Intermittent Fault Diagnosis in Sensors using Artificial Neural Network: A Comparative Study

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***Abstract*— Processing algorithms and processing hardware have developed at a very rapid pace in the last three decades. Sensors play a vital role in the condition monitoring of various components of a manufacturing system and to measure different variables that may affect the performance of these systems. Real-time collection of data, processing of the collected data, and decision-making are challenges. Intermittent fault diagnosis is difficult as it occurs randomly and does not follow a pattern. Non-availability of a suitably labeled dataset for testing the algorithms is also a challenge. Keeping these things in mind in the present research fault-injected sensor signals are developed from the publicly available Intel Lab dataset for temperature and light sensor signals. With the help of the proposed algorithm, a Matlab code for intermittent fault injection is developed. The performances of the various machine-learning algorithms extensively used in literature are also compared with the help of accuracy, precision, recall, and F1 score values. The performances of the artificial neural networks are compared with SVM, Ensemble, and k-NN in classifying various intermittent fault modes using the classification learner application of Matlab. The trained bilayer neural network has achieved an F1 score of 0.89 which is the highest among the other tested machine learning algorithms.**

Keywords*— *artificial neural network, fault classification, fault diagnosis, intermittent fault, sensor

I. Introduction

The reduction in the cost of manufacturing sensors played a catalytic role in their extensive use in modern industries. They are deployed in critical applications including space explorations, nuclear reactors, manufacturing systems, and in almost all types of industries. Faults in the sensors may occur due to degradation of the material, wear and tear over time, change in the environment, manufacturing defects, and faulty installations [1]. Timely fault detection and their isolation in sensors are critical as they can help in avoiding breakdown and saving a lot of resources. Isolating the faulty readings from the normal readings and taking real-time decisions accordingly is vital for avoiding major breakdowns. As the systems are becoming increasingly complex setting threshold levels and implementing a model-based approach is a cumbersome task. Sensors are also manufactured using different materials and technologies so the data-based fault diagnosis approach has gained traction recently.

Intermittent faults occur randomly and don't follow a specified pattern so it is difficult to isolate them compared to constant faults like stuck sensor faults [2]. Non-availability of a suitable benchmark dataset for testing the fault classification algorithms is also a big roadblock in the research [3]. Researchers [4]-[9] have extensively used k-Nearest Neighbour(k-NN) based classifiers for fault diagnosis. In [4] and [5] K-NN was used for fault diagnosis in bearings. K-NN was also used in heat exchangers by [6], in wireless sensors by [7], in multimode by [8], and in chiller systems by [9]. Machine learning algorithms like Support Vector Machine(SVM) are used by [10]-[14] and ensemble by [15]-[19] for fault diagnosis. SVM was successfully used by [12] in wind turbines, whereas ensemble was used in the research of [15] and [19] in gas turbines and induction motors respectively.

Developments in machine learning-based approaches such as Artificial Neural Networks(ANNs) have also helped reduce the amount of human intervention [20]. Deep Convolutional Neural networks(DCNNs), soft computing used in [21], and hybrid systems like neuro-fuzzy used in [22] for fault diagnosis require higher processing speed and large training data. These systems are not suitable where the requirement of response time is very short. So in the present research, a code is developed for creating a dataset by injecting intermittent faults and using it to evaluate the different machine-learning algorithms. The performances of different types of ANNs are compared with the ensemble, SVM, and k-NN-based machine learning algorithms, and the best one i.e. the bilayer ANN for isolation and classification of intermittent faults of sensors is proposed. In the next section, the relevant literature related to the present research is discussed.

II. Literature Review

Sensor faults can be categorized on the basis of distortion in the original measurements. The study [1] attempted to model different fault modes of the sensors used in the aerospace industry. Faults are mentioned as unexpected deviations from their normal observations by [1]. Faults were also classified faults into five categories such as bias, drift, scaling, noise, and hard fault [1]. Random faults are described as intermittent spikes in the readings of the sensors which occur with a random frequency [1]. The study [3] used three available sensor datasets to create benchmark datasets for different fault models of sensors. Random faults are categorized as discontinuous and occur randomly in the sensor observations [3]. Proportional and multiple integral fault detection filters for FDI in an unmanned aerial vehicle(UAV) using existing sensors are proposed [23]. Five faulty scenarios with unknown disturbances were used by [23] for developing the model. The stuck and bias fault detection and isolation in the UAV are illustrated. The study [9] used k-NN based approach for the diagnosis of drift faults in chiller systems. The study of [2] emphasized the importance of the detection of intermittent faults and proposed a model-based approach for its diagnosis. The importance of diagnosing intermittent faults has attracted less attention from researchers compared to persistent faults [2]. In the present study, intermittent faults are used to describe the faults that occur randomly without following a pattern.

A. K-NN for Fault Diagnosis

The k-nearest neighbour(k-NN) algorithm classifies the sensor measurements into faulty or not faulty depending on the class membership of nearby neighbours. Time-frequency analysis approach was used by [4] for the diagnosis of the ball-bearing fault diagnosis. Five different types of bearing were successfully classified with the help of the proposed model and found k-NN to be the best machine learning classifier from the experimental data [4]. A hierarchical k-NN-based model for fault diagnosis and classification of automotive motors was used in [5]. The model accurately predicted the bearing faults from the vibration signal and classified the defects from the experimental data [5]. 1100 data vectors from an experimental heat exchanger system are used in [6] to train ANN for fault classification and fault isolation. K-nearest neighbours(k-NN) based model was found to be the best among all the tested classifiers with 90% of correct detections [6]. The performance of different fault detection machine learning algorithms for wireless sensor networks was compared by [7]. The algorithms were tested on the available dataset of physiological signals. k-NN was found to be the fastest among other machine learning but with the highest misclassification [7]. The study [8] proposed a standardized k-NN model for fault diagnosis in the multi-mode scenario. With the help of a case study, the effectiveness of the proposed method was proved [8]. A k-NN-based method for the detection of drift faults in the chiller system was proposed by [9]. A residual generator was designed for the drift fault from the collected sensor data for the identification of faulty sensors [9]. The performance of the proposed model of [9] was compared with other models in terms of accuracy, recall, and F1 score.

B. Ensemble for Fault Diagnosis

The ensemble approach has also attracted the researcher's [15]-[19] interest in fault diagnosis as it combines different models for better classification. A simulated setup of various gas turbine fault conditions was used and the FDI system using the multi-layer perceptron(MLP), radial basis function(RBF), and support vector machine (SVM) for training the NN proposed [15]. The study [15] achieved a very high rate of accuracy and reliability by using the dynamic ensemble method compared to other schemes. An ensemble learning-based supervised machine learning model for the classification of faults in photovoltaic systems was proposed [16]. The proposed approach uses different machine learning algorithms for improved accuracy through the analysis of the electrical signals from the photovoltaic system [16]. An ensemble learning method for the classification of sensor faults combining four different machine learning algorithms was used [17]. The model of [17] was validated using sensor bias fault data and could be deployed in the building for temperature control systems. The performance of the model was compared with other models using the area under the ROC curve and the false positive rate [17]. The study [18] proposed a classification model for the intrusion detection system. The proposed model of [18] is based on the ensemble method of best model selection from a group of machine learning classifiers. The proposed method of [18] was validated in terms of its efficiency using four available datasets. The performance of the ensemble algorithm with the decision tree machine learning model in diagnosing the induction motor fault was compared by [19]. The time domain features extracted from the signal of three phase induction motor were used for the study and achieved 95.8% accuracy using the ensemble-based model [19].

C. SVM for Fault Diagnosis

Support Vector Machine(SVM) has also been used for the classification of faults into different classes depending on the line or hyperplane that separates the classes. A multi-layered SVM model for fault diagnosis in temperature control systems was used [10]. Through the residual analysis method, the faults are detected using SVM in a simulated environment [10]. The study [11] compared the performance of SVM and relevance vector machine (RVM) for fault classification in the low-speed bearing under various load conditions. Both the original data without feature extraction and after feature extraction were used in the study [11]. RVM was found to be more effective for fault diagnosis under low-speed conditions compared to SVM and acoustic emission signals were found more suitable than the collected vibration signal from the experimental setup [11]. A data-based fault classification model using SVM for a wind turbine system was proposed by [12]. The study [12] investigated the suitability of the proposed diagnostic system on sensors and actuators using multiple sensors. Kalman filter and SVM algorithm was used by [13] for fault detection in chillers. The proposed model of [13] worked well even without the faulty dataset, which can help in the reduction of maintenance costs and energy consumption. SVM and a Fuzzy DNN-based approach for fault detection and diagnosis in a distributed sensor environment proposed [14]. The proposed model of [14] performed better compared to the other neuro-fuzzy approach like ANFIS. The central diagnosis approach for better utilization of computational resources was also emphasized [14].

D. ANN for Fault Diagnosis

Recently Artificial Neural networks (ANNs) are being extensively used for classification problems. The measure advantage of using ANN is that they can be trained with a variety of nonlinear data with a lot of predictor variables so they are highly adaptive. The parameters of the ANN classifier get auto-adjusted when real-time data are used for training. Both supervised learning and unsupervised learning are possible.

The research [20] proposed that ANN can be used in pneumatic valves and actuators for fault detection and isolation. Differential pressure and position measurements of the pistons of an actuator are used and also classified ANNs into two broad categories of feed-forward and recurrent types [20]. The study of [21] emphasized the use of soft computing techniques such as fuzzy logic along with trained neural networks for fault diagnosis of dynamic systems. The advantages of using hybrid neural networks for reducing false alarms and missing faults are also emphasized [21]. A hybrid model of NN combined with fuzzy logic, for isolating abrupt faults in sugar factory actuators was used by [22]. The research [24] investigated the performance of a multilayer NN in diagnosing actuator faults in valves. It was also demonstrated that the trained neural network can diagnose the fault levels even which are absent during the training process [24]. The study [25] proposed a two-layer perceptron-based NN control loop system for reducing errors in a nonlinear control system having unknown parameters. A stable fault-tolerant system through continuous updating of weights and biases in a simulated pH plant was achieved [25]. The study [26] used a hybrid technique of FDI and estimation of faults in a general nonlinear system using both parallel and series neural parameter estimators. The proposed model of [26] was tested in simulated wheel actuators of a satellite system. A knowledge-based expert system was proposed by [27] for FDI in an electromechanical actuator. Different outdoor sensor and system faults were modelled and demonstrated the robustness of the proposed model in situations of sensor dropouts i.e. even if signals were not received from some sensors [27]. A neural network and rule-based model for the supervision of heat exchangers was proposed by [28]. The proposed model of [28] successfully predicted the remaining life of the heat exchanger depending on the amount of fouling on the heat exchange surface.

A voltage control-based intelligent fault-tolerant system using NN for FDI in wind electrical systems was proposed by [29]. The study [30] proposed a model using recurrent neural networks for FDI in nonlinear systems with disturbances and also discussed the problems of using neural networks for FDI. Fault-tolerant observer for estimating neural network state even when the faults are present was proposed by [31]. The NN parameters were updated recursively in real-time using the backpropagation algorithm [31]. The model proposed by [31] performed well in a simulated environment even with the noise and other disturbances. Radial basis function-based NN for FDI in fuel cell stacks was proposed by [32]. The least-square method was used for updating the weights of the NN [32]. The method successfully detected and isolated faults up to ± 10% of the measured value in a simulated environment [32]. Two NNs were used by [33] for FDI in gas turbine engines having applications in aircraft. A multilayer perceptron network was used for fault classification by recognizing specific patterns of the fault signals [33]. The study [34] demonstrated that the parallel implementation of a field-programmable gate array(FPGA) of a NN using a few neurons can significantly reduce the processing time compared to software implementation of NN along with a high-performance computer. A deep learning strategy for fault isolation in analog systems with electronic components was used by [35]. The proposed system of [35] measures the signal only in the output point and generates fault patterns. The study [36] proposed a model for incipient fault detection by increasing the fault-trend ratio and fault-noise ratio in a simulated satellite altitude control system.

III. Research Methods

A. Objectives of the Study

The present research focuses on creating a benchmark dataset for intermittent faults of the sensors and uses it for training machine learning models, as the non availability of suitable testing datasets has been emphasized by [3]. It can be inferred from the literature that though different machine learning algorithms k-NN [4]-[9], Ensemble [15]-[19], SVM [10]-[14], ANN [20]-[22], [25]-[28] have been deployed, there is no consensus in the literature about the algorithm for the classification of sensor faults. Also, studies related to the diagnosis of intermittent faults in sensors are scarce. This gap in the literature creates a problem for researchers in identifying a suitable algorithm. Keeping these in perspective the objective of the present study is to propose an intermittent fault injection algorithm and a model for intermittent fault classification.

The study [6] achieved 90% accuracy with k-NN but the ensemble-based model provided the best results in the study conducted by [15]. So the present research uses state-of-the-art machine learning algorithms for the diagnosis of intermittent faults from the sensor signals. The performance of SVM, Ensemble, k-NN, and ANN for the classification of intermittent faults was compared using the fault-injected dataset created from [37]. Very little literature is available related to the isolation of intermittent faults and modelling them in different types of sensors. This gap in the literature is addressed through the present study.

B. Research Steps

The block diagram in fig. 1 constitutes the steps involved in the present research. As depicted in the block diagram raw dataset of sensors was pre-processed first to bring them into the required suitable format for fault injection. Then intermittent faults were injected into the pre-processed data using a proposed algorithm. The generated dataset containing intermittent faults was then labelled as per the different intermittent fault modes. Fault-injected and labelled data were then used for training different state-of-the-art machine learning algorithms. The performances of the machine learning algorithms were compared based on the different parameters. The training process was repeated, and training parameters are changed till satisfactory performance and proposed the best-performing model.

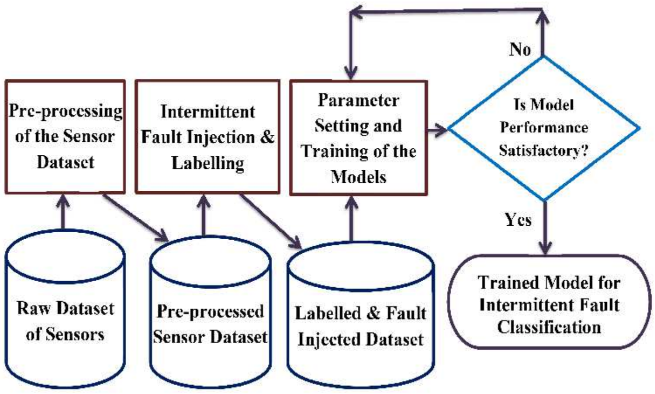

Fig. 1. Block diagram of the research steps

C. Data Pre-processing

The raw dataset for this research work was taken from the publicly available dataset [37]. The dataset contains 54 sensors deployed inside the lab measuring temperature, humidity, light, and voltage were downloaded for pre-processing. The dataset [37] contains time-stamped sensor readings of Mica2Dot sensors. The sensors were used along with a weatherboard for measuring the environmental parameters. For the present research mote-1, sensor data are used and analyzed, which contains 43,047 readings spread over 33 days. The raw data which was in the form of .txt format was imported to Microsoft Excel for pre-processing using tab, space, and colon delimitation. A subset of 20,000 observations of the mote-1 sensor for temperature and light were selected. The selected subset was manually analyzed for any missing observations. The missing measurements were removed and the selected subset was indexed from 1 to 20000 after sorting the data as per the time stamp of the observations.

The processed data were then imported into a table in the MATLAB workspace. The table containing the processed clean data of mote-1 were plotted with the help of the plot(X, Y) function of MATLAB as shown in fig. 2 and fig. 3 with the X-axis as a time index from 1 to 20000, each time index representing 30 seconds. Y-axis in fig. 2 represents the temperature in degrees Celsius and fig. 3 represents light in Lux. As can be observed from fig. 2 and fig. 3, light and temperature have some positive correlation and have 11 cycles. As the labelled benchmark datasets for testing algorithms are not available, the dataset for testing the algorithms for this research was developed from the raw sensor data. Intermittent faults were injected into the clean dataset with the help of a developed MATLAB code using the proposed intermittent fault injection algorithm.

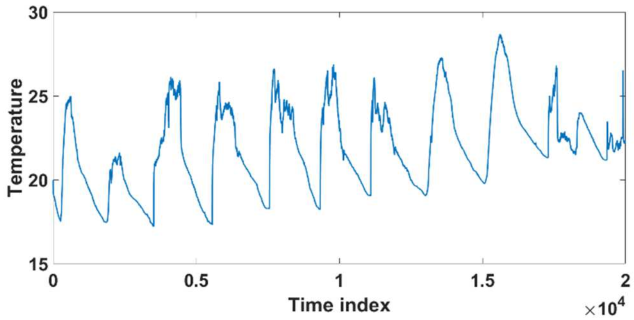

Fig. 2. Temperature (degree Celsius) vs. Time index (30 seconds)

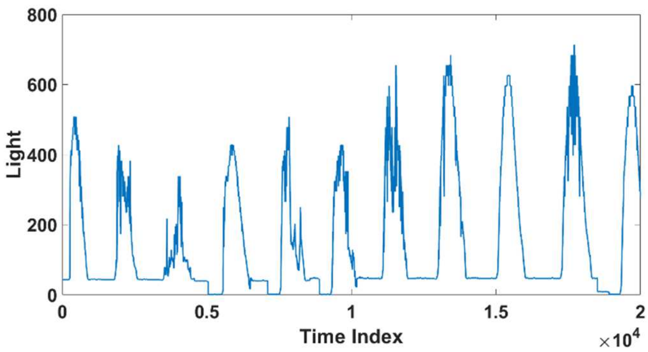

Fig. 3. Light (Lux) vs. Time index (30 seconds)

D. Fault Injection

The algorithm used for the injection of intermittent faults into the sensor data is mentioned in fig. 4. The input to proposed algorithm-1 shown in fig. 4 are the pre-processed dataset, the percentage of faults to be injected, and the range of the intermittent fault intensity. A for loop is used for the insertion of intermittent faults. The generated intermittent faults are either added to or subtracted from the original value depending on the counter variable of the loop. To generate the dataset for testing the algorithms the intensity of the intermittent faults varied from +1.5 to +2.5 times the original readings for both positive and negative spikes of intermittent faults. The study [3] used intensities of +1.5 to +2.5, in 4% of the clean data, and without any negative spikes. In the present study, 4 % of data contains the injected intermittent faults of which 2 % of the intermittent fault intensity is from -1.5 to -2.5 whereas the remaining 2 % of the readings have fault intensity from +1.5 to +2.5. The intermittent faults with random intensity within the specified range, throughout the subset of the clean dataset were injected at random points, unlike the study of [3], where the intermittent faults were injected in a specified percentage of the dataset.

Algorithm 1: Intermittent fault injection algorithm
Input:
D[1……..N] :Input vector of pre-processed signal
P :Percentage of faults to be injected
I [S,E] :The intensity vector, S and E as lower and upper range respectively
Output:
R[1……..N] :Fault injected output vector

Step 1: n ← N*P
Step 2: R [1…….N] ← D [1….N]
Step 3: **for** j=1 to n **do**
Step 4: R_N ←Generate random number
Step 5: R_I ← Generate random intensity
Step 6: **If** n is an odd number then
Step 7: R [R_N] ← D [R_N] * (1+ R_I)
Step 8: **else**
Step 9: R [R_N] ← D [R_N] * (1- R_I)
Step 10: **end if**
Step 11: **end for**
Step 12: **return R**

Fig. 4. Algorithm for intermittent fault injection

Out of the total measurement of 20000 light and temperature sensor readings, 800 intermittent faults were injected with the help of a developed MATLAB program. Random points for intermittent fault injection and random intensities were generated using the rand() function of MATLAB, which uniformly generates random numbers assuming Gaussian distribution in the specified range. Step 4 and 5 of algorithm 1 shown in fig. 4 generates the random values inside the loop. Fig. 5 shows the plot of temperature in degrees Celsius with injected intermittent faults versus the time index (30 seconds).

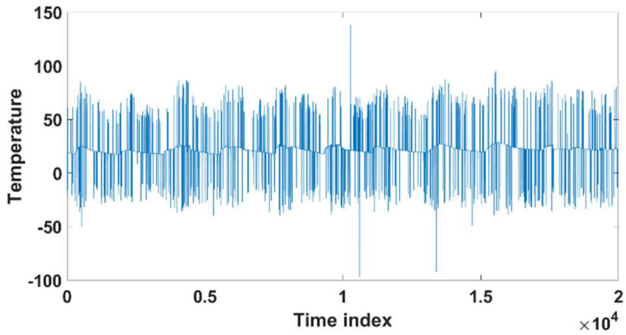

Fig. 5. Temperature(degree Celsius) with injected intermittent faults vs. Time index(30 seconds)

Fig. 6 shows the plot of light in Lux with injected intermittent faults versus the Time index (30 seconds). The injected intermittent faults in the temperature and light sensor measurements can be observed as spikes in both fig. 5 and fig. 6.

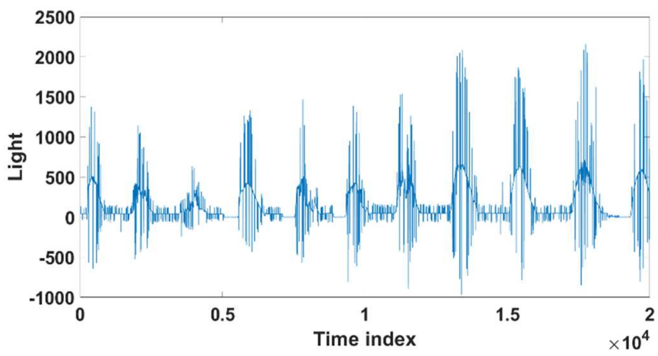

Fig. 6. Light (Lux) with injected intermittent faults vs. Time index (30 seconds)

E. Training of Models

The present research attempts to develop an optimum model with the help of available machine learning models used extensively in the literature for the classification of intermittent faults. A 3x20000 matrix was used for training the classification learner. The first two columns contained measurements of temperature and light sensors with intermittent faults whereas the third column contained code from 0 to 3 representing different intermittent fault modes. Fault mode 0,1,2 and 3 represents no faults, intermittent fault in the temperature sensor, intermittent fault in the light sensor, and intermittent fault in both sensors respectively. Column-1(temperature) having a range from -97.0556 to 138.432 and Column-2(light) having a range of -968.889 to 2158.89 were used as the predictor variables and column-3 (fault modes) had a range from 0 to 3 as the response variable. The five-fold cross-validation method was used for training the classification learner as it helps in avoiding overfitting the machine learning models, by dividing datasets into different folds and calculating accuracy for each fold of the dataset.

The performances of 22 tested models of five different machine learning algorithms such as ANN, Ensemble, SVM, and k-NN are compared as shown in Table 1. Five different types of ANN such as narrow, medium, wide, bilayer, and trilayer are tested. Rectified Linear Unit (ReLU) activation function was used in all five different ANN models. Narrow, medium, and wide ANN models contain one fully connected layer. The first layer sizes of narrow, medium, and wide ANN are 10,25, and 100 respectively. The bilayer ANN constitutes two fully connected layers having 10 nodes in each layer. The trilayer ANN model constitutes three fully connected layers having 10 nodes in each layer. Based on the ensemble method five models i.e. boosted trees, bagged trees, subspace discriminant, subspace k-NN, and RUSBoosted trees are trained. The number of learners was set at 30 for all the ensemble models. As the name signifies the learner type was a decision tree for boosted, bagged, and RUSBoosted trees ensemble models. For subspace k-NN and subspace discriminant ensemble models, the learner type was nearest neighbour and discriminant as the learner type respectively. Four types of SVM models based on their kernel function such as linear, quadratic, cubic, and Gaussian. fine Gaussian, medium, and coarse are also compared. Depending on the kernel scale used Gaussian SVM model was again subdivided into fine, medium, and coarse Gaussian SVM. A kernel scale of 0.35,1.4 and 5.7 was set for fine, medium, and coarse Gaussian SVM models respectively. Six k-NN models were also tested for comparing their performance with the other models in the classification of intermittent faults. The number of neighbours was set to 1, 10 and 100 for fine, medium, and coarse k-NN models respectively. The Euclidian distance was used among the data points and the distance weight was set to equal for fine, medium, and coarse k-NN models. The performance of cosine, cubic and weighted k-NN models with distance metrics as cosine, cubic, and Euclidean are also compared. The number of neighbours was set to 10 for all the cosine, cubic, and weighted k-NN models. Equal distance weights were used in cosine and cubic k-NN, whereas squared inverse distance among the data points was used in the weighted k-NN model.

IV. Results and Discussion

A. Performance Comparison of Models

Table 1 represents the performance comparison of the tested models. Speed is represented in 1000 observations per second. Values of accuracy, precision, recall, and F1 score are represented out of the maximum value of one.

TABLE I. PERFORMANCE COMPARISON OF MODELS

Sl. No.	Models	Speed	Accuracy	Precision	Recall	F1 score
1	ANN (Narrow)	230	0.9859	0.9663	0.8032	0.8772
2	ANN (Medium)	580	0.9858	0.9291	0.8103	0.8656
3	ANN (Wide)	350	0.9867	0.9040	0.8076	0.8531
4	ANN (Bilayer)	520	0.9860	0.9778	0.8172	0.8903
5	ANN (Trilayer)	480	0.9863	0.9579	0.7916	0.8668
6	Ensemble (Boosted Trees)	55	0.9854	0.9222	0.7843	0.8477
7	Ensemble (Bagged Trees)	42	0.9918	0.9126	0.8463	0.8782
8	Ensemble (Subspace Disc.)	42	0.9225	0.2306	0.25	0.2399
9	Ensemble (Subspace k-NN)	14	0.9243	0.5703	0.2640	0.3609
10	Ensemble (RUSBoosted Trees)	47	0.9403	0.6363	0.8413	0.7246
11	SVM (Linear)	270	0.9225	0.4808	0.2503	0.3292
12	SVM (Quadratic)	79	0.7328	0.7453	0.5819	0.6535
13	SVM (Cubic)	190	0.2406	0.3439	0.4715	0.3977
14	SVM (Fine Gaussian)	69	0.9833	0.7360	0.6505	0.6906
15	SVM (Medium Gaussian)	140	0.9777	0.9873	0.6500	0.7839
16	SVM (Coarse Gaussian)	100	0.9715	0.9853	0.5998	0.7457
17	K-NN (Fine)	300	0.9877	0.8123	0.7568	0.7836
18	K-NN (Medium)	170	0.9839	0.7254	0.6613	0.6919
19	K-NN (Coarse)	66	0.9797	0.7285	0.6300	0.6757
20	K-NN (Cosine)	38	0.9464	0.5692	0.4465	0.5004
21	K-NN (Cubic)	130	0.9838	0.7238	0.6622	0.6916
22	K-NN (Weighted)	240	0.9869	0.8418	0.7171	0.7745

As can be observed from Table 1, wide ANN achieved a classification accuracy of 98.67% whereas cubic SVM achieved the lowest classification accuracy among the 22 models tested in the present study. But the number of elements in different classes is not the same or the classes are imbalanced. As the classes are imbalanced classification accuracy cannot be used as a good metric for evaluating models. So F1 score of all the models for performance comparison along with other metrics like speed, accuracy, precision, and recall is used.

The last column of Table 1 contains the F1 score of all the models. The F1 score of a model is derived from the precision and the recall value of the model calculated from the confusion matrix. The F1 score is the harmonic mean of both the precision and recall values. It is evident from Table 1 that the F1 score of bi-layered ANN is 0.8903 which is the highest among all the tested models. The ensemble model(Subspace Discriminant) has the lowest F1 score of 0.2399 among all the models. F1 score of All the five ANN models has F1 scores of more than 0.85, whereas no other model except the ensemble(Bagged Trees) could achieve more than 0.85 F1 scores. Bi-layered ANN having two fully connected layers with 10 nodes each performed better than tri-layered ANN having 3 fully connected layers of 10 nodes each. Medium ANN achieved the highest prediction speed of 5,80,000 observations per second. Bi-layered ANN achieved the second-highest prediction speed of 5,20,000 observations in one second. Ensemble(Subspace k-NN) is the slowest among all the models with a prediction speed of 14,000 observations per second. The performances of the models shown in Table 1 were achieved by using a personal computer with a 1.6 gigahertz processor speed and 8 gigabytes of random access memory.

B. *Confusion Matrix*

The confusion matrix plays a significant role in selecting a prediction model. Fig. 7 shows the confusion matrix for the bi-layered ANN. Out of the total 20,000 data points 19,721 data points could be classified correctly by the trained bi-layered ANN resulting in an overall accuracy of 98.60%. There are four different classes i.e. class 0 (no fault) class 1 (fault in temperature sensor), class 2 (fault in light sensor), and class 3 (fault in both temperature and light sensor) represented as 0,1,2 and 3 respectively in the confusion matrix shown in fig. 7. Class 3 i.e. fault in both sensors was predicted with the lowest precision i.e. 0.5769, which is the ratio of true positive and total data points (true ppositives and false ppositives) in that class. The highest precision value of 0.9982 was achieved for class 0 i.e. no-fault case. The bi-layered ANN model achieved the second-best precision of 0.9947 for class 1 whereas for class 2 precision of 0.7421 could be achieved.

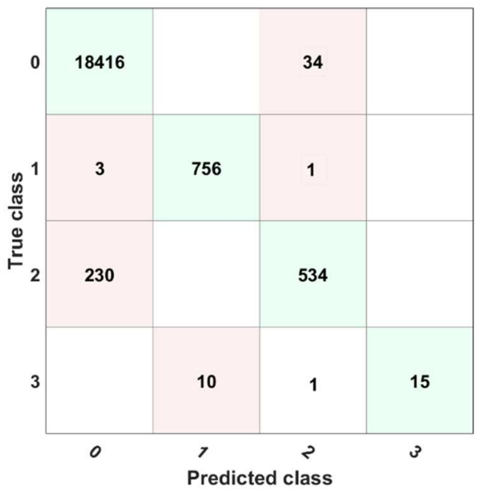

Fig. 7. Confusion Matrix of Bilayered ANN

V. CONCLUSION

There is little consensus in the literature regarding the use of any specific algorithm for intermittent fault diagnosis in sensors. As the complexity of the algorithm increase so the processing and response time also increases which is not acceptable for critical applications where the response time needs to be on a real-time basis. The availability of faulty and non-faulty data for training is also scarce. The present research addresses these problems by proposing an intermittent fault injection algorithm and a bi-layered ANN model for its classification. The accuracy of 98.6 % achieved by the model is comparable to the results obtained by other research. Also, the achieved F1 score of 89.09% is high compared to the k-NN, SVM, and ensemble-based algorithms. Increasing the number of fully connected layers and nodes did not yield better results compared to the bi-layered ANN as evident from the performance of tri-layered ANN. The proposed model has a higher speed of prediction compared to other tested models except for medium ANN. The proposed model's slightly lower rate of prediction is well compensated by its higher accuracy and F1 score. The proposed model is suitable for real-time critical applications having space, energy, and cost constraints.

Gaussian distribution at the time of injecting faults is assumed and used sensor measurement data from the Intel Lab dataset, which may be varied in future research for testing the performance of the proposed model.

REFERENCES

[1] E. Balaban, A. Saxena, P. Bansal, K. F. Goebel, and S. Curran, "Modeling, detection, and disambiguation of sensor faults for aerospace applications," IEEE Sens. J., vol. 9, no. 12, pp. 1907–1917, 2009.

[2] T. Sedighi, P. Phillips, and P. d. Foote, "Model-based intermittent fault detection," Procedia CIRP, vol. 11, pp. 68–73, 2013.

[3] B. D. Bruijn, T. Nguyen, D. Bucur, and K. Tei, "Benchmark Datasets for Fault Detection and Classification in Sensor Data," in Proceedings of the 5th International Conference on Sensor Networks, 2016, pp. 185–195.

[4] D. H. Pandya, S. H. Upadhyay, and S. P. Harsha, "Fault diagnosis of rolling element bearing with intrinsic mode function of acoustic emission data using APF-KNN," Expert Syst. Appl., vol. 40, no. 10, pp. 4137–4145, 2013.

[5] P. Baraldi, F. Cannarile, F. Di Maio, and E. Zio, "Hierarchical k-nearest neighbours classification and binary differential evolution for fault diagnostics of automotive bearings operating under variable conditions," Eng. Appl. Artif. Intell., vol. 56, pp. 1–13, 2016.

[6] J. C. Tudon-Martinez and R. Morales-Menendez, "Actuator Fault Diagnosis in a Heat Exchanger based on Classifiers-A Comparative Study," IFAC-Papers Online, vol. 48, no. 21, pp. 1210–1215, 2015.

[7] G. Pachauri and S. Sharma, "Anomaly detection in medical wireless sensor networks using machine learning algorithms," Procedia Comput. Sci., vol. 70, pp. 325–333, 2015.

[8] B. Song, S. Tan, H. Shi, and B. Zhao, "Fault detection and diagnosis via standardized k nearest neighbor for multimode process," J. Taiwan Inst. Chem. Eng., vol. 106, pp. 1–8, 2020.

[9] L. Gao, D. Li, L. Yao, and Y. Gao, "Sensor drift fault diagnosis for chiller system using deep recurrent canonical correlation analysis and k-nearest neighbor classifier," ISA Trans., vol. 122, pp. 232–246, 2022.

[10] J. Liang and R. Du, "Model-based Fault Detection and Diagnosis of HVAC systems using Support Vector Machine method," Int. J. Refrig., vol. 30, no. 6, pp. 1104–1114, 2007.

[11] A. Widodo et al., "Fault diagnosis of low speed bearing based on relevance vector machine and support vector machine," Expert Syst. Appl., vol. 36, no. 3, pp. 7252–7261, 2009.

[12] N. Laouti, N. Sheibat-Othman, and S. Othman, "Support vector machines for fault detection in wind turbines," IFAC proc. vol., vol. 44, no. 1, pp. 7067–7072, 2011.

[13] K. Yan, Z. Ji, and W. Shen, "Online fault detection methods for chillers combining extended kalman filter and recursive one-class SVM," Neurocomputing, vol. 228, pp. 205–212, 2017.

[14] S. U. Jan, Y. D. Lee, and I. S. Koo, “A distributed sensor-fault detection and diagnosis framework using machine learning,” Inf. Sci. (Ny), vol. 547, pp. 777–796, 2021.

[15] M. Amozegar and K. Khorasani, “An ensemble of dynamic neural network identifiers for fault detection and isolation of gas turbine engines,” Neural Netw., vol. 76, pp. 106–121, 2016.

[16] C. Kapucu and M. Cubukcu, “A supervised ensemble learning method for fault diagnosis in photovoltaic strings,” Energy (Oxf.), vol. 227, no. 120463, p. 120463, 2021.

[17] G. Li et al., “An improved stacking ensemble learning-based sensor fault detection method for building energy systems using fault-discrimination information,” J. Build. Eng., vol. 43, no. 102812, p. 102812, 2021.

[18] A. Alhowaide, I. Alsmadi, and J. Tang, “Ensemble detection model for IoT IDS,” Internet of Things, vol. 16, no. 100435, p. 100435, 2021.

[19] R. Jigyasu, V. Shrivastava, and S. Singh, “Smart classifier based prognostics and health management of induction motor,” Mater. Today, vol. 43, pp. 355–361, 2021.

[20] J. McGhee, I. A. Henderson, and A. Baird, “Neural networks applied for the identification and fault diagnosis of process valves and actuators,” Measurement (Lond.), vol. 20, no. 4, pp. 267–275, 1997.

[21] R. J. Patton, F. J. Uppal, and C. J. Lopez-toribio, “Soft computing approaches to fault diagnosis for dynamic systems: A survey,” IFAC proc. vol., vol. 33, no. 11, pp. 303–315, 2000.

[22] M. J. G. C. Mendes, M. Kowal, J. Korbicz, and J. M. G. S. da Costa, “Neuro-fuzzy structures in fdi system,” IFAC proc. vol., vol. 35, no. 1, pp. 465–470, 2002.

[23] D. Guo, Y. Wang, M. Zhong, and Y. Zhao, “Fault detection and isolation for Unmanned Aerial Vehicle sensors by using extended PMI filter,” IFAC-PapersOnLine, vol. 51, no. 24, pp. 818–823, 2018.

[24] M. Karpenko, N. Sepehri, and D. Scuse, “Diagnosis of process valve actuator faults using a multilayer neural network,” Control Eng. Pract., vol. 11, no. 11, pp. 1289–1299, 2003.

[25] M. J. Fuente, V. Mateo, G. I. Sainz, and S. Saludes, “Adaptive neural-based fault tolerant control for nonlinear systems,” IFAC proc. vol., vol. 41, no. 2, pp. 2595–2600, 2008.

[26] E. Sobhani-Tehrani, H. A. Talebi, and K. Khorasani, “Hybrid fault diagnosis of nonlinear systems using neural parameter estimators,” Neural Netw., vol. 50, pp. 12–32, 2014.

[27] J. C. da Silva, A. Saxena, E. Balaban, and K. Goebel, “A knowledge-based system approach for sensor fault modeling, detection and mitigation,” Expert Syst. Appl., vol. 39, no. 12, pp. 10977–10989, 2012.

[28] R. F. Garcia, “Improving heat exchanger supervision using neural networks and rule based techniques,” Expert Syst. Appl., vol. 39, no. 3, pp. 3012–3021, 2012.

[29] S. Rajendran, U. Govindarajan, S. Senthilvadivelu, and S. B. Uandai, “Intelligent sensor fault-tolerant control for variable speed wind electrical systems,” IET power electron., vol. 6, no. 7, pp. 1308–1319, 2013.

[30] H. A. Talebi and K. Khorasani, “A Neural Network-Based Multiplicative Actuator Fault Detection and Isolation of Nonlinear Systems,” IEEE Transactions on Control Systems Technology, vol. 21, no. 3, pp. 842–851, 2013.

[31] E. Sobhani-Tehrani, H. A. Talebi, and K. Khorasani, “A nonlinear hybrid fault detection, isolation and estimation using bank of neural parameter estimators,” IFAC proc. vol., vol. 41, no. 2, pp. 7251–7258, 2008.

[32] M. M. Kamal, D. W. Yu, and D. L. Yu, “Fault detection and isolation for PEM fuel cell stack with independent RBF model,” Eng. Appl. Artif. Intell., vol. 28, pp. 52–63, 2014.

[33] S. S. Tayarani-Bathaie and K. Khorasani, “Fault detection and isolation of gas turbine engines using a bank of neural networks,” Journal of Process Control, vol. 36, pp. 22–41, 2015.

[34] Z. Hajduk, “High accuracy FPGA activation function implementation for neural networks,” Neurocomputing, vol. 247, pp. 59–61, 2017.

[35] Z. Liu, “Capturing High Discriminative Fault Features for Electronics-Rich Analog System via Deep Learning,” IEEE Transactions on Industrial Informatics, vol. 13, no. 3, pp. 1213–1226, 2017.

[36] Z. He, Y. A. W. Shardt, D. Wang, B. Hou, H. Zhou, and J. Wang, “An incipient fault detection approach via detrending and denoising,” Control Eng. Pract., vol. 74, pp. 1–12, 2018.

[37] “Intel Lab Data,” Mit.edu. [Online]. Available: http://db.csail.mit.edu/labdata/labdata.html. [Accessed: 5-July-2022].