An Overview of Deep Learning Methods Used in Vibration-Based Damage Detection in Civil Engineering

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Abstract This paper presents a brief overview of vibration-based damage identification studies based on Deep Learning (DL) in civil engineering structures. The presence, type, size, and propagation of structural damage on civil infrastructure have always been a topic of research. In the last couple of decades, there has been a significant shift in the damage detection paradigm when the advancements in sensing and computing technologies met with the ever-expanding use of artificial neural network algorithms. Machine-Learning (ML) tools enabled researchers to implement more feasible and faster tools in damage detection applications. When an artificial neural network has more than three layers, it is typically considered as a "deep" learning network. Being an important accomplishment of the ML era, DL tools enable complex systems which are made of several layers to learn implementations of data with outstanding categorization and compartmentalization capability. In fact, with proper training, a DL tool can operate directly with the unprocessed raw data and help the algorithm produce output data. Competitive capabilities like this led DL algorithms perform very well in complicated problems by dividing a relatively large problem into much smaller and more manageable portions. Specifically for damage identification and localization on civil infrastructure, Convolutional Neural Networks (CNNs) and Unsupervised Pretrained Networks (UPNs) are the known DL tools published in the literature. This paper presents an overview of these studies.

Keywords Civil engineering structures · Damage identification · Damage localization · Infrastructure health · Deep learning

1 Introduction

Inspecting the overall performance of engineering structures has always been important for maintaining structural health. While the traditional way of damage monitoring on civil infrastructure has been through visual inspections [1–3], along with the advancements in sensors and monitoring technology, dynamic response of structures has started to be exploited for condition assessment [4–10] and serviceability evaluation [11–17] of structures. Along with the implementation of Machine Learning (ML) based procedures in structural damage detection (both nonparametric ML and parametric ML methods), it has been reported that both supervised ML procedures and unsupervised ML procedures need the step of feature extraction to be completed first, so that the input data is represented with reference to a certain number of manually selected features [18–20]. Even though some of the manually selected features operate very well for some specific cases, they might not necessarily work on other cases. Therefore, with the intention to keep away from manually selected features in complicated ML-based methods, Deep Learning (DL) methods were created. DL or "Deep Neural Network" is also referred to as "Deep Neural Learning" or "Representation Learning." It is a subset, indeed a special type of ML-based procedures. A great characteristic of the DL is, without programmer intervention, it can extract optimum input representation directly from the raw signal

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while enhancing the classification accuracy. DL has the capability to learn by correlating the features per training, and then process the feature extraction step based on the training. The competitive attribute of the DL is the fact that it can learn in an unsupervised manner from unstructured data which enables it to tackle large problems by dividing it into smaller, more manageable problems. DL has been in use by numerous other fields but their applications in vibration-based damage detection of civil infrastructure only are discussed in this paper.

Standard Artificial Neural Networks (ANNs) typically comprise an input layer. This layer is followed by hidden layers, which are followed by an output layer. ANNs comprising multiple layers excluding input and output layers are accepted as "deep" networks. It can also be considered as when the number of hidden layers increase, then the network "depth" gets increased, to make the network a "Deep" one. For DL development, the study by Hinton and Salakhutdinov [21] is considered as a pioneer study. DL structures are divided into four parts in [22]: Recursive Neural Networks; Recurrent Neural Networks; Convolutional Neural Networks (CNNs); and Unsupervised Pretrained Networks (UPNs). Unsupervised Pretrained Networks are further categorized into Generative Adversarial Networks (GANs); Deep Belief Networks (DBNs); and Autoencoders (Deep Autoencoders). For damage detection of civil infrastructure, the DL tools utilized in the literature have been CNNs and UPNs. Therefore, this review includes these studies.

2 Use of UPNs in Damage Detection of Civil Infrastructure

Within the UPN categorization structure, Autoencoders are found to be the only network found in literature that was deployed for damage identification and localization of civil structures. Within DL use, the Deep Autoencoders comprise multiple hidden layers and original data description is more efficient per the learned features which enhances the classification performance. An ensemble classification technique was used in [23] and then in [24] utilizing weight majority voting. In these studies, the Autoencoder methodologies were referred to as Deep Neural Networks. Since the damage indicators are often sensitive to environmental conditions such as temperature changes, in [23], the proposed damage identification method addresses these factors by employing Couple Sparse Coding (CSC) and Autoencoders. Using analytical and experimental data from bridges, the methodology was verified with noisy data conditions, temperature variations, and even modeling errors. Principal Component Analysis was also used. In [24], the similar methodology was repeated on a beam per impact hammer excitations using the demonstration in [25], focusing on different damage conditions via variations on frequency response functions. The procedure was also utilized on a truss bridge model and found to be successful in the presence of various uncertainties and changing external conditions.

On another identification study on a steel structure, the relationship learning and dimensionality reduction was used with the autoencoders in [26] where the correlation between the stiffness values and modal characteristics were investigated through pattern recognition. Modal parameters were the input information while the resulting damage was the output information of the system. A pre-training was applied on the hidden layers. The procedure was validated numerically and experimentally; also, the performance was reported to be better than the traditional ANNs.

3 Use of CNNs in Damage Detection of Civil Infrastructure

3.1 2D CNNs

Convolutional Neural Networks (CNNs) are a class of supervised ANNs and primarily used in face/object recognition in computers [27, 28]. They have quickly become well known and widely used among the rest of the DL algorithms because of their efficient and fast operation directly on the raw signals [29–33]. When the researchers realized that CNNs are surpassing performance of standard ML procedures in speed and accuracy, more focus has been placed on the application of CNNs on various engineering applications [28, 34, 35]. CNNs are indeed multi-layer feed-forward artificial neural networks in supervised format, inspired by the way mammalian brain's vision cortex operates [36]. CNNs are found advantageous to other networks because of their capability to comprise extraction and classification steps in one body while they process the training on the raw signal. They can adapt to different size of input meanwhile they operate well with the transformations like distortion, skewing, scaling, and translation.

The number of fully connected layers in CNNs typically supersedes the number of layers for pooling and convolution. The CNN architectures are governed by various combinations of subsampling factors: size of kernels; numbers of convolution, fully connected and pooling layers (hyperparameters); and neuron numbers in each of these layers. CNN trainings are in supervised format via the back-propagation (BP) loop procedures. With every BP loop, the sensitivities of network parameters are calculated to improve the parameters until a termination protocol is met. Further information on this procedure is reported in [37–40].

One example study for CNN use for damage identification is a 5-DOF laboratory benchmark structure which is investigated numerically in [41]. The structure demonstrated in [42] was employed for numerical investigation. 2D CNNs were used; therefore, 1D vibration signals were mapped into 2D format to be able to process the network model. The proposed CNN methodology was verified with the acceleration data of El Centro earthquake applied on the structural frame even in the presence of noise. The results were reported to outperform some of the traditional ML-based methods.

In another relevant study [43], a methodology based on CNNs was introduced for identifying and quantifying damage on a concrete bridge. Experimental verification was shown for the presented method where four damage scenarios were studied utilizing the acceleration response of the bridge. 2D CNNs were used again and based on 48 shake table tests, 40 sets of data were assigned for CNN training and 8 sets of data were assigned for validation. 2D CNN performance was reported to be successful for detection and quantification of damage.

In [44, 45], a CNN-based methodology was introduced for damage identification by processing images via functions of transmissibility where the stiffness reductions on members were simulated as damage. A beam and a spring-mass assembly was used to generate data and validate the proposed method using finite element models. The damage detection method was reported to perform successfully.

3.2 1D CNNs

The CNN applications discussed above were based on conventional 2D CNNs which—as the name implies—are a better fit for 2D inputs like videos and images. For 1D signals, One-dimensional CNNs were proposed in [38] for detection of arrhythmia in electrocardiograms and then utilized in numerous applications that employ 1D signals [36, 46–51]. 1D CNNs do have some architectural changes when compared to the 2D counterparts, but in a sense, they can be considered as similar. The performance of 1D CNNs, however, is found to be surpassing 2D CNNs in many platforms [52–55] due to several reasons. The most important one is the fact that 1D CNNs carry much less computational complexity than 2D CNNs. The other reason is 1D CNN architecture is compact and it is designed in a way that even when the training data is not plenty, difficult problems are successfully solved with the smaller number of neurons and hidden layers. On the other hand, for 2D CNNs, when the data is not plenty, overfitting problems tend to arise. On another note, back-propagation and forward-propagation procedures of 2D CNNs require special hardware like GPU farms, while 1D CNNs are mostly fine with standard CPU use on a basic personal computer. All these points make 1D CNNs a better fit for real-time use than 2D CNNs.

A relatively large laboratory structure was used in [40] where 1D CNNs were deployed to train and test 31 damage scenarios. A sensor is placed at each node of the structure and trained separately for that node, where the assigned 1D CNN processed the data collected at the corresponding sensor. The methodology was reported to be successful not only for single but also for double damage scenarios. It was also noted that the damage identification, localization, and quantification were performed in real time. The source code, the test data, benchmark dataset, and accompanied files are shared online on a public website [56]. The benchmark dataset is also published as a conference paper [57]. More information on the large laboratory structure can be found in [58]. Considering the fact that the introduced "damage" was only loosening the bolts at joint locations (an almost negligible rotational stiffness change), it can be stated that the compact 1D CNNs are capable of distinguishing very complex acceleration data with uncorrelated content. It is important to note that a basic personal computer was used in [40], and all of the damage scenarios were predicted accurately, faster than the requirements accepted for real time.

The material presented in [40] was followed by additional experimental studies such as [50] and [32] where the 1D CNN-based approach introduced in [40] was implemented on a Wireless Sensor Network working directly on the data collected by wireless sensors. 1D CNN architecture was in compact form with 2 CNN layers (four neurons/layer) and 2 MLP layers (five neurons/layer). The damage detection and localization performance results were reported to be satisfactory for all damage scenarios imposed on the laboratory frame.

Yet, it was noted that the classifier training operation discussed in [40] and [50] involves long data recordings, which was on the manageable side for a laboratory frame, yet it can be cumbersome (and sometimes unrealistic) for large civil infrastructure. In an attempt to address this, an updated version, "adaptive 1D CNNs" were proposed in [49] and [51] utilizing the data presented in [59]. It was reported that the training was conducted with less effort with the adaptive 1D CNNs, and damage detection, localization, and quantification tasks were processed successfully for all damage conditions discussed in [59].

4 Conclusions and Recommendations for Future Work

As discussed so far, the researchers all over the world have been using DL procedures for detecting, quantifying, and locating damage on civil infrastructure. It has been reported that the CNN procedures are relatively easy to implement since the CNN procedures do not mandate manual extraction of features, which means the users can operate straight with the raw signals. There is also no need for pre-processing because the system can operate directly on unprocessed signal. When it comes to a comparison between 2D and 1D CNNs, it was reported that training for 1D CNNs is a relatively easier process since they are in compact form. On another note, 1D CNNs were reported to comprise lower computational complexity than 2D CNNs. Especially in cases of sparse data, 1D CNNs were still able to perform satisfactorily for detecting, locating, and quantifying damage.

Yet, it is important to note that some of the identification methods per DL are involving supervised algorithms. For large civil engineering infrastructure, it is not always feasible to manage this since obtaining "before damage" and "after damage" recordings is logistically difficult and sometimes even the attempt itself is unrealistic. Based on this, there is a need for development of new methodologies to eliminate the dependency on data, especially for "after damage" conditions. In order to go around the need for data for damaged conditions, one alternative way would be researching the available data for the existing damaged conditions of structures (forming a library of structures) and establishing a link between an undamaged structure and computer simulations of a library of damaged structures. As a final note, it is observed that the number of studies involving unsupervised or semi-supervised studies for damage identification is relatively low; therefore, additional research is required on unsupervised methods.

References

1. Dwivedi, S.K., Vishwakarma, M., Soni, P.A.: Advances and researches on non destructive testing: a review. Mater. Today Proc. **5**(2), 3690–3698 (2018). https://doi.org/10.1016/j.matpr.2017.11.620
2. Wu, X., Ghaboussi, J., Garrett, J.H.: Use of neural networks in detection of structural damage. Comput. Struct. (1992). https://doi.org/10.1016/0045-7949(92)90132-J
3. Frangopol, D.M., Liu, M.: Maintenance and management of civil infrastructure based on condition, safety, optimization, and life-cycle cost. Struct. Infrastruct. Eng. (2007). https://doi.org/10.1080/15732470500253164
4. Ngoan, D.T., Mustafa, G., Osama, A., Onur, A.: Stadium vibration assessment for serviceability considering the vibration duration. In: Proceedings, Annu. Conf. - Can. Soc. Civ. Eng. (2017)
5. Celik, O., Catbas, F.N., Do, N.T., Gul, M., Abdeljaber, O., Younis, A., Avci, O.: Issues, codes and basic studies for stadium dynamics. In: Proc. Second Int. Conf. Infrastruct. Manag. Assess. Rehabil. Tech., Sharjah, UAE (2016)
6. Abdeljaber, O., Hussein, M.F.M., Avci, O.: In-service video-vibration monitoring for identification of walking patterns in an office floor. In: 25th Int. Congr. Sound Vib. Hiroshima, Japan (2018)
7. Chaabane, M., Ben Hamida, A., Mansouri, M., Nounou, H.N., Avci, O.: Damage detection using enhanced multivariate statistical process control technique. In: 2016 17th Int. Conf. Sci. Tech. Autom. Control Comput. Eng. STA 2016 - Proc (2017). https://doi.org/10.1109/STA.2016.7952052
8. Abdeljaber, O., Hussein, M., Avci, O., Davis, B., Reynolds, P.: A novel video-vibration monitoring system for walking pattern identification on floors. Adv. Eng. Softw. (2020). https://doi.org/10.1016/j.advengsoft.2019.102710
9. Mansouri, M., Avci, O., Nounou, H., Nounou, M.: A comparative assessment of nonlinear state estimation methods for structural health monitoring. Conf. Proc. Soc. Exp. Mech. Ser. (2015). https://doi.org/10.1007/978-3-319-15224-0_5
10. Mansouri, M., Avci, O., Nounou, H., Nounou, M.: Iterated square root unscented Kalman filter for state estimation - CSTR model. In: 12th Int. Multi-Conference Syst. Signals Devices, SSD 2015 (2015). https://doi.org/10.1109/SSD.2015.7348243
11. Mansouri, M., Avci, O., Nounou, H., Nounou, M.: Iterated square root unscented Kalman filter for nonlinear states and parameters estimation: three DOF damped system. J. Civ. Struct. Health Monit. **5** (2015). https://doi.org/10.1007/s13349-015-0134-7
12. Avci, O.: Effects of Bottom Chord Extensions on the Static and Dynamic Performance of Steel Joist Supported Floors. Virginia Polytechnic Institute and State University, Virginia (2005)
13. Avci, O., Davis, B.: A Study on Effective Mass of One Way Joist Supported Systems Struct. Congr. 2015 – Proc. (2015). https://doi.org/10.1061/9780784479117.073
14. Avci, O.: Retrofitting Steel Joist Supported Footbridges for Improved Vibration Response Struct. Congr. 2012 - Proc. (2012). https://doi.org/10.1061/9780784412367.041
15. Avci, O., Bhargava, A., Nikitas, N., Inman, D.J.: Vibration annoyance assessment of train induced excitations from tunnels embedded in rock. Sci. Total Environ. (2020). https://doi.org/10.1016/j.scitotenv.2019.134528
16. Avci, O., Setareh, M., Murray, T.M.: Vibration Testing of Joist Supported Footbridges Struct. Congr. 2010 (2010). https://doi.org/10.1061/41130(369)80
17. Avci, O., Bhargava, A., Nikitas, N., Inman, D.J.: Vibrations Assessment of Existing Building Foundations Due to Moving Trains in Underground Tunnels Conf. Proc. Soc. Exp. Mech. Ser. (2021). https://doi.org/10.1007/978-3-030-47634-2_8
18. Morgenthal, G., Hallermann, N.: Quality assessment of Unmanned Aerial Vehicle (UAV) based visual inspection of structures. Adv. Struct. Eng. (2014). https://doi.org/10.1260/1369-4332.17.3.289

19. Ghahramani, Z.: Probabilistic machine learning and artificial intelligence. Nature. (2015). https://doi.org/10.1038/nature14541
20. Kwon, D., Kim, H., Kim, J., Suh, S.C., Kim, I., Kim, K.J.: A survey of deep learning-based network anomaly detection. Cluster Comput. (2017). https://doi.org/10.1007/s10586-017-1117-8
21. Hinton, G.E., Salakhutdinov, R.R.: Reducing the dimensionality of data with neural networks. Science. **313** (2006). https://doi.org/10.1126/science.1127647
22. Patterson, J., Gibson, A.: Deep Learning: A Practitioner's Approach. O'Reilly Media, Newton, MA (2017). https://doi.org/10.1038/nature14539
23. Fallahian, M., Khoshnoudian, F., Meruane, V.: Ensemble classification method for structural damage assessment under varying temperature. Struct. Health Monit. (2017). https://doi.org/10.1177/1475921717717311
24. Fallahian, M., Khoshnoudian, F., Talaei, S., Meruane, V., Shadan, F.: Experimental validation of a deep neural network—sparse representation classification ensemble method. Struct. Des. Tall Spec. Build. (2018). https://doi.org/10.1002/tal.1504
25. Shadan, F., Khoshnoudian, F., Esfandiari, A.: A frequency response-based structural damage identification using model updating method. Struct. Control Health Monit. (2016). https://doi.org/10.1002/stc.1768
26. Pathirage, C.S.N., Li, J., Li, L., Hao, H., Liu, W., Ni, P.: Structural damage identification based on autoencoder neural networks and deep learning. Eng. Struct. (2018). https://doi.org/10.1016/j.engstruct.2018.05.109
27. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. Adv. Neural Inf. Process. Syst. **2012**, 1097–1105 (2012). https://doi.org/10.1145/3065386
28. Kiranyaz, S., Waris, M.A., Ahmad, I., Hamila, R., Gabbouj, M.: Face segmentation in thumbnail images by data-adaptive convolutional segmentation networks. In: 2016 IEEE Int. Conf. Image Process., pp. 2306–2310 (2016). https://doi.org/10.1109/ICIP.2016.7532770
29. Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., Inman, D.J.: 1D convolutional neural networks and applications: a survey. Mech. Syst. Signal Process. **151** (2021). https://doi.org/10.1016/j.ymssp.2020.107398
30. Avci, O., Abdeljaber, O., Kiranyaz, S., Hussein, M., Gabbouj, M., Inman, D.J.: A review of vibration-based damage detection in civil structures: from traditional methods to machine learning and deep learning applications. Mech. Syst. Signal Process. (2021). https://doi.org/10.1016/j.ymssp.2020.107077
31. O. Avci, O. Abdeljaber, S. Kiranyaz, S. Sassi, A. Ibrahim, M. Gabbouj, One Dimensional Convolutional Neural Networks for Real-Time Damage Detection of Rotating Machinery, Conf. Proc. Soc. Exp. Mech. Ser., 2021
32. Avci, O., Abdeljaber, O., Kiranyaz, S., Inman, D.: Convolutional Neural Networks for Real-Time and Wireless Damage Detection, Conf. Proc. Soc. Exp. Mech. Ser. (2020). https://doi.org/10.1007/978-3-030-12115-0_17
33. O. Avci, O. Abdeljaber, S. Kiranyaz, Structural Damage Detection in Civil Engineering with Machine-Learning: Current State of the Art, Conf. Proc. Soc. Exp. Mech. Ser., 2021
34. Ciresan, D.C., Meier, U., Gambardella, L.M., Schmidhuber, J.: Deep, big, simple neural nets for handwritten digit recognition. Neural Comput. **22**, 3207–3220 (2010). https://doi.org/10.1162/NECO_a_00052
35. Scherer, D., Müller, A., Behnke, S.: Evaluation of pooling operations in convolutional architectures for object recognition. In: Proc. 20th Int. Conf. Artif. Neural Networks Part III, pp. 92–101. Springer, Berlin (2010). https://doi.org/10.1007/978-3-642-15825-4_10
36. Kiranyaz, S., Ince, T., Gabbouj, M.: Personalized monitoring and advance warning system for cardiac arrhythmias. Sci. Rep. **7** (2017). https://doi.org/10.1038/s41598-017-09544-z
37. Kiranyaz, S., Ince, T., Hamila, R., Gabbouj, M.: Convolutional neural networks for patient-specific ECG classification. In: Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS (2015). https://doi.org/10.1109/EMBC.2015.7318926
38. Kiranyaz, S., Ince, T., Gabbouj, M.: Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Trans. Biomed. Eng. **63**, 664–675 (2016). https://doi.org/10.1109/TBME.2015.2468589
39. Kiranyaz, S., Ince, T., Abdeljaber, O., Avci, O., Gabbouj, M.: 1-D convolutional neural networks for signal processing applications. In: ICASSP, IEEE Int. Conf. Acoust. Speech Signal Process. - Proc. (2019). https://doi.org/10.1109/ICASSP.2019.8682194
40. Abdeljaber, O., Avci, O., Kiranyaz, S., Gabbouj, M., Inman, D.J.: Real-time vibration-based structural damage detection using one-dimensional convolutional neural networks. J. Sound Vib. **388**, 154–170 (2017). https://doi.org/10.1016/j.jsv.2016.10.043
41. Yu, Y., Wang, C., Gu, X., Li, J.: A novel deep learning-based method for damage identification of smart building structures. Struct. Health Monit. **18**, 143–163 (2019). https://doi.org/10.1177/1475921718804132
42. Wu, Y.M., Samali, B.: Shake table testing of a base isolated model. Eng. Struct. (2002). https://doi.org/10.1016/S0141-0296(02)00054-8
43. Khodabandehlou, H., Pekcan, G., Fadali, M.S.: Vibration-based structural condition assessment using convolution neural networks. Struct. Control Health Monit. (2018). https://doi.org/10.1002/stc.2308
44. Cofre-Martel, S., Kobrich, P., Lopez Droguett, E., Meruane, V.: Deep convolutional neural network-based structural damage localization and quantification using transmissibility data. Shock Vib. (2019). https://doi.org/10.1155/2019/9859281
45. Cofré, S., Kobrich, P., López Droguett, E., Meruane, V.: Transmissibility based structural assessment using deep convolutional neural network. In: Proc. ISMA 2018 - Int. Conf. Noise Vib. Eng. USD 2018 - Int. Conf. Uncertain. Struct. Dyn. (2018)
46. Kiranyaz, S., Gastli, A., Ben-Brahim, L., Alemadi, N., Gabbouj, M.: Real-time fault detection and identification for MMC using 1D convolutional neural networks. IEEE Trans. Ind. Electron. (2018). https://doi.org/10.1109/TIE.2018.2833045
47. Ince, T., Kiranyaz, S., Eren, L., Askar, M., Gabbouj, M.: Real-time motor fault detection by 1-D convolutional neural networks. IEEE Trans. Ind. Electron. (2016). https://doi.org/10.1109/TIE.2016.2582729
48. Avci, O., Abdeljaber, O., Kiranyaz, S., Inman, D.: Structural damage detection in real time: implementation of 1D convolutional neural networks for SHM applications. In: Niezrecki, C. (ed.) Struct. Heal. Monit. Damage Detect Proc. 35th IMAC, A Conf. Expo. Struct. Dyn. 2017, vol. 7, pp. 49–54. Springer International Publishing, Cham (2017). https://doi.org/10.1007/978-3-319-54109-9_6
49. Abdeljaber, O., Avci, O., Kiranyaz, M.S., Boashash, B., Sodano, H., Inman, D.J.: 1-D CNNs for structural damage detection: verification on a structural health monitoring benchmark data. Neurocomputing. (2017). https://doi.org/10.1016/j.neucom.2017.09.069
50. Avci, O., Abdeljaber, O., Kiranyaz, S., Hussein, M., Inman, D.J.: Wireless and real-time structural damage detection: a novel decentralized method for wireless sensor networks. J. Sound Vib. (2018)
51. Avci, O., Abdeljaber, O., Kiranyaz, S., Boashash, B., Sodano, H., Inman, D.J.: Efficiency validation of one dimensional convolutional neural networks for structural damage detection using a SHM benchmark data. In: 25th Int. Congr. Sound Vib. (2018)

52. Eren, L.: Bearing fault detection by one-dimensional convolutional neural networks. Math. Probl. Eng. (2017). https://doi.org/10.1155/2017/8617315
53. Abdeljaber, O., Sassi, S., Avci, O., Kiranyaz, S., Abulrahman, I., Gabbouj, M.: Fault detection and severity identification of ball bearings by online condition monitoring. IEEE Trans. Ind. Electron. (2018) https://ieeexplore.ieee.org/document/8584489
54. Li, D., Zhang, J., Zhang, Q., Wei, X.: Classification of ECG signals based on 1D convolution neural network. In: 2017 IEEE 19th Int. Conf. e-Health Networking, Appl. Serv. Heal. 2017 (2017). https://doi.org/10.1109/HealthCom.2017.8210784
55. Xiong, Z., Stiles, M., Zhao, J.: Robust ECG signal classification for the detection of atrial fibrillation using novel neural networks. In: 2017 Comput. Cardiol. Conf. (2018). https://doi.org/10.22489/cinc.2017.066-138
56. Avci, O., Kiranyaz, S., Abdeljaber, O.: StructuralDamageDetection.com (Public Website). http://www.structuraldamagedetection.com/ (2019)
57. O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, D.J. Inman, A New Benchmark Problem for Structural Damage Detection: Bolt Loosening Tests on a Large-Scale Laboratory Structure, Conf. Proc. Soc. Exp. Mech. Ser., 2021
58. Abdeljaber, O., Younis, A., Avci, O., Catbas, N., Gul, M., Celik, O., Zhang, H.: Dynamic testing of a laboratory stadium structure. Geotech. Struct. Eng. Congr. **2016**, 1719–1728 (2016). https://doi.org/10.1061/9780784479742.147
59. Dyke, S., Bernal, D., Beck, J., Ventura, C.: Experimental phase II of the structural health monitoring benchmark problem. In: Proc. 16th ASCE Eng. Mech. Conf., pp. 1–7 (2003)