ENERGY PERFORMANCE PREDICTION OF RESIDENTIAL BUILDINGS USING NON-LINEAR MACHINE LEARNING TECHNIQUES

A PROJECT REPORT

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ABSTRACT

Energy consumption refers to the amount of energy consumed by an individual or organization or to the process, or to perform an action. The consumption of energy in buildings is increasing steadily and occupying approximately 35- 40% of total energy used by the environment. Indoor climate is an account for most of the energy used in the buildings which rely on heating, ventilation and air-conditioning. It is necessary to predict the heating and cooling loads of a building in the initial stage of design to find out best solutions among various design options, as well as in the operational stage after the building has been completed for energy efficient operation. To obtain the efficient building design the amount of heat energy need to be added to and removed from a space to maintain the temperature in an acceptable range should be measured. This project proposes a deep learning model to predict the heating load and cooling load of a building based on simulation data for building energy performance. In a deep learning network, the neurons of each layer are trained on a different set of parameters using the prior layer's output. In the proposed Deep Learning model different numbers of hidden layers, different hidden neurons, and various types of activation functions have been used to achieve the optimal structure of DL for energy consumption prediction.

ஆய்வுசுருக்கம்

எரிசக்தி நுகர்வு என்பது ஒரு தனிநபர் அல்லது நிறுவனத்தால் அல்லது செயல்முறைக்கு அல்லது ஒரு செயலைச் செய்யக்கூடிய ஆற்றல் அளவைக் குறிக்கிறது. கட்டிடங்களில் ஆற்றல் நுகர்வு சீராக அதிகரித்து, சுற்றுச்சூழலில் பயன்படுத்தப்படும் மொத்த ஆற்றலின் சுமார் 35-40% ஆக்கிரமிக்கிறது. உட்புற காலநிலை வெப்பம், காற்றோட்டம் மற்றும் காற்றுச்சீரமைத்தல் ஆகியவற்றில் தங்கியுள்ள கட்டிடங்களில் பயன்படுத்தப்படும் பெரும்பாலான ஆற்றலுக்கான ஒரு கணக்கு. கட்டடத்தின் துவக்க கட்டத்தில் வெப்ப மற்றும் குளிரூட்டும் சுமைகளை பல்வேறு வடிவமைப்பு விருப்பங்களிடையே சிறந்த தீர்வுகள் மற்றும் ஆற்றல் செயல்திறன் நிறைந்த செயல்பாட்டிற்காக கட்டி முடிக்கப்பட்ட பிறகு செயல்பாட்டு கட்டத்தில் கண்டுபிடிப்பது அவசியம். திறமையான கட்டிடம் வடிவமைப்பு பெற வெப்ப ஆற்றல் அளவு சேர்க்க வேண்டும் மற்றும் ஒரு ஏற்கத்தக்க வரம்பில் வெப்பநிலை பராமரிக்க ஒரு இடத்தில் இருந்து நீக்க வேண்டும் அளவிட வேண்டும். ஆற்றல் செயல்திறனை உருவாக்குவதற்கான சிமுலேஷன் தரவை அடிப்படையாகக் கொண்டிருக்கும் ஒரு கட்டிடத்தின் வெப்ப சுமை மற்றும் குளிரூட்டும் சுமை ஆகியவற்றைக் கணக்கிட அல்லாத நேரியல் இயந்திர கற்றல் உத்திகளில் இது ஒரு ஆழமான கற்றல் மாதிரியை முன்மொழிகிறது. ஒரு ஆழமான கற்றல் நெட்வொர்க்கில், ஒவ்வொரு அடுக்கின் நியூரான்களும் முன்னரே அடுக்கு வெளியீட்டைப் பயன்படுத்தி வேறுபட்ட அளவுருக்கள் மீது பயிற்சி அளிக்கப்படுகின்றன. எனவே, ஆழ்ந்த கற்றல் பல ஆராய்ச்சியாளர்களின் கவனத்தை ஈர்த்திருக்கிறது, ஏனெனில் இது நிஜ உலக பிரச்சினைகளை தீர்க்க மிகவும் திறமையானது. ஆற்றல் நுகர்வு கணிப்பிற்கான DL இன் உகந்த கட்டமைப்பை அடைவதற்கு முன்மொழியப்பட்ட ஆழமான கற்றல் மாதிரி, மறைந்த அடுக்குகள், வெவ்வேறு மறைக்கப்பட்ட நரம்பணுக்கள் மற்றும் செயல்பாட்டு செயல்பாடுகளை பல்வேறு வகைகள் பயன்படுத்தப்படுகின்றன.

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LIST OF ABBREVATIONS

ANFIS	Adaptive Neuro Fuzzy Inference System
ANN	Artificial Neural Network
ARX	Auto-Regressive with Exogenous
BPNN	Back-Propagation Neural Network
CART	Classification And Regression Tree
CHAID	Chi-squared Automatic Interaction Detector
CL	Cooling load
CV	Cross Validation
DELM	Deep Extreme Learning Machine
DL	Deep Learning
ELM	Extreme Learning Machine
ENB	Energy and Building
EUI	Energy Use Intensity
FL	Fuzzy Logic
GLR	General Linear Regression
HL	Heating Load
HVAC	Heating,Ventilation,Air-Conditioning
IRLS	Iteratively Reweighted Least Squares
LS-SVM	Least Square Support Vector Machine
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MTD	Multi Target Dataset
MTR	Multi Target Regression
MSE	Mean Square Error
NLP	Natural Language Processing
OSLEM	Online Sequential ELM

R2	R-squared
RBFN	Radial Basis Function Network
RF	Random Forest
RMSE	Root Mean Square Error
SAE	Stacked Auto Encoder
SRM	Structural Risk Minimization
SVM	Support Vector Machine
SVR	Support Vector Regression

CHAPTER 1

INTRODUCTION

1.1 Overview

The energy consumption in residential buildings has significantly increased in the last decade. The energy performance of a building is the calculation of the amount of energy actually consumed in the building to meet the different needs associated with a standard use of the building including heating/cooling, lighting. Efficient energy use aims to cut the amount of energy needed to supply products and services. Energy efficiency means using less energy to provide the same service to the products. For example, an LED light bulb is more efficient than a traditional incandescent bulb as it uses much less electrical energy to produce the same amount of light. Energy efficiency also helps the economy, by saving millions of dollars in energy costs.

Energy efficiency preserve our environment for sustainable development. Use of energy efficient appliances reduces the utilization of natural resources. Energy efficiency enhances preservation of these sources as a way to achieve sustainable development. The buildings where we live and work account for 30 percent of overall greenhouse gas emissions in the United States. Technologies such as more economic heating, air conditioning, and lighting modify buildings to use less energy, which helps to reduce greenhouse gas emissions. Energy-saving actions are defined as the daily and usual practices of households that focus on specific reductions in energy use. Households decide how to keep their home warm in the winter and how to keep cool it in the summer to use their major energy system.

Most of the energy and environmental discussion focus on building energy performance and the energy performance improvement programs are focused on building retrofits. Incentives are given for installing energy efficient technologies: lighting, high efficiency heating and cooling systems etc. Yet there is no conclusive evidence that the technology measures alone necessarily lead to improved performance, one way to alleviate the ever increasing demand for additional energy supply is to build more energy efficient building with improved energy conservation properties. To reduce total energy consumption of buildings, it is very important to know heating and cooling loads when the building is designed. In the design stage, architects and designers need some parameters to analyze, like overall height, relative compactness, surface area, wall area, roof area, orientation, glazing area, and glazing area distribution of building. Designers also need to decide which parameters have big impacts on heating and cooling loads of the building.

Recently, designers use some building energy simulation programs to investigate the effects of these parameters on HL and CL. However, such simulation programs require deep user knowledge to use effectively and also the process of determining which parameters affect the HL and CL is very time consuming. After machine learning techniques such as ANN, fuzzy logic (FL) and SVM gain popularity; many researchers attempt to use these techniques in different fields and also in building energy efficiency studies. Various machine learning techniques such as random forest (RF), least square support vector machine (LS-SVM), artificial neural network (ANN), extreme learning machine (ELM) are used to predict the HL and CL.

Nowadays the deep learning approaches have also been used in various areas for prediction purposes, such as a deep neural network, deep belief network, and a recurrent neural network. The term of deep learning states the number of layers through which data are transferred. The deep learning techniques are strong tools to obtain healthier modeling and prediction performance. The deep learning algorithm uses deep architectures or multiple-layer architectures adopting the layer wise pre-training method for parameter optimization to obtain great feature learning ability. The inherent features of data extracted from the lowest level to the highest level of the deep learning model are more typical than for the traditional shallow neural network. Hence, the deep architectures have greatly better performance for the modeling, classification and visualization problems.

In [15], a single convolutional neural network architecture with a multi-task learning strategy was designed for natural language processing (NLP). In [16], the deep auto encoder network was utilized to convert high-dimensional data to low-dimensional codes, and experiments demonstrated that it works much better than PCA for dimensionality reduction. In [17], a stacked auto encoder (SAE) was applied for organ identification in medical magnetic resonance images. The deep learning methods have also been applied to time series prediction problems. Additionally, in [18], a deep learning-based approach for time series forecasting with an application to electricity load was given. In all these applications, the results demonstrated that the deep learning approaches can outperform the comparative methods. However, in these applications, the deep learning approaches, still performed better than some traditional machine learning methods because of the relatively deeper architectures and the improved or newly proposed learning strategies in the deep learning approaches.

In this project, the effect of eight input variables: relative_compactness, surface area, wall area, roof area, overall height, orientation, glazing area, and glazing area distribution, is predicted to estimate the output variables heating and cooling loads of residential buildings. This project statistically explore the data and analyze the properties of input and output variables, and use non-linear machine learning techniques (deep learning) to predict the HL and CL. To enhance the prediction performance, a deep learning approach is proposed to estimate building energy consumption. Finally, the proposed approach is compared with some popular methods, such as the artificial neural network (ANN), support vector regression (SVR), Chai-squared automatic interaction detector (CHAID), Classification and regression tree (CART), General linear regression (GLR). The experimental results shows that the proposed deep learning model has the best prediction ability.

1.2 Organization of the report

- Chapter 1 starts with a brief introduction about the energy performance, energy performance prediction and the existing techniques followed in this work.
- Chapter 2 briefly discuss the literature review related to this project.
- Chapter 3 presents the existing techniques used for the energy efficient data. It also describes the various algorithms individually.
- Chapter 4 shows the proposed technique in this project. The proposed technique describes about the modules used here.
- Chapter 5 presents the software and hardware require in this project.

- Chapter 6 discuss the result obtained from the experiment. Then it compares the various existing machine learning algorithms with the proposed technique.
- Finally this project ends with a comprehensive summary, conclusion and result of this project.

CHAPTER 2

LITERATURE SURVEY

This chapter discuss the literature review related to current work. Initially the techniques already used for the energy efficient data is discussed. Then the review about deep learning approach is discussed.

Athanaios et al [1] presented "Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools". In this study a classical linear regression, iteratively reweighted least squares approach are compared against a powerful state of the art nonlinear non-parametric method, random forests, in order to identify the most strongly related input variables. Then HL and CL is predicted with low mean absolute error obtained from IRLS and RF. It accurately estimate HL with only 0.5 points deviation and CL with 1.5 points deviation from the ground truth which is established using Ecotect (0.51 and 1.42, respectively). The statistical tools used here indicate that relative compactness, wall area and roof area appear mostly associated with HL and CL. The RF massively outperformed IRLS in finding an accurate functional relationship between the input and output variables. Classical regression settings (such as IRLS) may fail to account for muti-collinearity. On the contrary, RF optimizes the selection of the variable for each split, and thus can internally account for redundant and interacting variables.

Zhun et al [2] presented "A decision tree method for building energy demand modeling". In this paper Decision Tree method is used to estimate residential building energy performance indexes by modeling building energy use intensity (EUI) levels. This method is used as it have competitive advantage over other widely used modeling techniques, such as regression method and ANN method. The results shows that the use of decision tree method can predict building energy demand levels more accurately (93% for training data and 92% for test data). Decision Tree method is unstable, that a small change in the data can lead to large change in the structure of the optimal decision tree.

Abraham et al [3] presented "An applied artificial intelligence approach towards assessing building performance simulation tools". This paper presents an approach towards comparing building performance simulation results to actual measurements, using artificial neural networks (ANN) for predicting building energy performance. The predicted results show a best fitness with the mathematical model with a mean absolute error of 0.9%. The suggested approach can reduce costs in data collection and provides trustworthiness in the predicted consumption. The size of the network should be controlled by the ratio of free parameters to the number of training samples. If the ratio is too large, the prediction accuracy will be affected.

Sholahudin et al [4] presented "Prediction and Analysis of Building Energy Efficiency using Artificial Neural Network and Design of Experiments". In this paper, an artificial neural network model has been developed to predict heating load and cooling load of a building based on simulation data for building energy performance and analysis of variance to determine the effect of input variables based on the data in the literature. ANNs have an advantage in estimating output values for given input values satisfactorily, but it has a limitation in acquiring the effects of input variables individually.

Betul et al [5] presented “ Building Energy Load Prediction by using LS-SVM”. In this paper, building energy performance has been investigated using least square support vector machine (LS-SVM) model which is a regularized and modified version of original SVM to predict heating and cooling loads. The main advantage of the LS-SVM is the much lower computational complexity. The suggested LS-SVM method gives very satisfactory results with 0.99 error rate for HL prediction and 0.976 error rate for CL prediction which is nearer to the result of ANN method, but the training time of ANN is longer than SVM.

Sachin et al [6] presented “A Novel Method Based on Extreme Learning Machine to Predict Heating and Cooling Load through Design and Structural Attributes”. This paper provides modification in energy load assessment of the buildings by novel methods based on ELM and its variants online sequential ELM(OSELM) to predict HL and CL.The experimental results show that the proposed models on ELM gives the minimum MAE(kW) 0.0348 and 0.0389 for CL and HL respectively and run time which outperform other popular machine learning approaches such as the artificial neural network(ANNs), support vector machine(SVM), radial basis function network(RBFN), random forest(RF) and existing work in the energy and building domain. An ELM is fundamentally a 2-layer neural network in which the first layer is fixed and random, and the second layer is trained.

Bing et al [7] presented "Applying support vector machines to predict building energy consumption in tropical region". This paper uses support vector machine (SVM), a new neural network algorithm, to forecast building energy consumption in the tropical region. The objective of this paper is to analyze the feasibility and applicability of SVM in building load forecasting area. The performance of SVM, in terms of CV and MSE, is better than other related research using neural networks and genetic programming. Structural risk minimization (SRM) principle, which is the most outstanding feature of SVM, is implemented to minimize the upper bound of the generalization error rather than the training error, which is applied in NN. However, for the neural networks, there are lots of free parameters needed to adjust such as number of neurons in the hidden layers, the learning rate, number of epochs, the stop criteria and the transfer functions. Furthermore, NN can never reach a global solution. However, the solution of SVM is unique and optimal because SVM is like solving a linearly constrained quadratic programming.

Mauro et al [8] presented "Prediction of Energy Performance of Residential Buildings: a Genetic Programming Approach". In this paper, a machine learning framework is suggested to predict the HL and the CL of a large set of residential buildings. Three different Genetic Programming systems are compared: GSGP, GSGP with local search (HYBRID) and a third system that uses the HYBRID approach integrated with linear scaling (HYBRID-LIN). Moreover, the GP systems were also compared to a set of state-of-the-art machine learning techniques. This paper provides two contributions: from the point of view of the energy performance prediction, a system able to outperform existing state-of-the-art techniques has been defined; from the machine learning perspective, this case study has shown that integrating a local searcher and linear scaling in GSGP can speed up the convergence of the search process.

Jui-Sheng et al [9] presented “Modeling heating and cooling loads by artificial intelligence for energy-efficient building design”. In this paper various data-mining techniques, including ANN, SVR, CART, CHAID, GLR and ensemble model, were compared in terms of speed and performance in predicting building CL and HL. This work confirms that the ensemble model (SVR +ANN) and SVR substantially improve performance in predicting CL and HL, respectively. This paper also reduce the amount of work required to develop complex computing algorithms. Specifically, the robustness and prediction accuracy of the proposed model are superior to those of other models. Notably, the suggested SVR requires only 1.03 seconds to predict HL, and the ensemble model (SVR +ANN) requires 1.01 seconds to predict CL. Therefore, these models provide a good basis for developing a real-time building energy performance management system in future works. However, the limitation of this work is that it used default settings in the single and ensemble models. Additionally, the developed models are only applicable to the twelve specified building types with a controlled experiment setup.

Muhammad et al [10] presented “A Prediction Methodology of Energy Consumption Based on Deep Extreme Learning Machine and Comparative Analysis in Residential Buildings”. In this paper, the deep extreme learning machine (DELM) is used for energy consumption prediction. Further, the adaptive neuro-fuzzy inference system (ANFIS) and artificial neural network (ANN) also applied. In the DELM different numbers of hidden layers, different hidden neurons, and various types of activation functions have been used to achieve the optimal structure of DELM for energy consumption prediction. Similarly, in the ANN, a different combination of hidden neurons with different types of activation functions are used to get the optimal structure of ANN. To obtain the optimal structure of ANFIS, a different number and type of membership functions are applied. In the performance evaluation layer for the comparative analysis of three prediction algorithms, the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) are calculated. The results shows that the performance of DELM is far better than ANN and ANFIS.

Chengdong et al [11] presented “Building Energy Consumption Prediction: An Extreme Deep Learning Approach”. This study aimed to utilize one popular deep learning approach, the SAE method to improve the predicted results of building energy consumptions. Theoretically, this study provided a novel learning method by combining the SAE method and the ELM method. The main difference between the suggested method and the traditional SAE method is that the suggested method does not need the fine-tuning of the whole network by the iterative back-propagation algorithm, but immediately utilizes the ELM method to find the output weights without iterations. This can speed up the learning and strengthen the generalization performance. The observational and comparison results demonstrate that the deep learning method outperforms several popular traditional machine learning methods. The reason for this may be that the proposed deep learning method has deeper architecture and improved learning strategies compared with the other comparative methods.

Qiong et al [12] presented “Applying support vector machine to predict hourly cooling load in the building”. This paper applies SVM to forecast the hourly building cooling load and the performance of SVM is compared with traditional back-propagation (BP) neural network model. Through the comparison to the prediction results of two models, the root mean square error and the mean relative error from SVM model are found to be about 50% of those from BP network model. The results show that SVM method can achieve better prediction accuracy than the conventional back-propagation neural networks. The SVM method’s quick and correct learning performance, particularly when the available training set is limited, makes it open a new avenue in load forecasting. The research results demonstrate that SVM method is a promising alternative approach for the prediction of the cooling load in the building. The main drawback of the SVM is that it has several key parameters that need to be set correctly to achieve the best classification results for any given problem.

Chengliang Fan et al [13] presented “Development of a cooling load prediction model for air-conditioning system control of office buildings”. To promote the feasibility of regression methods for cooling load prediction of office buildings, an efficient regression model based on sensitivity analysis and the traditional autoregressive with exogenous (ARX) model (named as improved ARX model) is suggested in this paper. The improved ARX model keeps the constitution of ARX model, but uses specified variables that selected by sensitivity analysis. The quadratic terms of vital variables are included to reduce the impact of system non-linearity. Comparison studies are used to evaluate the prediction accuracy of the improved ARX model. The used model will largely improve prediction accuracy and more adaptive for real applications in the perspective of optimal control for HVAC systems. A least square method was used to get weight coefficient matrix for reducing the error in model training. Application and comparisons showed that the improved ARX model had much better accuracy in cooling load prediction. The determination coefficient ***R***2 of prediction was 0.982 and error evaluation indices, RMSE, EEP, CV and MAE were decreased dramatically when comparing with the traditional regression models. The improved accuracy and simple model mechanism will make the improved ARX model more adaptive for real applications in HVAC system optimal control of office buildings.

Shrikant et al [14] presented "Artificial Neural Networks for Predicting Cooling Load Reduction using Roof Passive Cooling Techniques in Buildings". The objective of this work is to train an artificial neural network (ANN) to learn to predict the reduction of cooling load of buildings. Five training algorithms traincgb, traingdx, traingda, trainlm, and trainsc were used to create an ANN model. An ANN has been trained based on number experimental data of cooling load. The network output is reduction in heat gain though roof. A neural network model based on a back propagation algorithm was used for estimation of hourly cooling load reduction. Training and testing values of cooling load reduction were compared with the experimental data it was found that the neural network could successfully simulate the cooling load reduction. The Intelligent model predicts reduction in cooling load with accuracy more than 90%. The results also show that the average %

reduction of heat gain from roof was found to be 45 %, 30%, using roof pond, using insulation (thermocol) respectively. The lowest RMSEvalue for test data was obtained using a trainlm algorithm. The network gave lowest RMSE, and fastest result for trainlm algorithm, so most situations; this paper recommend that you try the Levenberg-Marquardt algorithm first. If this algorithm requires too much memory, then try one of the conjugate gradient methods.

CHAPTER 3

EXISTING TECHNIQUES

In this chapter the existing techniques for the energy efficient data is briefly discussed. The step by step working of the previous algorithms are described below.

3.1 EXISTING ALGORITHMS

3.1.1 Artificial Neural Network (ANN)

The ANN act as the human brain, that it functions as same as the human brain to make learning and prediction process. The ANN is founded on biological learning and its structure is parallel to that of the human nervous structure. A neural network utilizing interrelated neurons as processing elements, input features, synaptic strength, activation target and bias values are related characteristics for that. The interrelated among neurons handle the strength of the network [19]. The network having neurons can be categorized as input features, hidden layers and target neurons. Very effective neural network model is the back-propagation neural network (BPNN) it's widely used in recent times. Hidden layer consist of many neurons that are activated to output layer and estimated. Through the learning process, the BPNN stores non-linear data between manipulating elements and their related assets. Training process deliver predicted values close to target values through the connection weights are adjusted. So, BPNNs commonly obtain the efficient training process.

Where $network_n$ is the activation of n^{th} neuron; j is the collection of neurons in the preceding layer; w_{nj} is the connection weight between neuron n and neuron j; T_j is the target of neuron j; and y_n is the logistic transfer function or sigmoid.

$$network_n = \sum w_{nj} T_j \ and y_n = f(network_n) = \frac{1}{1 + e^{-network_n}}$$

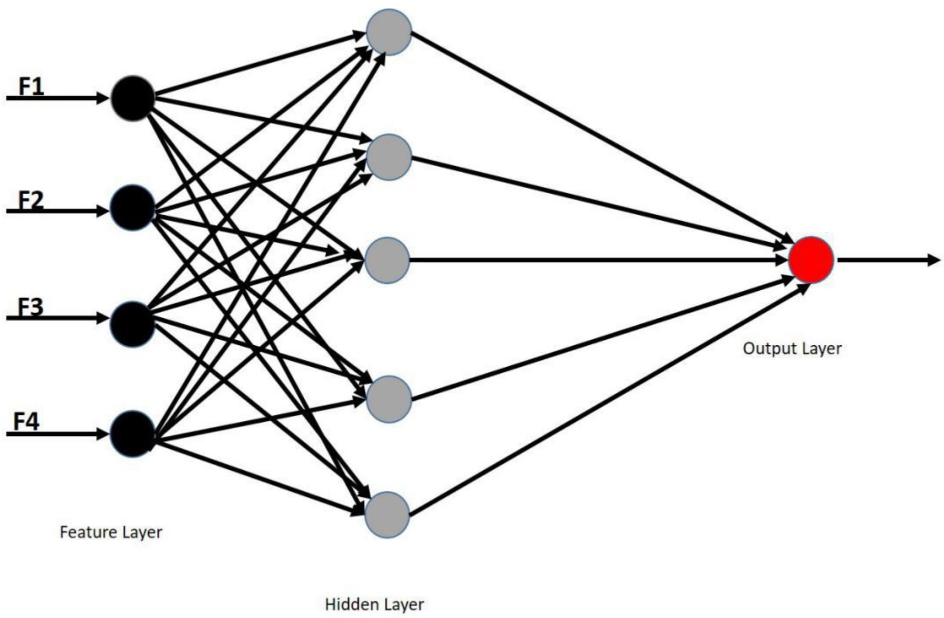

Fig 3.1 Diagrammatic representation of ANN model

3.1.2 Chi-squared Automatic Interaction Detector (CHAID)

The chi-squared automatic interaction detector (CHAID) is a machine learning decision tree classification algorithm introduced by Kass [20]. It performs chi-square test independently to evaluate whether fragmented node expands the accuracy. The features with the solidest combination (p-value) with the target at each node is utilized as a root node. When the tested features show there is no any statistical significant improvement, no split operation is performed, the algorithm will be ended. This study, suggest the use of complete CHAID algorithm to classify the target field, which reports the restrictions of CHAID algorithm [21].

Especially, CHAID may not enhance the split for a feature variable because it ends merging types as soon as it catches all residual types expressively it may vary. CHAID avoids this problem by endlessly merging feature types until only two excellent types remain. After finding the feature in the sequence of merges, it catches the collection of categories that has the solidest combination with the target and calculates an adjusted p-value for the association. Thus, CHAID discovers the best split for each feature and then chooses which features to split by associating their adjusted p-values [22].

3.1.3Classification And Regression Tree (CART)

Classification And Regression Tree (CART) [23] to perform the DT. The creation of a CART is an iterative method of constructing a binary decision tree that can be utilized both for classification as well as for regression. Its support both categorical and numeric target type [24]. In the rule-based CART, data are divided into two subsets of features such that the new feature subset records have large homogeneity, i.e., high accuracy, compared to those in the previous subset.

For classification trees, CART utilize the Gini coefficient reduction principles for feature selection and produces a binary tree. After reaching the homogeneity principle it needs an iterative splitting method. A CART is adequately flexible to consider misclassification costs and to denote the probability distribution in a classification problem. In a CART model, accuracy is well-defined as the similarity between values and target values are measured faultless when all feature subset values are identical. To obtain the target field, three impurity measures can be used to find splits for CART models. In addition to that, the target field is usually represented using Gini while the least squared deviation method is used for selecting continuous targets without clarifying the selection.

The Gini index g(t) at a node t in a CART is defined by the following equations:

g(t) = p(j|t)p(i|t)

$$p(j|t) = \frac{p(j,t)}{p(t)}; p(j,t) = \frac{\pi(j)N_j}{N_j}; p(t) = \sum_j p(j,t)$$

where i and j are target variable types, (j) is the prior probability value for type j, $N_j(t)$ is the number of records in type j of node t, and N_j is the number of records of type j in the root node. Notably, when the Gini index is utilized to estimate the upgrading, afterward a split during tree growth, only records in node t and the root node with valid values for the split-features are used to compute $N_j(t)$ and N_j, respectively.

3.1.4 Support Vector Regression (SVR)

Support vector machine is used for classification methods, whereas it can also be used for regression problem. The generalized form of support vector machine (SVM) is known as support vector regression (SVR) which is mainly used for regression problems. Both SVM and SVR are similar with a slight difference that SVR relies on kernel functions. SVR is mainly used in fixing the error rate within some threshold. In SVR, first the input(x) is mapped into high-dimensional feature space through non-linear mapping and then linear regression is done in that feature space.

The feature is first of all mapped onto an large dimensional feature set space through non-linear functions as follows:

$$f(F,w) = \{w,F\}+c \text{ with } w \in \mathbf{z}, \quad \mathbf{c} \in \mathbf{z}$$

where {•, •} represents the dot product in z. Thus, the accuracy of the f (F) can be projected depend on the loss function L(F) as follows:

$$L(F, w) = [T,f(F, w1)] = 0 \text{ if } |T - f(F, w1)| \leq \varepsilon\, |T - f(F, w1)|$$

3.1.5 General Linear Regression (GLR)

General linear regression (GLR), is one of the more springy type of linear regression (LR), in this algorithm's data points are have an arbitrary distribution method. It makes the connection between F (feature variables) and T (target variable) by utilizing a link function permitting to its distribution pattern. The (F − T) relational model is consequently denoted as:

$$G(E(T)) = F\times \beta+o,\ T\sim D$$

Where G(•) is the nominated link function, o is the offset variable, Dis the distribution model of T, F is the feature, T is the target variable, and β is the regression coefficient. The Newton–Raphson method used to GLR provide a continuous evaluation like (F× β +o) methods GE (T)).The last proximal calculation is framed as a (F − T) relational notations. While some of the additional parameters added to can be increase the GLR model instability in efficiently, GLR has a broader application limit and it provide a more accurate relationship model compared to Linear Regression.

CHAPTER 4

PROPOSED SYSTEM

In this chapter the proposed Deep Learning technique is briefly discussed. The work done in this project is splited into different modules and that modules also briefly discussed here.

4.1 PROPOSED ALGORITHM

4.1.1 Deep Learning

Deep Learning is evolved from multi-layered neural networks, but there is a bit difference between multi-layered neural networks and deep learning. The difference is that, deep learning models are build on more than 2 hidden layers as compared to a neural network which is built on up to 2 hidden layers.A multi-layered neural network is formed by the interonnection of neurons, this group of neurons forms the neural architecture.

As shown in Fig 4.1, the neural architecture consists of input and output layers along with that, it also consists of many hidden layers. The input layer contains number of neurons equal to the number of input variables in the data given. The number of neurons in the hidden layer can vary according to the user. There are most appropriate number of neurons in the hidden layer in R tool using a cross-validation performance. If the the provided data contains many features, then multi-layered neural networks are preferred. There are many types of neural networks; in that the Feedforward Neural Network is widely used. In Feedforward Neural Network, the information goes from the input layer to the output layer in one direction.

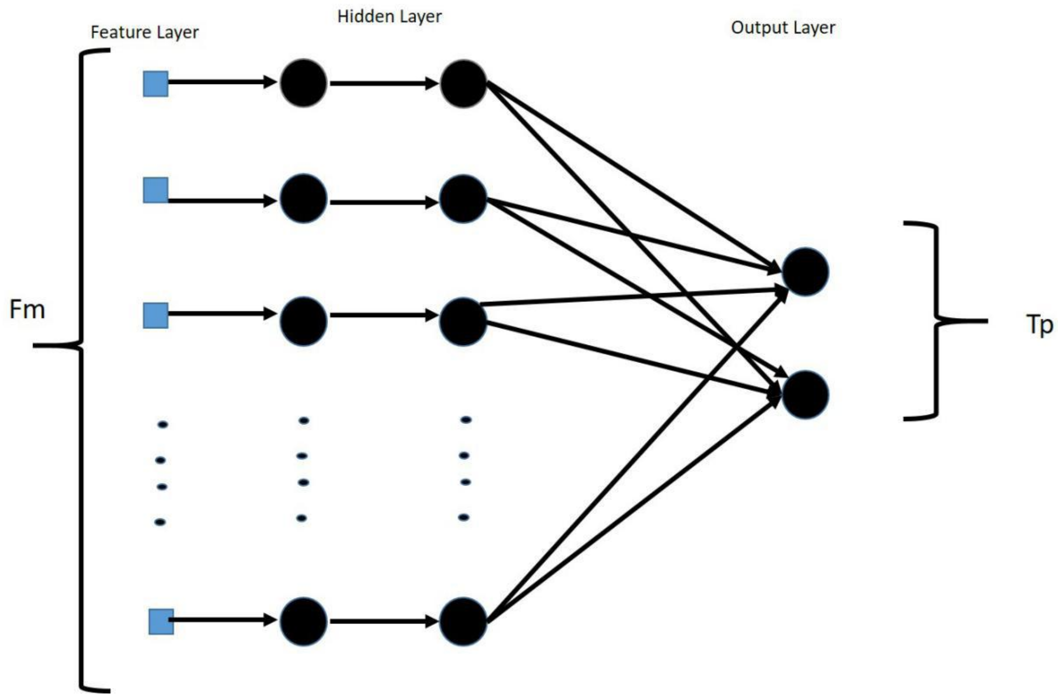

Fig 4.1 Diagrammatic representation of Deep Learning model

4.2 DATASET DESCRIPTION

Taking the elementary cube (3.5 × 3.5 × 3.5) 12 building forms are generated where each building form is composed of 18 elements (elementary cubes). The simulated buildings were generated using Ecotect. The buildings are considered as they are having same volume, which is 771.75 m3, but different surface areas and dimensions.

Table 4.1 shows the mathematical representation of Input or output variable and the number of possible values such that, X1 Relative compactness 12, X2 Surface area 12, X3 Wall area 7, X4 Roof area 4, X5 Overall height 2, X6 Orientation 4, X7 Glazing area 4, X8 Glazing area distribution 6, y1 Heating load 586, y2 Cooling load 636. The selection was done by the newest and most usual materials in the building construction industry and by the lowest U-value. Specifically, the following building characteristics are used (the associated U-values appear in parenthesis): walls (1.780), floors (0.860), roofs (0.500), windows (2.260).

For the thermal properties mixed mode is used with 95% efficiency, thermostat range 19–24 ◦C, with 15–20 h of operation on weekdays and 10–20 h on weekends. Three types of glazing areas are used, which are expressed as percentages of the floor area: 10%, 25%, and 40%. Moreover five different distribution assumption for each glazing area were simulated: (1) uniform: with 25% glazing on each side, (2) north: 55% on the north side and 15% on all the sides, (3) east: 55% on the east side and 15% on each of the other sides, (4) south: 55% on the south side and 15% on all sides, and (5) west: 55% on the west side and 15% on all other sides. In addition to this, the samples are also obtained with no glazing areas.

At last, all shapes were rotated to face the four cardinal points. Thus, considering twelve building forms and three glazing area variations with five glazing area distributions each, for four orientations, the simulation obtained 12 × 3 × 5 × 4=720 building samples. Additionally twelve building forms are taken for the four orientations without glazing. Therefore, in total there are 12 × 3 × 5 × 4 + 12 × 4=768 buildings. Also, for each of the 768 buildings HL and CL is recorded(henceforth these parameters will be called output variables and will be represented with y). Simulating building energy aspects is a widely used approach despite the fact that it is impossible to guarantee that the simulation findings will perfectly reflect actual data in the real world (here HL and CL). That is, even if the data used in this study obtained via the 562 A. Tsanas, A. Xifara / Energy and Buildings 49 (2012) 560–567 simulations could be biased in some way, they represent actual real data with high probability and as such will be considered as ground truth. Moreover, any inconsistency in the simulated data and actual real-world data does not affect whatsoever the methodology developed in this project.

Notation of features & targets	**Feature and Target Variables**	**Number of possible values**
F1	Relative Compactness	12
F2	Surface Area	12
F3	Wall Area	7
F4	Roof Area	4
F5	Overall Height	2
F6	Orientation	4
F7	Glazing area	4
F8	Glazing area Distribution	6
T1	Heating Load	586
T2	Cooling Load	636

Table.4.1 Mathematical representation of input and output variables

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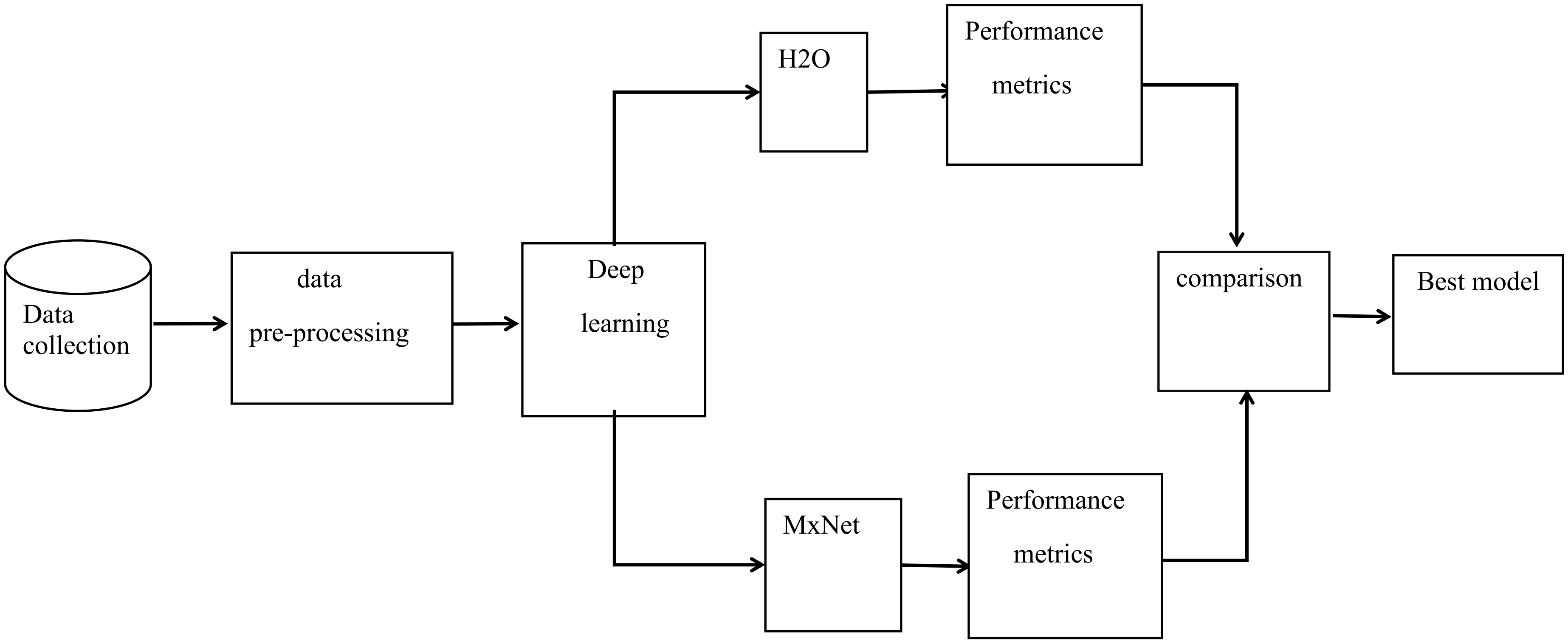

Fig 4.2 Architecture of proposed system

4.3 SYSYEM MODULES

4.3.1 Module 1 Data Collection

The collected data is a multi-target dataset as it contains more than one target variable. The energy efficient data is collected from the UCI repository, which is a repository for machine learning which contains 8 attributes and 2 target variables.The dataset consists of 768 samples of building design and 8 features, aiming to predict two real valued responses heating load (HL) and cooling load (CL).The eight input attributes arerelative compactness, wall area, roof area, surface area, orientation, overall height, glazing area, the glazing area distribution and the two output variables are heating load and cooling load.

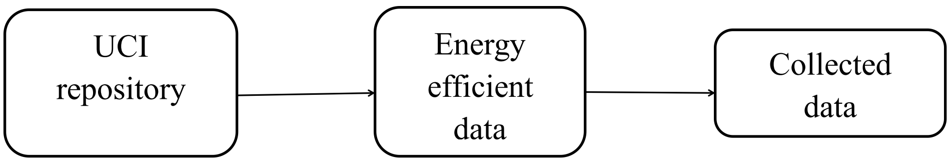

Fig 4.3 Data collection

4.3.2 Module 2 Data pre-processing

Data pre-processing is known as any type of processing performed on raw data to change it for another processing operation. Data pre-processing converts the data into a format that will be more easily and effectively prepared for the purpose of the user. The energy efficient data is in unstructured format hence it is pre-processed to convert it into a structured format. Thus the data is in converted from (.arff) format (unreadable) to (.csv) format which is a readable format. This conversion is done in weka tool.

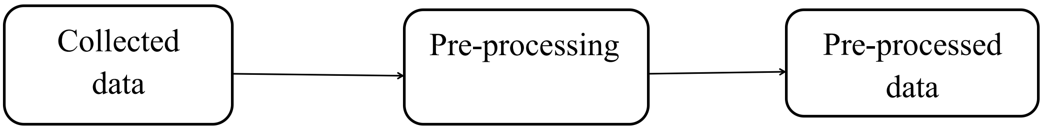

Fig 4.4 Data pre-processing

4.3.3 Module 3 Deep Learning

Deep Learning is evolved from multi-layered neural networks, but there is a bit difference between multi-layered neural networks and deep learning. The difference is that, deep learning models are build on more than 2 hidden layers as compared to a neural network which is built on up to 2 hidden layers. A multi-layered neural network is formed by the interonnection of neurons, this group of neurons forms the neural architecture. The neural architecture consists of input and output layers along with that, it also consists of many hidden layers. The input layer contains number of neurons equal to the number of input variables in the data given. The number of neurons in the hidden layer can vary according to the user. There are most appropriate number of neurons in the hidden layer in R tool using a cross-validation performance. If the the provided data contains many features, then multi-layered neural networks are preferred. There are many types of neural networks; in that the Feedforward Neural Network is widely used. In Feedforward Neural

Network, the information goes from the input layer to the output layer in one direction.

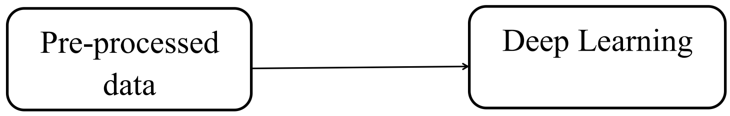

Fig 4.5 Applying deep learning

4.3.4 Module 4 H2O

H2O is an awful machine learning framework. It is really outstanding for data scientists and business analysts “who need scalable and fast machine learning”. H2O is scalable, open-source machine learning and deep learning methods. With H2O, organization like PayPal, Nielsen Catalina, Cisco and others can use all of their data without sampling and get accurate predictions easier and faster. Modern algorithms, like Bagging Ensembles Deep Learning, Boosting, and are promptly available for application designers to build smarter applications through elegant APIs. Using in-memory compression techniques, H2O can manage billions of data rows in-memory, even with a fairly little cluster. H2O implements almost many popular machine learning algorithms, such as Naive Bayes, linear regression, logistic regression, principal components analysis, time series, k-means clustering, and others. H2O also enforces best-inclass algorithms such as Random Forest, Gradient Boosting, and Deep Learning at scale. Customers can build thousands of models and analyse them to get the best prediction results.

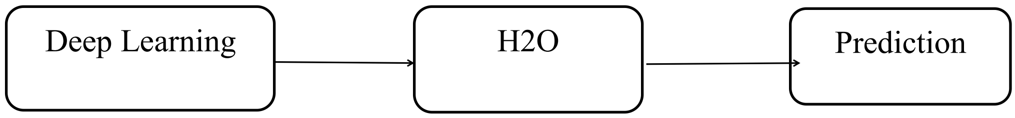

Fig 4.6 H2O module

4.3.5 Module 5 MXNet

MXNet is an open-source machine learning and deep learning methods. MXNet is used in the R programming language. The MXNet R package brings flexible, easy and efficient GPU computing and state-of-art deep learning to R. It enables you to write seamless matrix computation with multiple GPUs in R. It also used to construct and customize the state-of-art deep learning models in R, and apply them to tasks, such as image classification and data science challenges.

Fig 4.7 MXNet module

4.3.6 Module 6 Performance metrics

Performance metrics are measures of quantitative assessment commonly used for measuring, comparing, and tracking performance or production. Here three types of performance metrics is used.

4.3.6.1 MSE

Mean squared error (MSE) is a single value that provides information about the goodness of fit of the regression line. The smaller the MSE value, the better the fit, as smaller values imply smaller magnitudes of error. MSE is defined as the average of squares of the "errors".

$$\text{MSE} = \frac{1}{i}\sum_{n=1}^{i}(Y_n - \hat{Y}_n)^2$$

Where, i is the number of data points,

Y_n represents observed values,

$\hat{Y}_n$ represents predicted values.

4.3.6.2 RMSE

The root mean square error (RMSE) a type of measure of error. It is a very frequently used measure of the differences between value predicted value by an estimator or a model and the actual observed values. Root mean square error is defined as the square root of differences between predicted values and observed values.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{I}(\Pr edicted_n - Actual_n)^2}{I}}$$

The individual differences in this calculation are known as "residuals". The RMSE estimates the magnitudes of the errors. It is a good measure of accuracy which is used in order to perform comparison forecasting errors from different estimators for a certain variable, but not among the variables, since this measure is scale dependent.

4.3.6.3 R^2 VALUE

R-Squared (R^2 or the coefficient of determination) is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable. In other words, r-squared tells how well the data fit the regression model (the goodness of fit).R-squared can take any values between 0 to 1.Generally, a higher r-squared indicates a better fit for the model.

$$R^2 = 1 - \frac{SSE}{SSrr}$$

Where $SSE = \sum (x - \hat{x})^2$,

$SSrr = \sum (x - \bar{x})^2$,

x is the actual value

$\hat{x}$ is the predicted value of x,

and $\bar{x}$ is the mean of the x values.

4.3.7 Module 7 Comparison of Performance Metrics

In this module the performance metrics of both Deep Learning packages such as H2O and MXNet are compared with the existing techniques like SVR, CART, CHAID, GLR and ANN, to estimate which model gives the best prediction. The comparison of these models are done based on the error rate and the accuracy rate.

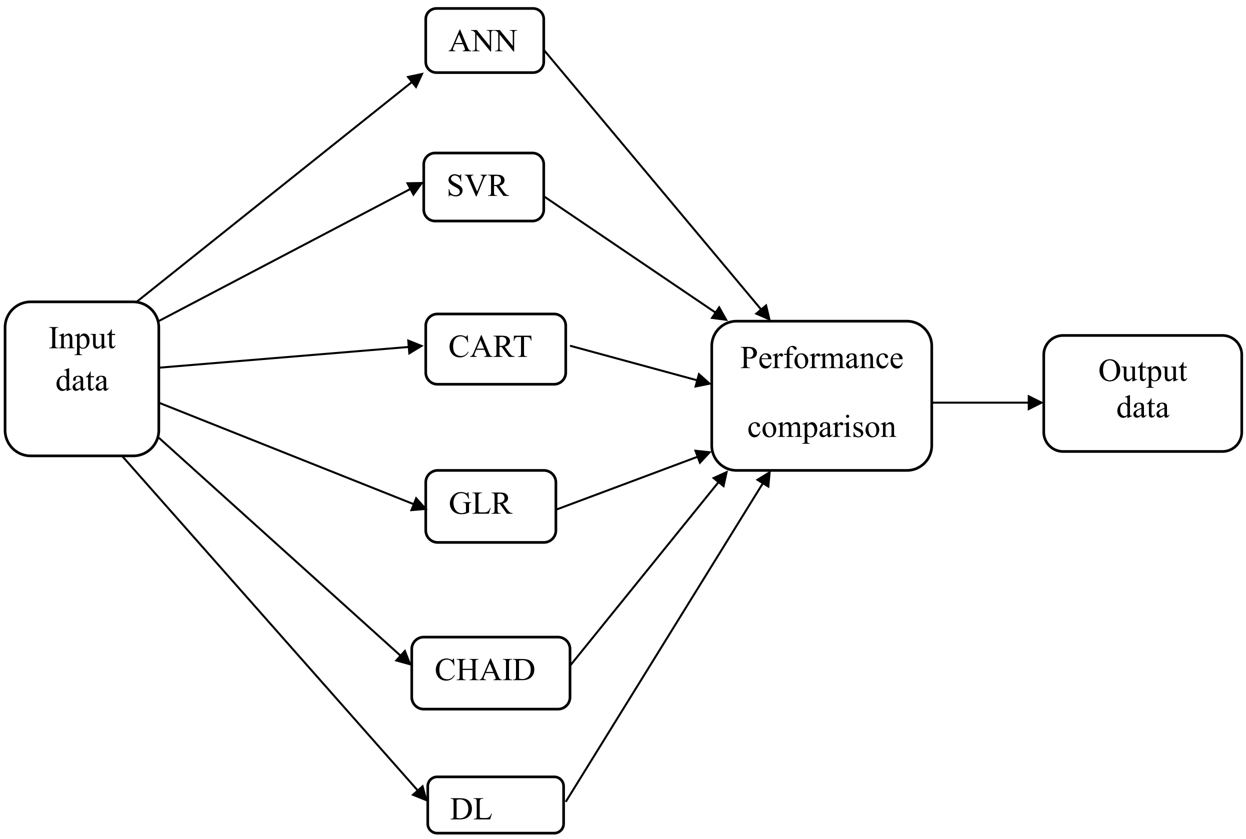

Fig 4.8 Comparison of performance metrics

4.3.8 Module 8 Best model

In this module the comparison results are discussed. Based on the comparison the best model is identified for prediction operation. The comparison is done between the existing and proposed technique and also between the two packages H2O and MXNet.

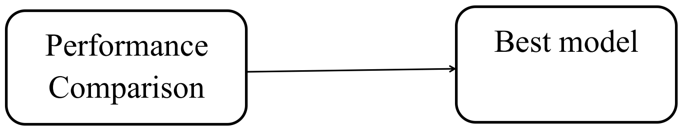

Fig 4.9 Best model

CHAPTER 5

REQUIREMENT SPECIFICATIONS

5.1 HARDWARE AND SOFTWARE SPECIFICATION

5.1.1 HARDWARE REQUIREMENTS

RAM : 4 GB

Hard Disk : 500 GB

Processor : Intel processor

Monitor : 15' LCD Monitor

5.1.2 SOFTWARE REQUIREMENTS

Front End : Java

Tools : R, R studio

Back End : MS-Excel

Operating System : Windows 10

CHAPTER 6
EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the result obtained from the experiment is discussed. Initially this project compare various existing machine learning algorithms like ANN, SVR, CART, CHID, GLR with the proposed machine learning technique Deep Learning. Then it also compares the performance metrics of two deep learning packages such as H2O and MXNet.

1. R-squared (R^2), which is the proportion of variation in the outcome that is explained by the predictor variables. In multiple regression models, R2 relates to the squared correlation between the observed outcome values and the predicted values by the model. The Higher the R-squared, the better the model.
2. Mean Squared Error (MSE), which measures the average error performed by the model in predicting the outcome for an observation. Mathematically, MSE is the average squared difference between the observed actual outcome values and the values predicted by the model. So, MSE = mean((observations - predictions)^2). The lower the MSE, the better the model.
3. Root Mean Squared Error (RMSE), which measures the average error performed by the model in predicting the outcome for an observation. Mathematically, the RMSE is the square root of the mean squared error *(MSE)*, RMSE = sqrt(MSE). The lower the RMSE, the better the model.

	CL			HL		
	MSE	**RMSE**	**R2**	**MSE**	**RMSE**	**R2**
ANN	2.8156	1.672	0.9682	0.3721	0.61	0.9961
SVR	2.7126	1.647	0.9702	**0.1197**	**0.346**	0.9982
CART	3.3892	1.841	0.9623	0.64	0.8	0.9921
CHAID	3.4559	1.859	0.9623	0.8262	0.909	0.9911
GLR	3.0276	1.74	0.9663	1.0795	1.039	0.9911
DL H2O	0.9965	0.9982	**0.99995**	0.9961	0.998	**0.9999**
DL MXNet	**0.7301**	**0.8544**	0.9027	0.7383	0.8592	0.9427

Table 6.1 Comparison of experimental results with DL

Results are reported in Table 6.1, by comparing the performance metrics MSE, RMSE and R-Squared. For showing which model is the best, the error rate and the R-squared value should be 0 to 1. If the error rate is <0.3 then the model is considered to be fit for prediction. If the R-squared is >0.7 then the model is considered to be strong in order to suggest that the model is best fit for prediction of building energy consumption performance.

Table 6.1 shows the cooling Load achieved by Deep Learning using MXNet gives the lowest error rate for the two measures MSE (0.7301), RMSE (0.8544) and Deep Learning using MXNet achieved the highest R-Squared value (0.9027). SVR gives the second lowest error rate for the two measure MSE (2.7126), RMSE (1.647) and also achieved the highest R-Squared value (0.9702). ANN achieved the third lowest error rate, MSE (2.8156), RMSE (1.672) and the R-Squared value (0.9682). GLR achieved the fourth lowest error rate for the two measures MSE (3.0276), RMSE (1.74) and highest R-Squared value (0.9663). For the cooling Load CART achieved the fifth lowest error rate for the two measures MSE (3.3892), RMSE (1.841) and also achieved the highest R-Squared value (0.9623). CHAID achieved the sixth lowest error rate for the two measures MSE (3.4559), RMSE (1.859) and also achieved the highest R-Squared value (0.9623).

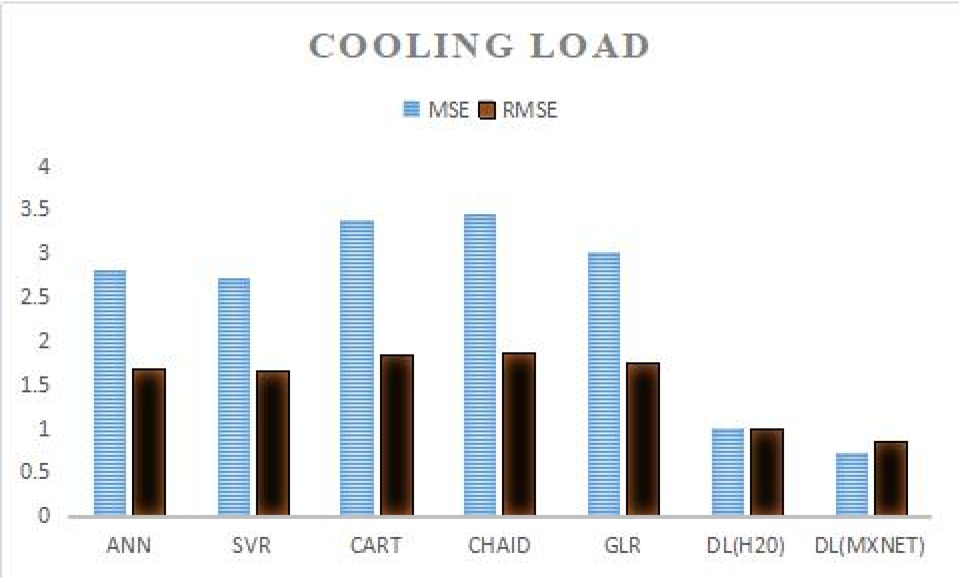

Fig 6.1 Comparison of cooling load for RMSE and MSE

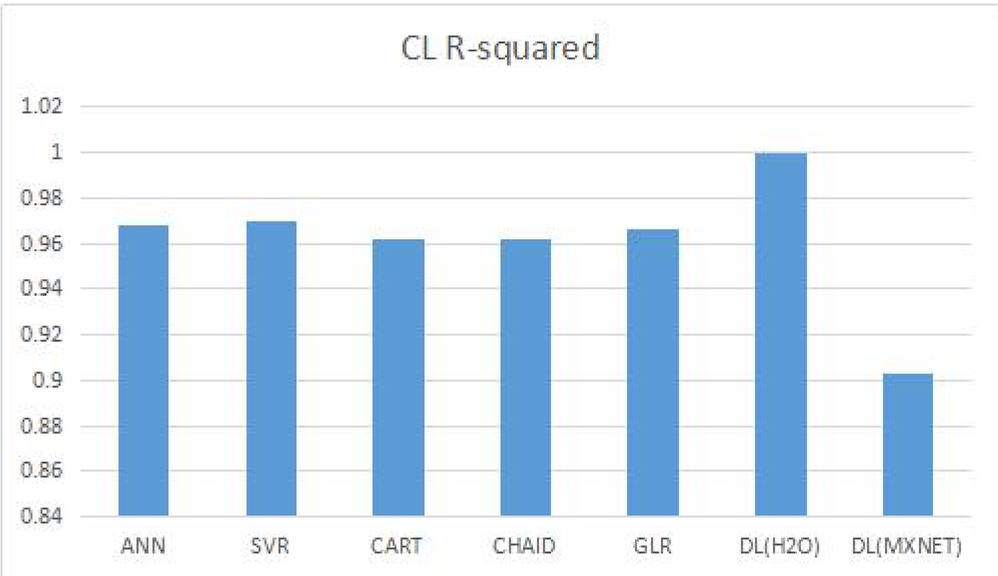

Fig 6.2 Comparison of cooling load for R^2

For the Heating Load SVR achieved the lowest error rate for the two measures MSE (0.1197), RMSE (0.346) and also achieved the highest R-Squared value (0.9982). ANN achieved the second lowest error rate in all the two measure MSE (0.372), RMSE (0.61) and also achieved the highest R-Squared value (0.9961). For the Heating Load CART achieved the third lowest error rate in all the two measure MSE (0.64), RMSE (0.8) and also achieved the highest R-Squared value (0.9921). For the Heating Load CHAID achieved the fourth lowest error rate in all the two measure MSE (0.8262), RMSE (0.909) and also achieved the highest R-Squared value (0.9911). For the Heating Load DL achieved the fifth lowest error rate for the two measures MSE (0.7383), RMSE (0.8592) and also achieved the highest R-Squared value (0.9427). For the Heating Load GLR achieved the sixth lowest error rate in all the two measure MSE (1.0795), RMSE (1.039) and also achieved the highest R-Squared value (0.9911).

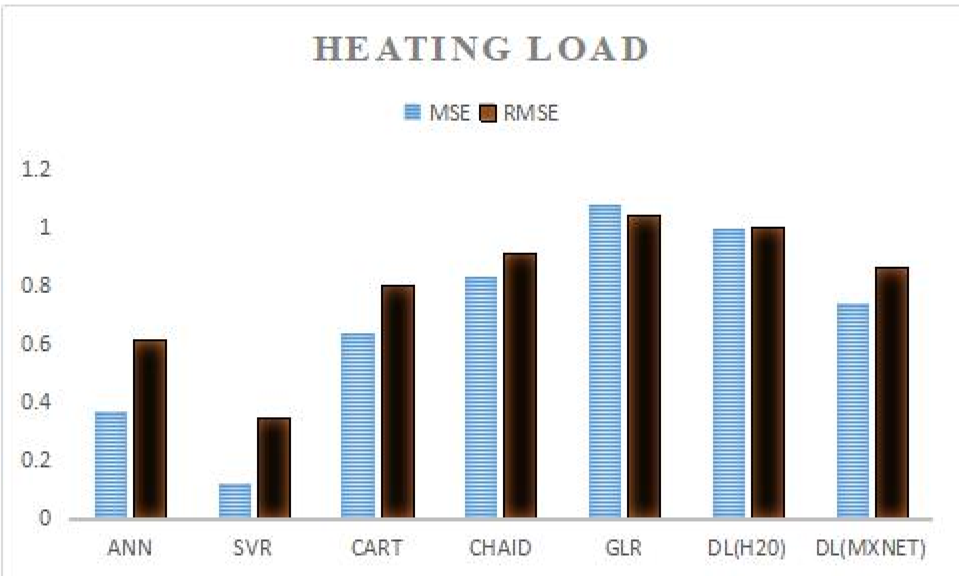

Fig 6.3 Comparison of heating load for RMSE and MSE

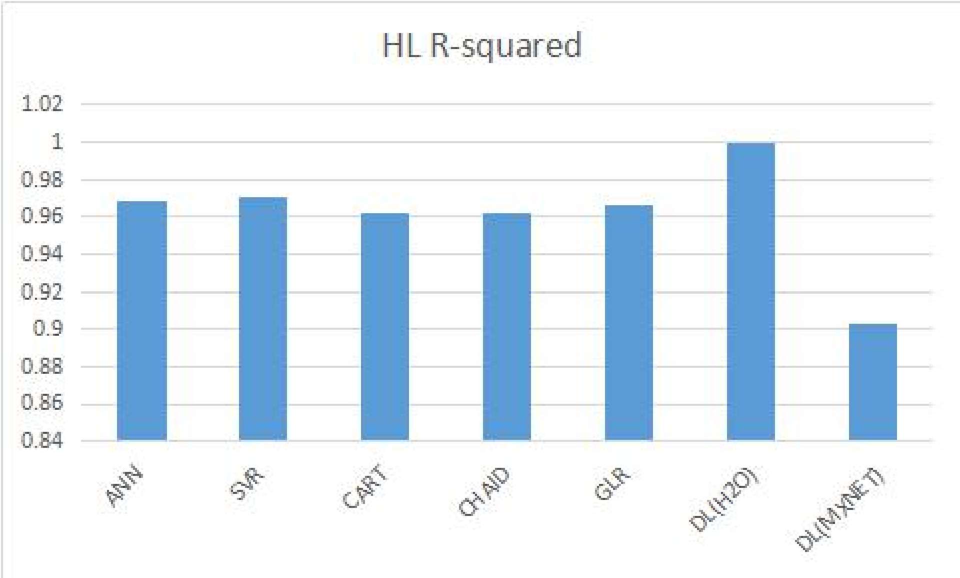

Fig 6.4 Comparison of heating load for R^2

The experimental results clearly shows that in the proposed deep learning model the MSE is very low (0.7301) and RMSE is also very low (0.8544) for the cooling load while using MXNet package and the R-squared value is high (0.99995) for cooling load while using H2O package compared to the existing techniques. The MSE for heating load (HL) is moderate and RMSE is also moderate in both the deep learning packages than the other existing methods, but the R-squared value is high (0.9999) in the H2O package than all the other existing techniques.

Therefore the proposed deep learning model provides high accuracy for prediction of both CL and HL. Hence proposed deep learning techniques is most suitable algorithm for predicting the CL and HL because it gives high accuracy compared to the existing techniques.

CHAPTER 7

CONCLUSION

Different machine learning techniques, like ANN, SVR, CART, CHAID and GLR’s working performance are compared with simulated building design to predict HL and CL. The proposed deep learning method effectively performed in various environmental applications like building energy consumption. Several building features were utilized as input feature to HL and CL. 768 simulated building designs are used for this prediction model.

A cross-validation process is applied to the generated model and their performance are compared. The experimental results illustrate the suitable machine learning algorithm for predicting energy consumption for the building designs. This project also authorizes that the deep learning model extensively expand the performance in forecasting CL and HL, correspondingly. It similarly diminishes the quantity of effort needed for prediction. The strength and forecasting correctness of the proposed algorithm are greater than the previous models. Hence, the deep learning model delivers a best idea for the emerging building energy consumption performance system in future works.

The proposed algorithm is very easy to utilize, and take less number of metrics and tests to regulate when compared to building simulation software. The Support Vector Regression can be the suitable forecasting model for Heating Load while the proposed Deep Learning model is most suitable for Cooling Load prediction. The proposed deep learning algorithm is an effective algorithm for planning and examining energy efficient building designs, it can perform a significant role in the energy preservation. It’s also, a rapid and exact forecasting method for measuring the buildings CL and HL, that can help engineers, architects to construct efficient building design. Hence, its minimize the cost to build energy efficient building and further time of the building works.

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