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Assessing the Influence of Sustainability Using Artificial Neural Networks in Construction Projects

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Abstract: Sustainability is maintained by regular practices, but many factors may directly or indirectly affect sustainability in the construction industry. This paper introduces an enhancement in manageability to improve the factors that can actualize some imperative factors with the help of an ANN framework approach. The primary approach of this paper is to discover the present variables that influence supportability in the development of the construction industry. This paper considers the qualitative meta-analysis approach for collecting all information and contents. The major problems and sub-problems are identified through a combination of literature study, case studies, and conversational interviews which inform the development of the questionnaire survey. A statistical analysis was conducted to explore the most impacting factors causing/affecting sustainability in construction projects. Furthermore, a comparative study between various assigned personnel was analyzed. This investigation will recognize the factors that impact sustainability the most in construction projects. The investigation reveals that sustainability in a development venture is primarily influenced by job security, which is distinguished as the basic factor. The other major factors are material usage and facility; internal and external challenges within the construction industry are the main considerations which are fundamentally in charge of the sustainability of construction projects.

Keywords: artificial neural network (ANN); factors; construction industry; statistical analysis; sustainability

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1. Introduction

Sustainable practices are of significant concern in the construction industry since this division is one of the best among the three worldwide initiatives to reduce carbon emissions and a significant effort is required for energy conservation. Bakhtiar et al. (2008) [1] say that the construction industry has a major impact on sustainability and the construction professionals moving towards working for sustainable construction.

Carbon emissions cause rises in global temperature, affecting flora and fauna. Reduction in carbon emission by sustainable advancement is, in this manner, a basic errand for all nations worldwide to spare the earth from global temperature issues [2–5]. The World Commission on Environment and Development (WCED), otherwise called the Brundtland

Commission, clearly defines the concept of sustainable development. It has characterized feasible advancement in "The Common Future" which tends to the present issues without compromising on the ability of the future generations to meet their own needs. The three main concerns are individuals, the planet, and benefits. The Brundtland Commission report emerged from the crumbling human condition and normal assets. The construction industry became the most energy-consuming industry by utilizing and depleting natural resources. Also, it is responsible for the high generation of waste, greenhouse gas emissions, pollution, and collapsing the environment [6].

Notwithstanding the natural, financial, and social elements of sustainability, it is very difficult to engage the construction professionals, updates in technology, and policymakers to enhance sustainability in the construction sector [7–9]. This paper aims to establish different types of variables present in the construction industry that are ignored in everyday works, which autonomously may not be so important but, when taken together, are assumed to be of high importance. Given current investigations and reviews, the most critical points examined in various sites in Chennai, India: material usage and facilities, internal and external challenges within the construction industry, CO_2 emission, political issues, lack of people awareness, inadequate safety precautions, material waste generated in construction and demolition sites, materials, and other factors. This study was mainly focused on residential and commercial projects and was limited to the Chennai region. The scope was to make sure a deep and detailed analysis of the factors influencing the sustainability in construction projects for urban development. Chennai city in India is a rapidly developing city in infrastructure and construction.

1.1. Construction Industry and Sustainability

Sustainable construction has minimal energy consumption and prevents harmful environmental impacts. The construction industry plays a major part in the construction of the world; also, they are responsible for global greenhouse gas emissions, which is an impact of human-made actions [10]. It also provides necessary information for the client to update decision-making [11]. Construction activities can be categorized into four dimensions: on-site activities, the entire project lifecycle, the broader construction industry, and the overall process of human settlement creation [11,12]. Construction projects in developing countries have significant impacts on communities, the environment, and social structures while also placing a substantial burden on the economy. These facts highlight the notable sign of coordination. The above facts underline the significant signs of integration of sustainability into the transmission of development in developing nations [13–17]. The main goal of development efforts is to construct long-lasting physical facilities, like infrastructure and buildings. A physical facility's construction process has a significant impact on its sustainability performance, suggesting that sustainable development is essentially project-specific. Sustainable construction is named thus to indicate the responsibility of the construction industry over global sustainability [18]. Sustainable construction helps in providing the current and future requirements for living beings by saving energy, water, and natural resources. This can be achieved by reusing the waste, recycling the resources, and reducing the pollution [19].

1.2. Artificial Neural Network (ANN)

An artificial neural network (ANN) is one of the data-processing systems that draws inspiration from biological systems structures [20]. The ability of ANNs to represent human cognition is impressive. Its processing components, which are made up of layers of computing units, are similar to neurons in biological entities. One of the most widely used ANN architectures is the multilayer perceptron, which is a feed-forward network.

The effectiveness of ANNs in resolving complex engineering issues is the reason for their broad adoption and use [21–23]. A neural network is essentially a mathematical model that is used to examine an artificial system's general properties. Equations that reflect the first-order time derivative of the weight state for synaptic elements and the activation state for processing units are commonly used to express these models. Despite being nonlinear, these expressions are typically straightforward enough to forecast the network's overall behavior [24]. The artificial neural network (ANN) models permit researching undertakings which rely upon numerous physical wonders and are additionally utilized for a substantial assortment of uses, for example, grouping, information mining, design acknowledgement, picture pressure, a process demonstrating, etc. In this manner, it is conceived that further investigation into the structure and inner procedure inside the neural system will offer better informative knowledge into the impact of autonomous factors in the displaying procedure. The prediction and validation of constituent materials for concrete manufacturing in the RMC are necessary to develop the proper productivity [25]. ANNs are so adaptive in connecting the data of various sets. While solving a set of data, if the ANN obtains another set of data, it converts its logic according to new set of data. That nature of solving data makes it perfect for nonlinear calculations [26].

1.3. ANN Structure

A neural system is made out of various commonly associated neurons gathered in layers of ANN. This engineering comprises three layers, which are the input layer, the hidden layer, and the output layer as shown in Figure 1. Neurons (or nodes) and the links that connect them are the main components of an artificial neural network (ANN). A neuron receives input (signals) from surrounding (neighboring) connected neurons and processes the information as a whole, which gives rise to an output. Neurons that detect the initial stimulus are called input neurons. In terms of ANN modelling, a basic assumption underlying this claim can be seen in generalization, which means that a model that provides a reliable solution for data (i.e., the model should provide reliable predictions as per input fed to the model) should be removed for training data range of data from the population of interest, and as such, the probability that the instance of interest is as general as possible can be achieved by dividing the input data into appropriate training and valuation sets. The main dataset is used to train the ANN, while the validation set is used to evaluate the trained ANN. Many statistical methods are available for deriving solutions from a dataset. Collection and analysis of the data for identifying the factors that influence sustainability in construction requires more details to be collected from the personnel working in the construction activities. The data collected need to be analyzed further with proper tools, which can provide a more accurate prediction. A delay analysis in construction projects was performed in Turkey by Murat et al. (2013) [27], with 83 factors causing delay based on the questionnaire response by 64 respondents using RII. Choudary et al. (2014) [28] used Statistical Package for the Social Sciences software for a data analysis on risk management in construction. Statistical approaches have a negative of dealing with simple linear relationships which are not suitable for issues based on real-world scenarios. The ANN approach was used in many studies related to the construction project, where they had both big and small datasets. Al-Zwainy et al. (2012) [29] and Baba et al. (2017) [30] used ANN in their research studies to analyze data from 8 to 65 factors in their research. ANN can be used to solve problems which are not properly defined and for the nonlinear relationship. In this study, the data which have been collected comprise a dataset of 101 with 84 variables. The dataset used in this study has a nonlinear relationship which can be analyzed using tools such as ANNs.

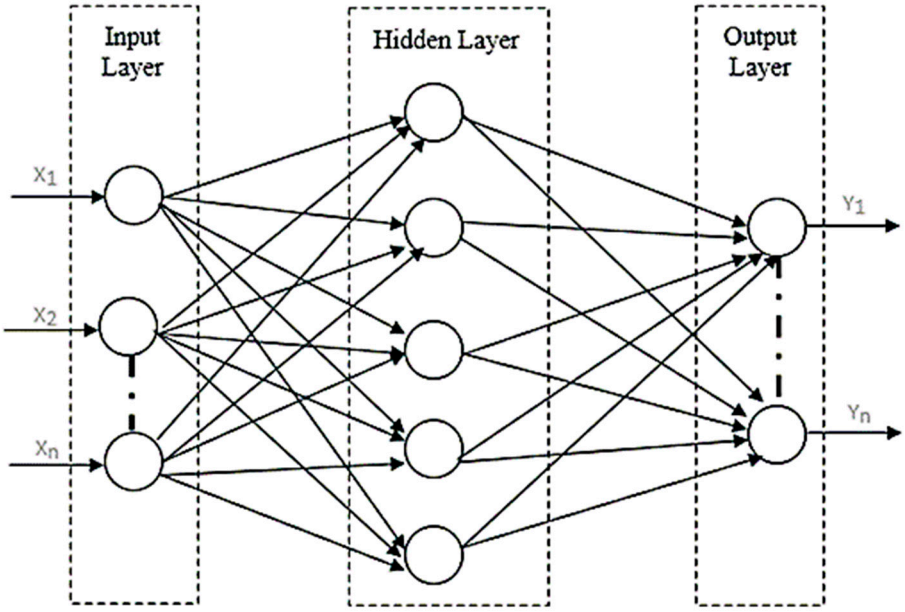

Figure 1. Artificial neural network structure.

2. Data Collection

The data collection was performed by using a questionnaire survey for this project. The questionnaire was prepared via a literature study and case study at different construction and demolition sites in Chennai. For the response purpose, this questionnaire was sent to the different categories of personnel like Project Manager, Assistant Engineer, Junior Engineer, Civil Engineer, Site Engineer, Sub Engineer, Contractor, Supervisor, and others who have more experience and knowledge in the construction field. The responses were collected from construction professionals having experience with a minimum of 1 year to a maximum of 22 years. The age and experience details of the respondents are given in Table 1. The survey utilized in this overview was separated into two areas. Segment 1 looked for the respondent's statistical data. In Segment 1, the details comprise the name of the respondent, the name of the firm, the assignment of the respondent, age, and involvement in the construction sector. The 84 questions in Segment 2 are based on 16 primary aspects that contribute to sustainability in the building industry. The literature review and one-on-one interviews served as the foundation for these investigations. Primary and secondary sources were used to identify every performance indicator variable. Every question uses a Likert scale and is closed-ended. Every question in this section is a nominal question.

Table 1. Details on the respondent's age and experience.

	Years of Experience	No. of Respondents		Age in Years	No. of Respondents
Experience	1–2 years	22	Age	20–25 years	24
	3–5 years	37		26–30 years	39
	6–10 years	26		31–35 years	21
	11–15 years	11		36 to 40 years	10
	15+ years	5		41–50 years	7

A five-point Likert scale, with 1 denoting Strongly Disagree and 5 denoting Strongly Agree, was used to rate the various factors affecting the construction project's duration. Because it is comparatively simple to create, makes data collection and analysis easier, and works well for surveys, the Likert scale was used. On this scale, respondents were asked to indicate how they scored. In order to choose a sample of Project Managers, Assistant Engineers, Junior Engineers, Civil Engineers, Site Engineers, Sub Engineers,

Contractors, Supervisors, and others, 150 surveys were disseminated once the questionnaire was developed. To emphasize the goal of the test, a cover letter was included with the survey. It also included standards for non-participation, informed permission, anonymity, secrecy, security, and protection from exploitation, distress, and injury. A total of 101 of the 150 surveys that were initially sent out were returned by respondents.

2.1. Preparing the ANN Model

In order to educate the system to produce the desired result, the weights of the neurons are changed. First, the input weights are allocated to the node-to-node connections after being assigned and established. By comparing the output with the predicted values, the system's learning algorithm determines the error and modifies the weights to reduce the mean squared error (MSE). A predefined number of epochs are then covered by this iterative procedure, which involves reprocessing the input values using the recently modified weights. A single training cycle is referred to as an era. The MSE, which is calculated using Equation (1), is among the most often used training algorithms. The framework of the ANN is shown in the flowchart in Figure 2.

$$\text{MSE} = \frac{\sqrt{\sum_{i=1}^{n}(x_i - E_i)^2}}{n} \quad (1)$$

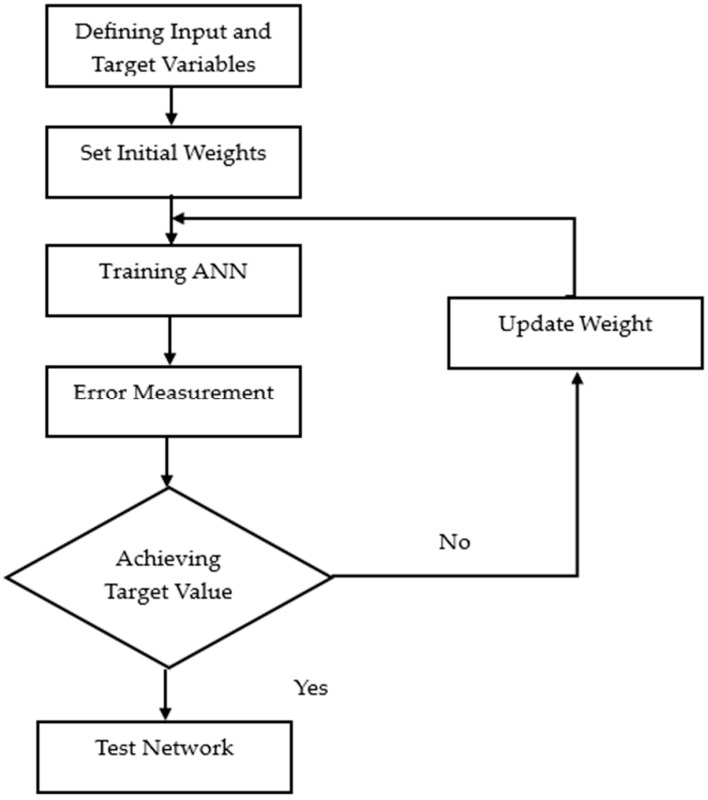

Figure 2. Artificial neural network framework.

The root mean squared error (RMSE) is the squared root of the mean squared error of the difference between observed (x) values and prediction output (E) values. The estimation of RMSE has an indistinguishable unit from the variable and ought to be as low as could reasonably be expected. The RMSE is determined using Equation (2).

$$\text{RMSE} = \sqrt{MSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - E_i)^2}{n}} \quad (2)$$

The coefficient of efficiency R^2 has a range between—∞ and one, one representing an ideal model, zero representing the model being as exact as the methods for the observed information, and negative esteem representing the observed information being a superior estimator than the model. R^2 is determined using Equation (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(x_i - E_i)^2}{\sum_{i=1}^{n}(x_i - \overline{E}_i)^2} \quad (3)$$

where n = number of tests in the preparation set; x_i = yield identified with the example; E_i = target output; $\overline{E}_i$ = mean of the observed sample point.

2.2. Training the ANN Model

The neural system toolbox of MATLAB v 9.7 programming is used to make, train, validate, and test the systems. The education of the community is performed to alter the weights of the neurons so one can gain the preferred output. First, the weights of the inputs are to be initialized, which can be assigned to the hyperlinks in between the nodes. An error is calculated through the learning algorithm of the network by comparing the output with the desired values, and it is adjusted to minimize the generated mean squared error. For a predefined period of epochs, the input data are processed once again using the recently modified weights. A single training cycle is referred to as an era. Among the most widely used training algorithms, this is considered to be one of the better ones. After the preparation procedure, the system ought to have the capacity to produce outputs for new information not the same as the preparation ones.

2.3. Application of ANN

Classical methods of solving may not be applicable for the nonlinear multi-scale problems. The ANN model is a recent advance in machine learning that can be used to analyze such data [31]. ANNs can be used to analyze the survey data in the application of sustainable construction with respect to energy, materials, performance, and maintenance management [32]. The development of a neural network application is highly problem-specific. The application advancement strategy comprises three stages structure, learning, and review. Moselhi et al. (1992) [33] presented neural systems as a promising administration apparatus that can improve current computerization endeavors in the construction business, including master framework applications. Flood et al. (1994) [34] originally exhibited a graphical translation of how ANNs work and showed the manners by which distinctive sorts of structural designing issues can be handled utilizing ANNs. Yeh (1998) [35] studied a novel system design, the logarithm neuron organize, for its proficiency and exactness in an amount evaluation of steel and RC buildings. Murtaza and Fisher (1994) [36] manage the structure and advancement of a nonpartisan system-based decision-making framework, Neuromodex. The framework assists management in deciding whether to use traditional construction methods, such as complete or partial modularization. In the paper, Predicting Construction Material Prices [37], it is discussed that the cost of certain construction materials can fluctuate significantly within short periods. The ability of construction contractors to accurately predict these price changes is crucial for the future growth of their companies. Planning, scheduling, and guaranteeing alignment with the client's available budget, timeframe, and labor requirements all depend on an accurate estimate of construction costs. To increase accuracy and dependability, genetic algorithms have been applied to cost estimation [38–40]. Son et al. (2013) [41] examined a model for anticipating the vitality utilization of government-claimed structures dependent on the information-mining strategy. The model uses ANNs for displaying as well as expectation. Lazarevska et al. (2014) [42] discussed the use of neural systems for prognostically displaying the season of imper-

viousness to the fire resistance of reinforced concrete columns and eccentrically loaded columns. A paper titled Measuring and Predicting Labor Productivity [43] adds to the development venture of the board assortment of information by researching the influential factors on work profitability and building up an artificial neural system to gauge and anticipate work efficiency in creating nations, utilizing the Bayesian regularization and early stopping techniques. Climate safety prediction and safe work behavior in construction projects [44,45] discuss how to assess and separate the construction industry, dependent on their well-being atmosphere, and to decide the critical build of a security atmosphere and safe work behavior of employees in nonlinear and complex conditions. [21] created a counterfeit neural system quality prescient model to predict the compressive strength of concrete, incorporating agricultural and construction wastes and pliable-part quality of cement, consolidating RHA and RAP dependent on foreordained properties of solid constituent materials. It is also used for predicting compressive strength in fly-ash-modified recycled aggregate concrete [46]. The ANN used in high-strength fibrous concrete, which is subjected to elevated temperatures [47]. An AI-based ANN is used to evaluate the compressive strength of polypropylene fibers in high-strength concrete [48].

$$RII = \frac{\Sigma W}{(AXN)} \quad (4)$$

where RII = Relative importance index;

W = Weightage given by respondent for each factors.
A = Highest weight.
N = Total number of respondents.

3. Reliability Analysis

Cronbach's alpha is most frequently employed when a scale consisting of several Likert questions in a study or questionnaire needs to be evaluated for reliability. Kappa (κ) might also be helpful if dependability is a problem. The questionnaire's good performance, as shown in Table 2, suggests the study's dependability. Internal consistency is commonly measured using the Cronbach's alpha coefficient, which normally has values between 0 and 1. Low reliability is indicated by a Cronbach's alpha of less than 0.3, which is unacceptable. On the other hand, the list table exhibits a high degree of consistency and can be widely accepted if the Cronbach's alpha is higher than 0.7. The Cronbach's alpha for this analysis was 0.946.

Table 2. Cronbach's alpha value for sustainability-affecting factors.

Factors	Cronbach's Alpha Value
Equipment	0.687
Political issues	0.422
Improper equipment maintenance	0.783
Unavailable of labor at project	0.518
Material waste generate on construction and demolition site	0.610
Inadequate safety precautions	0.537
Pending payment of workers	0.617
CO_2 emission	0.713
Materials	0.521
Political issues	0.608
Environmental factors	0.646
Contract and conflict	0.675
Internal challenges in the construction industry	0.732
External challenges in the construction industry	0.626
Material usage and facility	0.832
Other factors	0.607
Overall	0.946

3.1. Relative Importance Index

Shi et al. (2014) [49] assessed the overall importance of several factors in the construction sector using the RII (relative importance index) technique. In order to determine the most important factors influencing sustainability in building projects, a similar methodology was used in this study. Equation (4) was used by the RII to determine the relative importance and ranking of these causes. Higher RII values indicated a higher consumption frequency; the values ranged from 0 to 1. The elements that have the biggest effects on sustainability in building projects were determined using the RII. According to Figure 3, the most important factor is job stability. The values fall between zero and one, as shown by the ranking of important elements based on the average RII value. A greater frequency of responses from the respondents is indicated by higher RII values. According to Figure 4, other elements are the most important factor influencing sustainability in building projects.

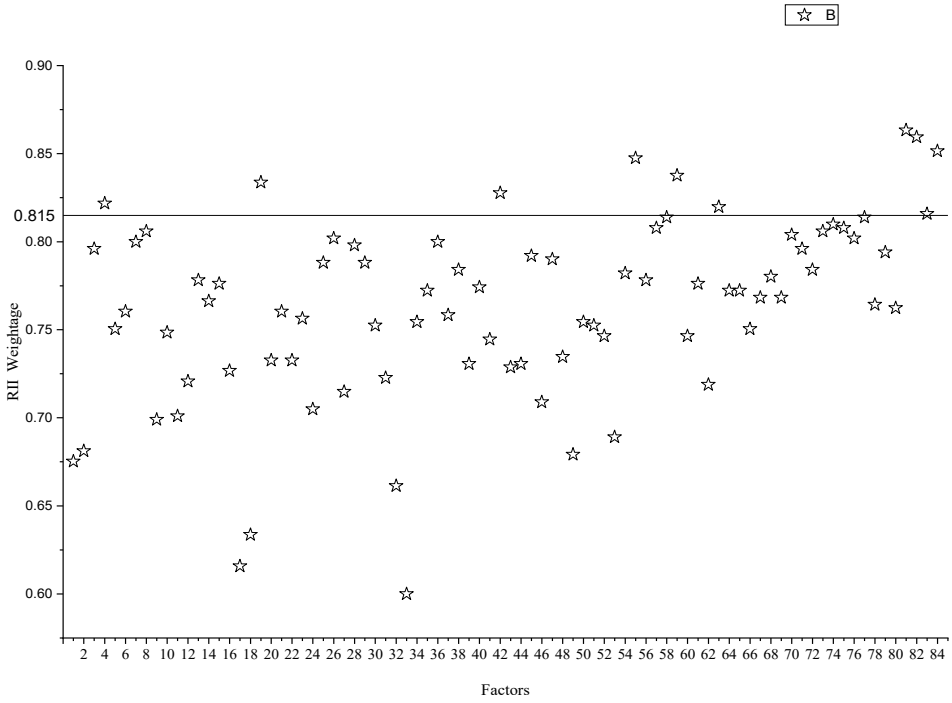

Figure 3. Influence of the factors on the sustainability in construction projects.

3.2. ANN Model

The ANN model is comparatively performing better for correlating the nonlinear relations than other methods. The ANN also gives higher prediction accuracy and is easily adaptable towards diverse factors. It can be challenging to describe the results that the ANN system produces. A sensitivity analysis, on the other hand, can outline the causal connections between a neural model's sources, inputs, and outputs. This is an effective way to separate the rate at which each component affects the neural network. It pinpoints the elements that most significantly impact the system's anticipated performance.

The data were verified using a 5-fold cross-validation process. In each fold, 20 different values were kept as test data and the rest as training data. The average sensitivity value was used for further analysis. The network had 20 hidden neurons, and 85 samples were selected at random for the study. With an average R^2 value of 0.94036, the regression model is ideal because it is close to one and greater than zero. The optimum system was chosen based on these two criteria (MSE and R^2 values). As seen in Table 3, the R^2 value for job security is greater than that of other relevant variables, showing the mean squared error, based on the top 10 factors as well as the mean squared error and root mean squared error values. Figures 5 and 6 provide a summary of the neural-network-training results.

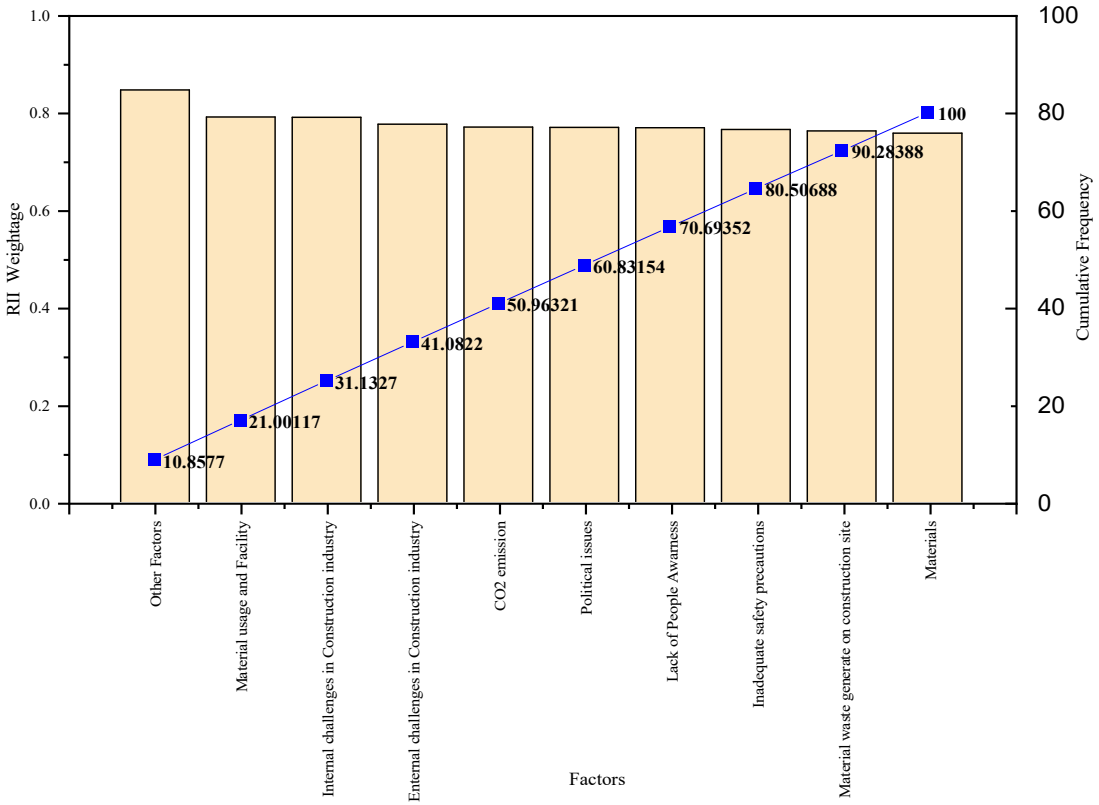

Figure 4. Pareto chart with RII of top 10 factors in construction projects.

Table 3. Statistical parameters for top 10 factors in ANN model.

Factors	MSE	RMSE	R^2
Job security	0.40415	0.635728	0.979484
Lack of motivation for workers	0.430563	0.656173	0.97798
Uses of new technology	0.465502	0.682277	0.975718
Lack of awareness and knowledge	0.50067	0.707581	0.97278
Lack of past performance analysis	0.551436	0.742588	0.971601
Lack of skills and experience of construction workers	0.519269	0.720603	0.971151
Frequency of design changes change orders	0.567124	0.753076	0.969377
Change in law and regulation	0.539761	0.734684	0.969348
Local authority and government	0.522114	0.722574	0.963263
Top management commitment	0.824271	0.907894	0.959482

The input and intended output vectors are randomly divided into three sets (70% for training, 15% for validation, and 15% for testing), as shown by the three lines in Figure 5. The system's capacity to generalize is measured by the green line, which ends training when generalization stops becoming better, and the blue line, which displays the decreasing error on the training data. In order to prevent overfitting, training ends when the validation error stops becoming smaller. Figure 5's performance result addresses the overfitting problem by demonstrating that the training error was less than the validation error. While mistakes based on the validation set gauge the model's predictive performance (its capacity to predict new data), forecast errors (residuals) based on the training set tell us about the model fit. The model's ability to generalize the data and offer a gauge of system performance both during and after training is indicated by the red line, which displays the error on the test data. Based on the system's optimal mean squared error, Figure 5 shows how well neural network tools function across 11 epochs, starting at a high number and

progressively declining to a smaller one. At epoch 5, the best validation performance is 4.2978. R^2 values for the training, validation, and test data scatter plots created by the NN tools are 0.98636, 0.95715, and 0.90335, respectively, with a final regression value of 0.94036, as seen in Figure 6. In machine learning, regression is a statistical method used to predict the connection between one or more independent variables and a dependent variable. The final overall regression value is 0.94036, with the regression values for the training, validation, and test data being 0.98636, 0.95715, and 0.90335, respectively. These numbers show how strongly and in which direction the input and output variables are related. The relationship between changes in one or more independent variables and changes in the dependent variable can be better understood with the use of regression analysis. Often referred to as the correlation coefficient or R-squared, the regression value falls between 0 and 1. While a rating close to 0 suggests a weak or no link, a score around 1 shows a strong positive association.

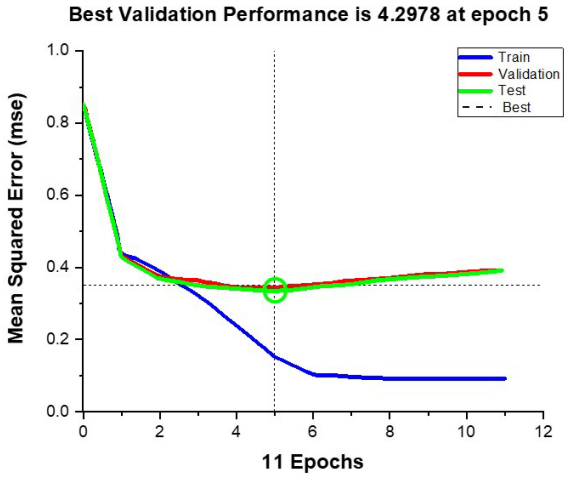

Figure 5. Performance of neural network tools.

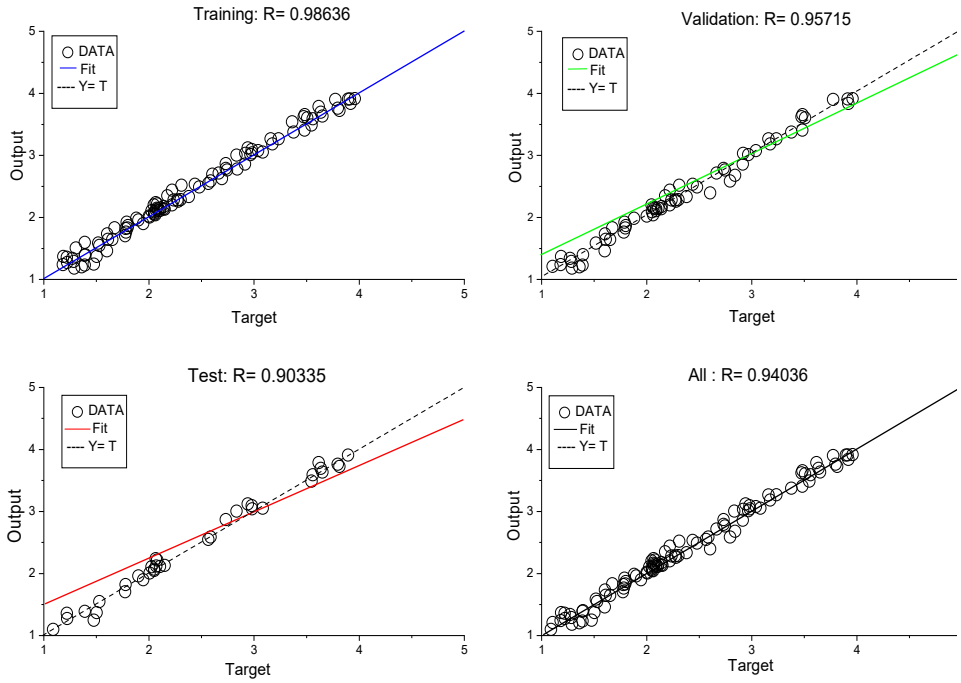

Figure 6. Regression plots of training, validation, and test data by NN tools.

The scatter plots shown in Figure 6 most likely show the regression line and the distribution of data points for the training, validation, and test sets. The model has

effectively caught and generalized the underlying patterns in the training (0.98636) and validation (0.95715) datasets, according to the high regression values for these datasets. The test data's marginally lower number (0.90335) might suggest some degree of divergence or trouble forecasting data that have not been observed yet. The regression model's overall performance, measured by the final regression value of 0.94036, shows that it can capture the relationships in the dataset. Strong generalization to new, unknown data (validation and testing datasets) and high accuracy on training data must be balanced. The model's performance and capacity to provide precise predictions outside of the training data are revealed by these regression findings. Although the results are encouraging overall, more research and analysis could be required to validate the model's dependability and applicability in actual situations. Other elements rank first in causing sustainability in construction projects, as seen in Figure 4.

Among several factors considered for the analysis, some of them were more crucial. Job security is one of those more critical factors influencing sustainability. The employee must feel stable in his workplace for the long term, and thus the commitment toward sustainability would be very active. Also, the training and awareness of sustainable construction towards the short-term workforce may have an impact on the profit. The investment in the short-term workforce seems to be of no use; hence, the training and development in the use of new technology is neglected. On the other hand, the skills and experience of the workers with knowledge of green materials and their handling are very low. The awareness has now been spreading in the world of construction workers, and in the future, there will be a change in the trend.

4. Conclusions

The most crucial elements influencing sustainability in building projects have been identified utilizing the computed data. Furthermore, utilizing the relative importance index (RII) based on respondent frequency, the main factors driving sustainability were found and contrasted with the outcomes of the artificial neural network (ANN) method. Although the results from both methods were comparable, they were obtained in different orders. The RII analysis found that the following factors have the greatest effects on sustainability in construction projects: job security, employee dissatisfaction, adoption of new technology, lack of awareness and knowledge, lack of historical performance analysis, lack of skills and experience of construction workers, frequency of design changes and change orders, changes in laws and regulations, involvement of local authorities and the government, and top management commitment. The type and structure of the neural network, training techniques, and the arrangement and interpretation of input and output data all affect how well a neural network performs, in addition to the caliber of the data used for training. Therefore, the nature of the problem to be solved determines whether the selected design is appropriate.

The most important sustainability aspects in the building sector can be accurately predicted by training the ANN. Both ANN and RII methods offer a thorough comprehension of the factors involved. A useful perspective on the relative importance of each component is provided by the RII analysis, which is based on response frequency and identifies critical factors like job security, worker motivation, adoption of new technology, awareness and knowledge gaps, past performance analysis, construction workers' skills and experience, design changes, legal and regulatory shifts, and top management commitment. By taking into account network design, training techniques, data quality, and structure, the ANN approach, on the other hand, supports and improves these conclusions. The variations in outcomes between ANN and RII demonstrate how flexible and adaptive these approaches are, enabling a more sophisticated and nuanced comprehension of sustainability issues in

building projects. The neural network's efficacy as a prediction tool is demonstrated by its successful training to forecast significant sustainability factors, offering stakeholders in the construction sector insightful information to improve project sustainability. A strong model for capturing associations is indicated by the regression scores of 0.98636 (training), 0.95715 (validation), and 0.90335 (test), which add up to an overall value of 0.94036. While the lower test result indicates possible difficulties with predicting unseen data, the excellent training and validation scores demonstrate good generalization. The overall performance of the model is indicated by the final regression coefficient of 0.94036. It is essential to strike a balance between generalization to new data and training accuracy. Even though these findings are encouraging, more research is required to validate the model's dependability and suitability for use in practical situations.

Overcoming these factors may be possible by engaging sustainability in government policies, self-motivation of the laborers, management dedication towards usage of green materials, and providing awareness and training to the workers. By providing job security, modern technology usage, and investment in training activities, the construction industry can move towards sustainability. This study primarily focused on the residential and commercial projects in the Chennai region. Future studies can be conducted on other projects, such as industries, infrastructure, etc. Also, this study can be extended state- or nationwide. Not only focusing on the urban areas, but also this study can be performed in suburban and rural areas to obtain the insight of sustainability in those areas.

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Abbreviations

ANN	Artificial neural network
CO_2	Carbon dioxide
k	Cohen's kappa coefficient
MATLAB	Matrix laboratory
MSE	Mean squared error
NN	Neural network
RAP	Reclaimed asphalt pavement
RII	Relative importance index
RHA	Rice husk ash
RMSE	Root mean squared error

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