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DIAGNOSING RAILWAY WHEEL CONDITIONS WITH THE AID OF AI-TECHNIQUES

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ABSTRACT

The significant intention is to design an Artificial Intelligence (AI) based predicting model to diagnose railway wheel conditions. This intention originates from obstacles like identifying rail wheel conditions which is complex and consumes time to compute. This urge incorporating AI techniques to predict railway wheel conditions to overcome the obstacles. The preliminary research initiate by generating arbitrary database with the aid of fuzzy logic technique. This database holds input attributes like vibration level, the frequency, and velocity of the train, on other hand wheel conditions as output attribute. Subsequently, this database utilize for training AI model-Artificial Neural Network (ANN) to diagnosis railway wheel conditions. Here, the diagnosing railway wheel conditions categorize as Good (G), Low Damaged (LD), Faulty (F) and Dangerous (D). This investigation evident, over manual computation the AI techniques are proficient in predicting railway wheel conditions in less computational time. Over contest techniques, the LevenbergMarkovic (LM) training technique associate with ANN exhibit superior predicting performance of 97.5% accuracy in diagnosing railway wheel conditions consequent the need of preventive maintenance.

Key words: Artificial Intelligence (AI) techniques, Artificial Neural Network (ANN), Feed Forward Back Propagation (FFBN), railway wheel conditions.

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1. INTRODUCTION

The railway transportation has a foremost significance in the world [1], the checking of the trains' movement state is of amazing noteworthiness to create the moving specialists and promise the ensured activity of railways [2]. With the current enormous increments of train speed and axle load, forces on both vehicle and track on account of wheel flats or rail surface disfigurements has extended and fundamental imperfection sizes at which move must be made have been diminished. This extends the consequence of early recognizable proof and change of these faults [3]. Fault diagnosis in light of the examination of vibration signals has exhibited a marvellous enhancement, in perspective of the portrayal of mechanical system condition and allowing early recognition of a possible fault [4]. Wheel flats are the most generally recognized local surface defects in railway wheels. They can bring about cyclic wheel-rail influence in the midst of the running method, consequently instigating the coupled vibration of the entire vehicle-track framework. This vibration in roll endangers running security and breaks the wheel and the rails help [5].

Wheel flat fault can express extraordinary harm to the rail, and additionally decrease the comfort execution [6]. Because of the criticalness of this issue for railway framework, the analysts from all over world have consideration in discovering techniques to recognize wheel flat fault [7]. On the other hand, the use of some essential formulas to compute these forces could give vague outcome [8]. In this manner, early analysis and mediation in railways is amazingly essential. There are many contact and contactless methods for condition checking and fault identification on the railway line [9]. To plan the repairs of the track circuits in the most productive and successful way, it is significant to detect and classify the faults as fast as time permits [11]. Fault classification has been a subject of attention for a few years and as a result of this a number of fault classification techniques have been produced by different researchers [10].

The related parameters are depicted using fuzzy linguistic variables and a fuzzy rule-based structure is used as a piece of the extension work to manage indeterminate causal associations between these parameters and risk level [12]. Then again, it has different disservices also. It is tedious to make fuzzy rules and membership functions and fuzzy outputs can be deciphered in different ways making analysis hard. In like manner, it requires lot of information and mastery to develop a fuzzy system. It doesn't give generalizable results and the program must be continuing running for each individual patient [13]. To keep away from the issues we are using neural network, where are used and joined with various elements, with the essential focus of get the best execution for the structure [14]. Artificial neural networks have recently achieved best in class execution on a range of testing design acknowledgment assignments, for instance, image classification [15] and speech recognition. A part of the advances made in these regions can be associated with fault diagnosis issues as well, which makes the use of neural networks an interesting choice in this area [16]. The ANN is trained via experimental information and it has been exhibited that the time domain features are powerful in fault diagnosis [17].

MdSazzadHossain et al. [18] 2017, had planned Radial Basis Function Network (RBFN) for conceivable further enhancement in effect identification task. In generally speaking, RBFN enhanced the effect localization and quantification accuracies by diminishing 32.98% and 40.91% error individually contrasted with MLP.

Reza Rooki [19] 2016, had anticipated pressure loss calculations in annulus is usually conducted dependent on an extension of empirical correlations produced for Newtonian fluids and extending pipe flow correlations. The predicted values utilizing GRNN intently pursued the experimental ones with an average relative absolute error less than 6.24%, and correlation coefficient (R) of 0.99 for pressure loss estimation.

HakanGuler [20] 2014, had planned to demonstrate track geometry crumbling using a far reaching field examination accumulated over a time of 2 years on roughly 180 km of railway line. The attained results demonstrated that ANN may be an option strategy for predicting track geometry deterioration.

S. Rajakarunakaran et al. [21] 2008, had suggested the detection and diagnosis of faults in specialized frameworks are of awesome practical significance and principal significance for the protected operation of the plant. That paper displays the advancement of artificial neural network-based model for the fault detection of centrifugal pumping system.

DimitrisSkarlatos et al. [22] 2004, had recommended the strategy depended on vibration estimations at various train speeds on healthy wheels and wheels with defects known from the earlier. The fuzzy-logic demonstrate stores the acquired involvement in a database and plays out the decision-making on damage extent and thus the need of preventive maintenance.

2. PROPOSED METHOD

This methodology investigates, diagnosing the defectiveness of railway wheels byincorporating AI system. These railway wheels defective has monitor via generated vibration signals and need to prevent failure. A decade back, fuzzy-logic utilize to identify railway wheel defects by consider vibration level of the wheel, the frequency and the train velocity as input on other hand wheel condition as output. Following limitations such as arduous to design a fuzzy system, complex in deciding appropriate membership function, fuzzy system could be handling only via *if-then* rule generation urge alternate intelligent technique called ANN. It is a computational model inspired from human brain, comprised of a three layers; input layer, hidden layer and output layer to perform computational operation. To identify the railway wheel conditions via ANN, it is mandatory to have a certain quantity of database. Here, fuzzy logic employed to generate arbitrary (1000) database; amid 80% utilize for training the ANN model and remaining for testing the model.

The techniques implemented in this research are Feed Forward Back Propagation (FFBN) and their associate training techniques like LM, BFGS Quasi-Newton (BFG), Resilient Back-propagation (RP), Scaled Conjugate Gradient (SCG), Conjugate Gradient with Powell/Beale Restarts (CGB), Fletcher-Powell Conjugate Gradient (CGF), Polak-Ribiére Conjugate Gradient (CGP), One Step Secant (OSS), Variable Learning Rate Back-propagation (GDX), Gradient Descent with Adaptive learning rate (GDA), Gradient Descent (GD), Gradient Descent with Momentum (GDM) along with Radial Basis Function Network (RBFN), General Regression Neural Network (GRNN) and Enhanced Radial Basis Function Network(ERBFN). In general, ANN consists of three layers namely input layers, hidden layers and output layer. Here, input layer have three nodes for vibration level, frequency and train velocity; hidden layer have single layer with ten associate neurons to transfer informations; output layer has one node to exhibit wheel condition. The following sections details the mathematical computation process about FFBN and LM in the context of diagnosing railway wheel conditions.

2.1. Feed Forward Back-Propagation Network (FFBN)

As made reference to ahead of schedule, the structure of FFBN holds three layers; in the midst of, input layer get data, computational process happen in hidden layer and finally output layer out processed information. This structure execute with adequate database (learn by experience) by training, the training stage of ANN can be either supervised (training with both inputs and outputs) or unsupervised (training with only inputs). This research used supervised training to accommodate the prediction procedure. The input layer gets the data and multiplied to randomly corresponding weights. The products are summed up and the error is dictated by comparing with the measured value. Back propagation is a sort of methodology that uses to train the model with the past output (feedback). Three significant transfer functions *Tansig*, *Logsig* and *Purelin* are usually utilized in FFBN here utilize tan-sigmoidtechnique. The foremost assignment of training FFBN is to determine the finest weights that can make predictions that are in close proximity to the target output as given by Eq. (1).

$$w* = \arg\min O_p(w) \quad (1)$$

Where, *w* is weight matrix and *O(w)* is an objective function on *w*. *O(w)* is to be minimized and calculated at any point of *w* given by Eq. (2).

$$O(w) = \sum_p O_p(w) \quad (2)$$

p is the number of instances in the training set and $O_p(w)$ is the output error for each *p* as represented in Eq. (3).

$$O_p = \frac{1}{2}\sum_p (d_{pj} - y_{pj}(w))^2 \quad (3)$$

The FFBN uses the MSE as its error function as showed in Eq.(4)

$$O(w) = \frac{1}{2}\sum_{p=1}\sum_{j=1}[d_{pj} - y_{pj}(w)]^2 \quad (4)$$

Where $y_{pj}(w)$ and d_{pj} are the predicted output and measured output respectively. The performance of FFBN is additionally founded on different components, for example, the number of hidden neurons, choice of training algorithm and activation function. The optimal number of hidden neurons was chosen dependent on a trial and error technique. [23] MSE is used in training procedure to assess execution internally until desired threshold error value accomplish. The following figure-1, shows the architecture of ANN.

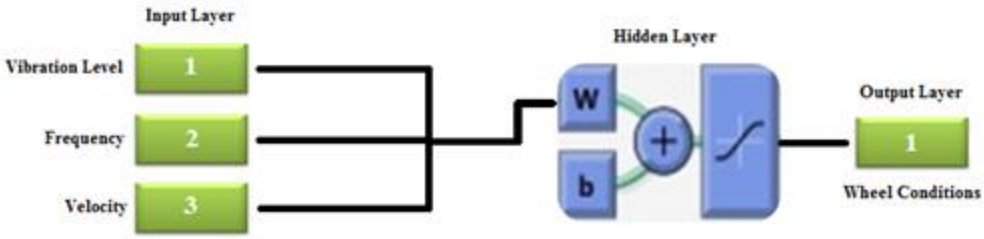

Figure1 Architecture of Artificial Neural Network

2.2. Levenberg–Marquardt algorithm

The LM algorithm is an optimization procedure which is an estimate of Newton’s technique, more great than the gradient descent, however requires more memory. The LM update rule for the weights is given by,

$$\Delta w = -\left(J^T J + \mu I\right)^{-1} J^T e \quad (5)$$

Where J is the Jacobian matrix of the derivative of each error to each weight, μ is a scalar, and e is an error vector. In the event that the scalar μ is very large, the above expression approximates to gradient descent; while μ is small the above expression becomes the Gauss–Newton technique. The Gauss–Newton technique is quicker and additional accurate nearer the minimum error. So the point is to move toward the Gauss–Newton technique as fast as possible. Consequently, μ is diminished after each fruitful advance and expanded just when a step increases the error. The LM algorithm performs extremely well and its efficiency is observed to be of a few orders above the conventional back propagation with learning rate and momentum factor (MATLAB ANN toolbox). [24]

3. RESULTS AND DISCUSSIONS

The purpose of diagnosing railway wheel conditions with the aid of AI techniques evaluates through different performance investigations. The standard measures utilize in this investigations are accuracy, False discovery Rate (FDR), False Negative Rate (FNR), False Positive Rate (FPR), F1 score, Matthews Correlation Coefficient (MCC), Negative Predictive Value (NPV), precision, sensitivity and specificity. The investigation results evident that FFBN associate with LM exhibits superior results over contest techniques. The following sections illustrate the performance of proposed techniques over other techniques during training and testing.

3.1. Performance investigation on training

The figure-2 obtained from MATLAB for Mean Square Error (MSE) exhibits the performance of FFBN in associate with LM during training; the results evident best validating performance is 0.060151 at epoch 21 which is superior over other techniques in this context of predicting wheel conditions. This investigation includes training, validation and testing results along with best results. The following figure 3 shows the graphical representation of regression and training state performance for FFBN associate LM training technique.

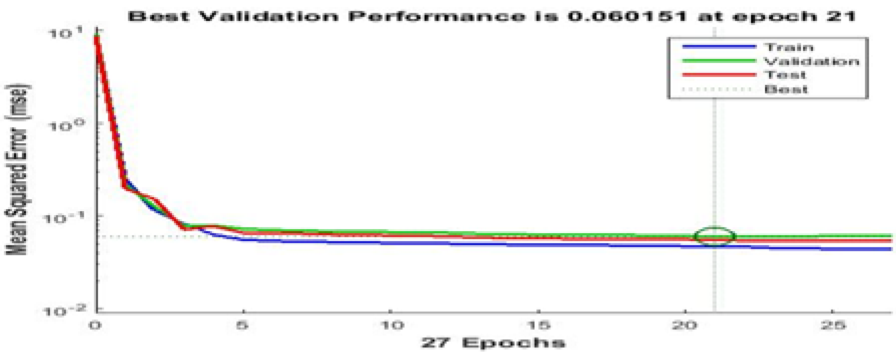

Figure2 Mean Square Error performance of FFBN-LM during training

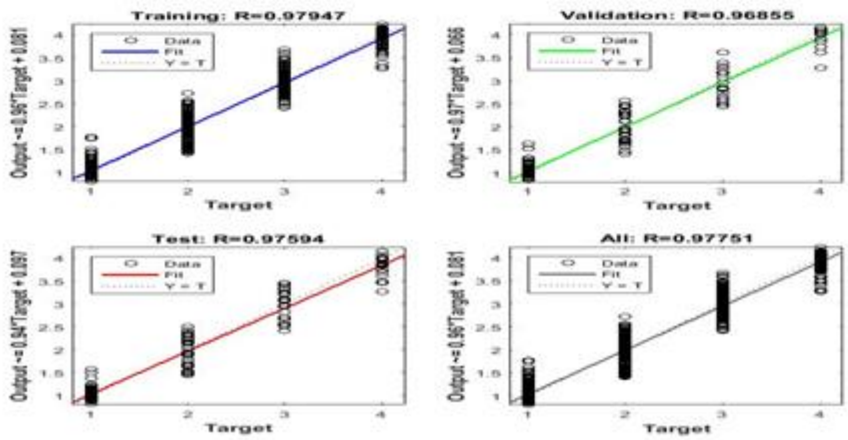

Figure 3 Regression representation of FFBN-LM during training

3.2. Performance investigation on testing

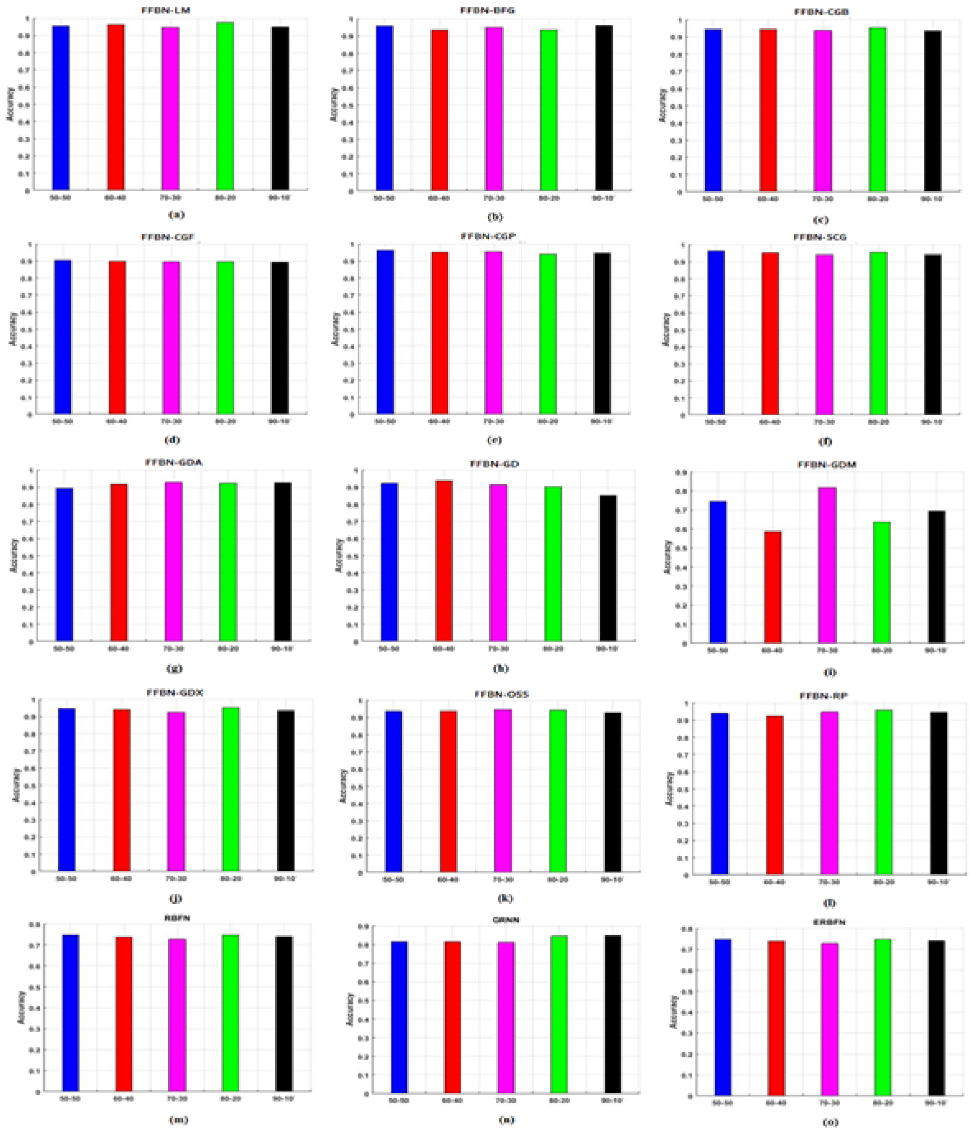

Figure 4 Performance evaluation of AI-techniques w.r.t accuracy

Figure-4 exhibits the performance of AI techniques with respect to predicting accuracy while varying training and testing databaseratio. The investigation evident that by considering 80% database for training and rest for testing unveil superior results in most of the employed techniques over other database partition. Amid, FFBN associate with LM exhibits proficient predicting performance over other implemented techniques.

3.3. Performance of AI techniques with standard measures

The following graphical representation exhibits the performance evaluation of various AI techniques with respect to standard measures. These performance measures calculate through True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values exhibits in table-1 and the mathematical calculation to evaluate AI technique shown in table-2. Figure 5 and 6 illustrates the performance of AI techniques evaluate with different standard measures exhibits the superiority of FFBN-LM over other AI techniques.

True Positive -	Railway wheelconditioncorrectlyidentified
False Positive -	Railway wheelconditionincorrectlyidentified
True Negative -	Railway wheelconditioncorrectlyrejected
False Negative -	Railway wheelconditionincorrectlyrejected

Table 1 Source-Measure to Compute Performance Measures

AI-Techniques	**TP**	**TN**	**FP**	**FN**
FFBN-LM	47.5	147.5	2.5	2.5
FFBN-BFG	43.5	143.5	6.5	6.5
FFBN-CGB	45.25	145.25	4.75	4.75
FFBN-CGF	32	147.25	2.75	18
FFBN-CGP	44	144	6	6
FFBN-SCG	45.5	145.5	4.5	4.5
FFBN-GBA	42.25	142.25	7.75	7.75
FFBN-GD	40.25	140.25	9.75	9.75
FFBN-GDM	13.75	113.75	36.25	36.25
FFBN-GDX	45.25	145.25	4.75	4.75
FFBN-OSS	44.25	144.25	5.75	5.75
FFBN-RP	45.75	145.75	4.25	4.25
RBFN [19]	24.75	124.75	25.25	25.25
GRNN [20]	34.5	134.5	15.5	15.5
ERBFN [23]	24.75	124.75	25.25	25.25

Table 2 Computational methodology of performance measures to evaluate AI techniques

Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
FDR	$\frac{FP}{FP+TP}$
FNR	$\frac{FN}{FN+TP}$
FPR	$\frac{FP}{FP+TN}$
F1 Score	$\frac{2TP}{2TP+FP+FN}$
MCC	$\frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$
NPV	$\frac{TN}{TN+FN}$
Precision	$\frac{TP}{TP+FP}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$

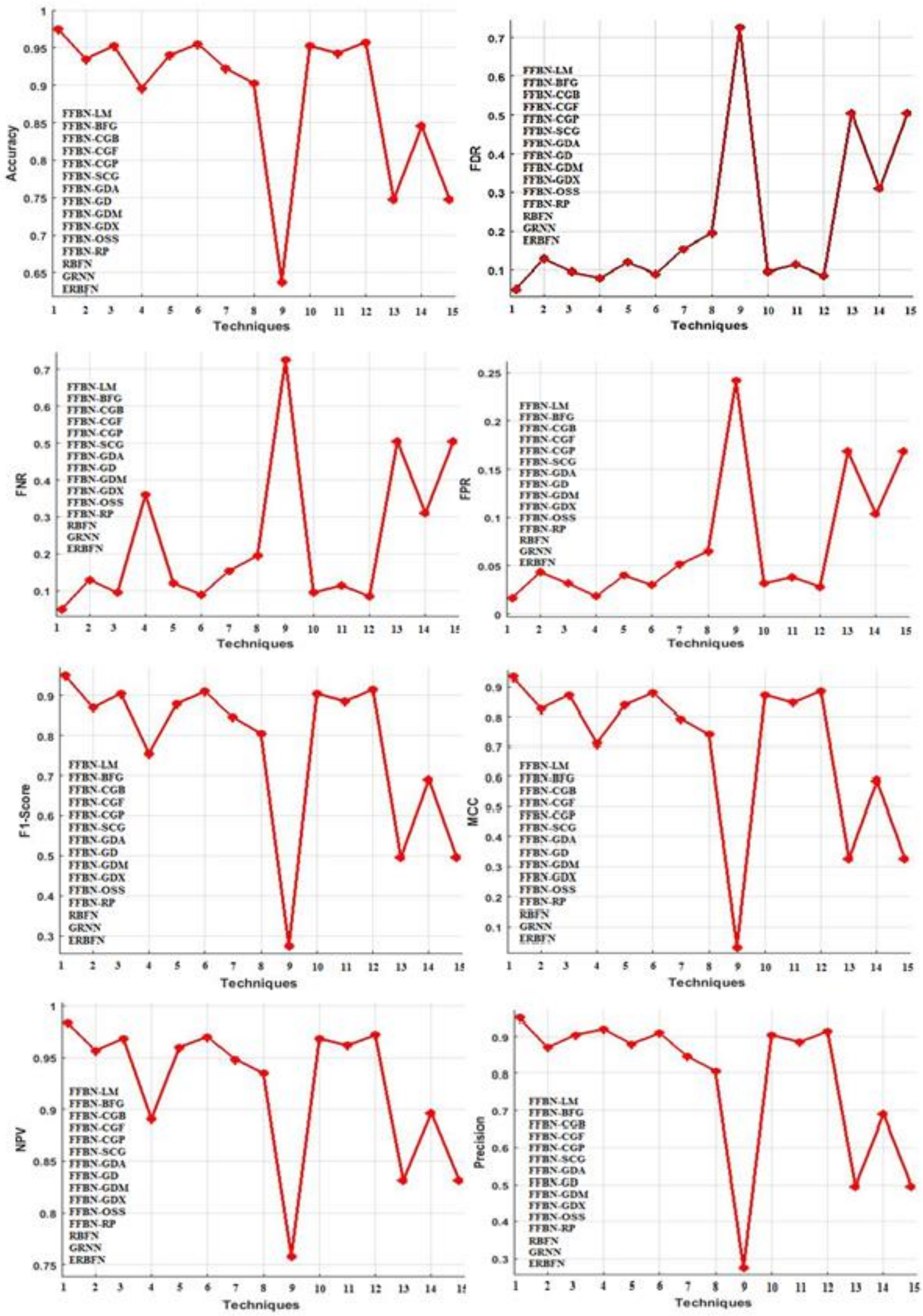

Figure 5 Performance Evaluation of AI techniques w.r.t accuracy, FDR, FNR, FPR, F1-Score, MCC, NPV and Precision

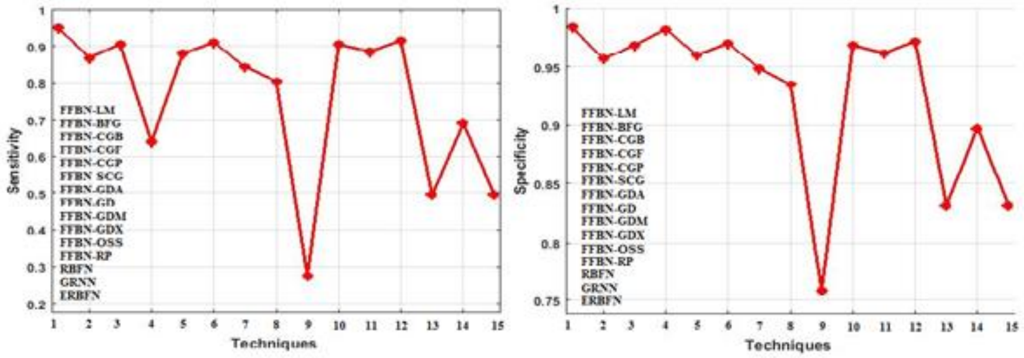

Figure 6 Performance Evaluation of AI techniques w.r.t Sensitivity and Specificity

5. CONCLUSION

The investigation concludes the proficient performance of AI techniques on railway wheel condition diagnoses. Different standard measures are employedto evaluate the performance of implemented AI techniques. The results evident that LM technique associate with ANN exhibits accuracy-0.975, FDR-0.05, FNR-0.05, FPR-0.016, F1-Score-0.95, MCC-0.933, NPV-0.983, precision-0.95, sensitivity-0.95, specificity-0.983 which is superior performance over contest techniques. The proposed model diagnose the railway wheel conditions in four classes, this consequently direct the need of preventive maintenance. This research further extend by refurbish default ANN model to enhance their predicting performance.

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