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Structural Damage Detection in the Wooden Bridge Using the Fourier Decomposition, Time Series Modeling and Machine Learning Methods

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ABSTRACT

In this article, a novel approach has been employed to identify structural damage in the wooden bridge structure by utilizing vibration data. This method encompasses the Fourier decomposition method that decompose the response of the bridge into a sequence of Fourier Intrinsic Band Functions (FIBF). These functions comprise the responses of the structure that contain inherent information of structure as well as noise from the vibrations. The time series modeling is utilized to extract damage-sensitive features. The residuals of the time series model of both undamaged and damaged structures are extracted for detecting any damage. To ascertain the presence of damage, supervised classification machine learning algorithms are employed. The algorithms are utilized consist of Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), support vector machines (SVM), ensemble learning, and decision tree. The results indicate that the proposed method of feature extraction is highly effective and reliable in detecting damages. In addition, the capacity of decision tree and ANN algorithms to minimize type 2 error and enhance accuracy is demonstrated when evaluating different machine learning algorithms. The value of the type II error in the ANN model and the decision tree is equal to 13.85% and the accuracy of the model is 93.02%.

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1. Introduction

The process of condition assessment of structural system and damage detection using vibration data and vision data is called structural health monitoring (SHM) [1,2]. At the beginning, visual inspection methods were used to evaluate the performance and health of structures. With the advancement of technology in the production of vibration sensors, data acquisition devices and analyzers, the process of monitoring the health of the structure is carried out using vibration measured data [3–5]. Damage detection in the SHM process, in general, is investigated in four main phase, including early damage detection, location, severity, and predicting the life of the structure after the damage occurs [6,7]. In the first phase, the overall condition of the structure is evaluated. In other words, based on the results in this method, it is possible to find out the occurrence or non-occurrence of damage in the structure. In the second phase, after determining the structural damage, an attempt is made to identify its location of damage. Next, the severity of the damage is estimated at the different states. Finally, with the information obtained from the previous steps, the remaining life of the structure and its performance can be predicted. In the health monitoring of the structure, these steps can be done based on two general solutions, including methods based on the vibration data (data based) and methods based on a physical model of the structure (model based) [8]. In these methods, autoregressive models (AR) have been used for modeling and prediction of structures responses [9,10]. The coefficients and residuals of these models are considered as damage-sensitive features (features). After the characteristics of the structure's response are extracted, the damage is determined by machine learning algorithms (ML) or statistical methods [11]. These time series modeling are combined with signal processing methods like Empirical Mode Decomposition (EMD) [12,13] method to obtain much better features for the decision-making process. Recently, a new decomposition method called Fourier Decomposition Method (FDM) [14–16] has been proposed. This method decomposes the response into a set of vibrations called intrinsic band Fourier functions (FIBF). The first researches in time series modeling is belong to Fugate et al. [17] and Sohn and Farrar [18]. In both studies, AR modeling were used to model the acceleration-time responses, and finally, the coefficients and residuals of these model were extracted as damage-sensitive features. Sun et al. [19] used AR model coefficients to identify damage in a concrete column and damage-sensitive features. Figueiredo et al. [3] used four different methods, including Akaike information criterion (AIC), relative correlation function, root mean square error (RMSE), and singular value decomposition (SVD), which are used in the AR model to extract features, to identify damage in a three floors model. Stefano et al. [20] proposed a series of damage detection methods using the concept of multiple models, the AR parameters, unsupervised machine learning algorithms as well as dimensionality reduction methods. Latour et al. [21] fitted two AR models on time series data of a three-story bookcase and ASCE laboratory benchmark structure. The extracted coefficients of the models were used as a damage-sensitive features for the input of a classification artificial neural network (ANN). The non-stationary multicomponent signal analysis is used in many fields such as medical signal analysis [22], seismic signal analysis [23], vibration analysis [24,25] and sound processing [26]. Multicomponent signals generated by real physical systems include several signals, which are known as signal modes [27] and contain significant information of the system.

One of the disadvantages of traditional time series methods like EMD is the mixing of modes [28,29]. This mixing of modes causes a decomposed vibration to contain two or more main frequencies of the original vibration. Zheng et al. [30,31] by using the Fourier decomposition adaptive power spectrum method by comparing the frequencies obtained from the spectrum of each FIBF, were able to identify the possible failure. Using a similar method, Zhao et al. [32] were able to obtain the peaks of the Fourier decomposition spectrum in the rolling bearings of the machine. After analyzing the resulting vibrations, they were able to distinguish between undamaged and damaged conditions. Zhang et al. [33] used the FDM method to detect the failure of a gear wheel in a car gearbox. Yin et al. [34] proposed a damage detection method by combining relative entropy energy and mixed FDM. This method can be used to detect damage and reduce vibration noise. Yao et al. [35] used the FDM to detect damage in the gearbox of cars based on guided sound waves. Betti et al. [36] identified damage in the structure using four indices related to the frequency and shape of the structural modes. Feed-forward neural network with back propagation (BP) algorithm was used for identification and genetic algorithm was used for optimal calculation of neural network structure. Abdeljabr et al. [37] used one-dimensional convolutional neural network (1D-CNN) for damage detection. They proposed a vibration-based algorithm for structural damage detection based on adaptive one-dimensional convolutional neural network. In this article, a new feature extraction method based on signal decomposition method and time series modeling is presented. In the phase related to feature extraction, a FIBF signal representing the behavior of the structure is selected. Then, by the time series, the residuals of the time series model are extracted as damage-sensitive features. In the next step, algorithms are trained by undamaged and damaged structures features. These algorithms are trained and tested by classifications machine learning methods. Machine learning algorithms have been used in many fields of civil engineering. These algorithms have been used in topics related to regression and classification [38,39]. Finally, the accuracy of the proposed method is determined by various evaluating criteria.

2. Research significance

Based on the literature review and the proposed methods in the SHM, so far no data-based method has been presented that can detect damage in the structure using FDM and time series modeling. For this reason, in this article, by using structural response analysis in damaged and undamaged states and FIBFs with time series modeling, a reliable feature extraction is proposed. Also, the decision-making part of aforementioned strategy can be done using machine learning algorithms such as SVM, KNN, ANN, Ensemble learning and Decision Tree.

3. Methods

Using the Fourier decomposition method (FDM) [14], the responses of the structure are decomposed to obtain a series of FIBFs functions which can be effectively utilized for damage detection.

3.1. The Fourier decomposition method

The Fourier decomposition method is a new method for decomposing nonlinear and non-stationary signals based on Fourier Theory. In the FDM, each signal x(t) is decomposed into orthogonal signals, which are called Fourier intrinsic band functions, FIBFs. An analytical presentation of signal, x(t), can be expressed by

$$z(t) = x(t) + jy(t) = x(t) + j\,\mathrm{H}(x(t)) \tag{1}$$

Where y(t) is imaginary part of analytical signal, $j = \sqrt{-1}$ and $\mathrm{H}(\cdot)$ is the Hilbert transform of x(t). also x(t) can be written as below

$$x(t) = \sum_{k=1}^{K} G_k(t) \tag{2}$$

Where $G_k(t)$ is FIBFs of signal, x(t). Note that z(t) can expressed in Fourier series:

$$x(t) = a_0 + \frac{1}{2}\sum_{k=1}^{\infty}\left[(a_k - jb_k)\exp(jm\omega t) + (a_k + jb_k)\exp(m\omega t)\right] \tag{3}$$

Where $\omega_0 = 2\pi/T$ and:

$$a_0 = \frac{1}{T}\int_{t_1}^{t_2} x(t)dt\ ,\ a_k = \frac{2}{T}\int_{t_1}^{t_2} x(t)\cos(m\omega_0 t)dt\ ,\ b_k = \frac{2}{T}\int_{t_1}^{t_2} x(t)\sin(m\omega_0 t)dt \tag{4}$$

Equation (3) can be rewritten as below

$$x(t) = a_0 + \mathrm{Re}\{z(t)\} \tag{5}$$

In above equation, $z(t)$ analytic function is written as

$$z(t) = \sum_{k=1}^{\infty}(c_k)\exp(jm\omega t) \tag{6}$$

Also, for specific analytic FIBFs, $z(t)$ is written as follow

$$z(t) = \sum_{i=1}^{M} a_i(t)\exp(j\phi_i(t)) \tag{7}$$

From above equations, we can write general form of equation as

$$a_i(t)\exp\left(j\phi_i(t)\right)=\sum_{k=N_{i-1}+1}^{N_i} c_k \exp\left(jm\omega t\right) \tag{8}$$

This equation is for $i=1,\cdots,M$ and for FIBFs from high to low frequency, N_i. Initially, FIBF functions are extracted from the response of the undamaged structure, and subsequently, a suitable model is fitted on the function using time series modeling. After fitting a time series model for the undamaged structure, the residuals of the model are acquired. Proceeding further, the response of the damaged structure is analyzed using FDM and the appropriate FIBF function is selected. The FIBF function of the damaged structure is assessed with the time-series model of the undamaged structure, and the residuals are determined. Ultimately, by employing machine learning methods, the decision-making process pertaining to damage assessment is carried out.

In the figure 1 the flowchart of structural damage detection of the Wooden bridge in shown.

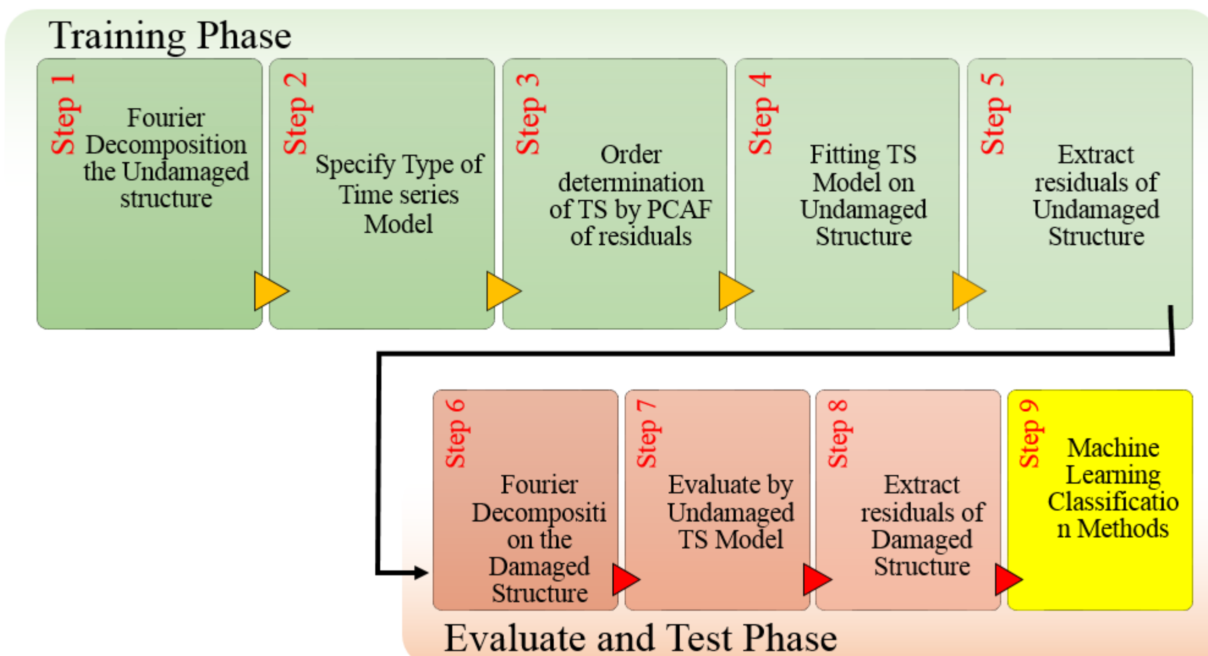


Fig. 1. Flowchart of Structural damage detection methodology.

4. Wooden bridge benchmark

The wooden bridge structure shown in Figure 2 is excited by a random excitation. Fifteen accelerometers measured the response of the structure in different positions. The sampling frequency was 256 Hz and the total duration of sampling was 32 seconds. The measurements were done during several days and damage was done in the structure by adding point masses on the structure. The mass sizes were 23.5, 0.47, 70.5, 132.2 and 193.7 gr. The added mass was very small compared to the total weight of the structure (36 kg) and the maximum mass increase was only half percent. Table 1 shows the damage states of this benchmark problem [40].

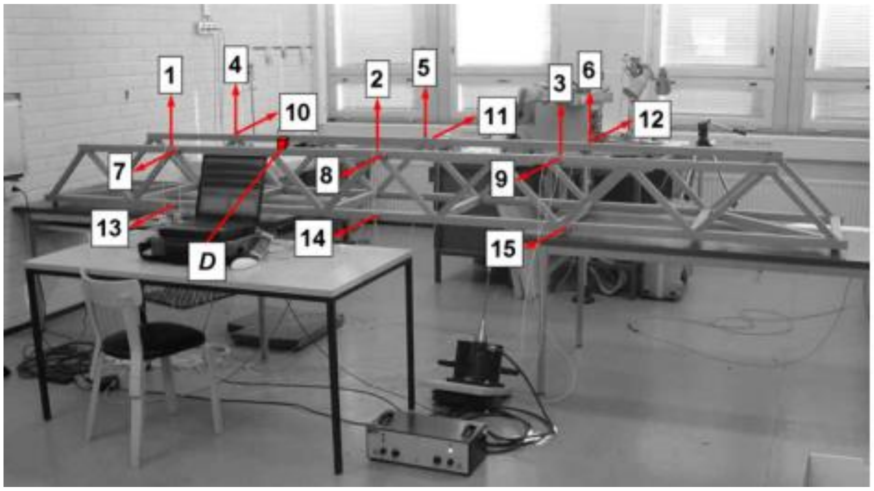


Fig. 2. The wooden bridge structure description and sensor locations [40].

Table 1
The wooden bridge damage conditions.

No	Test Day	Mass	Location	Condition	Description
1	18-May	-	-	undamaged	-
2	25-May	-	-	undamaged	-
3		23.5	sensor 1-2	Damaged	Scenario -1
4		47	sensor 1-3	Damaged	Scenario -1
5		70.5	sensor 1-4	Damaged	Scenario -1
6	28-May	123.2	sensor 1-5	Damaged	Scenario -1
7		193.7	sensor 1-6	Damaged	Scenario -1
8		-	-	undamaged	-
9		-	-	undamaged	-
10		-	-	undamaged	-
11		23.5	sensor 4	Damaged	Scenario -2
12		47	sensor 5	Damaged	Scenario -2
13	29-May	70.5	sensor 6	Damaged	Scenario -2
14		123.2	sensor 7	Damaged	Scenario -2
15		193.7	sensor 8	Damaged	Scenario -2
16		-	-	undamaged	-

5. Results

5.1. Signal decomposition using FDM

The acceleration response of the structure is decomposed into FIBF functions using the FDM. After the structural response is decomposed, one of the FIBFs that has the highest correlation with the original acceleration signal is selected. In the following, the entire feature extraction and damage detection process is performed on this signal. Figure 3 shows the acceleration response of the decomposed undamaged wooden structure.

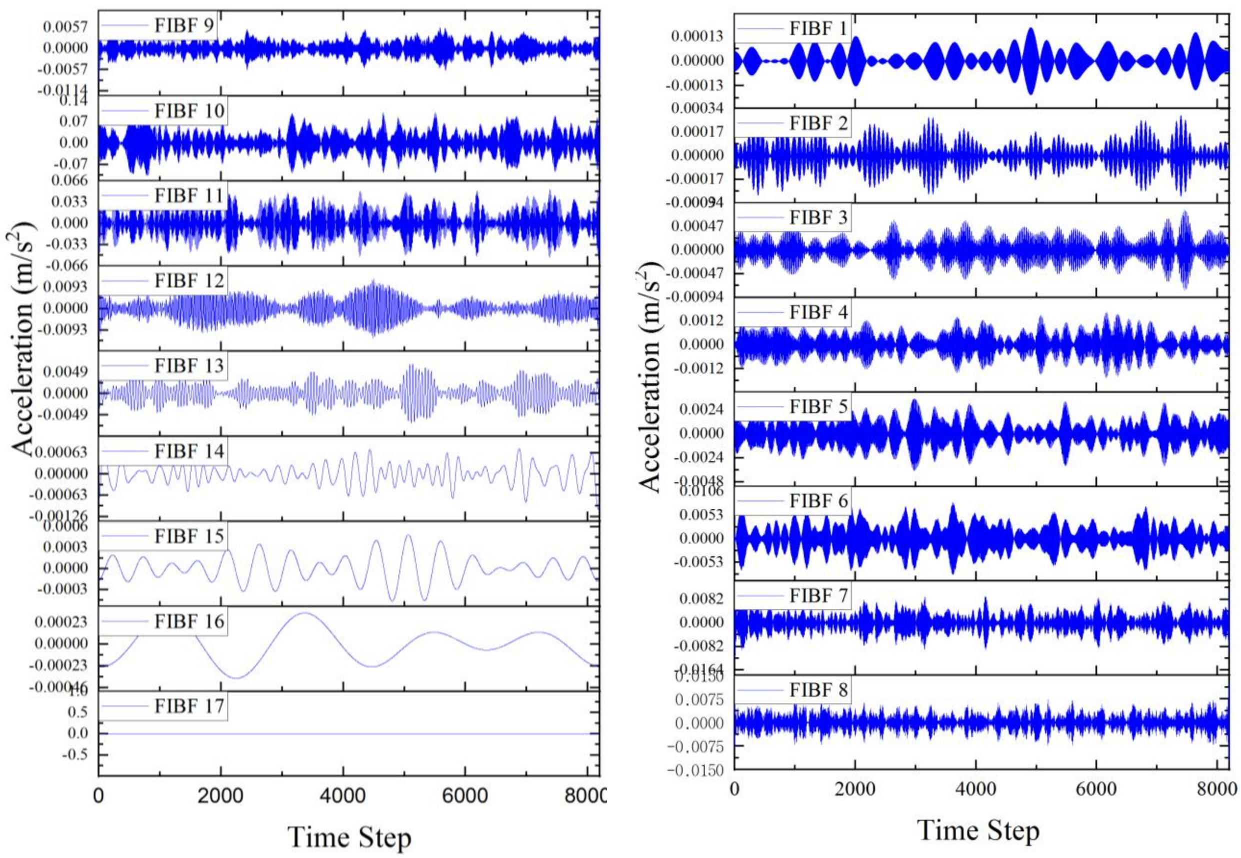


Fig. 3. The FIBFs for undamaged structure.

The response of the wooden bridge structure in the undamaged state is divided into 17 FIBFs. According to the correlation coefficient in this case, FIBF No. 7 has the highest correlation coefficient. In the following, this FIBF is considered in the wooden bridge structure.

5.2. Time series modeling

After examining the acceleration response of the structure in its original condition, the autocorrelation function (ACF) and partial autocorrelation function (PACF) diagrams of the data are generated (Figures 4 and 5). The ACF curve exhibits oscillatory behavior and does not converge to zero, while the PACF curve changes exponentially. The most suitable model for the time series is the AR model. Hence, by employing the AR model, a time series function can be applied to the decomposed response of the wooden bridge structure [41].

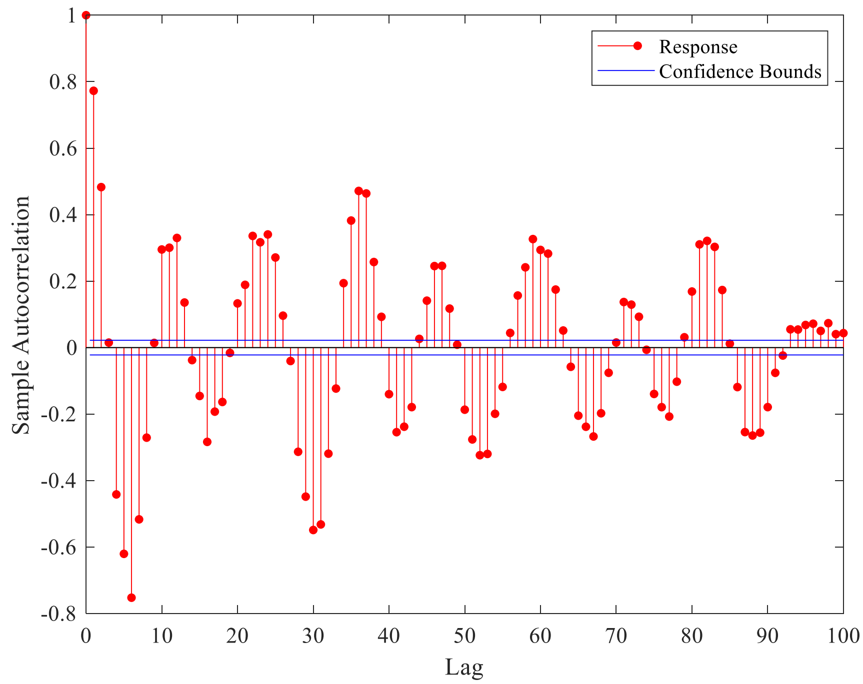


Fig. 4. ACF plot of FIBF number 7.

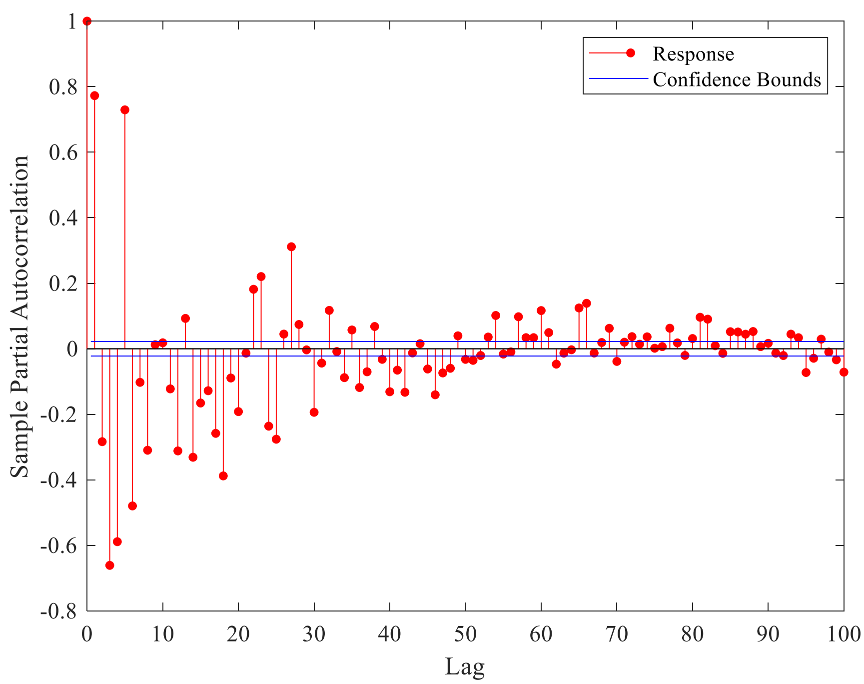


Fig. 5. PACF plot of FIBF number 7.

After the degree of AR function is determined, a time series function is fitted. After fitting the time series model, the normal curve of the residuals and the ACF for the AR model with degree 68 with the lags of 100 are shown in Figure 7.

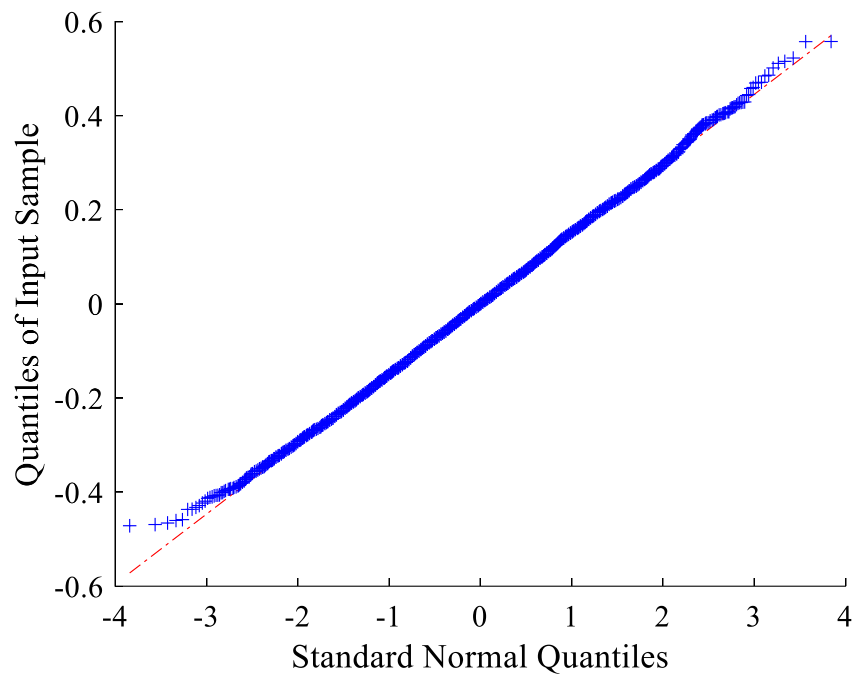


Fig. 6. The Normal plot for AR (65) residuals.

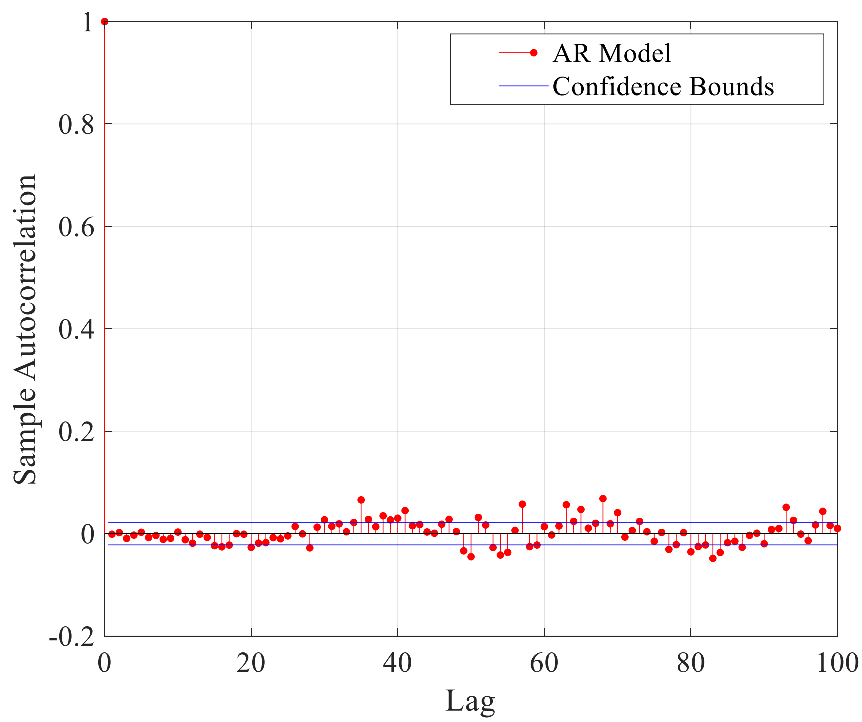


Fig. 7. The ACF plot for AR (65) residuals.

As observed, the distribution of the residuals follows a normal pattern, which is a key indicator that the AR model is fitting appropriately. In a normal distribution, data points up to three times the standard deviation lie on the normal curve without any deviation. The autocorrelation function of the fitted time series model falls within the confidence level. Considering that the delayed points of the function also fall within the statistical confidence level, it can be concluded that the correct model has been chosen. There are some points that lie outside the range of confidence, but they do not pose any problems for the entire modeling process or the degree of modeling.

In order to utilize machine learning models, it is necessary to identify the model hyper-parameters. Many machine learning models consist of a series of internal parameters, and modifying these parameters can significantly impact the algorithm's response and performance. These parameters are known as hyper-parameters, and they need to be carefully selected in order to minimize errors and optimize learning performance. However, setting these parameters can be a time-consuming process that often involves trial and error. For instance, in neural network models, the internal parameters include the number of hidden layers, the activation function type, the layer size, and the lambda parameter. The optimal values for these parameters can be found through trial and error or by utilizing optimization algorithms. In this section, machine learning models such as SVM, KNN, Ensemble learning, ANN, and decision Tree are employed. Since configuring the parameters of these models requires trial and error, the Bayesian optimization method is utilized to determine the optimal values. The selected hyper-parameters and their corresponding optimal values are presented in Table 2.

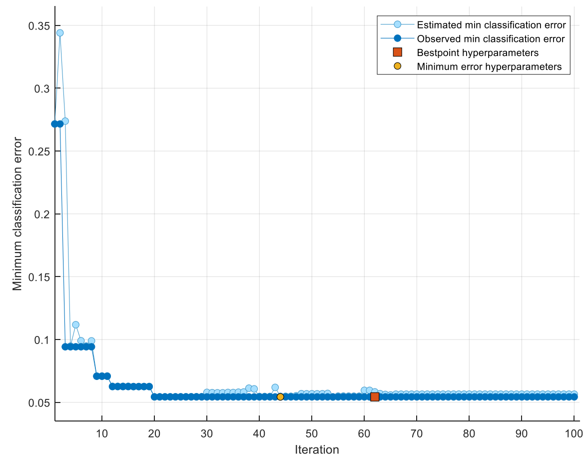
Table 2
Hyper-parameters optimization ranges and parameters.

Model	Hyper-parameter	Ranges and options	Optimum Values or parameters
SVM	Multiclass level	One-vs-one, One-vs-All	One-vs-one
	box constrain	[0.001,1000]	0.0437
	Kernel function	Gaussian, Linear, Quadratic, Cubic	Cubic
	Standardize data	Yes, No	True
KNN	Number of neighbors	$[1, max(2, round(n/2))$	63
	Distance method	Euclidean, City Block, Chebyshev, Minkowski (Cubic), Mahalanobis, Cosine, Correlation, Spearman, Hamming, Jaccard	City Block
	Distance weight	Equal, Inverse, Squared Inverse	Squared inverse
	Standardize data	Yes, No	True
Ensemble Learning	Ensemble method	AdaBoost, RUSBoost, LogitBoost, GentleBoost, Bag	Bag
	Learners number	[10,500]	26
	Number of predictor to sample	$[1, max(2, p)]$	1
	Maximum number of splits	$[1, max(2, n-1)]$	74
ANN	Number of fully connected layers	1, 2, 3	1
	Activation functions	ReLU, Tanh, None, Sigmoid	ReLU
	Standardize data	Yes, No	Yes
	Regularization strength (Lambda)	$[1e-5/n, 1e5/n]$	7.1852e-4
	First layer size	[1,300]	26
Tree	Maximum number of splits	$[1, max(2, n-1)$	2
	Split criterion	Gini's diversity, Towing rule, Maximum deviance reduction	Maximum deviance reduction

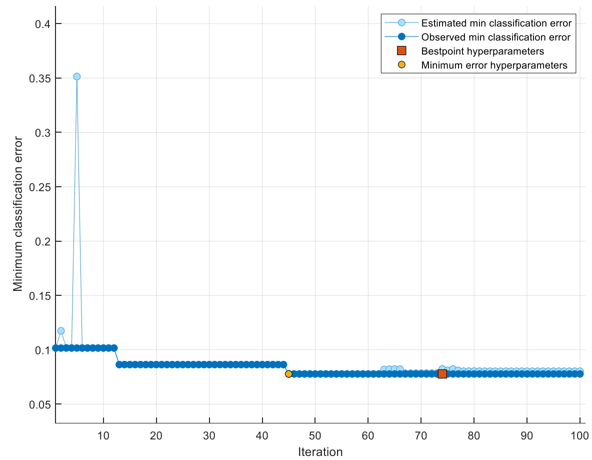
Figure 8 shows the optimization process and classification error in different models for 100 iterations. The estimated minimum classification error of the light blue line corresponds to the estimate of the minimum classification error calculated by the optimization process considering all the sets of hyper-parameter values that have been tried so far, including the current iteration. The minimum observed classification error of the dark blue line corresponds to the minimum observed classification error calculated so far by the optimization process. For example, in the third iteration, the dark blue point corresponds to the minimum classification error observed in the first, second, and third iterations.

In the case of the SVM model, the parameter optimization error of zero value has been reported, which means that the hyper-parameters of the model have been selected in the most optimal possible state. The duration of optimizing hyper-parameters in the decision tree model is less than all models, and the duration of the neural network model is the highest. The number of iteration for all models was chosen equal to 100, but the number of parameters to be optimized are different in the models. In the decision tree, two hyper-parameters include criteria and the number of split, and in the neural network model, five hyper-parameters include the number of layers, size of layers, activation function, data standardization, and Lambda coefficient. Therefore, the number of hyper-parameters that must be optimized is directly related to the required time. Figure 9 shows the confusion matrix for all models in the wooden bridge structure. All confusion matrix are presented for test data (damaged data).

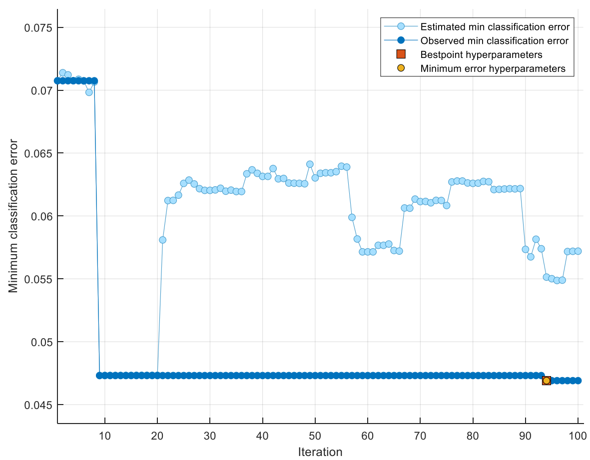
In the trained SVM model, there is no classifications error in the undamaged part of the structure, but there is a 14.1 % classification error in the damaged state of the structure. In the KNN model, the classification errors for test data is 25%. This shows that this model could not classify the damaged structures very well. In this case, about 25% of the data have a Type II error, which is a large value. This error occurred in the case of test data, which is why the model may suffer from errors that lead to the destruction of the structure and high costs in the decision-making process. In the ensemble model, in the case of test data, the accuracy value decreased to 82.8% and the classification error value increased to 17.2%. In the ANN model, in the state of test data, the accuracy value is 85.9% and its error is 14.1%. The errors in the neural network model is similar to the SVM model, which has the same performance. Regarding the decision tree model, in the testing data, the Type II error is similar to SVM and ANN models, which is lower than other models.



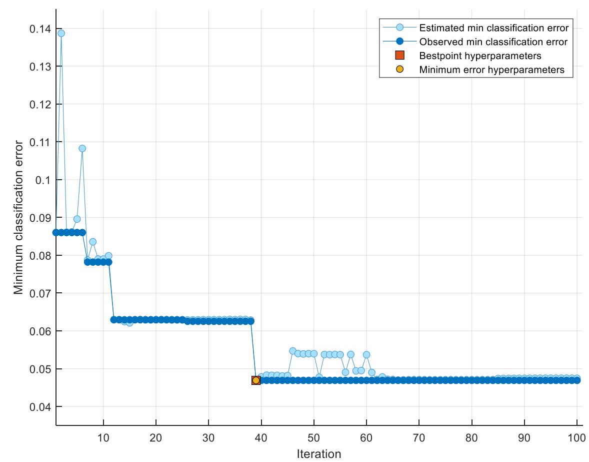
SVM



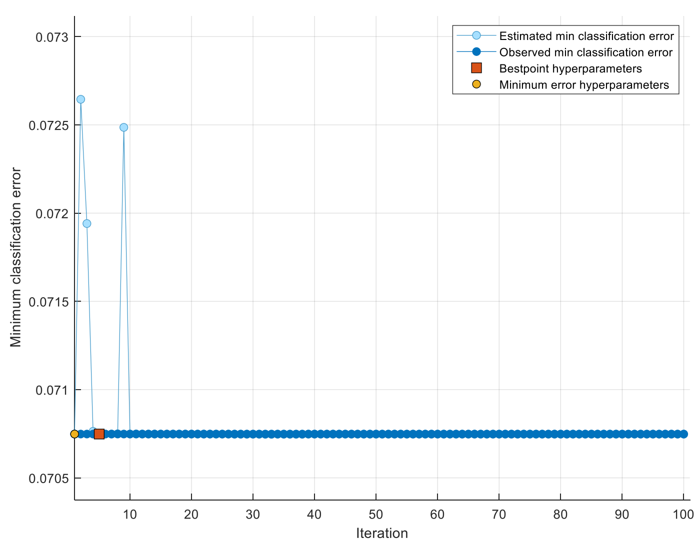
KNN



Ensemble Learning



ANN



Decision Tree

Fig. 8. Minimum classifications error for machine learning methods.

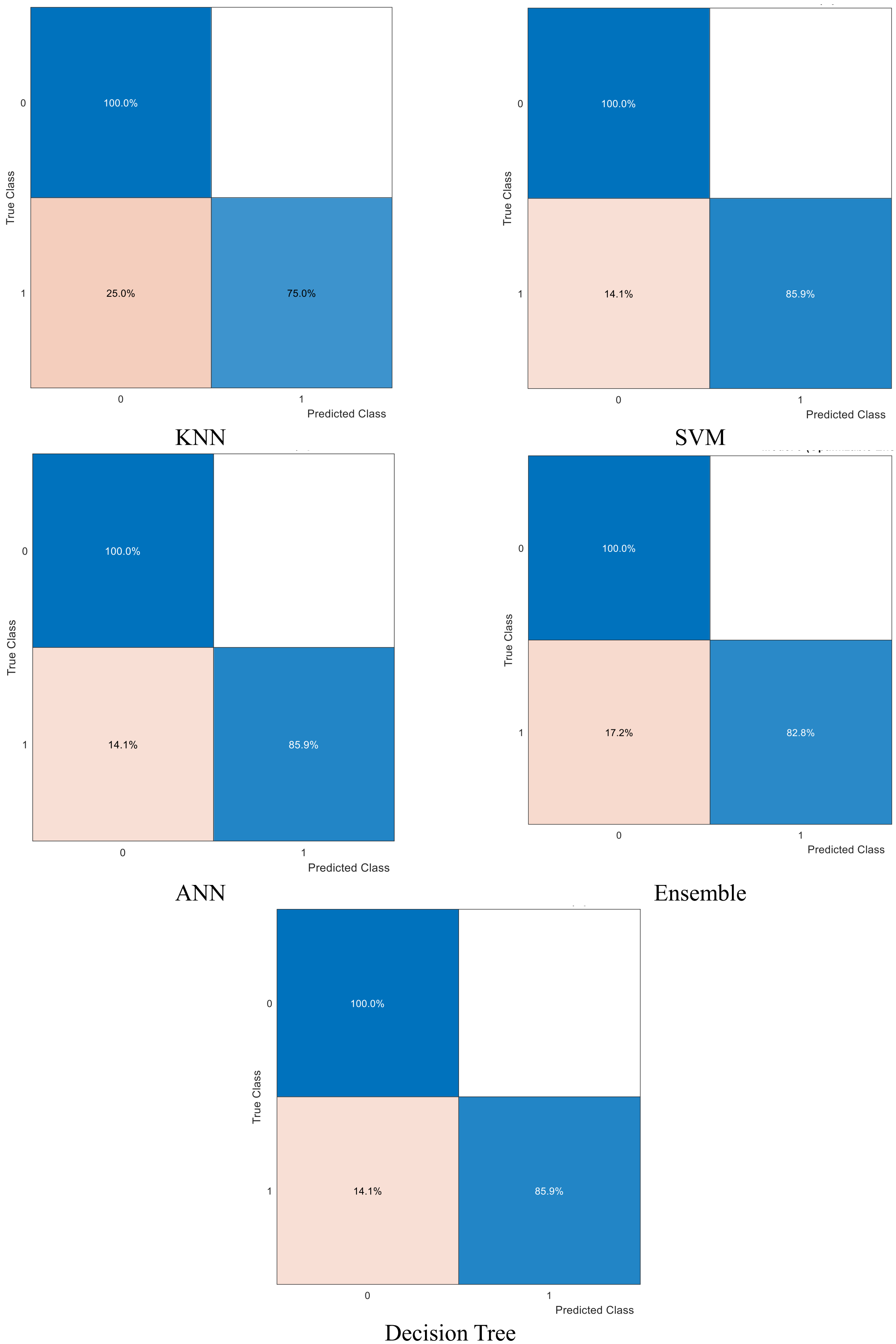


Fig. 9. Confusion matrix for machine learning methods for wooden bridge.

6. Discussion

The parameters of sensitivity (TPR), specificity, accuracy, precision (PPV), F score criterion and the area under the curve are defined based on equations 9 to 14 [42].

$$Sensitivity = \frac{TP}{TP+FN} \quad (9)$$

$$Specificity = \frac{TN}{FP+TN} \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (12)$$

$$F - Score = \frac{2 \times sensitivty \times precision}{sensitivty + precision} \quad (13)$$

$$AUC = Area\ under\ the\ ROC\ curve \quad (14)$$

The criteria of sensitivity, specificity, accuracy, precision, F score criterion and AUC for all wooden bridge structure models were calculated and listed in Tables 3.

Table 3
Evaluations criterion for machine learning methods.

Validation	Sensitivity	Specificity	FPR	Precision	Accuracy	FSC	AUC
SVM	1.0000	0.8594	0.1406	0.8767	0.9297	0.9343	0.9773
KNN	1.0000	0.7500	0.2500	0.8000	0.8750	0.8889	0.9858
Ensemble	1.0000	0.8281	0.1719	0.8533	0.9141	0.9209	0.9718
ANN	1.0000	0.8615	0.1385	0.8767	0.9302	0.9343	0.9692
Tree	1.0000	0.8615	0.1385	0.8767	0.9302	0.9343	0.9297

From the table 2, it can be seen that the sensitivity of all models is the same, which of course shows that the structures without damage are correctly classified in the experimental model. This shows that one should not use only one evaluation criterion to evaluate the models and consider other performance criteria as well. Neural network and decision tree models have similar performance in terms of properties, false positive rate, accuracy, precision and F score criterion have performed better than other models. At this stage, the worst performance is related to the KNN model. In Figure 10, these criteria are shown as radar curves.

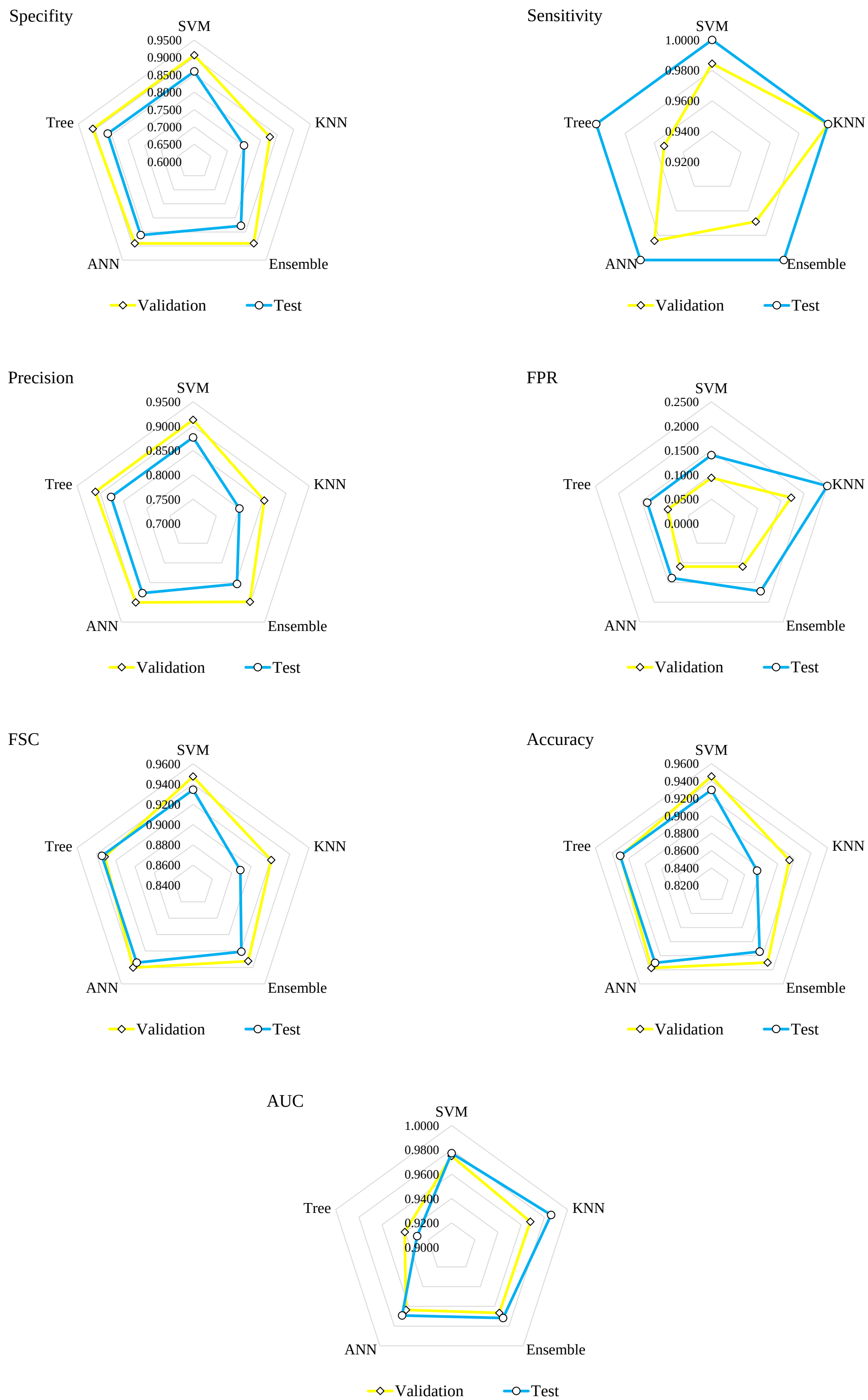


Fig. 10. The radar curves for evaluation criteria for different models.

It can be seen in the sensitivity curve that all the points are unity and it shows that the structures without damage (TP) are well classified. In this example, sensitivity is not a suitable criterion for comparing the results, and other criteria are used. A proportion of the damaged class (TN) that are correctly classified determines the specifity. In this case, the neural network and decision tree models worked well and the KNN model did not have an acceptable performance. The false positive rate (FPR), which indicates the misclassification of damaged structures in the undamaged class, is also minimal in neural network and decision tree models. These models have less Type II error than other models. For example, the KNN model has a Type II error of 25%, which indicates that a quarter of the data has been misclassified. Regarding the accuracy parameter, it can be seen that in all models, except for KNN, the model was able to perform the classification well. The F score criterion, which has both sensitivity and specificity parameters, has similar and good performance in neural network, decision tree, and SVM models compared to other models.

7. Conclusions

In this article, a new feature extraction method was introduced using Fourier decomposition and time series modeling. This method can provide damage-sensitive features for structural health monitoring. Supervised machine learning models were used in the decision-making stage. These models include ANN, decision tree, SVM, KNN and ensemble method. Based on the analysis, the following results were obtained:

- By utilizing FDM, the signal of the structure, inclusive of noise, decomposed into FIBF functions, hence separating these noises from the vibration of the structure.
- With applying time series modeling with degree 68, distribution of the residuals was random and followed the normal distribution. Additionally, ACF of the residuals was within the limits of statistical threshold.
- The utilization of the Bayes algorithm is efficacious in optimizing hyper-parameters of machine learning algorithms.
- The classification accuracy of all machine learning algorithms was satisfying. However, in the case of the KNN model, the type II error was 25%, indicating that this model has a considerable amount of error.
- The neural network and decision tree models have more properties than other models, with the false positive error being the lowest in these models.
- The neural network and decision tree models had the highest the F-score criterion, whereas the nearest neighbor model had the highest value for the AUC.
- According to the analysis, unsupervised learning method such as clustering can be used in future research. Also, this method can be used in the online structural health monitoring process for early damage detection in the structure.

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Conflicts of interest

The authors declare no conflict of interest.

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