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Appliance Energy Prediction Using Time Series Forecasting: A comparative analysis of different Machine Learning Algorithms

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Abstract: *Energy prediction of appliances requires identifying and predicting individual appliance energy consumption when combined in a closed chain environment. This experiment aims to provide insight into reducing energy consumption by identifying trends and appliances involved. The proposed model tries to formalize such an approach using a time series forecasting- based process that considers the correlation between different appliances. The entire work has been conducted in two parts. The first part highlights and identifies the energy consumption trends. The second part focuses on the comparison and analysis of different algorithms. The main objective is to understand which algorithm provides a better result in predicting energy consumption. A comparison of algorithms for appliance usage prediction using identification and direct consumption reading is presented in this paper. The work is presented on real data taken from the REMODECE database, which comprises 19,735 instances with 29 attributes. The data records the energy for 10 minutes over about 4.5 months.*

Keywords: Energy, Prediction, Algorithm, Data.

INTRODUCTION

Time series forecasting helps to understand future values by predicting the upcoming outcome based on past observations. Appliance energy prediction requires the usage of the past data and gathering its insight over the period. This is exactly where time series forecasting will be very much useful. Appliance energy prediction has been an essential topic of research over a period where researchers are continuously trying to find better and more efficient ways to predict the energy utilization of appliances with more accuracy [1], [2], [3] [4], [5]. A study done in the UK highlighted a 10.2% increase in electrical consumption for domestic buildings, appliances, televisions, and consumer electronics [6]. It makes sense that energy prediction will play an essential role in smart homes and smart cities. Reducing energy consumption in the present scenario is highly important, considering the financial burden and resource constraint that can affect the mass. Hence, reducing energy consumption will positively affect the environment and its economy.

The paper stresses time series forecasting, where ensemble methods and LSTM are both used. Insight taken on possible algorithms can be useful in the future when dealing with these types of cases. It is a comparative study to understand whether series time series forecasting still stands the test of time to be used efficiently when several factors come into play.

LITERATURE REVIEW

Much research has been taken place over the years for predicting the home appliance energy consumption with different datasets with different machine learning algorithms. Some of the works discussed below. A paper from the National College of Ireland highlighted a predictive modeling of home appliances' energy consumption in Belgium. Here the dataset was taken from REMODECE database. Here Oracle was used for the entire working mechanism in which the output fed to three classification algorithms, i.e., Bayesian network, Decision tree and Decision table classification of which Decision Tree resulted in the highest accuracy [7].

Table 1: Model Prediction Output

Model	RMSE	MAE	MAPE
Multiple Regression with all parameters	85.72	49.20	53.6%
Multiple Regression with reduced parameters	88.60	50.92	56.1%
Lasso Regression	85.93	49.55	54.27%
Ridge Regression	86.46	49.26	53.6%
SVM with all parameters	88.93	55.38	64.87%
SVM with reduced parameters	91.44	57.08	66.49%
Random Forest	197.48	177.33	72%

From Table 1 we get an overview that multiple regressions provided the best result. Though the dataset is different the application of different regression models provided a RMSE which is quite high. A research conducted on the energy use of appliances in a low-energy house highlighted the prediction of appliance energy consumption with four regression models namely (a) multiple linear regression model (lm), (b) support vector machine (SVM-radial), (c) random forest (RF) and (d) gradient boosting machine (GBM) as discussed in Figure 1 [8]. Working on the same dataset we can understand that Random forest provided the best result with RMSE of 29.61. There has been similar research conducted for prediction of home appliance energy consumption where the use of Multi-Layer Perceptron, Logistic Regression, K-Nearest Neighbours and Random Forest has taken place. The proposed methodology that has taken place resulted in the accuracy of 98.07% for Logistic Regression with 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 [9]. Five accuracy measurement has been conducted on the above four models which has been illustrated in Figures 2,3,4,5 and 6.

Model	Parameters/features	Training				Testing			
		RMSE	R^2	MAE	MAPE %	RMSE	R^2	MAE	MAPE %
LM	Light, T1,RH1,T2,RH2,T3, RH3,T4, RH4,T5,RH5,T6, RH6, T7,RH7,T8,TH8,T9,RH9, To,Pressure,Rho,WindSpd, Tdewpoint, NSM, WeekStatus, Day of Week	93.21	0.18	53.13	61.32	93.18	0.16	51.97	59.93
SVM Radial	Light,T1,RH1,T2,RH2,T3,RH3, T4,RH4,T5,RH5,T6,RH6,T7,RH7,T8,TH8,T9,RH9,To, Pressure,Rho,WindSpeed, Tdewpoint,NSM, WeekStatus, Day of Week	39.35	0.85	15.08	15.60	70.74	0.52	31.36	29.76
GBM	Light,T1,RH1,T2,RH2,T3,RH3, T4,RH4,T5,RH5,T6,RH6, T7,RH7,T8,TH8,T9,RH9,To, Pressure,Rho,WindSpeed, Tdewpoint,NSM, WeekStatus, Day of Week	17.56	0.97	11.97	16.27	66.65	0.57	35.22	38.29
RF	Light,T1,RH1,T2,RH2,T3,RH3, T4,RH4,T5,RH5,T6,RH6,T7, RH7,T8,TH8,T9,RH9,To, Pressure,Rho,WindSpeed, Tdewpoint,NSM, WeekStatus, Day of Week	29.61	0.92	13.75	13.43	68.48	0.54	31.85	31.39

Figure 1: Model prediction output

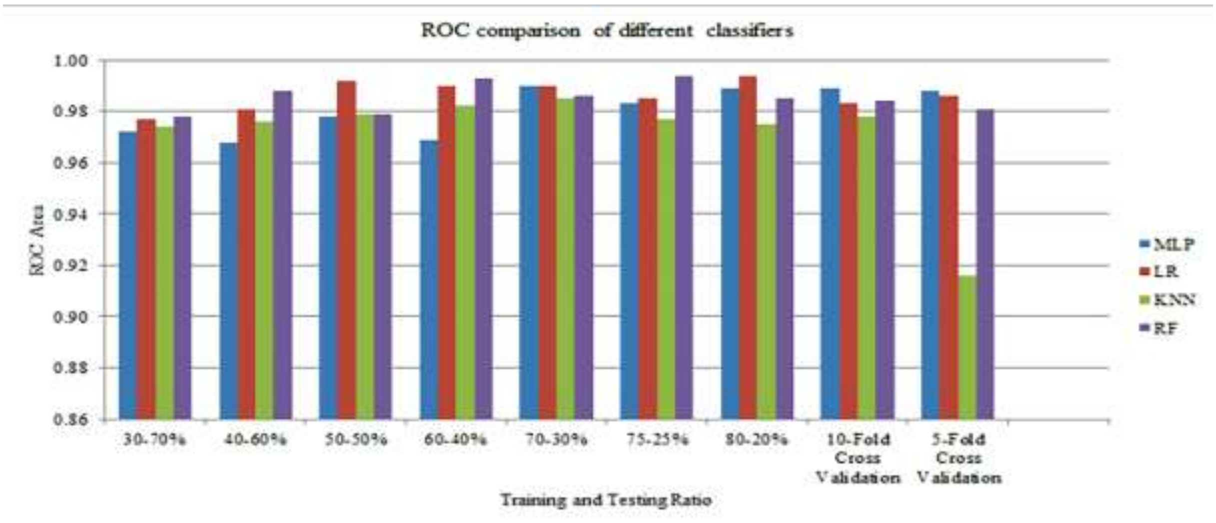

Figure 2: Classification accuracy comparison among different classifiers

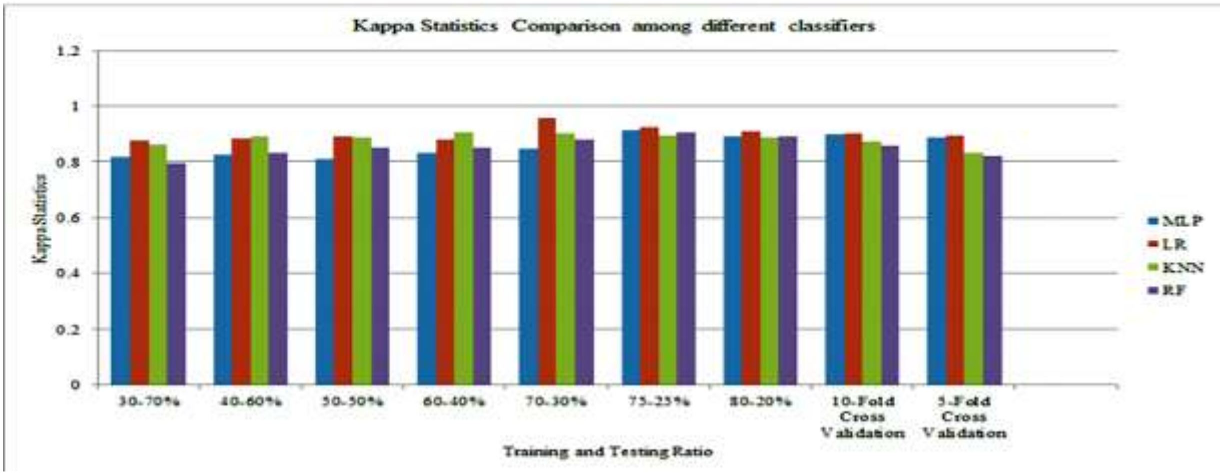

Figure 3: Kappa Statistics comparison among different classifiers

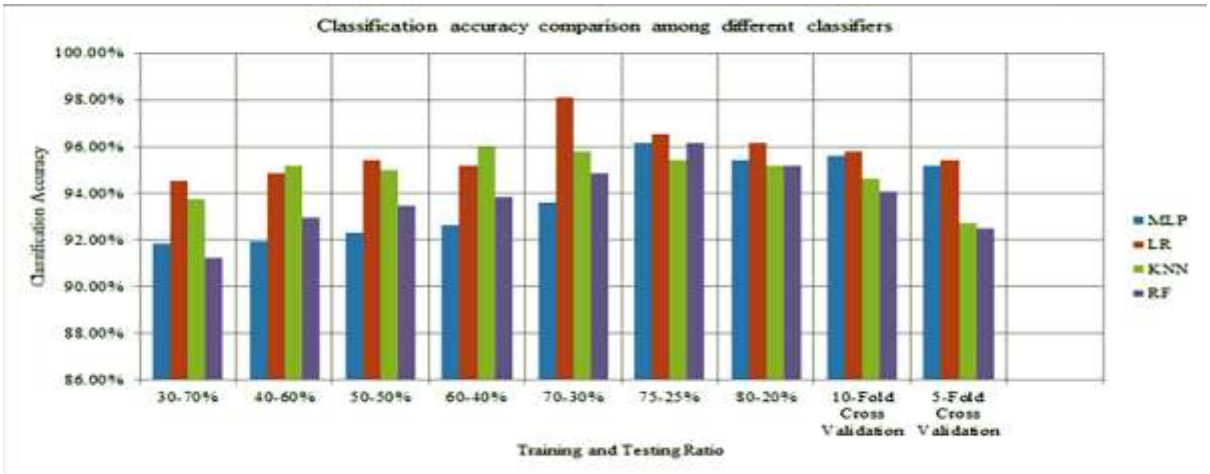

Figure 4: Sensitivity comparison among different classifiers

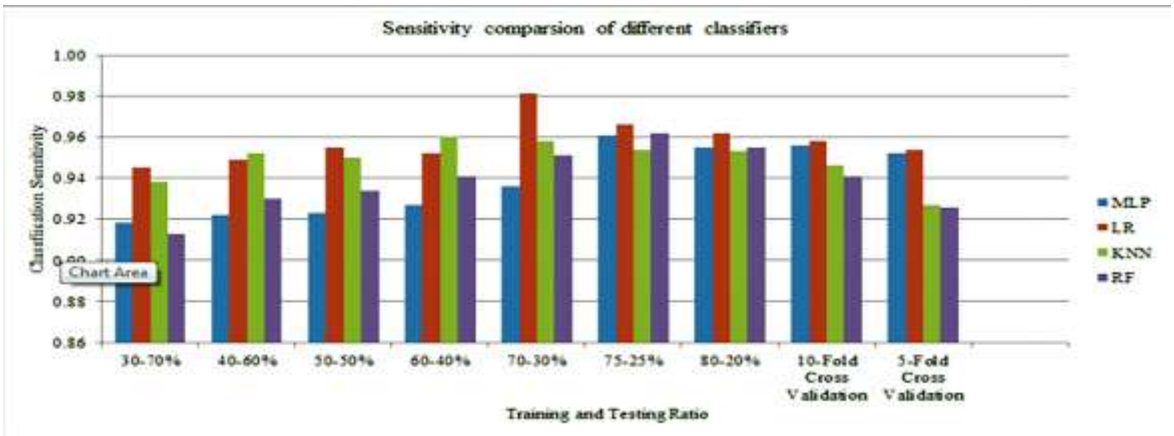

Figure 5: Specificity comparison among different classifiers

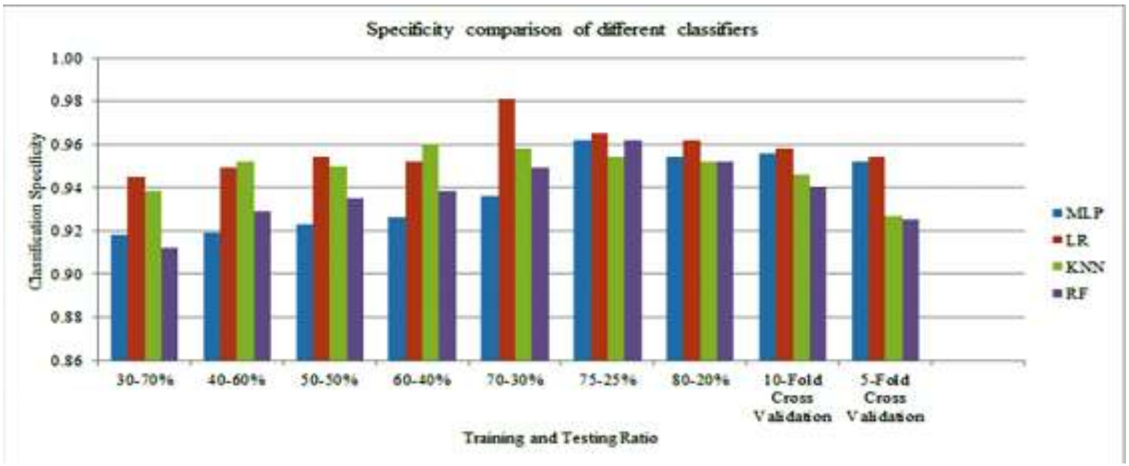

Figure 6: ROC comparison among different classifiers

Hence, it has been observed that many approaches have taken place by using many algorithms. Hence, in this paper, Time series forecasting needed to make a run to understand what effects it will have on the problem.

METHODOLOGY AND WORKFLOW

There are many steps being followed to execute the proposed mechanism with different approaches as mentioned. In Figure 7, begin with the stage from reading the data to predicting the results were strictly considered.

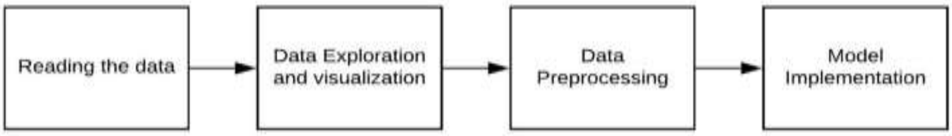

Figure 7: Flowchart of the workflow

A. Reading the dataset

At the primary stage, understanding of the data is very essential, like the number of attributes, attribute's name, type of data, whether the given columns have null or not etc. It is the fundamental properties of the dataset. Python's pandas have been used to execute the procedure as it has inbuilt functionality for reading the data. Here the popular dataset which is used is during a period of 2016. A lot of work has been done on it and the primary focus of the paper is to highlight the importance of time series forecasting in the continuous data. The dataset taken from data.org comprises 19735 instances having 29 attributes. The data records the energy for 10 min over about 4.5 months. ZigBee wireless sensor network has used in keeping track of the temperature and humidity conditions. The wireless node was responsible for transmitting the data for the temperature and humidity conditions around 3.3 min which then aggregated for 10 minutes. The energy data which was received were recorded for every 10 minutes with m-bus energy meters. From a public data set from Reliable Prognosis (rp5.ru), and merged with the experimental data sets using the date and time column weather from the nearest airport weather station (Chievres Airport, Belgium) was downloaded. Regression models and non-predictive attributes needed to be evaluated out which required the necessity for two random variables in the dataset.

B. Data exploration and visualization

Here we get the detailed information of the datasets where the number of rows, columns, nulls gets identified. Python 3 environment comes with many helpful analytics libraries. Here the libraries used are NumPy, Pandas, matplotlib—pyplot, seaborn and from sklearn: preprocessing, model_selection, metrics etc.

In this process, the dataset split into train and test dataset using sklearn's train_test_split. Columns split based on the category independent and dependent.

While visualizing the data, the focus should be made on the essential features to highlight. Graphically intensive visualization can be helpful in quick identification of the critical traits and features of the datasets. Several features considered because of the distinct factors that might affect the prediction. A statistical histogram is useful in determining the cumulative and individual effect on the consumption of electricity.

For univariate distribution, seaborn distplot with the KDE (kernel density estimation) fits on the histogram helps in estimating the probability distribution function of the random variable.

In the dataset, features with irregular distribution required smoothing. Kernel density estimation is a fundamental data smoothing problem where inferences about the population take place, based on a finite data sample. A correlation plot with the features that affect the most consumption in electrical energy is highlighted to give the readers a visual idea of how different features put in together can have a drastic effect on the consumption of electricity [7].

The dataset split into training and testing set using train_test_split from sklearn .model_selection with test size of 25% and a random state of 40. Visualization required the use of graph_objs from plotly, which is a module of chart_studio.

In Figure 8 the appliance energy consumption is done over four months. From the graph, we can say that a particular pattern shows a spike in the consumption of energy at a periodic fashion.

The appliance energy consumption pattern has been broken down corresponding to weekdays and week-ends, which will help to differentiate the pattern of energy consumption over a week for four months duration. This will help in estimating the general electric consumption.

To understand the distribution of all the features of the dataset, histogram is created and represented in Figure 11. The detailed inspection of all the features is needed to find the irregularity. From the above distribution, the histograms for RH_6, RH_out, Visibility, Wind-speed are irregular.

Hence, distplots are required for the analysis as shown in the Figure 12.

Consumption of energy from appliances varies on the frequency of use and the device, [10]. Different devices have different rates for consumption of energy. For that, a visual plot helped to understand the distribution, as shown in Figure 13.

A correlation between weather, temperature, appliances with random features is visualized in Figure 14.

The inference can be made that T1-T9 and T_out showed a positive correlation with the target Appliances. In case of indoor temperatures, the correlations are high as expected with ventilation driven by the HRV unit while minimizing air temperature differences between the rooms. T9-T3, T5, T7, T8 also T6 & T_Out has high correlation (both temperatures from outside). T6 & T9 eliminated from training set as other fields can provide information provided by them.

Hence, the correlation plot provided will help the understanding the general trend of electric consumption.

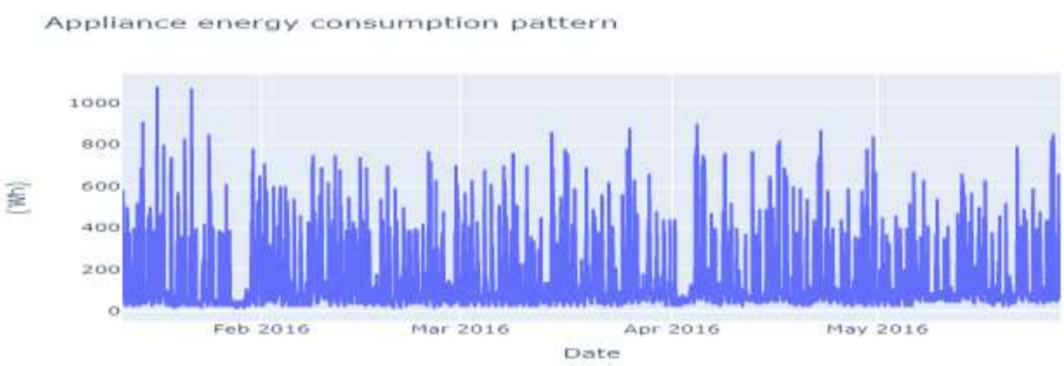

Figure 8: Graphical representation of energy consumption over 4 month duration

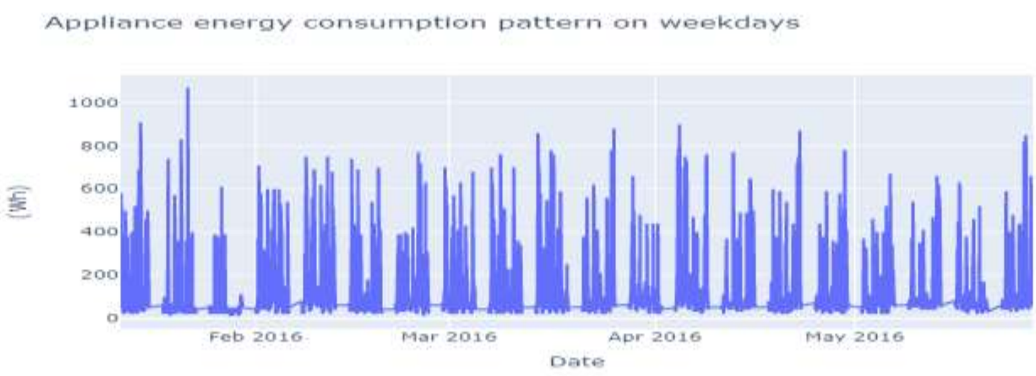

Figure 9: Graphical representation of energy consumption over 4 month duration during weekdays

Figure 10: Graphical representation of energy consumption over 4 month duration during weekends

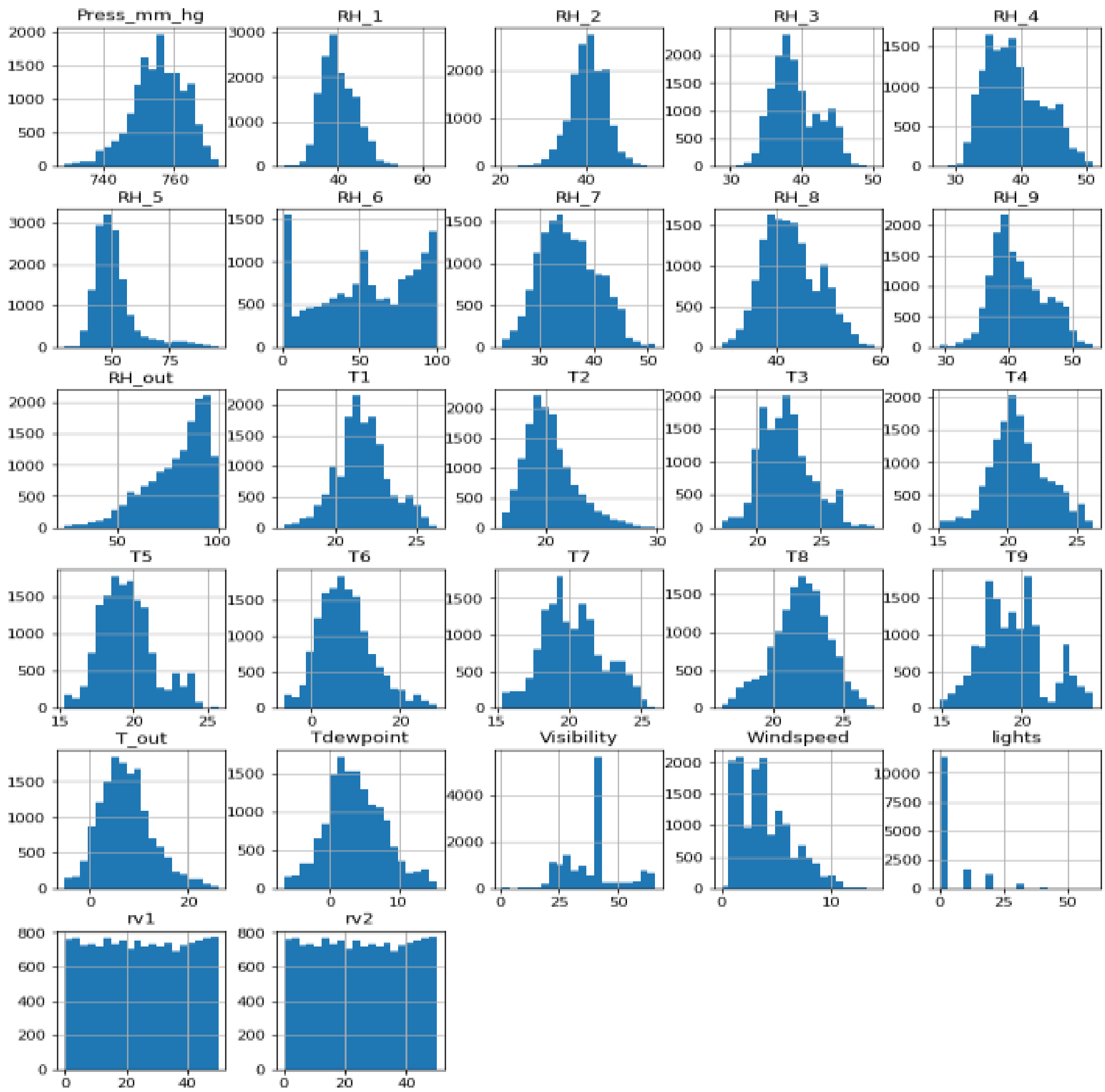

Figure 11: Feature description (I)

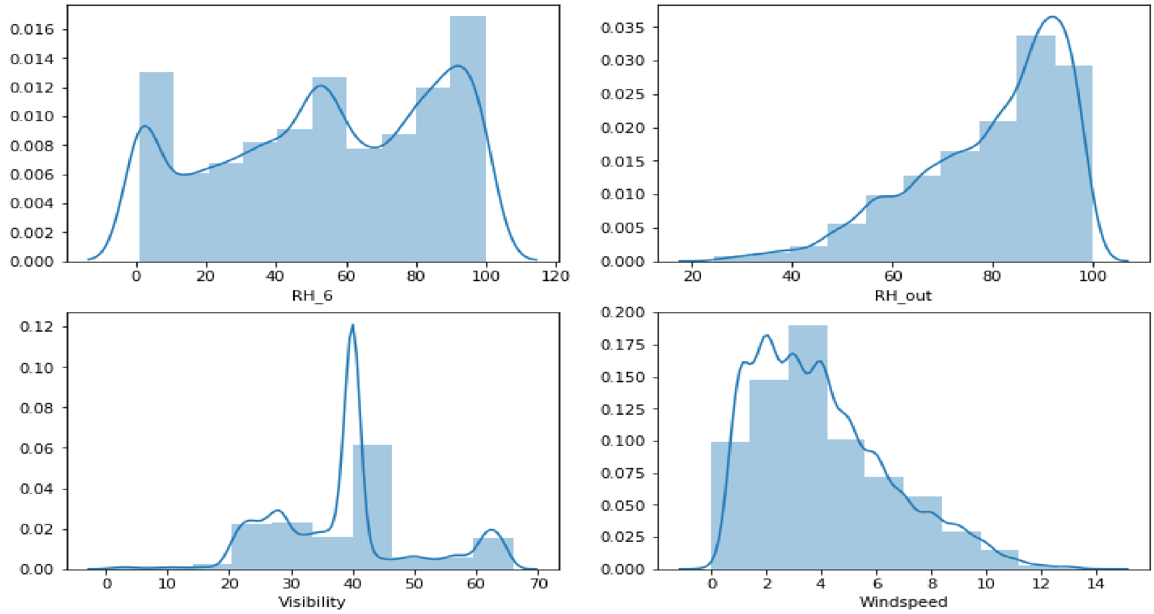

Figure 12: Analysis of irregular features

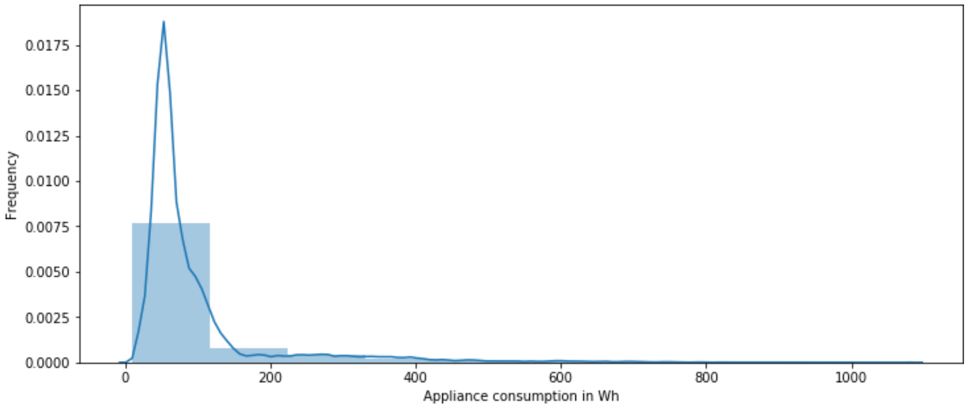

Figure 13: Energy consumption of different devices

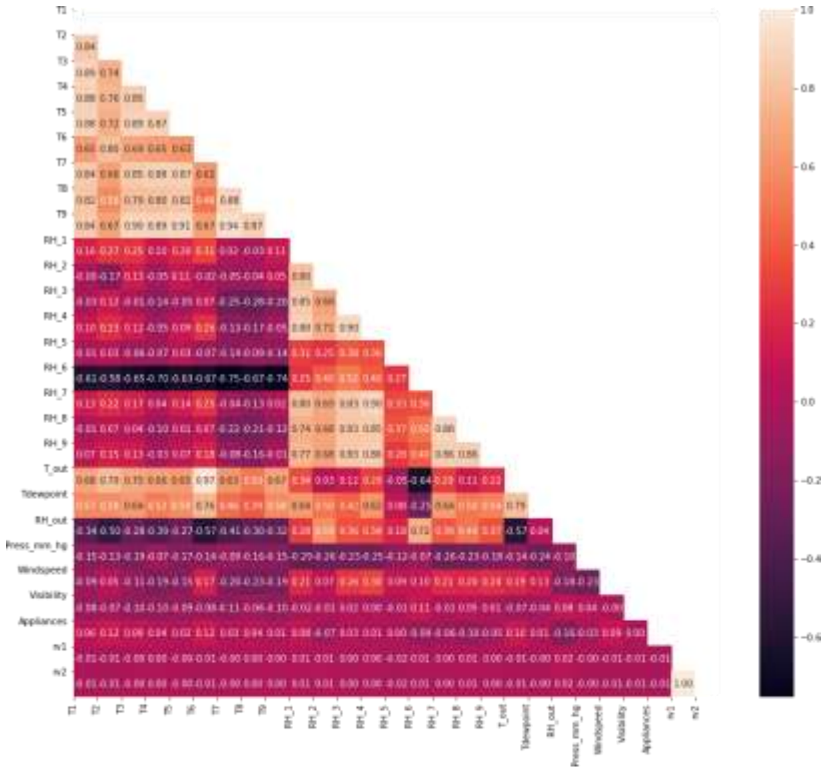

Figure 14: Correlation plot of most important features

C. Data Preprocessing

The preprocessing stage can be divided into the following stages as shown in Figure 15.

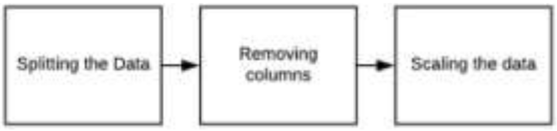

Figure 15: Steps during the data preprocessing

Here the training and test dataset had to be divided based upon independent and dependent variables. The reason for it is that feature variables are independent, and target variables are dependent on the features. Hence, the target variables can be cross-referenced to feature variables upon which we can predict electric consumption. Removal of columns with low correlations is necessary to make a better prediction [11], [12], [13], [14]. Hence, the columns are removed such that it results in better prediction. The scaled-down values are needed to store in a dummy test and training set. The reason why standardized scaling is required because the dataset might behave unpredictably if the individual features are not standardized normally. Boruta algorithm is used for feature selection. Boruta follows an all-relevant feature selection method where features relevant to outcome variables got captured. The Boruta package which is capable of detecting the two random variables that have no predicting power for the appliances' energy consumption, compares the importance of attributes with focus on shadow attributes that are created by shuffling original ones [15], [16], [17]. The result from correlation plot resulted in removing "rv1"," rv2"," Visibility"," T6"," T9" from independent training set and "rv1","rv2"," Visibility"," T6"," T9"," date" from independent test training test. A dummy test and training sets are created with the appliance column to hold the scaled values using StandardScaler. Visualization of the feature of importance done to represent which feature plays the most crucial role in the consumption of appliance energy is shown in Figure 16.

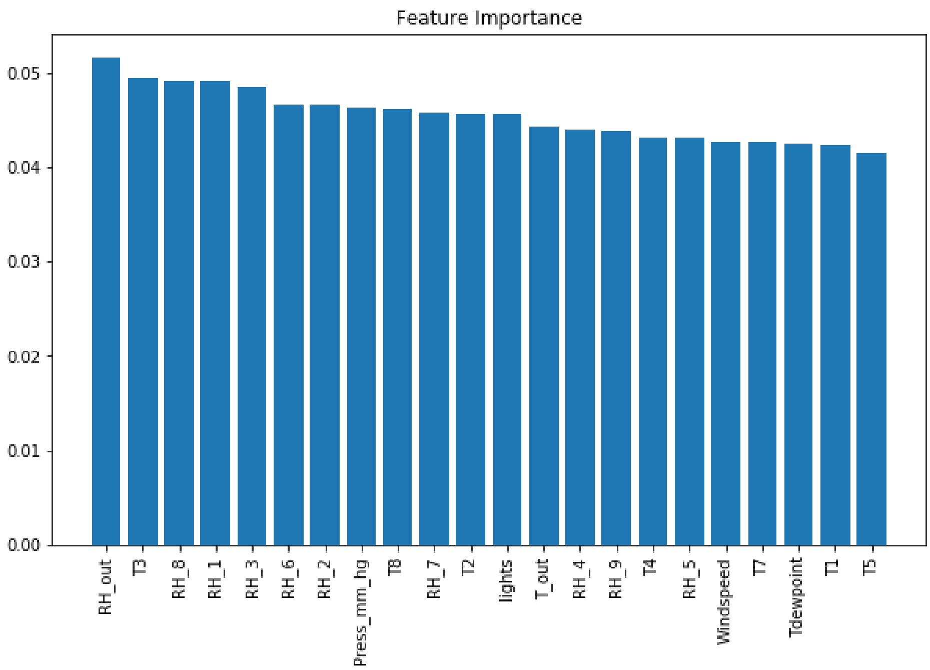

Figure 16: Feature importance graph

D. Model Implementation

Here the specific model that got implemented and focused on are time series forecasting. The problem statement defined here is mainly concerned with the future prediction of electrical energy consumption. The algorithms that are used:

- Random Forest Regressor
- Extra Tree Regressor
- LSTM
- SARIMAX

1. Ensemble Methods

Random forest Regressor and Extra Tree Regressor are ensemble methods which can be used in for forecasting. Hence, considering the requirement, the implementation of the above two ensemble methods take place. "Train_Time", "Train_R2_Score", "Test_R2_Score", "Test_RMSE_Score" is measured and compared for ensembling with Random Forest Regressor, Extra Trees Regressor. A random forest which is a meta estimator uses averaging to improve the predictive accuracy and controls overfitting by accumulating several classifying decision trees on various sub-samples of the dataset. Extra Trees Regressor is a meta estimator which uses averaging to improve the predictive accuracy and controls overfitting by fitting some randomized decision trees (a.k.a. extra-trees) on various sub-samples of the dataset. The main difference between random forests and extra trees (usually called extreme random forests) can be explained in computing where locally optimal feature/split combination (for the random forest) for each feature under consideration has to be taken along with a random value selection for the split (for the extra trees) took place [18], [19], [20]. The output has been shown in Figure 17 and Table II.

2. LSTM

LSTM can be used for problem requiring solving time series prediction. A benefit of it is that LSTM adapts better than linear models for multivariate or multiple input forecasting problems.

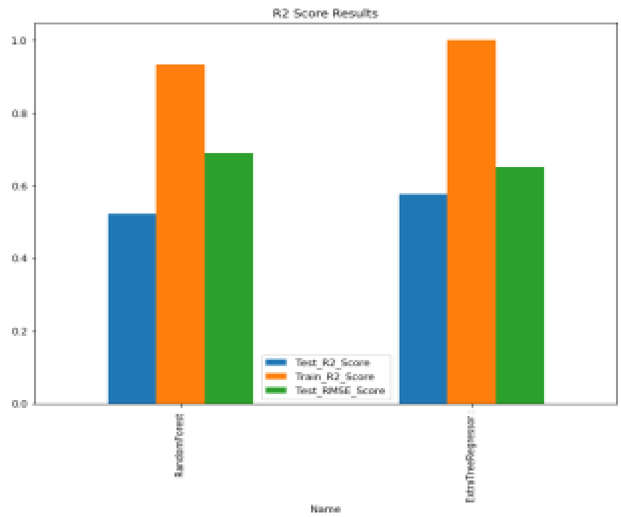

Figure 17: Graphical representation of test result for Ensemble methods

Table 2: Test result of ensemble methods

Name	Score (1)	Score (2)	Score (3)	Train Time
Random Forest Regressor	0.525681	0.688708	0.913691	2.930315
Extra Tree Regressor	0.577183	0.650244	1.000000	0.750407

The Long Short-Term Memory is capable of predicting the output with long sequences of data as it is trained using Backpropagation through time which in process overcomes the vanishing gradient issue, [21]. Here the features have been normalized by scaling using MinMaxScaler in a range of (0,1) and then made to fit with fit_transform of all the values comprising all the features with a target column (Appliance) and time column(date).

In order to use machine learning techniques, the problem is re framed for supervised learning. Out of 43, 22 values need re framing and rest are removed. The removal of the 21 values were done in order to reduce outlier and prevent too much distortion. The reframed values were split into train and test set with test set size of 0.3 with sample shape '0' time step '1' and feature shape '1'. The network architecture of the model is sequential with a batch size of 50 for LSTM layer and 1 for the dense layer. The compilation took along with ADAM optimizer. The fitting of the model is done with an epoch of 70, batch size of 10. The validation dataset created with a 2d and 1d array test data.

The pyplot represents the train and test plot in Figure 18, while executing LSTM (Long Short-Term Memory) on the dataset. The corresponding graph reflects the difference between the train and test output.

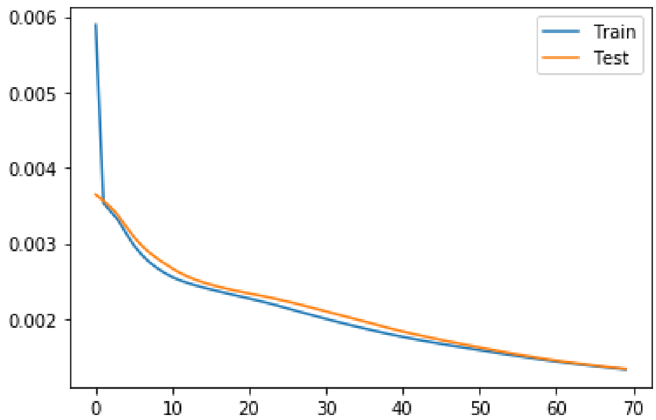

Figure 18: Train and Test plot of LSTM

Calculating the test MSE the result obtained is 0.000941. R2 score for train and test set is calculated using sklearn.metrics where the result obtained for train set is 0.973 and for test set is 0.969 are shown in Figure 19, Figure 20, Figure 21, Figure 22.

Figure 19: Mean Square Error of LSTM

Figure 20: R2 score of Train and Test set

The test RMSE score of LSTM is 32.820. A check if time series data is stationary or not Dickey–Fuller test is done. Dickey–Fuller test the null hypothesis that a unit root is present in an autoregressive model. The corresponding output confirms that the data is stationary in Figure 23.

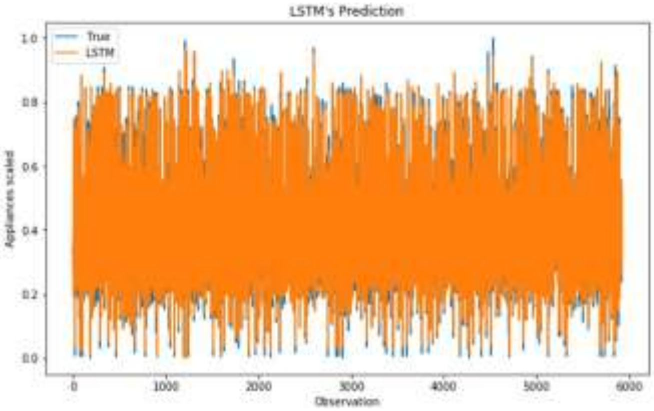

Figure 21: Graphical representation of LSTM prediction

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Test RMSE: 32.820
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Figure 22: Total Root Mean Sqaure Error for LSTM

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Dickey–Fuller test: p=0.000000
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Figure 23: Dickey-Fuller test result

3. Sarimax

SARIMAX (Seasonal Autoregressive Integrated Moving Average) which includes a seasonal component of the series in Arima. It is one of the most popular time series forecasting methods.

The stress was made mainly on these algorithms due to the prediction of time series forecasting as a practical requirement for solving the problem. Sarimax applied on the data frame of the appliance in order of (0,1,1) with seasonal order of (1,0,0,12) 18 keeping enforce stationarity and invertibility as false. A plot for Appliance in 2016 is observed with the predicted mean plot keeping alpha =0.7is shown in Figure 24

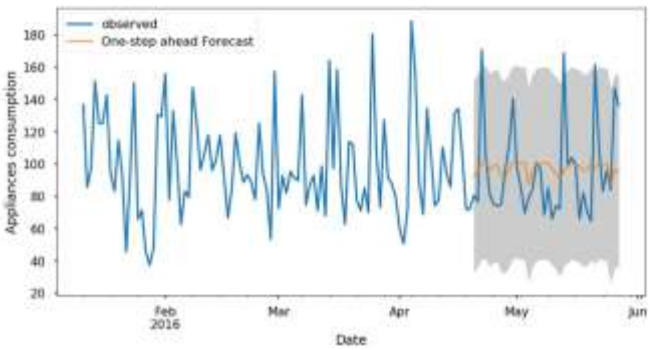

Figure 24: Forecast of Sarimax prediction

The calculated mean square error and root mean square error is done as shown Figure 25 and Figure 26.

```
The Mean Squared Error of our forecasts is 803.0
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Figure 25: Mean Sqaure Error of Sarimax

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The Root Mean Squared Error of our forecasts is 28.34
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Figure 26: Root Mean Square Error of Sarimax

RESULT

From Table III, it can be said that among ensemble methods, neural networks and time series forecasting, the latter has provided the best result.

Table 3: Result Analysis

Model Implemented	RMSE
Random forest Regressor	0.6887
Extra Tree Regressor	0.6502
Long Short-term Memory	0.3280
Sarimax	0.2834

Earlier work which has highlighted many different algorithms provided satisfactory result, yet it missed out the time series forecasting. Sarimax which has provided the best result in the following proved that Time Series Forecasting has the ability to provide more than satisfactory result. It is because of the time component which plays an integral part in the prediction of the consumption of energy.

FUTURE SCOPE AND CONCLUSION

With time series forecasting model to provide the result, we might want to look into other algorithms like Prophet from Facebook which follows the same pattern of its model API. The Prophet's input parameters are considered two columns: ds and y as a data frame. Predictions made on a data frame with a column ds containing the dates for which a prediction took place. Implementing the model keeping interval width of 0.95. Using make_future_dataframe with period =10 and frequency of 'H' which represents the hourly rate. Hence, operating on fbprophet related to this kind of scenario can provide an excellent result as time series forecasting has seemed to provide an excellent result with it. A general can be made that time series forecasting is useful in prediction with continuous data which has been demonstrated by doing a comparison with the relevant and popular algorithm. This in turn might help while approaching similar problems in order to get more effective and precise result.

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