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Economic Sustainability of Building and Construction Projects Based on Artificial Intelligence Techniques

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***Abstract* - Artificial intelligence (AI) has been shown to be an effective replacement for conventional modelling approaches. AI is a subfield of computer science that develops software and tools that mimic human intelligence. AI offers advantages over traditional methods for handling ambiguous circumstances. In addition, AI-based solutions can successfully replace testing when identifying engineering design parameters, saving a lot of time and resources. AI can also increase computer efficiency, decrease mistake rates, and speed up decision-making. Recently, there has been a lot of interest in machine learning (ML), a new area of cutting-edge intelligent methods for use in structural engineering. Consequently, this work presents a study on the economic management of building and construction projects based on creating ML techniques. It begins with an overview of the value of applying AI techniques in building and construction industry. The analysis of the prediction of reinforced concrete's compressive strength while taking cost into account is then done using empirical data based on a case study. Accordingly, the findings showed that the support vector regression (SVR) and k-Nearest Neighbour (KNN) intelligence techniques are helpful in the construction business for controlling the strength of concrete based on sustainable cost reduction.**
***Keywords:* Artificial Intelligence, Building, Construction, Industry, Machine Learning**

I. INTRODUCTION

The economic management of modern building and construction work involves a lot of critical engagements both financially and technically due to some dynamic evolving situations. Modern technologically evolving AI techniques are being used to resolve some challenges associated with Building Information Modelling (BIM) in construction project management. The application of BIM in the construction industry is essentially relevant due to its evolving ability to facilitate the adoption of emerging building and construction technologies. Our modern-built environments require improvement in reliability, safety, efficient cost reduction, precision and creative appealing view. These can thus be managed effectively via the application of AI design and computational techniques. The application of AI techniques in the building and construction industry has tremendously transformed the industry into a fourth industrial revolutionary conception [1]. AI concepts involve the application of integrated smart and digitalized technologies through fast computing design and automated construction approaches.

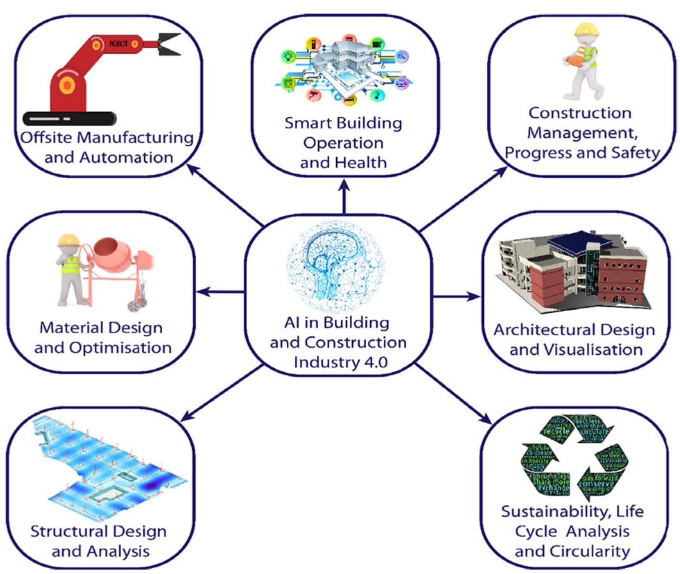

Fig. 1 Application areas of AI in building and construction [1]

The design of modern buildings requires that they are planned and executed based on modern innovative building architectural and structural concepts. Figure 1 shows the application areas of AI in building and construction in the fourth industrial revolution.

The development of new technologies in construction project management that can enhance the strength of the building and increase the safety of the occupants is necessary. There are huge significant benefits in effective project management that involve adequate building and construction strength. From a climate change perspective, the design of buildings is to accomplish the potential capability to cope with possible changes on different fronts [2]. The application of some emerging technological concepts in the construction of buildings ensures that traditional buildings are replaced with smart and intelligent buildings. Figure 2 shows the technological conceptions required for the transition from traditional to smart or intelligent buildings. An intelligent or smart building can be equipped with creative services that drive for comfort, safety, and environmental friendliness. Regardless of the type of building such as residential, commercial, or industrial, it is absolutely possible to integrate smart concepts based on AI-embedded computing technologies and the Internet of Things (IoT). The aim of the study was to investigate the performance of different modern AI techniques based on the prediction of the flexural strength of concrete in building constructions. Measured in tensile strength, concrete's flexural strength is a representation of concrete materials' design that determines its ability to resist bending when subjected to the desired stresses.

II. STRUCTURAL DESIGN AND OPTIMIZATION

In the construction industry, structural design, and optimization of the strength of materials from an economic and safety perspective are very important. The design and optimization of intelligent algorithms of AI have proven their capability in various problems solving mechanisms relating to the structural design of buildings, optimization of construction materials and management of building facilities [4]. Of greater concern is the strength of construction materials used in buildings based on the production of concrete. In construction project management, standard reinforcement of construction materials must be taken into consideration. The quality of materials is a core factor in the construction industry. Utilization of concrete is the foremost artificially created material used in building construction for reinforcement. Basically, concrete is a composite material based on a mixture of sand, stones, water and cement. The most common constraint in the production of concrete is the prediction of its properties toward achieving the desired reinforcement. The prediction usually involves a number of factors thereby determining the qualities of the mixture of concrete produced for the safety of the structure of the building created.

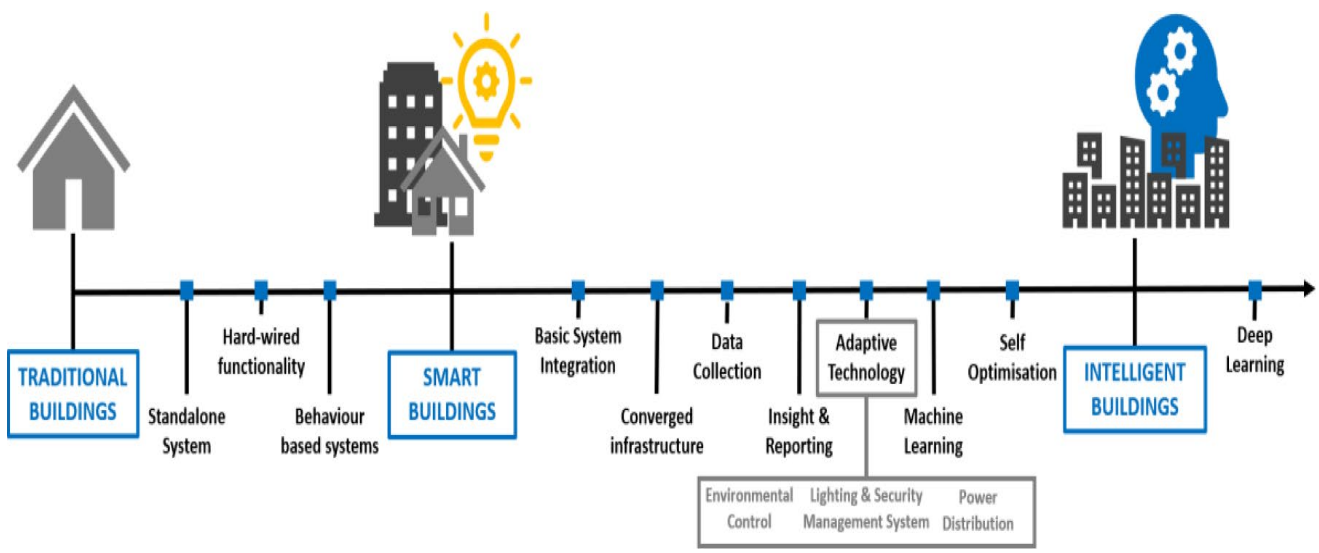

Fig. 2 Development and evolution of smart and intelligent buildings [3]

The technological prescription method of mixing concrete is absolutely important to ensure proper strength control of the final output involved. Manual production of concrete is usually not a good means since it could be prone to errors and violation of technical strength that can lead to premature failure in any situation of a slight increase in load-bearing conditions. Therefore, the components of concretes in various buildings and construction structures must be determined appropriately to avoid unanticipated significant damages. Thus, the application of artificial intelligence techniques is highly beneficial for the determination of the exact concentration of the component materials. Unrealistic concrete mixture is a major setback to the building and construction industry worldwide, especially in developing countries. There are different kinds of concretes as shown in Figure 3. Generally, concrete can be lightweight or heavy-weight based on its rated weight. Traditional heavy-weight concrete is usually around 2400 - 2500 kg/m3 while the lightweight type could be 23–80% lighter having a dry density in the range of 320 kg/m3 - 1920 kg/m3 [5].

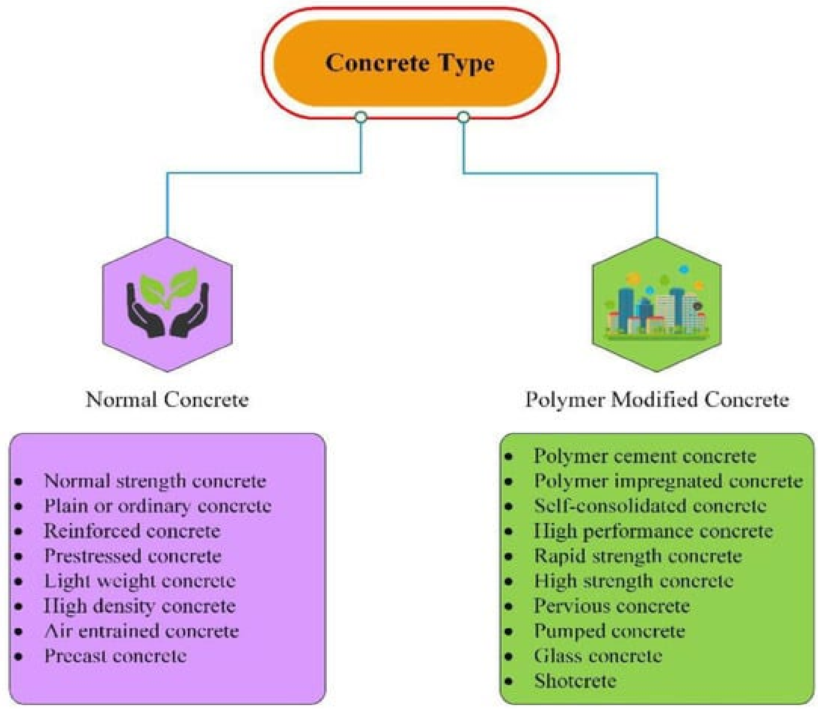

Fig. 3 Different types of concrete [6]

III. ARTIFICIAL INTELLIGENCE TECHNIQUES IN CONSTRUCTION PROJECT

The non-linear characteristics of concrete present challenges to predict its compressive strength at different phases like the design and construction stages [7]. In this context, some of the traditional empirical methods such as the non-destructive techniques are usually inadequate for the prediction of the strength. Consequently, the alternative techniques of artificial intelligence have provided some better results based on the reports available in the literature [8]. The overall strength determination of the building absolutely depends on the strength of the concrete used. Concretes have varieties of properties such as flexural strength, resistance to fire, water permeability, compressive strength, and others. There are several AI techniques that have been applied to solve problems involving concrete mixing technologies. Over the years, AI techniques have been used extensively for many types of research in building and construction engineering [7-12]. The prediction of mechanical strength of concretes has widely been predicted by AI methods [13-14] such as genetic programming technique (GPT) and soft computing technique (SCT) [14]. The varieties of commonly used machine learning algorithms in the context of artificial intelligence algorithms are shown in Figure 4. Therefore, two different artificial intelligence algorithms techniques were used in this study. The intelligent techniques are the k-nearest neighbour and support vector regression (SVR) algorithms.

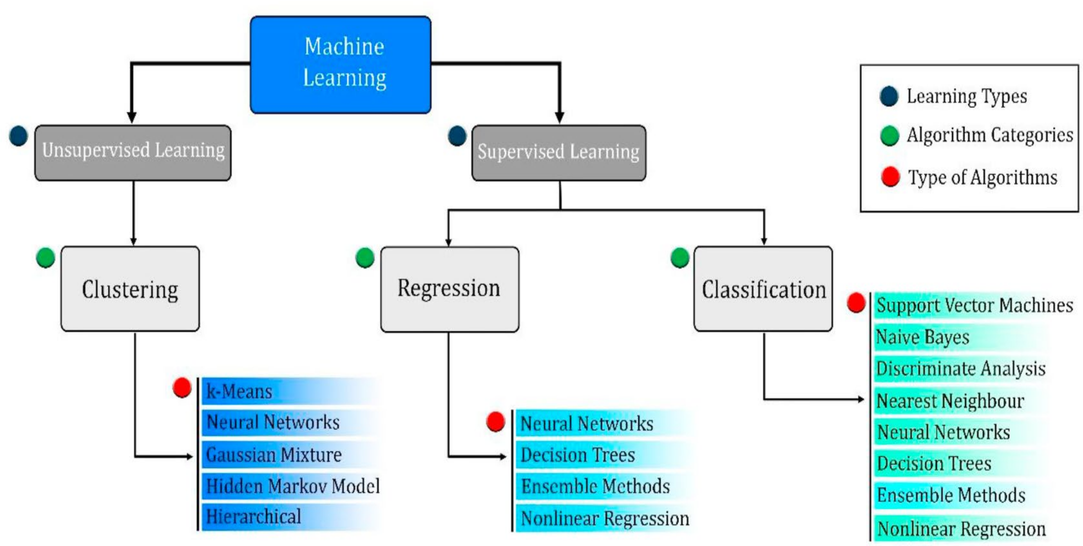

Fig 4 Variety of commonly used machine learning algorithms [15]

A. K-Nearest Neighbour (KNN) Algorithm

This machine learning algorithm has relevant applications in regression analysis. KNN uses a supervised learning classifier mechanism based on proximity predictions for the grouping of data points. KNN is a non-parametric algorithm that manipulates data based on the classification of the similarity between new and available data through a well-suited category. It is a supervised machine-learning algorithm that is simple to use and can be applied to both classification and regression problems. The method selects the k instances closest to the query to find the distances between the query and all examples in the data. If a regression problem is present, the program then averages the labels. Information for fault detection and diagnosis can be accurately determined using dependable KNN classification models. The representation of KNN regression algorithm is as follows:

Input:
Training example (x_i, y_i)
1. x_i…… characteristic value representation
2. y…… real-valued target

Testing point x for which prediction is to be made.

Prediction:
1. Evaluate the distance $\mathrm{d}(x, x_i)$ based on each of the training examples.
2. Select k neighboring instances $x_{i1} \dots x_{ik}$ with their corresponding labels $y_{i1} \dots y_{ik}$
3. Generate the mean of $y_{i1} \dots y_{ik}$

$$\bar{y} = f(x) = \frac{1}{k}\sum_{j=1}^{k} y_j \tag{1}$$

Where k represents the nearest instances and the actual value of the output parameter is denoted with y_j.

B. Support Vector Regression (SVR) Algorithm

For a common classification problem, the support vector regression (SVR) can be utilized as a base for the support vector machine (SVM). Characteristically, SVR has an added parameter Ɛ (epsilon) that allows for the determination of the width of the tube in the hyperplane during its implementation. The general structure of SVM is shown in Figure 5.

It is a well-known technique for dealing with classification problems based on supervised machine learning. In dealing with the classification problems using SVR, all the points within the tube are taken as the accurate prediction and are accepted by the algorithm. Contrarily, points out the tube is penalized by exclusion from the classification. The illustration of the SVM classifier system is shown in Figure 6.

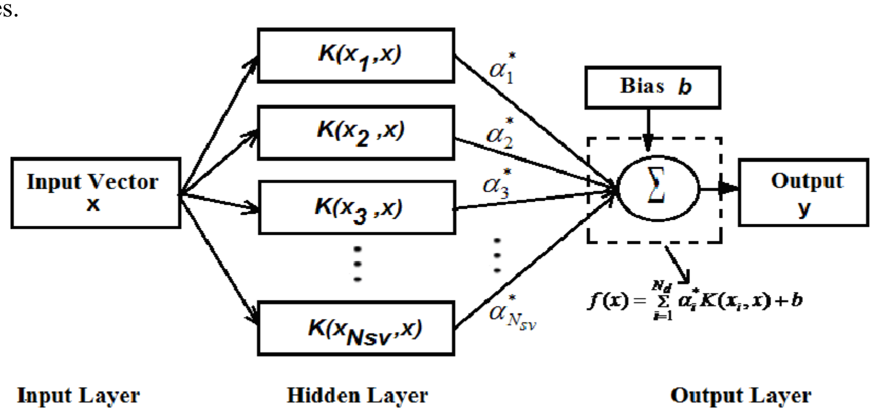

Fig. 5 General structure of support vector machine [16]

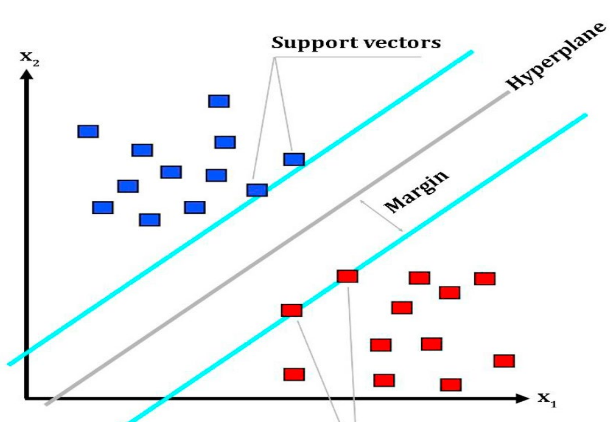

Fig. 6 Support vector machine classifier [15]

C. Training of Algorithms and Application of Metric Models

The selected algorithms for problem-solving were trained and the training processes were conducted based on correct model building and careful selection of important parameters. The selected adjustable parameters for the two algorithms are shown in Table I. The training process of the KNN involves the selection and utilization of several adjustable parameters such as the number of neighbours. The weight function to determine the model's generalization ability is very important. In the SVR, proper tuning of the parameters and prediction accuracy determine the outstanding generalization capability. Therefore, the selection of the value of epsilon, penalty coefficient C and other adjustable parameters requires a great deal of attention.

TABLE I TRAINING OPTIMIZATION PARAMETERS

Number	KNN Parameter	KNN Value	SVR Parameter	SVR Value
1	Neighbours	2,4,6,10,14,19,25	Epsilon	0.2, 0.6, 1, 1.5, 1.8
2	Sheet size	2,5,9,13	Regularization parameter C	1,2,3,4,5
3	Weight function	"uniform" "distance"	Kernel type	"linear" "poly" "sigmoid"

Furthermore, the evaluation of the regression model demands the use of mathematically evaluative regressive indices as shown in Eq. 2 – 6. Therefore, this study considers the mean mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), mean absolute percentage error (MAPE) and the coefficient of determination R^2 as the regression analytical models.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \quad (2)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (3)$$

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (4)$$

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_{i_i}}{\hat{y}_i}\right| \times 100 \quad (5)$$

$$R^2 = \frac{(\sum_{i=1}^{N}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}}_i))^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2(\hat{y}_i - \bar{\hat{y}}_i)^2} \quad (6)$$

The measured compressive strength of concrete is given by y_i, the predicted value $\hat{y}_i$, the average value of y is $\bar{y}$ and $\hat{y}_i$ has a mean value given as $\bar{\hat{y}}_i$.

IV. DISCUSSION ON RESULTS

The rise of AI as a promising predicting tool has been seen across a wide range of construction technologies, representing a potential replacement for commonly used empirical techniques. The exponential evolution in relevant literature over the past few years is evidence of the expanding application of AI in concrete engineering technology for building constructions. The results obtained for the prediction is shown in Table II. The ability to estimate concrete's compressive strength accurately and quickly is crucial for construction industry and has recently gained popularity as a research topic. The prediction model of the KNN has high accuracy of predicting strength of $R^2 = 0.99$, MSE = 5.6 and RMSE = 2.03. In the SVR model, the values of R^2, MSE and RMSE are respectively 0.98, 6.1 and 2.16. The two-predicted models were compared based on their individual learning algorithms and they significantly perform to the level of expectations. Compared with other learning algorithmic techniques such as AdaBoost and CatBoost, the algorithms of KNN and SVR are more advantageous. The cross-validation analysis conducted also revealed that the algorithms R^2 and RMSE obtained performed accurately as expected.

TABLE II RESULTS OF THE ANALYTICAL METRICS OF THE MODELS

Model	MAE	MSE	RMSE	MAPE	R^2
KNN	1.86	5.6	2.03	4.24	0.99
SVR	1.91	6.1	2.16	4.47	0.98

In addition, the results of investigation of the economic aspect of the study based on the input data for the KNN and SVR models are also presented. The estimation of the Net Present Cost (NPC) was conducted. A building located No. 2392 at Apo Resettlement Zone E in the Federal Capital Territory (FCT), Abuja was used as a case study. The construction of the building began in March 2022 and completed in February 2023. The total cost of the structural component of the building was valued to be $52,860.47 at official dollar rate of $1 = N416.19 in 2022. This total amount of $84,096.21 was presented by the contractor in the bidding package for the proposed building. The total cost covers site preparation, tunnel construction, pile and non-column works. A sum of 55.5% of the total cost representing $46,673.39 was estimated for the entire Reinforced Concrete Construction (RCC) of the building.

The reinforced concrete construction of the building covers foundation, beams, slabs, columns, and other miscellaneous concrete work including the metallic materials. In the case study, building columns was a continuous process that began after the foundation was finished and continued until the last column was built at the roofing point. From the comparative analysis conducted between the two algorithms, KNN model is the most economical advantage compared to the SVR. The algorithms were compared for the cost required for the reinforced concrete construction. The results are shown in Figure 7. Compared with the estimated RCC cost of $46,673.39, the estimated KNN and SVR cost are $41,234.26 and $43,004.59 respectively. There exists a percentage cost difference of approximately 11.7% between the estimated contract of the RCC and KNN while about 7.9% percentage difference was observed between the estimated contract RCC and SVR. The difference, thus, indicated that the KNN presented the most efficient cost saving advantage.

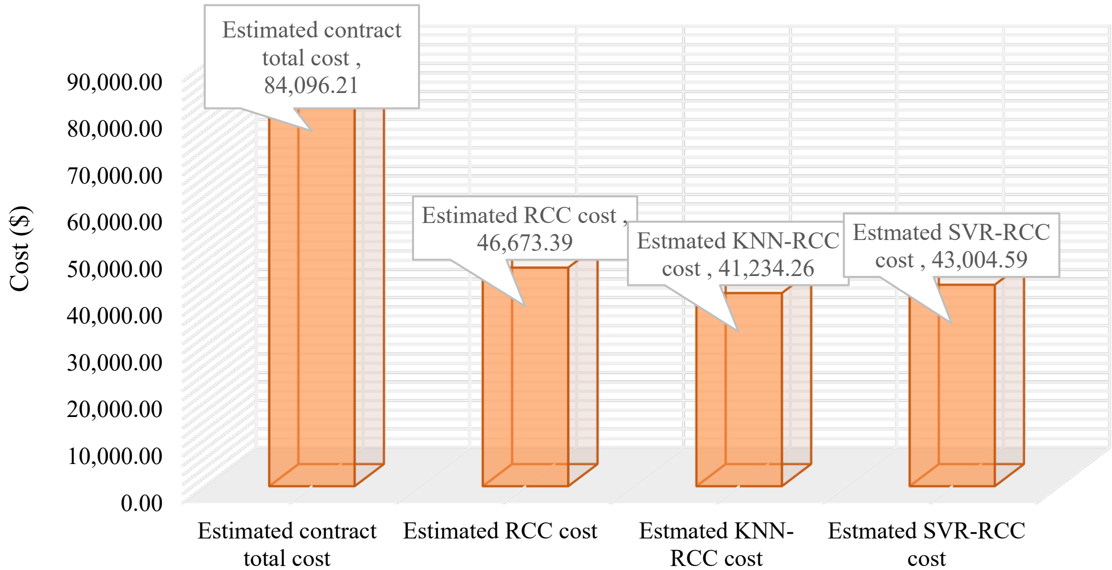

Fig. 7 Comparative cost analysis

V. CONCLUSION

To assist the community of building and construction industry, which is not familiar with machine learning, to create their realistic applications, this study was presented. The global construction industry uses concrete reinforcement as the basic support required to guarantee the needed strength in buildings and construction works. A reliable concrete reinforcement comprises materials characterization, concrete mix design, concrete properties, calculation of the desired mechanical properties, service durability, lifespan and early or abnormal crack detections. Model prediction through the use of learning algorithms is thus an important research endeavour which can serve as valuable resources. The reliability, dependability, performance, and production capacity of concrete can be determined through the use of ML techniques. Therefore, this study has presented the comparative analysis of two ML algorithms in the prediction of the cost of compressive strength of RC via the application of empirical data. It consequently established the fact that modern intelligence techniques have useful applications in the concrete industry with minimal mean absolute percentage error in the numerical coverage of 4.24 - 4.47%.

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