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A Simple and Easy Approach for Home Appliances Energy Consumption Prediction in Residential Buildings Using Machine Learning Techniques

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ABSTRACT

The accurate analysis of energy consumption by home appliances for future energy management in residential buildings is a challenging problem due to its high impact on the human surrounding environment. In this paper, a prediction methodology is presented for energy consumption of home appliances in residential buildings. The aim of the paper is the daily power consumption prediction of home appliances based on classification according to the hourly consumed power of all home appliances being used in residential buildings. The process consists of five stages: data source, data collection, feature extraction, prediction, and performance evaluation. Different machine learning algorithms have been applied to data containing historical hourly energy consumption of home appliances used in residential buildings. We have divided data into different training and testing ratios and have applied different quantitative and qualitative measures for finding the prediction capability and efficiency of each algorithm. After performing extensive experiments, it has been concluded that the highest accuracy of 98.07% has been observed for Logistic Regression for 70-30% training, and testing ratio. The Multi-Layer Perceptron and Random Forest have achieved 96.53%, 96.15% accuracies for 75-25%, training, and testing ratios. The accuracy of KNN was 94.96% with 60-40% training, and testing ratios. For finding the further effectiveness of the proposed model, cross-validation with different folds have been applied. Each classifier also shows significant variations in the performance with different ratios of training and testing proportions.

KEYWORDS: Energy Prediction, Home appliances, Power management, Multi-layer Perceptron, K-Nearest Neighbors, Logistic Regression, Random Forest.

1 INTRODUCTION

The modern power management systems face different challenges to manage the power in an efficient manner. The major drawback associated with power management systems is mostly their manual operation. For making the power management systems more efficient and reliable, the automation of these systems is very compulsory. The energy management systems are made fully automatic with the introduction of the concept of smart grids. The major components of the power management system, including sensors, actuators, and other components are integrated into the smart grid for bringing enhancements in the overall functionalities of power management systems [1].

To bring improvements in energy consumption and minimizing the energy cost, the smart grid makes use of modern technologies for efficient operation, planning, and maintenance of the whole energy management system [2]. The smart grid has strong ability to handle complex tasks of performing the self-healing ability, active involvement of the energy consumers in the smart grid operation; handling the external attacks, provide high-quality energy to customers and efficient management of energy by the energy markets for providing power to the end users.

The smart grid also ensures an efficient production of energy according to the demands of the end users. The energy market plays a vital role in setting prices of energy according to the energy production, supply, and consumption. For getting good prices of energy, a higher accuracy for the next day energy consumption prediction is very compulsory. The energy consumption by home appliances represents a large proportion of total energy consumption and therefore, energy suppliers have strongly focused on the residential sector. The interaction between smart homes and smart grids is described in Figure, 1.

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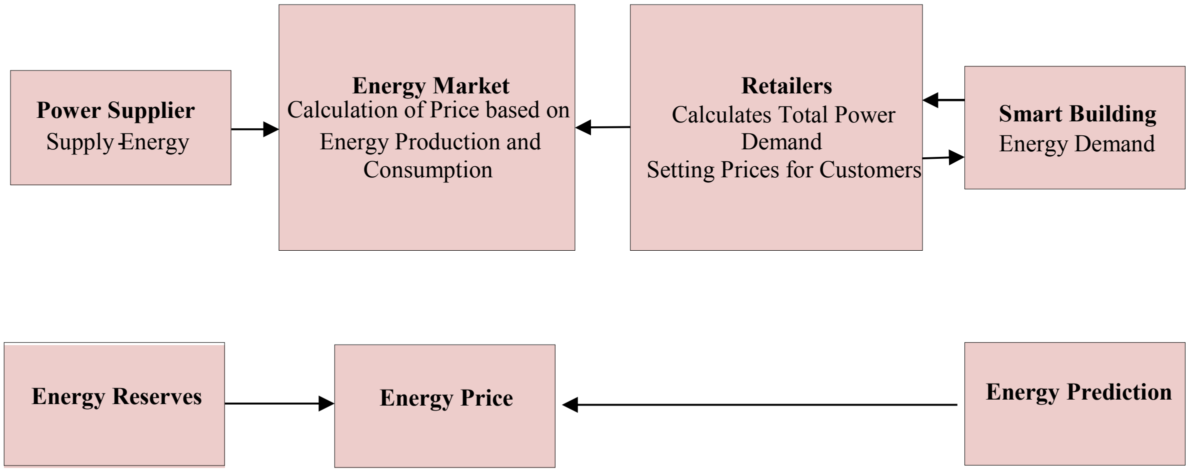

Figure 1: Interaction between smart homes and smart grid

A large portion of total power consumption is represented by the residential sector and therefore the energy consumption prediction of the housing sector is of vital importance. For energy consumption prediction in the residential sector, many approaches have been proposed and developed. An important approach of these approaches is the bottom-up approach.

According to the bottom-up approach, first, energy consumption of individual home appliances is predicted on the hourly or daily basis. Based on energy consumption of individual home appliances, the total energy of the whole home is predicted. The prediction of energy consumption by individual home appliances is very important but in order to manage the supply of energy to the residential sector, the total energy consumption prediction irrespective of individual home appliances is very important.

The main aim of this paper is to predict daily energy consumption of all the home appliances based on hourly consumption of appliances. The purpose is to divide the whole daily energy consumption of appliances into either low power consumption or high power consumption which will help the power supplier in making the proper decision in energy provision to their customers. This prediction will also be helpful in managing the automation system of the residential building [3].

A three layer energy management system has been presented for the management of the smart environment by authors in [4], as shown in the figure, 2. The three layers in which the authors have divided the whole energy management systems are the local layer, anticipative layer and reactive layer. All types of predictions e.g. weather prediction, energy prediction, cost prediction and other types of predictions are the responsibility of the anticipative layer. The anticipative layer provides complete information to the reactive layer to assist in functionalities.

The reactive layer is responsible for providing this information to the local layer where it is used for controlling the status of home appliances for achieving the user comfort. The power consumption by different home appliances at the local layer is transferred to the anticipative layer for forecasting. There is also the external layer that helps the power supplier to supply energy to customers according to their demands. There are different sources of energy, for suppliers to get the energy like hydropower plant, a thermal power plant, renewable resources and nuclear power plant [5].

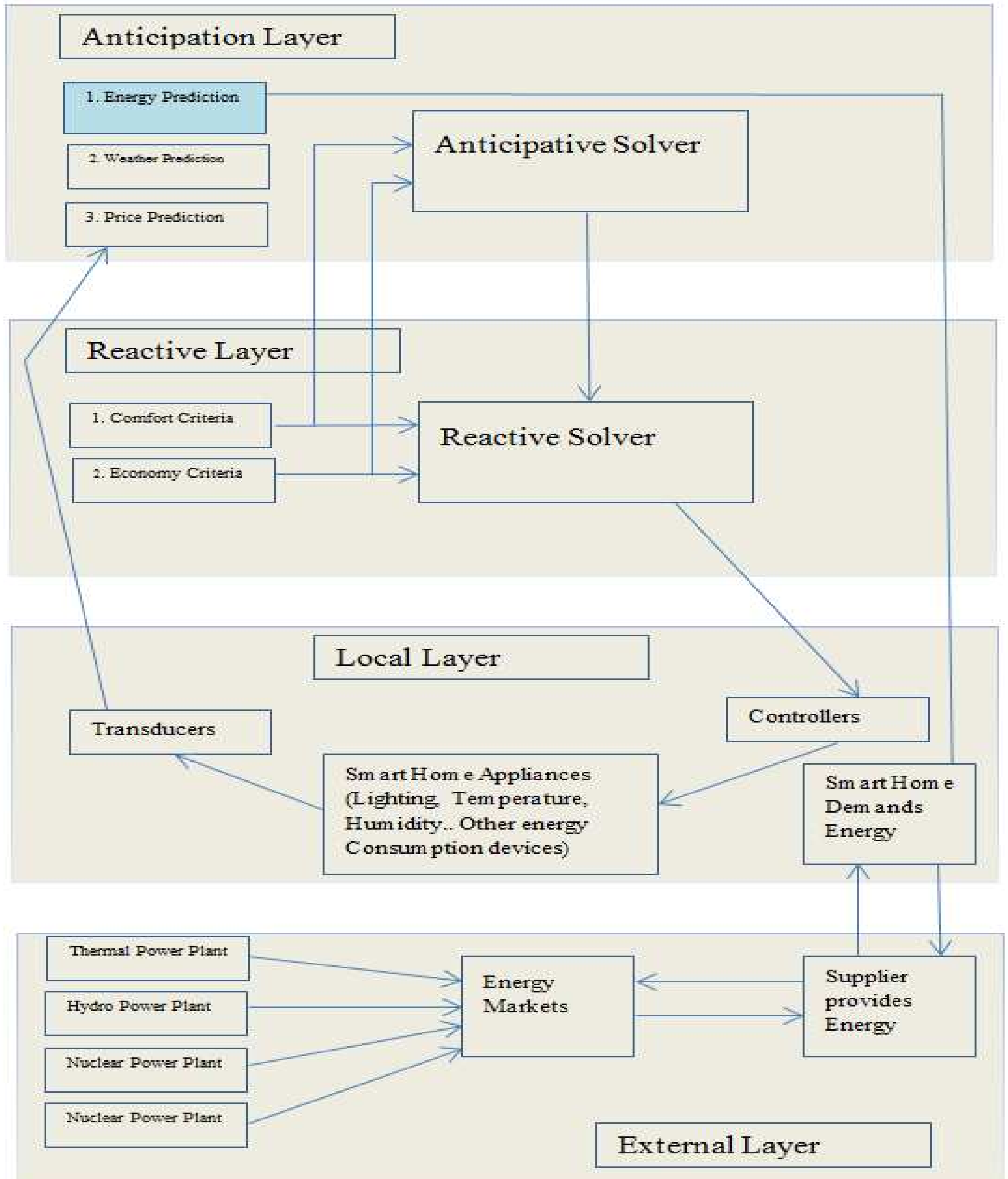

Figure 2: Interaction among different components in energy management system

Many techniques and methods have been proposed for power consumption forecasting. For short-term power forecasting, neural networks have been applied in [6] and [7]. Time series and regression models have been proposed in [8] for load prediction. The authors in [9] have discussed the applications of different prediction methodologies for different purposes. For short-term energy prediction, the authors in [10] and [11] applied Kalman filter. For power prediction, management and optimization in residential buildings, the authors in [12] applied Genetic Algorithm (GA). The authors in [13] and [14] applied the Fuzzy Logic for short-term energy prediction whereas the authors in [15] and [16] applied a Fuzzy Neural Network for the same purpose. Some authors have applied hybrid models for different types of forecasting which are the combinations of some statistical methods with the artificial neural network e.g. the authors in [17], [18], [19], [20], [21] and [22] applied these hybrid models for forecasting.

Bayesian neural networks have been applied in [23], [24] whereas the authors in [25] and [26] applied Decision Trees for classification and prediction. Decision Tables have been applied in [27] for classification. In this paper, Multi-Layer Perceptron, Logistic Regression, K-Nearest Neighbors and Random Forest have been applied for the prediction of energy consumption of home appliances. A linear regression model was developed by the authors in [28] to evaluate the thermal consumption that takes into consideration both the cooling and the heating load for two residential buildings in Switzerland, some office buildings and also some industrial buildings. The air temperature difference between the outside and inside was considered as the independent variable, which considered both the internal and solar heat gains. A high impact on heat and solar gains was observed especially during the cooling season. The authors in [29], [30] developed a model that simulates the cooling and heating thermal loads of commercial buildings located in the USA. The research presented by these authors was based on an in-depth analysis of temperature, solar radiation, and humidity. For analysis of the effects of different parameters, the Fourier series of data was considered. The authors in [31] conducted a study that was based on some non-residential buildings of South Korea for the annual energy consumption. A model was created for simulation of yearly energy consumption that considered the energy consumed and the outside average temperature. A very high deviation was observed for one day and one week control period, whereas a satisfactory result was reported for three months control period. A linear regression model was developed in [32] for the monthly energy consumption prediction of residential buildings in some areas of France. The authors have considered different parameters for an accurate prediction. The parameters considered were the compactness of buildings, the ratio of opaque and glass surfaces, the thermal diffusion of roof and walls and the time constant of buildings. A maximum deviation of 5.1% between the actual and calculated consumption was observed whereas the average deviation observed in the simulation was 2%. The authors have concluded that the energy consumption can be optimized by keeping in consideration the strong relationship between the building compactness and the heat consumption during the construction of buildings. Some other parameters e.g. thermal inertia has also noticeable impact. The authors in [33] applied artificial bee colony and fuzzy controllers to effectively manage the energy consumption inside the residential buildings. The authors in [34] have applied random forest for energy consumption prediction based on classification to divide the power consumption into either low power consumption or high power consumption of the home appliances being utilized by the residential buildings. The accuracy observed by the authors was 94.87 for 70-30% training and testing ratios. The authors in [35] used K-nearest neighbors for the classification of the apartments into either low power consumption apartments or the high power consumption apartment based on energy consumption of appliances. The prediction accuracy observed by the authors was 95.96% for 60-40% training and testing ratios. In our proposed approach, the accuracy of 98.07% has been observed for Logistic Regression for 70-30% training and testing ratio. The Multi-Layer Perceptron and Random Forest have achieved 96.53%, 96.15% accuracies for 75-25%, training, and testing ratios. The accuracy of KNN was 94.96% with 60-40% training, and testing ratios, which is higher than the results, previously reported in the published literature.

2 PROPOSED METHODOLOGY

In the proposed approach we have presented a prediction model which is based classification of historical energy consumption data of home appliances, and this type of model is one of the simplest models for forecasting. The process consists of five stages: data source, data collection, feature extraction, prediction, and performance evaluation. The proposed method is shown in Figure 3.

2.1. Data Source

The data containing hourly consumption of all the home appliances collected from 400 houses has been used for experimentation.

2.2. Data Collection

In this stage, the historical hourly consumed energy of home appliances on the daily basis is collected from all the appliances and stored in a database for retrieval to be processed further for prediction.

2.3. Feature Extraction

In the feature extraction stage, the hourly consumed energy of home appliances is retrieved from the database and statistical features like mean, variance, skewness and kurtosis on the hourly energy consumption basis are calculated. The description of statistical features is provided in the table 1.

In table 1, xi represents the power consumption of appliances over the ith hour of the day where i = 0, 1, 2, 23. N represents the total number of hours i.e. 24. M (μ) represents mean, V represents variance, S represents skewness and K represents Kurtosis.

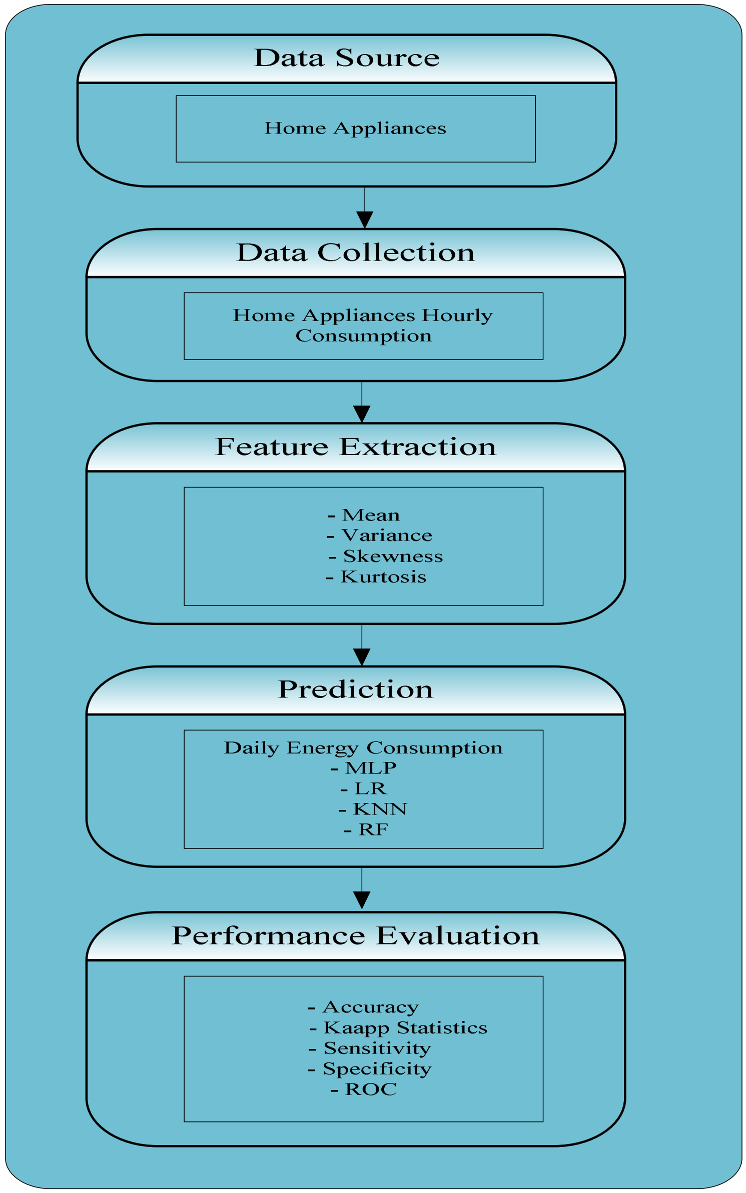

Figure 3: Proposed Methodology

Table 1. Extracted Features

Feature	Equation	Description
Mean	$M = \frac{1}{N}\sum_{i=1}^{N} x_i$	Mean represents the average of hourly energy consumption over the whole day.
Variance	$V = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$	Variance represents the variations in the hourly energy consumption over the whole day.
Skewness	$S = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^3$	Skewness represents the asymmetry in the hourly energy consumption over the whole day.
Kurtosis	$K = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^4$	It represents peakedness or frequency of extreme hourly energy consumption over the whole day.

2.4.Prediction

In the prediction stage, energy consumption is predicted according to the daily power consumption of all the home appliances based on their hourly consumed power. For the prediction, four predictors: Multi-Layer Perceptron, Logistic Regression, K-Nearest Neighbors and Random Forest have been used.

2.5. Performance Evaluation

The performance of all classifiers has been evaluated using Sensitivity (SE), Accuracy (AC), Specificity (SP), Kappa Statistics (KS) and the ROC for each classifier as described in the table 2.

Table 2. Performance Measurements

Evaluation Parameter	Equation
Accuracy	(TP+TN)/(TP+TN+FP+FN)
Sensitivity (TPR)	TP/(TP+FN)
Specificity	TN/(TN+FP)
False Positive Rate (FPR)	FP/(FP+TN)
ROC	TPR, FPR required to draw the curve
KS	(P0-PC/(1-PC))

Where
TP = True Positive: High Power Consumption Identified as High Power Consumption.
TN = True Negative: Low Power Consumption Identified as High Power Consumption.
FP = False Positive: Low Power Consumption Identified as Low Power Consumption.
FN = False Negative: High Power Consumption Identified as Low Power Consumption.
P0 represents total agreement probability; PC represents hypothetical probability of chance agreement.

3 CLASSIFIERS

3.1.Multi-layer Perceptron

The multi-layer perceptron is a type of artificial neural network with two or more than two layers. In the proposed approach, three layers neural network with one input, one hidden and one output layer has been used. In multi-layer perceptron, each layer consists of computation nodes known as artificial neurons. The artificial neurons may also be called as perceptron due to which the artificial neural network may also be called as the network of a perceptron.

In machine learning, a multi-layer perceptron is a supervised technique in which the output is obtained from a given set of inputs. It is a linear classification approach that combines some weights to the inputs to map them to the output. In order to solve the complex computational task, neurons work in groups known as layers. In multi-layer perceptron, there are many layers which are connected to each other via directed graphs. Neurons in each layer are fully connected to each neuron in the next layer.

Multi-layer perceptron uses back propagation supervised learning technique for training. Neurons form a linear combination for the calculation of the single output from multiple inputs. The calculation has been carried out on the basis of weights of inputs and some activation function. The experimental results for multi-layer perceptron are shown in the Table 3.

3.2. Logistic Regression

The logistic regression classifier is a probabilistic classifier which is mainly applied for the purpose of binary classification. The logistic classifier uses two types of variables (dependent and independent) for classification. The independent variables are the inputs of the classifier whereas the dependent variables are the output of the classifier. In order to find the probability for the description of the outcome of the input variables, a function is known as a logistic function is used the logistic classifier. The logistic classifier uses a logistic function to find the probability of input vector (combinations of different input variables) belonging to a specific class. The logistic function always takes values between 1 and 0 [36]. The logistic function can be mathematically represented by(1).

$$F(y) = \frac{1}{1 + e^{-y}} \tag{1}$$

Where F (y) is known as a logistic function or the function of input (independent) variable and e represents the exponential function.

If y is the linear function of a single input variable x or several input variables, then the logistic function can be mathematically expressed by (2).

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \quad (2)$$

Where F (x) represents the probability of the outcome of input vector, β_0 represents the intercept of linear regression, $\beta_1 x$represents the regression coefficient of value of input variable.

The mathematical expression of $\beta_1 x$ for more than on input variables will be(3).

$$B0 + \beta_1 x_{1+} \beta_2 x_{2+} \ldots\ldots\ldots\ldots\ldots B_m xm \quad (3)$$

The logit function which is the inverse of the logistic regression function can be given by (4).

$$g(x) \quad = \quad \ln\frac{F(x)}{1 - F(x)} = \beta_0 + \beta_1 x \quad (4)$$

The Logistic regression model is mainly used for the prediction of the odds: which combination of input variables will belong to some given class. The experimental results for logistic regression are shown in the table 4.

3.3. K-Nearest Neighbors (KNN)

Many data mining and machine learning applications use a well-known instance-based learning algorithm known as K-Nearest neighbors [37],[38]. In K-Nearest Neighbor classification approach, the data sets are divided into training and testing data sets. The training data set, have input vectors whose class labels are known whereas in the testing data set, the input vectors of class labels are not known. The first phase of classification is called training in which the data set for which class labels are known is provided to the classifier for training. The second phase is testing in which the data set whose class labels are not known is provided to the trained classifier for testing. The classifier decides the class of the unknown dataset on the basis of training data. The experimental results for KNN are shown in table 5.

3.4.Random Forest (RF)

Random forest classifier is considered to be one of the most popular and strongest ensemble classifiers that have been applied in many classification and pattern recognition applications. [39]. The major drawback associated with the decision tree is that it has high variance.

The hierarchical nature can result in the different decision tree for the training data set having small changes in the data for which the classifier is trained. A small error near to the root node can be propagated to the leaves. For bringing stability in the classification capability of decision tree classifier, the authors in [39],[40], and [41] proposed the methodology called decision forest.

Random forest is an ensemble classifier of decision trees. It can be considered as a classifier containing different classification methods or one method having several parameters. Suppose we have a learning set L = ((m1, n1),.., (mi, ni)) with i vectors with m ∈X and n ∈Y where X represents the observations and Y represent the class labels. For the prediction of a class, the classifier performs the mapping X → Y. Each individual tree in the forest is used for the classification of the instances. The experimental results for RF are shown in table 6.

4 EXPERIMENTAL SETUP AND RESULTS

The experiments were carried out on Intel (R) Core (TM) 2 Quad CPU with 3.25 GB of RAM. For the results' computation, both MATLAB R2010a and Weka 3.7 were used. The classification results for multi-layer perceptron (MLP), logistic regression (LR), K-nearest Neighbors (KNN) and random forest (RF) for different training/testing ratios and cross-validations are shown in table 3-6.

Table 3. Different types of accuracies' measures for different training and testing ratio of MLP

Ratios (Training, Testing)	Prediction Accuracy	Kappa Statistics	Sensitivity	Specificity	ROC Area
30-70%	91.8269	0.8176	0.918	0.918	0.972
40-60%	91.9231	0.8231	0.922	0.919	0.968
50-50%	92.3077	0.8091	0.923	0.923	0.978
60-40%	92.6282	0.8306	0.927	0.926	0.969
70-30%	93.5897	0.8479	0.936	0.936	0.990
75-25%	96.5385	0.9198	0.965	0.965	0.990
80-20%	95.3846	0.8902	0.955	0.954	0.989
10-Fold Cross Validation	95.5769	0.8974	0.956	0.956	0.989
5-Fold Cross Validation	95.1923	0.8885	0.952	0.952	0.988

Table 4. Different types of accuracies' measures for different training and testing ratio of LR

Ratios (Training, Testing)	Prediction Accuracy	Kappa Statistics	Sensitivity	Specificity	ROC Value
30-70%	94.5055	0.8752	0.945	0.945	0.977
40-60%	94.8718	0.8846	0.949	0.949	0.981
50-50%	95.3846	0.8902	0.955	0.954	0.992
60-40%	95.1923	0.8818	0.952	0.952	0.990
70-30%	98.0769	0.9566	0.981	0.981	0.990
75-25%	96.5385	0.9229	0.966	0.965	0.985
80-20%	96.1538	0.9087	0.962	0.962	0.994
10-Fold Cross Validation	95.7692	0.9030	0.958	0.958	0.983
5-Fold Cross Validation	95.3846	0.8935	0.954	0.954	0.986

Table 5. Different types of accuracies' measures for different training and testing ratio of KNN

Ratios (Training, Testing)	Prediction Accuracy	Kappa Statistics	Sensitivity	Specificity	ROC Value
30-70%	92.7500	0.8515	0.928	0.928	0.964
40-60%	94.1923	0.8821	0.942	0.942	0.960
50-50%	94.0000	0.8787	0.940	0.940	0.969
60-40%	94.9615	0.8969	0.950	0.950	0.972
70-30%	94.7692	0.8927	0.948	0.948	0.975
75-25%	94.3846	0.8835	0.944	0.944	0.967
80-20%	94.1923	0.8762	0.943	0.942	0.965
10-Fold Cross Validation	93.6154	0.8645	0.936	0.936	0.968
5-Fold Cross Validation	91.6923	0.8213	0.917	0.917	0.906

Table 6. Different types of accuracies' measures for different training and the testing ratio of RF

Ratios (Training, Testing)	Prediction Accuracy	Kappa Statistics	Sensitivity	Specificity	ROC Value
30-70%	91.2088	0.7941	0.913	0.912	0.978
40-60%	92.9487	0.8317	0.930	0.929	0.988
50-50%	93.4615	0.8519	0.934	0.935	0.979
60-40%	93.8462	0.8516	0.941	0.938	0.993
70-30%	94.8718	0.8819	0.951	0.949	0.986
75-25%	96.1538	0.9063	0.962	0.962	0.994
80-20%	95.1923	0.8893	0.955	0.952	0.985
10-Fold Cross Validation	94.0385	0.8590	0.941	0.940	0.984
5-Fold Cross Validation	92.5	0.8202	0.926	0.925	0.981

5 RESULTS COMPARISON

The authors in [34] have applied random forest for energy consumption prediction based on classification to divide the power consumption into either low power consumption or high power consumption of the home appliances being utilized by the residential buildings. The accuracy observed by the authors was 94.87 for 70-30% training and testing ratios. The authors in [35] used K-nearest neighbors for the classification of the apartments into either low power consumption apartments or a high power consumption apartment based on energy consumption of appliances. The prediction accuracy observed by the authors was 95.96% for 60-40% training and testing ratios. In the proposed method the highest accuracy of 98.07% has been observed for Logistic Regression for 70-30% training and testing ratio. The Multi-Layer Perceptron and Random Forest have achieved 96.53%, 96.15% accuracies for 75-25%, training and testing ratios. The accuracy of KNN was 94.96% with 60-40% training, and testing ratios, which is higher than the results, previously reported.

6 DISCUSSION

In this section, comparisons of all the predictors for percentage split, cross-validation, and accuracy, sensitivity, specificity, Kappa Statistics and the ROC for both the percentage split and cross-validation of each predictor have been graphically compared. Figure 4-8 show the prediction accuracy, Kappa Statistics, Sensitivity, specificity and ROC comparison of all the predictors. If critically analyzed, different predictors give different accuracies for different training and testing ratios, which shows the effectiveness of different predictors for different conditions, but overall the logistic regression and multi-layer perceptron prove to be the best predictors as compared to the state of the art classifiers.

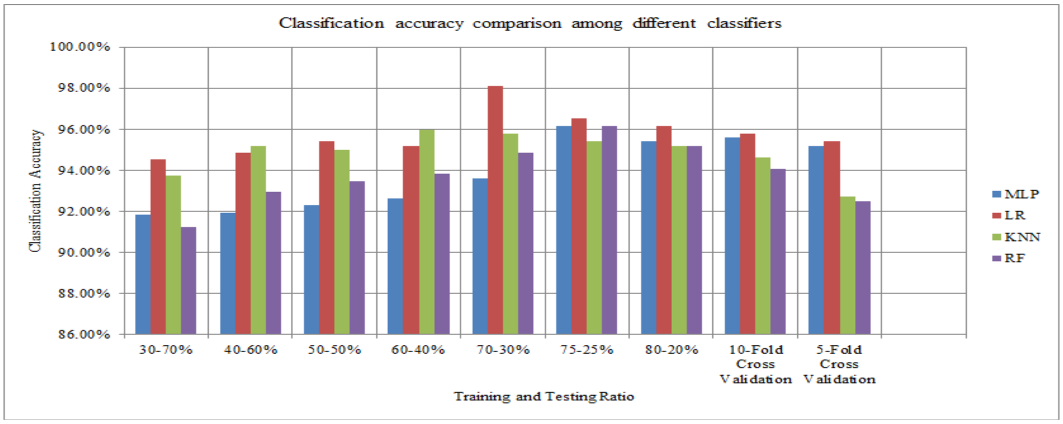

Figure 4: Comparative analysis of accuracies of predictors for different training and testing ratios 1. Multi-layer Perceptron (MLP) 2. Logistic Regression (LR) 3.K-Nearest Neighbors (KNN) 4. Random Forest (RF)

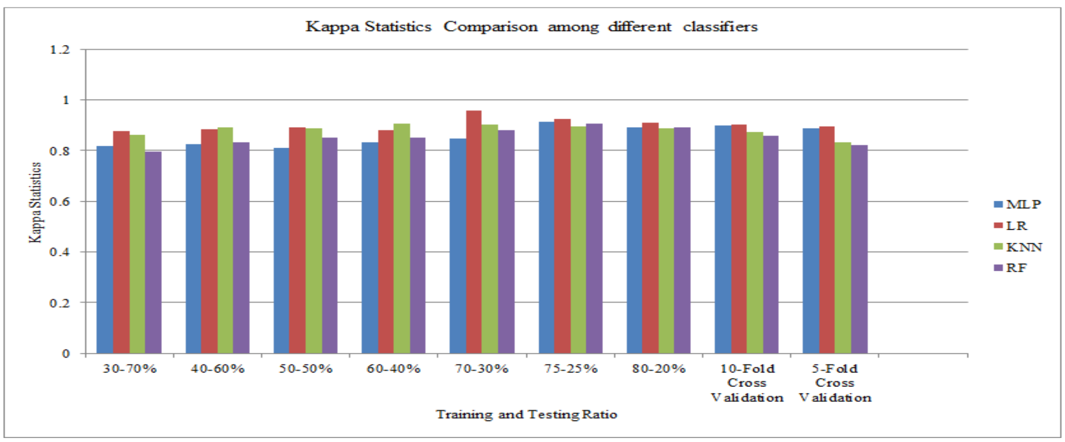

Figure 5: Comparative analysis of Kappa Statistics of predictors for different training and testing ratios 1. Multi-layer Perceptron (MLP) 2. Logistic Regression (LR) 3. K-Nearest Neighbors (KNN) 4. Random Forest (RF)

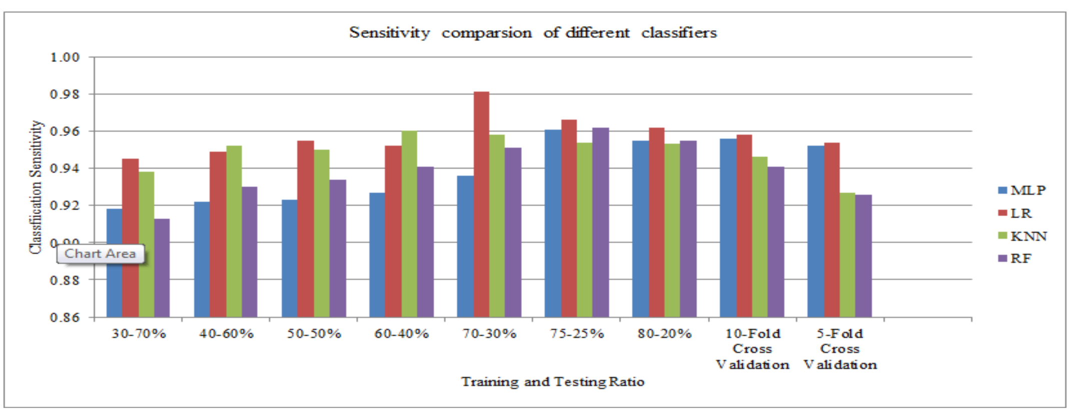

Figure 6: Comparative analysis of sensitivity of predictors for different training and testing ratios 1. Multi-layer Perceptron (MLP) 2. Logistic Regression (LR) 3.K-Nearest Neighbors (KNN) 4. Random Forest (RF)

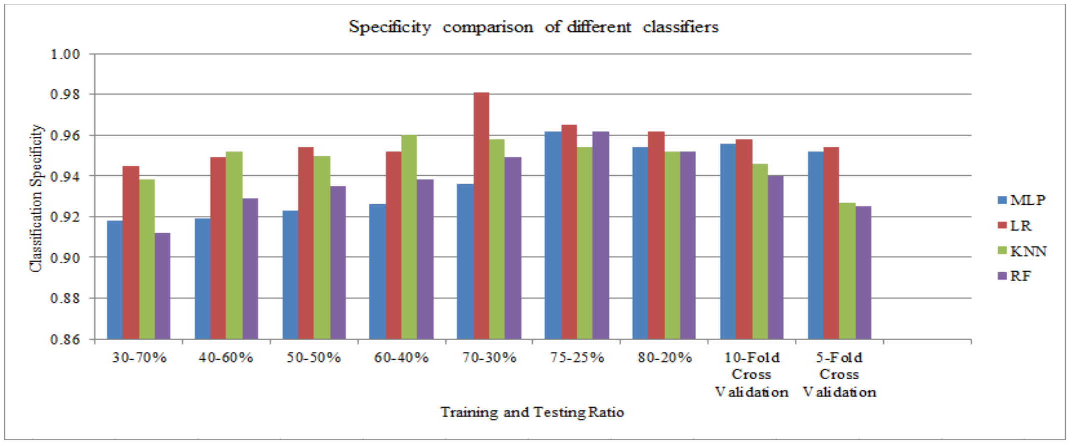

Figure 7: Comparative analysis of specificity of predictors for different training and testing ratios 1. Multi-layer Perceptron (MLP) 2. Logistic Regression (LR) 3. K-Nearest Neighbors (KNN) 4. Random Forest (RF)

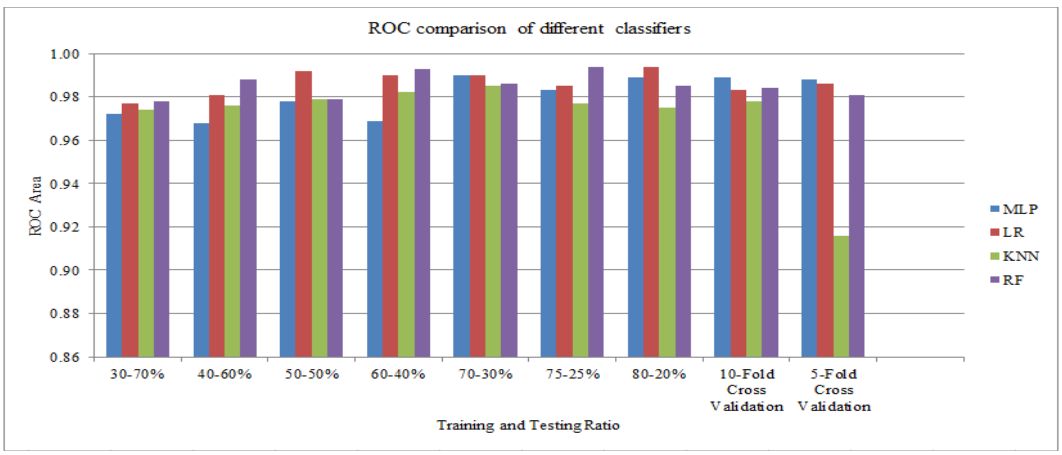

Figure 8: Comparative analysis of the ROC of predictors for different training and testing ratios 1. Multi-layer Perceptron (MLP) 2.Logistic Regression (LR) 3.K-Nearest Neighbors (KNN) 4. Random Forest (RF)

7 CONCLUSION

The prediction of power consumed by home appliances is very important for overall better production, distribution, and management of energy being used by the residential sector. In this work, the focus has been on the hourly daily power consumption prediction of home appliances. The prediction will be helpful in the better management of energy requirements by the residential sector.

In this work, a simple model of energy consumption prediction has to be developed that will be helpful for better organization of energy production and consumption. This will also help the energy management system in setting the prices of energy according to consumption of different residential buildings. In this paper, we have performed the prediction of energy consumption in residential buildings based on classification.

The process of prediction consists of five stages. Four predictors multi-layer perceptron, logistic regression, K-Nearest Neighbors and random forest have been used for prediction based on classification. The whole data set consists of data of appliances of400 residential buildings which were divided into different training and testing ratios. After performing extensive experiments, it has been concluded that the highest accuracy of 98.07% has been observed for Logistic Regression for 70-30% training and testing ratio. The Multi-Layer Perceptron and Random Forest have achieved 96.53%, 96.15% accuracies for 75-25%, training and testing ratios. The accuracy of KNN was 94.96% with 60-40% training, and testing ratios.

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