Deep Learning Fault Detection Algorithms in WSNs

Prof. Dr. Gouri Patil[1], S. Kaneez Rabiya Quadri

[1,2]Dept. Of CSE Engineering, Guru Nanak Dev Engineering College, Karnataka, India

---***---

Abstract - Networks of wireless sensors are deployed in harsh environments. Their main advantages are flexibility and low cost. But they may face many shortcomings that lead to the need to improve data accuracy. Many artificial intelligence techniques have displayed outstanding performance in error detection and diagnosis. Recently, machine learning has grown into a potent method based on artificial intelligence to solve the failure difficulty with WSN. Deep learning approach is been introduce for fault awareness. Deep learning neural networks (artificial neural networks) use a combination of data inputs, weights, and biases to try to replicate the human brain. These components cooperate to correctly identify, categorise, and describe items in your data.

Key Words: WSN, Sensor, Deep Learning, CNN, ANN, LSTM

1. INTRODUCTION

The term "wireless sensor network" (WSN) extends to a group of unconnected sensor devices connected by a wireless channel. These are structures of understanding that work closely with the environment. They are designed for very limited tasks. Basically, the sensor is real-world apparatus that records information on a real-world thing, process, or change in temperature or pressure. WSN has real-time monitoring potential and is already implemented in military applications, health monitoring, industrial applications, environmental monitoring, etc. WSN limits include node power and disk space limits.

Wireless sensor networks can now support a range of identification applications because to recent developments in wireless communication and embedded computing.. Utilizing wireless sensor networks to support a variety of monitoring and control applications such as environmental monitoring, industrial sensing, and traffic control. Environmental monitoring, industrial sensors, traffic sensors, and other small, low-power radio devices are all included in a WSN. Small, low-power wireless devices are frequently used in crowded or isolated areas and make up a significant portion of WSNs. Various mobile and inescapable applications constantly collect and process data from the physical world, providing data on detected situations or opportunities in great detail. In particular, The benefits of information sparsity, global optimality, and broad applicability make SVM a desirable classification approach.

WSNs are prone to failure because they are routinely installed in high-risk, unmonitored, inaccessible environments. These conditions can be further categorised into several groups.

- software errors;
- Hardware failure and
- Communication failure.

In conjunction with the information gathered, The following descriptions perhaps utilised to classify errors.

• Gain Error: when the rate of change of the acquired data is different from the expected value. • Stuck on Error: When there is no change in the set of collected data.
• Out of Range: When an observation falls outside the expected range.
• Peak error: when the estimated time series's excess beyond the time series' projection is greater than the predicted trend of change.
• Noise error: when randomly distributed numbers are added to the expected value.
• Data Loss Error: When a certain amount of data is missing from the collected values during a certain time interval. • Random error: This is an error in which the observed data is unbalanced.

To identify various problems that can occur in wireless sensor networks, we employ a variety of algorithms and deep learning techniques in our study.

1.1 Motivation

There have been significant advancements regarding wireless sensor networks and technologies recently. They are mainly used for communication. Communication between different devices is wired or wireless, so the risk of fire and explosion over the network is increasing every day. Identification and reduction of fraud are the main priorities when it comes to secure communication. As a result, testing of exposure and penetration prevention techniques has become an important part of the engineering field. Using an exposure and intrusion prevention system, we can identify and then report normal and unusual user activity. Therefore, For wireless sensor networks, it is essential to use deep learning and machine learning to create an efficient intrusion detection and mitigation system. In this piece, a trial involved and evaluating the effectiveness of several deep learning and machine learning for malware detection and mitigation systems. The performance estimation of these techniques was performed by experiments performed on the WSN-DS dataset. Comparative evaluation shown by deep learning classifications is better penetration exposure results than machine learning techniques.

1.2 Problem Definition

Using deep learning to detect Wireless sensor network faults can arise for a number of reasons. WSNs are used in risky, unattended and inaccessible environments, making them more susceptible to power outages. These errors fall into three groups: software errors, hardware failures, and communication errors.

1.3 Challenges

Error detection in WSN faces many challenges due to the following reasons:

• The facilities and resources at the node level are very limited, which forces the nodes to use classifiers because they do not require complex computations.

• Sensor nodes are installed in hazardous environments, for example. at home, indoors, in war zones, in hurricanes, earthquakes, etc.

• The error detection process must be accurate and fast to avoid any loss, for example, the process must determine the difference between the abnormal and the normal, so that it can be lost in the event of a collection. Collecting wrong data can lead to erroneous results.

2. EXISTING SYSTEM

WSNs are built with many sensor nodes connected and sharing the information collected by them. Administering a network that is so vast and intricate requires scalable and efficient algorithms. Also, for some reason, WSNs can change dynamically and require a redesign of the entire network architecture. This may sometimes require changes to routing strategy, location of specific nodes, interlayer design, etc. Algorithms for machine learning are required to deal with such situations. With ML, machines learn on their own without human intervention or any kind of reprogramming. ML algorithms can accurately test complex data at node speed. The foundation of WSN is constituted of ML algorithms, which have the capacity to deliver optimum solutions through self-learning.

2.1 Disadvantages of Existing System

• Power outages are reported in the WSN for a number of reasons. One of the reasons could be the location where the WSNs are deployed. Reliance on sensor nodes' batteries, hardware and software failures, as well as required topology changes can be other reasons. The multi-error detection classifier might not be able to be found by the existing system.

• Due to resources being scarce, it can be challenging to identify these errors., the harsh environment in which the WSN is deployed, or the separation of failed and non-faulty nodes

2.3 Datasets:

Data is collected from two outdoor multi-step sensors. It is temperature and humidity data detected. Each vector consisted of data collected at three consecutive cases t0, t1 and t2, and each case was constructed from two temperature measurements and two humidity measurements T1, T2 and H1, H2. Then, different types of errors (lag, boost, freeze, out of bounds, spike and data loss) are randomly caused at different rates (10%, 20%, 30%, 40%) and 50%). A total of 40 datasets were assembled with a set of 9566 tests (vectors) and 12 dimensions for each set. Data sets labeled with a target column are marked as one for normal testing and -1 for outliers.

2.4 Proposed System

Networks of wireless sensors are deployed in harsh environments. Their main advantages are flexibility and low cost. But they may face many shortcomings that lead to the need to improve data accuracy. Many artificial intelligence techniques have displayed outstanding performance in error detection and diagnosis. Recently, machine learning has grown into a potent method based on artificial intelligence to solve the failure difficulty with WSN. In this essay, For defect awareness, a deep learning technique was introduced.

3 DESIGN

3.1 Architecture

Error detection mechanisms are considered to be of great importance to ensure the normal operation of WSNs. To prevent loss and clearly indicate the condition of the data, they must be precise and quick. However, due to the sensor's restricted properties, faults are challenging to detect. The mechanism of anomaly detection has been the subject of numerous studies from various perspectives. Few approaches are distributed, centralized, or hybrid. They are based on dynamics, auto-detection, and machine learning. Artificial intelligence is implemented through machine learning, which gives systems the capacity to autonomously learn from the past and get better. Classification is a frequently often used strategies. to data mining, It is a part of artificial intelligence. It clearly divides data into different categories and helps in decision making. According to data details, there are three classes of machine learning techniques:

Supervised Learning: Data mining strategies are applied to data labeled with predefined classes.

Unsupervised learning: Approaches applied to unlabeled data. Data is classified without prior knowledge.

Semi-supervised learning: Here, both unsupervised and supervised learning are combined.

For fault detection, Convolutional Neural Network, Artificial Neural Network (ANN), Decision Tree (DT), LSTM and Random Forest (RF) classifiers, are used to classify the sensed data into two cases, i.e. normal cases or abnormal cases.

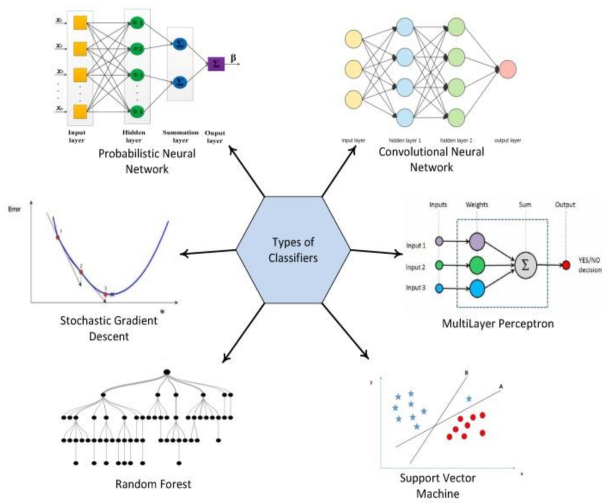

Fig. 3.1 Types of classifiers

3.2 Fault detection Algorithms

3.2.1 Decision Tree

Classification is a two-step process, a learning step and a prediction step, in machine learning. During the training phase, the model develops based on the given training data. In the prediction step, the model is used to predict the response to the given data. Decision trees are straightforward and often used classifications algorithms to understand and interpret.

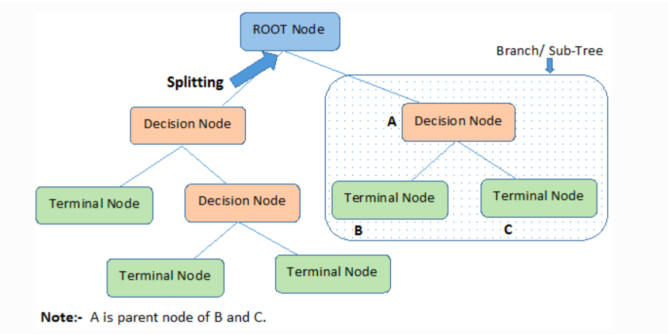

Fig. 3.2 Decision Tree

3.2.2 Random Forest

Individual decision trees are combined to create a random forest, and finally, each decision tree votes in making the correct prediction for the concerned problem.

3.2.3 CNN

A deep learning method called Integrated Neural Network (ConvNet/CNN) can process photos as input, assign importance (weights and assimilable biases) to other aspects/objects images and can distinguish between them. Preprocessing requirements in ConvNet are much lower than in other classification algorithms.

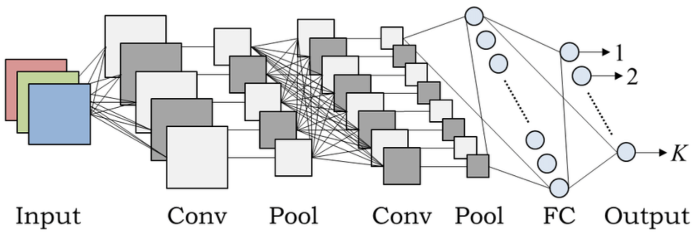

Fig. 3.4 Convolutional neural network architecture

3.2.4 Artificial Neural Network

A good way to think of a NN is as an aggregate function. You give it an input and it gives you an output.

Three parts make up the architecture of the basic NN. These are:

- Units / Neurons.
- Connections / Weights / Parameters.
- Prejudices.

To create a basic NN architecture, you require all of the aforementioned components.

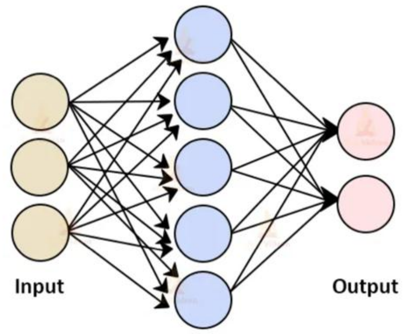

Fig. 3.5 Artificial Neural Network Architecture

3.2.5 LSTM

Neural networks are a set of algorithms that closely resemble the human brain and are designed to recognize patterns. Through automated perception, categorization, or grouping of unprocessed inputs, they evaluate sensory data. They are able to identify the digital patterns found in the vectors that must be used to transform all real data (such as pictures, sounds, texts, or time series).

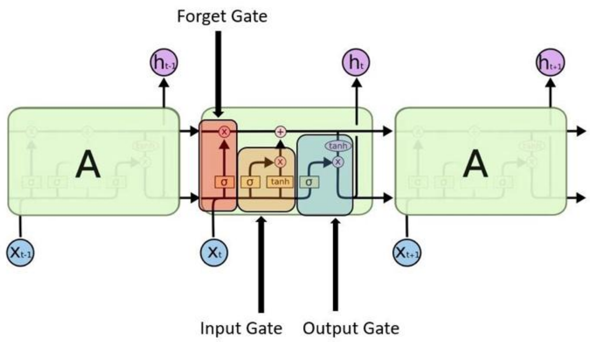

Fig. 3.5 LSTM Architecture

5 RESULT

Provide input:

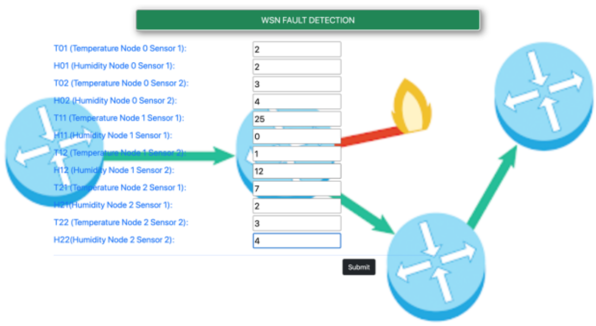

Fig. 5.1 Snapshot of providing input for fault detection

Output: Fault Not Found

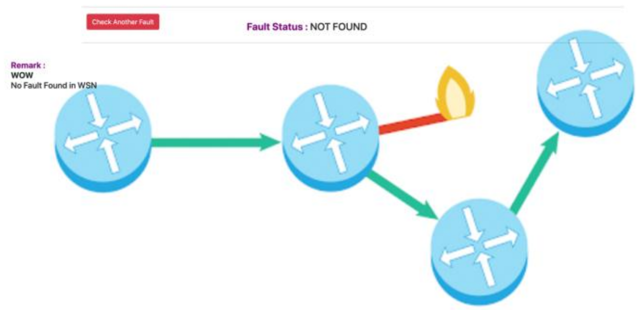

Fig. 5.2 Snapshot of getting output for fault detection

Provide input:

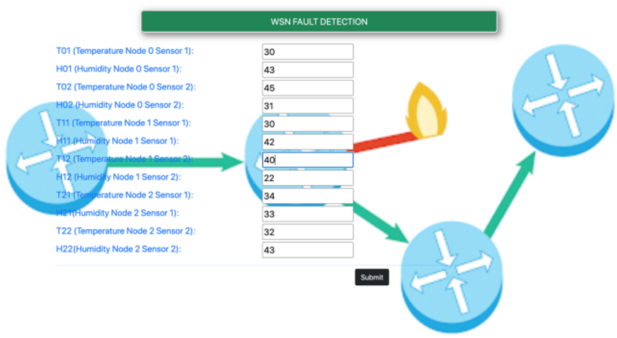

Fig. 5.3 Snapshot of providing input for fault detection

Output: Fault Found

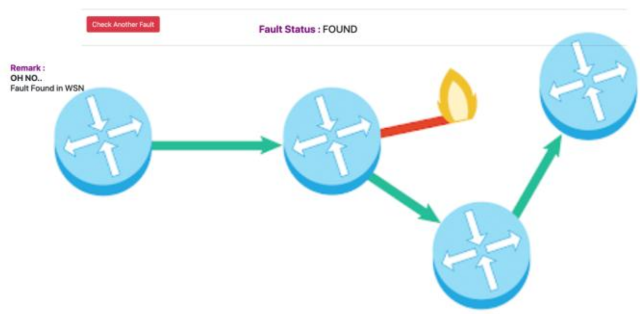

Fig. 5.4 Snapshot of getting output for fault detection

4. CONCLUSIONS

The research work for this project is preceded by a dataset preparation block. The insight makes up the dataset vector Vt, which consists of her two water measurements H1 and H2 and two temperature measurements, T1 and T2, are present three times in succession. Two errors with different error rates (10%, 20%, 30%, 40%, and 50%) are then inserted into the record: a spike error and a data loss error. Next, six classifiers, ANN, CNN, KNN, DT, RF, and LSTM applied to outdoor data collected from multi-hop WSNs. Classifiers are scored based on four different performance metrics.

In future work, we will use the same classifier to predict the next error in the data and develop an error avoidance mechanism. In addition, we will work on WSN failure detection to accurately identify and subsequently detect failures at the sensor (node) level. The sturdiness of the algorithm can also be confirmed by expanding the sensor count. This helps us understand her WSN's resilience to attacks.

5 REFERENCES

1. "Wireless sensor network survey," B. Mukherjee, D. Ghosal, and J. Yick, Computer Networks, volume. 52, 2008, pp. 2292-2330.

2. R. A. Shaikh and M. Thaha, "An examination of fault detecting algorithms in wsns," Journal of Network and Computer Applications, vol.78, no.3,2017, pp. 267–287.

3. "Fault detection in wsns by SVM classifier," IEEE Sens. J., no.18, pp.340-347,2017. Moulahi, S. Zidi and B. Alaya

4. "A Data_Driven_Design for Fault Detection of Wind_Turbines Using Random Forests and XGboost," IEEE Access, vol. 6, pp. 21020-21031, 2018. D. Zhang, L. Qian, B. Mao, C. Huang, B. Huang, and Y. Si

5. Probabilistic neural networks: a quick introduction of theory implementation and application, Elsevier, 2020, pp. 347–367. M. Behshad, T. Amirhessam, M. B. Anke, and G. H. Amir.

6. "A Review of ML Based Fault Detection Algorithms in WSNs," Suman Avdhesh Yadav.

7. Agarwal, A., Sinha, V. K., & Palisetty, R. (2019). Performance analysis and FPGA prototype of variable rate GO-OFDMA baseband transmission scheme. Wireless Personal Communications, 108, 785–809.