Wavelet Scattering and Artificial Neural Network Based Model for Drift Fault Diagnosis in Sensors

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Abstract-

Modern manufacturing is moving towards automation, reducing or even eliminating human intervention in control mechanisms. Both for quality control and measuring the system state sensors play a vital role. Environmental factors along with aging can introduce drift faults into the sensor readings. The uncompensated drift faults can result in a wrong control system response and the system may become unstable incurring a huge loss of resources. Linear drift is well documented in the literature but nonlinear drift has not yet been properly investigated and literature is also scarce. Keeping these in perspective we propose a wavelet scattering and Artificial Neural Network(ANN) based framework for the detection and isolation of both linear and non-linear drift faults in temperature sensors. The linear and nonlinear sensor drift faults are simulated by injecting the faults into the normal temperature sensor signals. For the purpose of validating the proposed framework, the IntelLab dataset is used. MATLAB software is used for the purpose of simulating drift faults, coding, and training the models. The performance of the proposed model is compared with other ANN and SVM models. The proposed model achieved an overall classification accuracy of 96.7% in classifying the linear and nonlinear drift faults. The proposed model is found to be more efficient in classifying linear drift faults compared to nonlinear drift faults in terms of the number of misclassifications from the non-drifted signals. In critical operations, automatic diagnosis and compensation of the drift faults of sensors need to be implemented as they can avert major accidents. The proposed model can be implemented in real-time data-driven applications for drift fault diagnosis.

Keywords- Wavelet Scattering, Artificial Neural Network(ANN), Sensor Fault, Drift Fault.

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1. INTRODUCTION

The creation of residuals and the determination of the residual threshold for the identification of faulty signals are key to research on the model-based fault classification of sensors [1, 2]. In the case of slow varying faults like drift faults detecting the residual and setting of threshold is difficult. As new and complex algorithms are getting introduced in the literature on sensor fault diagnosis, there is a tradeoff between the speed of fault diagnosis and the cost of the processing hardware. Artificial Neural Networks(ANNs) have brought the researcher's focus on the data-driven approach for fault diagnosis in complex systems [3-5]. ANNs have considerably decreased the need for human involvement in industrial control systems that demand real-time response in the event of sensor failures. Due to their lower cost and ease of deployment in challenging working environments, wireless sensors are gaining attention from industries, making fault detection and classification in these sensors vital. Noise and interference from external electromagnetic fields cause the signals sent by wireless sensors to become corrupted, necessitating filtering before they can be processed by any algorithm. In this situation, the signals' time-frequency scattering helps in the extraction of signal features [2, 6-9]. Additionally, it helps in decreasing noise and other interferences while

simultaneously compressing the size of the signal. The extracted features can then be fed into model-based algorithms or ANN to classify faults. Further, while studies have been conducted on isolating drift faults[10-14], there is limited research done on the isolation of nonlinear drift faults [5]. The objective of this study is to identify fault signatures in the measured data received from the sensors. In the current study, we offer a unique method for classifying linear and nonlinear drift faults from the temperature measurement of wireless sensors. We used the temperature sensor measurements of the publicly available dataset, to validate the model.

2. REVIEW OF LITERATURE

We are discussing the relevant literature in this section. Undiscovered faults lead to increased energy waste and can also result in system failure. Model-based on the Bidirectional Long Shot Term Memory (BLSTM) and correlational analysis for the classification of drift fault is proposed [15]. The residual vectors generated by the model were used as input to the k-NN classifier. The performance of the model has been validated in a chiller system [15]. A threshold-based sensor fault diagnosis technique using centroid score and k-means clustering has been proposed for the central air conditioning system [1]. Drift fault, up to 0.025 degree centigrade per hour, could be isolated using the proposed model. Based on the threshold set centroid scores, the model distinguished between positive drift fault, negative drift fault, bias, and complete failure [1]. The modified version of the Kalman filter is used by [16] to detect sensor drift faults. The performance of the model is compared to the Kalman filter-based approach in terms of accuracy and detection time [16]. A neural network-based model for the automatic correction of sensor faults such as the replacement of missing data and noise reduction has been proposed [17]. The model trained by the no-fault datasets of the Heating, Ventilation, and Air Conditioning(HVAC) system has been compared with PCA based model in terms of accuracy [17]. An artificial intelligence-based data-driven method using wavelet transform for drift fault detection in sensors has been proposed [18]. Wavelets were used for frequency domain feature extraction which is given as input to the neural network for learning. The neural network trained with the normal no-fault sensor data was used for the detection and classification of faulty sensor signals in a simulated multi-sensor environment [18].

The performances of the machine learning algorithms such as SVM, ANN, and k-NN in detecting drift faults were compared in terms of accuracy, specificity, and sensitivity [19]. The performance of ANN and k-NN was found to be better compared to the SVM with leakage, noise, tilt, and resistance as input parameters. The proposed method is suitable for deployment in oil exploration and was tested in offline mode which can also be used for online fault diagnosis of sensors. Chemical sensors are more prone to performance degradation because of the operating conditions of their deployment and are more prone to drift errors. The slow degradation in performance gets reflected in the sensor readings which affects the controlling mechanism and may lead to breakdown and interruption of operation [20]. A model for the automatic classification and repair of faulty sensors was proposed by [20]. The performance of the model was validated with the help of measurements of 18 months and compared with the other classification algorithms including k-NN.

In the study of [6,21], DCNN models for fault classification are used. EfficientNet CNN for the classification of breast cancer from the microscopic images of cancer cells was proposed by [21]. The model achieved a classification accuracy of 98.9% using the BreakHis dataset and seven-fold cross-validation. The model with two additional dense and dropout layers was found suitable for cancer classification using the patient's biopsy images [21]. A pre-trained GoogLeNet-based DCNN model for the classification of sensor faults using time-frequency representation of fault scenarios was proposed [6]. The model achieved higher classification accuracy for the bias, sine, and noise faults whereas a high number of misclassification was reported in the case of drift faults in a real-time velocity control system [6].

A hybrid model was proposed by [22] for fault using state transition probability as input

to the NN. They achieved 98.66% accuracy in fault classification with a false positive rate of 0.005 and classified drift, bias, random, and spike sensor faults [22]. Their study[23] emphasized the requirement for automated fault diagnosis and rectification as manual interventions are not possible all the time. A Radial Basis Function Neural Network(RBFNN) model with genetic algorithm-based optimization of weights was proposed [23]. The model classified stuck-at, drift, and oscillation sensor faults in a simulated environment with higher accuracy compared to the model without genetic algorithm-based optimization.

Multiresolution analysis has gained the attention of researchers[2,7-9,24] in the area of fault detection. Wavelet-based fault diagnosis method using permutation entropy was proposed by [7]. The model was tested for drift, bias, and stuck sensor fault classification with the help of experimental data. A three-layered back propagation neural network was used for fault classification with the help of the extracted fault features from the sensor signals [7]. Wavelet transform was used as a feature extractor from the signal of current sensors which are used as the input to the LSTM model for random drift fault diagnosis [8]. The proposed model by [8] was found to be suitable for current sensors of fiber optic networks compared to the backpropagation NN. Using discrete wavelet transform and threshold setting [2] proposed a model for the classification of drift sensor faults having high prediction accuracy, and low computational resources compared to neural networks. Time series predicted and the denoised sensor data were used for the residual generation which was subsequently compared with the set threshold for detection of the drift fault [2]. The model was tested with the help of simulated sensor data and the actual measurements from the temperature sensor without the assumption of Gaussian distribution [2]. For the detection of series arc faults in the power system of aircraft, a wavelet transform-based denoising, and optical diagnosis method is proposed [9]. The series arc has less intensity than the load current, which makes it difficult to detect. The proposed optical diagnosis method was found to be superior compared to the electric method as it eliminates electromagnetic interference. The proposed method by [9] was tested with the help of experimental data obtained from the different anode materials. A method for fault detection in water treatment plants was proposed by [24]. The features of bias, variance, and drift fault were extracted with the help of a multiscale representation of the signal. The fault detection method was evaluated with the help of average run length, false alarm, and missed detection rate in the simulated wastewater treatment plant [24].

Researchers[11-14,25,26] investigated and proposed models for drift fault classification in their study. Fault identification and correction of faulty sensor signals in critical applications like nuclear power plants are vital where immediate access to the sensors is not possible. A method was proposed by [11] for the isolation of drift, spike, noise, bias, and dead sensor faults with the help of a nuclear reactor model. The model is suitable for applications where frequent maintenance is not possible and the stability of the system must be maintained even after the sensor failures. Implementation of nonlinear PCA and advanced NN architectures for fault classification was also emphasized [11]. A general likelihood ratio-based approach for drift fault diagnosis in linear systems was proposed [12]. They simulated three types of drift faults and predicted the time of the fault occurrence in the sensor signal [12]. The importance of the time of fault occurrence, place of occurrence, and the magnitude of the occurred fault for the implementation of the control mechanism was emphasized. Detecting fault occurrence time is difficult in slow drifts because of the lack of sufficient data points and if the slope is very small the drift fault may not get detected by the proposed method [12]. CNN-based sensor fault classification approach for the detection and classification of missing, spikey, drift, and random faults was proposed by [14]. The model performance was tested with both the simulated and experimental data and achieved 100% accuracy in isolating faulty sensors whereas 98.7% accuracy in detecting the type of sensor faults was achieved. The model is suitable for deployment in the health monitoring of structures [14]. Bank of Kalman filters with the fuzzy algorithm for fault detection and isolation in sensors was proposed by [13]. The proposed model estimates the states and predicts the output which is used for correcting the faulty sensor data. The proposed model by [13] was tested for the diagnosis of both abrupt and drift

faults in a simulated environment. sensors and actuators. The simulation testing of the model demonstrates its suitability as a fault-tolerant system in the case of both the sensors and actuators. Faults in the wireless sensors may occur because of aging and environmental factors that can lead to unstable systems. Context-aware fault diagnostic method for the classification of six types of commonly occurring sensor faults based on an ensemble learning algorithm was proposed [25]. The proposed model is suitable for wireless sensor networks with limited availability of memory, energy, and computational capability. The model was tested with the help of temperature and humidity sensor data. F1 score, training time, accuracy, and area of the ROC curve of the model were compared with the SVM and NN algorithms [25]. An SVM-based classifier was proposed by [26] for sensor fault diagnosis using the non-faulty data collected from a temperature to voltage converter. The faults were injected into the normal sensor measurements and were used for time domain feature extraction from them for training three different SVM classifiers i.e. liner, polynomial and radial basis functions. Increasing the number of features did not improve the classification accuracy whereas increasing the training samples from 40 to 60 resulted in overfitting. The number of data elements per sample affected the performance of the SVM classifier, ROC curve of SVM and NN were compared [26].

Speed of diagnosis is vital in IoT and cyber-physical systems as the control system need to respond in real time. A DNN model using fuzzy logic for fault diagnosis was proposed for IoT and cyber-physical systems [27]. Detecting drift faults in comparison with abrupt fault diagnosis is difficult. An ANN-based model for classifying drift faults and isolating the faulty sensor from the healthy ones was proposed by [5]. The performance of the six different ANN algorithms was compared in different fault scenarios. Among the tested ANNs, auto-associative BPNN performed better than others in classifying faulty signals. The proposed method is suitable for drift fault diagnosis in non-linear systems like wind turbines [27]. The performance of the proposed Kalman filter-based system by [28] in faulty sensor scenarios was found to be more accurate compared to the other two models. ANN performed poorly compared to the Kalman filter-based observer system in terms of error [28].

Wavelet scattering transform was proposed by [29] for translation invariant representation of the signals. They demonstrated the higher classification accuracy of the method for music genre and phone classification. Wavelet scattering transform has also been used for feature extraction from the ECG signals for classification purposes [30]. A model for fault detection using the vibration signal of the gear was proposed [31]. For fault detection, statistical parameters of both the fault and healthy vibration signals were compared [31]. A support Vector Regression based model was proposed by [32] for the prediction of different mechanical properties of the alloy at high temperatures. The performance of the model was evaluated in terms of the obtained correlation coefficient and prediction error. Researchers[3,4,33] used ANN to analyze the mechanical properties of materials in their study. A trained ANN model for the prediction of mechanical properties in the blue brittle region was proposed by [3] and obtained satisfactory performance by comparing the experimental and modeling results.

For the prediction of the mechanical properties of the alloy a trained feed-forward ANN model was used [33]. The predicted and experimentally obtained values were compared and significance was tested using the f and t-test [33]. Computation of frictional and wear properties of composites based on polycarbonate was performed using a trained ANN [4]. They also emphasized the use of ANN in studying the composite parameters that can help in optimum composite design [4].

For fault classification ANN [6-8,17-19,21-23], k-NN [19,20], SVM[19,26,32] and Kalman filter [13,16,28] are being used by the researchers in the studies. Researchers [2,7-9,29,30] have used wavelets for signal analysis in their studies, recently researchers[6,14,21,27] have also focused on the use of DCNNs for fault diagnosis.

3. RESEARCH METHODOLOGY

3.1 *Objective of the study and research steps*

Literature related to simulating and classifying nonlinear drift faults is limited [10]. The assumption that all drift faults are linear is not

valid because of numerous external and internal factors that affect the measurement. Also in real-time monitoring, the control system must quickly and automatically diagnose the nonlinear drifts from linear and non-faulty sensor signals. We used the wavelet scattering as proposed by [29]. So in the present research, the main objective is to propose a wavelet and PCA-based model for the classification of both linear and nonlinear sensor drift faults

Figure 1 shows the sequence of steps followed in the present research work. We used MATLAB software running on a 1.6 GHz Windows10-based personal computer for the present study. The dataset of sensor measurements is taken from the publicly available Intel Lab dataset [34]. The presence of errors in the Intel Lab dataset [34] is mentioned by [35] in their study. We used it because the real-world measurements are similar in nature and the efficacy of the models can be tested better compared by using clean and processed measurements. In the present research, the raw datasets are pre-processed and both the linear and nonlinear sensor faults are injected with the help of developed MATLAB code. We used wavelet scattering previously used by [29] for feature extraction and time-frequency decomposition of the pre-processed signals. Principal Components Analysis(PCA) has been performed on the decomposed signals to isolate the components that explain maximum variance. After setting up the model parameters the models are trained using a supervised learning process and the classification accuracies are compared. The model parameters are varied recursively for selecting the best-performing model for the classification of the drift faults as shown in fig.1.

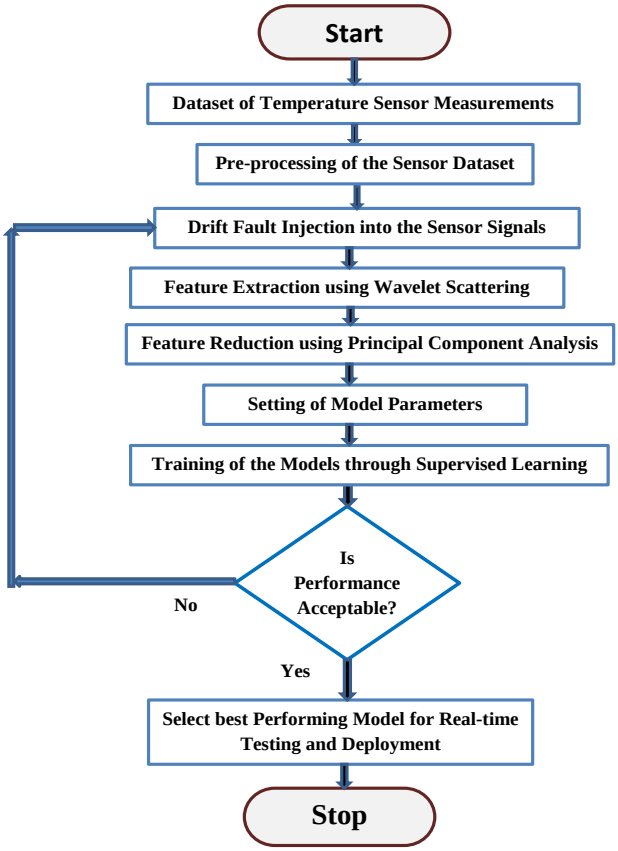

Figure.1: Flow chart of the research process followed

3.2 *Pre-processing*

We used the publicly available dataset of sensor measurements from the Intel Lab dataset [34]. It contains sensor measurements deployed inside the Intel Berkeley Lab having temperature, humidity, light, and voltage. The dataset has 54 sensor motes, out of which we considered temperature measurements of 24 motes. Mote numbers 1 to 26 excluding mote numbers 5 and 15 are used for the present study. Mote 5 and 15 measurements are removed because of the less number of measurements and high errors. The dataset contains sensor measurements at 30-second intervals representing one epoch. The initial 100 measurements of the sensor measurements are removed because of the transients present in the measurements. The dataset contains a lot of missing epoch values which we filled using the backward interpolation method. The temperature sensor measurements also have outliers present which are replaced by the previous non-outlier measurements. The sensor measurements that are greater than three MAD (Median Absolute Deviations) are treated

as outliers and are replaced. A total of 480 temperature signals are generated from the 24 motes, each containing 10,000 temperature measurements. Figure 2 shows the plotting of 480 generated temperature signals from the 24 motes. The X-axis represents the time in epoch and the Y-axis represents the temperature in degrees Celsius.

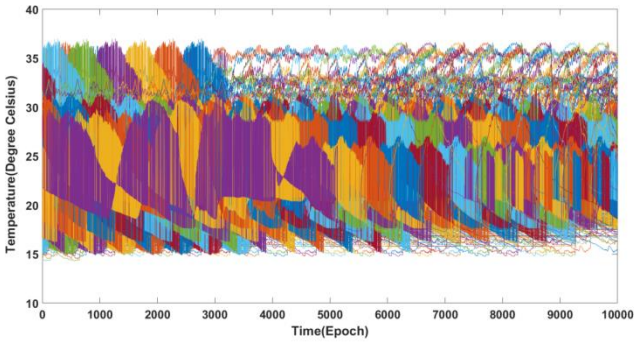

Figure.2: Plot of the temperature signals without drift fault

3.3 *Simulating Drift fault*

Drift faults occur in the sensors when the nominal statistics of the sensor signals change over time [10]. Drifts can be linear or nonlinear, depending on the drift characteristic of the sensor signal. We simulated the nonlinearity of drift fault by keeping the rate of drift constant for 1000 epochs and then varying it randomly assuming Gaussian distribution within a specified range. Both the linear drift and the nonlinear sensor drift faults are injected into the sensor measurements. Linear Drift and nonlinear drift faults are injected into the sensor measurements and are plotted in fig.3 and 4 respectively. The linear drift fault induced in the readings was set at 0.001 degrees Celsius/ Epoch or 0.12 degrees Celsius/Hour. Figure 3 shows the plot of 480 drifted temperature signals after the linear drift fault injection. It can be observed that the signals drift linearly, we induced additive positive drift where the measurements keep increasing in the same direction at a constant rate.

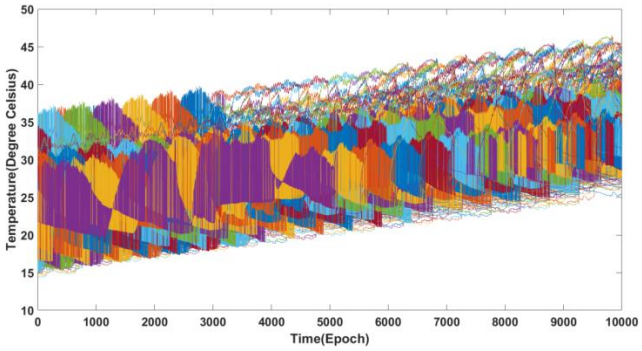

Figure.3: Linearly drifted temperature signals

Figure 4 represents the signals containing non-linearly drifted temperature measurements. The nonlinear drift faults are injected using the developed MATLAB code. To induce nonlinearity in the signal we varied the rate of drift randomly from 0 to 0.001 degrees Celsius/Epoch. The nonlinear drift values are uniformly distributed between 0 to 0.001 and are generated using the rand() function of MATLAB. We have not used any negative drift values in simulating both the linear and nonlinear drift faults in the temperature measurements. The nonlinearities are introduced after every 1,000 epoch, which can be observed in Fig.4. After the injection of linear and nonlinear drift faults, 50 dB white Gaussian noise has been added to all the drifted and non-drifted signals using the awgn() function assuming signal strength as zero dBW.

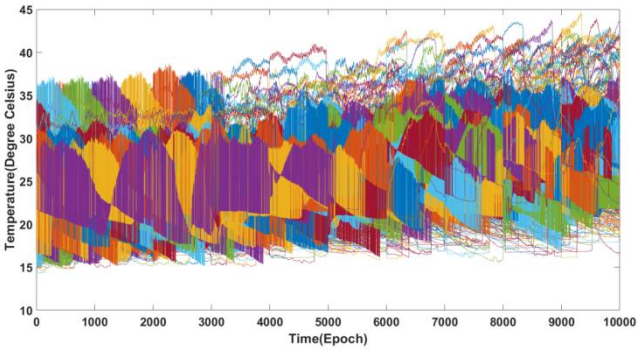

Figure.4: Temperature signals with nonlinear drift fault

4. RESULTS AND DISCUSSION

4.1 *Feature extraction and component reduction*

For real-time application and reduction of signal size processing the features need to be extracted and the features that represent the highest variance need to be retained for analysis. We used wavelet scattering as proposed by [29] for

feature extraction from both the drifted and non-drifted signals. The wavelet time scattering of the signal having 10,000 samples generates five-time windows. We used the Gabor wavelet for the time decomposition with an invariance scale and sampling frequency set to 80 and 120 respectively. The scattering network contains two filter banks for the wavelet scattering of the signal with the first filter having 8 wavelets per octave and the second one with one wavelet per octave. The feature matrix has five-time windows with 332 real values extracted from the signals of both drifted and non-drifted signals. We performed Principal Component Analysis(PCA) on the extracted feature matrix to eliminate unimportant features i.e. components explaining very less variance from being analyzed by the machine learning model. We performed PCA for the number of features that explains 99%,97%, and 95% variance. Six extracted components after PCA are retained from the fourth time window(TW4) which explained 99% variance.

Seven components of the third time window(TW3), nine components of the second time window(TW2), and ten components of the first time window(TW1) are retained for training the models which explained 99% variance. We also performed PCA for the proposed model for 95% and 97% explained variance. PCA significantly reduced the number of components from 332 to 6 explaining 99% variance in the fourth time window(TW4) which is then used as input to the machine learning algorithms for training and validation of the models. We tested five ANN models and six SVM models for classification accuracy on drift faults.

Table 1 represents the classification accuracy obtained in classifying the signals into three categories i.e. no-fault, linear drift fault, and nonlinear drift faults labeled as zero, one, and two respectively. It can be observed from Table 1 that the fourth time window(TW4) of the Gabor wavelet scattering provided the highest classification accuracy among all other time windows i.e. TW1, TW2, TW3, and TW4. The proposed wide NN model with one fully connected layer and 100 neurons in the first layer with six extracted components from the fourth time window of wavelet scattering resulted in the highest validation accuracy of 96.9%. We used ReLU (Rectified Linear Unit) activation function for all the tested ANN models. Narrow, medium and wide NN models have one fully connected layer having 10,25, and 100 neurons respectively in the first layer. Bilayered and trilayered NN models have two and three fully connected layers respectively with 10 neurons in each layer.

Six SVM models having different kernel functions and kernel scales are compared with the ANN models as shown in Table 1. As the name signifies linear, quadratic, and cubic SVM models have kernel functions as linear, quadratic, and cubic respectively with the kernel scale set to automatic. Three SVM models with kernel function as Gaussian having kernel scale set to 4.6,18 and 73 for fine, medium, and coarse respectively are also tested. Performance in terms of validation accuracy of the coarse Gaussian SVM model was found to be the worst among all the models across all the five-time windows. Validation accuracy of wide NN was found highest across all the time windows except the third time window(TW3). The performance of all the tested ANN and SVM models in the proposed fourth-time window(TW4) was found to be better compared to the other time windows.

Table.1: Classification accuracy of the NN and SVM models

Model Name	TW1	TW2	TW3	TW4	TW5
Narrow NN	85.1	87.6	93.0	94.7	92.4
Medium NN	85.0	87.4	93.5	95.4	94.9
Wide NN	85.8	88.3	93.0	96.9	95.1
Bilayered NN	83.4	87.1	92.6	95.4	93.3
Trilayered NN	82.8	85.6	92.4	95.1	93.1
Linear SVM	78.3	83.2	89.8	93.6	91.2
Quadratic SVM	85.6	88.0	93.1	96.4	94.1
Cubic SVM	85.3	87.7	93.1	96.2	94.2
Fine Gaussian SVM	83.8	86.8	93.3	95.6	94.0
Medium Gaussian SVM	77.1	82.7	89.6	92.8	90.3
Coarse Gaussian SVM	74.2	75.6	79.5	80.1	82.2

4.2 *Confusion Matrix*

Figure 5 represents the confusion matrix of the wide neural network and shows the classification results of the signals using the six extracted features from the fourth time window of the wavelet scattering. Zero represents the signals without drift fault, one represents the signals with linear drift fault and two represents the

signals with nonlinear drift fault. Out of the total 1440 labeled signals the proposed model could correctly classify 1395 signals with 96.9% accuracy.

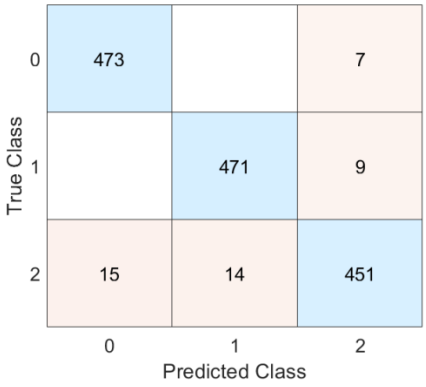

Figure.5: Confusion Matrix of the proposed wide NN

5. CONCLUSION

The present study validates the suitability of wavelet scattering transform as a feature extractor as proposed by [29] and used by [30]. We demonstrated that wavelet scattering can also be used for extracting features from both linearly and nonlinearly drifted sensor signals. Six components extracted from the fourth time window of Gabor wavelet scattering of the simulated input signal successfully captured the drifted signal features. The wide neural network with 100 neurons in combination with the extracted components resulted in 96.9% validation accuracy in classifying drift faults. We achieved 98.12% accuracy using the proposed approach in classifying linear drift of 0.12 degrees Celsius/Hour compared to 93.96% accuracy for nonlinear drift faults. So it can be concluded that the proposed approach is more suitable for the classification of linear drift faults than nonlinear drift faults. The proposed model also performed better than the widely used SVM models for drift fault classification. As the proposed approach is purely data-driven, it is suitable for automated drift compensation and the generation of control signals in real-time applications. The sensitivity of the model may be tested in future studies in comparison with other models having different drift values.

Conflict of Interest

Authors declare there is no conflict of interest.

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