Deep Convolutional Neural Network and Wavelet Transform based Model for Intermittent Fault Diagnosis in Sensors

Aruna Kumar Mishra[1,*], Dr.Subrat Kumar Mohanty[2]
[1]Research Scholar, Faculty of Engineering, Biju Patnaik University of Technology(BPUT), Rourkela, India-769015
[2]Professor and Principal, College of Engineering Bhubaneswar (COEB), BPUT, Odisha, India-751024

[*]Corresponding Author email: akmishra201077@gmail.com

Abstract-

The use of wireless sensors for patient monitoring and extensive use of telemedicine has thrown a challenge for medical professionals as they have to rely on sensor signals for disease classification. Timely detection and classification of faulty sensor signals from healthy ones are vital for the accurate diagnosis of the disease. Intermittent fault detection and classification had always been a challenge because of their unpredictable nature. Recent advancements in deep convolutional neural networks have opened a new dimension to the sensor fault diagnosis approach. Researchers are also using multiresolution analysis for denoising and feature extraction from the sensor signals. Datasets for testing fault diagnosis algorithms are scarce because of the difficulty in collecting pre and post-fault occurrence data. As suitably labeled benchmark datasets for testing intermittent fault diagnosis algorithms are not available, we generated two intermittent fault modes using the temperature sensor signals of the Intel Berkeley Lab dataset. The time-frequency representation of faulty and non-faulty sensor signals was generated using the continuous wavelet transform. The two-dimensional scalograms were used as input to the headless pre-trained deep convolutional neural network models for generating feature vectors which were subsequently used as input to the Dense layer for the classification of intermittent faults. Using the proposed model validation accuracy of 100% was achieved in both the intermittent fault modes. The performance of the proposed model was also compared in terms of validation accuracy and loss with other DCNN-based models.

Keywords- DCNN; Intermittent fault; Scalogram; Transfer learning; Wavelet transform.

DOI Number:10.14704/nq.2022.20.8.NQ44564 **NeuroQuantology 2022; 20(8): 5327-5336**

1. INTRODUCTION

Sensors have wide-ranging applications in medical devices, manufacturing, automobiles, and home appliances. The reduction in the manufacturing cost of wireless sensors has increased their use for condition monitoring in diverse areas. Faults occur in sensors because of environment-related factors, faulty installation, degradation of the material, etc.[1]. Intermittent faults occur both in electronic and mechanical systems and are unpredictable in nature[2,3]. Timely detection and prognosis of intermittent faults in the sensor can avert major accidents and disasters which in turn can save a lot of resources [4-5]. As intermittent faults don't have a predictable pattern of occurrence detecting the faults becomes extremely difficult and sometimes may be shadowed by the noise[1,3]. Compared to literature related to the constant fault, literature concerning intermittent faults is less[2]. Researchers have used multiresolution analysis for residual extraction from signals for fault isolation in nuclear power plants[6], ball bearings[7,8], chemical industries[9], analog circuits[10], etc. Recent developments in the field of Artificial Neural Networks(ANNs) have opened a new domain for learning-based fault detection and classification. Studies have also been conducted combining the multiresolution analysis and ANN for detection of surface water quality change[11], fault detection in internal combustion engines[12], and fault diagnosis in aeronautical systems[13]. Studies have also demonstrated the suitability of pre-trained Deep Convolutional Neural Networks(DCNNs) in extracting features from 2D images for classification[14-16]. The 2D time-frequency representations or scalograms contain the fault signatures of the signal and can be used as training input to the DCNNs. Recent studies have successfully used scalograms for heartbeat classification[17], bearing fault diagnosis[18], leakage detection[19], analysing vibration signals from drilling[20], and fault classification in induction motors[21]. Wrong disease diagnosis, system breakdowns, and loss of patient life can be prevented by early fault detection and isolation either through analytical methods or having hardware redundancy. Model-based fault diagnosis[3] requires extensive expertise in their respective domains for residual selection and threshold setting. So we proposed a knowledge-based offline model using transfer learning of pre-trained DCNN for intermittent fault diagnosis in sensors. The proposed model is suitable in the field of medicine and other areas where professionals are dependent only on sensor signals for decision making.

2.REVIEW OF LITERATURE

2.1 *Types of sensor faults and diagnosis methods*

Carvalho L.K. et al. [5] proposed two different tests for identifying the presence of intermittent faults in the sensors. They divided the methods of fault diagnosis of sensors into three categories i.e. hardware redundancy, model-based, and knowledge-based approach, and discussed different issues involved in the diagnosis of intermittent sensor faults[5]. Kullaa J. [22] modeled 7 different types of sensor faults and isolated them with the help of hardware redundancy. The reduction in the cost of sensors and the deployment of a large number of sensors in the health monitoring of structures has increased the failure probability of sensors. Assuming a Gaussian system they used only the sensor data for identifying, classifying, and quantifying the different sensor faults[22]. They used a laboratory setup of a wooden bridge and 15 accelerometers to test the proposed method[22]. Mehranbod et al. [4] proposed both single and multiple sensor-based approaches for the detection and classification of bias, drift, and noise sensor faults. The proposed model performs well both in real-time and data-driven scenarios without compromising on accuracy. The method is suitable for fault identification and classification in both the steady state and transient state[4]. Yan R. et al. [1] described intermittent faults in linear systems as the faults that occur without any known reasons, they proposed a parity space technique in classifying intermittent faults in sensors. The performance of the system gets affected because of the random and discontinuous nature of the intermittent fault as the system switches between healthy and faulty conditions. Because of the sensor degradation the intermittent faults occur and disappear which is difficult to isolate from noise[1]. Zhang et al. [2] proposed a method for the detection of intermittent faults in a simulated environment for linear time-varying systems. Intermittent fault detection was classified into two categories first one being the offline approach and the second one being the online approach[2]. Both the additive and multiplicative intermittent faults can be diagnosed using statistical data without prior knowledge of the monitoring structure. In their research work [3] proposed a model-based system for the detection of both intermittent and continuous faults using residual and threshold approaches. Sedighi T. et al.[3] classified faults into three categories such as abrupt, incipient, and intermittent. Intermittent faults occur more frequently as time passes, are unpredictable in nature, and occur for a short time in both electronic and mechanical systems[3]. The observer-based model proposed by [3] is suitable for nonlinear systems and uses adaptable thresholds and residuals that are sensitive to faults.

Sharma A.B. et al. [23] categorized the sensor faults as short, constant, and noise and also analyzed prevalence in real-world setups by examining four publicly available datasets. They also classified the fault classification techniques into 4 categories such as time series, rule, estimation, and learning-based approach [23]. They used short as the terminology for intermittent faults and described them as sharp changes in sensor measurements[23]. It was also found by [23] that 15 to 35% of the Intel Lab dataset have faults whereas the SensorScope dataset contains the least amount of faulty readings. Even though there is no consensus on the terminology to be used for intermittently occurring faults we used the terminology of [1,2]. The problems in residual selection were highlighted by Jung and Frisk [24] and an optimisation method for residual selection under uncertain conditions and noise was also proposed. They tested the method using the data from an internal combustion engine[24]. As the system grows in complexity the number of fault monitors increases and the fault monitors are not equally sensitive to a particular type of fault.

2.2 *Multiresolution analysis for fault classification*

Yellapu et al. [6] proposed a hybrid system comprising steady-state data reconciliation and multiresolution methods to overcome the noise corruption of data in nuclear reactors. Using this method noise and high-frequency sensor faults from the measured values were removed. They applied the proposed multi-scale technique to the coefficients of the wavelet transform for the classification of sensor and process faults, and also found it to be better than the single-scale technique using simulation [6]. Kankar et al. [7] used continuous wavelet transform on the vibration signal of the bearing for fault diagnosis and extracting features from the vibration signal. The extracted features were used as input to the machine learning models for fault classification [7]. The results of the machine learning algorithms in terms of classification accuracy were compared, support vector machine (SVM) provided the best result for both the selected base wavelets in comparison with Artificial Neural Network(ANN) and Self Organising Map(SOM) [7]. The proposed method is suitable for real-time deployment for fault diagnosis in industries. Madakyaru et al. [9] used a multiresolution analysis based method for monitoring the process in a distillation column. A generalised likelihood ratio was used to select the residuals obtained from the model output[9]. Wavelet transform was also used for denoising the sensor data and for reducing the correlation. The proposed model of [9] generated better results compared to the partial least square based approach in the simulated environment. They also emphasised the suitability of multiresolution analysis in extracting features from the sensor measurements[9].

Zhong et al. [10] proposed a model for the detection of intermittent faults from the amplitude and frequency component of the voltage signal collected from analog circuits. Pearson correlation coefficient was used on extracted fault features for optimising the number of features of intermittent fault caused by defects in soldering or because of soldering degradation [10]. Through simulation[10] demonstrated the suitability of the proposed method in analog circuits for the diagnosis of intermittent faults. Zhang et al. [8] emphasised the early diagnosis of faults in rotating parts of the machines such as bearing and gear for preventing breakdowns. They proposed a concise and adoptive wavelet transformation method for fault diagnosis in bearing and also proposed an indicator based on weighted unbiased autocorrelation for fault diagnosis[8]. Through simulation,[8] demonstrated that the proposed method has higher sensitivity to periodic signals even in noisy environments. Shi et al. [11] used a wavelet and artificial neural network based model for surface water quality measurement and warning. They used wavelet decomposition and denoising of the signal and used it as the input to a back propagation based artificial neural network for prediction. Control signals are generated when the residual error reaches the set threshold level. The proposed method [11] can be used for warning in case of a major spill, managing urban watershed systems, and for monitoring the surface water quality [11]. The system was tested using the data from the various time periods and found suitable for use along with other water quality monitoring instruments.

Sound signals emitted from rotating machinery were used by Wu and Liu [12] as an alternative for the vibration signal for fault diagnosis of the engine. They used discrete wavelet transform for signal decomposition into time and frequency domain with the help of Daubechies wavelet functions of 2,8 and 20 resolution [12]. Features of the signals were extracted using multiresolution analysis and are fed into a neural network for fault classification. The proposed method can be used for fault classification in different engine operating conditions even for short sound signals. Cannarile et al. [13] used a novel fault diagnosis method for aerospace systems using Discrete Fourier Transform(DFT) for analysing the vibration signal received from the condition monitoring sensors. The ElasticNet algorithm was used for feature selection purposes after applying DFT to the vibration signals. The model performance was tested with the help of three case studies and found to be suitable where training data are scarce[13].

2.3 *DCNN and Scalograms for fault classification*

Arvanaghi R. et al. [17] classified the heartbeat as normal or abnormal using blood pressure signal as the input to the model rather than ECG. They took discrete wavelet transform of the blood pressure signals in the form of scalograms and used it as input to a DCNN for classification of the heartbeat after denoising it. Classification accuracy of 89.03% was achieved on the PhysioNet database which can help in removing the human error in diagnosing the abnormal heartbeat[17]. The importance of automated heartbeat classification through reduction of human intervention in medical diagnosis was also emphasised by [17]. An et al. [18] proposed an intelligent RNN model for bearing fault diagnosis under various load and speed conditions. With the help of available bearing datasets, the superiority of the proposed method was proved in comparison to traditional fault diagnosis methods of bearing fault diagnosis. The process consists of segmentation of input signal, storing the classification information on the LSTM network, and finally estimating the likelihood of the different health conditions of the system[18].

Vibration signals of the gearbox and bearing dataset were used by Chen et al. [25] for classifying the mechanical faults. They used the wavelet transform to convert the vibration signals into the two-dimensional time-frequency representation i.e. scalograms. The scalograms were used as input to the proposed CNN-based model for feature extraction and classification of the mechanical faults[25]. The proposed model was tested and the results were compared with the widely used classifiers such as SVM and Softmax on datasets under various working conditions[25]. Guc and Chen [26] deployed transfer learned DCNN for diagnosis of faults in health monitoring systems. They used GoogleNet structure instead of training a new DCNN model for the classification of nominal and bias faults of sensors and actuators through data analysis[26]. Scalograms generated from the continuous wavelet transform of the data streams were fed into a pre-trained DCNN for classification. The proposed approach of [26] performed well in training, validation, and test sets which can also be used for online fault diagnosis.

Shukla and Piratla [19] proposed a model for leakage detection in buried pipelines from the vibration signal collected using accelerometers. Scalogram images obtained from the wavelet transform of vibration signals were used as the input to a pre-trained DCNN i.e. AlexNet in this case[19]. The proposed model of [19] achieved 95% accuracy in detecting leakages of PVC pipelines in the experimental setup. which can be deployed for real-time automated leakage monitoring. Afebu et al. [20] proposed an intelligent model for use in drilling systems. The scalograms of the signals generated from the oscillators after impact are used for classification into high and low-performance impacts based on the rate of penetration [20]. High-performance impacts classified by the model can be further continued and the low-performance impacts can be ignored for increased penetration performance and improved life span of the drilling bit[20]. Both experimental and simulation data were used by [20] for comparing the classification accuracy of feature extraction-based algorithms.

A model for the classification of different fault modes of induction motor from its current signals was proposed by Hsueh et al. [21]. Wavelet transformed current signals from the five different fault modes of the three-phase induction motor were resized and the grayscale images were used as input to the DCNN models. Data collected from the experimental setup was used and it was demonstrated by [21] that single variable input features have high classification accuracy of 97.37%. Szegedy et al. [14] proposed an Inception model for improved classification of images with a moderate increase in the cost of computation suitable for deployment in the field of computer vision. They achieved a top 5 error of 5.6% using the ImageNet dataset. EfficientNetV2 proposed by Tan and Le [15] uses a progressive learning approach during the training process for reducing the size and increasing the training speed of the network. It can be achieved through increasing the size of the image and regularisation process during the training process. Proposed deep residual CNN ResNet of He et al. [16] with pre-activated residual unit achieved a top-5 error of 4.8% on the ILSVRC 2012 dataset with a test image size of 320X320, whereas InceptionV3 [14] achieved a top-5 error of 5.6% on the test image size of 299X299.

Rajasree et al. [27] proposed DCNN based BiLSTM model for the detection of brain tumors. They achieved 95.13% accuracy using the BRATS15 dataset. Vairaprakash S. et al. [28] used DCNN based model for the detection of Alzheimer's disease from the MRI images of the patients. Motivated by the research of [14-16] we used these pre-trained DCNN models for feature extraction in our present study for intermittent fault classification. We downloaded the headless pre-trained model of the InceptionV3, EfficentNetV2, and ResNetV2 from https://tfhub.dev/google [29-31].

3. RESEARCH METHODOLOGY

3.1 *Problem formulation and research steps*

Research related to the classification of intermittent faults in sensors is scarce, and the unavailability of a suitably labeled benchmark dataset for testing classification algorithms and the recent advancement in DCNN research [14-16] motivated us for this study. The primary objective of the study is to propose a model for the diagnosis of intermittent faults in sensors using scalograms and pre-trained DCNN.

Our proposed model for intermittent fault classification is based on the feature extraction from the scalograms using pre-trained weights of InceptionV3 [14]. InceptionV3 is trained on ImageNet to classify images. To reduce the requirement of computational resources for training a DCNN from scratch we used the pre-trained weights and compared the accuracy of the proposed model with ResNetV2 [16] and EfficientNetV2 [15] based models. Two intermittent fault modes from the temperature signal were generated for comparing the performance of the models.

We used MS Excel, Matlab R2021b, Python 3.9, TensorFlow, TensorBoard, and Keras API software for the present study. The software were run on a personal computer with Intel 8th generation 1.6 GHz microprocessor and 8 GB DDR4 RAM. We used the Keras API of TensorFlow in Python 3.9 for testing and training the DCNN-based models. Tensorboard was used for observing the model parameters like accuracy and loss function of the tested models. We used Microsoft Windows 10 (64bit) operating system-based personal computer for the present study.

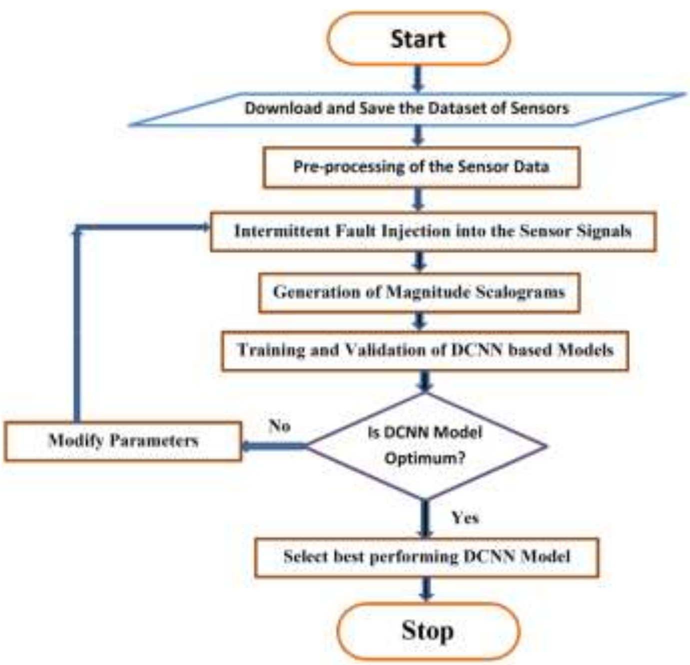

Figure.1: Flow chart of the research process followed

The flow chart shown in fig. 1 depicts the research steps we followed in the present study. As mentioned first the publicly available sensor measurement dataset from the MIT website[32] was downloaded and saved for further analysis and experimentation. The downloaded dataset from [32] was then pre-processed to make it suitable for fault injection. Intermittent faults of specified intensity and occurrence were then injected into the pre-processed dataset of sensor measurements. The magnitude scalograms of the sensor signals containing intermittent faults and without intermittent faults were generated. The generated scalograms were then used for supervised learning of the transfer learned DCNN model. Fault and DCNN parameters are changed for analysing the performance and sensitivity of the DCNN models. After achieving satisfactory performance the performance of the models was compared and the best model was selected.

3.2 *Generation of temperature sensor signals*

The dataset for the present study was taken from the publicly available dataset of Intel Berkeley lab downloaded from [32]. The dataset contains 54 sensor nodes and data of 2.3 million measurements collected from Mica2Dot sensors. For the present research, we used the temperature sensor data of 5 nodes i.e. of the 1st to 4th node and 6th node. The downloaded data were first saved into an MS Excel spreadsheet for visual analysis and then were imported to the Matlab workspace for pre-processing. The data contained sensor measurements of different sensors at intervals of 30 seconds for one epoch.

The missing epoch values were replaced with values by using the backward interpolation technique. The initial transients of the temperature measurement were removed by the selection of the measurements from the 4100th epoch to the 14000th epoch. Temperature sensor data also contains many outliers which were removed by the filloutlier() function of Matlab. The outliers of temperature measurements which have values more than 3 the median absolute deviation was replaced by the previous measurement which is non-outlier using filloutlier() function. We generated 100 signals from the temperature measurements of the 5 nodes i.e. 20 signals from each sensor node. One of the signals generated after pre-processing from node 3 is shown in fig.2. Fig. 2 represents the plotting of the temperature signal from mote-3 in degrees Celsius and time in the epoch. Temperature is plotted on the Y axis and Time in epoch is plotted on X-axis in fig. 2 As it can be observed from fig. 2 outliers and the transients present in initial readings are removed after pre-processing of the temperature signals. We used only 10,000 epochs or temperature measurements of mote-3 to plot in fig. 2.

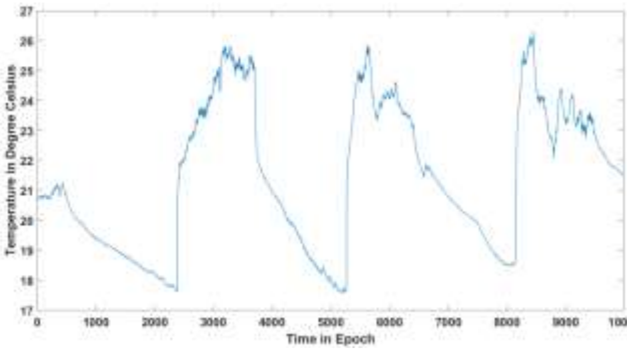

Figure.2: Temperature sensor measurements of Mote-3 versus time after pre-processing

The intermittent faults are then injected into the generated 100 temperature signals where each signal contains 10,000 temperature readings. A Matlab code was developed for injecting the faults into the temperature measurements as suitably labeled benchmark datasets are not available for testing the DCNN models used in the present study.

We used two different types of intermittent fault modes for testing the sensitivity of the DCNN-based models. In the first mode, the intensity of the fault was varied randomly from -0.5 to +0.5 times the measurement and was inserted in 50 random points out of the 10,000 sensor readings. Thus we created 100 temperature signals with injected random faults of varying intensity from -0.5 to +0.5 times the original measurement with a 0.5% occurrence. In the second fault mode, we injected the intermittent faults varying intensity from -0.2 to +0.2 times the original measurement with 0.3% occurrence i.e. fault injected in 30 points out of 10000 points. Thus generating 100 temperature signals containing the second intermittent fault mode. In both, the fault modes the random points and intensities were generated uniformly in the given interval using the rand() function of Matlab. Both the intermittent fault modes were used in the present study to test and compare the performance of the proposed model.

Fig. 3 shows the plotting of mote-3 temperature measurements of 10,000 epochs after the injection of intermittent faults. The first fault mode of the intermittent faults was generated by varying intensity randomly between -0.5 to +0.5 percent of the measured value. The random spikes were added or subtracted from the original measurements in 0.5% of the total readings i.e. in 50 points generated randomly as shown in fig. 3.

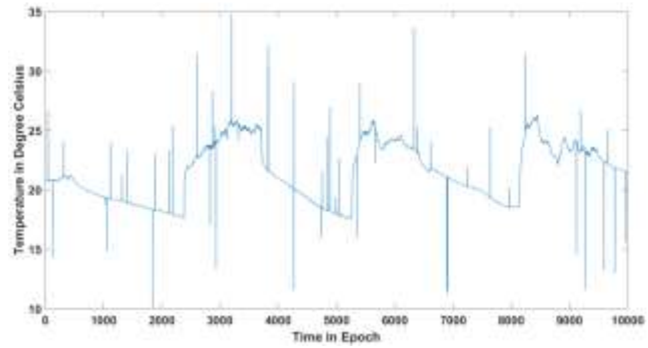

Figure.3: Plot of temperature sensor measurements of Mote-3 verses time after intermittent fault injection (First fault mode)

Fig. 4 represents the second fault mode of the injected intermittent fault into the temperature signals of mote-3. The faults were injected in 30 temperature measurements out of 10,000 readings and intensity varied from -0.2 to +0.2 times the measured values. The intensities and the points for intermittent fault injection were determined randomly. Injected spikes i.e. the second fault mode can be seen in fig. 4.

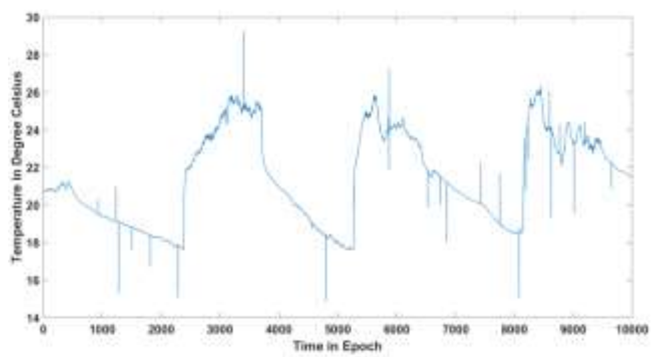

Figure.4: Plot of temperature sensor measurements of Mote-3 versus time after intermittent fault injection (Second fault mode)

3.3 *Generation of magnitude scalograms*

Magnitude scalograms were generated using the signals having both the intermittent fault modes and the signals without intermittent fault. Thus 300 scalograms were generated using the cwt() function of Matlab. The generated scalograms were stored separately in 3 different folders i.e. one for no fault signals and two folders for the two different intermittent fault modes for supervised training of the models. Scalograms were generated by continuous wavelet transform using the analytic Morse wavelet. Scalograms are suitable for capturing both the transients which are high frequency and the slowly varying components of a signal. The parameters of the wavelet transform i.e. time-bandwidth product, gamma, and voices per octave were set to 60,3 and 10 respectively. The labels of the axis from the X-axis, and Y-axis and the colour labels for the magnitude of the scalograms were removed and stored in JPG format in separate folders before training the models.

Fig. 5 represents the magnitude scalogram of the temperature signal from mote-3 after pre-processing. The scalogram does not contain any intermittent faults. Normalised frequency in logarithmic scale is plotted on the Y-axis versus time samples on X-axis. The absolute values or the magnitudes of the wavelet transform are represented in the form of colour variation in the scalogram as shown in fig. 5.

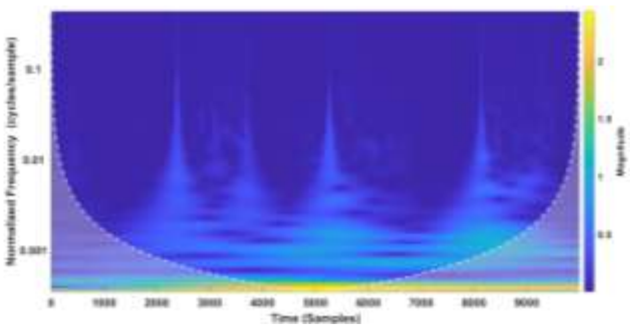

Figure.5: Magnitude scalogram of Mote-3 temperature sensor signal after pre-processing

The magnitude scalogram shown in fig. 6 represents the continuous wavelet transform of the temperature signal of mote-3 after intermittent fault injection in the first fault mode. The magnitude scalogram in fig. 6 is the representation of the continuous wavelet transform using the analytic Morse wavelet of the temperature signal shown in fig. 2. The intensity of the faults varied from -0.5 to +0.5 times the measured values and are injected in 50 random points. The changes in the scalogram of fig. 5 and fig. 6 are distinguishable as the scalogram in fig. 6 can capture the intermittent spikes of the signal.

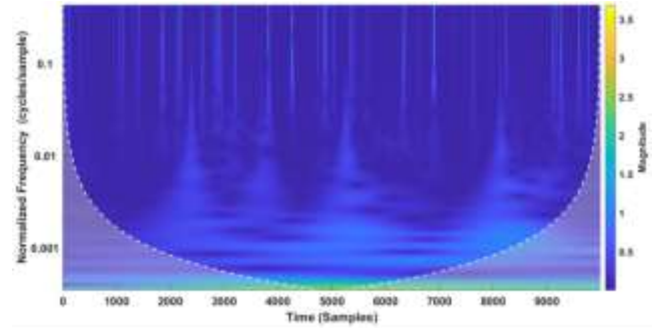

Figure.6: Magnitude scalogram of Mote-3 temperature sensor signal after intermittent fault injection (First fault mode)

The scalogram in fig. 7 represents the wavelet transform of the temperature signal shown in fig. 4 i.e. second fault mode. The intensity of the injected intermittent faults varied from -0.2 to +0.2 times the original observations and was injected in 30 random points out of the total 10,000 observations. If we compare the scalograms of fig. 5, fig. 6 and fig. 7, it can be observed that the continuous wavelet transforms can capture the presence of intermittent faults in the signals.

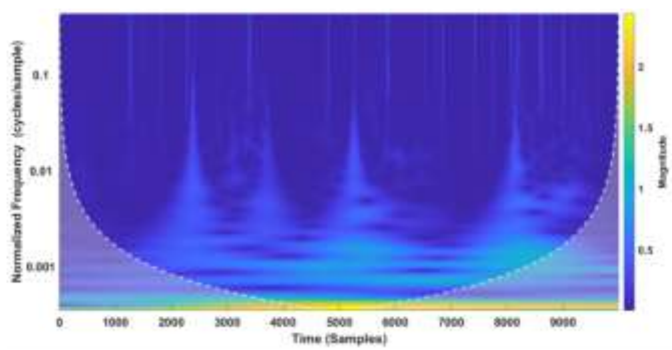

Figure.7: Magnitude scalogram of Mote-3 temperature sensor signal after intermittent fault injection (Second fault mode)

4. RESULTS AND DISCUSSION

For feature extraction and classification of intermittent faults from the scalograms, we created a sequential DCNN model having two layers. The first layer of the model contains the feature extractor layer and the second one is a dense layer that is fully connected to the feature extractor layer.

The headless models of InceptionV3 [14], EfficientNetV2 [15], and ResNetV2 [16] were downloaded from https://tfhub.dev/google/imagenet [29-31] and were used as the feature extractor layer.

The feature extractor layer of the models contains the pre-trained parameters which were used to extract the features from the input scalograms and are passed on to the dense layer of the model. The dense layer has 4,098 trainable parameters and the feature extractor layer for the InceptionV3-based DCNN model has 2,18,02,784 pre-trained parameters. The feature extractor layer generates 2,048 features from each scalogram image which are then used as input to the dense layer for supervised training and validation of the model. The output of the dense layer classifies the scalograms into two classes i.e. with intermittent fault and without fault.

Table-1 compares the three DCNN-based models on the basis of trainable parameters, nontrainable parameters, input image size, and the number of extracted features. The proposed model i.e. Model-1 in table-1 and table-2 is the InceptionV3 feature extractor with a dense layer, model-2 is the EfficentNetV2 feature extractor with a dense layer and model-3 is the ResNetV2 feature extractor with a dense layer for intermittent fault classification.

Table.1; Model Parameters

Models	Size of Feature Vector in MB	Non Trainable Parameters	Trainable Parameters	Input Image Size	Extracted Features
Model-1 (Proposed)	84.63	21802784	4098	299x299	2048
Model-2	31.54	8769374	2818	260x260	1408
Model-3	83.72	23564800	4098	224x224	2048

Table-2 represents a comparison of the output of the three DCNN-based models in terms of validation accuracy and validation loss after 10 epochs of training. The 200 input scalograms were divided into two classes one having 100 images without fault and 100 images with intermittent faults.

Table.2: Model Accuracy and Loss Function

Models	First Fault Mode		Second Fault Mode	
	Validation Accuracy	*Validation Loss*	*Validation Accuracy*	*Validation Loss*
Model-1 (Proposed)	1.00	0.00088236	1.00	0.0194
Model-2	0.85	18013908	0.5250	42222888
Model-3	1.00	0.00	0.8000	1.2269

The sequential models were trained with 80% images i.e. 80 images of each class and 20% images were used for validation i.e. 20 images of each class. Table-2 represents the comparison of the three models in terms of validation accuracy and validation loss. As it can be observed from table-2 the EffcientnetV2 [15] based model did not perform well for both the intermittent fault modes. In the second fault mode, the performance degraded significantly and the validation loss is too high so it can be concluded that it cannot classify the intermittent faults with specified parameters. The performance of the ResNetV2 [16] based model was 100% in the first fault mode but degraded in the second fault mode where loss increased to 1.2269 from 0 and accuracy decreased from 100% to 80%. The proposed model i.e. InceptionV3 [14] based model performed better even in the second fault mode. For both, fault modes the validation accuracy of the proposed model was found to be 100% the validation loss increased from 0.0009 to 0.0194 in the second fault mode.

Fig. 8 represents the plot of accuracy versus epoch for model-1 in second fault mode. The blue colour line represents the training accuracy and the orange colour line represents the validation accuracy. It can be seen from fig. 8 that both the training and validation accuracy increases along with the training progress i.e. epochs.

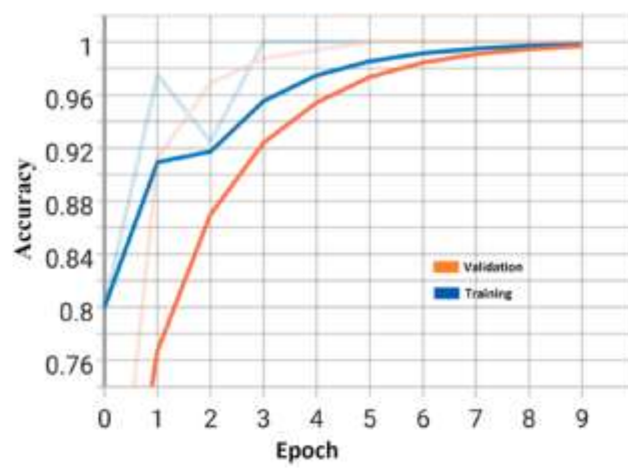

Figure.8: Accuracy versus Epoch of the proposed model (model-1) in second fault mode

Fig. 9 represents the plot of loss function versus epoch of the proposed model i.e. model-1 for the second fault mode. The blue line represents the training loss whereas the orange line represents the validation loss function It is clear from the fig. 9 that the prediction error of the proposed model (model-1) decreases as the training progresses.

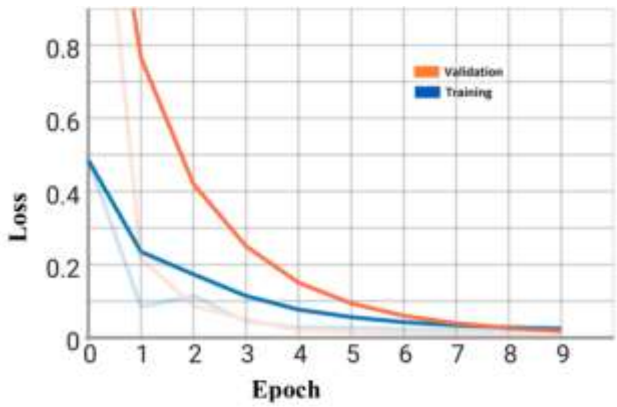

Figure.9: Loss verses Epoch of proposed model (model-1) in second fault mode

So from the present study, it is clear that the proposed model (model-1) has higher sensitivity in classifying intermittent faults compared to the other two models. The proposed model (model-1) even with less number of parameters and comparable size to the ResnetV2 [16] based model performed better in the second fault mode where the fault intensity and occurrence are less compared to the first fault mode.

5. CONCLUSION

Detection and isolation of intermittent faults of sensors are important to prevent breakdowns and to take corrective actions. In the present study, we used a novel approach for the classification of intermittent faults using the feature extraction capabilities of both DCNN and multiresolution analysis. He et al. [16] compared the performance of InceptionV3 with the ResNet model and got comparable performance using different test image sizes. But in the present study, we achieved higher validation accuracy of 100% using the InceptionV3 [14] based model in both the fault scenarios, whereas the performance of ResNetV2 [16] based model-3 degraded significantly in the second fault mode. So we propose model-1 i.e. the InceptionV3 [14] based model for classification of intermittent fault in sensors, as its performance was found to be superior in terms of validation accuracy and loss compared to the other two models. The proposed model can be deployed for online automated intermittent fault diagnosis of sensors.

We have not used any method for residual selection or elimination depending on the residual correlation, which may be done in future studies. We conducted the sensitivity analysis of the three models under two fault scenarios and compared the results which may be extended to other fault scenarios and models.

Conflict of Interest

Authors declare there is no conflict of interest.

REFERENCES

[1] Yan R, He X, Zhou D. Detecting intermittent sensor faults for linear stochastic systems subject to unknown disturbance. Journal of the Franklin Institute 2016; 353(17): 4734-4753.

[2] Zhang J, Christofides PD, He X, Wu Z, Zhao Y, Zhou D. Robust detection of intermittent sensor faults in stochastic LTV systems. Neurocomputing 2020; 388: 181-187.

[3] Sedighi T, Phillips P, d Foote P. Model-based intermittent fault detection. Procedia Cirp 2013; 11: 68-73.

[4] Mehranbod N, Soroush M, Panjapornpon C. A method of sensor fault detection and identification. Journal of Process Control 2005; 15(3): 321-3

[5] Carvalho LK, Moreira MV, Basilio JC. Diagnosability of intermittent sensor faults in discrete event systems. Automatica 2017; 79: 315-325.

[6] Yellapu VS, Zhang W, Vajpayee V, Xu X. A multiscale data reconciliation approach for sensor fault detection. Progress in Nuclear Energy 202; 135: 103707.

[7] Kankar PK, Sharma SC, Harsha SP. Fault diagnosis of ball bearings using continuous wavelet transform. Applied Soft Computing 2011; 11(2): 2300-2312.

[8] Zhang K, Ma C, Xu Y, Chen P, Du J. Feature extraction method based on adaptive and concise empirical wavelet transform and its applications in bearing fault diagnosis. Measurement 2021; 172: 108976.

[9] Madakyaru M, Harrou F, Sun Y. Improved data-based fault detection strategy and application to distillation columns. Process Safety and Environmental Protection 2017; 107: 22-34.

[10] Zhong T, Qu J, Fang X, Li H, Wang Z. The intermittent fault diagnosis of analog circuits based on EEMD-DBN. Neurocomputing 2021; 436: 74-91.

[11] Shi B, Wang P, Jiang J, Liu R. Applying high-frequency surrogate measurements and a wavelet-ANN model to provide early warnings of rapid surface water quality anomalies. Science of the Total Environment 2018; 610: 1390-1399.

[12] Wu JD, Liu CH. Investigation of engine fault diagnosis using discrete wavelet transform and neural network. Expert Systems with Applications 2008; 35(3): 1200-1213.

[13] Cannarile F, Compare M, Baraldi P, Diodati G, Quaranta V, Zio E. Elastic net multinomial logistic regression for fault diagnostics of on-board aeronautical systems. Aerospace Science and Technology 2019; 94: 105392.

[14] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition 2016; 2818-2826.

[15] Tan M, Le Q. Efficientnetv2: Smaller models and faster training. In Proceedings of 38th International Conference on Machine Learning PMLR 2021; 139: 10096-10106.

[16] He K, Zhang X, Ren S, Sun J. Identity mappings in deep residual networks. In Proceedings of European

conference on computer vision 2016; 630-645, Springer, Cham.

[17] Arvanaghi R, Danishvar S, Danishvar M. Classification cardiac beats using arterial blood pressure signal based on discrete wavelet transform and deep convolutional neural network. Biomedical Signal Processing and Control 2022; 71: 103131.

[18] An Z, Li S, Wang J, Jiang X. A novel bearing intelligent fault diagnosis framework under time-varying working conditions using recurrent neural network. ISA transactions 2020; 100: 155-170.

[19] Shukla H, Piratla K. Leakage detection in water pipelines using supervised classification of acceleration signals. Automation in Construction 2020; 117: 103256.

[20] Afebu KO, Liu Y, Papatheou E. Feature-based intelligent models for optimisation of percussive drilling. Neural Networks 2022; 148: 266-284.

[21] Hsueh YM, Ittangihal VR, Wu WB, Chang HC, Kuo CC. Fault diagnosis system for induction motors by CNN using empirical wavelet transform. Symmetry 2019; 11(10): 1212.

[22] Kullaa J. Detection, identification, and quantification of sensor fault in a sensor network. Mechanical Systems and Signal Processing 2013; 40(1): 208-221.

[23] Sharma AB, Golubchik L, Govindan R. Sensor faults: Detection methods and prevalence in real-world datasets. ACM Transactions on Sensor Networks (TOSN) 2010; 6(3): 1-39.

[24] Jung D, Frisk E. Residual selection for fault detection and isolation using convex optimization. Automatica 2018; 97: 143-149.

[25] Chen Z, Gryllias K, Li W. Mechanical fault diagnosis using convolutional neural networks and extreme learning machine. Mechanical systems and signal processing 2019; 133: 106272.

[26] Guc F, Chen Y. Fault Cause Assignment with Physics Informed Transfer Learning. IFAC-PapersOnLine 2021; 54(20): 53-58.

[27] Rajasree R, Rajakumar S, Josephin SP. Deep Convolutional Neural Networks for Multi-Modality Brain Image Classification. NeuroQuantology 2022; 20(5): 3610-3627.

[28] Vairaprakash S, Appathurai A, Gayathri. Classification of Alzheimer’s Disease Stages using A DeepaquilaConvolutionalneural Network. NeuroQuantology 2022; 20(6): 1327-1333.

[29] https://tfhub.dev/google/imagenet/inception_v3/classification/5 (Accessed Date: June 1, 2022).

[30] https://tfhub.dev/google/imagenet/inception_v3/classification/5 (Accessed Date: June 1, 2022).

[31] https://tfhub.dev/google/imagenet/efficientnet_v2_imagenet21k_b2/feature_vector/2 (Accessed Date: June 1, 2022).

[32] http://db.csail.mit.edu/labdata/labdata.html(Accessed Date:June 1,2022).