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Research paper

Structural Health Monitoring using Varied Machine Learning Algorithms

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Abstract

Structural Health Monitoring is essential in today's world where large amount of money and labour are involved in building a structure. There arises a need to periodically check whether the built structure is strong and flawless, also how long it will be strong and if not how much it is damaged. These information are needed so that the precautions can be made accordingly. Otherwise, it may result in disastrous accidents which may take away even human lives. There are various methods to evaluate a structure. In this paper, we apply various classification algorithms like J48, Naive Bayes and many other classifiers available, to the dataset to check on the accuracy of the prediction determined by all of these classification algorithms and ar-rive at the conclusion of the best possible classifier to say whether a structure is damaged or not.

Keywords: *SHM, Machine Learning Algorithms, WEKA.*

1. Introduction

Structural Health Monitoring is not confined to civil structures but also mechanical and aerospace which also includes a lot of cost and labour in building a structure. The damage detection strategy monitors change in material and geometric properties. The main objective of Structural Health Monitoring is to enhance the performance of existing structures, monitoring the effect of external factors on structures and aiding in taking precautionary measures to avoid disastrous accidents. Steps in Structural Health Monitoring include: (1)Determining the existence of damage, (2)Identifying the location of damage, (3)Quantifying the severity of damage, (4) Life span prediction of the Structure. There are many ways in which SHM can be done in practice. These methods include: Visual Inspection, Non-Destructive Evaluation(NDE), Static-Based SHM and Vibration-Based SHM. Each of these methods is having it's own ad-vantages and disadvantages. In case of Visual Inspection, we can say that it is subjective that is non-quantitative and fully experience based. When we discuss about NDE, it is time-consuming, costly, requires priori knowledge of the damaged region and high degree of expertise, also labour intensive and risky. Static-Based SHM is based on the premises that damage will alter the static properties of the structure like displacements, rotations and others. The drawback of this method is that considerable static deflection requires large amount of static force. Vibration-Based SHM is based on the premises that structure's dynamic properties will be altered due to the damage like structural response, frequencies, mode shapes and others. It can be done either in modal domain or physical domain. Among the various forms of dynamic structural responses like displacement, velocity, acceleration and strain, the one that has to be measured depends on the monitoring conditions and objectives. Different sensors are available based on what is to be measured. These include Laser Displacement Sensors, Velocity Transducers, Seismometers, Piezoelectric Accelerometers and Strain Gauges.

There are two types of techniques in Vibration-Based SHM. They are Model-Based techniques and Data-Based techniques. The Model-Based technique is based on the physical models of the structures. This technique allows dam-age detection, damage location identification, dam-age type estimation and also to estimate the structure's remaining life. It also has some drawbacks like requiring high expertise, too many unknowns, computationally expensive and modeling assumption induced errors. The Data-Based technique is based on statistical model of the features rather than on physical models of the structures. This technique does not require high expertise, free from modeling assumption errors, highly computationally efficient and ideal to understand using machine learning knowledge. This technique also has some drawbacks like it requires sufficient data to be available since it uses statistical model and it can only reach upto the second level of hierarchy in damage detection which is damage location, since it does not use physical model. Some barriers in SHM today are Conventional cables, High installation costs, Size and complexity of large Structures, Vulnerable to noise and Vulnerable to earthquake conditions. Structures can be measured based on acceleration, strain, climatic conditions, curvature, Displacements, load, Slope and Scour. By measuring these parameters, we can identify corrosion, cracking, Strength and Tension.

In this paper, we discuss about various metrics to evaluate the structure and the best classification algorithm that provides the highest value for this evaluation metric.

Here we discuss the accuracy produced by various evaluation methods for a given data set and predict which method produces the best required accuracy under which conditions. For this purpose we use data mining tool called WEKA which represents the data in various forms and shows the accuracy based on the parameters like TPR, FPR, precision, recall, ROC area, F-

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measure, PRC area and many other parameters resulted from all the methods.
Also it shows the percentage of data instances classified correctly and those classified wrongly based on the class types mentioned in the dataset. Among the various parameters derived by using the tool we use only accuracy information for our discussion. The reason for selecting accuracy as the parameter of discussion is that it shows how accurately the particular method produces the result.

2. Related Work

In [1], Tatsuki Fujiwara et al proposed the use of MSMA with SDR processing delay for time synchronization in wireless sensor networks. The need for time synchronization arises due to the fact that the structure is sensed at multiple points by various sensors and at any time. In [2], Nilajan Mallik et al proposed that Neural network with Fiber optic sensors can be deployed for predicting the damage location in addition to predicting whether it is damaged or not. Also it uses back propagation algorithm and He-Ne laser for this application. The reason that Fiber optical sensors are used instead of traditional sensors is that it is lightweight, installation is easy, durability and multiplexing capability. In [3], a brand new prototype called NetSHM for implementing SHM applications with much greater abstraction is introduced. This is a reusable software which achieves efficiency in energy usage by processing the raw sensor data locally at the sensors. It explains the proposed NetSHM Architecture elaborately that has two lackings as duty cycling and concurrent execution of SHM applications. In [5], Panos Sak-kos et al proposed a SHM model where mobile de-vices are used for decentralized computation and distributed node clustering. The computation and storage capabilities of mobile devices compel to utilize them in Structural Monitoring. In [4], Halit Kaplan and Tarik Ozkul proposed a novel fatigue sensor used in monitoring mechanical systems that has been employed. In[6], the structure is monitored on the basis of wind flow around the structure and the vibrations caused by it. It makes use of an accelerometer, an anemometer which is a wind-direction sensor and Compact RIO, a data acquisition hardware. In [7], Satyam Paul and Wen Yu have proposed modeling bidirectional excitations and some intelligent techniques that can be implemented under bidirectional forces.
In [8] Mohamoud .,et al presented technique for monitoring structures using Multivariate Statistical Process Control(MVSPC) based on Artificial Neural Networks. .In [9],Chong monitored structures and got better precision using genetic algorithms In [10], Arkaprabha conducted a survey for prediction of anxiety and depression using different machine learning algorithms in WEKA. In [11], Siva ., et al developed an innovative Non-Destructive Evaluation(NDE) using vibrational energy of PZT sensors to monitor the health of the structures. Following this Arthur .,et al [12] used Discrete Wavelet Transform along with Artificial Immune System improving the NDE meth-od. In [13], Adam .,et al conducted a survey for comparing various algorithms deployed for SHM along with discussion on the challenges faced in the design of network. In [14], Sarfraz Nawaz .,et al deployed a sensors to monitor the excavation site and discussed the challenges they faced thereby urging the need for improvising the current protocols.

3. Proposed Setup

The data set is taken from [15] .The 3 storey-building was monitored with a load cell (channel-1)and four accelerometer (channel 2-5).The ana-log signals were converted into digital values at a sampling rate of 2560Hz followed by down sampling at a rate of 320Hz.The data was collected every 3.125 ms, resulting in 8192 samples contributing a single instance. Similarly 170 instances of data were collected, which were classified into 17 states among which 1-9 were damaged and 10-17 were undamaged. The average of the data samples pertaining to the single instances were taken to re-duce the volume of data, resulting in 170 data sets which were labelled as D(Damaged) or U(Undamaged) according to the states they belong to. This data is converted into desired CSV file. The training set was provided to WEKA Evaluator and tested using different binary classifier algorithms using a ten-fold cross validation.

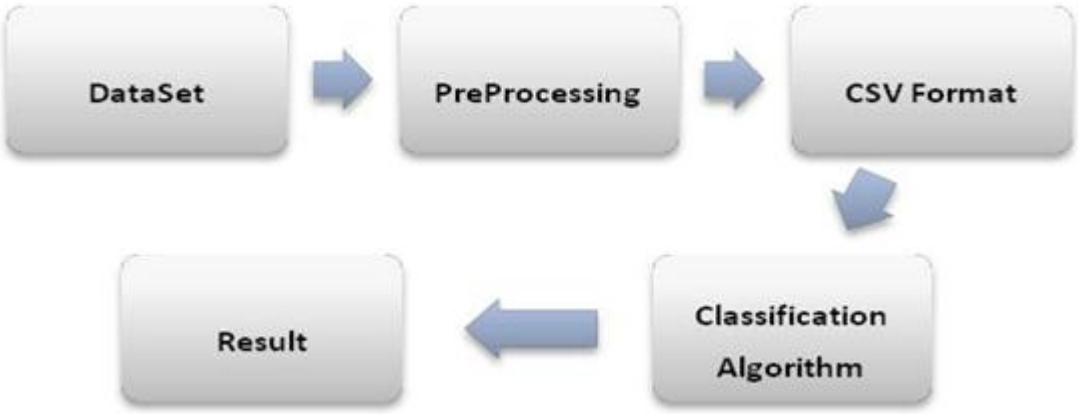

Fig. 1: Proposed method

4. Experiments and Results

4.1 Experimental Setup

The following parameters True Positive Rate (also known as Recall, fraction of those that are actually classified Undamaged.), False Positive Rate(fraction of wrongly classified damaged to total number of actually damaged),Precision (fraction of relevant instances), F-measure(weighted harmonic mean of precision and recall), Matthews correlation coefficient(measure of the quality of binary classifications) were observed using the formulas given in table 1.The confusion matrix summarises the correctness of the classifier with respect to the actual results. The format of the confusion matrix in given in table 2.

TUD:	True Undamaged	number	of	instances
	categorized undamaged that		are	actually
	undamaged			
FUD:	False Undamaged	number	of	instances
	categorized undamaged that are actually			

	damaged			
TD:	True Damaged	number	of	instances
	categorized damaged that are actually dam-			
	aged			
FD :	False Damaged	number	of	instances
	categorized damaged that are actually un-			
	damaged			

Table 1: Calculation of Parameters

Parameters	Formula
TPR(Recall)	$TPR = \frac{TUD}{TUD+FD}$
FPR	$FPR = \frac{FUD}{FUD+TD}$
Precision	$Precision = \frac{TUD}{TUD+FUD}$
F-Measure	$F - Measure = 2 * \left(\frac{Precision * Recall}{Precision + Recall}\right)$
MCC	$MCC = \left(\frac{TUD*TD-FUD*FD}{\sqrt{(TUD+FUD)(TUD+FD)(TD+FUD)(TD+FUD)}}\right)$

Table 2: Confusion Matrix Format

Actual \ Predicted	Yes	No
Yes	TUD	FD
No	FUD	TD

4.2 Experimental Analysis

Binary Classification algorithms under each category was considerd for classifying the dataset. The best ten algorithms along with the details are listed in the table below. In OneR classification algorithm, a single rule for each predictor is calculated from which the rule with minimum or null total error is selected for classification.

Table 3: Comparison of Different Classifiers

Algorithm	TP Rate	FP Rate	Precision	F-Measure	MCC	Accuracy
OneR	**0.853**	0.15	0.853	0.853	0.705	**85.2941**
Random Forest(RF)	**0.853**	**0.145**	0.855	0.853	0.707	**85.2941**
LMT	0.835	0.162	0.838	0.835	0.672	83.5294
J48	0.829	0.171	0.83	0.829	0.658	82.9415
RandomCommittee(RC)	0.829	0.171	0.83	0.829	0.658	82.9412
ClassificationViaRegression(CR)	0.824	0.171	0.829	0.824	0.653	82.3529
Jrip	0.824	0.176	0.824	0.824	0.647	82.3529
Random Subspace(RS)	0.824	0.174	0.826	0.824	0.649	82.3529
REPTree	0.8	0.206	0.801	0.799	0.598	80
Kstar	0.766	0.214	0.789	0.776	0.566	77.6471
NaiveBayes	0.429	0.56	0.434	0.429	0.425	42.94

Table 3: Derived Confusion Matrix

Category	Algorithm	Classified (U)	Classified (D)
Bayes	NaiveBayes	79	11
		14	66
Lazy	Kstar	63	27
		11	69
Meta	Classificationvia Regression	70	20
		10	70
	Random Committee	75	15
		14	66
	Random Subspace	72	18
		12	68
Rules	Jrip	74	16
		14	66
	OneR	79	11
		14	66
Trees	J48	75	15
		14	66
	LMT	73	17
		11	69
	Random Forest	75	15
		10	70
	REPTree	76	14
		20	60

Random Forest algorithm which tries to reduce the overfitting i.e low bias and high variance, by taking average of multiple deep decision trees which are trained on the same training set. Logistic Model Tree(LMT) is a classification algorithm which combines

logistic regression and decision tree learning in which leaves have the logistic regression functions.J48 can account for missing values ,pruning of decision trees and rules derivation. Applying J48 on new dataset record will help in predicting the target variable accurately. Kstar is an instance based classifier which uses an entropy-based distance function. For a test instance to be classified in Kstar, it must have a similar training instance. NaiveBayes classifier uses Bayes' Theorem for making predictions by deriving the probability of prediction from the observed data. It can be used for both binary and multi-class classification problems. REP Tree is a fast decision tree learner. It builds a decision tree using variance information and prunes it with reduced- error pruning. JRip is one of the most popular algorithms which examines classes in order of their increasing sizes and an initial set of rules is generated. Random Subspace classifier chooses random samples of features rather than the entire training set to reduce correlation. The values obtained for parameters like TP rate, FP rate, Precision, F-Measure, MCC, Accuracy with respect to these algorithms are listed in Table 3.

Among the various classification algorithm OneR and Random Forest Algorithms gives high percent-age of correctly classified instances i.e 85 %. LMT algorithm provides 83% correctly classified instances. Whereas Algorithms like J48, Random Committee, Classification Via Regression, Jrip ,Random Subspace gives 82% of correctly classified instances. The higher TP rate of 0.853 is obtained in both OneR and Random Forest but l FP rate is lower in Random For-est (0.145) than OneR(0.15). From the confusion matrix table it is clear that OneR has high TUD instances (79) among all the other algorithms. Whereas TD instances are higher in Random Forest. On the whole Tree based algorithms gives better results for the given dataset than other algorithms. We have provided figure 2, a pictorial representation of the comparison of these classifiers based on the parameters explained in Table 3.

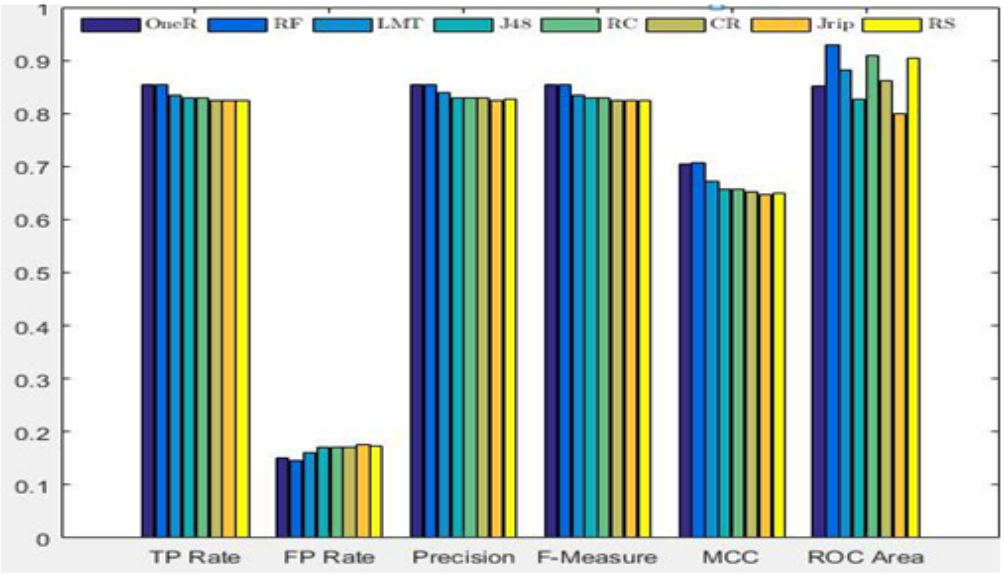

Fig. 2: Comparison of values for various algorithms

5. Conclusion

The dataset of three storey building was taken from [15] .After volume reduction the dataset was analyzed using WEKA. This paper gives a comparative analysis of different classification algorithm and their performance based on the measures like TP rate, FP rate, Precision, MCC, ROC Area. The best and optimal algorithms for the considered dataset are identified to be OneR and Random Forest which gives 85% of correctly classified instances. This method can be adopted to any kind of dataset and thus any structure can be monitored effectively.

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