Performance Comparison of Multiple Neural Networks for Fault Detection of Sensors Array in Oil Heating Reactor

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***Abstract*—Fault detection is an important issue for early failure revelation and machine components preserving before the damage. The processes of fault detection, diagnosis and correction especially in oil heating reactor sensors are among the most crucial steps for reliable and proper operation inside the reactor.The fault detection in sensors array of heating reactor is considered as an important tool to guarantee that the controller can take the best possible action to insure the quality of the output. In this paper, fault detection for the temperature sensor in oil heating reactor using different types of faults with different levels is addressed. Multiple approaches based on Neural Network (NN)s such as the classical Fully Connected Neural Network (FCNN), Bidirectional Long Short Term Memory network (BiLSTM) based on Recurrent Neural Network (R.N.N.) and Convolutional Neural Network (CNN) are suggested for this purpose. The suggested networks are trained and tested on real dataset sequences taken from sensors array readings of real heating reactor in Egypt. The performance comparison of the suggested networks is evaluated using different metrics such as "confusion matrix", accuracy, precision, etc. The various NN are simulated, trained and tested in this paper using MATLAB software 2021 and the advanced tool of "DeepNetworkDesigner". The simulation results prove that CNN outperforms the other comparative networks with classification accuracy reached to 100% with different levels and different types of faults.**

Keywords*—Fault detection; sensor array; oil heater reactor; confusion matrix; neural network; recurrent neural network; convolution neural network; bidirectional short term memory

I. Introduction

Sensor faulty readings is considered one of the major source of industries inefficiencies, detection and diagnosis have a strong ability to improve the operational precision and processes stability inside factories and reduce any inefficiencies in the production cycle. Therefore the objective of fault detection and diagnosis is to reduce the production losses, while assuring the safety to both human and devices.

With the high number of sensors used in monitoring industrial operation, it is very time consuming and a large number of labor is needed to follow whether they work properly or not.

Automatic fault detection is one stage of multi-stage processes system to detect-diagnose-correct any fault at sensors array in a complex control systems. Literature review to some techniques was presented to detect the faults such as serial principal component analysis (SPCA) [1], Decision Tree, Random Forest, Nearest Neighbors [2] Support-Vector Machine (SVM) [3], [4], Fuzzy Deep N.N (FDNN) [5], principal component analysis (PCA) [6], independent component analysis (ICA) [7], Serial Principal Component Analysis [8], lossless compression method [9], KNN rules [10], Kalman Filter [11], and hidden Markov models (HMM) [12],

and other methods [13], [14], [15] , [16], [17], , [18], [19] and [20].

In oil heating reactor many sensors are used to monitor and control the processes inside it because any malfunctions in processes inside the heating reactor may lead to the non-quality production and high cost.

Therefore, it is very crucial to detect any sensor anomalies as early as possible to avoid any product defect.

The stages of detection, diagnosis and correction for a faulty sensor reading using N.N-based classification are shown in Fig. 1 and are illustrated as follows:

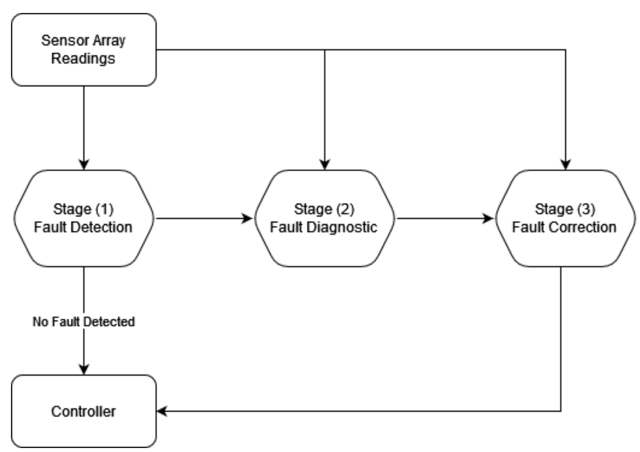

Fig. 1. Sensor array reading possessor

1) Fault detection: in this stage, the sensor array processor will review all sensors readings by using a trained NN based classification to determine if there is a fault in the sensor readings or not and define the faulty sensor if there is a fault.
2) Fault diagnosis: in which the sensor array processor will use the number of the faulty sensor from the previous stage to compare its reading with all other sensors readings to determine the type of the fault using trained classification NN.

3) Fault correction: in this stage, the sensor array processor will utilize the type of fault from the previous stage and the other sensor readings to predict the true reading value of this sensor and send the corrected value to the controller.

This papers presents three N.Ns for fault detection of temperature sensor from sensors array in oil heating reactor and evaluate their performance through comparison using different metrics. The suggested networks are Fully connected neural network (FCNN),Bidirectional long short term memory(BiLSTM) based on recurrent neural network(RNN) and Convolution neural network (CNN). Where, from the simulation results comparison will be used to assess the best performance one of the suggested networks to be recommended in future work in detecting the faulty sensor.The remaining of this paper is organized as follows:

Section II introduces oil heating reactor and description to its physical functions.
Faults types and their mathematical models are displayed in Section III.
Section IV discuss the suggested networks for fault detection, data sets used and how the data is Prepared to be used
Section V is show the construction of the NNs, training parameter and training/test data.
The simulation results of comparing the suggested networks with their performance evaluation using different metrics are displayed in Section VI.
Finally, Section VII concludes the work and discusses the future work.

II. Oil Heating Reactor and its Physical Function Description

This section will discuss the physical construction of the reactor, sensor array, and control system. The physical system consists of heating element for oil before it is separated in later stages.the System also has multiple numbers of sensors - for monitoring the temperature and the flow of natural gas - which are illustrated in the following section. The construction of oil heating reactor and the schematic diagram of its control system are shown in Fig. 2 and Fig. 3.

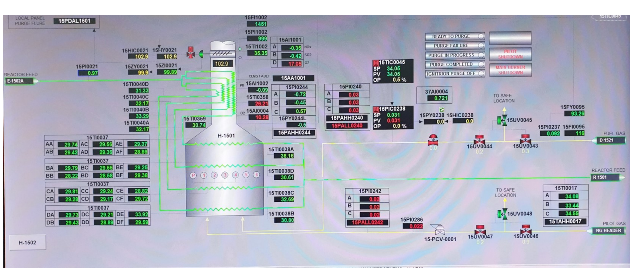

Fig. 2. Oil heating reactor

1) Sensor array: The sensor array consists of 37 sensors in total divided into:

i- 1 oil flow Sensor
ii- 34 Temperature sensors
iii- 1 Gas flow Sensor
iv- 1 Gas Pressure Sensor

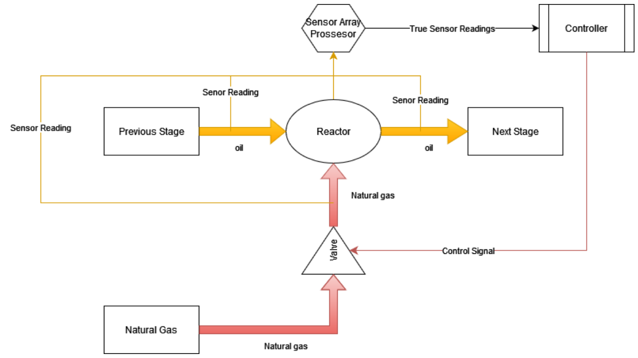

Fig. 3. Control system schematic diagram

All these sensors are installed in various places to monitor the temperature and flow of oil and natural gas through the reactor to help the controller to control the flow of natural gas that will be burned to heat the oil that exits the reactor to be at specific temperature.

2) Heating element: The heating element consists of two stages:-

i- Preheating: where the exhaust of heater is used to preheat the oil.
ii- Main heating:burning natural gas to heat oil passing through some pipes.

III. Fault Types Mathematical Models

This section will discuss the mathematical model of the various types of faults [21], [22], [23], [24].

A. The drift fault

As shown in Fig. 4,

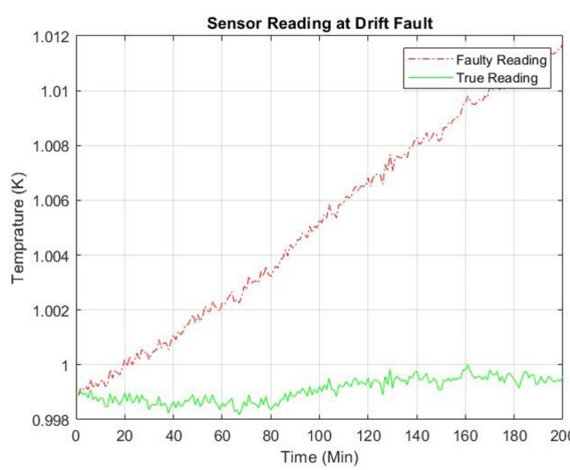

Fig. 4. The drift fault sensor reading

the value of sensor reading will increase in positive feedback loop, so the faulty sensor reading X will be modeled by the following equation:

$$X = X_o + \delta X.t \tag{1}$$

Where $\frac{\delta X}{\bar{X}}$ called fault level, X is the sensor reading, $\bar{X}$ is the average of Sensor readings, t is the time stamp, and X_o is the true reading.

B. The Bias Fault

As shown in Fig. 5,

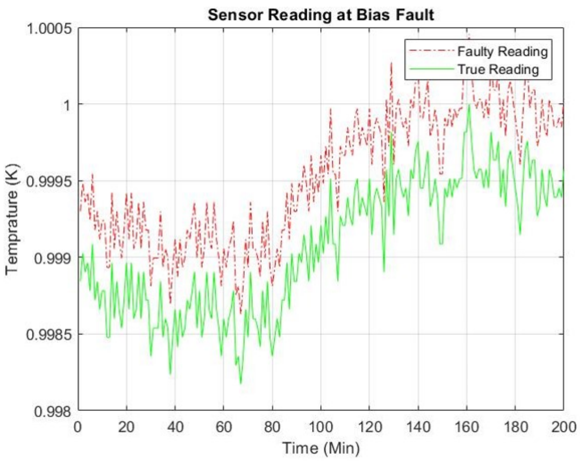

Fig. 5. The bias fault sensor reading

the value of sensor reading will increase by constant value, so the faulty sensor reading will be modeled by the following equation:-

$$X = X_o + \delta X \quad (2)$$

Where $\frac{\delta X}{\bar{X}}$ called fault level, X is the sensor reading, $\bar{X}$ is the average of sensor readings, and X_o is the true reading.

C. The Precision Degradation Fault

As shown in Fig. 6,

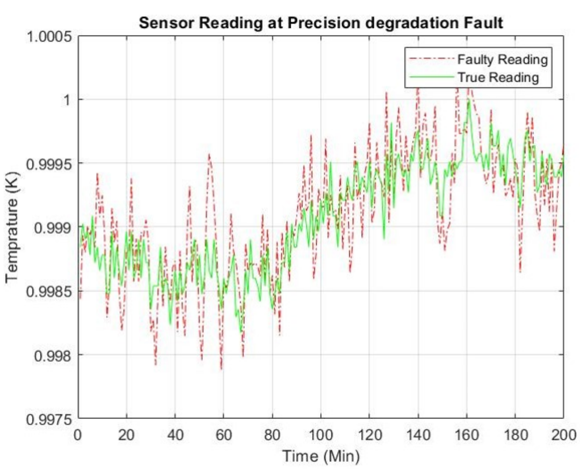

Fig. 6. The precision degradation fault sensor reading

the value of sensor readings will be mixed with white Gaussian noise (WGN), so the faulty sensor reading will be corresponding to the following equation:

$$X = X_o + \delta X.W.G.N \quad (3)$$

Where $\frac{\delta X}{\bar{X}}$ called fault level, X is the sensor reading, $\bar{X}$ is the average of sensor readings, WGN is white Gaussian noise with value varying form (0 to 1), and X_o is the true reading.

D. The Spike Fault

As shown in Fig. 7,

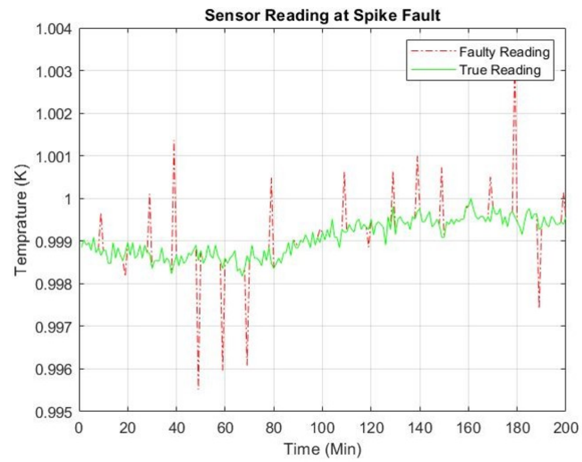

Fig. 7. The spike fault fault sensor reading

the value of sensor readings will be mixed with spike noise [22], [23], [24], so the faulty sensor reading will be modeled according to the following equation:

$$X = X_o + \delta X.W.G.N\delta(t - t_0) \quad (4)$$

Where $\frac{\delta X}{\bar{X}}$ called fault level, X is the sensor reading, $\bar{X}$ is the average of Sensor readings, WGN is white Gaussian noise with value varying form (0 to 1), t is time Stamp X_o is the true reading, and t_0 is the time of the spike.

E. The Stuck Fault

As shown in Fig. 8

the value of sensor reading will be stuck in a certain value, so the faulty sensor reading will be calculated according to the following equation:

$$X = \delta X \quad (5)$$

Where $\frac{\delta X}{\bar{X}}$ called fault level and X is the sensor reading, and $\bar{X}$ is the average of sensor readings.

IV. The Proposed Networks for Classification-Based Fault Detection

In this paper, fault detection stage is implemented by NNs based-classification. After training the networks on series data-set of sensors readings,the network classifies the readings into faulty or non-faulty. The suggested NNs are described in the following section.

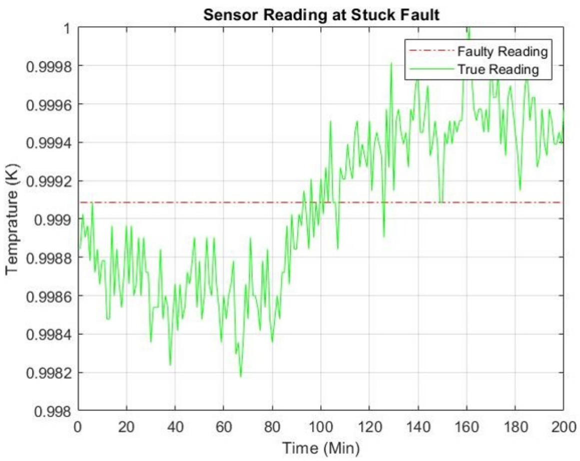

Fig. 8. The stuck sensor reading

A. Description of Suggested Networks

This part is dedicated to show the construction of the used NNs in this Paper.

1) FCNN: A FCNN [25] consists of a series of fully connected layers as demonstrated in Fig. 9.

A fully connected (FC) layer is a function from multiple inputs to one output.

Each output dimension depends on each input.

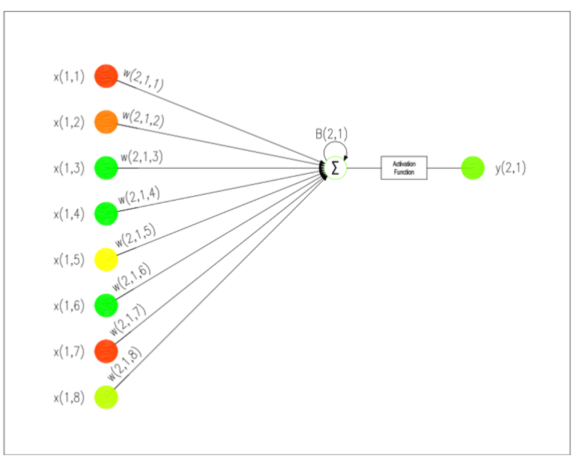

Fig. 9. FCNN construction

2) BiLSTM: BiLSTM network has the ability to learn bidirectional long-term dependencies between time steps of time series data which is helpful for a network to learn at each time step from the total time series data.

BiLSTM handles input sequences in two directions using two sub-layers.

It includes two recurrent network layers, in which the first one processes the sequence of inputs in forwards direction while the second processes the inputs sequence in backwards. Both layers are connected to the same output layer. Thus, BiLSTM network captures the total information about preceding and future sequence of data points [26], [27], [28], [29].

BiLSTM network utilizes the past states to determine the output of the current states as shown in Fig. 10.

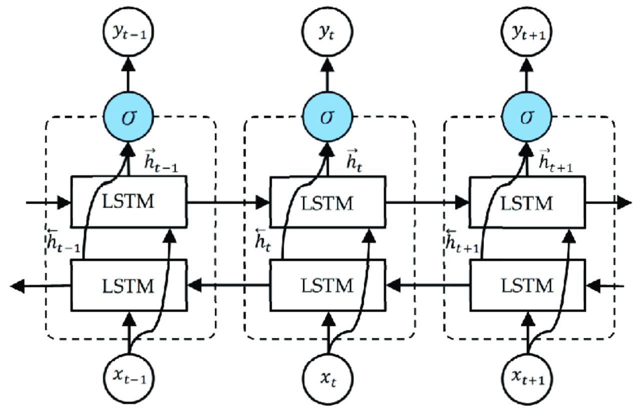

Fig. 10. BiLSTM NN construction

3) CNN: The structure of CNN is depicted in Fig. 11, which consists of convolution layers, pooling layers, and FCL where these layers adaptively learn spatial hierarchies of features through the back-propagation learning [30], [31], [32] and [33].

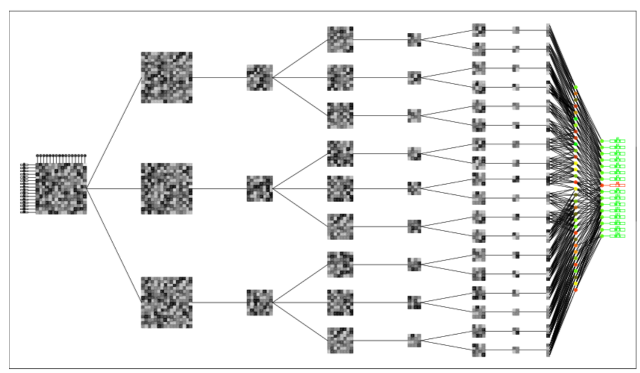

Fig. 11. CNN construction

B. Data sets

The real non-faulty data set collected from sensors array of real oil heating reactor in Egypt over a period of one month is used for training the suggested networks.

This stage of the work in this paper focuses on the temperature sensors readings of 34 sensors arranged in a matrix of 42660 rows and 34 columns.

The Faulty data is created using the different types of faulty models mentioned previously. Thus, the suggested network will be trained for classifying the sensor readings into faulty or non-faulty class.

C. Processing Data

The following procedures are conducted for preparing the data-set for classification:

1- The data will be divided into test and training data, in which the test data is 25% from the total data.
2- Choosing the fault type that will be used to test the NN, where the faulty data is detected from this type.
3- Choosing the fault level that will be used to test the NN, where the faulty data is detected from this fault level.
4- Label both of the training and test data without and with the corresponding type of fault and its level by using two classes to be inputs to the suggested N.Ns

V. Construction of Used NN

In this paper, the performance of three types of neural networks based-classification (FCNN, BiLSTM and CNN) are compared for detecting the faulted temperature sensor using various fault types with different levels .

A. FCNN

FCNN used in this paper is consist of the following layers as shown in Fig. 12:

- Input layer consist of 34 input nodes; one for each sensor reading.
- Hidden layer has 70 nodes.
- Output layer consist of 1 output (label) node for the (+ev) result which means that the sensor is faulty and (-ev) result which means that the sensor is not faulty.

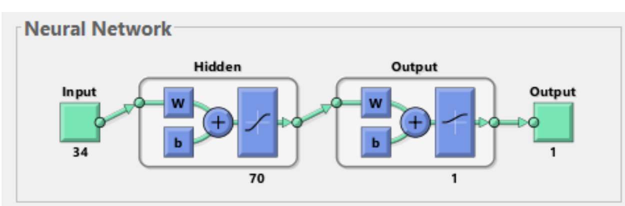

Fig. 12. Proposed FCNN construction

The training parameter used in the FCNN will be as follows:-

- Scaled conjugate gradient back propagation "trainscg" [34] is used as the training function.
- Mean Square Error "mse" [35] is used to evaluate the training result by calculating the error between actual and network outputs.
- Maximum of 1000 epoch will be applied.
- 6 validation checks will be used.

The FCNN have 31995 non-faulty readings and 31995 faulty readings.

In test phase, 10665 faulty readings and 10665 non-faulty readings are used for testing each sensor.

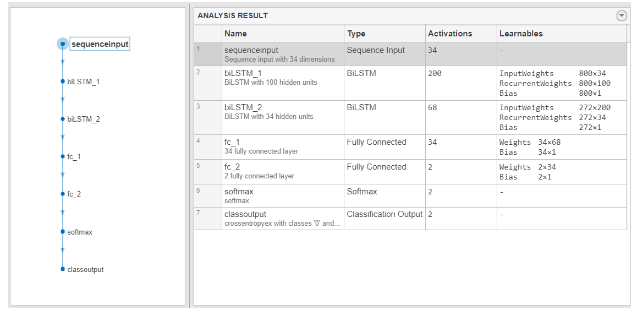

Fig. 13. Proposed BiLSTM RNN construction

B. BiLSTM

BiLSTM is used to classify a Sequence of data as shown in Fig. 13. The BiLSTM network consists of sequence input layer, two BiLSTM layers, two fully connected layers, soft-max layer and finally classification layer.

1) The data sequences of sensors readings is divided into batches; each batch consists of 15 consecutive readings.
2) Thus, the input data to BiLSTM network consists of array of size (15x1) to each sensor reading where for all sensors are (15x34).
3) 2133 non-faulty and 2133 faulty readings are used for training the network, while 711 readings from each of the faulty and non-faulty data are utilized for test phase.

- There are 34 input nodes; one for each sensor; 15 consecutive reading.
- The BiLSTM NN uses 200 BiLSTM nodes in one hidden layer.
- The BiLSTM NN uses 68 BiLSTM nodes in one hidden layer.
- The BiLSTM NN uses 34 nodes in FCL.
- The BiLSTM NN uses 2 output nodes; one for (+ve) Faulty sensor and one for (-ev) non faulty sensor.

The training parameter used in the FCNN will be as follows:

- "adam" is used as the training function.
- 40 epochs maximum will be used.
- 30 iterations per epoch applied.

For the BiLSTM training there is 2133 non-faulty reading runs and 2133 faulty reading runs.

For each sensor test there is 711 faulty reading runs, and 711 the non-faulty runs.

C. CNN

The inputs to CNN must be of two dimension matrix as the gray scale picture shown in Fig. 15. The data sequences of sensors readings are divided into batches; each batch consists of 15 consecutive readings. Thus, the input data to CNN network consists of matrix of size (15x34).

Fig. 14. Input picture to CNN

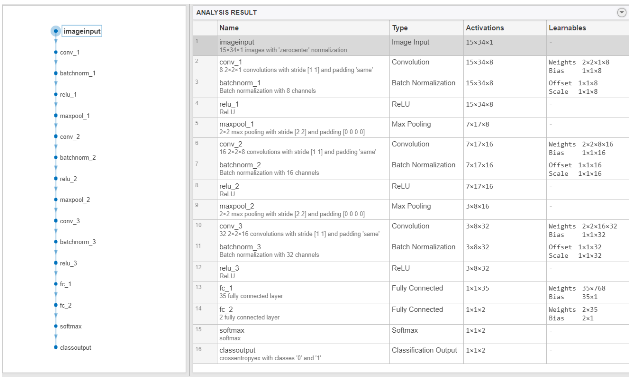

Fig. 15. Proposed CNN construction

Consequently, 2133 non-faulty and 2133 faulty readings are used for training the network while 711 faulty readings and 711 non-faulty readings are utilized for test phase.

The CNN construction is shown in Fig. 14.

so there is 2133 non-faulty and 2133 faulty training runs and 711 non-faulty and 711 faulty test run each consist of (15X34) Reading.

- The CNN has 15×34×1 images as input.
- The CNN has 8 (2×2) convolutions.
- The CNN has (2X2) Max Pooling.
- The CNN has 16 (2×2) convolutions.
- The CNN has (2X2) Max Pooling.
- The CNN has 32 (2×2) convolutions.
- The CNN has (2X2) Max Pooling.
- The CNN has 35 nodes in F.C.L.
- The CNN has 2 nodes in F.C.L.
- The CNN has Softmax Layer.
- The CNN has 2 output nodes one for (+ve) Faulty sensor and one for (-ev) non faulty Sensor.

The training parameter used in the CNN will be as follows:

- The Optimization algorithm named stochastic gradient descent with momentum “sgdm” is used for more efficient neural network weights during the network training [36] is used as the Training Function.

TABLE I. NETWORK PARAMETERS COMPARISON

Parameter	FCNN	BiLSTM N.N	CNN
Input Type	Value	Matrix	Picture
Number Of Layers	3	5	11
Input Layer	34 Node	34 Node	1 Node
Layer-2	F.C	BiLSTM	Convolution
Layer-3		BiLSTM	Max Pooling
Layer-4		F.C	Convolution
Layer-5			Max Pooling
Layer-6			Convolution
Layer-7			Max Pooling
Layer-8			F.C
Layer-9			F.C
Layer-10			Soft Max
Output Layer	2 node	2 node	2 node
Maximum Epoch	1000	40	100
Validation Check	6		
Iteration/epoch	1	30	16
Training Points	63990	4266	4266
Training Function	trainscg	adam	sgdm
Test Points	21330	1422	1422

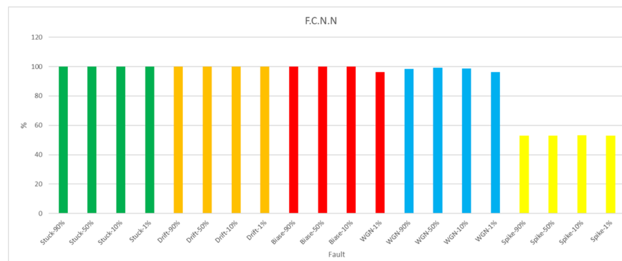

Fig. 16. FCNN performance

- 100 epoch maximum is used.
- 16 iteration per epoch is used.

D. Parameter comparison

Summary combining the comparison between the different neural networks constructions is shown in Table I.

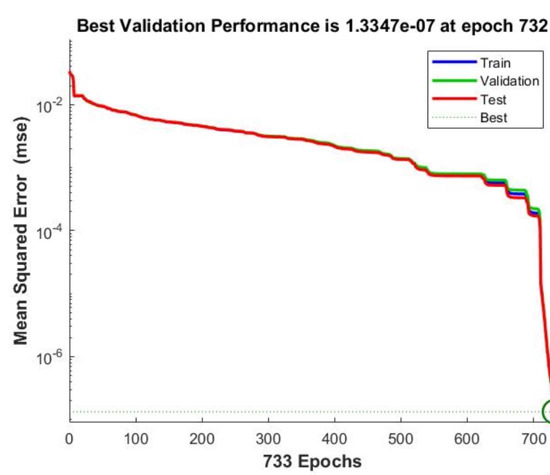

Fig. 17. FCNN training result

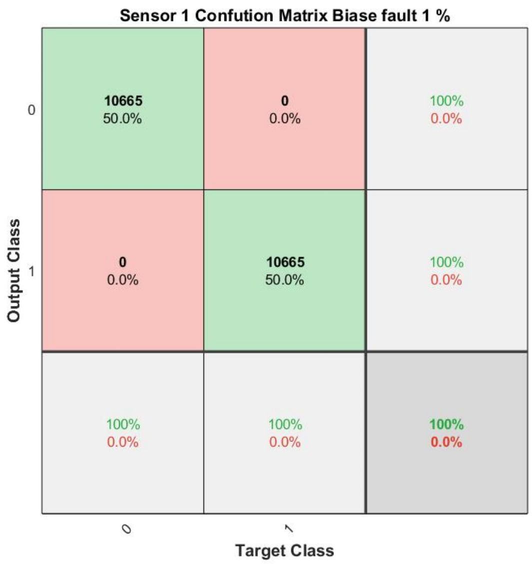

Fig. 18. FCNN confusion matrix

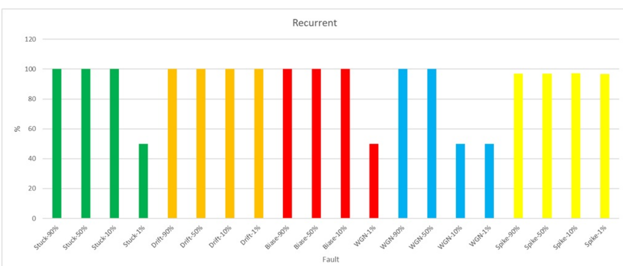

Fig. 19. BiLSTM performance

VI. Network Results Comparison

This section is dedicated to discuss the results of training the N.Ns used in this paper.

A. Performance Metrics for the Suggested Network

The performance of the suggested N.Ns is compared and evaluated using the following metrics [37]:

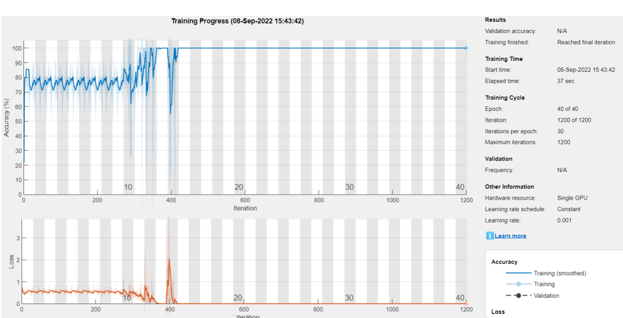

Fig. 20. BiLSTM training result

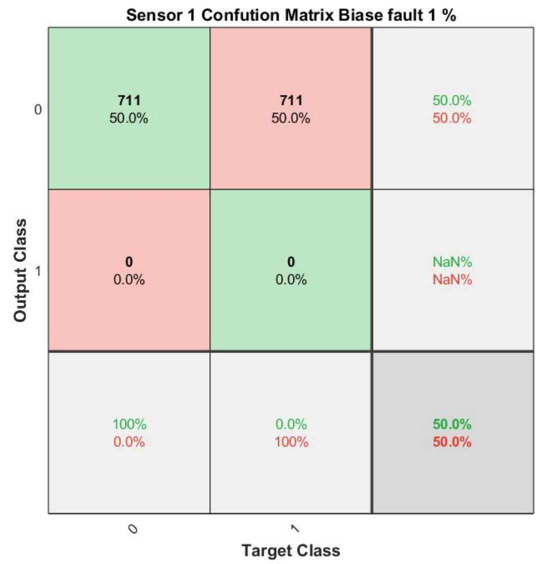

Fig. 21. BiLSTM confusion matrix

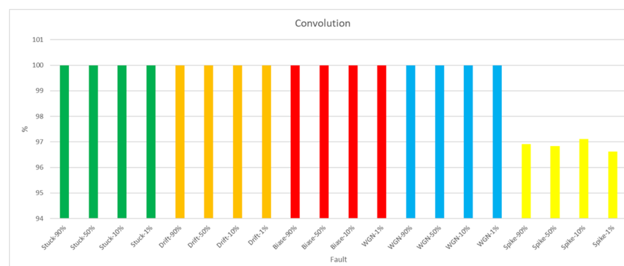

Fig. 22. CNN performance

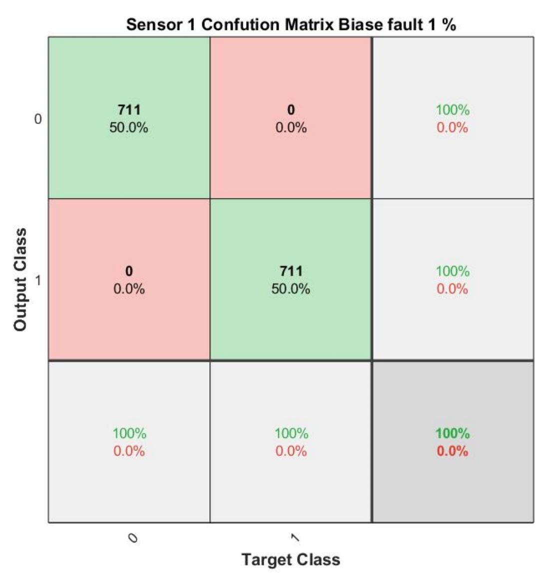

Fig. 23. CNN confusion matrix

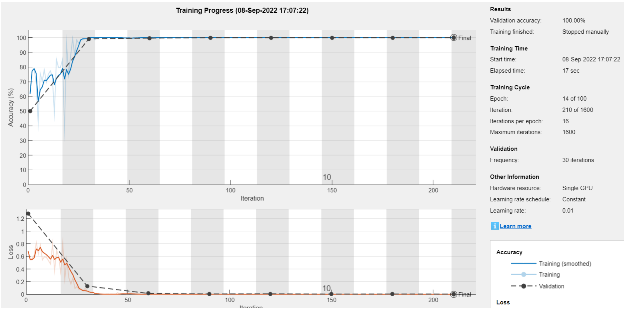

Fig. 24. CNN training result

Fig. 25. 1% fault level comparison for all NNs

1- Accuracy: It is the ratio of correct predictions to total predictions.
2- Precision: the ratio of correct fault detection to all fault predictions.
3- Recall:It is the ratio of correct fault detection to all true fault readings.
4- F-Score:It is the harmonic mean of precision and recall

The results of NNs classification include four types of data samples which are described as follows:

I) True positive (TP): is the number of samples that the network label as faulty while they are in-fact a faulty readings.
II) True negative (TN): is the number of samples that the network label as non-faulty while they are in-fact a non-faulty readings.
III) False positive (FP): is the number of samples that the network label as faulty while they are in-fact a non-Faulty readings.
IV) False negative (FN): is the number of samples that the network label as non-Faulty while they are in-fact a faulty readings.

The aforementioned metrics according to the four types of classified data are calculated by the given equations as follows:

1- Accuracy

$$= \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

2- Precision

$$= \frac{TP}{TP + FP} \tag{7}$$

3- Recall

$$= \frac{TP}{TP + FN} \tag{8}$$

4- F-Score

$$= \frac{1}{\frac{1}{Percition} + \frac{1}{Recall}} \tag{9}$$

5- False positive rate (FPR)

$$= \frac{FP}{TN + FP} \tag{10}$$

6- False negative rate (FNR)

$$= \frac{FN}{TP + FN} \tag{11}$$

B. *Results and Discussion Simulation*

The suggested networks are trained by all types of fault with different levels which are: [1%, 10%, 50% and 90%]. The performance results of the suggested networks for detecting all types of fault with there different levels in metrics of accuracy, precision and recall are given in Table II:

C. *Results*

The following results is obtained after the training and testing of the N.Ns

1) FCNN performance: The comparison of classification accuracy of FCNN for detecting the different fault types with its different levels is shown in Fig. 16.

As shown above the FCNN is very weak in detecting spike fault with accuracy of 50% while its good in detecting the other faults with their different levels where the results of detection are acceptable with accuracy ranges from 96% to 100%.

While the mean square error versus the number of epochs in training FCNN is shown in Fig. 17, confusion matrix is shown in Fig. 18.

2) BiLSTM performance: The comparison of classification accuracy of BiLSTM network for detecting the different fault types with its different levels is shown in Fig. 19.

As shown above, the accuracy of BiLSTM in detecting Basie, stuck and P.D.E faults is weak at fault levels (1%).On contrast, the accuracy results are acceptable with other faults.

While the network accuracy and the losses versus the number of epochs in training BiLSTM network are shown in Fig. 20, confusion matrix is shown in Fig. 21.

TABLE II. NN RESULTS COMPARISON

NN TYPE	Fault Type	Fault Level	Accuracy	Precision	F-score
CNN	Bias	90%	100%	100%	100%
CNN	Bias	50%	100%	100%	100%
CNN	Bias	10%	100%	100%	100%
CNN	Bias	1%	100%	100%	100%
CNN	Drift	90%	100%	100%	100%
CNN	Drift	50%	100%	100%	100%
CNN	Drift	10%	100%	100%	100%
CNN	Drift	1%	100%	100%	100%
CNN	Spike	90%	96.9%	100%	100%
CNN	Spike	50%	96.8%	100%	100%
CNN	Spike	10%	97.1%	100%	100%
CNN	Spike	1%	96.6%	100%	96.8%
CNN	Stuck	90%	100%	100%	96.7%
CNN	Stuck	50%	100%	100%	97%
CNN	Stuck	10%	100%	100%	96.5%
CNN	Stuck	1%	100%	100%	100%
CNN	P.D.E	90%	100%	100%	100%
CNN	P.D.E	50%	100%	100%	100%
CNN	P.D.E	10%	100%	100%	100%
CNN	P.D.E	1%	100%	100%	100%
BiLSTM	Bias	90%	100%	100%	100%
BiLSTM	Bias	50%	100%	100%	100%
BiLSTM	Bias	10%	100%	100%	100%
BiLSTM	Bias	1%	50%	0%	0%
BiLSTM	Drift	90%	100%	100%	100%
BiLSTM	Drift	50%	100%	100%	100%
BiLSTM	Drift	10%	100%	100%	100%
BiLSTM	Drift	1%	100%	100%	100%
BiLSTM	Spike	90%	96.9%	100%	96.8%
BiLSTM	Spike	50%	96.8%	100%	96.7%
BiLSTM	Spike	10%	97.1%	100%	97%
BiLSTM	Spike	1%	96.6%	100%	96.5%
BiLSTM	Stuck	90%	100%	100%	100%
BiLSTM	Stuck	50%	100%	100%	100%
BiLSTM	Stuck	10%	100%	100%	100%
BiLSTM	Stuck	1%	50%	0%	0%
BiLSTM	P.D.E	90%	100%	100%	100%
BiLSTM	P.D.E	50%	100%	100%	100%
BiLSTM	P.D.E	10%	50%	0%	0%
BiLSTM	P.D.E	1%	50%	0%	0%
F.C.N.N	Bias	90%	100%	100%	100%
F.C.N.N	Bias	50%	100%	100%	100%
F.C.N.N	Bias	10%	100%	100%	100%
F.C.N.N	Bias	1%	100%	100%	100%
F.C.N.N	Drift	90%	100%	100%	100%
F.C.N.N	Drift	50%	100%	100%	100%
F.C.N.N	Drift	10%	100%	100%	100%
F.C.N.N	Drift	1%	100%	100%	100%
F.C.N.N	Spike	90%	53.1%	100%	11.6%
F.C.N.N	Spike	50%	53.1%	100%	11.5%
F.C.N.N	Spike	10%	53.2%	100%	11.9%
F.C.N.N	Spike	1%	53.1%	100%	11.7%
F.C.N.N	Stuck	90%	100%	100%	100%
F.C.N.N	Stuck	50%	100%	100%	100%
F.C.N.N	Stuck	10%	100%	100%	100%
F.C.N.N	Stuck	1%	100%	100%	100%
F.C.N.N	P.D.E	90%	98.5%	100%	98.4%
F.C.N.N	P.D.E	50%	99.2%	100%	99.2%
F.C.N.N	P.D.E	10%	98.6%	100%	98.6%
F.C.N.N	P.D.E	1%	96.4%	99.8%	96.2%

3) CNN performance: The comparison of classification accuracy of CNN for detecting the different fault types with there different levels is shown in Fig. 22.

As shown above the result of the CNN is accepted even at spike fault and low level faults.

While the network accuracy and the losses versus the number of epochs in training CNN network are shown Fig. 23, confusion matrix is shown in Fig. 24.

4) The networks accuracy comparison at 1% fault level:: The comparison between all NN performance at various fault types and 1% fault level is shown in Fig. 25.

As shown in this figure, the results demonstrate that the CNN has the best performance in detecting all fault types and levels.

VII. CONCLUSION

In this paper, different neural networks are suggested for detecting the fault in temperature sensor of sensors array in oil heating reactor.

From the given results in this paper, the networks performance in metrics of Accuracy, Precision and Recall are varying depending on the network type, fault type, and fault level.

The CNN performance for fault detection outperforms the other networks, and it is the best so far to detect even very low level faults such as 1% fault level with accuracy reached to 97%.

This results show that the CNN is the best candidate to be implemented for fault diagnosis in future works, that will be focused on fault diagnosis and fault elimination.

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