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Machine Learning Empowered Structural Deformity Analysis for Improved Damage Control and Health Monitoring

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Abstract-A maintenance technique known as structural health monitoring (SHM) uses sensing equipment to keep an eye on the health of structures. Domain knowledge is essential for applying SHM techniques successfully because it permits the use of machine learning techniques and makes it easier to extract damage-sensitive features for interpretation by machine learning algorithms. The two main SHM issues that this study focuses on are damage identification and substructure clustering. The researchers make recommendations for how to overcome these difficulties based on robust feature extraction approaches and machine learning techniques. The researchers used a frequency domain decomposition method to extract damage sensitive characteristics for the first issue. For damage identification, they next employed a reliable one-class support vector machine. The researchers used a novel clustering method and a spectral moment characteristic to group substructures with comparable behaviour and find spatial anomalies in the second challenge.The researchers analysed data from lab-based constructions and data gathered from the Sydney Harbour Bridge to assess the efficacy of their suggested solutions. The findings of their study show excellent damage detection and damage severity assessment capabilities. They also successfully identified spatial abnormalities and grouped substructures with similar behaviour using their clustering technique. Overall, this research aids in the development of SHM procedures that are more effective and efficient and can help maintain the security of vital civil infrastructure.

Keywords: Structural health monitoring,Unsupervised learning, Clustering Anomaly detection, Environmental variability Threshold

1. Introduction-Important and complicated civil structures are crucial to modern society, yet natural disasters, climate change, and heavy use can damage them. Age and material deterioration threaten the safety and integrity of some of these structures, which are approaching the end of their original design life. Regardless of culture, region, or economic status, structural health monitoring (SHM) has become necessary for most governments to improve structural performance and serviceability while decreasing retrofit and rehabilitation costs. Recently, civil engineers have been able to take advantage of AI in a variety of SHM [1,2] and other civil engineering jobs [3,4]. Raw data preparation is now a bottleneck in civil engineering under these conditions.

In contrast, developing an automated learning model for decision-making and properly utilizing such rich data under uncertain variability sources are two of the biggest obstacles. Many feature extraction methods, including those based on hand-crafted (e.g., modal data) and learned features, have been proposed to address the first problem. The goal of the second challenge is to use one of the supervised, semi-supervised, or unsupervised learning algorithms [3, 4] to analyze measured data and extracted features to construct a robust machine-learning model. Selecting the optimal algorithm requires paying close attention to the labels of data samples or extracted characteristics. Completely labeled data for the learning process is notoriously difficult to prepare. Unsupervised learning is the best method to use here. Because there is no good reason to deliberately harm essential and expensive civil infrastructure in order to collect labeled (damaged) data, this technique is beneficial for SHM.

Data points are grouped according to how similar they are using the unsupervised learning process known as clustering. To find damage or anomalies in structures, this technique has been widely used in structural health monitoring (SHM). For SHM, a variety of clustering algorithms, including partition, hierarchical, density, spectral, and graph-based techniques, can be used. SHM frequently employs partition-based clustering methods including k-means, k-medoids, fuzzy c-means, Gaussian mixture model (GMM), and spectral clustering. Clustering methods are used on the data during the training phase, and a damage index or anomaly score function is developed based on the clustering outcomes. Using test samples that reflect the structure's current state, the anomaly score is utilised to determine scores for the relevant portion of the structure.

Novel clustering techniques have been proposed for SHM in a number of research. An adaptive kernel spectral clustering method, for instance, that can change the number of clusters over time was developed by Langone et al. To identify damage in the face of severe environmental unpredictability, Silva et al. devised agglomerative concentric hypersphere clustering with offline initialization and bottom-up clustering phases. To establish the number of clusters and the Chebyshev distance as the major score function for early damage assessment, Sarmadi et al. suggested an effective hyperparameter selection technique. Sarmadi created an automated hyperparameter selection approach to choose the ideal amount of GMM components in order to lessen the impact of operational and environmental fluctuations. In order to identify damage, Qiu et al. suggested an adaptive GMM technique based on clustering density peaks and an expectation-maximization algorithm.

Despite clustering's value for SHM, there are certain issues that still need to be resolved. Variations in measured data or features might result in false alarms or false detections, depending on the operational environment. Three main tasks can be carried out to reduce the negative effects of operational and environmental variability: identifying and isolating multiclass anomalies, modelling the link between features and variability data, and implementing unsupervised feature selection methods. This paper suggests a novel method to lessen the impact of irrelevant variables without sacrificing data quality, based on data clustering and unsupervised closest neighbour searches.

The other significant difficulty is selecting and optimizing the hyperparameters of the partition-based clustering algorithms. A hyperparameter is an unknown variable in a computational or statistical model or learner that has a significant impact on the model's or learner's output [31]. For instance, in many partition-based clustering methods, the number of clusters serves as the primary hyperparameter. While the Silhouette value and Bayesian information criterion (BIC) [5] are two examples of classical cluster number selections that can be used with any partition-based clustering algorithm, they may not be adequate for data clustering when there is a great deal of variance in the unlabeled data.This emphasizes the need for a more reliable method of counting clusters. Therefore, this article suggests an automated self-cluster selection, wherein any unlabeled data is selected as a local cluster without any additional technique. Estimating an alarm threshold is another complex problem in an unsupervised learning-based SHM strategy [16: Chapter 10]. This is because decision-making mistakes and false alarms or detections can occur when the threshold is off. Probabilistic properties of anomaly scores in the training data are typically taken into account during the threshold estimation process [27,32]. Compared to the more standard practice of using confidence intervals based on central limit theory, threshold estimators grounded in extreme value theory (EVT) have proven to be the most reliable probabilistic methods. The Weibull, Gumbel, and Fr'echet models [33–35], the generalized extreme value distribution (GEVD) [27,36–39], and the generalized Pareto distribution (GPD) [32,38–39] are the most common parametric extreme value models used in EVT-based threshold estimation.The EVT can be used for both anomaly detection and threshold estimation. Still, its main drawback is that it requires another method for estimating the hyperparameters of a parametric extreme value model (e.g., the maximum likelihood estimation). Semi-parametric radical value theory (SEVT) [44] can be used to work around this restriction. To this end, Vignotto and Engelke [45] proposed an anomaly detector that utilizes the GPD model and nearest neighbor search to identify out-of-the-ordinary samples. Based on their findings, they quantile value of extreme pieces (i.e., negated maximum distances) was computed and used as an anomaly score using the Hill estimator [44]. They used the Hill estimator, which always produces a positive EVI or shape parameter, despite their novel approach to developing a probabilistic anomaly detector via the SEVT. This is problematic because the Hill estimator cannot provide an accurate shape parameter if outliers are consistent with a negative EVI.

Limitations may lead to erroneous anomaly detection findings. Daneshvar and Sarmadi [19] showed that without needing model selection, parametric modeling, and parameter estimation, the SEVT is superior to the EVT for establishing a warning threshold. Further, compared to parametric models, semi-parametric extreme value distributions require less flexibility in setting hyperparameters. The SEVT-based entry estimator relies on an anomaly detector and its outputs to perform well. Unreliable anomaly scores prevent any additional technique, such as a threshold estimator, from accurately estimating an alarming threshold in the problem of anomaly detection. An integrated framework for the concurrent application of anomaly detection and threshold estimation must be developed to address this matter adequately.

The project described in the book uses data-driven structural health monitoring (SHM) approaches to examine the Sydney Harbour Bridge (SHB), one of Australia's most recognisable landmarks. Damage detection and substructure clustering are two major issues that civil infrastructure must deal with. Strong feature extraction approaches based on domain expertise and machine learning techniques were used to solve the first issue. They specifically used a frequency domain decomposition (FDD) method to fuse and extract damage-sensitive information from various sensors. The next step was to employ a brand-new self-tuning one-class support vector machine (SVM) to find structural component degradation over time. The project's second challenge is to identify shared traits among the structure's elements by comparing and categorising them across different places. The researchers used a unique spectral moment characteristic for substructure grouping and anomaly detection in addition to extending a reliable clustering technique to accomplish this. Data from controlled lab-based structures and data gathered from a real-world deployment on the SHB were both used to evaluate the research team's approaches. The project seeks to support the advancement of stronger and more effective SHM practises that can aid in ensuring the security and durability of vital civil infrastructure.

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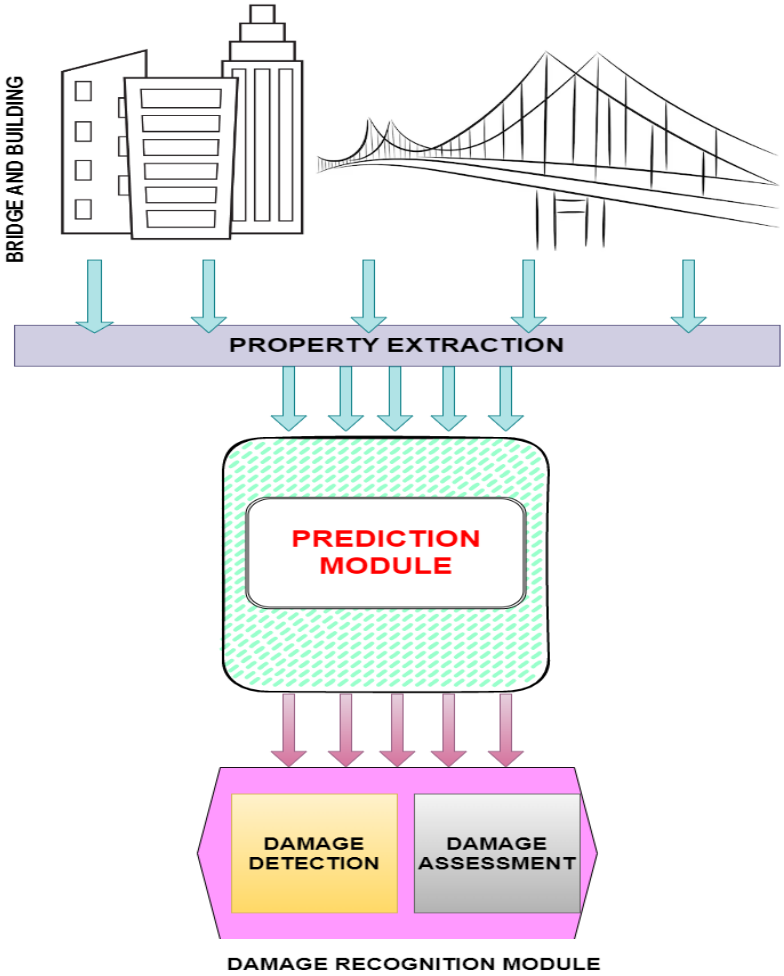

Figure.1. A suggested technique for evaluating earthquake damage based on acceleration data from instrumented objects.

Theory for extreme values in semi-parametry-The Extreme Value Theory (EVT) is a subfield of probability analysis in statistics that studies and models outliers, or the highest and lowest points in a given sample, or extremely unusual events [43,44]. The EVT is a method of modelling the tails of patterns of distribution, as opposed to the CLT, that emphasises the mean of sampling data or the centre of a probability density function (PDF). The highest and lowest value distributions for data that is both independent and identically distributed can be chosen via the Weibull, Gumbel, or Fr'echet models, contingent upon the shape of the prevailing distribution. One major drawback of utilising such distributions, however, is that analytical methods are required for both selecting the optimal model and then confirming that choice [44].

On the other hand, the generalised extreme value (GEV) and generalised Pareto (GP) distributions can be used effectively because they combine the three separate probabilities into a single, more manageable one. It's important to keep in mind that both the GEV and GP distributions are parametric models, despite the fact that their use makes it easier to predict the highest and lowest values. This emphasises the importance of obtaining a precise estimate for the hyperparameters involved in the modelling of extreme values. (i.e., the shape, scale, and location). All three distributional models—Weibull, Gumbel, and Fr'echet—require the same approach.

2. SHM Framework

Two railway tracks and eight lanes of traffic are supported by the Sydney Harbour Bridge (SHB), with Lane 7 on the eastern side reserved for buses and taxis. The 800 concrete and steel jack arches that support this lane are prone to cracking because of the ageing of the building and the weight of the traffic. Early detection of such damage is essential, yet some of these jack arches can only be visually inspected once every two years.

A Structural Health Monitoring (SHM) system has been created and put into place on the SHB in order to solve this problem. Approximately 2400 sensors that are dispersed beneath Lane 7 of the infrastructure are used by this system to gather, combine, and analyse a sizable amount of data. Four layers make up the SHB system, the first of which consists of three tri-axial accelerometers fastened to each of the 800 jack arches. These sensors are low-cost MEMS (microelectromechanical systems), which record the vibrations of the structure.

Smart nodes and gateways at the second layer, known as data management, are responsible for gathering data from the sensors. When a vehicle passes over a given jack arch, the nodes record vibration data at a frequency of 250 Hz from the three sensors on that particular jack arch. Additionally, each node records ambient vibration continuously at 1500 Hz for 10 minutes at midnight. The gathered information is transferred and used in the layer below for data analytics.

Different algorithms are used in the third Data Analytics layer to extract useful information from the data. A few algorithms are active and in use, using real-time data to give the bridge management and engineers information. Other algorithms are running on previously gathered data while they are offline and in the research phase. Finally, a secure web-based visualisation dashboard has been created in the Service layer to enable the bridge management and engineers to continuously monitor all the jack arches. By offering a more precise and timely evaluation of the infrastructure's status, this element aids in the optimisation of maintenance schedules.

2.1 Domain Knowledge-based Extraction of Features

Affected dynamic responses come from structural deterioration, which modifies a structure's physical characteristics such stiffness, mass, and damping [39]. It is essential to choose a suitable damage-sensitive characteristic from the structure's recorded vibration response in order to deploy vibration-based structural health monitoring (SHM) methodologies successfully . The identification of such features in a variety of domains, such as the modal domain [20], frequency domain [38], time domain [11], and time-frequency domain [43], has been the focus of numerous investigations.

Modal-based features, which include modal characteristics such natural frequencies , damping [14], and mode shapes, as well as their derivatives like modal strain energy and flexibility matrix [44], were one of the first types of features employed for SHM applications. The effectiveness of these features in detecting damage in real-world applications has recently come under scrutiny, despite the fact that many implementations of these features have been successful. The primary disadvantage of modal-based features is that they do not provide broadband data and only supply information at a few specific frequency resonances. Additionally, the complicated modal analysis needed to extract these properties from recorded temporal responses might lead to computational mistakes [40]. Because they are not explicitly assessed, modal-based features are equally susceptible to inaccuracies. The information on higher modes, which are more sensitive to minute changes in structural integrity, is frequently overlooked in real-world applications because only a few lower modes are typically assessed. As a result, it is impossible to extract the full set of modal characteristics from the measurements. Finally, it is crucial to remember that environmental changes have a significant impact on modal characteristics, particularly natural frequencies [45]. Modal-based approaches are less appropriate for real-world SHM applications as a result of these drawbacks.

As they don't need domain transformation, SHM techniques based on time-domain features have gained popularity recently and speed up monitoring applications [11]. On the basis of differences in the observed responses in the time domain, damage identification is directly attempted in these situations. Time-domain features may not have a clear physical significance and can instead be viewed as data-based features rather than physics-based features. Damage is determined by statistically comparing the present characteristic quantity with its baseline. One of the initial statistical frameworks used for tracking acceleration measurements was the use of time series statistics, such as mean and variance, to spot data that did not match earlier data (such as the undamaged condition) [22].

Numerous SHM applications have also integrated features based on autoregressive models. These characteristics are either based on the residuals between an autoregressive model's forecast and the actual observed time history at each interval, or they are based solely on the model's coefficients .

In order to detect damage in mechanical components subjected to stochastic loadings, frequency-based parameters, such as power spectral density (PSD), frequency response functions, and their derivatives, can be used. Broad-band data with a wide variety of frequencies can now be extracted with the help of spectral-based algorithms in the frequency domain. These techniques have been widely employed in damage detection, and non-Gaussian signals buried in a Gaussian background are characterised using spectral moments, which indicate the statistical features of a stochastic process.

The first, second, and third moments were frequently used to estimate the modal parameters of dynamically excited structures from ambient response data in the early studies in the field of structural health monitoring (SHM). Higher-order spectral moments, including spectral kurtosis, were then used to forecast the pace at which fatigue damage builds up in structures subjected to random processes. Time-frequency analysis utilising the wavelet transform is a potent method that has been developed for identifying changes in structural qualities brought on by damage. The wavelet analysis's varied granularities and close approximations to the original signals allow for the variable-intensity examination of local data. Wavelet analysis is also helpful for analysing non-stationary systems since it can spot minute changes in signals across time.

Data fusion, which involves combining data from many sensors, is an essential component of SHM. Various data fusion techniques have been used, including data-level fusion, feature-level fusion, and decision-level fusion. Data from different sensors are combined in data-level fusion to produce new raw data that are predicted to be more informative than data from a single sensor. The features from various sensors are integrated in feature-level fusion to produce more pertinent information. Advanced methods, including Bayesian approaches, neural networks, and Principal Component Analysis (PCA), have been developed for feature-level fusion. Last but not least, decision-level fusion can be accomplished by using methods like voting or fuzzy logic to make a final conclusion based on every decision gathered from various sensors.

The damage-sensitive feature is extracted from the measured acceleration response in the current study using a spectral-based approach that makes use of the notion of spectral moment. The power spectral density (PSD) of a signal is used to determine the spectral moment, which is correlated to the signal energy in the frequency domain. In addition, the study integrates frequency data from several sensors utilising a feature extraction and data fusion approach employing FDD. The feature extraction and fusion methods used in this work are thoroughly described in the section that follows.

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2.2 Damage Identification

The application of domain knowledge for feature extraction in machine learning to address structural health monitoring (SHM) issues is covered in this section. It emphasises how crucial it is for machine learning models to incorporate domain knowledge in order to get correct results. The next two issues in the section—damage detection and substructure clustering—are also prevalent issues with civil infrastructure. Robust characteristics are extracted utilising domain knowledge and machine learning techniques are used in the proposed solutions to these issues. In particular, damage identification is accomplished using a fault detection and diagnosis (FDD) approach and a self-tuning one-class Support Vector Machine (SVM), whereas substructure grouping is accomplished using a spectral moment feature and k-means clustering.

2.3 ML for SHM

When a structure's structural integrity is threatened, its vibration properties alter. Therefore, the fundamental goal of vibration-based structural health monitoring (SHM) is to spot any variations in these traits from a reference condition. A physics-based model of the structure or a statistically-based model of the system under study can both be used to do this. The first way entails creating a numerical model of the structure through the use of optimisation and finite element methods, which is calibrated to provide a benchmark state. To find any prospective changes in the system, future observed responses of the structure are compared to predictions made by the numerical model. However, there are drawbacks to this technique, especially when it comes to large-scale structures and the presence of real-world uncertainty. In contrast, a data-based or machine learning model just uses measured data and uses domain expertise to translate it into useful information. This is a more viable option since it gets over the issues caused by operational and environmental unpredictability and is more applicable to real-world SHM applications.

The bulk of vibration-based structural health monitoring (SHM) systems are less practical for massive infrastructure since they call for input and output signals. On the other side, output-only dynamic test methods, where the structure is activated by organic or haphazard environmental variables, including traffic, winds, waves, or human activity, are more practical. These techniques rely exclusively on reaction measurement data to determine the structural integrity; the input driving forces are not known. It is necessary to use an original method called output-only modal identification to determine the structure's vibrational characteristics. In order to extract the most distinguishing characteristics from the measured response, this technique depends on the domain expertise of specialists.The domain knowledge of output-only modal identification is used to explain two alternative features in the following sections.

2.4 Identifying Damages in Civil Structures

The technique for spotting damage as it develops over time in structural components is described in the section that follows. Figure 1 offers a graphic picture of this strategy. First, using FDD, damage-sensitive features are identified from the measured data, and then random projection is used to reduce the dimensionality. The reduced dimensions space is then subjected to an adaptive (self-tuning) one-class SVM application to look for any indications of damage.

3. Extraction of Features using Data Fusion

The authors of the study used FDD to combine data from a sensor network at the data-level. The FDD methodology implies the availability of the vibration responses from "l" different points inside the structure. To be more precise, a correlation function in the time domain, Rpq, can be used to probabilistically define the response process at two locations, "p" and "q" (where p and q belong to the range [1:l]).

$$R_{pq}(\tau) = E\left[x_p(t)x_q(\tau + t)\right]$$

The relationship between the vibration responses of two sites within a structure is here described by the correlation function Rpq(). The correlation function, which is a function of temporal separation, shows the relationship between two signals as it develops through time. The calculation makes use of the lag operator and the expected value operator, respectively. The random stationary process can then be frequency characterised by taking the Fourier transform of the correlation function to derive the PSD function.

$$S_{pq}(w) = \int_{-\infty}^{+\infty} R_{pq}(\tau)e^{-iw\tau}d\tau$$

The cross power spectral density (PSD), which is utilised in vibration-based structural health monitoring, is computed for a random stationary process in the text. Spq () stands for the cross PSD of the response at frequency and two separate locations p and q. When p = q, the auto-power is Spq (), and when p q, it is cross-power. In order to fill a symmetric matrix Sl(), the frequency spectra of the cross PSD for each pair-wise location are used. At each frequency spectrum, the matrix S can then be decomposed using singular value decomposition (SVD).

$$S(w) = U \sum U$$

With this method, the response's cross PSD at various places and frequency spectra is obtained. The correlation function Rpq, which describes the correlation between the response at locations p and q with a time gap, is Fourier transformed to produce the PSD. When p = q, the cross PSD of the response at locations p and q and frequency is known as auto-power and cross-power, respectively. The auto and cross-power data gathered earlier can be used to create a symmetric matrix of Sl(). The diagonal matrix of singular values and the matrix of singular vectors, represented by and and U, respectively, are produced by the SVD decomposition of the matrix S, where H denotes the conjugate.

The first singular value is the highest and the singular values are placed in descending order. An m-dimensional vector is created by merging the initial singular values found at each frequency spectrum; this vector is used as a feature vector for additional analysis. This technique fuses l signals from l sensors into a single feature vector, where m is the quantity of spectral lines or qualities.

3.1 Dimensionality Reduction

In order to extract intrinsic low dimensional information from high dimensional datasets, dimensionality reduction is a crucial step. Its main objective is to reduce the number of dimensions in a high-dimensional dataset while retaining the key factors that can explain the original dataset. This phase is crucial for Structural Health Monitoring (SHM) applications because there are frequently fewer observations relative to characteristics in these applications.

Dimensionality reduction can be accomplished using the well-known PCA (Principal Component Analysis) method. Its main goal is to calculate the eigenvalues and eigenvectors of a covariance matrix constructed from a given dataset in order to identify the variables with the highest variance in the data. However, because to the eigen decomposition of the covariance matrix, where m is the dimension of the data, PCA has a high computational complexity of O(m3). Due to this, it is impractical to employ for datasets with very high dimensions, which is a prevalent problem in SHM sensing data. Additionally, the quantity of chosen components affects how well it performs.

A practical method for lowering the dimensionality of data with several dimensions is random projection. Regardless of the initial data dimension m, it is an effective method that can be used with high-dimensional data because its dimensionality is purely based on the number of data points n. The preservation of pairwise Euclidean distances between data points is the main goal of random projection. This is accomplished by transforming the high-dimensional data into a subspace at random with O(log n) columns. A formula was created in a study by Achlioptas [1] to help identify the right number of dimensions required for random projection.

$$k = log\left(\frac{n}{\varepsilon^2}\right)$$

High-dimensional data can be effectively and efficiently reduced in dimension using the random projection method. Random projection is an alternate method that simply depends on the number of data points n, regardless of the original data dimension m, in contrast to PCA, which can be computationally expensive and sensitive to the number of selected components. The objective of random projection is to project the data points into a random subspace spanned by O(log n) columns while maintaining the pairwise Euclidean distances between them. A formula that takes into account the desired number of dimensions k, a small positive number, and the number of data points n can be used to determine the number of dimensions needed for random projection. The next step is to create a random matrix Rmk, where each entry ri j is chosen at random from a probability distribution.

$$r_{ij} = \begin{cases} +1\ with\ pr\left({}^{1}/_{2s}\right) \\ 0\ with\ pr\left(1-{}^{1}/_{2s}\right) \\ -1\ with\ pr\left({}^{1}/_{2s}\right) \end{cases}$$

The material that was quoted explains how random projection is used in high-dimensional data to reduce dimension. This is accomplished by creating a random matrix R in which each entry, ri j, is chosen at random from a probability distribution. The equation k = log n/2, where n is the total number of data points and is a small positive number, can be used to determine the number of dimensions in the low-dimensional space, or k. The proportion of non-zero entries in each column of the random matrix R is determined by the projection sparsity, s. There is a good chance that the projection Y = XR roughly maintains the pairwise Euclidean distances for all X data points. Since k is typically a small integer, Venkatasubramanian and Wang proposed that in reality, kRP = 2 ln n/0.252.

3.2 OC-SVM Model

It is more practicable to adopt a one-class technique that only uses data from a healthy structure when there is a paucity of data pertaining to damaged states of structures for supervised learning. For the purpose of detecting anomalies, this study uses a one-class support vector machine (SVM) [52]. Given a set of data $X = \{x_i\}_{i=1}^{n}$taken from the original sensor data (feature vector) obtained from a healthy structure, where n is the number of training samples, the one-class SVM maps the data using a function through the kernel $K(x_i, x_j) = \emptyset(x^i)^T \emptyset(x_j)$Then, using a one-class SVM, a hyperplane is learned that maximises the separation between the data points and the origin.A vector of m items, each of which is an attribute, is referred to as a feature vector.

The categorization model is expressed in the form of the function *f: R^m*→ $\{-1,+1\}$.

$$f(x) = sgn(w.\emptyset(x) - \rho)$$

A collection of data $X = \{x_i\}_{i=1}^{n}$taken from the sensor data of a healthy structure is utilised to train the one-class SVM for anomaly detection. Using a function and kernel $K(x_i, x_j) = \emptyset(x^i)^T \emptyset(x_j)$, the SVM maps the data samples into a high-dimensional feature space. The SVM then trains a hyperplane to separate the data points from the origin by maximising the distance between them. The classification model f(x) is described as a function *f: R^m*→ $\{-1,+1\}$, where *f(x) = +1* if *(w(x)) > 0* denotes that the structure is healthy and *f(x) = 1* denotes that the structure's status has altered. By minimising the classification error on the training set while maximising the margin, the model parameters w and are learned from the training data X. This is comparable to the minimization issue depicted below:

$$\min_{w,\varepsilon,p} \frac{1}{2}\|w\|^2 + \frac{1}{vn}\sum_{i=1}^{n} \varepsilon_i - \rho$$

$$s.t., w.\emptyset(x_i) \geq \rho - \varepsilon_i, \varepsilon_i \geq 0$$

A slack variable named *i* is introduced in order to regulate the amount of training error permitted. In order to balance *i* (the training error) and *w* (the margin), a user-specified variable *v* [0, 1] is also included. The model parameters w and are determined during the training phase using the data samples$X = \{x_i\}_{i=1}^{n}$The objective is to maximise the margin while minimising the classification error on the training set. This can be expressed mathematically as the following minimization problem:

$$\min_{a1,a2,\cdots,an} \sum_{i,j}^{n} a_i a_j K(x_i, x_j)$$

$$s.t., 0 \leq a_i \leq \frac{1}{vn}, \sum_{i=1}^{n} a_i = 1$$

The model parameters w and are established by minimising the classification error on the training set and maximising the margin after the one-class SVM model has been trained using a set of healthy structural data samples, $X = \{x_i\}_{i=1}^{n}$. The decision values can be calculated using the learned model to categorise a new data instance, xnew. The decision value is determined mathematically by:

$$f(x) = sgn\left(\sum_{i=1}^{n} a_i K(x_i, x_{new}) - \rho\right)$$

A negative decision value generated for a new data instance x_{new} in the context of a one-class SVM used for anomaly detection in structural health monitoring suggests that the instance is an outlier or an anomaly. This negative value is due to the instance being mapped outside the hyperplane border separating normal and abnormal states in the learned model. In other words, the negative decision value shows that x_{new} is likely linked to structural damage because it does not belong to the same distribution as the training samples of healthy data.

3.3 Gaussian Kernel:

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In one-class SVM applications, the Gaussian kernel specified in the below equation has gained popularity in the machine learning community. However, it needs a parameter,, which has a considerable impact on the one-class SVM's performance. Selecting an incorrect value for can result in either overfitting or underfitting, which can have a detrimental influence on the algorithm's performance.

$$K(x_i, x_j) = e^{\left(\frac{-\|x_i - x_j\|^2}{2\sigma^2}\right)}$$

Support vector machines (SVM) with one class are frequently employed for classification and anomaly detection tasks. In these scenarios, one class of data is taught to simulate typical behaviour and then spot any departures from it. The shape of the decision border, which is determined by the kernel parameter, has a significant impact on how well a one-class SVM model performs.

Usually, during the training phase, is tuned using K-fold cross-validation. This method, however, is not appropriate for one-class learning since it has a propensity to choose a value that performs well just on the training class data, which might result in overfitting and subpar generalisation on new data.

Different alternative methods for tuning in one-class SVM have been put forth to solve this issue. The Appropriate Distance to the Enclosing Surface (ADES) algorithm is a contemporary technique that has produced promising results on a number of datasets.

According to above equation, the ADES algorithm determines the ideal value of by maximising the objective function f(i). The edge and interior samples' spatial placements, as well as their separations from the one-class SVM's enclosing surface, are taken into consideration by this function. Using a normalised distance function, the method looks for a hyperplane that is farthest from the interior samples and closest to the edge samples.

In one-class SVM, the ADES algorithm provides an efficient and dependable method for tweaking the kernel parameter that can increase the model's generalisation ability and enhance its performance with fresh data.

$$f(\sigma_i) = E(d_n(x_n) \in \omega_N) - E(d_n(x_{IN}) \in \omega_{ED})$$

A hard margin linear SVM is used to identify the sets of inner and edge samples in the healthy training data points. These sets are indicated by the letters *IN* and *ED*, respectively. The following definition defines dN, which is the normalised distance between these samples and the hyperplane:

$$d_n = \frac{d(x_n)}{1 - d_n}$$

d(xn) is the distance between the sample xn and the hyperplane, and d is the distance from a hyperplane to the origin, denoted by the formula d = w. It is determined by using:

$$d(x_n) = \frac{f(x_n)}{\|w\|}$$

$$d(x_n) = \frac{\sum_{i=1}^{n} a_i K(x_i, x_j) - \rho}{\sqrt{\sum_{i,j}^{n} a_i a_j K(x_i, x_j)}}$$

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wherei are the Lagrange multipliers, w is a vector perpendicular to the decision boundary, and is the bias term. [4] contains additional information on the ADES approach.

4. Clustering Algorithm

In data mining applications, clustering is a prevalent technique. Its main goal is to use predefined features to categorise objects in a collection into groups or clusters that are similar to one another. The k-means algorithm is one of the most widely used clustering techniques.

The data are divided into k clusters by the k-means algorithm, indicated as $C = C1,..., C_k$. The within-cluster sum of squares, a measurement of the overall distance between the data points and their respective cluster centroids, is what the method seeks to minimise. In other words, the goal of the k-means algorithm is to reduce the total squared Euclidean distance between each data point and the centroid of the cluster to which it is assigned.

In general, the k-means algorithm is a useful and popular method for grouping data into sets of related items, and it has a wide range of uses in areas like image segmentation, anomaly detection, and customer segmentation.

$$\arg\min \sum_{i=1}^{k} \sum_{x \in C_i}^{k} \|x - \mu_i\|$$

The k-means algorithm's optimisation function is locating the cluster centroids that reduce the within-cluster sum of squares. The mean of the data points in the ith cluster, represented by Ci, corresponds to each centroid i.

The k-means technique uses an iterative process that alternates between two steps to obtain these ideal centroids. Each data point is assigned to the cluster with the nearest centroid in the initial phase. By calculating the mean of all the data points assigned to that cluster, the cluster centroids are updated in the second phase. Until there are no more modifications to the clustering of data points, this process is repeated.

The k-means algorithm's iterative structure enables it to gradually enhance the clustering of data points and update the centroids to reduce the sum of squares inside each cluster. In the end, this causes the algorithm to converge and stable clusters to be found.

5. Results and Discussions

A concrete cantilever beam was created and tested to examine the structural behaviour of the Sydney Harbour Bridge (SHB). As seen in Figure 2, the beam had an arch section that was quite similar to that of the SHB. A 200UB18 steel I-Beam with 50 mm concrete coverings was used to construct the beam. It measured 2 metres long, 1 metres wide, and 0.375 metres deep. The specimen was fully clamped for the first 400 mm of the beam and secured at one end with a steel bollard to create a cantilever. To prevent the tip from splitting under its own weight, a support was positioned 1200 mm from it [42].

To quantify the vibration response brought on by impact hammer stimulation, ten PCB 352C34 accelerometers were mounted on the specimen. As seen in Figure 2, the accelerometers were positioned on the beam's front face. An impact hammer with a steel tip was used to strike the specimen's top surface just above sensor A9 in order to excite the beam. The structure's acceleration response was recorded for 2 seconds at an 8 kHz sampling rate, yielding 16000

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samples for each excitation event. The healthy beam specimen was subjected to 190 impact tests.

The specimen was then sliced using a cutting saw at the point indicated in Figure 2 between sensor sites A2 and A3, gradually enlarging the crack towards sensor location A9. The cut's length steadily expanded from 75 to 150, 225, and finally 270 mm. The cut was made at a consistent depth of 50 mm. A total of 190 impact tests were performed on the beam specimen at the same site following each damage case. Gradually introducing damage allowed for a systematic analysis of how it affected the beam's structural behaviour.

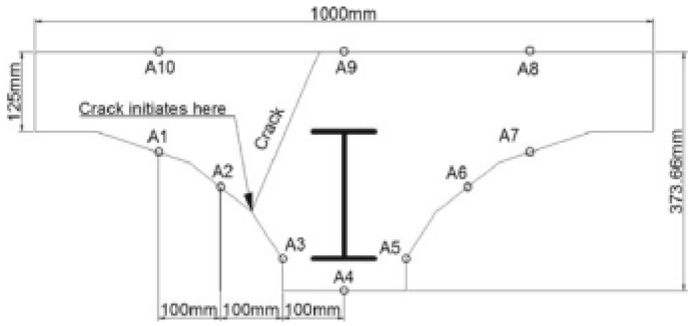

Figure2 Specimen of laboratory with cracking.

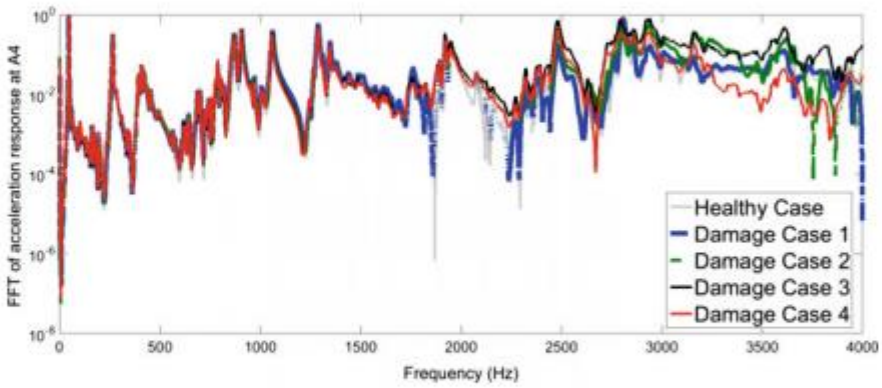

Figure 3: Comparison of the healthy state and the four damage scenarios for sensor location A4's frequency response function (inertance)

We compared the frequency response function (FRF) of the structure to better understand how damage to the concrete cantilever beam might affect it. Analysing the measured results from the healthy case and four different harm cases was required for this. In Figure 3, the findings of this investigation are displayed.

On a dataset of 950 samples taken from a structure, the authors used their suggested framework for damage detection and severity evaluation, as shown in Fig. 1. Each sample consisted of an 8,000 attribute measured vibration response in the frequency domain. Healthy samples (190) and damaged samples (760) were isolated from the data. All of the damaged data was used for testing, whereas the training datasets were randomly divided into training (80%) and testing (20%) datasets. The training data were first subjected to feature extraction and fusion from ten sensors using FDD, then dimensionality reduction using random projection. The ADES approach was used to determine the ideal value of, and a one-class SVM was built as a damage detection model.

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With an F1-score of 0.95, the model was validated using the testing data and was successful in identifying the damaged cases. Fig. 4, which displays the decision values of all test data and the average decision values for each healthy and injured instance, provides a summary of the findings. All damaged samples were correctly classified, with the exception of four events in Damage Case 1 that had positive decision values. Only three healthy events were incorrectly labelled as damaged samples. This shows that despite variances in operational settings, the model is well-generalized, capable of identifying damaged and healthy samples, and able to evaluate the progression of damage.

An alternate strategy without using FDD for sensor fusion was used to examine the efficacy of feature fusion. utilising information from the healthy case, a separate damage detection model for each sensor was built utilising only the frequency properties of the acceleration response collected from each sensor. Results of this method for identifying damage in sensors A1, A2, A3, and A4 are shown in Fig. 4 through Fig. 7. It is clear that this method is unable to keep track of how much damage has been done, and the decision values have not consistently done so either. This leads to the conclusion that FDD is resistant to excitation variations and can deliver accurate data regarding the extent of damage in the structure.

For each pair of (k, o), the findings are shown in Figure 8 as the Silhouette, Davies-Bouldin, and Dunn indices. A selection criterion was used to keep the pairs that match the specified extremum values. Based on this standard, the pairs (k = 2, o = 3), (k = 2, o = 4), and (k = 3, o = 0) were chosen. Figure 9 shows the 3D scatterplots for the second order spectral moment in x, y, and z for these chosen pairs to give further information. It also shows the values of the associated indexes. The nodes 184, 427, and 433 were used to indicate anomalies that were discovered as a result of the intersection of these pairs.

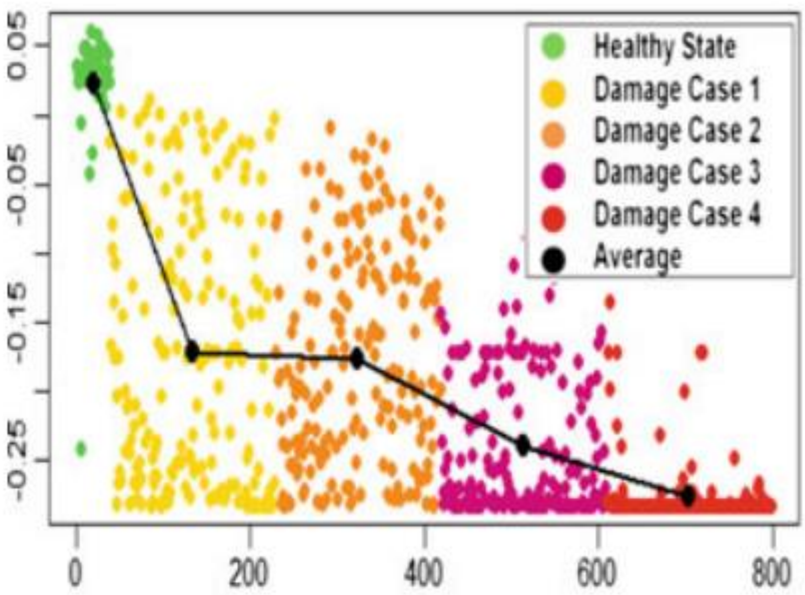

Figure 4: Decision value vs test event index for Sensor a1.

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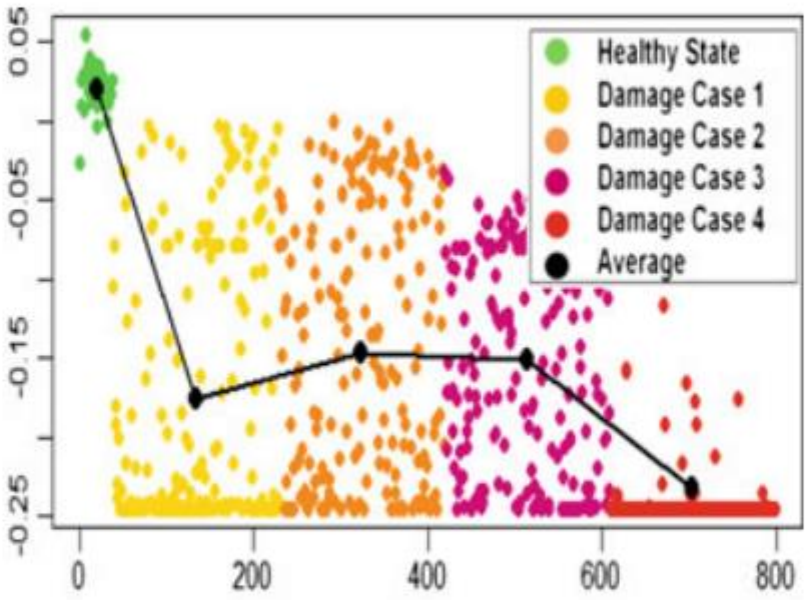

Figure 5: Decision value vs test event index for Sensor a2.

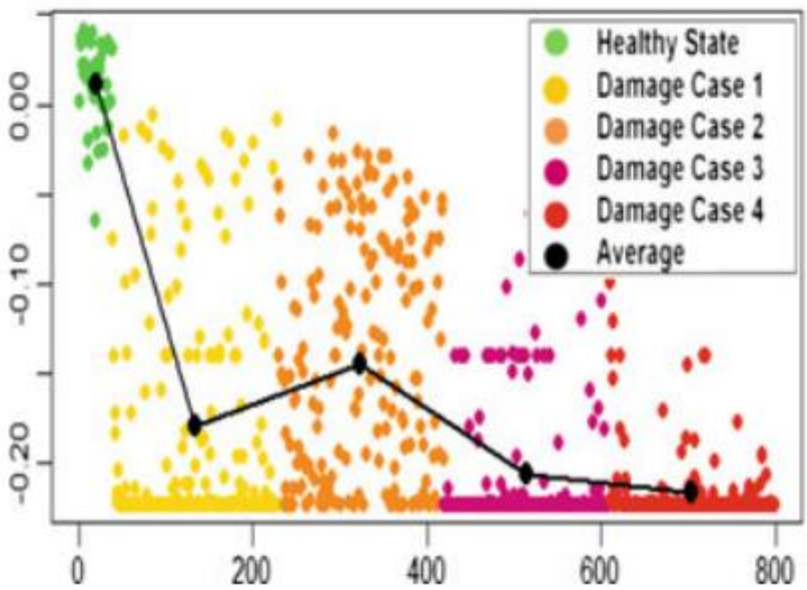

Figure 6: Decision value vs test event index for Sensor a3.

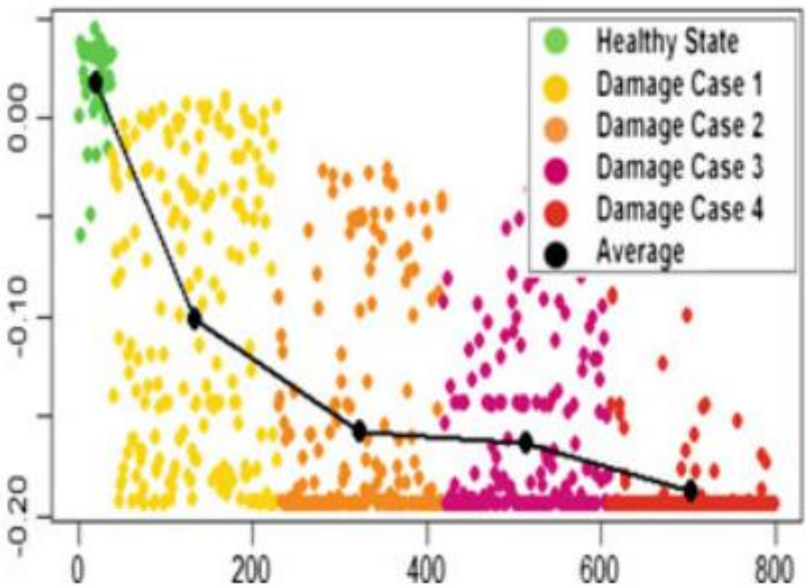

Figure 7: Decision value vs test event index for Sensor a4.

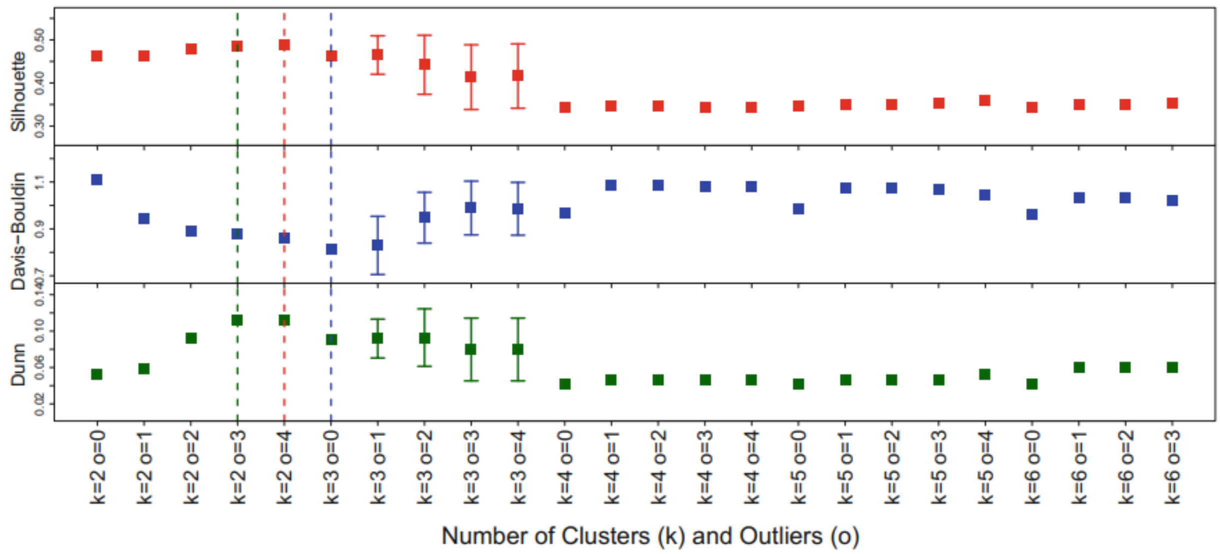

Figure 8: Representation of various (k, o) parameters, silhouette, Davies-Bouldin, and Dunn indices

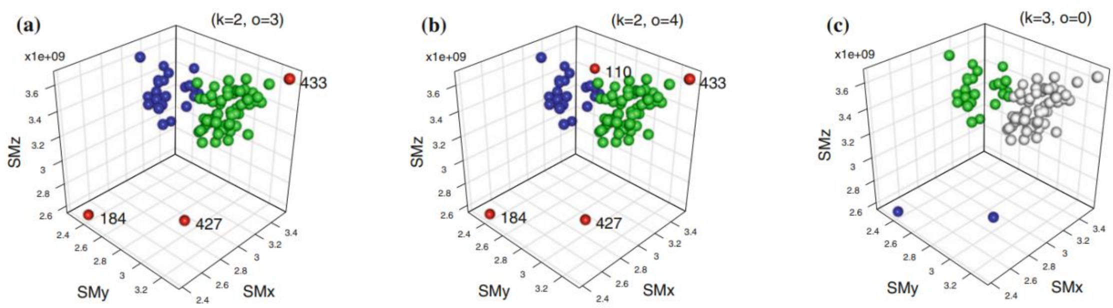

Figure 9: Selected 3D scatter plots of spectral moments (SM) for each node, coloured according to the node's participation in the cluster for particular parameters.

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6.Conclusions

In order to extract damage-sensitive features and interpret machine learning results, this research proposes two machine learning-based methodologies for structural health monitoring (SHM) applications. In the first method, a feature space fused from several sensors using FDD and random projection for dimensionality reduction is utilised to create a structural benchmark model using a self-tuning one-class SVM. Using decision values from the SVM, the model is then used to identify damage and determine how serious it is. In the second method, substructure grouping and anomaly detection are accomplished using a strong clustering methodology on spectral moment characteristics. The method was successfully used on actual SHB data to group substructures with comparable behaviour and find anomalies related to sensor problems. The suggested methods for finding damage and geographically locating anomalies had excellent accuracy and few false positives. As part of their ongoing endeavour to create Smart Infrastructures that optimise maintenance and services, the authors intend to put the suggested ideas into practise on their production system on the SHB and apply them using data gathered from other structures.

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