Let's Vibrate with Vibration: Augmenting Structural Engineering with Low-Cost Vibration Sensing

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ABSTRACT

Using low-cost piezoelectric sensors to sense real structural vibration exhibits a great potential in augmenting structural engineering, which is yet to be explored in the literature to the best of our knowledge. An example of such unexplored augmentation include classifying diverse structures (such as building, flyover, foot over-bridge, etc.). To explore these aspects, we develop a low-cost piezoelectric sensor based vibration sensing system aiming to remotely collect real vibration data from diversified civil structures. We dig into our collected sensed data to classify five different types of structures through rigorous statistical and machine learning based analyses. Furthermore, we design a light-weight Convolutional Neural Network architecture and perform necessary hyperparameter tuning to achieve better accuracy in classification. Our analyses achieve a classification accuracy of up to 97% with an F1 score of 0.97.

1. Introduction

In the domain of Structural Engineering, vibration pattern of civil structures exhibits applications in diversified areas such as designing architectures of the structures, Structural Health Monitoring, occupancy estimation, etc., [1, 2]. In the case of designing architectures, every structure follows specific vibration criteria that should be fulfilled when designing the structure. Concrete structures such as building, concrete foot overbridge, etc., are generally considered to generate less vibration. On the other hand, steel foot overbridge, suspension bridge, etc., generate more vibration. These characteristics are very crucial when designing the architecture of a structure as misinterpretation of any of the characteristics or even ignorance of any of them may result in possible damage or structural health hazard in future.

Due to the importance mentioned above, the dynamics of structural vibration has been investigated by several recent research studies [3, 4, 5, 6]. However, these approaches lack some important considerations. Most of the existing studies consider a single structure, i.e., bridge, building, railline, wind turbine, machine structures, etc., [7, 8, 9, 10]. However, a study covering diverse civil structures is yet to be explored in literature to the best of our knowledge. There exist research studies on implications of vibration generated by civil structures, e.g., structure and machine fault classification, engine classification, human identification, etc., from the pattern of vibration [3, 7, 11, 12]. However, classifying diverse structures from their vibration patterns is yet to explored in literature. The relation only pertains to *frequency* domain specially applicable for vibration data collected using high-cost sensors [2]. It is yet to be explored how the relationship would be in the case of vibration data collected using low-cost sensors. Moreover, it is important to know whether the relationship in the case of vibration data collected using low-cost sensors would work in the conventional *frequency* domain or it would get shifted to any other domain (such as the *time* domain).

Keeping all these considerations in mind, in this paper, we present a novel approach of classifying diversified civil structures based on their generated vibration. To do so, first, we devise and develop a low-cost piezoelectric vibration

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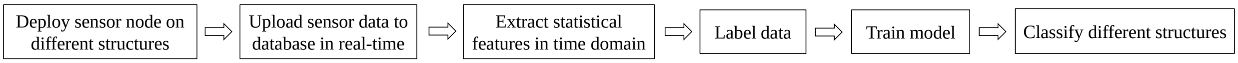
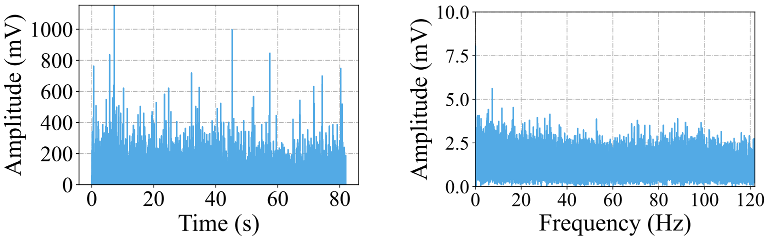


Figure 1: Illustration of our proposed methodology on classifying structures.



(a) Time domain (b) Frequency domain

Figure 2: No significant frequency component after FFT

sensing module. Using the vibration sensing module, we build a diverse dataset through sensing vibration from five different types of civil structures after a year-long on-field data collection. We show that there is a significant difference in vibration generated by different types of civil structures and the structures can be classified based on their generated vibration patterns. To the best of our knowledge, this finding is yet to be revealed in the literature.

The overall methodology of our study includes developing a customized sensing system, deploying the sensing system in real environment, sending vibration data to cloud and storing the vibration data there, visualizing the data on a real-time dashboard, performing statistical and machine learning based analyses for structure classification Here, for our machine learning based classification, we perform feature selection according to correlation and regression. Further, for Deep Learning based analysis, we perform hyperparameter tuning, i.e., tuning batch size, kernel size, number of filters, and activation function.

Based on our study, we make the following set of contributions in this paper.

- We design and develop a low-cost vibration sensing module using piezoelectric sensor. Using the sensing module, we collect real vibration data from 12 different civil structures having five different categories through a year-long on-field study.
- We classify the five categories of civil structures based on their generated vibration through statistical and machine learning based analyses. Further, for achieving better accuracy, we develop a customized Deep Neural Network and utilize it for the classification task.

Our contribution in classifying structures from their *time* domain vibration may contribute in future in the field of SHM through classifying faults in structures. In this study we have not devised any SHM solution, rather proposed a new aspect of structure classification which may contribute to the *time* domain signal processing in SHM.

2. Related Work

In this section, we discuss existing studies in the field of vibration and its applications.

2.1. Vibration source detection

There have been several studies on detecting the source of vibration through different sensor-based data analytics [3, 4, 5, 12]. For example, Kucukbay et al., [3] classified human, vehicle, and animal induced acoustic and vibration data. According to the type of vibration data, their proposed system triggers a camera event as an action for detecting intruders (human or vehicle). Besides, Rivas et al., [4] proposed a wireless sensor network on road that can precisely detect presences of vehicles. Their proposed system can calculate vehicle speed and travel direction from Accelerometer data. Sigmund et al., [9] showed that vibration sensed from distant vehicles may be used to help in identifying key vehicle features such as engine type, engine speed, and the number of cylinders.

Garrity et al., [12] classified the category of vehicles in an airport by distinguishing flight landing and vehicle movement on the runway. They developed an automated real-time monitoring and alert system that integrates a GUI based software to handle data collection and analysis. For data collection, they used a 2-axis Accelerometer.

Berlin et al., [6] classified train type and estimate train length from data accumulated by 3D MEMS Accelerometer. They studied Europe's busiest railroad sections and collects vibration patterns of 186 trains. They classified them into six categories using various methods. Chakraborty et al., [13] proposed a WSN based automated system that can sense vibration induced by a running train from a long distance and can detect if there is any missing rail-block on the track so that it can inform the train driver about a possible accident ahead.

2.2. Structural damage detection

Identifying structural damage is another important study in Structural Engineering. There have been several studies in recent years regarding vibration-based Structural Health Monitoring (SHM) [14, 15, 16, 13]. For examples, Lee et al., [14] presented an effective method for damage estimation of steel girder bridges using ambient vibration data. They used frequency domain decomposition technique to identify modal perimeters.

Goyal et al., [1] presented the most used signal processing techniques in SHM such as time series models, wavelet transform, and HHT. Magalhaes et al., [10] installed a dynamic monitoring system in a concrete arch bridge at the city of Porto, in Portugal. They proposed a strategy to minimize the effects of environmental and operational factors on the bridge's natural frequencies, enabling identification of structural anomalies.

Zonzini et al., [17] proposed a sensor network which can be used with either MEMS accelerometers or piezoelectric sensor to extract modal parameters of structures . Testoni et al., [18] proposed a sensor network based on low-power, low-cost, and light-weight MEMS sensor nodes to measure tilt angles of structures .

2.3. Machine fault detection

Another important field of study is classifying faults in machine structures from their vibration characteristics. There have been many studies regarding such fault detection and classification [8, 11, 7, 19, 20, 21]. Joshuva et al., [8] developed a data model for a multi-class wind turbine blade fault diagnosis. From acquired Accelerometer data, they developed several models using data modeling techniques. Ahmed et al., [11] presented an engine fault detection and classification technique using vibration data. They built a four-stroke gasoline engine for experimentation. Their proposed fault diagnostic system can detect known engine faults with various degrees of severity.

From the study of existing literature, we find studies focusing on vibration source detection, structural damage detection, and machine fault detection. However, classifying structures from their vibration characteristics is still unexplored in the literature. Nonetheless, existing studies are mostly based on high-cost sensors and focused on the *frequency* domain. Thus, it has to be investigated whether we can still work on the *frequency* domain or not while using the low-cost sensors.

3. Methodology

In this study, first, we build the sensing module, and deploy it on the surfaces of building floors, flyover/overbridge spans, and rail-block to collect vibration data. We collect and store collected vibration data to a database in real-time. Then, based on the collected vibration data, we formulate the problem of identifying source of a structure as a classification problem and attempt to solve it. A brief overview of our proposed methodology is illustrated in Figure 1.

The most straightforward approach to classify structures involves directly performing Fast Fourier Transform on the vibration signal, and then looking for the fundamental *frequency* component for the signal. So, we first remove DC components from the time domain signal as shown in Figure 2a. However, as shown in Figure 2b, after FFT, we do not observe any obvious *frequency* component. As a result, the classical approach of exploring fundamental frequency of the structure fails in the case of low-cost piezoelectric sensors. Also, we can not address the comparison between response of accelerometer and piezoelectric sensor as existing studies focused on the *frequency* responses of the accelerometer and we can only analyze time domain response of piezoelectric sensors [1, 2, 10].

Hence, we move forward to time-domain analysis. In time domain, we first extract different statistical features from raw data points. We label the data according to their sources. In our study, we explore five different sources covering

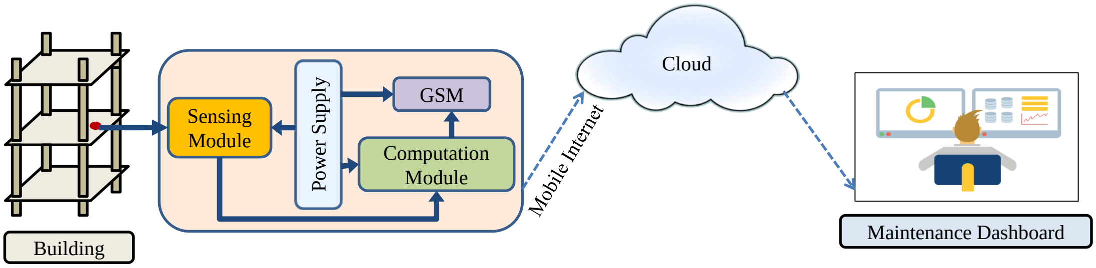
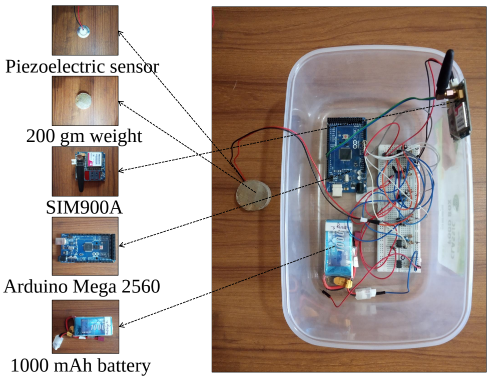
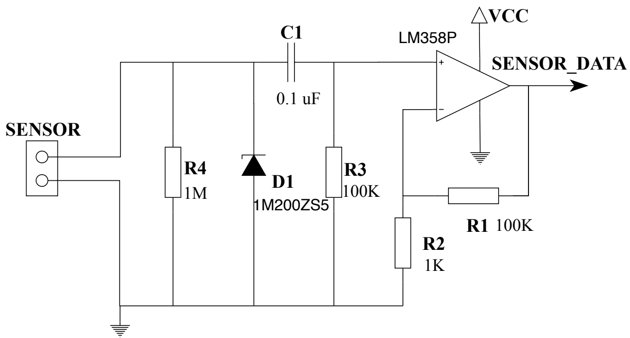


Figure 3: Our proposed system architecture: sensing, communication, computation, power supply, and maintenance dashboard



(a) Our hardware setup



(b) Circuit diagram of Sensing module

Figure 4: Hardware components and circuit diagram of sensing module

building, flyover, steel overbridge, concrete overbridge, and railline. We collect vibration data from 12 different locations in Dhaka city covering the above mentioned five classes of structures. For flyover, we collect data for multiple spans. In the case of building, we collect data from every floor. Subsequently, we train several classification models to classify each type of structure. We present detail results and findings in Section 6 and 7.

4. Proposed sensing system

tended tasks, we design and develop a customized sensing system. Here, we use low-cost components to make sure that the whole system remains low-cost in nature. Main components of our system include sensing module, computational module, communication module, power supply module, and a real-time dashboard. Figure 3 shows the architecture of our proposed system and Figure 4a shows the hardware setup. We elaborate each of the components below.

Sensing module: We use a low-cost piezoelectric disc [22] to sense the ambient vibration of structures. We use 200 gm weight bar on top of piezo sensor to fix the piezo disk and get stable signal as shown in Figure 4a. The raw analog signal collected by piezoelectric disc is first amplified through an amplification circuit as shown in Figure 4b. We choose the LM358P as the operational amplifier which is a low power dual operational amplifier. The natural *frequency* of bridge and other concrete-made structures varies in range 2-4 Hz , but values 0-14 Hz have also been reported [23]. LM358P's cutoff frequency is 200 Hz which is favorable considering the input signals' frequency response.

The amplification factor of the amplifier circuit is 100. We have also tried amplification factor of 200, 500, and 1000. However, for some structural vibration, signal cuts at analog value of 1023 for amplification factor greater than 100. Also, more the amplification factor, more the power consumption. That is why we choose the amplification factor of 100. Then, we feed the amplified signal to a 10-bit analog-to-digital converter (ADC) on an Arduino Mega [24] whose range is 0 to 5 V having the maximum sampling frequency of 9615 Hz which is greater than the operational

Table 1
Cost analysis of necessary hardware equipment

Component name	Model name	Quantity	Unit price (USD)
Piezoelectric sensor	7BB-20-6L0	1	1
Amplifier	LM358P	1	6
Resistor	1M,1K,100K	4	0.25
Zener Diode	5 V	1	0.5
Capacitor	0.1 uF	1	0.5
Microcontroller	Arduino Mega2560	1	14
GSM Module	SIM900a	1	16
Power supply	Polymer Lithium Ion Battery - 1000mAh	1	10
Total price	50 USD per node		

amplifier's output signal (200 Hz). Thus, the choice of LM358P supports both the input signals' frequency response and the sampling frequency of ADC.

Computational module: We use the Arduino Mega 2560 as our computational module. It takes sensed data from the sensing module at an interval of eight seconds. Subsequently, it determines 12 statistical features from the captured time-series data. The statistical features are mean, median, mode, standard deviation, max, min, rms, total number of peaks, average of peak values, skewness, kurtosis, and creast factor.

Communication module: We use SIM900A [25], which is a GSM-based device, to send statistics of our sensed data to the server in real time. The use of SIM900A gives robustness to our system by providing network support outside home or office where WiFi or broadband is not available. This is why we can deploy our sensing module at diversified places covering the structures, such as flyovers, overbridges, and raillines.

Power Supply module: We can choose either direct or battery power options as a source of power. In room environment, we use a direct power supply unit with a 220 V to 5 V adapter. For outdoor cases such as flyover and overbridges, we use a 5V 1000 mAh battery as the source of power.

Real-time dashboard: We send the statistical measurements from the collected raw data as HTTP post request in a URL which is then stored in a database. We develop a dashboard to display the data points in real-time.

Table 1 presents a breakdown of equipment costing of our proposed sensing system. Equipment cost of the system is 50 USD per unit, which is comparable to that of a widely-adopted smartphone unit. Thus, our system exhibits a potential to be a ubiquitous solution.

5. System deployment

We deploy our sensing module in 12 different locations in Dhaka city. This enables sensing from 12 structures having five different categories among them. The five different categories are flyover, building, steel overbridge, concrete overbridge, and railline. In all cases, we place the sensor on a horizontal surface to sense vertical vibration. Figure 5 shows some snapshots of such deployment. A brief overview of position of nodes, duration of data collection, and characterstics of structures is presented in Table 2

In the case of flyover, we consider four different spans for data collection. We choose the middle of each span to deploy our sensing module so that maximum vibration can be captured. Besides, we deploy the module on both left and right sides of the flyover to achieve symmetry as well as diversity.

We collect data from four academic and residential buildings. In each building, data from every floor contribute to our dataset. In case of two of the buildings, vibration of two columns contribute the dataset.

In the case of foot overbridge, Our dataset contains data collected from four different steel-made and one concrete-made foot overbridges. When we collect data from these structures, varying number of crowds: light, medium, dense are crossing over the bridges. We collect data for at least 2 different positions on each overbridge.

We also cover raillines. In raillines, data from both meter gauge and broad gauge lines, contribute to the dataset. Here, the data is collected only when no train passes by. We cover crossings over railline where buses, cars, bikes, cycles, and people cross railline from one side to another.

As mentioned earlier a web server keeps all data collected by the sensor. We organize the data by location and type of structure and store them accordingly. From all structures under investigation, we collect data of a total interval of 4

(a) Overbridge (b) Flyover (c) Building (d) Railline

Figure 5: Deployment of sensor nodes on different structures

Table 2
Details of different structures (node positions, duration of data collection, structural demographics, etc.) where sensor module is deployed

Flyover	#Spans covered	Duration (minutes)	Position of deployment
Flyover-1	5	30	On surface of road

Building	Type of building	#Floors	Duration (minutes)	Position of deployment
Building-1	Office	11	60	Floor, column
Building-2	Office	5	30	Floor, column
Building-3	Office	3	10	Floor
Building-4	Residential	4	20	Floor

Foot overbridge	Type of overbridge	Crowd density	Duration (minutes)	Position of deployment
Overbridge-1	Steel-made	High	10	Middle position between 2 columns
Overbridge-2	Steel-made	Medium	10	Middle position between 2 columns
Overbridge-3	Steel-made	Low	20	Middle position between 2 columns
Overbridge-4	Steel-made	High	10	Middle position between 2 columns
Overbridge-5	Concrete-made	High	10	Middle position between 2 columns

Railline	Line type	#Tracks	Duration (minutes)	Position of deployment
Railline-1	Meter and broad gauge	2	30	Attached with steel block
Railline-2	Meter and broad gauge	2	20	Attached with steel block

Table 3
A small portion of our dataset (single row is shown from each type of structures)

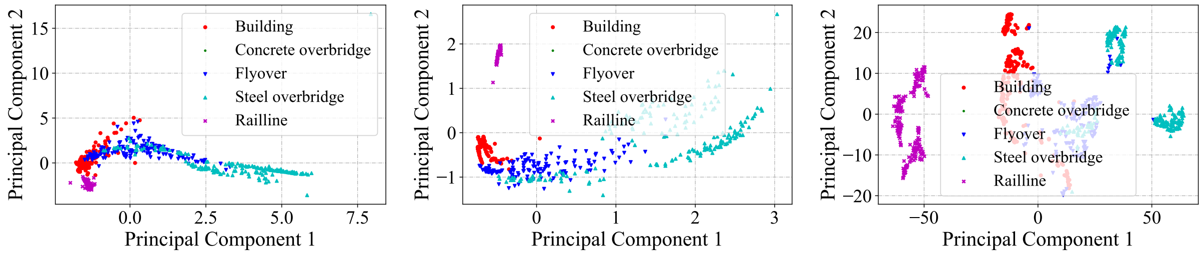
Mean	Mode	Median	Standard deviation	Max	Min	RMS	Number of peaks	Average of peak values	Skewness	Kurtosis	Creast factor	Type of structure
20.16	19	21	10.38	96	0	22.68	651	26.59	1.9	10.03	4.23	Building
28.21	0	0	35.72	255	0	45.52	579	66	1.68	3.68	5.6	Flyover
62.86	5	63	1.89	66	37	62.89	498	63.77	-4.81	49.46	1.05	Railline
154.67	0	0	178.66	747	0	236.31	613	297.05	1.19	0.85	3.16	Steel overbridge
24.9	68	0	24.45	259	0	34.9	630	44.88	1.78	7.29	7.42	Concrete overbridge

hours and 20 minutes. As we have on an average 200 data points at each second, our dataset contains summary of a total of 3 million raw data points. To be specific, our dataset contains 1,159 summary data points.

After collecting the time-series data, we extract 12 statistical features from those data points. Table 3. shows some sample entries in our dataset.

6. Classifying structures from vibration data

We perform different visualization methods, statistical analysis, and learning-based analysis over the collected data using scikit-learn version 0.23.1 [26]. The analyses help to visualize the data effectively and at the same time signifies the possibility of better classification.



(a) Principle component analysis (PCA)

(b) Factor analysis

(c) T-distributed stochastic neighbor embedding (t-SNE)

Figure 6: Graphical representation of clusters formed by different structures

Table 4
Correlation matrix and regression matrix(p-value) of type of structure with all features

Features	Correlation value	Prediction value
Mean	0.716656053	0.000000023
Median	0.090901681	0.190540928
Mode	0.154416336	0.025589244
Standard deviation	0.584570249	0.00000163
Max	0.406880713	0.000000041
Min	0.26979996	0.000078
RMS	0.784558941	0.000000001
Number of peaks	-0.274614018	0.0000572
Average of peaks	0.756443394	0.000000017
Skewness	0.228503295	0.000875476
Kurtosis	0.123029244	0.075948388
Creast factor	0.195535324	0.004549568

6.1. Visualization of data

To better visualize the data, we use principle component analysis (PCA). This reduces feature dimension from 12 to two principal components and forms clusters of same type of structures as shown in Figure 6a. We also conduct T-distributed Stochastic Neighbor Embedding, and Factor Analysis for better visualization. We present outcomes of all these analysis in Figure 6. These figures clearly portray that there is significant difference in vibration of the five structures.

6.2. Correlation between statistical features and the type of structure

We use Pearson's correlation coefficient (pearsonr() available in scipy stats package [26]) to identify- 1) how different statistical features and the type of structure are correlated with one another, and 2) whether there exist any statistically significant association ($r >= 0.4$ and $p < 0.00005$) [27]. Here, we first generate the correlation matrix, and then then we determine prediction values of the regression matrix. In a correlation matrix, the feature having the highest absolute correlation coefficient value is highly related to the type of structure. On the other hand, in a regression matrix, feature with the least prediction value is highly significant to the type of structure.

Table 4 shows the correlation and prediction values for all the features with the different types of structures. The table demonstrates that RMS, average of peaks, mean, standard deviation, and max exhibit the strong correlation values. The same features also exhibit the lowest prediction values. Thus, we can deduce that RMS, average of peaks, mean, standard deviation, and max are highly significant features in terms of getting correlated. Accordingly, we conduct further analysis on classifying the type of structure using machine learning algorithms based on the selected five features.

6.3. Machine Learning for classifying structures

We apply several machine learning algorithms on our prepared dataset. Here, we formulate the task of predicting the type of structure from associated feature values as a classification problem where each class corresponds to one of

Table 5
Performance matrix of some classifiers

Classifier	Accuracy(%)	Precision	Recall	F-Measure
k-NN(k=1)	91	0.92	0.91	0.91
RamdomForest	90	0.92	0.90	0.90
RandomTree	89	0.90	0.89	0.89
Bagging	84	0.88	0.84	0.84
DecisionTable	80	0.82	0.80	0.79
NaiveBayes	71	0.66	0.72	0.67

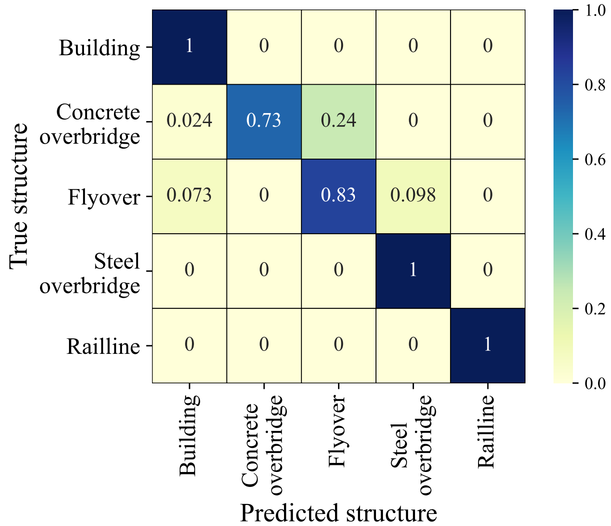


Figure 7: Normalized confusion matrix for testing phase in machine learning based approach (k nearest neighbour)

the five different structures. The accuracy in our case corresponds to the number of correctly classified instances over the number of total test instances. We calculate different performance metrics such as precision, recall, and F-measure in this regard. We use 10-fold cross-validation [28] for training each model. Then we conduct testing of each classifier model on unseen data points. In all cases, we maintain the ratio between training and testing dataset as 8:2.

Table 5 presents performance of all the classifiers under consideration. Among these classifiers, k-NN, Random-Forest, RandomTree perform the best in the metrics of accuracy, precision, recall and F-measure. Among them, k-NN (for k=1) shows 91% accuracy and outperforms others. For optimizing the value of k, here, we cross-validate the k-NN model for k out the range from 1 to 30 with the training dataset. Our cross-validation results show that when the value for k is 1, validation accuracy exhibits the highest value.

Figure 7 presents a normalized confusion matrix for k-NN (k=1). Here, among five structures, flyover gets misclassified as building or steel overbridge several times. Also, concrete overbridge gets misclassified as building and flyover in some cases. This leads to a high false-positive rate for flyover and concrete overbridge. The cause behind happening this is lower number of data points for flyover and concrete overbridge as we cover only one flyover and one concrete overbridge in our data collection phase. Besides, another reason is fact that both concrete overbridge and flyover are made of concrete. Thus, there can be a similarity of vibration for these two types of structures. Building, steel overbridge and rail line, on the other hand, get no false positive or false negative case. This is because we have substantial amount of data points for building, steel overbridge and railline. Also, vibration propagates more through metal structures, and, more importantly, in a more distinctive manner. Now, as there exists substantial room for further improvement, we employ Deep Learning for this purpose next.

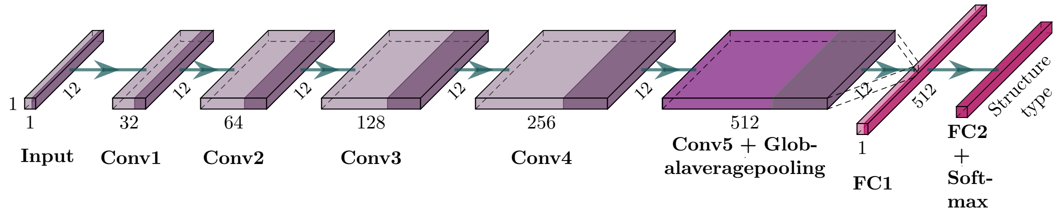
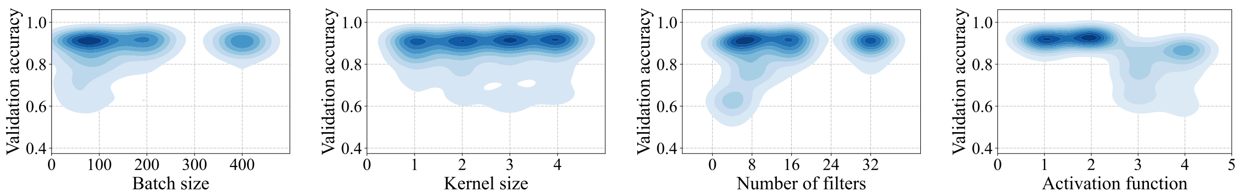


Figure 8: Architecture of our proposed Deep Learning based model



(a) Effect of batch size (b) Effect of kernel length (c) Effect of filter numbers (d) Effect of activation function

Figure 9: Kernel density estimation plot of the 256 experiments for each of the hyperparameters. In Figure (d), the number 1, 2, 3 and 4 indicate 'ReLU', 'ELU', 'Tanh' and 'Sigmoid' activation function respectively.

Table 6
Network parameters

Layers.	Output Size	Kernels
Input	1×12	-
Conv1D & elu	12×32	$f = 32, K = 3, s = 1$
Conv1D & elu	12×64	$f = 64, K = 3, s = 1$
Conv1D & elu	12×128	$f = 128, K = 3, s = 1$
Conv1D & elu	12×256	$f = 256, K = 3, s = 1$
Conv1D & elu	12×512	$f = 512, K = 3, s = 1$
Globalaveragepooling1D	1×512	-
Fully connected	$1 \times N$	-

* here f, K, s, and N represent number of filters, kernel length, filter stride and number of classes respectively.

7. Deep Learning

Among the 12 features in our dataset, we choose five features according to the correlation between the features and target classes. However, all models exhibit at most 90% accuracy except k-NN. Even k-NN exhibits substantial error in classifying two classes (flyover and concrete overbridge). This suggests that a more advanced feature extraction method might be required for better performance. Therefore, we employ Deep Convolutional Neural Network (CNN) which have shown excellent performance for different sensor-based classification tasks [29, 30]. In this regard, we propose a customized Deep Convolutional Neural Network for our intended task. In the next subsections, we demonstrate the architecture of our designed model and explain the experimental results.

7.1. Model architecture

The convolution block of our model consists of five convolutional layers. The input shape to this convolution block is $n \times 1 \times 12$ where n is the batch size and the number 12 is for all the 12 features from raw vibration data. The kernel size for each convolutional layer is 3×3. To learn a rich set of features, we increase the number of filters exponentially with the depth of the layers. The number of filters at the r^{th} convolutional layer is $2^r \times q$ where $0 <= r < 5$ and the value of q is selected as 32. The convolution operations are usually followed by activation functions that introduce non-linearity in the network. In our proposed model, we use the Exponential Linear Unit (ELU) as our activation

Table 7
Model performance on training phase

Training accuracy	Validation accuracy
97.7%	96.7%

Table 8
Model performance on testing phase

Testing accuracy	Precision	Recall	F-Measure
97.1%	0.97	0.97	0.97

function, which is defined as:

$$f(x) = \begin{cases} x & x > 0 \\ \alpha * (e^x - 1) & x \leq 0 \end{cases} \tag{1}$$

Our choice of hyperparameters is explained in the following subsection. We use a Globalaveragepooling layer [31] after the convolutional block to minimize the learnable parameters. Finally, we use a fully connected layer with N number of output neurons along with softmax activation function to map the N class scores to N probability values $p = [p_1, p_2, ..., p_N]$ for each class, which sums up to 1. We present an overview of the whole architecture in Figure 8 and table 6.

7.2. Experimental setup

The model hyperparameters for our network contains batch size, kernel size, number of filters, and activation function. Here, we vary the batch size as 50, 100, 200, and 400. Besides, we vary kernel length as 1, 2, 3, and 4. We also vary the number of filters (q) for the first convolution layer as 4, 8, 16, and 32.

At first, we split the dataset into 70% training set, 10% validation set, and 20% test set. We use 10-fold cross-validation to find the value the hyperparameters. This results in a total 10×256 experiments. Here 10 is the total number folds. The number 256 is the number of possible combination of hyperparameters. Some possible combination of hyperparameters (batch size, kernel size, number of filters, activation function) are (50, 1, 4, Tanh), (50, 2, 32, ELU), (200, 2, 4, ReLU), etc. The average results of the 256 experiments over the 10 folds are shown as kernel density estimation plots in Figure 9. It is evident that a combination of batch size 100, kernel length 3, number of filters 32, and 'ELU' activation function achieves the highest validation accuracy. Based on these results, we set the hyperparameters in our model as (100, 3, 32, ELU). All of the experiments regarding training, testing, and hyperparameter tuning of the networks are performed in Kaggle kernel environments which provides Nvidia K80 GPUs [32]. We write necessary codes in Python and implement the neural network models using the Keras API with TensorFlow in the back-end [33, 34].

7.3. Results

We evaluate the performance of our Deep Learning based model over the collected dataset in two stages. At first, we evaluate the performance of our model in the training phase with 10-fold cross-validation. In each fold, we train the model for 1000 epochs. We use Adam [35] as an optimizer with an initial learning rate of 10^{-2}. We also use a learning rate decay factor of 0.8 if the validation accuracy does not improve for 10 consecutive epochs. Table 7 represents the average training accuracy and validation accuracy of this experiment.

In the second stage, we evaluate our model over unseen test data, which can be of untrained building, railline, steel overbridge, and concrete overbridge. As we collect data from only one flyover, we use it for both training and testing. Among the 10 models from every 10 folds, we choose the best model having the highest validation accuracy. Then, we evaluate the model over several performance metrics, such as accuracy, precision, recall, and F1-score. Our Deep Learning based model outperforms the best found machine learning based k-NN (91%) in terms of all performance metrics. Table 8 presents values of all performance metrices.

Figure 10 presents a normalized confusion matrix for the test set evaluation. Among the five structures, flyover gets misclassified as concrete and steel overbridge for few times, though the false positive rate here is less compared

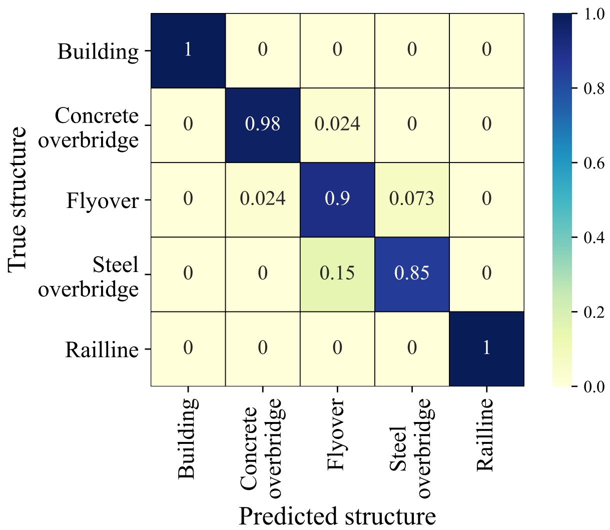


Figure 10: Normalized confusion matrix of testing phased in deep learning based approach

to machine learning based approach as in Figure 7. This happens as we cover only one flyover in our data collection phase, resulting in a relatively smaller amount of data. Besides, both concrete overbridge and flyover are made of concrete, and thus there can be a similarity of vibration from these two structures. Nonetheless, building and railline get no false positive or false negative case.

The reason for Deep Learning based approach performing better is that Deep Learning does not require any feature selection procedure. On the other hand, in our machine learning based approach, we select five statistical features among 12 from our dataset according to our analysis on correlation and significance. However, in our Deep Learning based approach we take all of the 12 features ignoring their correlation and significance. This helps in learning of our model significantly, and thus, in achieving a higher accuracy.

8. Conclusions

Analyzing the dynamics of vibration for diversified civil structures is little explored in literature - specially from the perspective of using low-cost vibration sensing. Therefore, in this study, we analyze the dynamics in depth by devising and utilizing a low-cost vibration sensing module. Our sensing module continuously uploads statistical features extracted from raw vibration data to remote cloud server and we can visualize the data points through an interactive dashboard in real-time. We then explore different machine learning based algorithms to classify different structures based on the collected vibration data, which gives an accuracy up to 91%. To improve the accuracy, we build a Deep Neural Network and tune its hyperparameters. Accordingly, we achieve an accuracy up to 97%.

One fundamental paradigm shift realized in our study is that we explore the *time* domain of vibration while analyzing the vibrations generated by the different civil structures, as only this domain exhibits considerable values in the case of using low-cost vibration (piezoelectric) sensors. This clearly differs from the existing research studies, which explore the *frequency* domain of vibration while analyzing the vibrations generated by civil structures, as *frequency* domain exhibits considerable values in the case of using high-cost vibration sensors. To the best of our knowledge, we are the first to reveal this finding.

Moving forward, there are several scope of future studies. Examples include - (1) tuning the time series window size, which is considered as eight seconds in this paper, (2) evaluating the power consumption of the system to confirm long-term energy-efficiency, (3) comparing our proposed system with existing high-cost accelerometer and geophone-based system, and (4) exploring specific applications of proposed sensing module in structural health monitoring

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