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 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 includes classifying diverse structures (such as buildings, flyovers, foot over-bridge, etc.). To explore these aspects, we develop a low-cost piezoelectric sensor-based vibration sensing system aiming to collect real vibration data from diversified civil structures remotely. 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 lightweight 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.

Keywords: Structure classification · Structural vibration · Piezoelectric sensor · Time domain signal · Sensor systems

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., [12,19]. In the case of designing architectures, every structure follows specific vibration criteria that should be fulfilled when designing the structure. Concrete structures such as buildings, concrete foot overbridges, etc., are generally considered

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to generate less vibration. On the other hand, steel foot overbridges, suspension bridges, 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 the future.

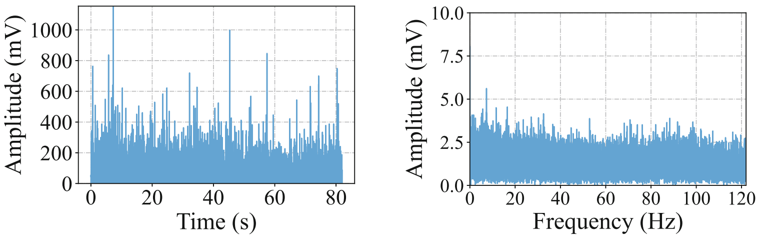
Due to the importance mentioned above, the dynamics of structural vibration have been investigated by several recent research studies [4,16,23,24]. However, these approaches lack some important considerations. Most of the existing studies consider a single structure, i.e., bridge, building, rail line, wind turbine, machine structures, etc., [3,14,21,26]. However, a study covering diverse civil structures is yet to be explored in the 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 [1,3,11,16]. However, classifying diverse structures from their vibration patterns is yet to be explored in literature. The relation only pertains to *frequency* domain specially applicable for vibration data collected using high-cost sensors [19]. 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 to classifying diversified civil structures based on their generated vibration. To do so, first, we devise and develop a low-cost piezoelectric vibration sensing module. Using the vibration sensing module, we build a diverse dataset by 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 a real environment, sending vibration data to the 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 the 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.



(a) Time domain (b) Frequency domain

Fig. 1. No significant frequency component after FFT

– We classify the five categories of civil structures based on their generated vibration through statistical and machine learning-based analyses. Further, to achieve 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 the 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 [11,16,23,24]. For example, Kucukbay et al., [16] 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., [24] proposed a wireless sensor network on the road that can precisely detect the presence of vehicles. Their proposed system can calculate vehicle speed and travel direction from Accelerometer data. Sigmund et al., [26] 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., [11] 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 GUI-based software to handle data collection and analysis. For data collection, they used a 2-axis Accelerometer.

Berlin et al., [4] classified train type and estimated train length from data accumulated by 3D MEMS Accelerometer. They studied Europe's busiest railroad sections and collected vibration patterns of 186 trains. They classified them into six categories using various methods. Chakraborty et al., [8] 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) [8,9,18,31]. For example, Lee et al., [18] presented an effective method for damage estimation of steel girder bridges using ambient vibration data. They used the frequency domain decomposition technique to identify modal perimeters.

Goyal et al., [12] presented the most used signal processing techniques in SHM such as time series models, wavelet transform, and HHT. Magalhaes et al., [21] 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 the identification of structural anomalies.

Zonzini et al., [33] proposed a sensor network that can be used with either MEMS accelerometers or piezoelectric sensors to extract modal parameters of structures. Testoni et al., [30] proposed a sensor network based on low-power, low-cost, and lightweight MEMS sensor nodes to measure the 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 [1,3,5,7,13,14]. Joshuva et al., [14] 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., [1] 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.

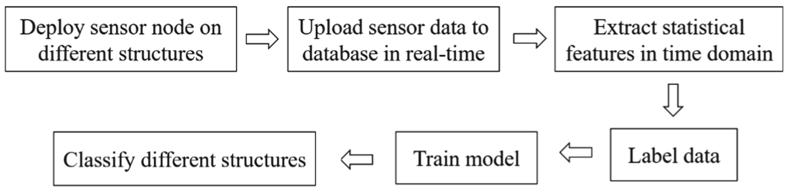


Fig. 2. Illustration of our proposed methodology on classifying structures.

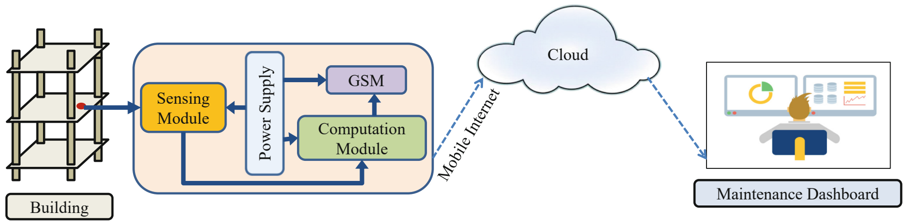


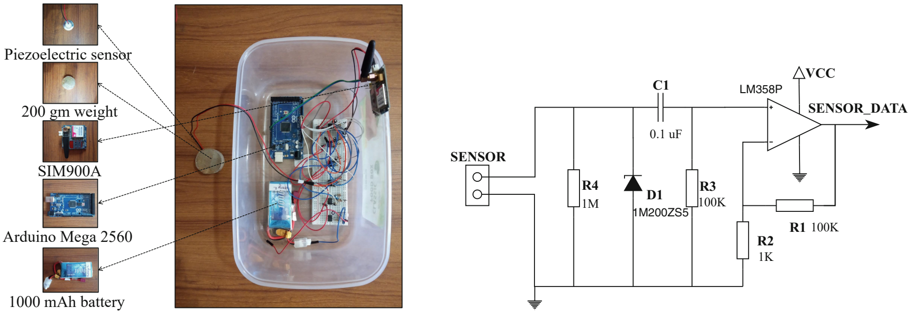
Fig. 3. Our proposed system architecture: sensing, communication, computation, power supply, and maintenance dashboard

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 in a database in real time. Then, based on the collected vibration data, we formulate the problem of identifying the source of a structure as a classification problem and attempt to solve it. A brief overview of our proposed methodology is illustrated in Fig. 2.

The most straightforward approach to classify structures involves directly performing the 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 Fig. 1a. However, as shown in Fig. 1b, after FFT, we do not observe any obvious *frequency* component. As a result, the classical approach of exploring the fundamental frequency of the structure fails in the case of low-cost piezoelectric sensors. Also, we can not address the comparison between the response of the accelerometer and piezoelectric sensor as existing studies focused on the *frequency* responses of the accelerometer and we can only analyze the time domain response of piezoelectric sensors [12,19,21].

Hence, we move forward to time-domain analysis. In the 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 building, flyover, steel overbridge, concrete overbridge, and rail line. 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 a building, we collect data from every floor. Subsequently, we train several classification models to classify each type of structure. We present detailed results and findings in Sects. 6 and 7.



(a) Our hardware setup (b) Circuit diagram of Sensing module

Fig. 4. Hardware components and circuit diagram of sensing module

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. The main components of our system include a sensing module, computational module, communication module, power supply module, and a real-time dashboard. Figure 3 shows the architecture of our proposed system and Fig. 4a shows the hardware setup. We elaborate on each of the components below.

Sensing Module: We use a low-cost piezoelectric disc [28] to sense the ambient vibration of structures. We use a 200 gm weight bar on top of the piezo sensor to fix the piezo disk and get a stable signal as shown in Fig. 4a. The total average weight of our system is around 250-300 gm. The raw analog signal collected by the piezoelectric disc is first amplified through an amplification circuit as shown in Fig. 4b. We choose the LM358P as the operational amplifier which is a low-power dual operational amplifier. The natural *frequency* of a bridge and other concrete-made structures varies in the range of 2–4 Hz, but values 0–14 Hz have also been reported [2]. 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 factors of 200, 500, and 1000. However, for some structural vibrations, the signal cuts at the analog value of 1023 for an amplification factor greater than 100. Also, the more the amplification factor, the more the power consumption. That is why we chose the amplification factor of 100. Then, we feed the amplified signal to a 10-bit analog-to-digital converter (ADC) on an Arduino Mega [27] whose range is 0 to 5 V having the maximum sampling frequency of 9615 Hz which is greater than the operational 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

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		

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, the total number of peaks, average of peak values, skewness, kurtosis, and crest factor.

Communication Module: We use SIM900A [29], 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 the 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 rail lines.

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 flyovers 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 an 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 the equipment cost of our proposed sensing system. The 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 the 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.

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

Fig. 5. Deployment of sensor nodes on different structures

The five different categories are flyover, building, steel overbridge, concrete overbridge, and rail line. 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 the position of nodes, duration of data collection, and characteristics 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 the 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 the case of two of the buildings, the vibration of two columns contributes to 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 numbers of crowds: light, medium, and dense are crossing over the bridges. We collect data for at least 2 different positions on each overbridge.

We also cover rail lines. In rail lines, 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 rail lines where buses, cars, bikes, cycles, and people cross rail lines 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 h and 20 min. As we have on average 200 data points at each second, our dataset contains a 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 extracted 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 [17]. The analyses help to visualize the data effectively and at the same time signify the possibility of better classification.

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)	Deployment position
Flyover-1	5	30	On surface of road

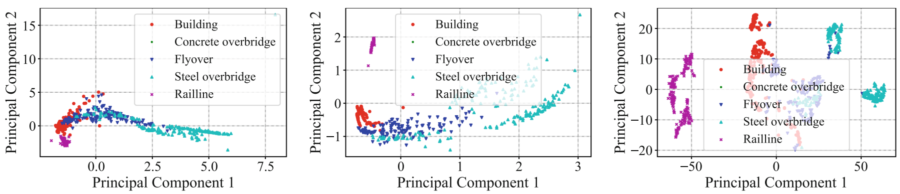
Building	Type of building	#Floors	Duration (minutes)	Deployment position
Building-1	Office	11	60	Floor, column
Building-2	Office	5	30	Floor, column
Building-3	Office	3	10	Floor
Building-4	Residential	4	20	Floor

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

Railline	Line type	#Tracks	Duration (minutes)	Deployment position
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



(a) Principle component analysis (PCA)

(b) Factor analysis

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

Fig. 6. Graphical representation of clusters formed by different structures

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 the same type of structures as shown in Fig. 6a. We also conduct T-distributed Stochastic Neighbor Embedding, and Factor Analysis for better visualization. We present the outcomes of all these analyses in Fig. 6. These figures clearly portray that there is a significant difference in the 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 [17]) to identify- 1) how different statistical features and the type of structure are correlated with one another, and 2) whether there exists any statistically significant association ($r >= 0.4$ and $p < 0.00005$) [25]. Here, we first generate the correlation matrix, and then we determine the 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, the 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, an average of peaks, mean, standard deviation, and max exhibits 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 to 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 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 for training each model. Then we conduct testing of each classifier model on unseen data points. In all cases, we maintain the ratio between the training and testing dataset as 8:2.

Table 5 presents the performance of all the classifiers under consideration. Among these classifiers, k-NN, RandomForest, and 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 of the range

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

Table 5. Performance matrices of different 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

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, the flyover gets misclassified as a 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 this is a 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. Another reason is the fact that both concrete overbridges and flyovers are made of concrete. Thus, there can be a similarity of vibration for these two types of structures. Building, steel overbridges, and rail lines, on the other hand, get no false positive or false negative case. This is because we have a substantial amount of data points for buildings, steel overbridges, and rail lines. Also, vibration propagates more through metal structures, and, more importantly, in a more distinctive manner. Now, as there

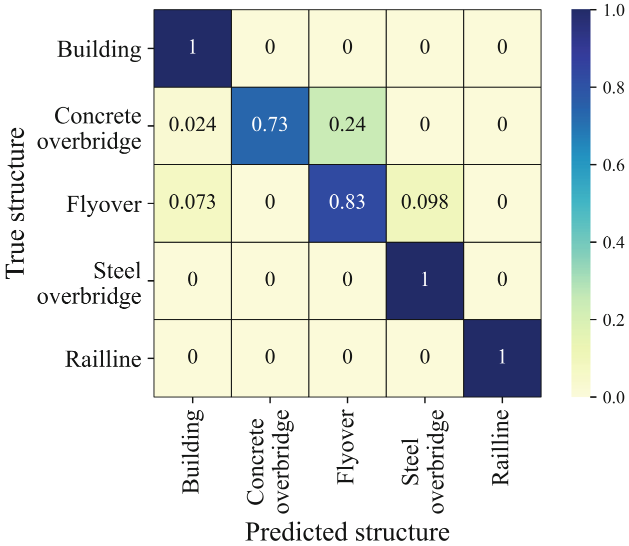


Fig. 7. Normalized confusion matrix for testing phase in machine learning based approach (k nearest neighbour)

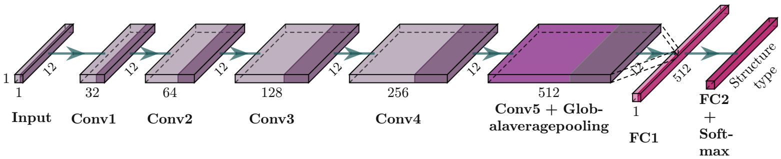
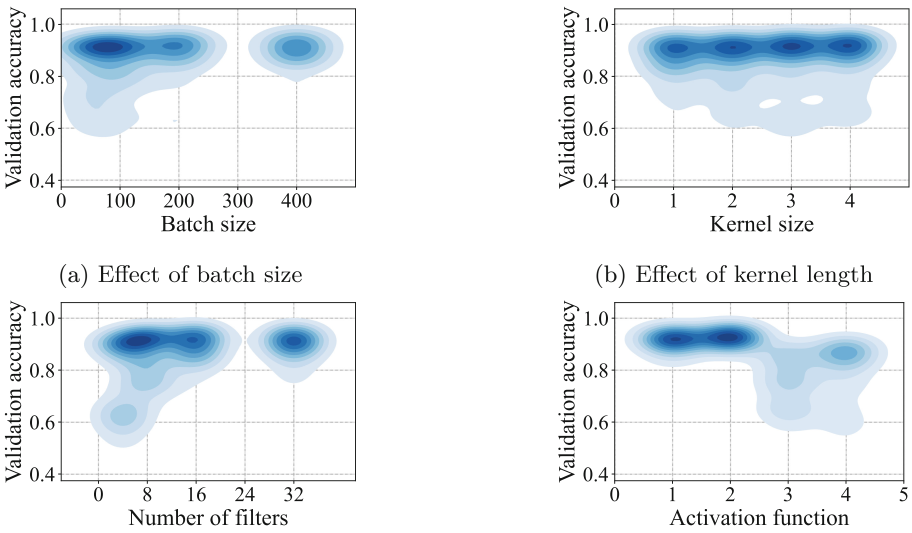


Fig. 8. Architecture of our proposed Deep Learning based model

exists substantial room for further improvement, we employ Deep Learning for this purpose next.

7 Deep Learning

Among the 12 features in our dataset, we chose 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 has shown excellent performance for different sensor-based classification tasks [22,32]. 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.



(a) Effect of batch size

(b) Effect of kernel length

(c) Effect of filter numbers

(d) Effect of activation function

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

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 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 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 Fig. 8 and Table 6.

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 the number of filters, kernel length, filter stride, and the number of classes respectively.

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

7.2 Experimental Setup

The model hyperparameters for our network contain batch size, kernel size, number of filters, and activation function. Here, we vary the batch size to 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 of the hyperparameters. This results in a total of 10×256 experiments. Here 10 is the total number of folds. The number 256 is the number of possible combinations of hyperparameters. Some possible combinations 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 Fig. 9. It is evident that a combination of batch size 100, kernel length 3, number of filters 32, and the '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 provide Nvidia

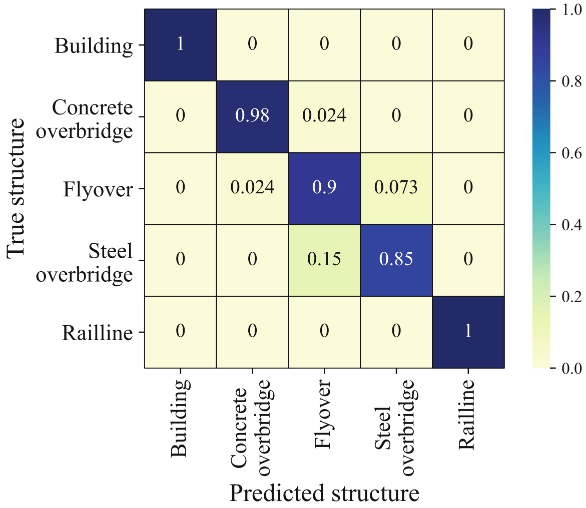


Fig. 10. Normalized confusion matrix of testing phased in deep learning based approach

K80 GPUs [20]. We write necessary codes in Python and implement the neural network models using the Keras API with TensorFlow in the back-end [6,10].

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 [15] 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 buildings, rail lines, steel overbridges, and concrete overbridges. 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 metrics.

Figure 10 presents a normalized confusion matrix for the test set evaluation. Among the five structures, the flyover gets misclassified as concrete and steel overbridge for few times, though the false positive rate here is less compared to machine learning-based approach as in Fig. 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 between these two structures. Nonetheless, building and rail lines 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 - especially 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 a remote cloud server and we can visualize the data points through an interactive dashboard in real-time. We then explore different machine learning algorithms to classify different structures by collected vibration data, which gives an accuracy of up to 91%. We build a Deep Neural Network and tune its hyperparameters for improvements resulting in an accuracy of 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.

Moving forward, there are several scopes for 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 systems, and (4) exploring specific applications of the proposed sensing module in structural health monitoring.

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