Smart Estimation Model for Energy Performance Certificates of Residential Buildings

DOI : 10.36909/jer.17597

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ABSTRACT

The wasted amount of energy has become a critical problem for many countries due to limited energy sources and energy production costs. These forced countries to increase energy usage awareness by making regulations in the construction sector, which might dramatically decrease energy consumption cause of the size of the domain. One of them is standardizing heating and cooling loads (HL/CL) to avoid energy waste. HL and CL need an advanced engineering process because of different parameters such as the thermal characteristics of the building, hot water supply, passive solar systems, etc. Hence, it can only be carried out by expert engineers in calculations. In this paper, a classification model as the decision support system is proposed for predicting the energy consumption of residents which is an efficient indicator of architectural features of the construction about energy consumption concept. The data is collected from architectural projects and energy performance certificates. Multilayer Perceptrons, Bagging, and Random subspace are used to predict the energy class of buildings. Based on findings, the most accurate results were achieved by Bagging. Moreover, main input features affecting the prediction performance of HL were revealed and classification success was observed.

Keywords: Energy management; energy efficiency; machine learning; intelligent systems

INTRODUCTION

Energy is an essential need for all people to maintain a high quality of life and it has been becoming more important with technological advancement. In today's world, almost everyone somehow needs to directly reach an energy source. For instance, many of us use technological devices which directly require an energy source. Supplying enough energy amount depends on energy sources from which some kind of energy (i.e. electricity) can be produced. In this case, authorities should focus on more efficient energy use. To handle this, some strategies can be applied to maximize energy efficiency in daily life. To avoid waste of energy, many countries have paid special attention to unnecessary energy consumption which is considered a vital problem. To meet the demand for energy needs, well-planned energy production strategies has become a key domain for countries. The low-cost energy production and energy-friendly electronic devices, production facilities, buildings, and some systems are encouraged by countries in many areas since the prevention of energy waste is mandatory by laws and regulations [1]. These countries specifically aimed to introduce certain energy efficiency standards to residential buildings, where energy consumption is very high [2]. To do this, the Buildings Energy Performance Directive (EPBD) was approved on 16 December 2002 and obligated on 4 January 2003. The main aim of the EPBD is to promote the improvement of energy performance of buildings, which is the amount of the primary energy consumption of building (kWh/m^2 year), within the EU through cost-effective measures. EPBD requires that an energy performance certificate (EPC) must be provided whenever a building is constructed, sold or rented out [3].

In construction area, there exist some main concepts that can help to reduce energy consumption such as sustainable/green building, energy-efficient systems, construction with less carbon emission, etc. These concepts aim not only to increase the awareness of energy efficiency but also to ensure correct energy consumption. So, to avoid energy waste, aiming for high standards for energy consumption of buildings, efficient household goods, laws, and regulation of energy performance standards will be required in the short-term for brand new and existing constructions [1]. Especially, over the last decades, EPC, which sets energy efficiency standards for buildings, aims to increase these standards in terms of energy consumption and it is obligated for all existing and brand new buildings.

The energy performance of existing and new buildings, as dictated by their plan and volumetric arrangements might be evaluated based on rating system framework standards [4]. These standards impose four fundamental energy efficiency prerequisites for structures that were expected to guarantee the achievement of the 20% headline target on the energy efficiency of the European Union by 2020, as well as to pave the way for further improvements in energy efficiency [5]. In buildings, the energy consumed is characterized by three classes including cooling and heating loads (HL/CL), boiling water provision, and lighting.

HL/CL – forming the largest part of energy efficiency procedures- is useful in the quantification of the amount of energy required to remove or add heat into space through ventilation, heating, and HVAC (air conditioning) systems to maintain the preferred ambient temperatures in the building [6]. The motivation for attaining a high degree of energy performance is to lower significantly the HL/CL. The installation of an accurately sized HVAC framework is crucial to the achievement of the above objective. As it has been proved, right-sizing calls for accurate comprehension of the CL/HL of a structure, since computed HL and CL values are the determinants for the specifications and design of the HVAC equipment important to optimize cooling and heating efficiencies. Therefore, the computed values for HL and CL affect the initial costs of construction in the operating and short-term efficiency, durability, indoor air quality, and occupant comfort of the building in time.

LITERATURE REVİEW

In recent years, scholars have investigated the sustainability issue by providing the usage of renewable energy for various fields [7-11], and energy consumption performance [12-14] of residential buildings and implemented Artificial Intelligence (AI) techniques for predicting energy consumption [15,16]. Numerous AI and statistical methods for inverse building energy consumption for cooling and heating have been implemented. Especially, Artificial Neurol Networks (ANN) which is one of the most commonly used techniques in prediction problems are extremely easy and convenient to use after the model has been developed. The ANN models do not need the characterization of obvious relationships between outputs and inputs as in the traditional regression. These models can be used in the modeling of cooling and heating models of multifaceted frameworks from autonomous or subordinate parameters [17]. For instance, Olofsson et al. integrated ANN with a semi-physical description for the prediction of heating demand per annual for various small household buildings [18]. Furthermore, Aydinalp et al. have implemented ANN with outdoor temperature values and usage of the household electric appliances as inputs through the training process for the prediction of annual energy consumption at the residential level [19]. With an ANN model, Kwok et al. predicted energy usage in Hong Kong [20]. Paudel et al. in 2017 studied low energy buildings that can be a solution for effective energy usage in structuring of the environment by using an AI system to predict energy consumption of low energy buildings in France [21].

An ANN model, in Hou et al., which was based on the technique of data fusing, was employed in the prediction of HVAC load and accomplished a marginal relative error [22]. Also, Ahmad et al. predicted hourly heating, cooling and ventilating energy consumption of a hotel in Madrid, Spain who compared the performance of widely-used feed-forward back propagation artificial neural networks with random forest [23]. Numerous AI approaches have been proposed for enhancement of the accuracy of energy usage prediction.

With this study, to create a classification model to determine building EP class with a minimum error was aimed by using the architectural project. As different from other studies, we target to create a classification model with optimum number of independent variables.

Contributions in the study can be listed as follows:

- A novel EP classification model has been developed using only appropriate and essential input features
- With the artificial intelligence model, there is no need for complex engineering calculations
- By using the developed prediction model, even without an expert can have a good prediction for possible EP class of a building before construction process
- It can be saved a considerable amount of time spent on engineering calculations by knowing the specific attributes of building having the most influence on EP class.
- Maintenance can be planned based on selected features to have a better EP class, for existing buildings which do not have an EPC

The primary motivation in this study is to demonstrate that an AI based model can be developed that enables the EP class, which can only be calculated by experts, to be estimated by non-experts with simple data entry.

Also, the research gap can be explained in various directions according to the other mentioned researches (below Table x). For this respect, some advantages should be mentioned for the present study. The first one is related with the data collection and size, which is consisted from creating a large dataset including different real residential buildings in Turkey. On the other side, both heating and cooling load classes were tried to predict with the usage of various AI and machine learning techniques like a type of ANN as multilayer perceptrons (MLP), random subspace, bagging etc. The other advantage is based on the prediction and performance evalution processes. While the prediction is realizing, multiple building samples were investigated with the help of different input parameters as glaze number, building height, roof area, existence of shop etc. When the performance of prediction model, different error metrics (mean absolute error, mean square error etc.), statistical measurements and other factors (precision, recall, accuracy etc.) were also evaluated to observe whether the model is a successful and effective tool or not to directly determine the heating and cooling classes for the buildings. Review for the related researches applied for energy consumption prediction and sustainability are given in Table 1.

The remainder of study is structured as follows. In problem statement section, the problem statement, collection and preparation of data for experiment, chosen algorithms we used through the experiment, evaluation metrics, validation method and model implementation are given. and detailed results and discussions are given in final Section.

Table 1: Review for the related researches applied for energy consumption prediction and sustainability

Reference	Objectives	Methodology	Case	Cite
Lotfi et al., 2020	Locating renewable energy sites	robust bi-level programming technique and game theory	the electricity distribution company	[7]
Lotfi et al., 2021a	Minimizing costs, CO_2 emissions, energy consumption, and maximizing employment	stochastic multiobjective programming model	-	[8]
Lotfi et al., 2021b	To make sustainable supply chain network	two-stage robust stochastic optimization	-	[9]
Lotfi et al., 2022a	To evaluate the sustainability conditions like cost, energy, pollution level etc. in scheduling projects	nonlinear robust programming	Tehran- Iran	[10]
Lotfi et al., 2022b	To generate the most convenient block chain technology by providing sustainability conditions	hybrid robust stochastic programming	The healthcare project	[11]
Baumont, 2018	Energy efficiency observation to model housing market prices	data envelopment analysis (DEA)	France	[12]
Funk, 2018	Review of certain performance contracts for energy conservation	-	-	[13]
Do and Cetin, 2018	Review for methods utilized about energy consumption prediction	-	-	[14]

Khayatian et al., 2016	Predicting energy performance by evaluating building heat demand indicators	ANN	Lombardy-Italy	[15]
Perroni et al., 2018	Measuring energy performance continuously	Monte Carlo simulation	-	[16]
Rabl and Rialhe, 1992	To improve energy signature models by investigating different parameters	ANN	Multiple commercial buildings	[17]
Olofsson et al., 1998	Predicting the annual building heating demand	ANN	Sweden	[18]
Aydinalp et al., 2002	Modeling of the appliance, lighting, and space-cooling energy consumptions	ANN	The residential sector	[19]
Kwok and Lee, 2011	Observing of the effect of occupancy to predict the building cooling load	entropy-based neural (PENN) model	Hong Kong	[20]
Paudel et al., 2017	Prediction of energy consumption	Support vector machine	France	[21]
Hou et al., 2006	Finding relevant factors to predict the cooling load	ANN	-	[22]
Ahmad et al., 2017	Determination of hourly HVAC energy consumption	ANN and random forest	Madrid-Spain	[23]
The present study	Directly prediction of heating and cooling load energy classes	A type of ANN as MLP, random subspace and bagging	Turkey	-

* HVAC: Heating, ventilation, and air conditioning.

PROBLEM STATEMENT

$p^* = \frac{\sum_{i=1}^{k} p_i}{k}$ **Machine Learning and Energy Consumption Classification**

To handle the problem of residential energy consumption classification, machine learning approaches can be straightforward and sophisticated methods creating a classification model based on observed data to estimate new outputs in a reasonable amount of time.

Machine learning approaches can be implemented in many different applications including the energy domain. Studies have been implemented to predict heating, cooling and electrical energy consumption of residential buildings [38]. Different approaches have been applied to residential energy prediction problems [16], and studies handle from predicting annual energy demand to hourly energy consumption [17]. Despite machine learning approaches is well implemented in energy prediction problems, classification of energy consumption problem, the main motivation has been overlooked for years.

For choosing a suitable machine learning algorithm, we have researched various methods based on previous impressive achievements in similar problems. In these studies, it is shown that Multi-Layer Perceptron gives highly accurate results for the energy estimation related tasks [39-40]. We also choose Bagging and Random Subspace methods which are commonly used approaches for classification problems. By doing this, we aim to create an algorithmic pool in which each chosen method has a different mathematical background with the aim of finding the best method for the proposed estimation task.

Dataset Collection

Table 2: Features of the dataset

Attribute	Type	Description	Content	Unit
Number of Glaze	Numeric	Refers to the glass windows of a building's exterior wall	Cardinal Number	Count
Surface area	Numeric	Basement floor area	Real Number	m^2
Number of Floors	Numeric	The number of total floors in a building	Cardinal Number	Count
Number of Open-door	Numeric	Total number of doors which directly contacts with open-air	Cardinal Number	Count

Apartment number	Numeric	The number of total residents in a building	Cardinal Number	Count
Roof Area	Numeric	The roof area of the building	Real Number	m^2
Height of Building	Numeric	The height of the building which is from the bottom level to the top of the building	Real Number	m
Glaze Area	Numeric	The total area of the glass windows in a building	Real Number	m^2
Warehouse	Numeric	Warehouse exists or not status	0 or 1	-
Shop	Numeric	Existence of shop	0 or 1	-
Energy Performance Class	Nominal	True class of sample	Character	B, C, D

Table 3: Notations of the research parameters

Case of Parameter	Parameter Name	Notation	Unit
INPUT	Number of glaze	N_g	Count
	Surface area	S	m^2
	Number of floors	N_f	Count
	Number of open-door	N_d	Count
	Apartment number	N_a	Count
	Roof area	S_r	m^2
	Height of building	H	m
	Glaze area	S_g	m^2
	Existence of warehouse	E_W	-
	Existence of shop	E_S	-
OUTPUT	Energy performance class for heating and cooling loads	C_{EP}	B, C, D

In our experiment, we use a dataset that consists of energy performance certificates (EPC) of 127 different architectural projects from Istanbul, Turkey. EPCs became mandatory for European countries under Energy Performance Building Directive (EPBD, Directive 2002/91/EC) in 2006 [41,42]. Therefore, EPC is given by Turkey, and calculated by experts using advanced national simulation tool. It consists of multiple steps to correctly determine EPC. Fig. 2 also illustrates whole EPC process [43]. During data collection process, we collected EPC files and extract some valuable information (attributes) for models. Each data sample has 10 attributes and 3 energy performance classes (Table 2) and Notations of the research parameters are shown in Table 3. Before running the experiment Number of Apartments feature is ignored because which does not make any contribution to determining energy class and other attributes are normalized with z-score.

It can be seen in Table 4, there exist 7 different energy performance classes, which determined the energy performance (EP), and are amount of primary energy consumption of building (kWh/m^2 year). Table 4 illustrates the energy classes and corresponding total energy consumption of buildings.

Table 3: Energy performance classes of buildings

Energy Class	Range of EP (kWh/m^2)
A	0-39
B	40-79
C	80-99
D	100-119
E	120-139
F	140-174
G	175- …

In collected dataset, we have buildings from three classes B, C, and D. Frequency of three classes as given in Fig. 1. Besides attributes given in Table 4, it can be taken more information about a building from EPC such as U-values referring to isolation coefficient of a material. U-values are main inputs of white-box methods (i.e. engineering calculations). The reason for not taking them into prediction model consideration is: 1) willing to build the best prediction model by using as few attributes as possible to save from a considerable amount of EP Class calculation time 2) almost same kind of materials are used in 127 buildings so that U-values is conceivably the same that does not give more contribution to prediction model.

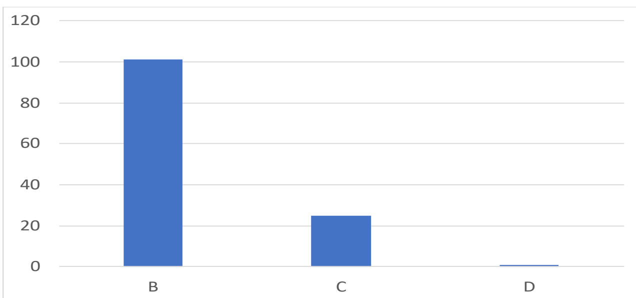

Figure 1: Output class frequency

Model Implementation

Chosen methods are created in Weka machine learning library using some modifications in training parameters as normalization. Also, initial dataset is collected from energy performance certificates. All them are officially given by experts so that all labels are correct. However, a pre-processing phase was necessary to ensure the usability of input-output data. Parameters of all methods are optimized to produce the best possible solution. The whole workflow of experiment can be summarized and illustrated as shown in Fig. 2.

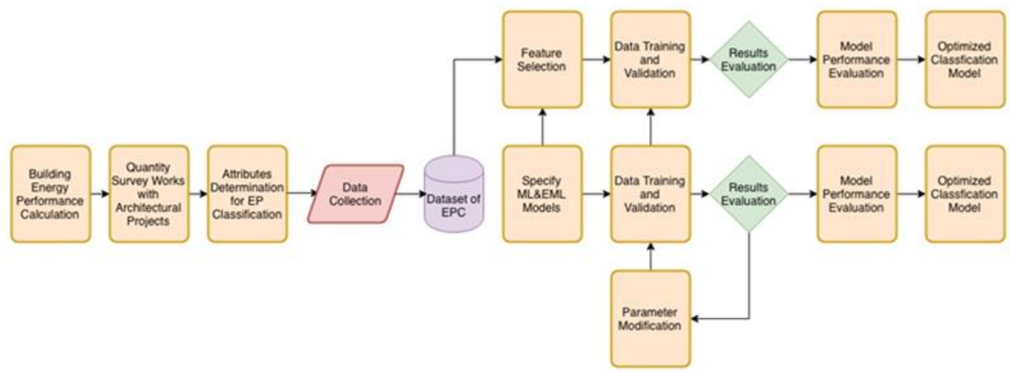

Figure 2: Flowchart of prediction methodology

Methodology

Multilayer Perceptions (MLP)

Multilayer Perceptrons (MLP) consist of some stacked fully connected layers which consist of nodes (neurons). The main goal of MLP is to find a nonlinear relationship between inputs and outputs. The main process is feeding each layer by a weighted sum of input values. Namely, each neuron takes value of a linear combination of previous values of nodes. Then, weights are adjusted to minimize errors by derivation steps which are known as backpropagation training [24]. Among various algorithms for measuring the performance of ANN, backpropagation algorithms have displayed promising performances. In this method, along with overall error of output, the performance of each neuron is also calculated. MLP is used in different energy prediction applications such as building energy benchmarking [20], electric energy reduction [26, 27], heating/cooling loads prediction [28–30]. The mathematical formulation of the MLP method is given in Appendix-A.

Bootstrap Aggregating (Bagging)

Another approach is called Bagging (known as bootstrap aggregating) which is one of the

Ensemble Machine Learning (EML) algorithms proposed by Breiman and Leo [31]. Bagging generates new and combined model, to provide increasing the accuracy by combining prediction results from multiple learners [24]. Resource of increasing accuracy is based on executing to variance decreasing by combined model [32]. Bagging method gives outstanding forecasting performance in different energy-related applications such as [33,34]. Mathematical formulation of Bagging is given in detail in Appendix-B.

Random Subspace Method (RSM)

The last method is Random subspace (RSM), which is a combination procedure proposed by [35]. By using RSM one can modify training set by choosing different features from original training data. Final decision can be given based on majority voting procedure. The details of RSM is given in Appendix-C.

Evaluation Metrics

To train and examine the performance of a machine learning algorithm and give a better approach, we have compared methods based on statistical evaluation metrics (Table 4). The formulation of chosen metrics is explained in Appendix-D.

Table 4: Evaluation metrics

Abbreviations	
MAE	Mean Absolute Error
RAE	Root Absolute Error
RMSE	Root Mean Squared Error
RRSE	Root Relative Squared Error
Acc	Accuracy
Precision	Precision
Recall	Recall
F-measure	F-measure
MCC	Matthews correlation coefficient

K-Fold Cross-Validation

K-fold cross-validation is a method that optimizes the calculation time and variance. Input data as randomly are parted to k groups/folds. Each group is used for test and remaining for training processes [36]. In short, algorithm tries to learn and test itself k times. Finally, the performance of method is calculated as average evaluation metric [37]. To utilize a cross-validation method with a classification method, dataset D is randomly split k different subsets $(\boldsymbol{D_1}, \boldsymbol{D_2}, \dots . \boldsymbol{D_k})$ such that $\cup_{i=1}^{k}\{\boldsymbol{D_1}, \boldsymbol{D_2}, \dots ., \boldsymbol{D_k}\} = \boldsymbol{D}$ (1)

During prediction process, as we mentioned above each D_i is saved for testing, and remaining is saved for training process. It is repeated until each subset of data is used as a test set. Finally, the performance of predictor is calculated as the average of k runs. where $(p_i\, , i = 1,2, \dots . k)$ is the performance of predictor in ith iteration.

$$\boldsymbol{p}^* = \frac{\sum_{i=1}^{k} \boldsymbol{p_i}}{\boldsymbol{k}} \quad (2)$$

RESULTS AND DISCUSSIONS

In this chapter, we give a detailed comparison of methods MLP, Bagging, and RSM in terms of evaluation metrics. Firstly, we compare algorithms that are trained by using all available attributes. Then, we give the results of algorithms that are trained by selected attributes.

Table 5 shows the performance of algorithms in terms of statistical evaluation metrics. Bagging method gives the best accurate prediction compared to other methods with a rate of 90.55%. Also, one can infer that its results are more reliable than other methods because it gives the higher F-measure (see Table 6) which is harmonic mean of precision and recall and calculated. Moreover, as shown in Table 5, for other evaluation metrics such as MAE, RMSE, etc. Bagging did not perform well enough compared to other methods. MLP algorithm outperforms other methods in terms of error metrics in the majority of evaluation metrics.

Table 5: Evaluation metrics

	MLP	Bagging	RSM
Accuracy	88.97%	90.55%	89.76%
Correctly Classified Instances	113	115	114
MAE	0,0845	0,0946	0,11
RMSE	0,2306	0,2389	0,2238
RAE	0,37528	0,42064	0,488905
RRSE	0,695594	0,720664	0,675243
Total number of instances	127,00	127,00	127,00

As we mentioned above, we can infer the reliability of algorithm as a result of F-measure. For the majority of other metrics. Bagging method also outperforms MLP and RSM for majority classification metrics. Detailed results can be seen in Table 6.

Table 6: The performance of classifiers the best values are bolded

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	Roc Area	PRC Area
MLP	0,89	0,256	0,881	0,89	0,885	0,651	0,89	0,914
Bagging	0,906	0,252	0,896	0,96	0,9	0,694	0,918	0,937
RSM	0,898	0,312	0,887	0,898	0,889	0,661	0,952	0,956

Dataset has three outputs, which are labeled as B, C, and D (Fig. 3) and rate of output values are %79.5, %19.6, and %0.78 respectively. Because there is only one sample in class D, none of algorithms correctly classify this sample as expected. It can be ignored during training process, however, we prefer to see the performance of the algorithm for the very rare sample. The study aims to create a classification model to predict total energy consumption of residential buildings. For this purpose, three well-known methods are chosen and utilized. Those methods are fairly compared based on commonly used evaluation metrics and the results shows that such a model can be created for the aforementioned problem, although there exist some limitations such as i) the data size is limited ii) available energy classes are limited to three iii) there is a imbalanceness problem. Even though those problems the models are successful to predict the energy class of the residential buildings. Among those models, bagging approach can be used to finalize the proposed approach, since it gives the highest accuracy with the rate of 90.55%.

MANAGERIAL INSIGHTS AND PRACTICAL IMPLICATIONS

The wasted amount of energy has become a critical problem for many countries due to limited energy sources and energy production cost. These forced countries to increase energy usage awareness by making regulations in construction sector, which might dramatically decrease energy consumption cause of size of the domain. One of them is standardizing heating and cooling loads (HL/CL) to avoid energy waste. HL and CL need an advanced engineering process because of different parameters such as thermal characteristics of building, hot water supply, passive solar systems, etc. Hence, it can only be carried out by expert engineers in calculations. Therefore, to carry on the process smoother and make it easy in terms of managerial side, we have tried to establish a classification model as a decision support system proposed for predicting the energy consumption of residents which is an efficient indicator of architectural features of the construction about energy consumption concept. To do this, we survey and gather some practical information from previously designed architectural structure to initialize the dataset that is later used to train chosen model. At the end of the application, it is shown that trained models achieved to accurately predict the energy class of the building. Therefore, those managers who are responsible to reduce the waste of energy consumption can easily use the proposed approach before the exact architectural design step in real life implications and this will ensure saving time and traceable process of determination of energy class of the residential buildings.

CONCLUSION AND OUTLOOK

Energy requirement is a global concern over the world so energy politics and investments shape the future of countries and international relationships. As well as researching alternative energy sources, it is also important to use efficiently in existing energy sources. That's why governments make operative legal rules for energy consumption for residential buildings. In the scope of rules calculated energy consumption has to meet the minimum requirements mentioned in regulations. In this study, a prediction model was developed for energy performance, which is the total energy consumption of residential buildings (kWh/m^2 year) for minimizing calculation time before the exact architectural design step. The first different architectural projects were examined one by one for quantity survey study. After that, generated data set was analyzed and attributes of model are determined for 127 different residential buildings.

According to Buildings Energy Performance Directive (EPBD) "energy performance certificates must be issued when a building is sold or rented, and inspection schemes for heating and air conditioning systems must be established" this means it is not allowed to rent or sell any house without energy performance certificates.

With the proposed model, the following results can be deducted; Comment 7

- Based on our findings, we can conclude that machine learning algorithms can be used to predict energy class of a building. By doing this, one can save a huge amount of time by ignoring more complex engineering calculations during the design process.
- People will be able to learn energy performance classes of their buildings with simple qualitative knowledge without help of a specialist and without needing complex calculations.
- Decision makers will be able to make the necessary renovations if energy performance of their buildings is insufficient by figuring out the energy performance class before the project proceed. Therefore, both project costs will be reduced and a waste of time will be prevented.

On the other hand, we had to deal with some limitations during our study. Considering those limitations, we can provide some suggestions to help and guide for the direction of the future studies as follows;

- Since the size of the collected data set is one of our limitations, more data can be collected to leverage the training process.
- The second limitation is that it was studied with residential buildings. Although it has been studied with residential buildings of different architecture, superior to other studies, enriching the data set with structures such as factories, schools, hospitals and warehouses may be an opportunity for future studies.
- The last one can be shaped around the dealing with the imbalance classification problem. To handle with this, a new approach can be derived or we might more focus on collecting data samples falling into minority class.

Finally, based on our findings, we can conclude that machine learning algorithms can be used to predict energy class of a building. By doing this, one can save a huge amount of time by ignoring more complex engineering calculations during the design process. As the models studied are self-learning systems, different structure samples will be added to the data set in the future will be successfully predicted with the model developed. Thus, this study can be a guide for those would like to develop a prediction model for the energy class classification.

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Appendix A. The Mathematical formulation of the Multilayer Perceptrons

Multilayer Perceptrons (MLP) consist of stacked fully connected layers which are formed some number of nodes –also called neurons- as shown in Fig. B.1. The main goal of MLP is to find a nonlinear relationship between inputs and outputs. The main process is feeding each layer by a weighted sum of input values. In other words, each neuron takes the value of the linear combination of the previous values of nodes. This is named as Feed Forward Neural Network. Then, weights are adjusted to minimize errors by derivation steps which are known as backpropagation training [19].

MLP has inherent skill –just like the other intelligence types to nonlinearly maps between input and output vector thanks to the ability of the backpropagation algorithm which realizes the learning process and adjusting connection weights simultaneously for a multilayer neural network [31]; [39].

Through our study, we use a conventional back-propagation MLP. The output of n^{th} neuron in l^{th} layer is calculated as:

$$y_l^n = \varphi\left[\sum_{j=1}^{p} w_{lj}^n(t) y_j^{n-1}(t) + \gamma_l^n\right] \quad (\boldsymbol{B.1})$$

where $\varphi(\cdot)$ is the activation function, w_{lj}^n is the connection weight, t is the time index, and $\gamma_l^n = w_{lj}^n(t)$ is weighted. For the n-layer network, the synaptic weight is calculated as:

$$w_{ji}^n(t+1) = w_{ji}^n(t) + \Delta w_{ji}^n(t) \quad \text{(B.2)}$$

Subject to $l \le n \le N$ and can be revised as given by:

$$\Delta w_{ji}^n(t) = \varepsilon \lambda_j^n(t) y_i^{n-1}(t) \quad \text{(B.3)}$$

Subject to $0 \le \varepsilon \le 1$

Where ε is the learning rate, and $\lambda_j^n(t) \equiv \partial E_t / \partial u_j^n$ is the local error gradient. To leverage the back-propagation algorithm, a momentum term α is added as:

$$\Delta w_{ji}^n(t) = \varepsilon \lambda_j^n(t) y_i^{n-1}(t) + \alpha \Delta w_{ji}^n(t-1) \quad \text{(B.4)}$$

Subject to $0 \le \alpha \le 1$

For the output layer, the local error gradient is given by

$$\lambda_j^N(t) = [d_j(t) - y_j^n(t)]\varphi[u_j^N(t)] \equiv e_j(t)\varphi[u_j^N(t)] \quad \text{(B.5)}$$

where $d_j(t)$ is the goal output signal, and $\varphi(\cdot)$ is the activation function.

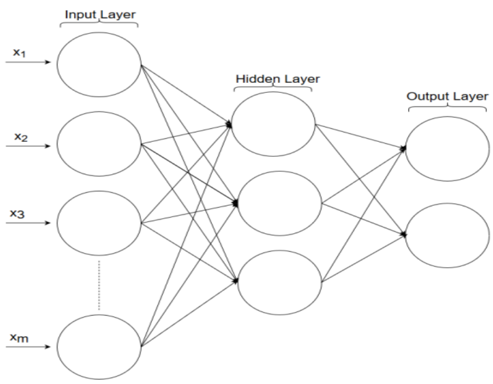

Figure B.1: The MLP structure for the classification problem**.**

Appendix B. The Mathematical Formulation of the Bagging Method

Bagging is one of the Ensemble Machine Learning (EML) algorithms which is also known as bootstrap aggregating, is proposed by Breiman and Leo [26]. Bagging method generates the new and combined model, to provide increase the accuracy by combined obtained prediction results from single learners in a single prediction [19]. The resource of increasing accuracy is based on executing to variance decreasing by the combined model [27]. On the other hand, this method's working principle is based on probability uniform, by select will process samples as randomly and independently.

In classification, a predictor φ(x,L) predicts a class label j Є{1,….,J}. Denoted by:

$$dQ(j|x) = \mathrm{P}(\varphi(x, \mathrm{L}) = j) \quad \text{(C.1)}$$

The interpretation of Q(j|x) is this: over many independent replicates of the learning set L, φ predicts class label j at input x with relative frequency Q(j|x). Let P(j|x) be the probability that the input x generates class j. Then the probability that the predictor classifies the generated state at x correctly is

$$\sum_j Q(j|x)\, P(j|x) \tag{C.2}$$

The overall probability of correct classification is

$$= \int [\textstyle\sum_j Q(j|x)P(j|x)] P_x(dx) \tag{C.3}$$

where $P_x(dx)$is the x probability distribution [30].

Appendix C. The Mathematical Formulation of the Random Subspace

Random subspace method (RSM) which is another EML algorithm is a combination procedure proposed by [30]. By using RSM one can modify training set by choosing different features from original training data. Assume we are given a data set $X = (X_1, X_2, \dots . X_n)$ where $X_i \in R^p$. Then we can randomly choose $r < p$ features from training data. So, the modified training data $\breve{X}^b = \breve{X}_1^b, \breve{X}_2^b, \dots, \breve{X}_n^b$ consist of r dimensional training samples $\breve{X}_i^b = (\breve{x}_1, \breve{x}_2 \dots \breve{x}_r)$. Then, a classifier can be constructed in random subspace $\breve{X}^b$ and final decision can be given based on the majority voting procedure. To wrap up, the RSM can be organized as follows:

a. Repeat the process for $b = 1,2, \dots, B$
b. Randomly select $r < p$ feature to create a random subspace $\breve{X}^b$

Construct a classifier $C^b(x)$ with a decision boundry is equal to 0.
Combine classifiers $C^b(x), b = 1,2, \dots, B$ by a simple majority voting procedure.

$$\beta\_x = argmax\_(y \in (-1,1)) = \sum\_b▒\delta\_(sgn(C\hat{}b\ (x)), y) \tag{D.1}$$

where $\delta_{i,j}$ is the Kronocker symbols and $y \in (-1,1)$ is the class label.

RSM can eliminate unuseful and redundant features in training data, so that might yield a better classification result. Also, it might be more successful than a single classifier's decision due to the combination process through the final decision [40].

Appendix D. The Formulations of the evaluation metrics

Correlation Coefficient R^2	$\left(\frac{n\sum y.y' - (\sum y)(\sum y')}{\sqrt{n(\sum y^2) - (\sum y)^2} - \sqrt{n(\sum y'^2) - (\sum y')^2}}\right)^2$ (A.1)
Mean Absolute Error (MAE)	$\frac{1}{n}\sum_{i=1}^{n}\lvert y - y'\rvert$ (A.2)
Root Absolute Error (RAE)	$\frac{\sum_{i=1}^{n}\lvert y' - y\rvert}{\sum_{i=1}^{n}\lvert \bar{y} - y\rvert}$ (A.3)
Root Mean Squared Error (RMSE)	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i')^2}$ (A.4)
Root Relative Squared Error (RRSE)	$\sqrt{\frac{\sum_{i=1}^{n}(y' - y)^2}{\sum_{i=1}^{n}(\bar{y} - y)^2}}$ (A.5)
Accuracy (Acc)	$\frac{(TP + TN)}{(TP + FP + TN + FN)}$ (A.6)
Precision	$\frac{TP}{TP + FP}$ (A.7)
Recall	$\frac{TP}{TP + FN}$ (A.8)
F-score	$2x\frac{Recall \times precision}{Recall + precision}$ (A.9)
MCC	$\frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}}$ (A.10)