FORECASTING ENERGY PATTERNS OF BUILDING PROJECTS THROUGH DEEP LEARNING MODELS TOWARD NET-ZERO CONSTRUCTION

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Abstract. Increasing energy needs and environmental concerns provide important problems for modern civilization, especially in developing nations where successful construction operations are crucial for ecological preservation and economic progress. The research develops and assesses a deep learning model to estimate energy consumption in Sri Lankan building projects, providing data-driven insights for improved construction practices and increased energy efficiency. The model uses a detailed dataset through a structured survey. Python programming language was used to develop the prediction framework using a Multilayer Perceptron (MLP) architecture. Of the complete dataset, 70% were utilized for training and 30% for testing. The results indicated that major variables impacting energy usage include insulation type, HVAC efficiency, lighting systems, and occupancy patterns. The model attained an area under the curve (AUC) of 0.83, suggesting excellent predictive skills. Additionally, research showed that the weighted scores for precision, recall, and F1 were 85.74%, 83.21%, and 87.68%, respectively. This shows that ANN models can be used to predict energy efficiency. Beyond technical results, the research revealed shortcomings in regulatory frameworks, especially the lack of required energy audits and established processes for energy-efficient designs in new structures. These inadequacies, combined with varied energy-use patterns, underscore the need for reforms in policy and implementation measures. Overall, the study shows that deep learning is a useful tool for predicting how much energy buildings will use in Sri Lanka. It also shows how important strict laws, careful data integration, and ongoing research are for supporting green building projects.

Keywords: energy forecasting, net-zero buildings, deep learning, artificial intelligence.

Introduction

The construction industry is vital to global economic progress, making a critical contribution to infrastructures and urbanization. Yet its environmental repercussions are enormous, with this sector contributing more than 30% of global greenhouse gases (GHG) and 40% of global urban waste yearly, making energy conservation and emission reduction crucial [1; 2]. Energy consumption in construction spans the complete lifespan of buildings, including material fabrication, transportation, and operational energy for heating, cooling, and lighting [3]. It is estimated that buildings utilize around 48% of global energy annually in construction and operation as embodied and operational energy [4]. Therefore, in the past few years, the need for sustainability has risen as the industry meets rising pressure to implement energy-efficient and net-zero construction practices [5; 6]. Attaining these targets is vital for mitigating climate change, adhering to international agreements like the Paris Agreement, and achieving global energy efficiency standards.

Artificial intelligence (AI) and deep learning models are developing as transformational technologies in several fields, including construction [7; 8]. These models are very good at breaking down large amounts of data, finding patterns, and making predictions that come true [9]. In construction, deep learning models show considerable promise for tackling concerns connected to the consumption of energy and sustainability. By integrating historical data and real-time inputs, these models can anticipate energy demand, enhance building performance, and help with the development of energy-efficient buildings [10]. Even though it has a lot of potential, AI-based solutions are still in the early stages of being used in the built environment. For example, only a few studies have looked at how deep learning can be used to predict energy trends in building projects [11; 12]. Furthermore, present techniques typically fail to appropriately estimate energy performance, resulting in inefficiencies and lost possibilities for improvement, particularly in developing countries [13]. While there is an expanding amount of literature on energy efficiency in construction, a large research gap remains in the use of deep learning models to anticipate energy consumption in building projects.

Therefore, this research attempts to overcome this gap by developing and evaluating an artificial neural network (ANN) model to estimate energy trends in construction projects. The primary aim is to examine if future buildings in Sri Lanka, under present approaches, can achieve energy efficiency and

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comply with net-zero development targets. The novelty of this study comes in its emphasis on integrating deep learning approaches to deliver useful, data-driven recommendations for boosting energy efficiency. By examining historical energy use data, environmental conditions, and occupancy trends, the research will produce a complete model capable of advising improved construction methods and encouraging sustainability.

Materials and methods

To find out how building features affect how energy-efficient they are, the study used a planned approach that included collecting data, preliminary processing, statistical analysis, ANN modeling, and visualization. The dataset comprised 347 records reflecting essential building characteristics, environmental characteristics, and operating indicators. The authors obtained these targeted data by distributing a questionnaire survey among industry practitioners in Sri Lanka over a period of 3 months. Rather than focusing on a case study approach, this method allowed researchers to capture data representing a variety of conditions in construction from different geographical parts of Sri Lanka. The target variable was defined as whether energy efficiency is achieved or not. The data incorporates categories and numerical variables to offer a comprehensive picture of energy efficiency parameters (Table 1).

Table 1

Summary of variables along with their definitions and data format

Variable code	Description	Data format
age	Age of the building in years	Numeric
area	Total floor area of the building in sq.m	Numeric
flrs	Number of floors	Numeric
occp	Number of occupants in the building	Numeric
tmp	Average outdoor temperate (ºC)	Numeric
engcost	Cost of energy in current units	Numeric
hum	Average percentage of humidity in the environment	Numeric
eeachiv	Energy efficiency will achieve/not achieve	Categorical

The authors performed Pearson correlation analysis to examine the linear correlations between significant building features, environmental variables, and operational indicators in the dataset. The study chose the most important features for further modeling by finding factors with moderate to significant correlations. This made sure that the ANN focused on the most important predictors. Correlation analysis also showed possible dependencies between variables, like the link between the area size and energy cost, which helped find deeper patterns in energy efficiency.

The authors then developed the ANN model to forecast energy efficiency accomplishment based on gathered building attributes and conditions. The ANN was trained using a backpropagation technique, with a learning rate of 0.005, and the dataset was divided into two, where 70% were allocated for training and the remaining 30% for testing. The model's performance was determined through F1 score, precision, and recall. Python was used for all analyses and models. Libraries such as Pandas and Scikit-learn provided data preparation and ANN training, while Seaborn and Matplotlib allowed sophisticated visualizations. These tools enabled precise calculations and clear graphical results.

Results and discussions

During the early stage of the study, the authors carried out Pearson correlation analysis to identify significant relationships among the variables (Fig. 1). The findings indicated numerous significant connections that give perspectives on the dynamics of building attributes and environmental influences. Notably, the findings showed a moderate positive association between the floor space and external temperature, with a value of 0.379. This demonstrates that when the area of a structure rises, there is a tiny tendency for the temperature to climb. This association may be ascribed to bigger areas needing additional energy to maintain temperatures or hold heat owing to increasing material consumption and occupant activities [14]. A similar pattern was detected between area and humidity, which had a correlation value of 0.316. This shows that bigger areas are likely to suffer greater humidity levels, either owing to outdoor exposure, variances in ventilation systems, or more interior moisture from humans and equipment. The floor area had the strongest correlation with the number of occupants, with a value of 0.495. This suggests that larger areas tolerate more people, perhaps reflecting the potential of greater places to support higher population densities. This research illustrates the connection between physical dimensions and use patterns in structures. Additionally, a modest positive association was identified between area and energy cost, with a value of 0.308. Larger spaces often demand more energy for heating, cooling, lighting, and other operational needs, resulting in increased energy expenses [15]. These significant relationships identify the necessity of energy-saving measures in bigger buildings to reduce operating expenditure. These relationships provide a fundamental understanding of the connections between building attributes and environmental elements. They stress the necessity for integrated methods in design and management to maximize energy usage, occupant comfort, and environmental sustainability.

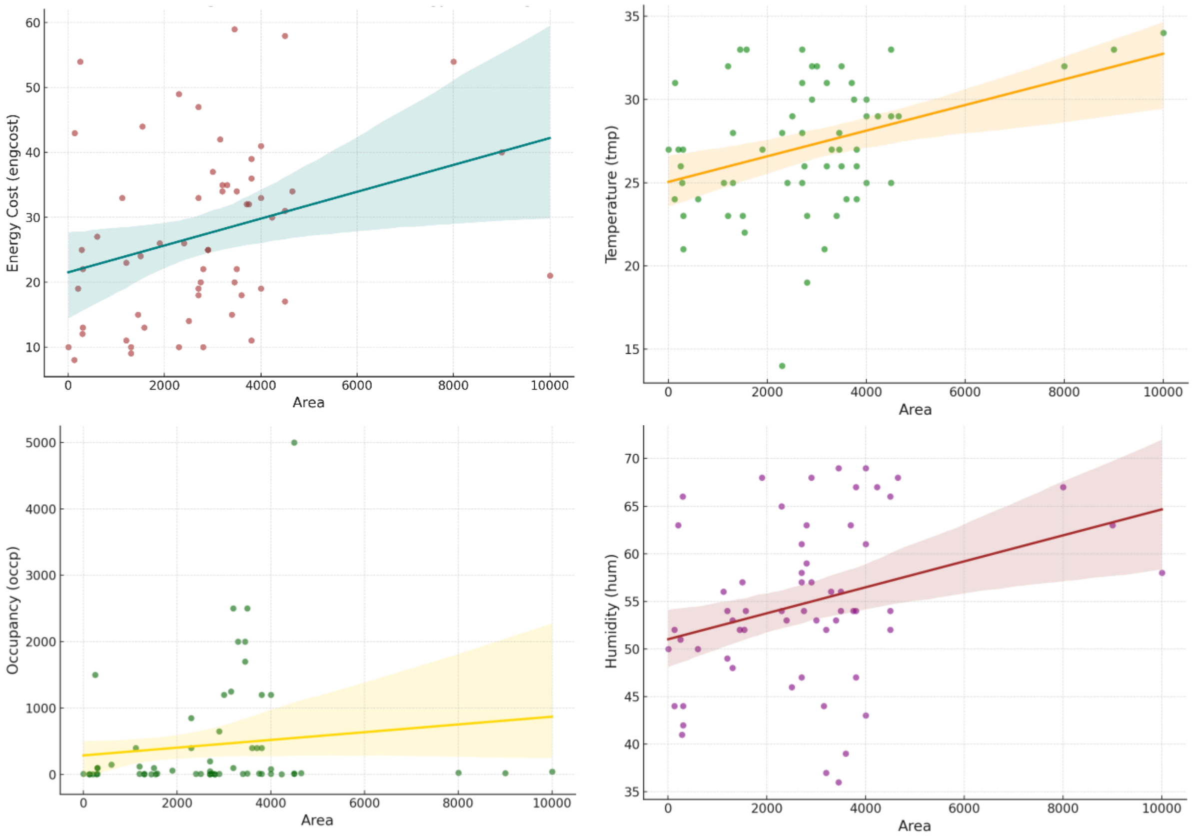

Fig. 1. **Significant relationship distribution among building characteristics and conditions**

The ANN design featured an input layer where the pre-processed data were entered for modeling. The hidden layer consists of two sublayers employing the ReLU activation function. The output layer supplied the findings using the softmax activation function. The authors used the Multilayer Perceptron (MLP) architecture due to its robustness and the nature of the dataset (Fig. 2). The authors tested the model performance on the test dataset using conventional classification measures such as precision, recall, and F1-score (Fig. 3). Precision, which quantifies the percentage of accurately detected positive predictions, was computed as 85.74%, reflecting the model's ability to reduce false positives. Recall, which measures the number of correct predictions of real positive cases, was 83.21%, showing how sensitive the model was to positive cases. The F1-score, which is a balanced metric that combines precision and recall, was 87.68%, which shows that the model was generally good at dealing with unbalanced data while still making accurate predictions. Overall, the ANN model shows that it might be possible to predict how energy-efficient buildings will be. This could be used to make smart decision-support systems for green buildings. These findings show that machine learning has the potential to support energy-efficient methods, especially when building characteristics are different and connected [16].

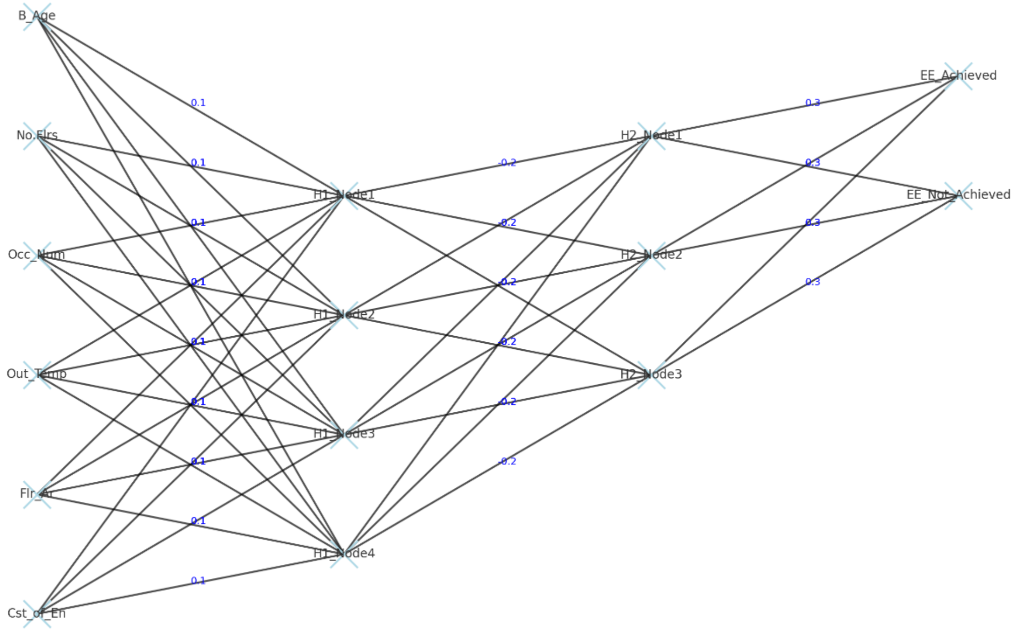

Fig. 2. **Developed ANN with MLP architecture**

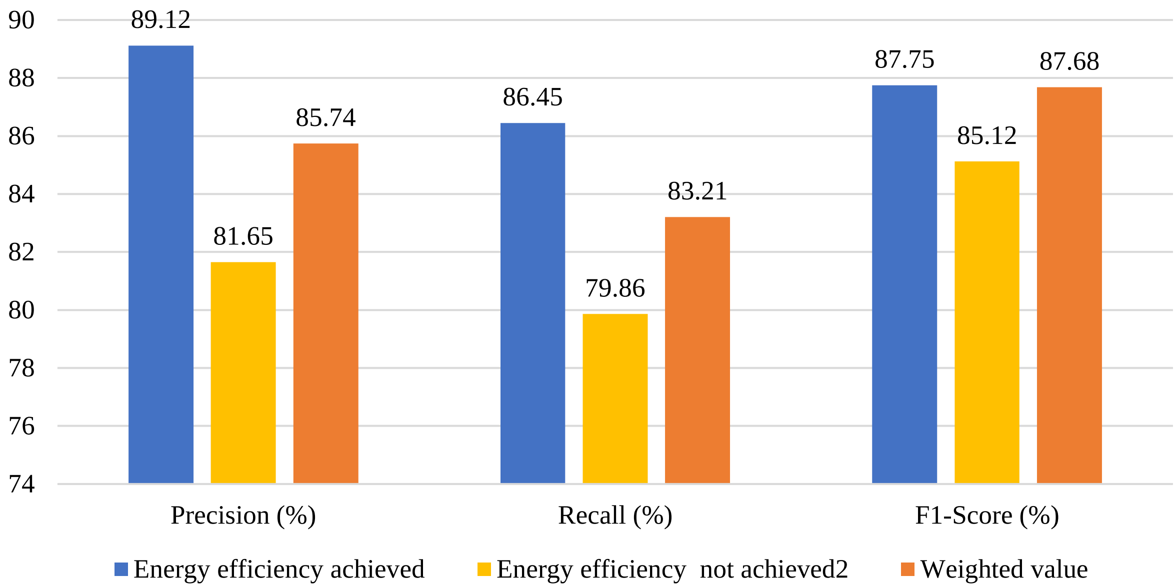

Fig. 3. **Model classification results**

The ANN model had a receiver operating characteristic (ROC) curve that showed a high performance of 0.83, which means that it was likely to rank positive events higher than negative ones. This is likely because the model is sensitive to certain thresholds (Fig. 4). The cumulative gain chart emphasized the usefulness of the ANN model in addressing the most crucial scenarios for energy efficiency success. The model's high initial slope suggests its ability to recognize several greater events with minimum effort. The lift chart validated its predicting capacity, with greater lift values indicating better performance than random selection. This helps decision-makers use resources more effectively, streamlining the process. The pseudo-probability chart visualizes the distribution of anticipated probabilities for the two distinct outcomes of the model. The strong difference between the two groups reflects the model's capacity to assign unique probabilities, demonstrating high confidence in its forecasts.

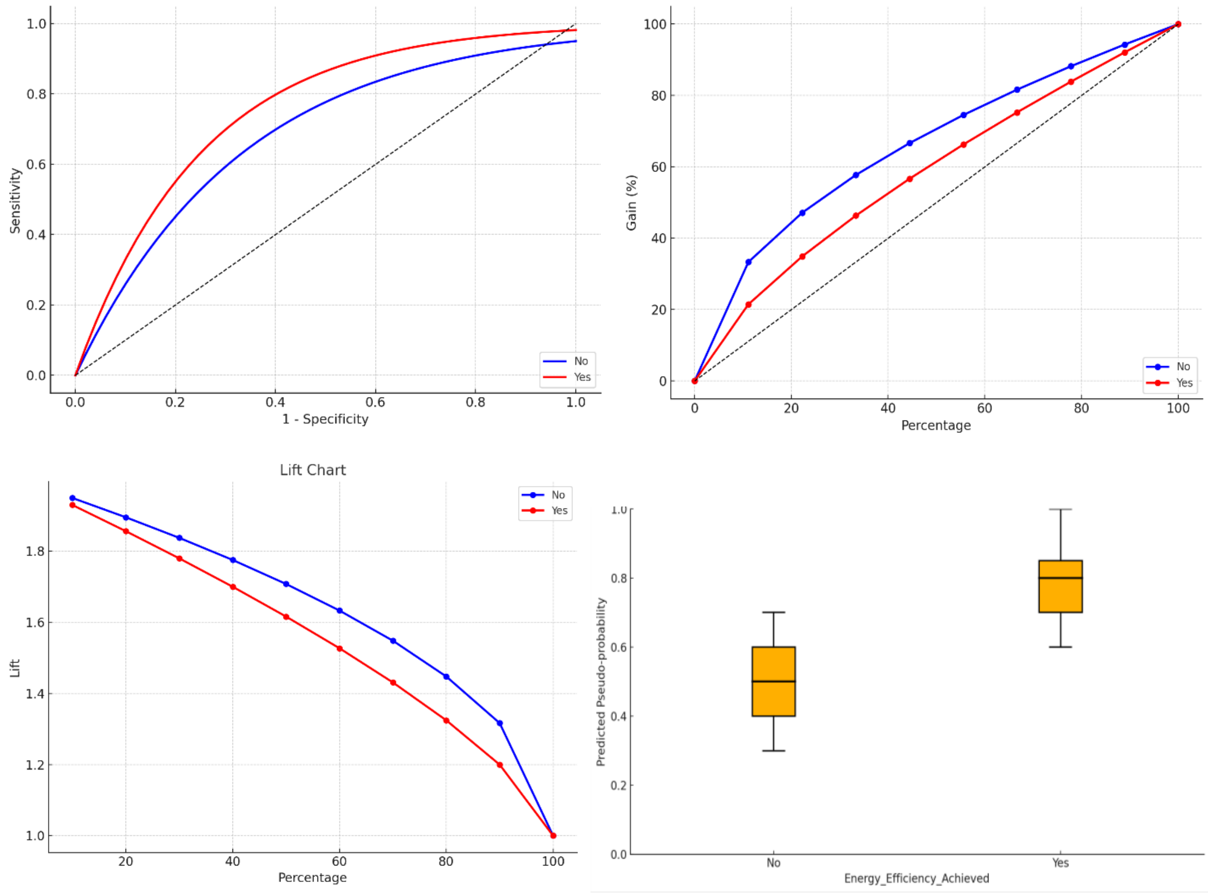

Fig. 4. **Model's ROC, lift, gain, and pseudo-probability charts**

Conclusions

This research demonstrates that ANNs can estimate the energy efficiency of buildings by using critical criteria such as architectural features, ambient circumstances, and operational metrics. The ANN model attained an AUC of 0.83, with high accuracy, recall, and F1 scores, emphasizing its confidence in energy efficiency categorization. The research identified substantial connections, such as those between the floor area and factors including temperature, humidity, occupancy, and energy cost, offering greater knowledge of the drivers impacting building energy efficiency.

The ANN model findings show that the analyzed building projects exhibit a reasonable degree of achieving energy efficiency; however, substantial opportunities for enhancement exist to get optimal outcomes. This modest performance underscores the potential of these initiatives to further the broader objective of net-zero buildings, establishing a viable basis for sustainable construction methods. The results highlight the need for enhanced and more stringent contributions from essential stakeholders, including the government, community, and industry. Joint initiatives, including the enforcement of rigorous energy efficiency regulations, promoting community awareness, and advocating for new industrial practices, are essential for expediting the shift toward a more sustainable and energy-efficient built environment.

For the construction sector in Sri Lanka, these results provide a realistic road toward strengthening sustainable construction methods. By implementing predictive technologies like ANNs, industry stakeholders may make educated choices to optimize resource allocation, minimize energy usage, and accomplish sustainability objectives. While the current work indicates the applicability of ANNs for energy efficiency prediction, future research may investigate numerous upgrades. Some of these are combining real-time data from IoT-enabled sensors to make the model more accurate, adding more factors like the use of renewable energy and patterns of occupant behaviour, and expanding the study to take into account changes in the climate in different areas.

Author contributions

Conceptualization, T.G.W.; methodology, T.G.W. and K.S.; software, T.G.W.; validation, T.G.W. and K.S.; formal analysis, T.G.W. and K.S.; investigation, S.W. and C.K.; data curation, K.S., C.K, and S.W.; writing – original draft preparation, T.G.W.; writing – review and editing, C.K. and S.W.; visualization, C.K. and K.S.; project administration, T.G.W.; funding acquisition, T.G.W. All authors have read and agreed to the published version of the manuscript.

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