Deep learning of structural changes in historical buildings: the case study of the Pisa tower

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Abstract: Structural health monitoring of buildings via agnostic approaches is a research challenge. However, due to the recent advent of pervasive multi-sensor systems, historical data samples are still limited. Consequently, data-driven methods are often unfeasible for long-term assessment. Nevertheless, some famous historical buildings have been subject to monitoring for decades, before the development of smart sensors and Deep Learning (DL). This paper presents a DL approach for the agnostic assessment of structural changes. The proposed approach has been experimented to the stabilizing intervention carried out in 2000-2002 on the leaning tower of Pisa (Italy). The data set is made by operational and environmental measures collected from 1993 to 2006. Both conventional and recent approaches are compared: Multiple Linear regression, LSTM and Tansformer. Experimental results are promising, and clearly shows a better change sensitivity of the LSTM, as well as a better modeling accuracy of the Transformer.

1 INTRODUCTION

Structural health monitoring (SHM) plays an important role in the diagnosis and evaluation of the stability and deformation of historical buildings. Over the ages, such buildings have been subject to various maintenance and renovations, using different materials and construction techniques, leading to a complex structural behavior.

Multi-sensor systems with high reliability and low cost, small size and weight, low power consumption and high rate data processing, are essential to SHM. However, their pervasive application is still in its infancy. As a consequence, long-term data are available only for world famous historical buildings. For such buildings, sensor systems gathering multiple parameters for long time allow the experimentation of agnostic techniques based on Deep Learning (DL) (Farrar et al., 2006).

In the literature, according to the type of parameters acquired, SHM systems are classified into two main categories: (i) *static systems*, which monitor the temporal evolution of quantities that change slowly over time (e.g., crack widths, wall slopes, relative distances, etc.) via periodic data sampling; (ii) *dynamic systems*, which monitor dynamic parameters such as velocities, accelerations, in order to gather information on general dynamic properties such as natural frequencies, mode shapes, and damping ratios.

Data pre-processing is also essential, because different sensing technologies can be employed over the ages, as well as to distinguish any evolutionary trends from seasonal and daily variations related to environmental effects (Baraccani et al., 2017).

As a methodology of data analysis for SHM, DL techniques have shown a significant potential for their capabilities of detecting implicit relationships in data, by requiring less domain knowledge. Some DL architectures have been already experimented for specific tasks on particular buildings (Mishra, 2021); e.g. a convolutional architecture to solve the damage localization task (Parola. et al., 2022). A relevant state-of-the art review is provided in next section.

In this paper, the Transformer architecture is proposed and compared with the Long-Short Term Memory (LSTM) for a specific SHM task. In the lit-

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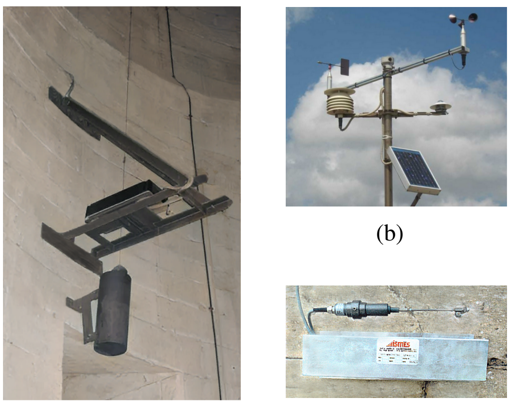
erature, it is well-known that a Transformer overcome an LSTM in the semantic capture of time-series data. The different solutions are compared in order to asses the structural changes in the Leaning Tower of Pisa (Italy) (Burland et al., 2009), which has undergone many maintenance intervention over the epochs. Specifically, the under-excavation intervention performed between 2000 and 2001 is considered (Burland et al., 2009) as a case study.

The SHM system installed on the Leaning Tower of Pisa is a static system, with a configurable sampling time period. Figure 1 shows some sensing subsystems installed inside the tower since 1993, delivering a synchronized Multivariate Time Series (MTS).

The data series hourly collected from 1993 to 2006, has been used for the assessment of the above mentioned under-excavation effects, via both conventional and recent approaches: Multiple Linear Regression, LSTM and Transformer.

The underlying strategy for the proposed approach is to create a model of the structural behavior before and after the maintenance intervention, exploiting the large availability of data, via a general purpose preprocessing, and without a knowledge-based supervision nor feature selection. This approach falls under the regression task, whose goal is the agnostic model of the relationship between input and output data. In particular, prediction is a special type of regression aimed to foresee the next values of a given time series. In the proposed approach, a multi input - multi output prediction is considered.



(a) (b) (c)

Figure 1: Some sensing subsystems of the tower of Pisa: (a) telecoordinometer - inclinometer and pendulum; (b) environmental parameters - wind speed and direction, solar radiation and termometer; (c) deformometer.

Finally, the assessment of the structural change is based on the differences in the prediction capability of the model before and after the maintenance event. Experimental results are promising, and clearly shows the higher accuracy of Transformer, with respect to LSTM and conventional Multi-Linear Regression, as well as the better sensitivity of LSTM.

The paper is structured as follows. Section 2 presents an overview of the related works. Section 3 covers material and methods, whereas experimental results and discussions are covered by Section 4. Finally, Section 5 draws conclusions and future work.

2 RELATED WORKS

A structural change of a building is measured via a change of the materials and/or physical properties of the structure. For example, an elastic material coefficient reduction and system connectivity, which adversely affect the system's current or future performance (Farrar and Worden, 2007).

In the literature, the structural changes of a maintenance intervention can be detected via a two-phase method: (a) to identify the stable key parameters of a behavioral model of the structure, corresponding to the periods before and after the intervention; (b) to identify a persistent variation of such parameters by comparing the two periods. The underlying idea is that a change of behavior on the structure will occur over time after the intervention in terms of deviation from the condition before the intervention (Reynders et al., 2014).

The main drawback of this approach is the knowledge needed to set up a model, the key parameters, and the baseline condition representing the state before the maintenance. A possible solution is to exploit multivariate clustering in feature space for the identification of the stable clusters/components that describe the behavior of the structure (Figueiredo et al., 2014). An alternative approach, requiring little knowledge, is to exploit regression analysis, where both environmental and operational properties are taken into account to generate a predictive model of the behavior before the maintenance, which can be used for the behavior after the maintenance, in order to assess a different deviation from the expected value (Wah et al., 2021).

In this work, a regression-based approach is proposed, by using the data provided by the multi-sensor system in order to model the related Multivariate Time Series (MTS). A MTS represents the evolution of a group of variables partially independent. The prediction of a MTS can be solved via a classical statistical approach, such as an auto-regressive integrated moving average method, which can be used to analyze the relationships between the different variables.

In the last decade, DL-based methods achieved widespread adoption, for their effectiveness. Different architectures have been experimented to solve the MTS prediction problem, such as Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU) or Long short-term memory (LSTM). More recently, Transformer have shown to perform better on both synthetic and real datasets, due to their attention mechanism (Li et al., 2019). In this research, both conventional and recent approaches are compared: Multiple Linear regression, LSTM and Tansformer.

3 MATERIALS AND METHODS

This section covers, on different subsections, the multi-sensor system providing the MTS, the preprocessing of the MTS samples, as well as the regression models adopted for MTS prediction.

3.1 Multi-sensor system and data preprocessing

A complex system consisting of over 60 sensors is available for the leaning tower of Pisa. In this research, only a subsystem of sensors are considered to address the structural change assessment occurred in 2000-2001. Such subsystem is defined in Table 1: (i) *operational sensors*, made of 25 deformometers and 2 telecoordinometers, which measure the physical condition of the tower, such as rotations or displacements; (ii) *environmental sensors*, which measure the external conditions, such as temperature, wind, solar radiation. Figure 2 shows the position on the tower of each sensor. In particular, the most of the deformometers (blue circles) are placed on the inclination side, on bottom-right in figure, where the high load / stress is located. Environmental sensors (yellow, red and purple circles) are placed on the top. Finally, the orange long plumb wire of the telecoordinometer is clearly visible in the middle.

Figure 3 and Figure 4 show a global plot over 13 years of the temperature and a deformometer time series. Series of samples related to very long periods are normally affected by different artifacts: outliers, missing samples, sensors re-calibration, sensors hardware replacement/maintenance, and so on. As a consequence, data preprocessing is of the utmost importance to avoid biases and false positives. Specifically, outliers are due to electronic devices errors, which are sometimes affected by sensor reading issues, resulting in out-of-scale samples. On the other side, missing data samples are due to hardware, power or network, failures that sometimes occur. Finally, hardware replacement, maintenance and recalibration cause scaling artifacts.

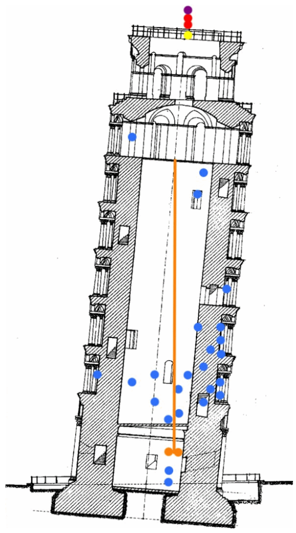


Figure 2: Multi-sensor system distribution on the tower, according to the color legend in Table 1

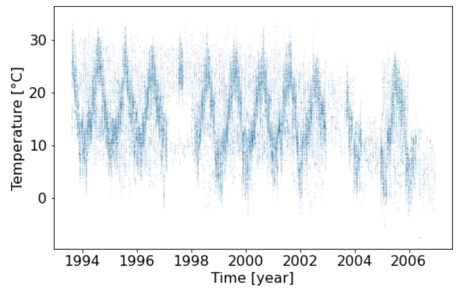


Figure 3: Global plot on 13 years of the temperature series.

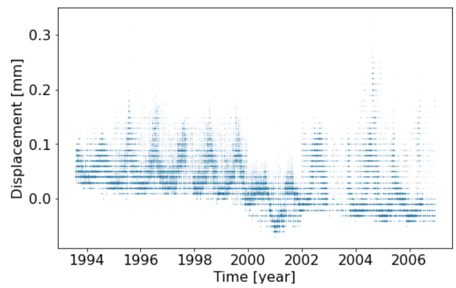


Figure 4: Global plot on 13 years of a deformometer series.

The pre-processing pipeline is made by different tasks:

1. *out-of scale outliers detection*, on the basis of lower and upper thresholds;
2. *z-score normalization*, to reduce artifacts related

to scaling. Equations (1) shows the formula of the z-score. Given a signal $x = [x_1, ..., x_n]$, the normalized signal z can be computed by subtracting from each element the mean value $\bar{\mu}_i$ computed on all elements as shown in Equation (2) and dividing by their standard deviation $\bar{\sigma}_i$ as shown in Equation (3);

3. *statistical outliers detection*, in which samples having value of ± 3 farther from the current moving average (window size, w=100) are selected;

4. *outliers/ isolated missing samples reconstruction*, in which a linear interpolation between the nearest neighbors is carried out for the outliers previously determined, and short sequences of consecutive missing samples (at most 4 elements). Long sequences of missing values, e.g. due to device failure, are not reconstructed at all.

5. *hourly data resampling*. Figure 5 shows a two-weeks plot of a deformometer time series. During the considered period, as a consequence of maintenance, some changes in the frequency of device reading activation occurred. To remove this type of artifact, the entire time series is resampled with one hour frequency.

$$z_i = \frac{x_i - \bar{\mu}_i}{\bar{\sigma}_i} \tag{1}$$

$$\bar{\mu}_i = \frac{\sum_{j=i-w}^{i-1} x_j}{w} \tag{2}$$

$$\bar{\sigma}_i = \sqrt{\frac{\sum_{j=i-w}^{i-1} (x_i - x_j)^2}{w}} \tag{3}$$

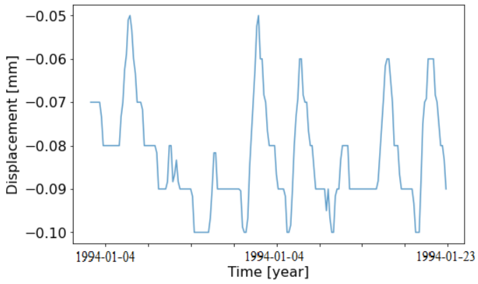


Figure 5: Two-weeks plot of a deformometer time series

Figure 6 shows the distribution of samples for each sensor in the considered period of observation, separated in pre-maintenance (blue circles) and post-maintenance (orange circles). Here, according to Table 1, each sensor is identified by a letter and an incremental number.

It is clear from the figure that the two distributions highly overlap. As a consequence, statistical or data mining approaches to structural change detection are human knowledge driven. As a consequence, in this paper, agnostic regression-based methodologies will be applied and compared.

3.2 Multivariate Linear Regression model and performance metrics

In the proposed regression approach to structural changes assessment three data sets are first created:

1. pre-maintenance set (*pre* for short);
2. post-maintenance set (*post*);
3. pre- and post- maintenance (*full*).

Table 1: Subsystem of sensors installed on the leaning tower and used for the proposed research

Sensor	#	Leg	Thresholds	Description
Deformometer (D)	25		[-0.5,0.5] mm	Detects dimensional deformations of a structure subjected to mechanical or thermal stresses.
Telecoordinometer (T)	2		[-2100,1800] ”	Measures a small rotation by reading the position of a plumb wire.
Termometer (TM)	1		[-10,42] °C	Measures the atmospheric temperature.
Wind speed sensor (WS)	1		[0,45] m/s	Measures wind speed; the wind drives the top three wind cups to rotate, and the central axis drives the sensing element to generate an output used to calculate the wind speed.
Wind direction sensor (WD)	1		[0,360] degree	Measure wind direction; it works through the rotation of a wind vane arrow and transmits its measurement information to the coaxial encoder board.
Solar radiation sensor (SR)	1		[0,1000] W/m^2	Measure broadband solar irradiance by detecting the photons that impact a physical or chemical device located within the instrument.

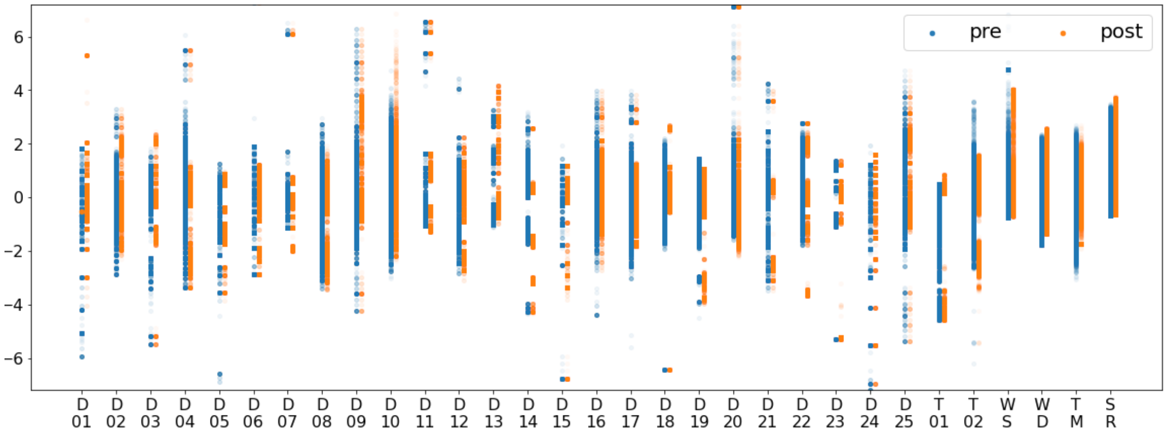


Figure 6: Values distribution (y-axis) for each separate sensor (x-asis), in the pre- and post- maintenance periods

Specifically, the intervals of the pre, post and full periods are, respectively: [Aug 1st, 1993 - Aug 31, 1999], [Jan 01, 2002 - Jun 30, 2006], [Jan, 08, 1993 - June 30, 2006]. Then, three different prediction models are generated, using related subsets of the pre, post and full sets, respectively, for training. Subsequently, the generated models are tested on other subsets of the pre, post and full sets.

Since a predictive model can be tested only on future samples, there are four possible experiments based on a combination of train and test sets: (a) full-full; (b) pre-pre; (c) post-post; (d) pre-post.

Finally, the structural change assessment is carried out by evaluating the difference in test performance between the four experiments: roughly speaking, if the test error is higher for the pre-post experiment with respect to the other experiments, it means that the model generated in the pre-maintenance period is unable to accurately predict the behavior in the post-maintenance period; and then, a structural change has occurred between pre and post periods; otherwise, if the error for the pre-post experiment is similar to the others, no structural change has occurred.

More formally, let us consider a set of n synchronized time series, $X(t) = \{X_j(t) : j = 1,...,n\}$, where $X_j(t)$ is a time series of length m, $X_j(t) = \{x_j(t) : j = 1,...,n;\ t = 1,...,m\}$. An MTS predictive model takes as an input a time window w extracted from the series, $X_w(\bar{t}) = \{x_{wj}(t) : j = 1,...,n;\ t = \bar{t},...,\bar{t}+w\}$, and predicts the next sample as an output The model can be formally described by a function $f : \mathbb{R}^{n\times m} \rightarrow \mathbb{R}^{n\times m}$:

$$f(X_w(\bar{t})) = X_w(\bar{t}+1) \tag{4}$$

where $X_w(\bar{t}+1) = \{x_{wj}(t) : j = 1,...,n;\ t = \bar{t}+1,...,\bar{t}+w+1\}$.

A conventional machine learning method to perform this task is to calculate a Multivariate Linear Regression, whose training is based on coefficients α_{ij} and β_j that are determined with n+1 equations, by minimizing the error function via partial derivatives:

$$\begin{aligned} x_{wj}(\bar{t}+1) &= \sum_{j=1}^{n}\sum_{i=\bar{t}}^{\bar{t}} \alpha_{ij}x_{wj}(i) + \beta_j \\ x_{wj}(\bar{t}+2) &= \sum_{j=1}^{n}\sum_{i=\bar{t}}^{\bar{t}+1} \alpha_{ij}x_{wj}(i) + \beta_j \\ &\dots \\ x_{wj}(\bar{t}+w+1) &= \sum_{j=1}^{n}\sum_{i=\bar{t}}^{\bar{t}+w} \alpha_{ij}x_{wj}(i) + \beta_j \end{aligned} \tag{5}$$

Given the set S of time series of length m, each related to n sensors, in order to evaluate the model error, trained and tested on related sets $Tr \in S$ and $Ts \in S$, the overall forecasting performance is measured via the Mean Relative Percent Difference, $MRPD(Tr;Ts)$, i.e., the mean value of the Relative Percent Differences of each sensor (Botchkarev, 2018):

$$MRPD_S(Tr;Ts) = \frac{1}{n}\sum_{s\in S} RPD_s(Tr;Ts) \tag{6}$$

The Relative Percent Difference between two values is the absolute difference between the two values divided by their absolute mean:

$$RPD_s(Tr;Ts) = \frac{2}{m}\sum_{k=1}^{m}\frac{|y_{ks}-\bar{y}_{ks}|}{|y_{ks}|+|\bar{y}_{ks}|};\quad y_{ks} \in Ts \tag{7}$$

The aggregation in Formula (6) of different types of sensors via the mean operator can be done under the assumptions that the data follow a Gaussian distribution and are also normalized. For the data sets used in this paper, this assumption is verified via a

Q_Q plot, and via the z-score normalization applied in the pre-processing phase, respectively.

Finally, by having the accuracy values of the predictive models via $MRPD_S(Tr;Ts)$ on the test dataset, the following metric of structural change assessment (SCA) can be derived:

$$SCA_S(pre;post) = \frac{2 \cdot MRPD_S(pre;post)}{MRPD_S(pre;pre) \cdot MRPD_S(post;post)} \quad (8)$$

Assuming a good accuracy of the model on the same period, the larger SCA is, the more the structural behavior change assessment between pre and post periods is larger. Because if the model of the pre period does not fit the post period, the difference at the numerator in Formula (8) is large with respect to the accuracy at the denominator. In contrast, a small value of the metric corresponds to a low structural change assessment.

3.3 Deep Learning models

Two DL models have been experimented to perform the MTS regression task: (i) a Long-Short Term Memory (LSTM) neural network, and (ii) a Transformer. The hyperparameters of the two models have been set via grid-search, with intervals established to keep a good accuracy and convergence. Table 2 and Table 3 summarizes the search space and the optimal values for each hyperparameter.

Table 2: LSTM hyperparameters optimization

Hyperparameters	Search space	Optimum
Layers	[1,2,3]	2
Units	[32,64,128, 256]	128
Linear layer	-	31

Table 3: Transformer hyperparameters optimization

Hyperparameters	Search space	Optimum
Embedding type	-	Abs pos enc
Attention Head	[4,5,6,7,8]	6
Layers per Head	[5,6,7,8,9]	8
Neurons per layer	[32,64,128]	128

In terms of parametric complexity, the Multivariate Linear Regression (MLR) defined in the previous section has 70 thousand trainable parameters. An LSTM model is designed to overcome the exploding/vanishing gradient problems that typically occur when using too many layers (Van Houdt et al., 2020). A common LSTM unit is composed of a cell that remembers values over arbitrary time intervals and three gate: an input gate, an output gate and a forget gate, which regulate the flow of information into and out of the cell. To model long-short term relationships, LSTM have a fairly complex internal structure, although it has been shown that similar but simpler networks can achieve similar performance (Galatolo et al., 2018). The LSTM architecture used has 210 thousand trainable parameters. Finally, a Causal Transformer is a DL architecture that does not process data in an ordered sequence, but analyzes the entire sequence of data and exploits a self-attention mechanisms to learn dependencies in the sequence, achieving the potential of modeling complex dynamics of time series (Vaswani et al., 2017). The Transformer architecture significantly exceeds the other architectures in terms of number of trainable parameters: about 2.5 million.

The training process of both LSTM and Transformer has been performed for 2500 epochs, with batch size 32, by setting the Adaptive Moment Estimation (Adam) as optimization algorithm to iteratively update the network weights.

4 EXPERIMENTAL RESULTS

The methodology has been developed on a python open-source environment, which has been publicly released (Galatolo, 2022), to foster collaboration and application on various infrastructures. This section summarizes and discusses the experimental results achieved with the three considered architectures. To this aim, Table 4 illustrates the results of the prediction models. In particular, the MRPD is computed aggregating each type of operational sensor (average $\pm$ standard deviation): 25 Deformometers (D*) or 2 Telecoordinometer (T*). Envirnomental sensors are not considered as an output because they are not related to structural changes but to environmental variations.

Let us consider test performance, i.e., $MRPD_{D*}test$ and $MRPD_{T*}test$ columns. In particular, let us focus on the values represented in boldface style, i.e., the test performance on pre and post sets for train and test, respectively. It can be clearly observed that DL models, i.e., LSTM and TRANS, perform better than MLR in pre-post prediction, with LSTM model achieving the highest score (.814 and 1.407). Furthermore, DL models are more accurate in pre-pre and post-post prediction, by having a lower score, especially TRANS model (.256, .324 and .119, .145). Overall, TRANS is the most accurate model whereas LSTM is the most sensitive model to structural changes.

In order to analyze the contribution of each sensor to the result, in Figure 7, the RPD value with

Table 4: *MRPD* on train and test set, for different models, using Deformometers (D*) or Telecoordinometers (T*) time series

Model	Train	Test	$MRPD_{D*}$ train	$MRPD_{D*}$ test	$MRPD_{T*}$ train	$MRPD_{T*}$ test
MLR	full	full	.234 ±.0081	.221 ±.0065	.276 ±.0068	.398 ±.0068
”	pre	pre	.406 ±.0117	.435 ±.0114	.378 ±.0076	.277 ±.0072
”	post	post	.393 ±.103	.434 ±.0118	.257 ±.0057	.212 ±.0041
”	**pre**	**post**	.406 ±.0117	**.522 ±.0122**	.378 ±.0076	**.605 ±.0161**
TRANS	full	full	.124 ±.0052	.141 ±.0050	.055 ±.0032	.112 ±.0038
”	pre	pre	.219 ±.0077	.256 ±.0095	.070 ±.0032	.119 ±.0041
”	post	post	.265 ±.0089	.324 ±.0096	.109 ±.0046	.145 ±.0044
”	**pre**	**post**	.219 ±.0077	**.573 ±.0125**	.070 ±.0032	**1.077 ±.0130**
LSTM	full	full	.113 ±.0051	.253 ±.0062	.045 ±.003	.144 ±.0010
”	pre	pre	.230 ±.0086	.277 ±.0091	.091 ±.0040	.146 ±.0054
”	post	post	.272 ±.0097	.356 ±.0103	.122 ±.0050	.151 ±.0045
”	**pre**	**post**	.230 ±.0086	**.814 ±.0149**	.091 ±.0040	**1.407 ±.0144**

the related standard deviation on test set is represented, as a coloured circle with a vertical line, respectively, for each DL model. Here, a horizontal red line represents the MRPD already calculated in Table 4. Here, it can be clearly observed that the LSTM model achieves better performance (i.e., larger RPD) than Transformer on the pre-post test.

Finally, in Table 5, for each model, the $\text{SCA}_{D*,T*}(pre;post)$ is computed, i.e. aggregating the contribution of both Deformometers and Telecoordinometers. Not surprisingly, it can be clearly observed that overall the most senstitive model to structural changes is LSTM, followed by the Transformer.

Table 5: $\text{SCA}_{D*,T*}(pre;post)$ for each model

Model	$\text{SCA}_{D*,T*}(pre;post)$
MLR	1.20
TRANS	2.13
LSTM	2.86

5 CONCLUSIONS

In this work, Deep Learning models for assessing structural changes in historical buildings have been compared, using a regression-based approach. As a case study, a multi-sensors data set related to the monitoring of the leaning Tower of Pisa from 1993 to 2006 has been used, for assessing a stabilizing intervention of 2000-2002. First, a data preprocessing pipeline has been developed and discussed. Then, the Multivariate Linear Regression, the LSTM and the Transformer models have been developed, together with modeling accuracy and change sensitivity metrics.

Although a more in-depth exploration of the approaches, and an enrichment of the case studies are needed, the experimental results are promising. In particular, the LSTM model has proved to be more sensitive to structural changes, whereas the Transformer model is more accurate in modeling. An extensive study in this direction can be a future work to bring a contribution in the field.

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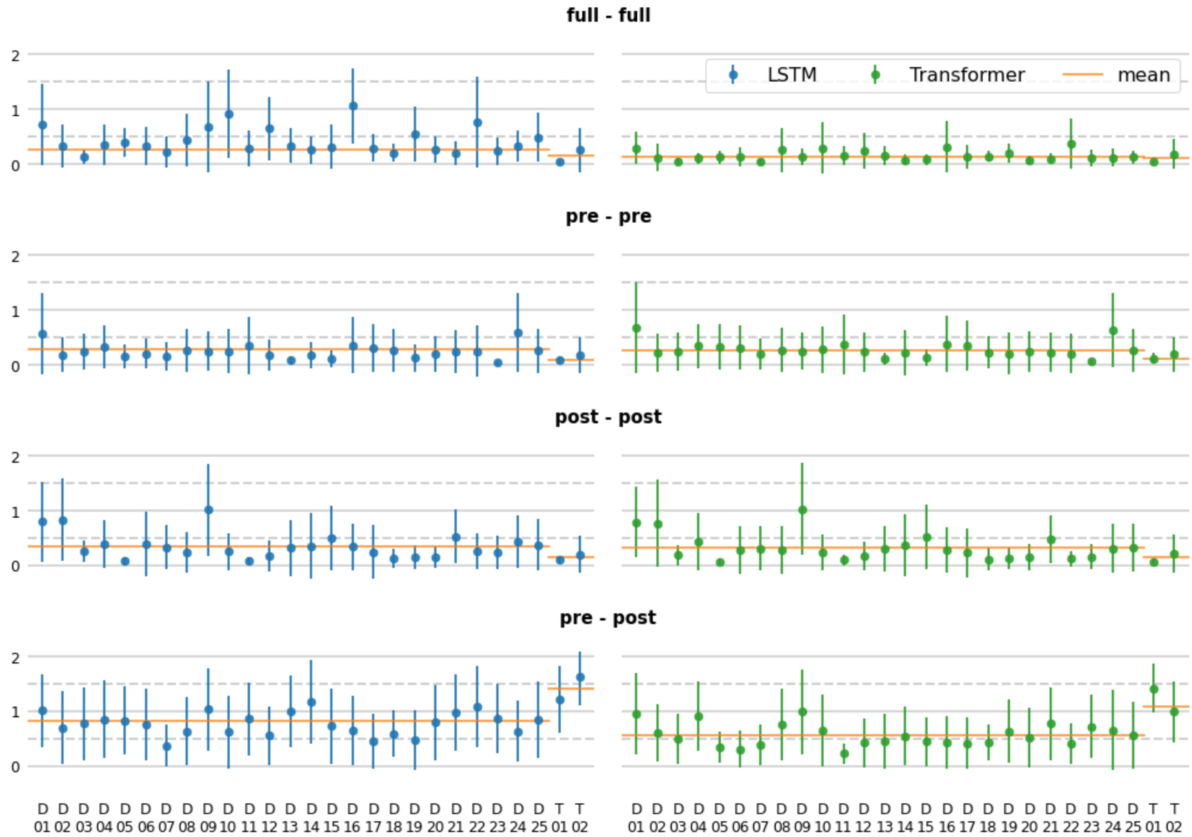

Figure 7: RPD values with the related standard deviation on test set, for each DL model and for each sensor.

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