faulty sensor nodes and eliminates it from communicating with other sensor nodes.

Keywords:Recurrent Neural Network, Fault diagnosis, Network Scalability, WSN

I. INTRODUCTION

A pack of unbiased sensor access points via wireless networks is said to be Wireless Sensor Networks (WSN). These structures are understandable, dealing intently with the environment. It is intended to carry out the tasks which is restricted Physical devices, such as a decrease in temperature or pressure, carry out the task of collection of data on a physical object and process[1].WSNs has the potential of time surveillance and is already used in the fields of military purposes, health surveillance, industrial uses, environmental security etc.

Usually WSNs are used to make them more sensitive to incompetence in hazardous, unattached and unusable environments. Mechanisms for fault detection is considered to be major importance to ensure that the WSNs operate properly. It should be accurate and fast to restrict losses and explicitly determine data status. The detection of failures due to the restricted features of the sensor is nevertheless a problem[1].

Many scientists have functioned with multiple perspectives on the object detection mechanism. Certain techniques are spread, unified, or hybrid[3]. Mostly they are based on dynamics and self-detection. Application of robotics is the learning machine that offers a system that can instantaneously learn from and enhance the experience. Categorization is one of the famous data mining approaches, an underlying computer education. It explicitly divides data into classes and assists in decision-making[2].

Deep learning became a hot topic in the area of fault diagnosis. The high-tech methods in many areas have been tackledbecause of its deep learning abilities. Naturally it is suitable for complex systems with multiple variables. The deep learning concepts available for fault diagnosis is very less, however, the techniques on machine learning is very less that includes [8] – [12]. Furthermore, deep learning for diagnostic faults is paid less attention.

With such motivation, the present paper aims to improve the fault diagnosis accuracy using deep learning architectures.In this paper, the lifetime and scalability of sensor nodes is increased using a passive fault diagnosis that encompasses deep learning approach named Conventional Neural Network. This method effectively classifies the faulty sensor nodes and eliminates it from communicating with other sensor nodes.

II. CNN

CNN is a traditional model of deep learning that learns hierarchical picture representation at different levels of abstraction[6]. From Figure 1,it can be observed that an iconic model CNN contains an input, convolutional layers, maximum pooling, output and a connected layer.

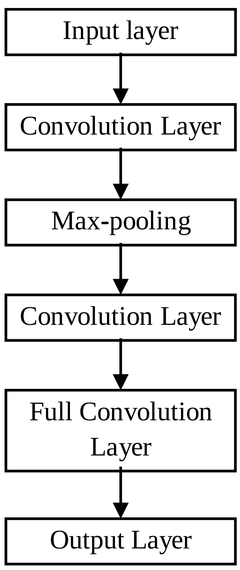

Figure 1. CNN Typical Structure

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As shown in the Figure 1, CNN architecture consists of convolutionallayers with pooling and fully connected layers. A convolutional layer’s primary objective is to identify borders, lines and other elements such as local design. The system teaches the configuration of advanced sensor operators known as convolutions. This mathematical operation is the reproduction by a certain kernel array of local neighbors from a given pixel.

The CNN architecture is comprised of convergent layers with allocating and fully connected layers, as shown in Figure1.The borders, lineages and other elements, such as local design, are the primary objective of a convolutional layer. The process informs advanced sensor operators, called convolutions, to be configured. This function is reproducing local neighbors from a certain pixel via a certain kernel array.

$$H_i = f\left(H_{i-1} \otimes W_i + b_i\right) \quad \textbf{(1)}$$

whereW_i is regarded as the convolutional kernel, b_i is regarded as a bias, and $\otimes$is regarded as a convolutional operation. Here, f (•) is regarded as a non-linear ReLU activation function.

For most applications the max pooling layer of the standard CNN closely follows the convolutional layer and the function map is then obtained by the pooling layer in accordance with a specific max pooling rule. The CNN relies on a completely linked network, which can classify extracted functions using a CNN framework in order to obtain an input-based probability distribution. The residue of the conventional CNN is spread by the method of descent from gradient[7].

III. CNN FOR FAULT DETECTION IN WSN

As shown in Figure 2, a system model can be divided into three phases, where two TelosB mote sensors are used for observations.

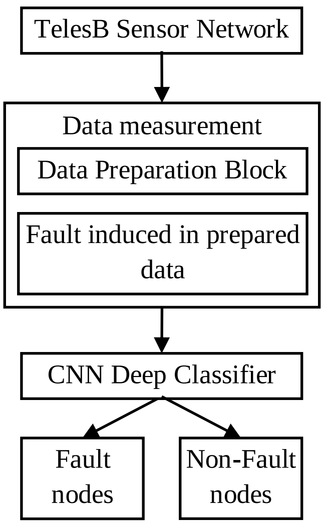

Figure 2. System model of fault detection

Phase 1

The measuring sensed readings are used for a data preparation block, which prepares for each new V_t data measurement a new observation vector. V_t consists of two measures of humidity, namely H_1, H_2, and two measures of temperature, e.g. T_1, T_2. A new observer vector is formed by three successive data measurement units V_t,V_{t-1}, V_{t-2}.

Phase 2

In the next phase, data sets with four faults gained, stacked, offset, and non-bounded were taken[1], and two other faults, i.e. spike and data loss, were entered in the second phase of the model system. The other two faults were reported in the data sets.

Phase 3

The WSNs consist of multiple interconnected node clusters. Each cluster consists of a cluster head that communicates with other nodes and between the network layers. This head is displayed in our system model with a zoomed-out view. In the learning phase, labeled data sets are used. The deep learning classification i.e. CNN is deployed in the cluster head during the third phase. This techniques is used to formulate a decision role with observation vectors.

The process is not computationally expensive since the algorithm used to deploy the decision-making function in the cluster head is uncomplicated. Data are classified into two classes after the deployment of the decision function. If the results are positive, the data will fall in the first class (normal nodes), otherwise the data will be treated as an abnormal (fault nodes).

IV. SIMULATIONS AND RESULTS

We carried out our simulations in Python in order to assess the performance of classifiers. The data set was used as a simulator input. The simulator worked for the i3 core processors and 4 GB RAM. The following section discusses the details of data and simulations.

Two outdoor multi-hop sensors collected the data. It was the temperature and humidity sensed data. Each vector consisted of data from three consecutive situations t_0, t_1, t_2 and each example of two measurements of temperature and two calculations of humidity T_1 and H_1, H_2, respectively. Subsequently, various fault types are randomly induced at different rates.

Four metrics were used for comparison to assess the presentation of SVM, RF, MLP, SGD, CNN and PNN. DA [4] was the first metric and is developed in the Eq.(2) as indicated:

DA = Total Detected Faulty observations / Total faulty observations (2)

TPR[4] was the other method used. It is the measurement of the actual positive ones that are identified correctly. The following is defined:

TPR = TP / TP + FN (3)

The True Positive (TP) in Eq.(3) refers to measurements which predict the true positive, whilst the False Negative (FN) refers to measures wrongly claimed to be negative.

The third method used for diagnosis of faults according to their DA is the Matthews correlation Coffined (MCC). The

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MCC is ranging between −1 and 1, where the former is incompatible and the latter for ideal one, while zero is analogous to random prediction. A closer value to +1 indicates a very strong connection between reality and testing. The following is defined by MCC:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad \textbf{(4)}$$

True Negatives (TN) declared in Eq.(4) that the defaults had been correctly defined, while False Positive (FP) was defined as the number of erroneous nodes incorrectly identified as the erroneous nodes. The CNN is tested for the accuracy of binary classification and rank algorithms in this scenario by applying the MCC

The F1 measure is the fourth metric used to evaluate statistical performance. The harmonic mean of precision and reminder is F1 score[5]. The results of CNN is assessed by FN and FP as a statistical measure. The accuracy is defined as precision, while the reminder identifies all examples in a test that show a certain element, i.e. fault or not faulty. In Eq.(5), the F1 score shall be defined below;

F1 = (2×Precision×Recall) / (Precision + Recall) (5)

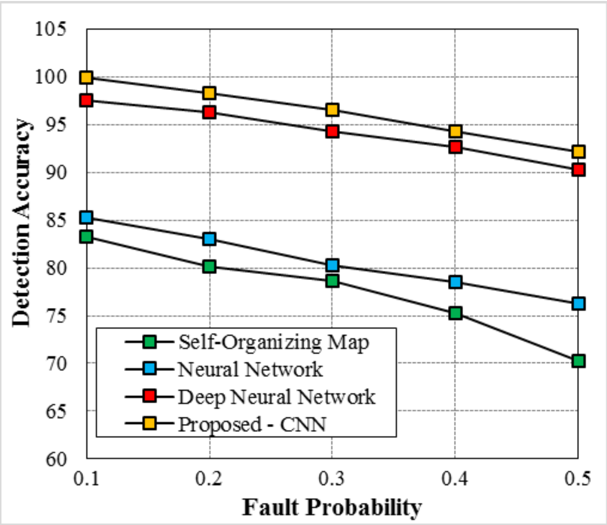

Figure 3: Detection Accuracythe proposed and existing methods

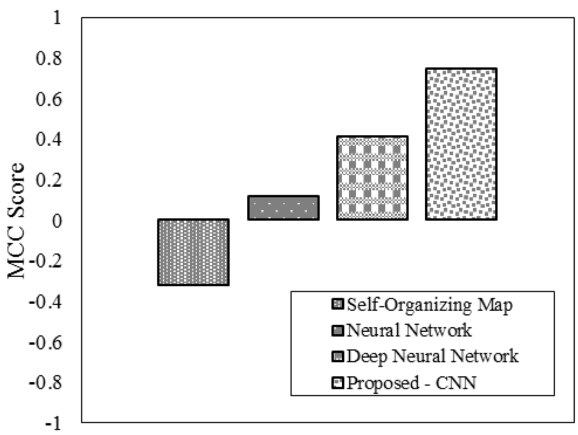

Figure 4: MCC Scorethe proposed and existing methods

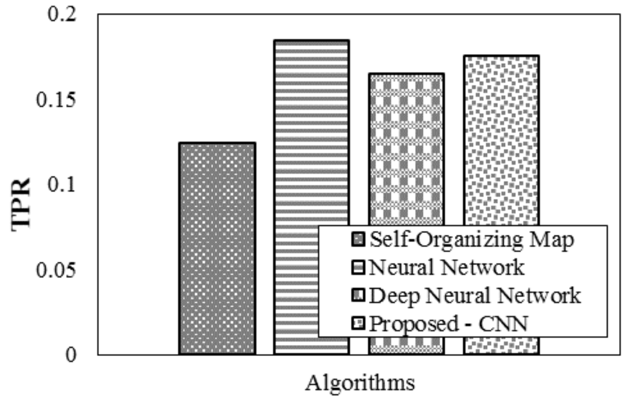

Figure 5: TPRthe proposed and existing methods

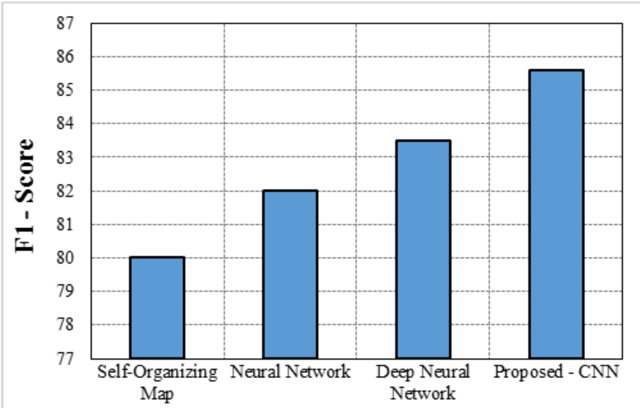

Figure 6: F-Score between the proposed and existing methods

Figure 3, 4, 5 and 6 shows the detection accuracy, MCC score, TPR and F-score between the proposed and existing methods. The result shows that the proposed method achieves higher accuracy, TPR, F-score and MCC score than other methods. This shows that the proposed method achieves higher fault detection rate than other methods.

V. CONCLUSION AND FUTURE WORK

In this paper, the study aims to improve the fault diagnosis accuracy using deep learning architectures. In this paper, the lifetime and scalability of sensor nodes is increased using a passive fault diagnosis that encompasses deep learning approach named Conventional Neural Network. This method effectively classifies the faulty sensor nodes and eliminates it from communicating with other sensor nodes. The classification results of fault diagnosis using detection accuracy, true positive rate, MCC and F1-score shows that the proposed CNN for fault diagnosis in WSN achieves improved result than the existing methods.

REFERENCES

1. Zidi, S., Moulahi, T., &Alaya, B. (2018). Fault detection in wireless sensor networks through SVM classifier. *IEEE Sensors Journal*, *18*(1), 340-347.
2. Muhammed, T., &Shaikh, R. A. (2017). An analysis of fault detection strategies in wireless sensor networks. *Journal of Network and Computer Applications*, *78*, 267-287.

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3. Miao, X., Liu, Y., Zhao, H., & Li, C. (2018). Distributed online one-class support vector machine for anomaly detection over networks. *IEEE transactions on cybernetics*, (99), 1-14.
4. Yuan, Y., Li, S., Zhang, X., & Sun, J. (2018, July). A Comparative Analysis of SVM, Naive Bayes and GBDT for Data Faults Detection in WSNs. In *2018 IEEE International Conference on Software Quality, Reliability and Security Companion (QRS-C)* (pp. 394-399). IEEE.
5. Li, L., Yu, Y., Bai, S., Hou, Y., & Chen, X. (2018). An Effective Two-Step Intrusion Detection Approach Based on Binary Classification and $ k $-NN. *IEEE Access*, *6*, 12060-12073.
6. Zhou, Z., Li, S., & Wang, B. (2014). Multi-scale weighted gradient-based fusion for multi-focus images. *Information Fusion*, *20*, 60-72.
7. Li, Y. D., Hao, Z. B., & Lei, H. (2016). Survey of convolutional neural network. *Journal of Computer Applications*, *36*(9), 2508-2515.
8. Lv, F., Wen, C., Bao, Z., & Liu, M. (2016, July). Fault diagnosis based on deep learning. In *2016 American Control Conference (ACC)* (pp. 6851-6856). IEEE.
9. Hinton, G. E., Osindero, S., &Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. *Neural computation*, *18*(7), 1527-1554.
10. Li, C., Sanchez, R. V., Zurita, G., Cerrada, M., Cabrera, D., &Vásquez, R. E. (2015). Multimodal deep support vector classification with homologous features and its application to gearbox fault diagnosis. *Neurocomputing*, *168*, 119-127.
11. Janssens, O., Slavkovikj, V., Vervisch, B., Stockman, K., Loccufier, M., Verstockt, S., ...& Van Hoecke, S. (2016). Convolutional neural network based fault detection for rotating machinery. *Journal of Sound and Vibration*, *377*, 331-345.
12. Li, C., Sánchez, R. V., Zurita, G., Cerrada, M., & Cabrera, D. (2016). Fault diagnosis for rotating machinery using vibration measurement deep statistical feature learning. *Sensors*, *16*(6), 895.