**Literature Review:**

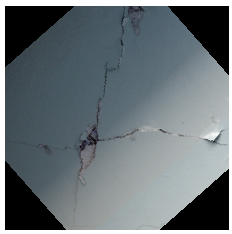
The amount of research on the intersection of structural health monitoring (SHM) and deep learning is quite limited. However, a quick glance at the available provides insight. Yu et. al (2019) proposed a CNN to identify and localize damages for the smart buildings instrumented with control devices. Their proposed network could automatically extract features from raw signals to meet the requirements of random objective functions. They used a high-dimension kernel in the first convolutional layer to reduce the noisy data. Also, several small-dimension kernels were utilized to characterize signal representations. Additionally, the ReLU function was used to mitigate overfitting. In the end, they developed a benchmark building equipped with smart isolators subjected to seismic excitation to assess the performance of their proposed model. Their proposed network demonstrated higher identification accuracy compared to other commonly used ML architecture [1]. Rashid and Louis (2019) used an RNN deep learning network to recognize construction equipment activities. For this task, they used data augmentation for training data and proposed a methodology to train and validate the train long short-term memory (LSTM) RNN, with combined synthetic and real data. They tested their proposed model against so-called “traditionally used classification algorithms for construction equipment activity recognition” and observed enhanced performance [2]. Iannelli et al (2022) proposed a [Deep Neural Network](https://www.sciencedirect.com/topics/engineering/deep-neural-network), made of several neural network layers with different functions, in particular bidirectional LSTM layers, fully connected layers, and SoftMax, for structural damage detection for the study of a large system. The model was trained, validated, and tested by processing the time responses of the sensors using different damage scenarios such as the ones generated by the finite element codes. Their proposed model demonstrated good performance and accuracy [3]

Structural Health Monitoring (SHM) usually refers to engineering assessment and evaluation that study the structural integrity of structural components which are usually statics while in mechanical systems, with moving parts and assemblies, the process is called Condition Monitoring (CM) or Health Monitoring (HM) instead of SHM. In terms of the procedure employed, SHM or [CM systems](https://www.sciencedirect.com/topics/engineering/condition-monitoring-system) are similar, which include the acquisition of structural response data over time and processing of the obtained dataset in order to identify features that contain information about possible or potential damage initiation and propagation [4]. For instance, Zhao et al. (2019) performed a systematic literature review of deep learning-based machine health monitoring systems (MHMS), which the results found applicable to SHM as well due to the inherent similarities of mechanical and structural systems, as discussed. They categorized the DL-based MHMS into four classes of architecture i.e., auto-encoder models, restricted Boltzmann machines models, convolutional neural networks (CNN), and recurrent neural networks (RNN). During their investigations, they found that the satisfactory performance of employed DL architecture highly depends on the quantity and quality of datasets being used. While they called the deep neural networks as “[black boxes” models](https://www.sciencedirect.com/topics/engineering/black-box-model), advances in data visualization may provide insights into some of the computation mechanisms used to solve structural health monitoring problems. They advocate the use of Transferred Deep Learning due to the lack of data in most MHMS areas.

**Preprocessing:**

**Data Augmentation:**

One of the current disadvantages of image datasets in the realm of structural health monitoring (SHM) area is the limitation of data size, in terms of the number of pictures. This lack of a sufficient number of pictures may cause several problems such as overfitting i.e. when the CNN learns a highly variant function[5]. To avoid such undesired performance, data augmentation is employed, which is a suite of techniques that enhance the size and quality of training datasets e.g., geometric transformations, color space transformations, kernel filters, mixing images, random erasing, etc. Figure 1 (a) shows a random image of a wall with orthogonal cracks, while Figures 1 (b), (c), and (d) show the same images after random rotation, blurring, and flipping operations. It is noted that image cropping, while largely popular in other applications, is deliberately avoided herein to prevent removing the damage from the image deliberately.



(a) (b)



(c) (d)

**Figure 1: (a) original image (b) random rotation (c) blurring (d) flipping**

Since the material type data set is imbalanced, i.e., one class of data is larger than the other one, over-sampling of the smaller class has been performed to achieve more balance. Additionally, after the data augmentation and over-sampling, data normalization is performed to achieve a more balanced dataset.

References:

[1] Y. Yu, C. Wang, X. Gu, and J. Li, “A novel deep learning-based method for damage identification of smart building structures,” *Struct Health Monit*, vol. 18, no. 1, pp. 143–163, Jan. 2019, doi: 10.1177/1475921718804132/ASSET/IMAGES/LARGE/10.1177\_1475921718804132-FIG2.JPEG.

[2] K. M. Rashid and J. Louis, “Times-series data augmentation and deep learning for construction equipment activity recognition,” *Advanced Engineering Informatics*, vol. 42, p. 100944, Oct. 2019, doi: 10.1016/J.AEI.2019.100944.

[3] P. Iannelli, F. Angeletti, P. Gasbarri, M. Panella, and A. Rosato, “Deep learning-based Structural Health Monitoring for damage detection on a large space antenna,” *Acta Astronaut*, vol. 193, pp. 635–643, Apr. 2022, doi: 10.1016/J.ACTAASTRO.2021.08.003.

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[5] C. Shorten and T. M. Khoshgoftaar, “A survey on Image Data Augmentation for Deep Learning,” *J Big Data*, vol. 6, no. 1, pp. 1–48, Dec. 2019, doi: 10.1186/S40537-019-0197-0/FIGURES/33.