Multi-sensor intelligent system for assessing the structural drift of the Leaning Tower of Pisa

Marco Parola$^{1[0000-0003-4871-4902]}$, Federico A. Galatolo$^{1[0000-0001-7193-3754]}$, Mario G.C.A. Cimino$^{1[0000-0002-1031-1959]}$, and Nunziante Squeglia$^{2[0000-0001-8104-503X]}$

[1] Dept of Information Engineering, University of Pisa, 56122 Pisa, Italy
[2] Dept of Civil and Industrial Engineering, University of Pisa, 56122 Pisa, Italy
{mario.cimino, federico.galatolo, marco.parola, nunziante.squeglia}@ing.unipi.it

Abstract. The intelligent monitoring of the structural health of buildings through agnostic methods is a difficult research area. Despite of recent advancements in multi-sensor systems, to date a limited amount of historical data are still available. As a result, data-driven techniques are often not practical for long-term evaluation. However, certain well-known historical buildings have been under monitoring for many years, prior to the emergence of smart sensors and Deep Learning technology. This paper presents a deep learning (DL) method for evaluating structural changes in an agnostic manner. The proposed approach has been tested on the stabilization intervention that took place on the Leaning Tower of Pisa in Italy from 2000-2002. The data set includes both operational and environmental measurements collected from 1993 to 2006. The approach is compared to both traditional and more recent methods, including Multiple Linear Regression, Long Short-Term Memory (LSTM) and Transformer. The results are encouraging and demonstrate that the LSTM method is more sensitive to changes, and that the Transformer method has a higher modeling accuracy.

Keywords: Structural Health Monitoring · Regression analysis · Deep Learning · Leaning Tower of Pisa · Structural Change Detection.

1 INTRODUCTION

The diagnosis and evaluation of the stability and deformation of historic structures depend heavily on structural health monitoring (SHM). Such structures have undergone several upkeep and upgrades over the years, utilizing different materials and construction methods, resulting in a complex structural behavior.

SHM relies heavily on multi-sensor systems with high dependability, cheap cost, small size and weight, and high rate data processing. Their widespread implementation, nevertheless, is still in its infancy. The only historical structures with long-term data are those that are well-known worldwide. For these structures, sensor systems collecting several parameters over an extended period of time permit the testing of agnostic Deep Learning approaches (DL) [7].

The structural health monitoring (SHM) literature defines two types of monitoring systems, based on the type of parameters they acquire for observation. One such classification is *static systems*, which keep track of the slow changes over time of quantities like crack widths, wall slopes, relative distances and others. The second classification is *dynamic systems*, which focus on the monitoring of dynamic parameters such as speeds and accelerations. This provides valuable insights into the general dynamic properties of structures like natural frequencies, modal shapes, and damping ratios, which can help understand the response of structures to external loads and vibrations.

Another important aspect concerns the pre-processing of data, indeed it is crucial to separate any evolutionary patterns from seasonal and daily changes caused by environmental factors and the employment of various sensing technologies across time [2].

DL techniques have demonstrated a significant potential for their capabilities to detect implicit relationships in data by necessitating less domain knowledge as a methodology of data analysis for SHM. Some DL architectures have already been tested for a variety of tasks on various buildings [13], for example, a convolutional architecture to address the problem of damage localization [14]. The next section offers a pertinent evaluation of the state-of-the-art.

In this study, the Transformer architecture is proposed for a particular SHM task and compared with the Long-Short Term Memory (LSTM) model. A Transformer is well-known in the literature to outperform the LSTM in the semantic capture of time-series data. The Leaning Tower of Pisa (Italy) [4], which has had several maintenance interventions during the epochs, has endured structural modifications that are assessed by comparing the various solutions. Specifically, the proposed case study concerns the under-excavation intervention that occurred between 2000 and 2001.

The SHM system installed on the Leaning Tower of Pisa is a static system, with a configurable sampling time period. Figures 1, 2(a) and 2(b) show 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.

1.1 Goals

By offering a thorough method to address the problem of structural change detection, this paper extends and improves previous research that was provided in [5]. The proposed approach's fundamental strategy is to build a model of the structural behavior before and after the maintenance intervention using a general-purpose pre-processing method without knowledge-based supervision or feature selection. This method takes advantage of the large amount of data that is available. The objective of the regression task, which includes this strategy, is to create an agnostic model of the relationship between input and output data. Regression that specifically aims to anticipate future values for a given time series is known as prediction. A multi input - multi output prediction is taken into account in the suggested approach.

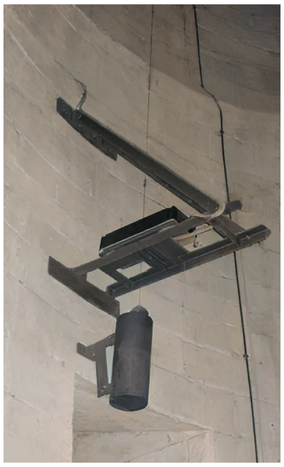
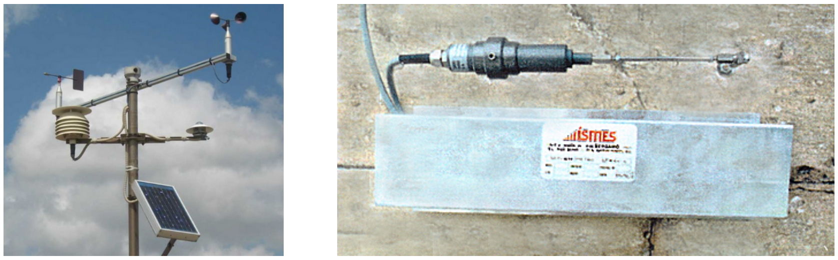


Fig. 1: Telecoordinometer - inclinometer and pendulum.



(a)

(b)

Fig. 2: (a) Weather tower composed of wind speed and direction, solar radiation sensor and termometer; (b) example of displacement sensor.

2 LITERATURE REVIEW

A building's structural change is determined by a change in the materials and/or physical characteristics of the structure. Examples include system connectivity and a reduction in the elastic material coefficient, both of which have a negative impact on the system's performance now and in the future [8].

According to the literature, a two-phase method can be used to detect structural changes caused by maintenance interventions: (a) identify the behavioral model of the structure's stable key parameters, which correspond to the times before and after the intervention; (b) determine if these parameters have a persistent variation by contrasting the two times. The basic tenet is that, over time, the behavior of the structure will vary in relation to how it differs from its pre-intervention state [15].

One of the main disadvantage of this method is the information required to set up a model, the crucial variables, and the baseline condition, which represents the situation prior to maintenance. Utilizing multivariate clustering in feature space to find stable clusters and components that accurately capture the behavior of the structure is one potential solution [9]. Leveraging regression analysis, which takes into account both the environmental and operational properties to create a predictive model of behavior before maintenance that can be applied to behavior after maintenance to determine a different deviation from the expected value, is an alternative strategy that requires little knowledge. [17].

The data produced by the multi-sensor system is used in this work to model the associated multivariate time series using a regression-based technique (MTS). A MTS depicts the development of a collection of partially independent variables. A traditional statistical strategy, such as the auto-regressive integrated moving average method, which can be utilized to investigate the correlations between the various variables, can be used to solve the prediction of an MTS. Transparent machine learning models can be also applied, with the advantage of being simple to understand. As an example, modular neural architectures refer to a design approach based on a collection of small neural [6]. However, such constrained architectures are limited in capturing input-output complex patterns.

Due to their effectiveness, DL-based approaches gained extensive adoption in the previous ten years. To address the MTS prediction problem, various designs have been tested, including Recurrent Neural Networks (RNN), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM). Transformer has lately demonstrated improved performance on both real and synthetic data by exploiting its attention method. [12]. During this study, both traditional and contemporary methodologies are used and analyzed: Tansformer, Multiple Linear Regressor, and LSTM architecture

3 METHODOLOGY AND MATERIALS

This section presents, on different subsections, the multi-sensor system providing the MTS, the time series pre-processing phase, as well as theDL regression models used for MTS forecasting.

3.1 Sensor network and signal preprocessing

For the Leaning Tower of Pisa, a sophisticated monitoring system relying on a sensor network composed of more than 60 devices is available. In this study, the structural change assessment that took place in 2000–2001 is only taken into account for a reduced subsystem of sensors. Such subsystem is described 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. Each sensor's location on the tower is illustrated in Figure 3. Specifically, the majority of the deformometers (blue circles) are positioned on the inclination side, bottom-right in the picture, where the high load/stress is located. The top has three circles of environmental sensors (yellow, red, and purple) representing the weather equipments. Finally, the centre clearly reveals the telecoordinometer's orange long plumb cable. Figures 4a and 4b present a 13-year overview of the temperature and displacement time series, respectively. Unfortunately, time series samples covering extended periods often suffer from anomalies and artifacts such as outliers, missing samples, sensor recalibration, hardware replacement/maintenance, etc. Consequently, to avoid bias and false positives, data preparation is crucial. In particular, outliers are typically produced by electronic device failures, which are sometimes affected by sensor reading problems and result in out-of-scale observations.

On the other hand, missing data samples are due to hardware, power, or network failures, which occasionally can occur. Finally, device recalibration, hardware replacement, and maintenance cause scaling problems.

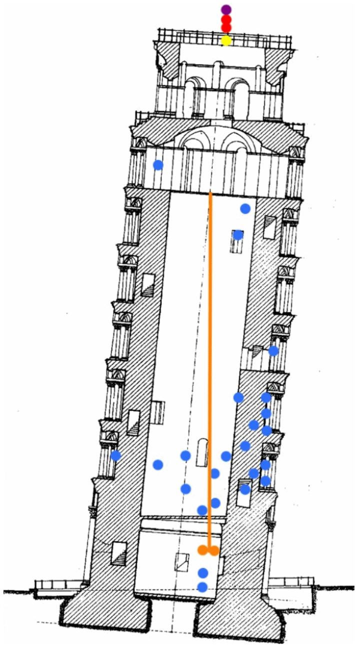
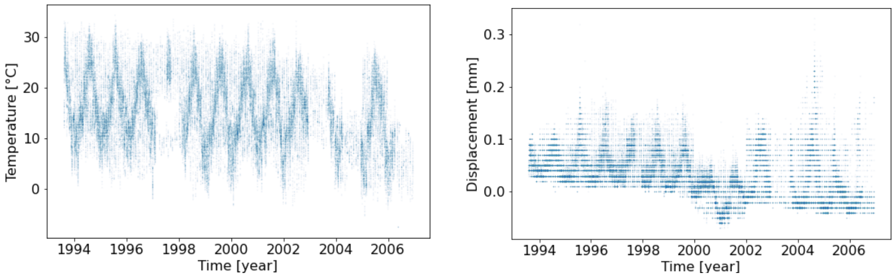


Fig. 3: Multi-sensor system location on the tower, according to the color legend in Table 1



(a)

(b)

Fig. 4: Scatter plot of the 13-year temperature time series and (b) scatter plot of the 13-year deformometer time series.

Table 1: Sensor network installed on the Leaning Tower of Pisa

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.

The data pre-processing phase is composed of the following subtasks:

1. *out-of scale outliers detection*, based on upper and lower thresholds;
2. *z-score normalization*, to normalize the data and reduce artifacts related to scaling phenomena. 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 observations having value of ±3 farther from the current moving average (window size, w=100) are identified and removed;
4. *reconstruction of isolated outliers/missing samples*, where a linear interpolation is fitted between the nearest neighbors for previously determined outliers, and short sequences of consecutive missing samples (maximum 4 elements). Long sequences of missing values, caused, for instance, by device failure, are ignored.
5. *hourly data resampling*. During the period under consideration, as an effect of maintenance work, there were some variations in the frequency of device

reading activation. To overcome this type of artifact, the entire time series is resampled at a 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 displays the distribution of samples for each sensor during the contemplated time of observation, grouped into 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.

The two distributions have a significant amount of overlap, as shown in the figure. As a consequence, data mining and statistical strategies to structural change detection are human knowledge driven. Consequently, in this paper, agnostic regression-based methodologies will be designed and evaluated.

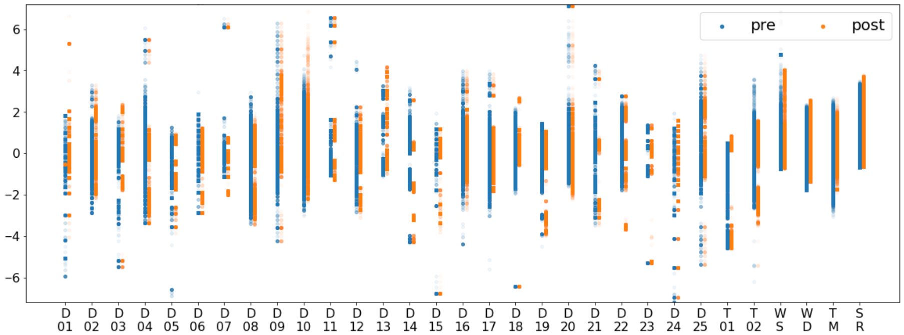


Fig. 5: Data distribution (y-axis) for each sensor channel (x-asis), in the pre- and post- maintenance periods

3.2 Multivariate Regression model and evaluation metrics

In the regression analysis approach proposed for evaluating structural changes, three sets of data are first generated:

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

Specifically, the pre-period interval is from August 1st, 1993 to August 31, 1999, the post-period interval is from January 1st, 2002 to June 30th, 2006, and the full-period interval is from January 8th, 1993 to June 30th, 2006. Three prediction models are created using different subsets of the pre, post, and full sets for training. The generated models are then evaluated using subsets of the pre, post, and full sets for testing.

Since a regressive model can be evaluated only on future observations, only four possible experiments based on a combination of train and test sets can be performed: (a) full-full; (b) pre-pre; (c) post-post; (d) pre-post.

Finally, the structural change assessment is thoroughly conducted by evaluating and comparing the accuracy performance results obtained from the four experiments. Essentially, the main goal is to determine if any significant changes had occurred in the structural behavior of the building during the maintenance period. To do this, we first compared the test error results obtained from the pre-post experiment with the results from the other three experiments. If the test error in the pre-post experiment is higher as compared to the other experiments, we can conclude that the model generated during the pre-maintenance period is unable to accurately predict the behavior observed in the post-maintenance period. This suggested that a structural change had taken place between the pre and post periods. On the other hand, if the error for the pre-post experiment is similar to the errors obtained from the other experiments, we can conclude that no structural changes had 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 common machine learning technique to accomplish this task is Multivariate Linear Regression, which trains coefficients α_{ij} and β_j by minimizing the error function through partial derivatives. These coefficients are determined using n+1 equations, defined as follows:

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

To assess the model error for a set S of m-length time series, each related to n sensors, the Mean Relative Percent Difference, $MRPD(Tr;Ts)$, can be used to measure the overall forecasting performance by calculating the mean of the Relative Percent Differences for each sensor. where $Tr \in S$ is the training time period, while $Ts \in S$ the test one [3]:

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

The absolute difference between two values is divided by their absolute means to determine the Relative Percent Difference (RPD) between the two values, as show bellow:

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

Under the assumptions that the data have a Gaussian distribution and are normalized, it is possible to aggregate multiple types of sensors in Formula (6) by adopting the mean operator.This hypothesis is verified for the dataset used in this research using a QQplot and the z-score normalization during the preprocessing phase. 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:

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

Under the assumption of good model forecasting performance over the same time period, the larger the SCA, the larger the assessment of the structural change in behavior between the pre and post periods. Indeed, if the predictive model from the the pre period does not fit the post period, the difference at the numerator in Formula (8) is large compared to the accuracy at the denominator. In the other hand, a low value of the metric corresponds to a small structural change assessment.

3.3 Deep Learning architectures

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.

For the experimental setup, we employed Optuna v2.9.1 [1] as automated hyperparameter optimization software. This framework grows effectively in distributed systems and includes all of the basic hyperparameter optimization algorithms. The entire hyperparametrization process is built over an objective function that is optimized at each iteration; since our DL models have to address a regression problem, we set Mean Absolute Error (MAE) as objective function. To propose the set of value parameters for the next iteration, we use the Tree-structured Parzen Estimator (TPE) sampler. As a result, finding a successful combination of hyperparameter values often requires several tries. Furthermore, the essential hyperparameter optimization is limited by significant calculation durations for each experiment.

One method for addressing this issue is to terminate trials with unfavorable hyperparameter values as soon as possible. The early stopping method employed in hyperparameter optimization, also known as pruning, differs from the early stopping strategy utilized by machine learning algorithms to avoid overfitting. It entails finding and ending unpromising hyperparameter value trials as soon as feasible while continuing to compute with the most promising combinations. The hyperparameter space can be explored quicker and/or deeper with the capacity to calculate more trials in less time, in order to save time, energy, and money. We adopt the median pruning strategy that prunes the current iteration if the trial's best intermediate result is worse than median of intermediate results of previous trials at the same step.

LSTM hyperparameter optimization. Table 2 presents a comprehensive overview of the search space explored during the hyperparameter optimization process for the LSTM model. The table showcases the optimal values obtained after the optimization procedure was completed. To understand the optimization process and how the optimal values were found, the reader can refer to Figure 6. The optimization process was conducted over a total of 519 iterations. The results showed that the MAE decreased steadily from its initial value of 1.222 to a final value of 0.147.

Table 2: LSTM hyperparameters

Hyperparameters	Search space	Optimum
hidden size	{32,64,128, 256}	128
num layers	{2,3,4,5,6,7 }	2
batch	{4, 6, 12, 16}	12
lr	[3e-5, 1e-2]	8.7e10-4

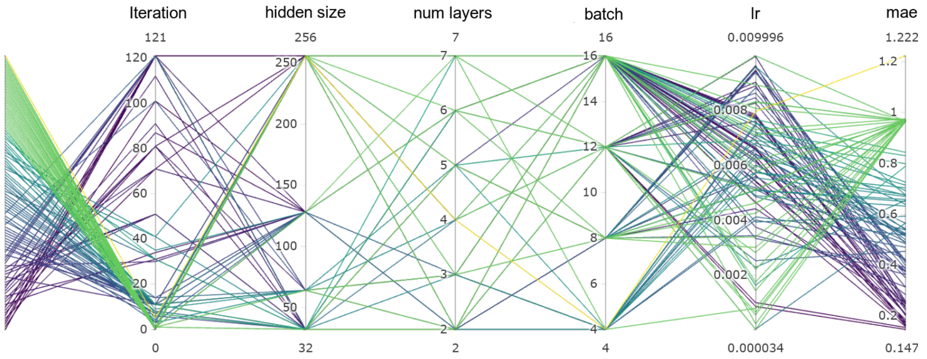


Fig. 6: Parallel coordinate plot of LSTM hyperparameter optimization process

Transformer hyperparameter optimization. The search space investigated throughout the transformer architecture's hyperparameter optimization process is shown in detail in Table 3. The final results of the optimization process are displayed in the table. The reader can refer to Figure 7 to learn more about the optimization procedure and how the best values were identified. 537 iterations of the optimization procedure were performed in total. The outcomes shown that the MAE continuously declined from a starting value of 1.131 to a final value of 0.1391.

Table 3: Transformer hyperparameters

Hyperparameters	Search space	Optimum
(Decoder) Depth	{2,3,4,5,6,7}	2
Decoder dim	{32,64,128, 256}	64
Dropout	{0, 0.05, 0.1, 0.15, 0.2}	0.05
(Attention) Head	{2,3,4,5,6,7}	2
Batch	{4, 6, 12, 16}	16
lr	[3e-5, 1e-2]	7.4e10-4

With regard to the parametric complexity, the Multivariate Linear Regression (MLR) presented in the previous section turns out to be the lightest model, with 70 thousand trainable parameters. Three gates — an input gate, an output gate, and a forget gate — that control the flow of data into and out of the cell make up a typical LSTM unit cell. The cell is able to remember values for any period of time. Although it has been proved that networks with a comparable but simpler structure can function similarly to LSTMs in terms of modeling long- to short-term interactions, LSTMs have a rather sophisticated internal structure [11]. The LSTM architecture used has 210 thousand trainable parameters. Finally, the Causal Transformer is a Deep Learning architecture that does not handle data sequentially. Instead, it analyzes the entire sequence of data and uses self-

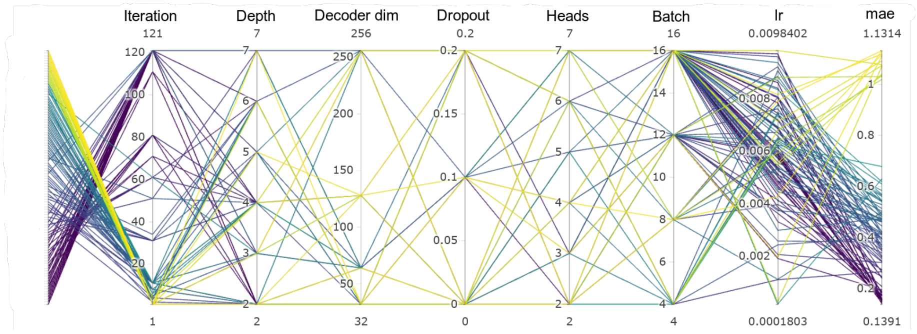


Fig. 7: Parallel coordinate plot of Transformer hyperparameter optimization process.

attention mechanisms to understand dependencies within the sequence, allowing it to model complex dynamics in time series. [16]. With over 2.5 million trainable parameters, the Transformer architecture significantly outnumbers the previous two models.

Adaptive Moment Estimation (Adam) is used as optimizer during the training phase for both LSTM and Transformer performed for of 2500 epochs with a batch size of 16.

4 EXPERIMENTAL RESULTS

The methodology has been implemented in a python open-source environment that was publicly provided at [10] in order to promote application and collaboration across the scientific community. This section presents and discusses the experimental results achieved by the three regression models. The experiments have been carried out on a virtual machine in the university cluster[3] powered by two Nvidia A30 GPUs. 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 ± 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.

The performance of the models is evaluated through $MRPD_{D*}test$ and $MRPD_{T*}test$ columns, with a focus on the boldface values, representing pre and post sets for train and test, respectively. The results show that LSTM and TRANS, both DL models, outperform MLR in pre-post prediction, with LSTM achieving the best score (.820 and 1.428). Additionally, DL models also show higher accuracy in pre-pre and post-post prediction, with TRANS having the lowest score (.252, .320 and .116, .141). Therefore, TRANS is the most accurate model while LSTM the most sensitive to structural changes.

[3] Crosslab

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	.233 ±.0080	.219 ±.0063	.274 ±.0067	.392 ±.0066
”	pre	pre	.399 ±.0115	.431 ±.0115	.375 ±.0074	.276 ±.0071
”	post	post	.389 ±.102	.429 ±.0117	.255 ±.0055	.209 ±.0039
”	**pre**	**post**	.399 ±.0115	**.526 ±.0122**	.375 ±.0074	**.611 ±.0164**
TRANS	full	full	.119 ±.0049	.138 ±.0048	.055 ±.0029	.108 ±.0037
”	pre	pre	.215 ±.0074	.252 ±.0093	.067 ±.0030	.116 ±.0039
”	post	post	.261 ±.0086	.320 ±.0094	.107 ±.0045	.141 ±.0042
”	**pre**	**post**	.215 ±.0074	**.580 ±.0126**	.067 ±.0030	**1.096 ±.0129**
LSTM	full	full	.109 ±.0048	.250 ±.0059	.042 ±.0028	.141 ±.0008
”	pre	pre	.227 ±.0085	.277 ±.0089	.088 ±.0038	.146 ±.0054
”	post	post	.269 ±.0096	.354 ±.0101	.120 ±.0049	.149 ±.0044
”	**pre**	**post**	.227 ±.0085	**.820 ±.0150**	.088 ±.0038	**1.428 ±.0146**

To assess the impact of each sensor on the outcome, Figure 8 displays the RPD value with its standard deviation on the test set, represented as a color-coded circle with a vertical line, for both Transformer and LSTM network. Here, a horizontal orange line represents the MRPD already calculated in Table 4. The MRPD, already calculated in Table 4, is represented by a horizontal orange line. We can clearly observe that the LSTM model outperforms the Transformer (higher RPD value) in the pre-post test.

Finally, in Table 5, for each model, the $\mathrm{SCA}_{D*,T*}(pre;post)$ 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: $\mathrm{SCA}_{D*,T*}(pre;post)$ metric for each predicting model

Model	$\mathrm{SCA}_{D*,T*}(pre;post)$
MLR	1.21
TRANS	2.20
LSTM	2.92

5 CONCLUSIONS

In this study, various Deep Learning models were evaluated for their ability to assess structural changes in historical buildings, using a regression-based approach. The models were applied to a case study involving the monitoring of the leaning Tower of Pisa from 1993 to 2006, specifically focusing on the impact of a stabilizing intervention that took place between 2000 and 2002.

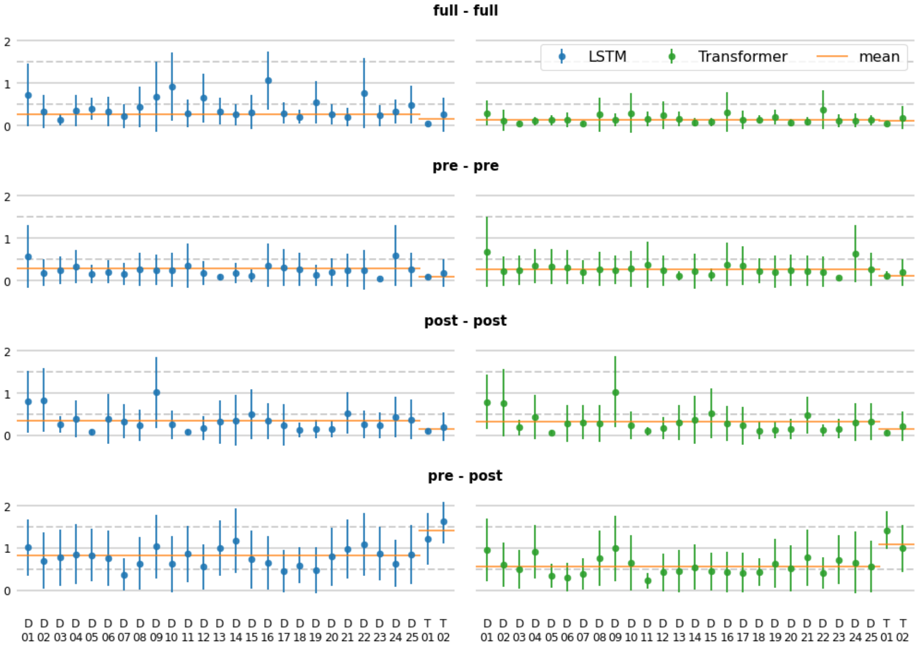


Fig. 8: RPD metric values and corresponding std on test set, for each sensor forecasting by Transformer and LSTM model.

A comprehensive data preprocessing pipeline was developed and discussed, including techniques such as data cleaning, feature selection, and normalization. Three different models were tested: the Multivariate Linear Regression, the LSTM, and the Transformer. The accuracy of each model was evaluated, and their change sensitivity was also assessed.

The results of this study demonstrate that Deep Learning models can be an effective tool for monitoring and assessing structural changes in historical buildings. In particular, LSTM model has proved to be more sensitive to structural changes, whereas the Transformer model is more accurate in modeling. Furthermore, this research can be extended by exploring other DL model architectures, such as CNNs and GANs.

Moreover, through a regression analysis, we aim to gain a better understanding of the relationship between the environment and structural stability. The findings of this research will contribute to the development of more robust and resilient building monitoring design practices and improve the safety of structures in various environmental conditions.

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