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Deep Learning Based Intelligent Rail Track Health Monitoring System

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Abstract: ***This paper describes the possible way of monitoring the health of the rail track to increase the comfort and ride quality of rail transportation. The abnormalities present in the track are identified and rectified at the initial stage. In this paper, Convolutional Neural Network and Extreme Learning Machine Algorithm (CNN-ELMA) based rail track monitoring is proposed to estimate the exact abnormality. The micro-electro-mechanical sensor (MEMS) accelerometers are fixed in the axle box for measuring the acceleration signal. The location of abnormality is measured by a new sensing method even if the signal of the global positioning system (GPS) is absent. To pre-process the raw signal received from the accelerometer is done by using a Continuous Wavelet Transform (CWT). Then the high-level features are extracted using CNN with a square pooling architecture. To evaluate the performance of the proposed CNN-ELMA, it is simulated and compared with four other methods. The comparison results show that the proposed CNN-ELMA is an effective and accurate method useful for the maintenance department of railways. An experiment has been conducted for the four different abnormal locations and the performance of the proposed method is studied.***

Keywords *:rail track health monitoring, MEMS accelerometer, abnormal location, deep learning, rail transportation*

I. INTRODUCTION

The Indian railway is one of the largest rail networks, which provides more than 0.12 million km distance for commercial travel. According to the global standard, the reliability and safety of passengers should be fulfilled. At present, two different methods are used to monitor the health of the rail track. The track inspection is performed with the help of portable devices during the night time. This is a manual method, consuming more time and the quality of the inspection depends on the worker [1]. Another method is an automatic recording of the health of the rail track which uses various sensors such as gyro sensors, optical sensors, and acceleration sensors. These methods are expensive and sensitive to the environment. Additionally, the continuous monitoring of the health of the rail track is needed to satisfy the required standards [2].

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Therefore, an early and precise
detection method is required to monitor the health of the rail tracks to avoid the risk of life and heavy loss [3]. The health of the rail track can be monitored through an in-service vehicle which contains position and acceleration sensors [4]. This type of in-service vehicle is used to measure the track geometry, monitor the health of the track any time, and it is cost-effective. This method can estimate the fault in the earlier stage and avoid the dangerous problems [5]. The wavelet transforms based analysis method is introduced by Bocciolone et al. in the real measurement of the health monitoring of the track. The analysis is carried out using the signal received from the accelerometer which is mounted in the axle box [6]. For continuous monitoring and processing, a huge amount of real-time data, extreme learning machine approach (ELMA) is widely used to identify the fault of the machine. Different diagnostic methods have been proposed to improve the performance of the classification process. The two major operations such as feature extraction and fault recognition are widely used. To obtain the knowledge of the machine, the health condition, and to disclose the relationship between discriminative features, the feature extraction operation is involved. To increase the efficiency of the diagnostic methods, different feature extraction methods, time-frequency analysis and wavelets are used [7,8].

The feature extraction methods are used to convert the raw signals received from the sensors into pertinent representations. After feature extraction, a classifier is used to optimize and train the decision function. The Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are the classification methods widely used to detect machine faults [9]. To increase the learning speed a single hidden layer feed-forward neural network is used, in which a suitable number of hidden nodes are generated [10]. Compared to SVM and ANN methods, learning algorithms provide better accuracy, a straightforward solution, and faster operation. As a result, extreme learning machine can be applied for fault detection and classification problem [11]. Deep Learning method has turned attention in the research community for fault identification. The previous learning algorithms are not capable of learning the representations deeply. The deep learning algorithms such as Deep Belief Networks (DBN), Stacked Auto Encoders (SAE), and the Convolutional Neural Networks (CNN) have been used to estimate the faults of the machine [12,13]. These algorithms have different features like enabling more intelligent thinking and automatically learn hierarchy features. The SAE and DBN methods are capable to extract various parameters from the vibration signals.

Additionally, CNN method has a pooling layer and the convolutional layer to capture the deep representation from the two-dimensional complex signals [14]. To estimate the vibration fault different CNN

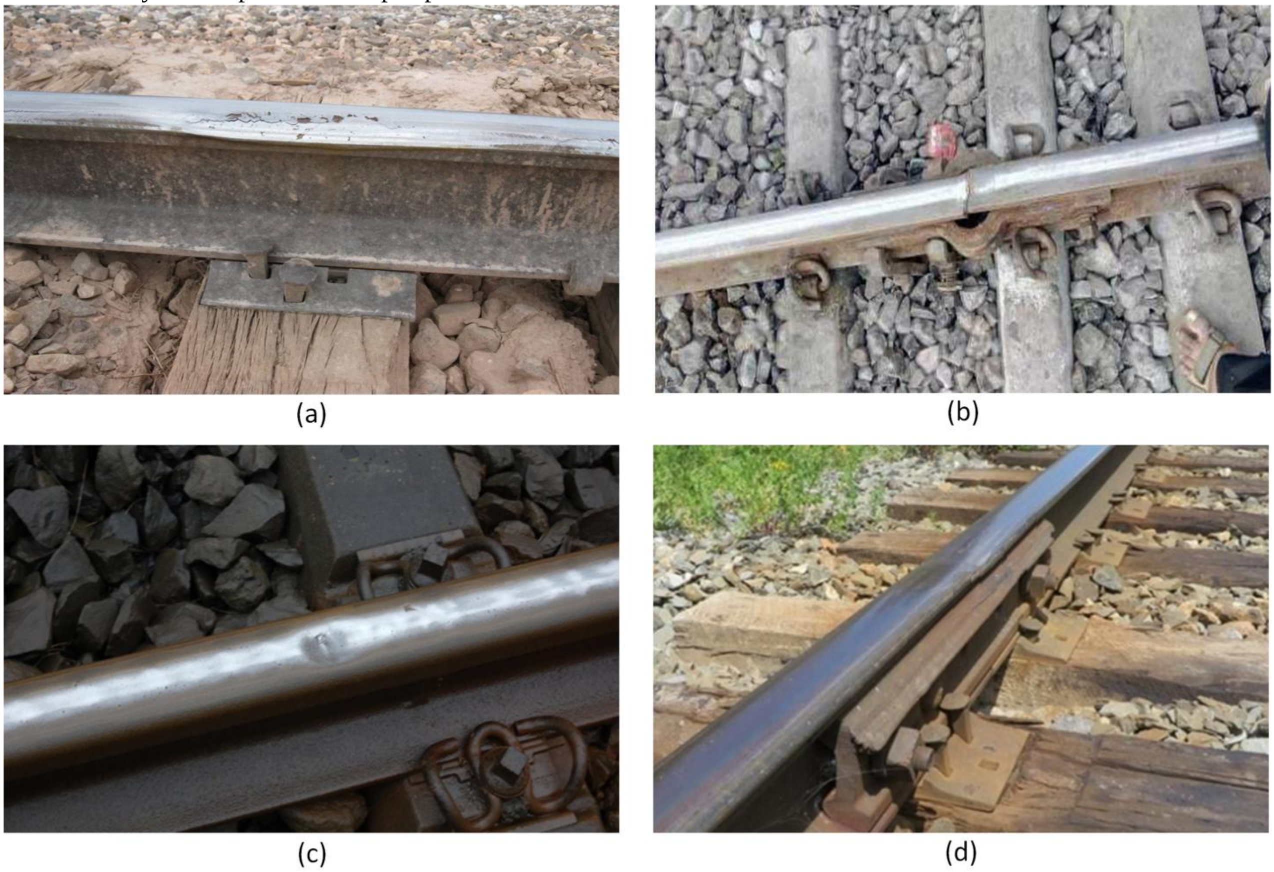

Fig. 1. Various abnormalities of the rail track (a) visible fault (b) minute crack (c) plastic deformation and (d) invisible fault.

models have been introduced. A Hidden Markov Models based CNN is used to classify and learn different features of the fault has been introduced by Wang et al [15]. A dislocated time series CNN is developed by Liu et al. for capturing different signals from the machine and classify its faults [16]. The bearing fault is detected using 2D CNN with one convolutional layer and the signal received from two accelerometers which are mounted on the axle box [17]. The frequency spectra and the vibration data received from the sensor are utilized in the above literature. Conversely, the dynamic behavior of the system represented by both of them is not capable to provide the best results. To disclose the dynamic behavior, wavelet transforms [18], and short-time Fourier transform [19] are adopted. A two-layer hierarchical diagnosis network is designed by Gan et al. for identifying the bearing fault and wavelet transform is used to extract deep representations [20].

From the above literature, CNN provides better performance in various vibration analysis and diagnosis. On the other hand, to select the network parameters such as batch size, size of the kernel, and the rate of learning, CNN meets challenges due to its sensitivity. The other problem is that the network should be retrained every time to find the best network architecture. As a result, the computational complexity will increase and it requires high power. In recent times, a deep learning algorithm (DLA) is widely used in signal analysis. The traditional algorithms such as ANN, support vector machine, and ELMA are not capable to learn deep representations but DLA provides deep learning and estimate the abnormality exactly. In this study, as a hybrid approach, CNN is combined with extreme machine learning is proposed to estimate the health of the rail track. Initially, the proposed method uses the CWT to analyze the vibration signal received from the accelerometer. Then the high-level features are extracted by using CNN with square pooling architecture. Random weights are used in the training process for reducing the computational complexity and ELMA is applied in the final classification. There are four different abnormal (fault) cases that affect the health of track. They are a visible fault, invisible fault, plastic deformation, and minute crack. The four different cases of abnormality is shown in Fig. 1. The rest of the paper is constructed as follows: In Section 2, the material and methods are described. In Section 3, the ELMA algorithm is explained. In Section 4, the proposed CNN-ELMA is described. Simulation and experimental results are given in Section 5. Finally, the conclusion has been drawn in Section 6.

II. PROPOSED ANALYSIS METHODOLOGY

There are three different types of rail tracks (subway track, normal track, and high-speed track) used for rail transportation. The normal rail track utilizes an E-clip or W-clip fastening system whereas the W-clip fastening is used in high-speed tracks.

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The subway introduces noise and more vibration. However, in the city environment, the underground pathway is unavoidable [21]. The abnormality (fault) present in the rail track affects the safety and comfort of the passengers.

Various simulation and experimental techniques have been proposed to improve the comfort and safety of the rail journey. In this paper, four different abnormalities: 1) invisible abnormality due to bolt loosening 2) visible abnormality due to missing or damaged bolts or clips 3) rusty deformation due to different environmental problems and 4) crack due to earth variation are considered. To measure the abnormality of the track, the MEMS accelerometers are fixed in the vertical and horizontal position of the axle box. The novelties of the proposed CNN-ELMA are:

- A hybrid algorithm, a combination of CNN and ELMA are utilized to extract the acceleration signal (vertical and lateral) measured from the MEMS accelerometers.
- A novel location of abnormality estimation system is introduced to determine the place of fault. It will estimate the exact location of vibration even if the GPS signal level is low or absent.
- The location of abnormality is sent to the control room or maintenance department for necessary action.
- The stability and accuracy of the system are improved.

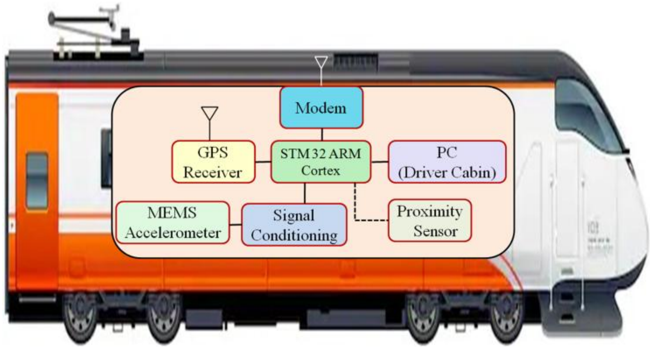

Fig. 2. Block diagram of the proposed rail health monitoring system.

The proposed CNN-ELMA contains four main sections: 1) MEMS sensors, used to capture the acceleration 2) controller, that process the signal 3) global positioning system, used to estimate the location of the abnormality and 4) modem for communicating the location of abnormality to the control room. The MEMS accelerometer is an electromechanical device that measures the vibration produced by the rail track. Here the three-axis linear accelerometer (LIS2DW12) utilizes ultra-low-power and provides high-performance. It senses the port once in every 120 ms and sends the information to the controller through the serial port. According to the physical displacement, the capacitance of fixed and moving plates will produce linear acceleration. It has a 32-level first-in-first-out buffer used to limit the host processor intervention. To process motion and acceleration, the LIS2DW12 has a devoted internal engine for processing the detected data. It operates under the temperature range from -35 °C to +87 °C and available in a small thin plastic grid package.

The signal which is received from the MEMS accelerometers are sampled with a frequency of 2 kHz and converts it into a digital signal and gives it to the controller. The received signal is applied to the CNN; initially, the CWT is performed to provide a better representation of raw acceleration signal and the high-level features are extracted using the square pooling architecture presented in the CNN. In this stage, fine-tuning is performed and a random weight is used to reduce the computational cost. Lastly, ELMA is applied for final classification. The location of abnormality is captured by the controller if an abnormality of the track is detected. The block diagram of the proposed health monitoring system is shown in Fig. 2.

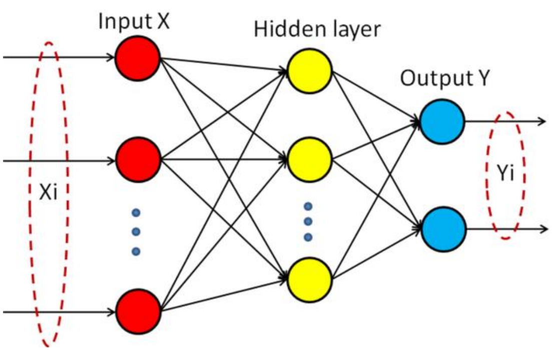

Fig. 3. Basic construction of ELMA.

III. EXTREME LEARNING MACHINE AND CNN

A. Extreme Learning machine

To train the single hidden layer feedforward neural network (SHFN) the extreme learning machine is proposed. All the parameters of the hidden nodes of SHFN are tuned initially, the weights are randomly generated. During the training procedure, the weights are kept fixed. The basic construction of the ELMA is shown in Fig. 3.

Here N hidden layer are considered for the input a=[a_1, a_2, …, a_m], then H(a)=[H_1(a), H_2(a),…,H_N(a)] is the hidden layer corresponding to mapping of ELMA. Now the output can be expressed based on [22] as:

$$Y(a_i) = \sum_{i=1}^{N} \gamma_i\, h_i a_i = h(a_i)\gamma \qquad i = 1,2,\dots,m \qquad (1)$$

Where $\gamma = \gamma_1, \gamma_2, \dots, \gamma_N]$ is the output weight matrix connecting both the hidden layer node and the output layer node, h(a) is the continuous nonlinear function. Two steps have been followed for training an ELMA: 1) the linear parameter solving and 2) the random filter mapping. Initially, the weights W=[W_1, W_2, …, W_N] and the biases B=[B_1, B_2, …, B_N] are generated randomly. Now the hidden layer node can be computed based on [23] as:

$$H = \begin{bmatrix} h(a_1) \\ \vdots \\ h(a_m) \end{bmatrix}$$

$$= \begin{bmatrix} h_1(w_1^T a_1 + b_1), \dots, h_N(w_N^T a_1 + b_N) \\ \vdots \\ h_1(w_1^T a_m + b_1), \dots, h_N(w_N^T a_m + b_N) \end{bmatrix} \qquad (2)$$

The output weight matrix, γ with minimized error for the respective training sample is solved in the next stage. Hung et al. introduced a new solution, $\gamma^* = H^+ Y$, where H^+ represents the Moore

Penrose generalized inverse of the matrix H [24].

$$\gamma^* - CH^1(Y - H\gamma^*) = 0 \qquad (3)$$

Now equation 3 can be written as:

$$\gamma^* = H^+Y = \left(H^TH + \frac{1}{c}\right)H^TY \quad (4)$$

where γ^* is the unique solution and it provides less training error with smaller norms of weight. Now the predicted output of the new test sample can be expressed as:

$$R = h(a)\gamma^* = \begin{cases} h(a) * \left(\left(H^TH + \frac{1}{c}\right)^{-1} H^TY\right) & if \;\; m \geq N \\ h(a) * \left(H^T\left(H^TH + \frac{1}{c}\right)^{-1} Y\right) & if \; m < N \end{cases} \quad (5)$$

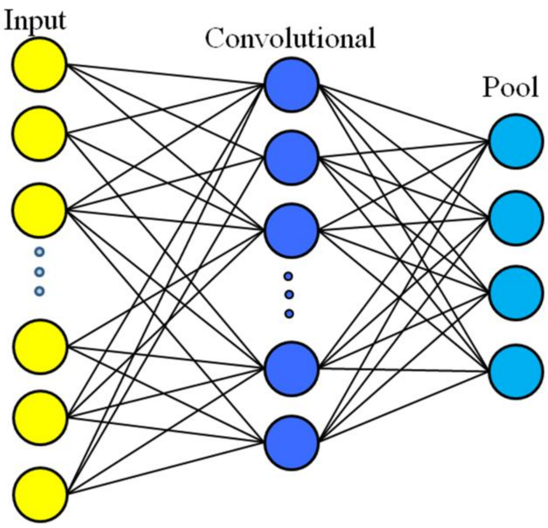

Fig. 4. The structure of topography independent component analysis including three different layers.

B. Convolutional Neural Network

A convolutional neural network is a feed-forward multi-layer neural network used to extract different features to carry out classification. The major building block of CNN is the convolutional layer which is constructed using a set of learnable kernels. The output feature map is obtained by passing the convolution sum through the non-linear activation function. The next layer feature map for the input is expressed based on [25] as:

$$a_i^l = f\left(\sum_{i=1}^{k} a_i^{l-1} * p_{ij}^l + s_j^l\right) \quad (6)$$

Where f(.) is the non-linear function, a_i^{l-1} is the i^{th} feature map of $(l-1)^{th}$ layer, k is the number of the kernel in the $(l-1)^{th}$ layer, p is the convolutional kernel, and s is additive biases.

A pooling layer can be added between the CNN layers after the convolutional layer. The output of a neighboring neuron is combined into a single neuron by the pooling operation. This combination provides more feature representations and helpful to reduce the computations. The pooling map operation can be expressed as:

$$a_i^l = f\left(\gamma_j^l down\left(a_i^{l-1}\right) + s_j^l\right) \quad (7)$$

Where down(.) pooling function or a sub-sampling function, b represents the additive bias for each feature map, and γ is the multiplicative bias.

IV. PROPOSED CNN-ELMA MODEL

In this section, an intelligent rail track health monitoring based on a hybrid technique called CNN-ELMA, which is capable to improve the speed of training deals with the high dimensional time-frequency images. The CNN is built by using a topography independent component analysis network including square pooling architecture. The raw signal from the MEMS sensor is directly taken for learning feature representation [26,27]. The structure of the topography independent component analysis consists of three different layers is shown in Fig. 4.

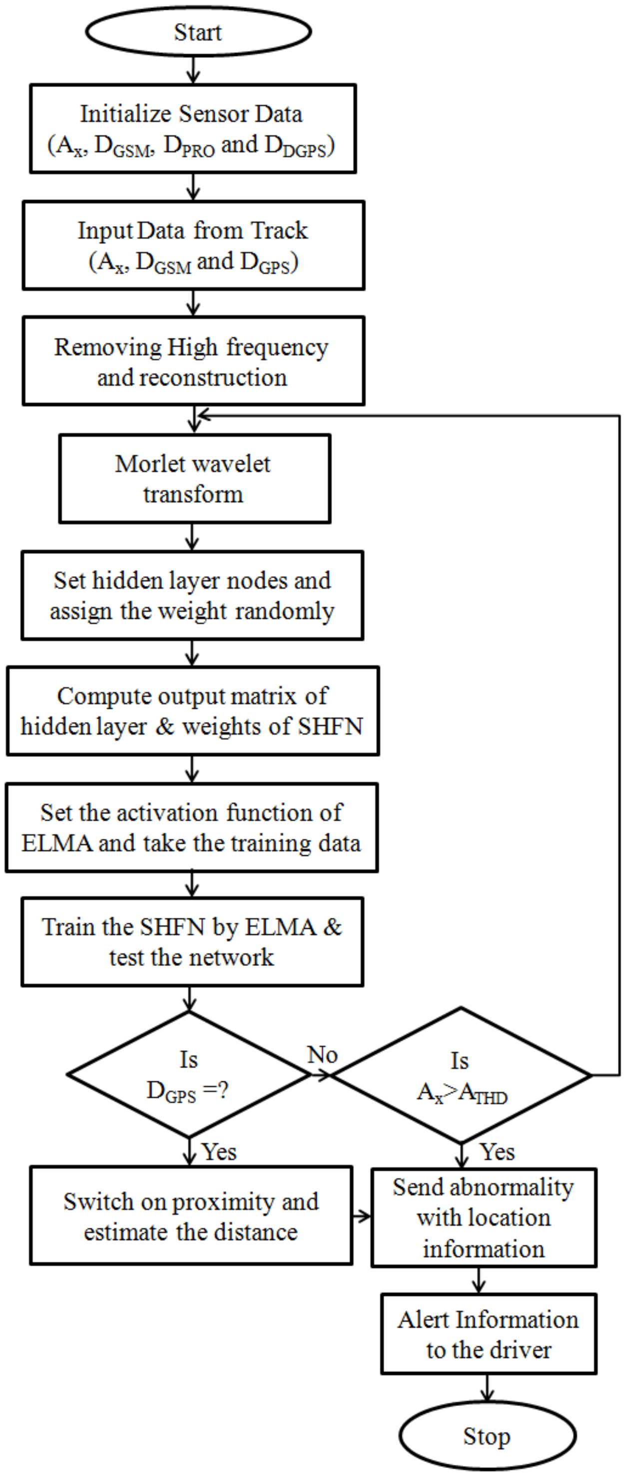

Fig. 5. Flow chart of the proposed CNN-ELMA method.

Initially, the CNN extracts the features by performing convolution on the raw signal received from the MEMS accelerometer. The weight W is added between the hidden and input nodes.

A set of the kernel is applied to the small place of the input signal and then the product of every location is estimated.

The k^{th} feature map convolutional operation can be expressed as:

$$d_k(a^t; W) = \sum_{i=1}^{m} W_{ki}\, a_i^t \;; \quad k = 1,2, \dots, n \qquad (8)$$

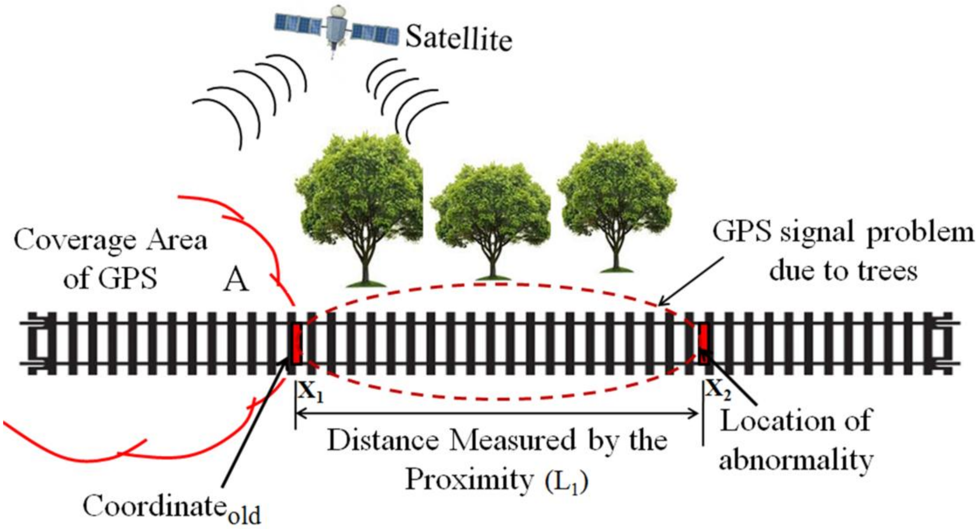

Fig. 6. GPS signal problem

Where n is the input dimension, the weight W is Gaussian probability distribution function which is initialized randomly, and m represents the number of units in a hidden layer. The square pooling layer followed by convolutional layer is combined the feature maps of the previous layer to the local neighborhood and produce a single value. The pooling units present in the square pooling layer consists of a summation and a square operation. The pooling layer activation functions are the sum of the squares of the units present in the previous layer. It can be expressed as:

$$U_i(a^t; W, Z) = \sqrt{\sum_{k=1}^{n} Z_{ik}\ (D_k)^2} = \sqrt{\sum_{k=1}^{n} Z_{ik}\ \left(\sum_{i=1}^{n} W_{ki}\, a_{i\,k}^{t}\right)^2} \qquad (9)$$

$$min \sum_{i=1}^{T} \sum_{i=1}^{n} U_i(a^t; W, Z) \quad , WW^T = 1 \qquad (10)$$

Where V_{ik} =1 and 0 represents whether the pooling neuron is connected and not connected to the previous layer mapping unit, Z is the weight between pooling layer and the convolution layer, and WW^T=1, the orthonormal constraints forces the network to provide diversity.

A. Abnormality Detection Based on CNN-ELMA

After the construction of CNN architecture, a framework to combine CNN and ELMA is proposed to estimate the abnormality in the rail track with location information. The input layer corresponds to the vibration signal received from the MEMS sensor in time-frequency representation. The structural features of the input image are extracted by the convolutional layer and preserved the relationship between the pixels. The CWT is implemented using 1024 scale for obtaining the time-frequency representation (two dimensional). Now the dimension of time-frequency can be calculated as, $1024 \times f_s/2$, where f_s is the frequency used in sampling. The real-time signal which is received from the MEMS accelerometer contains redundant information and it will not be processed easily by the neural network. The bicubic interpolation algorithm is utilized to downsize the image. As a result, smooth and less distortion is present in the reduced images [28]. The flow chart of the proposed CNN-ELMA is illustrated in Fig. 5.

The output weights are updated during the training process of the CNN-ELMA. The weights of the ELM and CNN are randomly initialized. Initially, to obtain the high-level representation of the acceleration signal the CNN is taking care of the training samples. The abnormality detection scheme of the proposed CNN-ELMA is summarized as follows:

- The time-series acceleration signal is measured by MEMS accelerometers which are mounted on the axle box.
- The CWT is used to convert the single-dimensional signal into two-dimensional time-frequencies for obtaining good features. Then the images are downsized into 32×32.
- The CNN is created, and various parameters such as a number of filters and size of the convolutional kernel are determined, the weights are randomly initialized.
- The ELMA is created to find the number of hidden nodes and the penalty functions are determined.
- All the features are combined concerning the input of ELMA.
- The signals received from the MEMS sensor are fed into the CNN-ELMA model to identify the health of the rail track.

B. GPS Signal Problem

The location of vibration is captured by the controller if abnormality is detected. The coordinates, longitude, and latitude, can be received from the GPS module GN-80 which is linked with the controller. In this study, two different cases 1) GPS signal is present and 2) GPS signal is not available has been considered. During the first case, the GPS signal is available and the controller captures the coordinates, if it detects the abnormality in the track then updates the information in the database. During the second case, the GPS signal is not available or the signal level (C_{old}) is less than the set threshold. In this case, the controller stores the coordinates where the GPS signal is absent and switches ON the proximity sensor.

The controller starts to estimate the distance where the GPS signal is absent. The distance can be calculated by multiplying the number of pulses generated by the proximity sensor with the diameter of the disk where the proximity is mounted. Fig. 6 illustrates the coverage problem of GPS.

From Fig. 6 it is observed that the signal is perfectly available in the areas A.

The signal is absent from X_1 to X_2. The location of the vibration

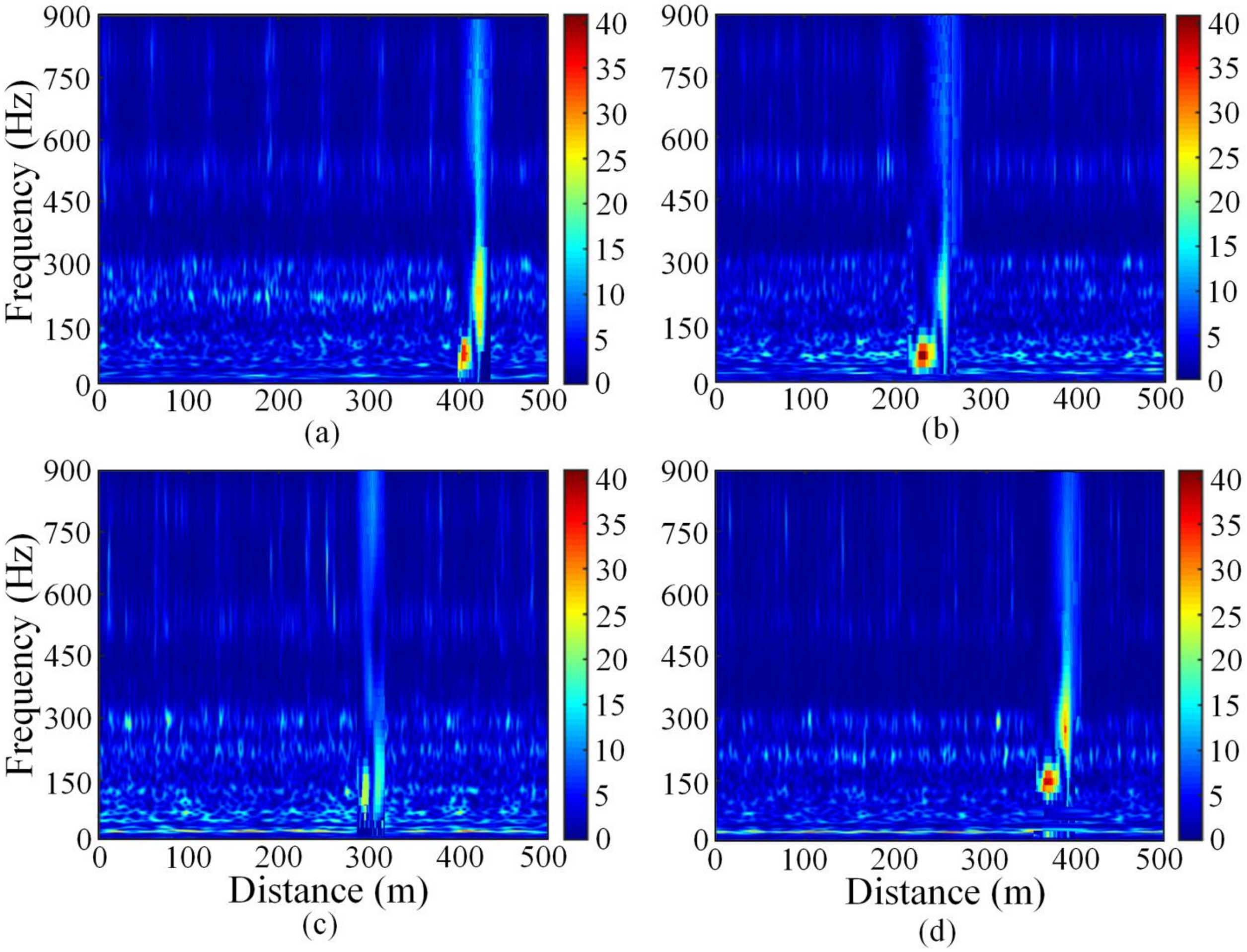

Fig. 7. Wavelet scalogram for four different cases of abnormalities. (a) invisible abnormality, (b) visible abnormality, (c) rusty deformation, and (d) minute crack.

is at L_1. Now the coordinate of L_1 can be estimated by adding the distance from X_1 to X_2 with the old coordinate, C_{old} measured from the endpoint of region A. By using this novel approach the CNN-ELMA exactly estimates the location of the abnormality.

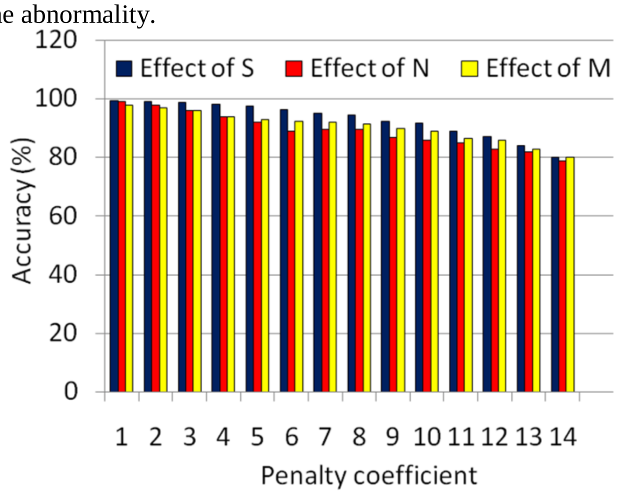

Fig. 8. The effects of different parameters of CNN-ELMA.

V. EXPERIMENTAL VALIDATION AND VERIFICATION

The effectiveness of the proposed CNN-ELMA, four different cases such as 1) invisible abnormality 2) visible abnormality 3) rusty deformation and 4) minute crack are considered using the benchmark data for the rail track taken from [29]. The CWT is used to decompose the raw signals received from the MEMS sensors into a time-scale plane [30]. It is the pre-processing procedure that utilizes Morlet wavelet function to identify the abnormalities present in the rail track.

A. Abnormality Detection of Rail Track

The time-frequency scalograms of four different abnormalities are measured at 70 km speed of the vehicle is shown in Fig. 7. From the scalograms, it is observed that the relative similarity of different categories of a frequency distribution is present. The meshing frequency indicates that the abnormal characteristic frequency so that the useful frequency component extraction for detecting the abnormality is difficult.

The time-frequency domain representation provides constructive information of the vibration signal received from the MEMS sensors. Additionally, the translational invariance property of the CNN, it is confirmed that the complex relationship can be captured by the CNN from the time-frequency representation and identify the abnormalities under different conditions.

B. Parameter Optimization of CNN-ELMA

Various key parameters such as the size of the kernel (S), number of filters (N), number of hidden nodes (M), and the penalty coefficients (P) are considered in the CNN-ELMA. The parameters influence on the performance is studied in this section. Due to the random weight adaptation of the proposed CNN-ELMA, a set of optimum parameters are determined in the feasible region with a shorter time. Here, the parameter combination such as (P,M), (P,S), and (P,N) are considered to explore the model. The range of parameters used for optimization is: size of the kernel, S starts from {3, 5, 7, 9, 11, 13}; number of filters, N from {2, 4, 6, 8, 10, 12}; the penalty coefficients, P starts from $\{10^{-2}, 10^{-1}, 1, 10^{1}, 10^{2}, 10^{3}\}$; and number of hidden nodes, M is from {2,7,12,20,35,50,65}. Various parameters used in the proposed CNN-ELMA is listed in Table 1.

Table 1. Various parameters used in CNN-ELMA.

Name of the Network	Parameters	Values
CNN	Pool size	2
	Size of the kernel, S	8
	Number of filters, N	9
	Activation function (Pool)	Square root function
	Activation function (Convolution)	Square function
ELMA	Number of hidden nodes, M	3000
	Penalty coefficient, P	0.1
	Activation function	Sigmoid function

The effects of different parameters of the proposed CNN-ELMA method are illustrated in Fig. 8. From Fig. 8 it is indicated that the CNN-ELMA provides good generalization if P takes value in the range $10^{-2}$to 1. The accuracy depends on the number of hidden nodes, if it is in the range 100-2000, the accuracy may be less. If the range is more than 2000 then steady-state accuracy can be achieved. Therefore, a large number of hidden nodes is required to obtain a good mapping of a complex problem. In addition to the kernel size, if the kernel size is larger it leads to loss of information during convolutional operation. On the other hand, if the kernel size is smaller it provides exact information during the operation, but it will easily be affected by the high-frequency noise produced by the industries. The number of filters influences the performance of the proposed method is analyzed, the accuracy of classification increases if the number of filters is increased from 2 to 8. Furthermore, the increase in the number of filters from 8 to 10 provides a slight decrease in system accuracy. It is concluded from Fig. 8, the proposed CCN-ELMA provides steady-state accuracy in the performance using 8 maps. Based on the analysis, in this study, different parameters are selected as [S, N, P, M]=[0.1, 2500, 8, 9] for the abnormality detection problem of the rail track

C. Result Comparison with Other Methods

To test the superiority of the proposed CNN-ELMA, five different algorithms such as the traditional DL methods (SAE, DBN, and CNN) and ML methods (KNN and SVM) are taken to study the performance of the abnormality of the rail track. All the parameters are selected in such a way that it is suitable for the random search space. The Fast Fourier Transform (FFT) is used in SVM, KNN, SAE, and DBN to get single-dimensional frequency spectra [31]. Moreover, the wavelet scalograms are utilized directly as an input in CNN and the proposed CNN-ELMA. The data processing of CNN-ELMA is carried out on laptop (i5, 3.2 GHz CPU, 8 GB RAM) with MATLAB 2018 environment. In this study, ten trials have been used and the average result is estimated to reduce the influence of randomization during the classification process. The accuracy of the proposed method is compared with four other methods under two different abnormalities such as visible abnormality and minute crack is shown in Fig. 9.

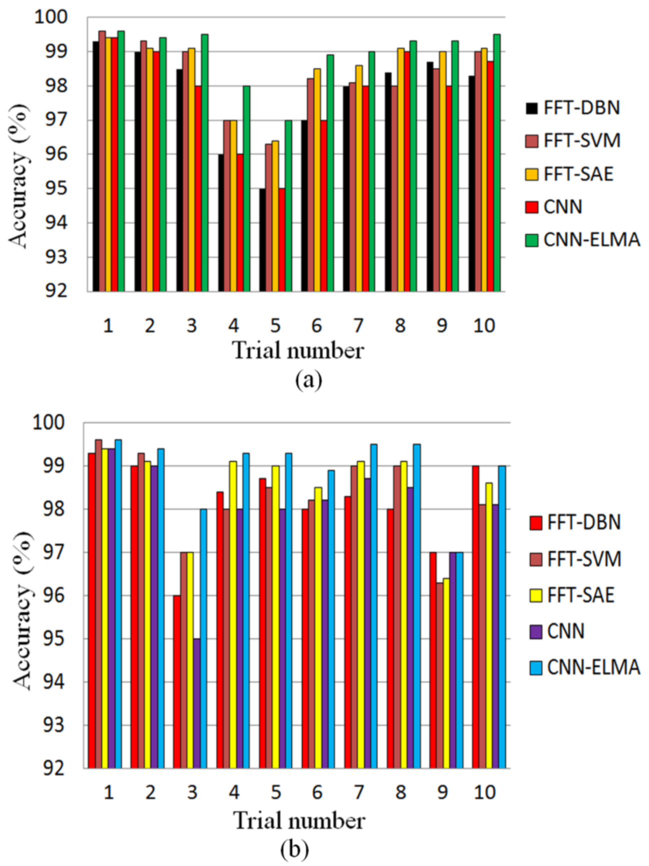

Fig. 9. Diagnostic results of different methods on rail track dataset. (a) visible abnormality and (b) minute crack.

From Fig. 9 one can easily understand that the FFT-SAE provides good steady-state output compared to DBN method. The DBN provides better output than the proposed CNN-ELMA in the fourth trial. The CNN with a single convolutional layer obtains stead-state result compared to FFT-DBN (trial 1,2,8, and 10). Considering the ten trials of the abnormality detection problem, the proposed CNN-ELMA obtained best results and robust performance. The minute crack fault is shown in Fig. 9 (b). From Fig. 9(b) one can easily understand that the minute crack is perfectly identified by the proposed method than other methods.

The accuracy of the proposed method is compared with four other methods under two different abnormalities such as invisible abnormality and plastic deformation is shown in Fig. 10. Here, the FFT-DBN provides a better result than CNN method in 4,6, and 8 trials as shown in Fig. 10 (a). When compared, the proposed method with all the other four methods, the CNN-ELMA provides better results in most of the trials. The performance of the proposed method under plastic deformation abnormality is shown in Fig. 19 (b). From Fig. 10(b) it is observed that the FFT-DBN method provides

Table 2. Diagnostic results of the proposed method and four other methods.

Algorithms	Accuracy of different abnormalities				Training accuracy (%)	Testing accuracy (%)
	Case 1	Case 2	Case 3	Case 4		
FFT-SVM	100	98.12	99.14	98.74	98.53±0.36	97.68±0.69
FFT-SAE	99.37	99.45	98.27	97.92	100±0.00	98.49±0.74
FFT-DBN	98.24	96.38	97.36	97.74	100±0.00	97.94±0.94
CNN	100	100	98.84	98.45	99.16±1.37	98.46±1.85
CNN-ELMA	100	100	99.85	98.97	100±0.00	99.59±0.73

better results than FFT-SAE in the trials 2,5, and 7. The performance of CNN is better than FFT-DBN method. From Fig. 10(b) it is observed that the proposed CNN-ELMA provides better results than the other four methods.

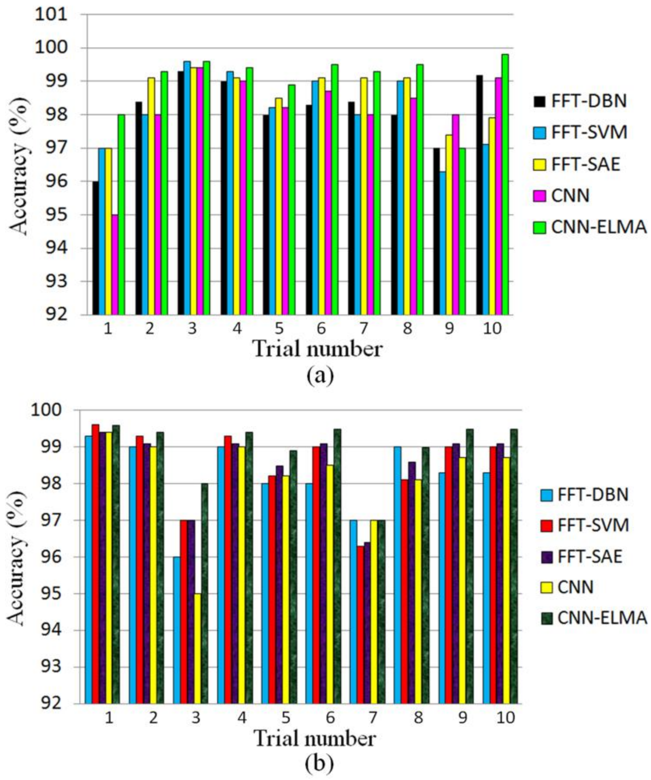

Fig. 10. Diagnostic results of different methods on rail track dataset. (a) plastic deformation and (b) invisible abnormality.

The training and testing accuracy of the proposed CNN-ELMA is compared with four other methods are listed in Table 2. From Table 2 it is observed that the FFT-SVM is the lowest training and testing accuracy compared to other methods. On the other hand, the proposed CNN-ELMA provides training accuracy of 99.91 % and testing accuracy of 99.81% followed by the FFT-SAE and FFT-DBN methods. Moreover, the SVM requires very less time for training because in this method Euclidean distance is used to estimate the nearest neighbor. From Table 2 one can conclude that deep learning has different advantages than other methods. However, the deep learning algorithm needs a larger training time compared to other methods.

The computational cost of the proposed CNN-ELMA is compared with four other methods are shown in Fig. 11. From Fig. 11 it is observed that the computational cost of the CNN and the proposed CNN-ELMA are larger than that of DBN and SAE methods. In contrast, the proposed CNN-ELMA requires 609 s for training to provide the best accuracy of 99.59%. Various parameters (number of iteration, rate of learning, and the momentum) of traditional algorithms such as SAE, DBN, and CNN should be selected carefully. Otherwise, it will reflect on the performance of the system. The proposed CNN-ELMA provides the best classification compared to other DL methods. Also, the deep learning architecture requires more weights during the training stage of abnormality detection of the rail track, which leads to an over-fitting problem.

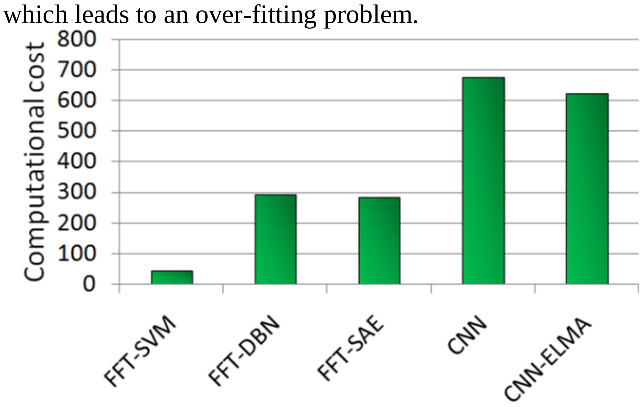

Fig. 11. Comparison of the computational cost of the proposed CNN-ELMA with other methods.

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There are four different abnormality cases studied at various places of Chennai city, India and the result is presented in Table 3. The missing bolt (visible fault) is identified in Saidapet area and the test is performed. In this case, the proximity is in the OFF condition because the GPS signal level is greater than the set threshold.

The abnormality is identified and the corresponding coordinate (latitude and longitude) is captured by the controller. In the same way, the other abnormalities are such as plastic deformation and minute crack are identified in T.nagar and Guindy locations. On the other hand in Guindy area, the GPS signal level is less than the set threshold, so that the controller switches on the proximity immediately. Based on the number of pulses the controller estimates the distance when the GPS signal is high. Here, the abnormality location, 1.53 km is estimated from the no signal area to the point where the abnormality is detected. From Table 3 it is observed that the proposed CNN-ELMA performs better and identifies the exact location of the abnormality.

VI. CONCLUSION

In this study, a novel hybrid method (CNN-ELMA) is introduced for monitoring the health of the rail track. The CNN has higher feature extraction capability and the ELMA is an efficient and accurate classification algorithm. Initially, the raw data that is captured from the MEMS sensors are processed using CWT, the scalograms of the raw data are used as input of the CNN. In the first stage of CNN, the square pooling architecture is utilized in CNN for improving the learning capability of feature extraction. ELMA is employed in the second stage to improve the learning speed and the performance of classification. The proposed CNN-ELMA is validated using the data set for four different abnormal cases of rail track. Finally, the comparison is performed using four different classical algorithms (SAE, DBN, SVM, and CNN). The comparison result shows that the proposed CNN-ELMA provides an optimal solution, greater generalization performance, and less human intervention.

Table 3. Location of abnormality and the corresponding GPS coordinates.

Location of abnormality	Type of abnormality	Latitude	Longitude	Distance estimated by proximity (km)
Saidapet	Visible	13.0212° N	80.2231° E	No
T.Nagar	Plastic deformation	13.0416° N	80.2349° E	No
Velachery	Invisible	12.9801° N	80.2184° E	1.53 km
Guindy	Minute crack	13.0065° N	80.2202° E	No

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