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Application of Machine Learning to estimate Retrofitting Cost of School Buildings

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Abstract

A significant number of school buildings in Italy require seismic and energy retrofits based on National laws, which contribute to the school environment's characteristics and health and safety in buildings. Moreover, government initiatives to promote ambitious national plans for the renovation and construction of new school buildings are gaining vast attention. For this purpose, the Ministry of Education, with the local authorities' collaboration, carries out a database to register national school buildings and their level of consistency and functionality, which is the fundamental knowledge tool for planning interventions in the sector. However, it does not provide a guideline to estimate future interventions' costs. This research aims to design a retrofitting cost estimation model for energy and seismic improvement and adaptation interventions using Artificial Neural Networks. It can serve as a beneficial tool for forecasting expenses based on the interrelated building features, which the public administration can use to optimize the management and planning of school buildings' funds. The proposed work focuses on a small sample of over 200 school buildings and their seismic and energy retrofitting costs. The ANN model uses the parameters of the case studies as the input to train the network to estimate the retrofitting cost of other projects based on the historical data. The parameters are categorized into three groups of features: i) building's characteristics, e.g., construction year and the number of floors, ii) energy retrofit parameters, e.g., class heating energy consumption, and iii) seismic retrofit parameters, e.g., seismic zone and structural type. Therefore, the goal is to facilitate the financial feasibility assessments and optimize the available resources related to the planning of interventions. The proposed model will contribute significantly to school buildings' resilience as a single integrated space, which has the characteristics of habitability, flexibility, functionality, comfort, and well-being.

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Keywords

Seismic retrofit; Energy retrofit; Cost estimation; Neural network; Machine learning

1. Introduction

School structures are defined as construction of buildings intended exclusively for school use, including all the teaching activities with direct pupil involvement. Hence, the field of school buildings can be extended from preschool to universities. Most school constructions were built before standards and regulations paid more attention to energy efficiency and seismic risk mitigation. Therefore, these buildings are often characterized by high levels of energy consumption and seismic vulnerability (De Santoli et al. 2014). According to the European Commission, the building sector is responsible for nearly 40% and 36% of the total energy consumption and CO2 emissions in EU (EU-Energy 2018). Therefore, European Union Directives stress the relevance of building retrofit as a strategy to overcome building sector issues and reach EU de-carbonization goals of 2050 (Seghezzi and Masera 2017).

In Italy, where the school buildings stock counts over 43,000 public schools that host about 8 million students (Re Cecconi, Moretti, and Tagliabue 2019), the Ministry of Education (MIUR), together with local autorithies, is carrying out a national database, called "Anagrafe dell'edilizia scolastica", that record the level of consistency and functionality of school buildings (Edilizia scolastica - MIUR. n.d.). The data show that school buildings generally have a high structural vulnerability linked to different causes, such as the construction techniques of the time, the supply of modest quality materials, and the mediocre execution of the works. Moreover, 75% of the school buildings stock dates before any national energy law. Consequently, more than half of these buildings highlight functional, usability, and safety issues. Among unsatisfactory performances, thermal comfort and air quality are extremely critical since they are closely related to the students' learning ability (Zhang and Barrett 2010). In these buildings, it is necessary to strike a good balance between cost reduction and high levels of comfort to influence student's performances (De Giuli, Da Pos, and De Carli 2012).

Building retrofit covers a large range of interventions. For instance, energy retrofit is the operational or physical change in a building, its energy consuming equipment, or occupants' behavior to reduce energy consumption (Jafari and Valentin 2018). In addition to energy inefficiency, fire safety, seismic aspects, indoor comfort, and exterior aesthetics are other drivers for building renovation and retrofitting (Ferreira and Almeida 2015). In addition to reducing building energy consumption and carbon footprints, retrofitting existing buildings offers significant opportunities to improve occupants' comfort and well-being, reducing global energy consumption and greenhouse gas emissions (Xu, Loftness, and Severnini 2021). Therefore, building retrofit is considered one of the main approaches to achieve sustainability in the built environment.

Recently, national governments in Italy have allocated increasingly substantial funding and, in particular, from 2014 to 2018, €9.5 billion was spent on retrofitting works (Legambiente 2021). Retrofit interventions on the envelope and thermal plants can heavily reduce energy consumption and associated running costs, though generating additional investment costs (Lohse, Staller, and Riel 2016). Nevertheless, approximately 40% of school buildings in Italy need refurbishment interventions, therefore the running cost mark-up gained thanks to energy improvements could compensate the overall costs for refurbishment interventions.

The information embedded in the national database provides the fundamental basic knowledge for planning interventions. However, a guideline to estimate future interventions' costs is not provided. Hence, The objective of this work is to define a model capable of evaluating the costs of retrofit intervention on school buildings. Recently, the adoption of Artificial Intelligence (AI) techniques in the management of built environment is rapidly gaining momentum (Darko et al. 2020), thanks also to a greater amount of data available thanks to initiatives such as the mentioned "Anagrafe dell'edilizia scolastica". These techniques allow reaching faster and highly precise predictions compared to traditional methodologies. The research sits in the broader context of the digitisation of the built environment: the introduced methodology aim at leading strategic decisions on retrofitting interventions on public school buildings.

2. Background

While various criteria are decisive for achieving cost-effective and sustainable retrofit solutions, the process is mainly governed by economic and technical considerations, focusing on single buildings (Caterino et al. 2021). Therefore, this study builds on the data collected from previous research and tries to apply AI techniques to estimate retrofitting cost of public school buildings concerning databases of previous retrofit projects. The rapid growth of data available triggers the use of this new computational techniques, and many applications have been recently studied in the field of cities and built environment management.

2.1. National school buildings stock status

The Ministry of Education (MIUR) in Italy establishes an open register to collect data about the stock of public schools in the territory. In particular, the school heritage comprises 40.160 active buildings, 3.042 non active buildings, and 34 not operational buildings due to environmental disasters (e.g., earthquakes, floods, and so on).

Between 1950 and 1980, the accelerated process of schooling required a rapid increase in the national stock of school buildings; however, the intense production met modest quality standards when not poor. Today, many school buildings present inadequate characteristics due to origin defects or premature obsolescence - often aggravated by lack of maintenance. School buildings are not evenly distributed since in Lombardy, Campania, and Sicily, there are about 33% of all buildings. Overall, approximately 43% of buildings nationwide fall in high-risk seismic zones (1 and 2). In the Southern Regions, like Sicily, Campania and Calabria, high exposure to seismic events involves more than 90% of the buildings (Figure 1).

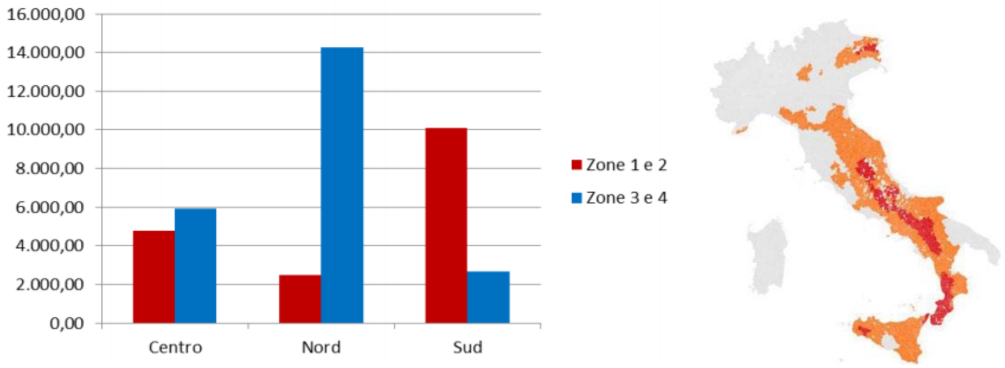

Figure 1 Distribution of buildings by territorial macro-area and map of seismic zones in Italy (Ministero delle Infrastrutture 2008)

More than 50% of school buildings were built before earthquake regulations came into effect (1976) and 43% from the post-war period to the mid-1970s (1946-1975). This class of buildings generally presents a high structural vulnerability related to the construction techniques of the time, the supply of materials of modest quality, and the mediocre execution of the works. Moreover, the data shows that 12.7% of schools are designed or adapted to seismic technical construction regulations. New construction – built with the new regulations included in the national technical standards for construction published in 2008 (Ministero delle Infrastrutture 2008) - represent only 2.4% of the total. The school building registry also confirms that, overall, the school building stock is old and of low quality, with significant deficiencies of various kinds, from seismic safety to the acquisition of the certificate of static suitability, fitness, and fire prevention as required by law.

On the side of energy efficiency, the data collected from Legambiente indicate that only 16.3% of buildings have been made energy efficiency measures in the last five years. The majority of the interventions concern windows, insulation, boilers, and renewable energy systems: the consequences of energy consumption are often imposed as a critical factor for school buildings, whose maintenance is binding, expensive, and weighs heavily on the budgets of local authorities, which are responsible for providing it.

2.2. Literature review on Retrofit cost evaluation

Since retrofitting is vital for buildings, it is crucial to have methodologies for accurately assessing the energy use and seismic requirements, predicting retrofit costs associated with each alternative, and selecting the most efficient one. The core of such assessment methodologies is the development of energy and seismic retrofit models of buildings, which are mainly categorized as white-box, grey-box, and black-box methods (Amasyali and El-Gohary 2018). The first two are mainly based on building physics and require a huge amount of detailed data, which makes the application process cumbersome. In contrast, black-box models rely on measured and historical data, which allows them to handle complicated system dynamics without being interrupted by the problem complexities and aspects. The black-box models are usually based on statistical, and machine learning (ML) techniques (Guo et al. 2017) and are trained by learning the relationships between input data features and their impact on the final output for future predictions. The black-box model makes predictions faster and more precisely than the other two methodologies (Azadeh, Babazadeh, and Asadzadeh 2013); therefore, it can replace complex and computationally intensive knowledge-based models (Stojiljković, Vučković, and Ignjatović 2021).

Previous literature on the topic is mainly about seismic and energy simulation and analysis of existing buildings, multi attribute decision making for selecting the most efficient and effective retrofit alternative, and predicting building retrofit cost. Moreover, Artificial Intelligence constitutes a significant share of the techniques used in previous literature. Figure 2 presents the co-occurrence keyword network of the systematic search conducted in Scopus, developed by the Bibliometrix package in R and the Biblioshiny library.

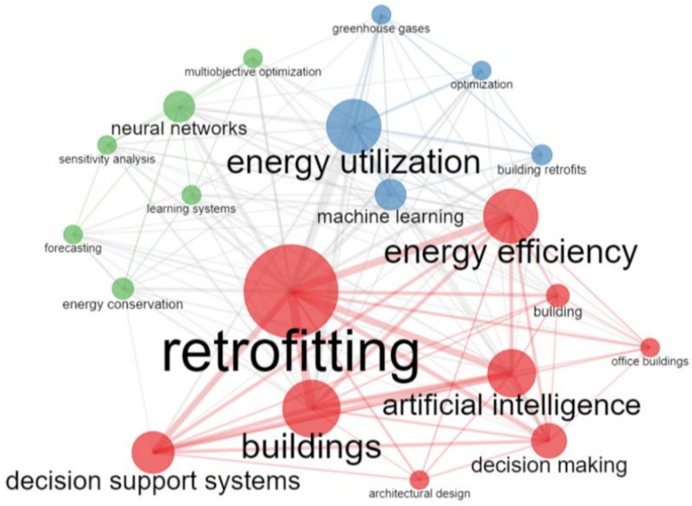

Figure 2 Co-occurrence network of keywords in the building retrofit cost literature

Other tools applied for seismic and energy retrofitting or renovation research are BIM (Scherer and Katranuschkov 2018) and Multi-Criteria Decision-Making (Esmaeel Asadi, Salman, and Li 2019). (Caterino et al. 2021) proposed an MCDM-BIM integrated framework as a decision support system for choosing the best seismic retrofit strategy, considering different alternatives. (Håkansson et al. 2013) developed a Decision Support System (DSS) based on the optimal ranking and sequencing of retrofit options with the purpose of emissions reduction in non-domestic buildings. (Woo and Menassa 2014) designed the Virtual Retrofit Model (VRM) framework, an affordable computational platform using Building Information Modeling (BIM), energy simulation, agent-based modeling, multi-criteria decision support system that supports streamlined decision making for building retrofit projects.

(Carofilis et al. 2020) examined retrofit alternatives for three case study school buildings in Italy by a seismic performance assessment using detailed numerical models that consider the main structural deficiencies documented for older Italian buildings built before the 1970s. (Sherstobitoff, Taylor, and Shuttleworth 2010) presented several cost-effective retrofit strategies for the seismic upgrading of clay masonry school blocks in British Colombia by conducting a retrofit construction cost estimate including structural, architectural, mechanical, and electrical work with conformance to the provisions of the Technical Guidelines (TG) of the Ministry of Education. (Seghezzi and Masera 2017) conducted an interview survey to identify relevant installation and economy parameters and develop a multi-criteria approach for choosing the most suitable building retrofit strategy.

2.3. Artificial Intelligence for Building Retrofit

Although the previously mentioned techniques are beneficial, they cannot be applied to many projects at once in a fast manner. Artificial Intelligence techniques seem to be the perfect solution to this problem due to their ability to provide accurate results in uncertain, dynamic, and complex environments and when encountered with huge datasets (Yaseen et al. 2020). AI's application in built environment management is proliferating due to asset-related digital information (Wei et al. 2018). However, its application for the building retrofit process is a relatively new direction.

As noticeable in figure 2, Artificial Neural Networks (ANNs) are the most used AI techniques in building retrofit literature. ANNs are one of the most applied and optimum algorithms in the building sector due to their ability to predict accurately despite low input variables. ANNs behave like the human brain and consist of layers of neurons that can be triggered for learning the relationships between the input variables (the input layer) and the final result (the output layer) with the help of activation functions.

(Deb, Dai, and Schlueter 2021) designed a Recurrent Neural Network (RNN) for cost-optimal retrofit analysis in a single-family residence, using the time series data on building variables gathered by a wireless sensor network (WSN).

(Thrampoulidis et al. 2021) presented an ANN-based surrogate model for evaluating the necessary building envelope and energy system measures for building retrofit in Zurich. (Ascione et al. 2017a) employed artificial neural networks (ANNs) and EnergyPlus simulations to assess energy consumption and occupants' thermal comfort for existing and renovated building stocks in the presence of energy retrofit measures (ERMs). Another study (Ascione et al. 2017b) proposed a multi-stage framework for cost-optimal analysis, applicable to different building types, by multi-objective optimization and ANNs, called CASA.

Other AI techniques were also applied in previous research. (Ali et al. 2018) proposed an intelligent knowledge-based recommendation system using ML algorithms to recommend energy retrofit measures and improve Ireland's residential buildings' energy performance. (Geyer, Schlüter, and Cisar 2017) developed an algorithmic clustering method, combined with time and cost data, to cluster large building stocks in Switzerland based on their sensitivity to different retrofit measures. (Marasco and Kontokosta 2016) analyzed the energy audit data for over 1100 buildings in NYC to identify opportunities for Building energy conservation measures (ECM) across building system categories, using a user-facing falling rule list (FRL) classifier. (Stojiljković, Vučković, and Ignjatović 2021) analyzed surrogate models that directly classify building retrofit measures by Random Forest algorithm according to the global cost. Moreover, they quantified the importance of each variable for the classification process to optimize energy renovation measures or rapidly identify projects worth financial support. (Seyedzadeh et al. 2020) used a ML-based deep energy retrofit decision-making model, using gradient boosted regression trees, for non-domestic buildings to predict energy performance and select optimal retrofit packages. (Jafari and Valentin 2018) introduced the sustainable energy retrofit (SER) decision support system to choose the optimum building energy retrofitting strategy while maximizing the project’s sustainability triple bottom line (TBL) benefits, namely Economic, environmental, and social indicators. (Xu, Loftness, and Severnini 2021) demonstrated a data-driven approach using data from a portfolio of 550 federal buildings in the US and generalizing past retrofits' effect to predict future savings potential when planning for retrofit.

School Buildings were explicitly the topic of few previous research works. (Re Cecconi, Moretti, and Tagliabue 2019) aimed to develop a data-driven method based on open data, ML, and Geographic Information Systems (GIS) to support Lombardy region energy retrofit policies on school buildings, potentially predicting the post-retrofit energy savings. (Ehsan Asadi et al. 2014) presented a multi-objective optimization model using genetic algorithm (GA) and ANNs to quantitatively assess technology choices for school buildings retrofitting, focusing on building’s characteristics and performance: energy consumption, retrofit cost, and thermal discomfort hours.

3. Methodology

The proposed research methodology is shown in Figure 3. As supported by the literature review, four ML Algorithms, namely Artificial Neural Networks, Random Forest, XGBoost, and Ridge, were selected for result comparison and selection of the most optimum method.

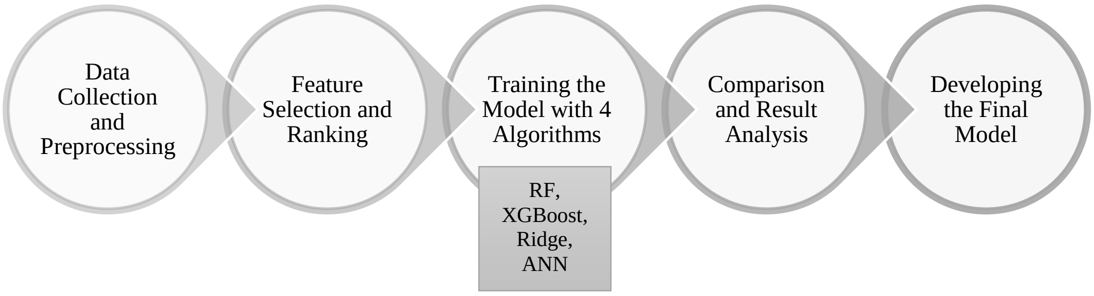

Figure 3. Methodology workflow

3.1. Data Collection and Preprocessing

The data used for this research is extracted from documents presented by the Ministry of Education. In the original database, numerous categories were included, most of which were irrelevant or inconsistent with the research purpose and scope. The features were grouped under three categories: “Energy Retrofit”, “Seismic Retrofit”, and “General” to have a clearer idea about the type of data available. Figure 2 depicts the features of each category.

Table 1. Feature Categories in the Database

General	Seismic Retrofit	Energy Retrofit
City	Type of Work	Type of Work
Gross Volume	Type and Place of Intervention	Type and Place of Intervention
Number of Floors	Seismic Zone	Climatic Zone
Construction Year	Seismic Acceleration	Number of Days with favorable degree
Number of Students	Soil amplification coefficient S (A, B, C, D, E)	Heated Gross Volume
Geographic Coordinate	Topographic amplification coefficient ST	Utilized heated area
Gross Area	Site Danger	Dispersing Surface
	Structure Type	S/V report
	Seismic Vulnerability	Energy Class (before and after intervention)
	Vulnerability Analysis Level	Zero Energy Building
	Building Usage Class (III or IV)	CO_2 Emission
	Topographic Category	Non-renewable Energy Performance Index (before and after intervention)
	Post Intervention Risk Index	Renewable Energy Performance Index (before and after intervention)

3.2. Feature Selection and Ranking

In order to select the most important features and for feature ranking, semi-structured interviews were conducted with experts in data science, construction engineering, and preservation. It is noteworthy that despite being important, some features included a lot of unretrievable missing values among the samples. Therefore, those features were eliminated. Accordingly, a database with 12 features and 209 projects was used for data analysis and data cleaning.

During the exploratory data analysis, features' importance and correlation were carried out, as a result of which “Building Usage Class” and “Subsoil Category” features were dropped from the feature set containing the same value for almost all the samples. Moreover, some features' importance was so limited that they could be easily dropped from the dataframe. Figure 3 shows the feature importance before and after the drop of three features: “Number of Floors”, “Zero Energy Building”, and “Seismic Zone”.

In addition to predicting the retrofit cost of school buildings, this research contributes to selecting and ranking the most relevant features while predicting the retrofitting costs. As shown in the figures below, the type of work (type of retrofit) with six different values, namely Seismic Adjustment, Energy Efficiency, Seismic Adjustment and Energy efficiency, Seismic Improvement, Seismic Improvement, and Energy Efficiency, and New Construction, have the biggest effect on the final cost; moreover, it is followed by Gross Surface Area, Type of Intervention (parts of the building intervented), Construction Year, Climate Zone, Number of Students, and Post Intervention Energy. It is noteworthy that the final cost is calculated as Cost per Square Meters to justify the effect of the area and minimize the number of features.

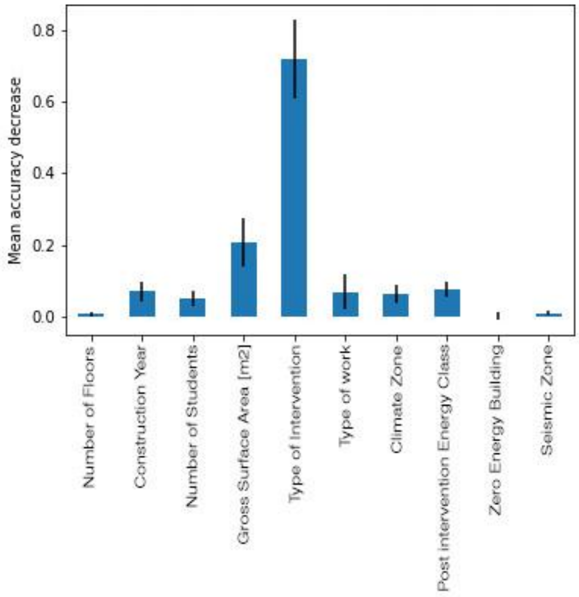

Figure 3 (a) Feature Importance with 10 features database

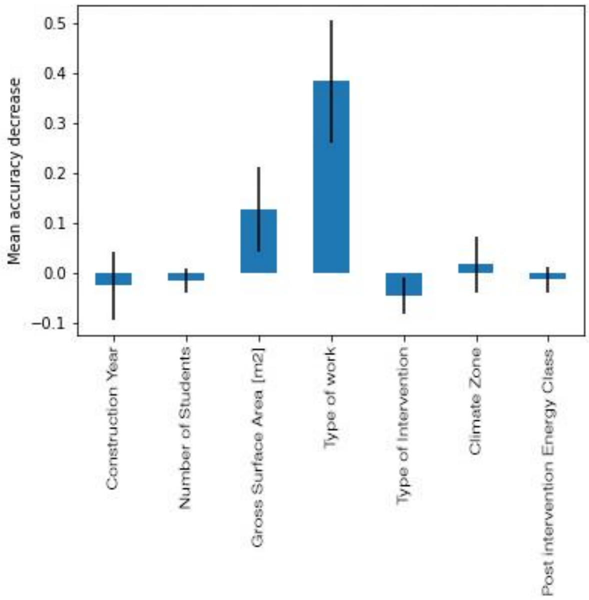

Figure 3 (b) Feature Importance with 7 features database

Since the type of retrofit work has the greatest impact on the final retrofit cost, the database was analyzed based on the share of each retrofit work type, which is presented in Figure 4.

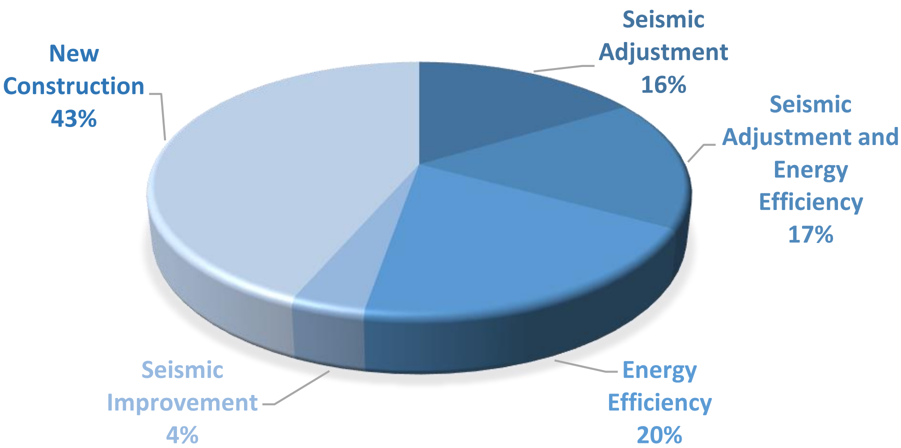

Figure 4. Share of each retrofit work type in the dataset

3.3. Training the ML Models

In order to reach the best prediction precision, four ML algorithms were selected for result comparison based on the literature review. Neural Networks, Ridge, Random Forest, and XGBoost are the algorithms. The database was divided into 80% training (20% of validation) and 20% testing. The training process aims to help the machine find the relationship between the input features and output data and learn from the previous projects. At the same time, the purpose of the test process is to check the precision of the algorithm's estimates when encountered with new data. In the case of Neural Networks, a validation process is also conducted to minimize overfitting of the training data. Figure 5 shows the training and validation loss during the training process for the proposed Neural Network on the dataset.

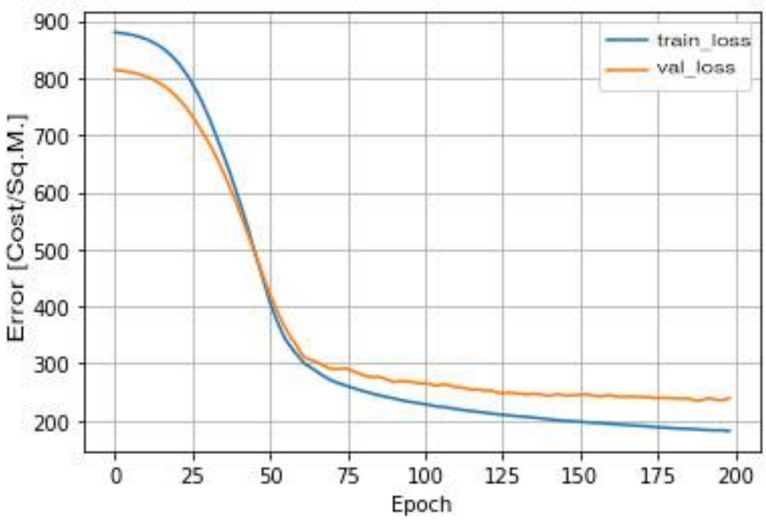

Figure 5. Train and Valuation loss during the Neural Network training process

4. Results

After the cleaning and training phases, the four different algorithm's results and performance are extracted and compared. The performance of each algorithm was measured using the Mean Absolute Error (MAE) metrics (Table 2). The MAE is the average of absolute errors for a group of predictions and observations. As shown in the table, the Neural Network has an acceptable performance. However, since they indicate better precision on big datasets and our dataset is relatively small, the MAE difference is not significant.

In order to make the predictions more precise, the average of predicted values for the test data set was calculated. The MAE of the average value was better than the previous algorithms. Therefore, the research framework proposes the average predicted value by the four algorithms as the most precise retrofit cost prediction.

Moreover, Figure 6 shows the correlation between the actual and predicted value of the test dataset Cost/Sq.M. for the four algorithms and the average of predictions by the fours algorithms. Also, it is evident in the figure that the average of the predictions is closer to the actual value.

In addition, the errors magnitude distribution was analyzed in the four algorithms. For this purpose, the histogram of the difference between the actual and predicted values was depicted in Figure 7. Most of the data have near 0 prediction error; therefore 0 value is the peak of the histograms.

Table 2. Comparison between the loss function of the proposed algorithms

Random Forest MAE	XGBoost MAE	Ridge MAE	Neural Network MAE	Predictions average MAE
315	343	320	329	311

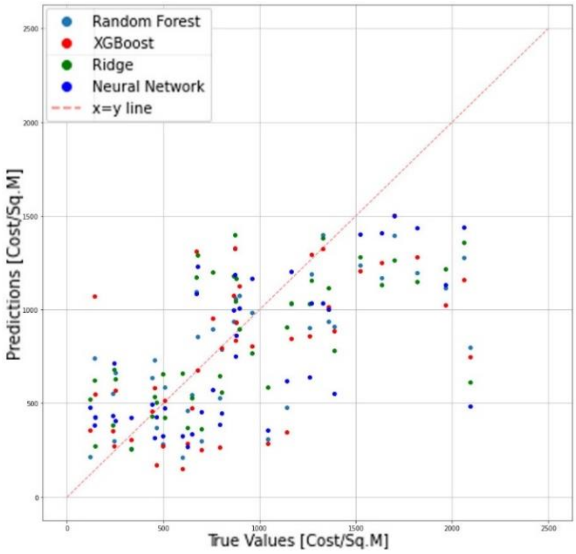

Figure 6 (a) Correlation between result actual value and prediction in the four algorithms

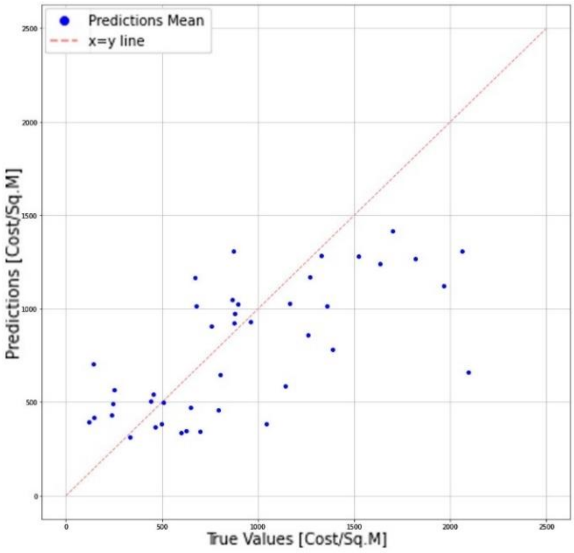

Figure 6 (b) Correlation between result actual value and the average of predictions of the four algorithms

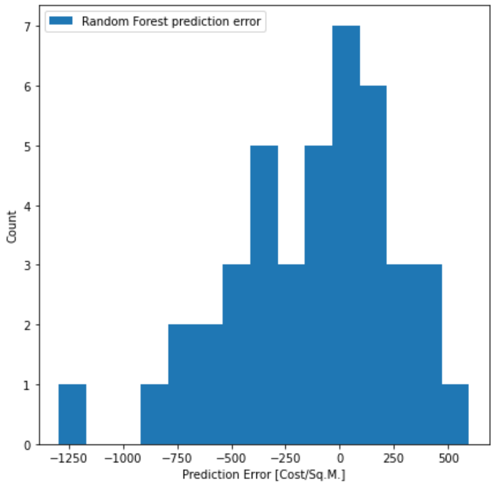

Figure 7 (a) Histogram of the prediction error for Random Forest

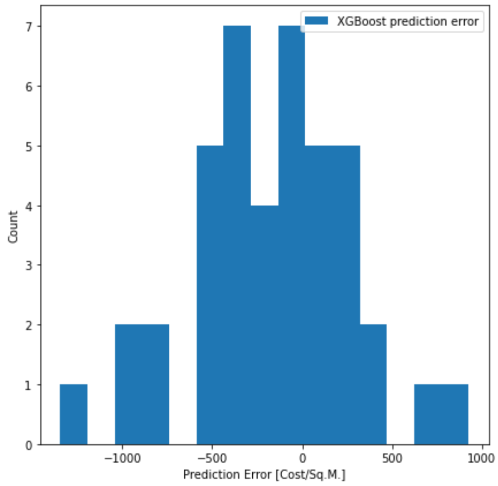

Figure 7 (b) Histogram of the prediction error for XGBoost

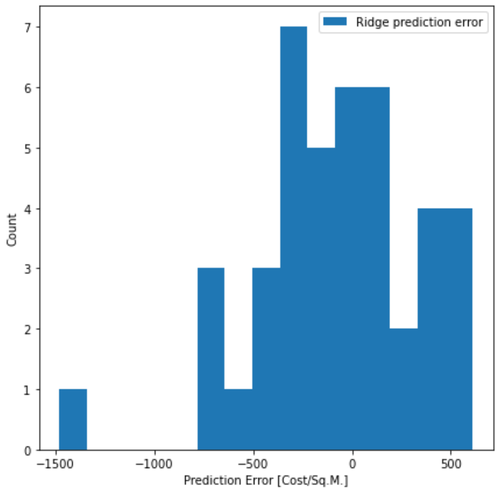

Figure 7 (c) Histogram of the prediction error for Ridge

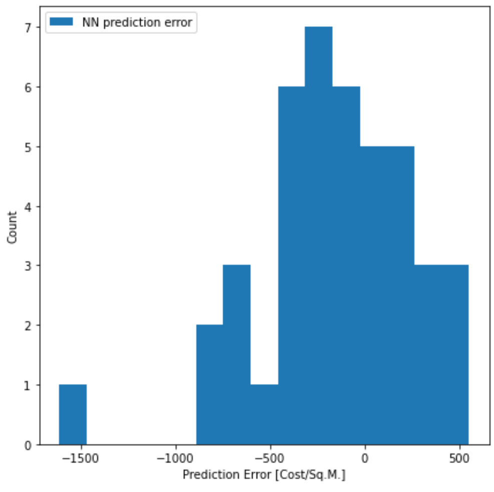

Figure 7 (d) Histogram of the prediction error for Neural Network

The same process was repeated for the average of the predicted values, shown in Figure 7. Moreover, the error per each actual cost is depicted in Figure 8, showing an inverse correlation between the retrofit cost amount and the average prediction error. Meaning the higher the retrofitting cost per square meter is, the better the model's prediction is. This could be due to the denser distribution of samples in higher cost values.

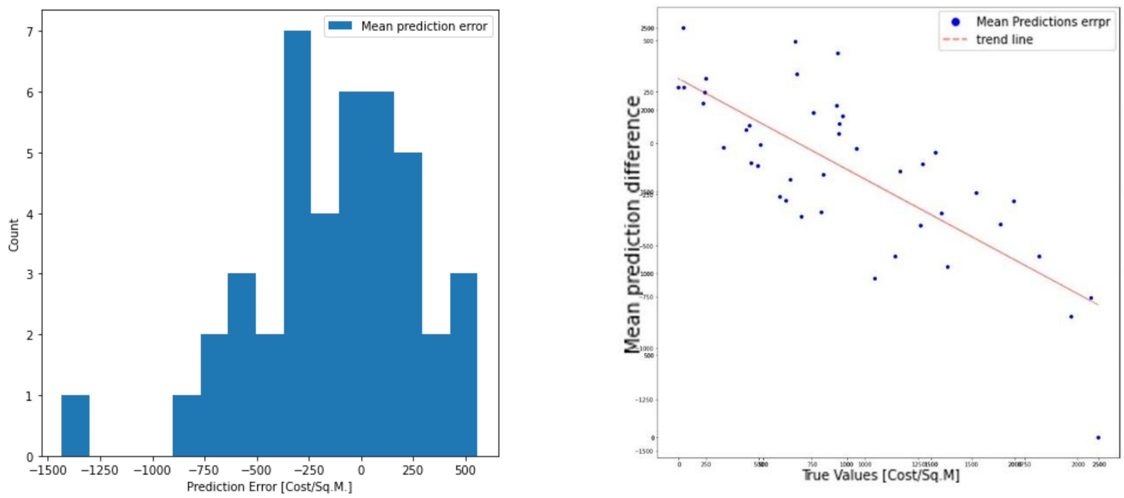

Figure 8 (a) Histogram of the prediction error for the average prediction value

Figure 8 (b) Mean prediction error of each test value

5. Discussion

The comparison between the obtained results by the four models indicates some important aspects. Neural Networks have the advantage of capturing the nonlinearity between the input features and the target data, with the ability to understand even complex links. On the other hand, the other three algorithms better capture the correlation between the features and the target. Since the dataset is relatively small, the advantage of Neural Networks is not apparent. However, in the case of bigger datasets with more features and nonlinearity, Neural Networks will probably outperform the other three algorithms.

The main limitations of the research are the small number of documented data and the existence of unretrievable missing data in the data set. Moreover, the input samples are not equally distributed, decreasing prediction precision and higher MAE. In order to solve this issue, the research suggests the average of the predictions as the most accurate output since it can benefit from the good performance of NNs for capturing the nonlinearity and the performance of the other three algorithms for capturing the correlation. The results also support this assertion, indicating a lower MAE for the average value.

Though this research uses the Italian school buildings as the case study, it applies to other building types like industrial or residential buildings due to its systematic and comprehensive approach. It is also applicable to other countries and datasets.

Another important contribution of the framework is the analysis of feature importance and impact on the final cost. It will enable the decision-makers to focus on the critical features while gathering data and deciding on the building retrofit alternative.

6. Conclusion

This research proposes a ML based retrofit cost prediction framework for school buildings. ML algorithms can deal with complex and abundant data, learn from previous cases, and predict accurately and automatically for future projects. In this context, the proposed framework determined the most relevant features in each category (energy retrofit, building retrofit, and general attributes) and trained four ML based models with Neural Networks, Random Forest, Ridge, and XGBoost algorithms. The cost prediction process was performed much faster and more accurately compared to traditional methods. Moreover, using this method, there is the possibility to do a sensitivity analysis of the features to make the predictions more accurate. Therefore, ML based model proves to be an apt replacement for traditional cost estimation methods.

Fostering the cost retrofit prediction, this research contributes to the resilience of school buildings in Italy, which are in poor maintenance condition. Consequently, it will result in increased quality of the interior space and seismic stability and decreased energy consumption and CO2 emission, which are some of the essential factors in achieving sustainability and resilience on building and urban scales.

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