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IMPROVED FAULT EVENT DETECTION AND CLASSIFICATION IN WIRELESS SENSOR NETWORKS USING DEEP LEARNING TECHNIQUE

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ABSTRACT: In this modern world, virtually every person must use an application web to transmit and receive information among both source and destination organizations respectively. Because of its positive effect on monitoring in its surroundings the Wireless Sensor Network (WSN) has gained popularity. This study elaborates the logic of WSN by incorporating a few safety metrics and related communication. This paper uses Profound Systems to learn fault detecting in wireless sensor networks. Every base station in WSN has special features that change depending on its ability to send or receive data. The present study looks at increasing the life span and expandability of sensor nodes through passive defect detection that used a method of deep learning known as Convolutional Neural Network (CNN). This cooperation reduces network cost to a minimum level by straight handling raw information on sensors and disclosing only the identified events. Accuracy (97.6%),True Positive Rate(TPR) (98.2%), and Matthews co - relation Coffined (MCC) are used to assess the described validity (0.91). This method successfully classifies defective nodes and prevents them from interacting with other sensor devices.

KEYWORDS: Fault detection and classification, Convolutional Neural Network, Wireless Sensor Network (WSN), Wireless links.

I. INTRODUCTION

Now-a-day the interaction businesses are expanding at a drastic level and Wireless sensory networks are an established and famous connectivity medium for transporting packets of data from one end to another in an innovative manner [1].

WSN is one of the most shared functions for industrial uses due to supercomputing advancements in IoT processors and reduced Power utilization of embedded electronic associations. [2].

Wireless Sensor Network (WSN) is made up of sensor node devices that can be attached via cellular connections [3]. The detector node's obligation is to convey packets base station to the distant sensor node through a network of middle sensor network. The detector nodes are organized into clusters, and each grouping may have a solitary root node, which is able to collect all parcels from all IoT devices in this clump region. The Wireless Sensor Network is made up of nodes that environmental remediation, such as air pressure, humidity, force, location, tension, and sound, among other things. These endpoints can be used for a range of sample tasks such as clever detection, neighbouring node exploration, knowledge distribution, objective tracking, data processing ,monitoring and managing, efficient routing, node location among cell towers and nodes. [4].

The WSN is made up of sensor network which can range from a large numbers and each sensor network is connected to one or more other sensor networks. Each sensor network consists of several components, including a micro - controller, a communication module (transmitter and receiver) an electronic system and a source of energy which is usually a battery . The sensor node size gets varies. Due to the sheer size and price of sensor nodes, funds such as stockpiling, power supply unit and speed of processing are limited.WSN is prone to damage and failings due to the many characteristics of WSN,including topology not being known before deployment, undependable radio transmission, limited resources and being dangerous and overlooked after implementation. Thus, it is critical to identify such flaws and eliminate them from the system in order to avoid unfortunate effects such as incorrect data reading, message drops, loss of information exchange, and so on, and to increase system service quality.

Faults that disrupt network connectivity, particularly in sensing devices can comprise the entire system [5]. The sensing of flaws, and subsequently based on those fault are the only ways to move forward with network recovery actions[5]. Concerning the above faults, because they are largely related to external events, it is preferable that the endpoints themselves make a contribution to their recovering, especially when consumers are unavailable or the endpoints are located in isolated places. Our contributions in this frame of reference have included the detection and detection of interaction faults in WSNs.

Sensor networks are typically low-cost devices that operate in unchecked or even dangerous conditions where they are becoming flawed and undependable. In wireless networks, base station flaws are classified into two types [6]. First sort, feature fault, in which the sensor fails to send the incoming packets correctly had also been researched for a long time. Many approaches were proposed to deal with this type of flaw. Other kind of fault is an information blame, that also occurs when the base station can properly convey the incoming packets but the information collected by the sensor node is incorrect. In so many application areas reading errors can lead to false alarm systems and did miss detection techniques so associated with the likelihood is critical. Furthermore to detect node with defective passages is critical for immensely boosting the effectiveness of the wireless sensor.

Learning has recently become a hot topic in the field of defect detection. For its deep learning high-tech methodologies have been tackled in many areas. It is appropriate for complex systems with many factors. The supervised neural notions obtainable for defect detection are limited and the techniques that includes on machine learning is very less. Moreover, less emphasis is placed on machine learning for diagnosing flaws. With this encouragement, the present literature aims to enhance the precision of defect detection using deep learning systems. This article is structured as follows: Part II describes the literature review, Section III describes the failure detection system technique, Section IV describes the evaluation results, and Section V paper is concluded in section.

II. LITERATURE SURVEY

Gao. Y, Xiao. F, Liu. J, Wang. R, et. al. [7] created a methodology for sensing de centralized flaws in WSN sensor network. By taking into account the underlying weight values of the each node in wireless networks a Stochastic matrix based on fuzzy logic was created. By utilizing their project design on a sensor nodes deployed in an environmental simulink library, the authors have provided 82.1% recognition accuracy.

Li. W, Bassi. F, Dardari. D, Kieffer. M, Pasolini. G, et al. [8] established a constricted mapped method for detecting non-static defects in a Heterogeneous WSN among two detection nodes. The data packets properly sender to receiver among two sets of sensor networks over a particular period was used to build the above map - based structure.

Hao Xing, Xiaoxia Zhao and Liyang Yu et. al. [9] created a Distributed Bayesian Algorithm (DBA) for detecting data faults. Though there were numerous fault diagnosis techniques, the precision was very lesser when there were closely packed endpoints with huge flaws. The failure likelihood of the endpoints has been calculated using a Bayesian network. The rate of false alarms was just very low when compared to the conventional DBA technique.

Banerjee.I, Chanak.P, Rahaman.H and Samanta.T et.al [10] suggested a fault detection re - usable scheme is based on Cellular Automata (CA), in which defective endpoints were handled by a particular set of CA regulations. Each detector node can send its sensor data to the central node which is generally sink/BS. The hub uses sensed data to make a diagnoses the failure condition of the each node and then has sent the fault condition to all nodes in the network. The main disadvantage was that if the hub failed, the accident condition of other nodes could not be determined. CA rules in the system made it complicated, which resulted in poor achievement.

Lau, Bill CP, Eden WM Ma and Tommy WS Chow et al. [11] Predicated on the Naïve Bayes framework we proposed a new centralized hardware failures approach to detect for an organized WSN. There have been issues with the device fault diagnosis method, such as hotspots. The system is broken down into sub-networks. The main disadvantage of the method was that some hubs also couldn't transmit messages to a single point via cellular connection due to the lack of detector updates.

R. N. Duche, N. P. Sarwade, et al. [12] To use an algorithms, misbehaving endpoints in wifi communication were discovered as a result of faults between two detection nodes. The author developed a matrix out of each sensor network and classed it using the sequential procedure technique. By instituting their proposed technique, the authors implemented a failure detection accuracy of 81.1%.

JIN Mu-jing, QU Zhao-wei, et al. [13] realized the self test and enhancement of WSN utilizing neighbor cooperative method and this answer has low consumption of electricity and excellent clinical precision character traits. To address these issues they propose a WSN base station damage detection methodology based on harsh set and gradient boosting device that is simple and effective in detecting and diagnosing link failures.

S. Guo, Z. Zhong, T. He, et. al. [14] Faulty Node Detection (FIND) was suggested to identify endpoints with information faults. FIND recently ranked endpoints due to its physical range from the occasion as well as their interpretations when ever an organic event occurs. If a datatype rank predicated on assessments differentiates from its rating based on the location, the base station is defective. This method can be used broadly without assuming that cluster members have due to widespread. However, this algorithm takes the position of the sensor network, which is not accessible in many apps.

Valizadeh and S. B. and Salahshoor, et. al. [15] suggested a fresh extraction-based classification-based leakage detection mechanism. They presented a dispersed leak detection method based on WSNs in this paper that enables a number of low power sensor nodes to work together to detect leaks in piping systems and estimate their size. They can train the system to detect even the smallest leaks and estimate their size. Because only the status of leakage is communicated between both the nodes in this method, the enhanced communication cost is decreased.

III. FAULT EVENT DETECTION AND CLASSIFICATION IN WSN

The architecture of Improved Fault detection and classification in Wireless Sensor Networks using Deep Learning technique represented in below Fig. 1.

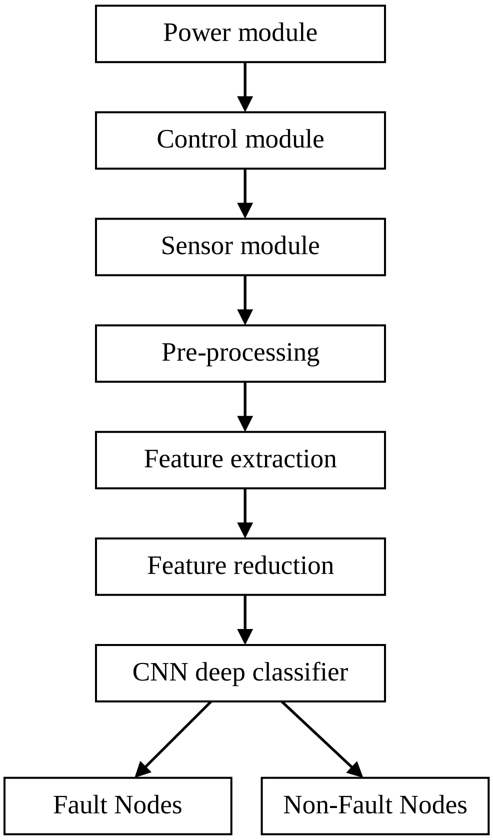

Fig. 1: ARCHITECTURE OF FAULT DETECTION AND CLASSIFICATION IN WSN

This analysis describes a solution for detecting and classifying wireless channel flaws among IoT devices in a Heterogeneous WSN. Each entity in a WSN has special features that change depending on its capacity to send or receives data. We recognize a 1-D sensor system in which the sensors are distributed evenly across the piping system guess it depends on the transmission range. The kth node's place in the circuit is known by dk=kd; k=f1, 2, 3,..., where dk represents the node's spacing and k is its identification number. Waspmote was employed as internet backbone sensor node. It has an array of devices, including air temp, stress, and moisture sensors. The micro - nutrient used for the test has the following features: Central processing unit: AT mega 1281, Frequency: 8MHz.

Sensor data acquisition: They pass this information with such a preset vocabulary to detach the rubbish data before validating sensory data. Observations from the pressure, temperature and accelerometer sensors, as well as the network node battery status are obtained in this manner.

Pre-processing: Noise removal has received a lot of attention in latest studies. There are numerous methods for locating transmission lines that have slow leakages. In order to restore the original message signal is filtered during counter. This issue can be resolved by using haar wavelet that also uncovers the bandwidth signal to remove noise level. The Negative Pressure Wave (NPW) message is denied using a low pass filter and daubechies wavelet packet**.**

The preparatory work of features for classification is a crucial component. The numerical volumes obtained from the data to be labeled are called attributes. The euclidean area is defined by functionality. The clustering of artifacts from same school in the subspace serves as the screening method for characteristics. The discriminator then identifies the amounts of room that corresponds to given class and gives the data contained within those areas a class.

A number of features are extracted to detect leakage in the pipelines. The features are as follows: Expected value (f1), Variance (f2), Gradient (f3), Kurtosis (f4), Pseudo spectrum (f5), Entropy (f6) of particular signal, Power Spectral Density (PSD) (f7), Percentage of energy (f8) and Entropy (f9).

The numerical features of the information that must be categorized are among the applicant characteristics. There could be a lot of applicant functionalities. A select group of the universe's characteristics must be chosen in order to improve classification efficiency. This is referred to as dimensional space or feature extraction. Trying to find a most set of capabilities is our goal. We conducted two exams for the extraction of attributes to be included in lowered features and functionality in order to achieve this goal. By running tests for the classifier that will be part of the diminished functionality, the characteristics are chosen from a collection of twelve functionalities. A first test, the Wilcoxon rank sum test, determines if there is a substantial difference between the median of the begin and non-benign classes. If school dividends are various in shape, nevertheless, a characteristic can also be chosen to be included in a lowered features and functionality rather than using median.
CNN is a well-known profound learning method that gets to know varying levels of hierarchies picture depiction. Convolutional to consolidation and connected directly layers make up the CNN model. The main goal of a convolution operation is to recognize frontiers, lines, as well as other components. Convolutionary are a class of robust adaptive contractors that the scheme teaches how to configure. This arithmetical procedure is the repetition by a kernel arrangement of local neighbours from a pixel location. The method doesn't require a lot of computer power because the group ability is deployed using a simple algorithm. After the classifier has been deployed, inputs are divided into two kinds. The data will fall in the first group (regular nodes) if the findings are favourable; however, the input will be viewed as unusual (fault nodes).

IV. RESULT ANALYSIS

In this study, the proposed failure detection and categorization system is simulated using Simulation Tool 2 (NS2). The tests to measure has a total width of 1000 m and 1000 m, accordingly, and has 100 sensor with an expected depth of 100 m between each node. Each node's baud rate is 150 bytes per second, and its initial bandwidth is fixed at 100 MHz. 15 network faults are created in the simulated environment over the course of the experiment session. The i3 core and 4 GB RAM were compatible with the game. Quality, Accuracy and Similarity True Positive Rate (TPR) are used to evaluate the fault event detection and Matthews correlation Coffined (MCC)

The Accuracy is used to evaluate the effectiveness of the fault detection classifier as shown in below equation (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \dots (1)$$

This alternative technique is called True Positive Rate (TPR). The evaluation of the genuine happy thoughts is what accurately identifies these. The following is defined:

$$TPR = \frac{TP}{TP + FN} \dots (2)$$

The Matthews Connection Coffined is indeed the third method for diagnosing problems based on their Digital Adapter (MCC). The MCC ranges from 1 to 1, with 1 denoting incompatibility and 1 denoting the ideal value, while 0 is equivalent to chance guess. A score that is nearer +1 denotes a really high correlation between test and actuality. The following is defined by MCC:

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FN)(TN + FP)}} \dots (3)$$

False Negative (FN) are tests that are falsely reported to be low while True Positive (TP) are data that accurately forecast the outlook. False positive (FP) was defined as the amount of faulty nodes wrongly recognized as the faulty nodes, but True Negative (TN) proclaimed that the defaults had been clear thinking. By using the MCC, the CNN's efficiency in this situation's classification and rank methods is evaluated.

Different Fault event detection and classification methods like Neutral Network (NN), Deep Neutral Network (DNN) and Convolutional Neural Network (CNN) performance parameters comparisons are described in below Table. 1.

Table 1: PERFORMANCE OF DIFFERENT CLASSIFIERS

Parameters	**Neutral Network (NN)**	**Deep Neutral Network (DNN)**	**Convolutional Neural Network (CNN)**
Accuracy (%)	85	86	97.6
TPR (%)	86	87	98.2
MCC	0.57	0.62	0.91

The graphical representation of Accuracy and True Positive Rate (TPR) is represented in below Fig. 2. Similarly, Matthews Correlation Coffined (MCC) parameter comparison is represented in Fig. 3.

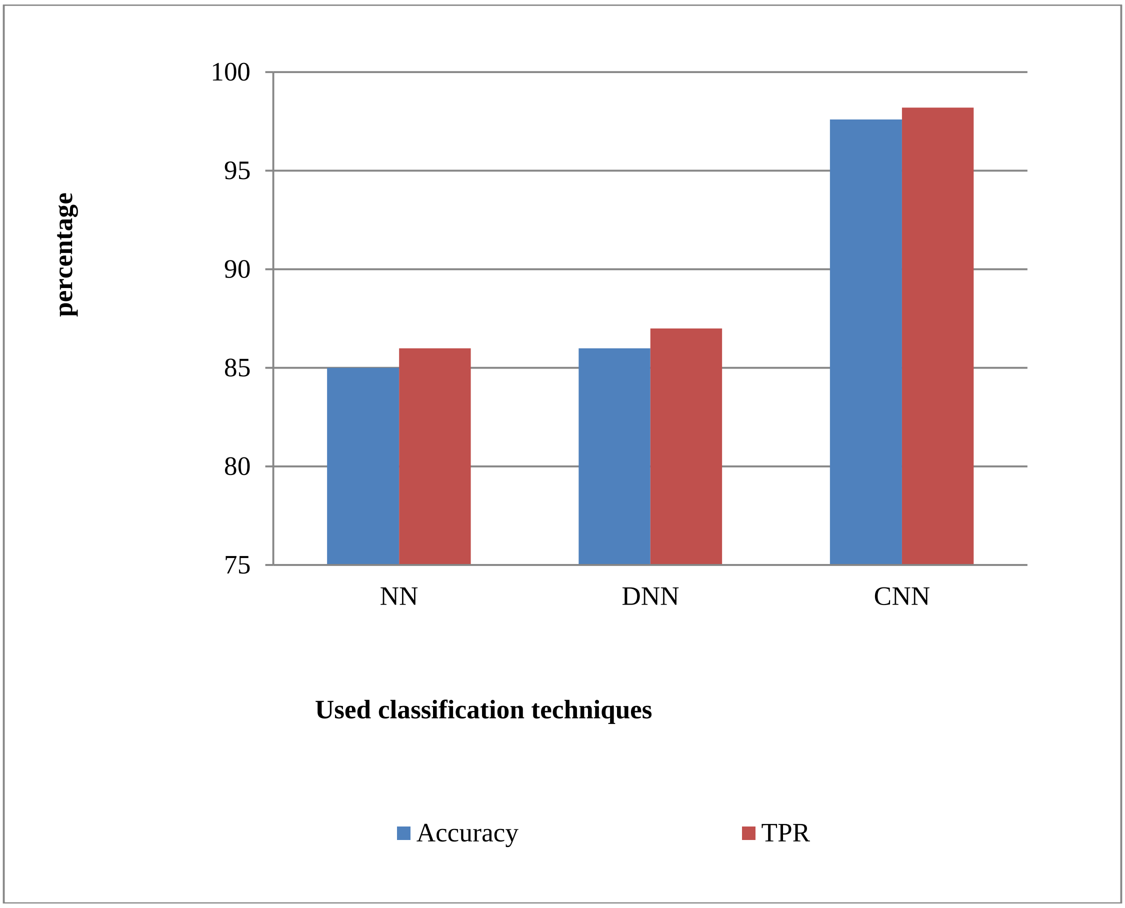

Fig. 2: COMPARATIVE ANALYSIS FOR DIFFERENT CLASSIFICATION TECHNIQUES

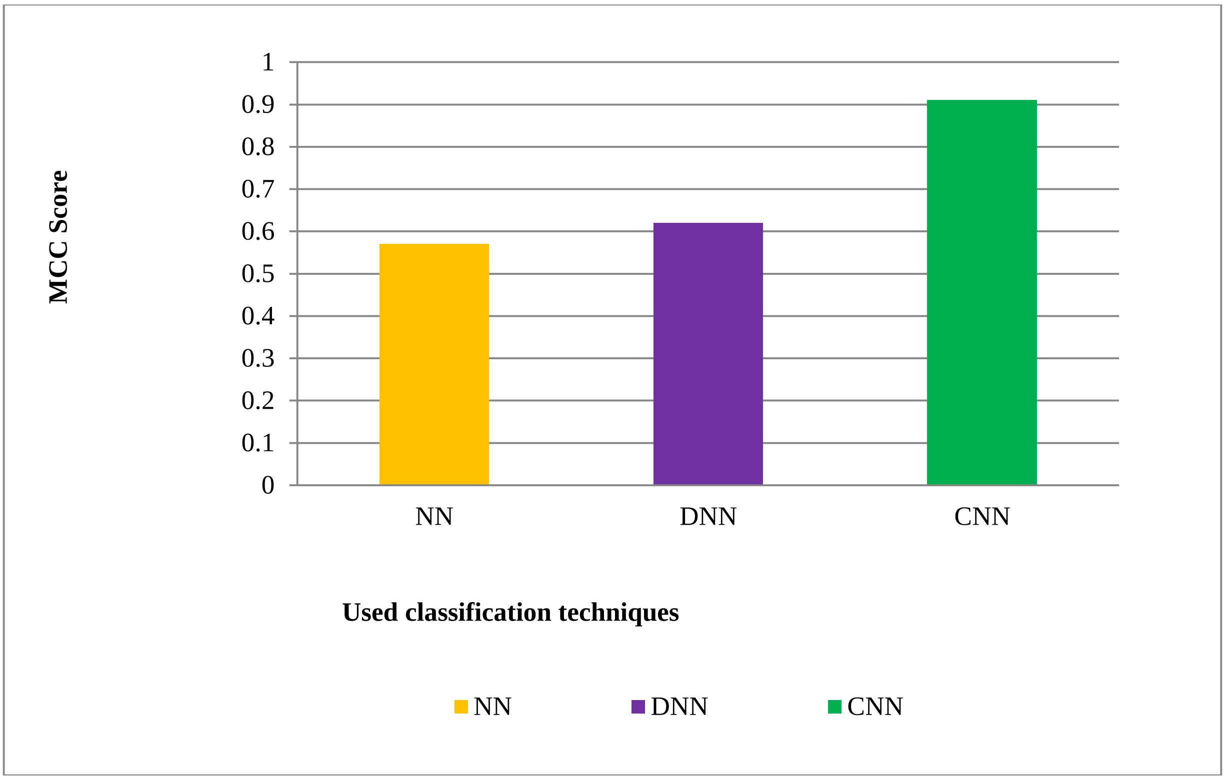

Fig. 3: MCC PARAMETER BASED COMPARATIVE ANALYSIS

The Accuracy, TPR, and MCC for defect classification and detection using the CNN-based technique are 97.6%, 98.2%, and 0.91 respectively. The outcome demonstrates that the shows approach is better other techniques of Accuracy, TPR and MCC. This demonstrates that the CNN approach of fault detecting has a greater fault detection rate than other approache.

V. CONCLUSION

Enhanced Wireless Sensor Networks fault and categorization using Deep Learning technique approach is discussed in this research. In this study technique carried out utilizing a back propagation algorithm called the Convolutional Neural Network (CNN). By taking raw data on sensor nodes and sending only the observed signals, this cooperative technique minimizes connection overhead. Accuracy, True Positive Rate (TPR), Matthews's correlation Coffined (MCC) to evaluate the faulty event classifying program's performance (MCC). was compared to Neutral Network (NN), Deep Neutral Network (DNN) and Convolutional Neural Network (CNN) techniques. The Accuracy, TPR, and MCC for error identification and tracking by using Convolution neural technique are 97.6%, 98.2%, and 0.91 respectively.

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