Convolutional Neural Networks (CNN) Model-Based Annual Peak Load Demand Forecasting For The City Of Uyo

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Abstract— **The study focus is to use some data records to train Convolutional Neural Networks (CNN) model for predicting the annual peak load demand for the city of Uyo in Akwa Ibom State. Furthermore, the CNN model was used to forecast the load demand for some years ahead. The study utilized a dataset with six different variable for the CNN model training and performance analysis. The six variables include population, GDP/Capita (USD), rainfall (mm), temperature (degree centigrade), wind speed (m/s) and peak load (MW). Feature importance for the CNN model was assessed using SHAP tool that helped determine the contribution each input variable has on the ANN model. The results showed that optimal selection of features using the SHAP values enhanced the CNN model's MSE by 73.99 % over the baseline case without feature selection. Also, the process improved the RMSE by 49.00 %, MAE by 48.89 % and R^3 by 9.04 %. The results on the load forecast show that the peak load forecasted increased from 48.5 MW in 2024 to 55.6 MW in 2028.**

Keywords— Convolutional Neural Networks (CNN), Peak Load Demand, Power System Planning, Forecasting, Energy Demand Pattern

1. Introduction

Effective power supply management to different clusters of user requires proper understanding of the load demand in the various clusters [1,2,3]. In a statewide power distribution network, each city within the State constitute a cluster of users. Hence, the knowledge of the energy demand pattern of each city is required for proper energy supply to the State [4]. This is particularly important for situations where there is inadequate energy supply for the entire clusters of users at the same time [5,6].

In addition, knowledge of the future energy demand is essential for power system planning [7,8,9]. It ensures that the present power system components are sized to accommodate the future power demand [10,11,12]. In order to know the future power demand, load model is required to capture the load demand pattern based on certain parameters of the user group and the time series load demand of the group [13,14]. Accordingly, in this paper, Convolutional Neural Networks (CNN) is used to model the electric load demand of the city of Uyo in Akwa Ibom State [15,16]. The model prediction performance is further enhanced by incorporating feature selection using SHAP tool [15,16]. In all, the CNN model is used to forecast the load demand for the city of Uyo for some years ahead.

2. Methodology

2.1 The study dataset

The study focus is to use some data records to train Convolutional Neural Networks (CNN) model for predicting the annual peak load demand for the city of Uyo in Akwa Ibom State. Furthermore, the CNN model was used to forecast the load demand for some years ahead. The study utilized a dataset with six different variable for the CNN model training and performance analysis. The six variables include population, GDP/Capita (USD), rainfall (mm), temperature (degree centigrade), wind speed (m/s) and peak load (MW). The summary of the data components in the case study dataset is shown in Table 1. The line plot of the normalized values of the six parameters used in the study is shown in Figure 1.

Table 1 The summary of the data components in the case study dataset

Groups	Population	GDP/Capita (USD)	Rainfall (mm)	Temperature (Degree Centigrade)	Wind Speed (m/s)	Load (MW)
Num of observations	5,113	5,113	5,113	5,113	5,113	5,113
Num of missing values	0	1	0	0	0	0
Minimum	338,273	1,607	0	21.82	1.97	23
Maximum	535,892	3,201	192.92	35.71	12.89	48
Range	197,619	1,594	192.92	13.89	10.92	25
Mean ($\bar{x}$)	429,533.80	2,354.83	10.8423	28.2979	5.4735	35.8029
Standard Deviation (S)	56,964.35	377.3984	14.2597	2.3178	1.3275	5.0226
Q1	379,507	2,072.85	1.5	26.78	1.7624	32
Median	425,767	2,220.07	6.55	28.77	4.95	35
Q3	477,666	2,634.78	15.18	29.76	4.97	39
Interquartile range	98,159	561.93	13.68	2.98	5.95	7

Each of the six variables was normalized using minmax approach (expressed in Equation 1) and the normalized is split into 70 % for application in the CNN model training, 15 % in the CNN model validation and 15 % in the CNN model testing.

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} \quad \text{for } x = 1,2,3,\ldots,n \tag{1}$$

where xmin and xmax are the minimum and maximum values of all observations for a given variable respectively and x is the xth data item in the given variable with n total data records in the dataset.

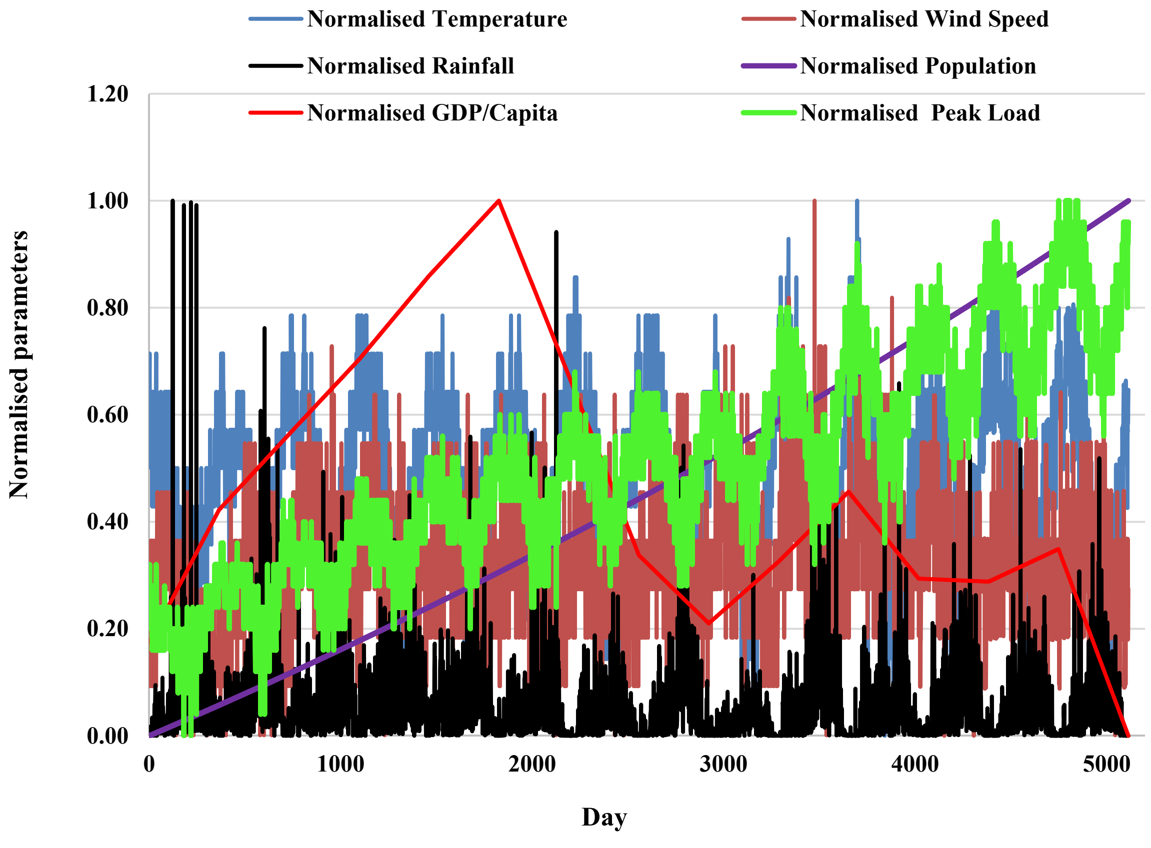


Figure 1 The line plot of the normalized values of the six parameters used in the study

2.2 The CNN Architecture, Training and Validation

In the CNN model architecture (shown in Figure 2), input data was passed through series of layers with filters which include input layer, convolution layer, pooling layer, fully connected layer and output layer. The activation function was then applied to make the classification which is the output. The arrangement in CNN models provided the layers with capability to extract valuable features embedded in the dataset. The architecture of the CNN model developed in this study has five layers as shown in Figure 2. The configurations of CNN model are summarized in Table 2 while the CNN hyperparameters configurations are shown in Table 3.

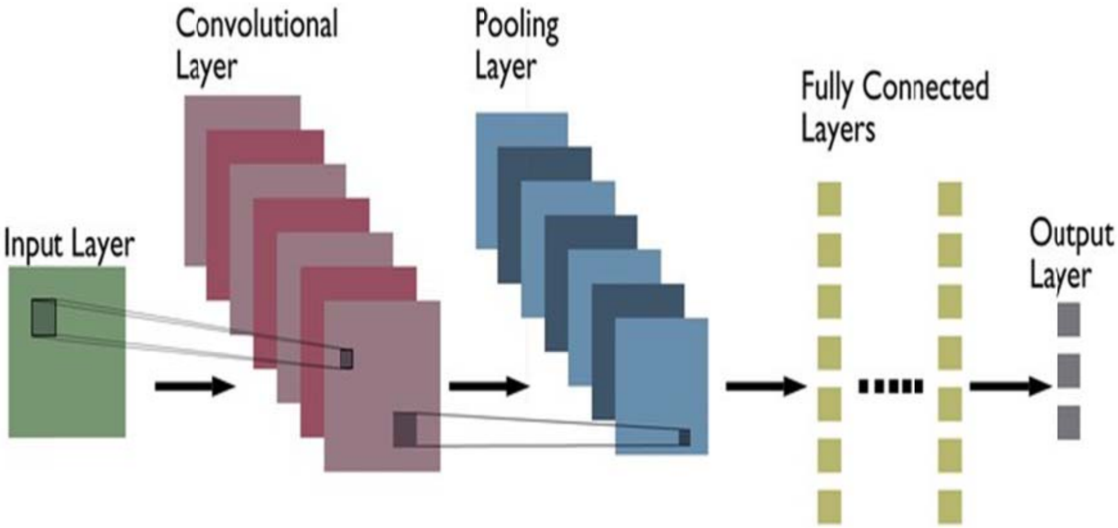


Figure 2: The Architecture of the CNN model.

Table 2: Summary of CNN model

Layer(type)	**Output shape**	**Param**
Conv1d(Conv1D)	(None, 4, 64)	1216
Max_pooling1d (MaxPooling1D)	(None, 2, 64)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 64)	8256
Dense_1(Dense)	(None, 1)	65
Total params: 9,537		
Trainable params: 9,537		
Non-trainable params: 0		

Table 3: Hyperparameters of CNN Model Tuning

Parameters	**Values**
learning rate	0.0001
number of layers	5
number of epochs	200
number of features	36
activation function	Rectified Linear Unit (ReLU)

Feature importance for the CNN model was assessed using SHAP tool that helped determine the contribution each input variable has on the ANN model. The CNN model base case implementation without the SHAP tool was conducted and then the SHAP tool was employed and analysis of the performance of this two versions were done compared.

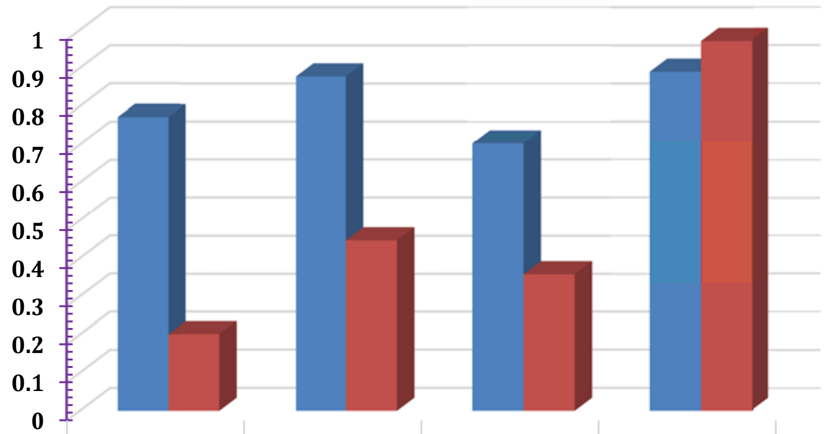
3. Results and Discussion

The results of the peak load prediction based on the baseline CNN model and enhanced CNN model after undergoing the SHAP values-based feature selection are shown in Figure 3 and Figure 4. The results showed that optimal selection of features using the SHAP values enhanced CNN models MSE by 73.99 % over the baseline case without feature selection. Also, the process improved the RMSE by 49.00 %, MAE by 48.89 %and R^3 by 9.04 %.

The results of the percentage improvement in MSE for the application of different features in SHAP values-based feature selection to the CNN model is shown in Figure 5, the results for the improvement in RMSE is shown in Figure 6, the results for the improvement in MAE is shown in Figure 7, and the results for the improvement in R^2 is shown in Figure 8.

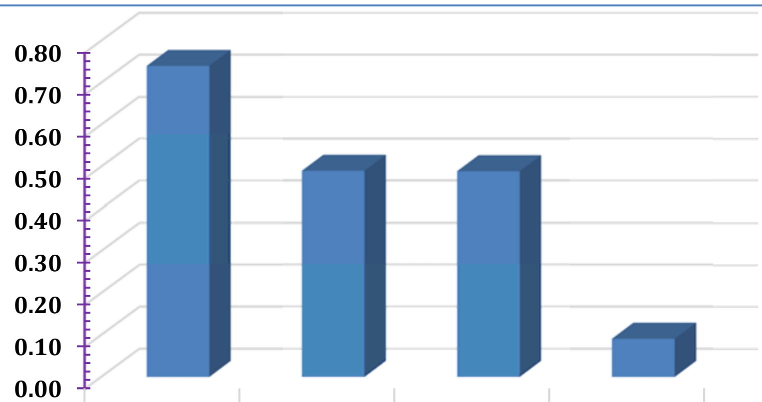
The results of the CNN model forecast of the peak load the for the baseline case after the CNN model was enhanced using the SHAP value are shown in Figure 9.

The graph plot of load demand forecast with the CNN model that was enhanced using the SHAP values are presented in shown in Figure 10 and Figure 11. The results presented in Figure 9 show that the peak load forecasted increased from 48.5 MW in 2024 to 55.6 MW in 2028.



	MSE	RMSE	MAE	R2
CNN (the baseline case)	0.772366	0.878843	0.702704	0.891114
CNN(after using SHAP models with 25 features)	0.200911	0.448231	0.359173	0.971676

Figure 3: The results of the peak load prediction based on the baseline CNN model and enhanced CNN model after undergoing the SHAP values-based feature selection



	MSE	RMSE	MAE	R2
Improvement in the performance metrics of the models after introducing feature importance using SHAP value (%)	73.99%	49.00%	48.89%	9.04%

Figure 4: Improvement in the CNN model performance metrics due to the application of SHAP values-based feature selection

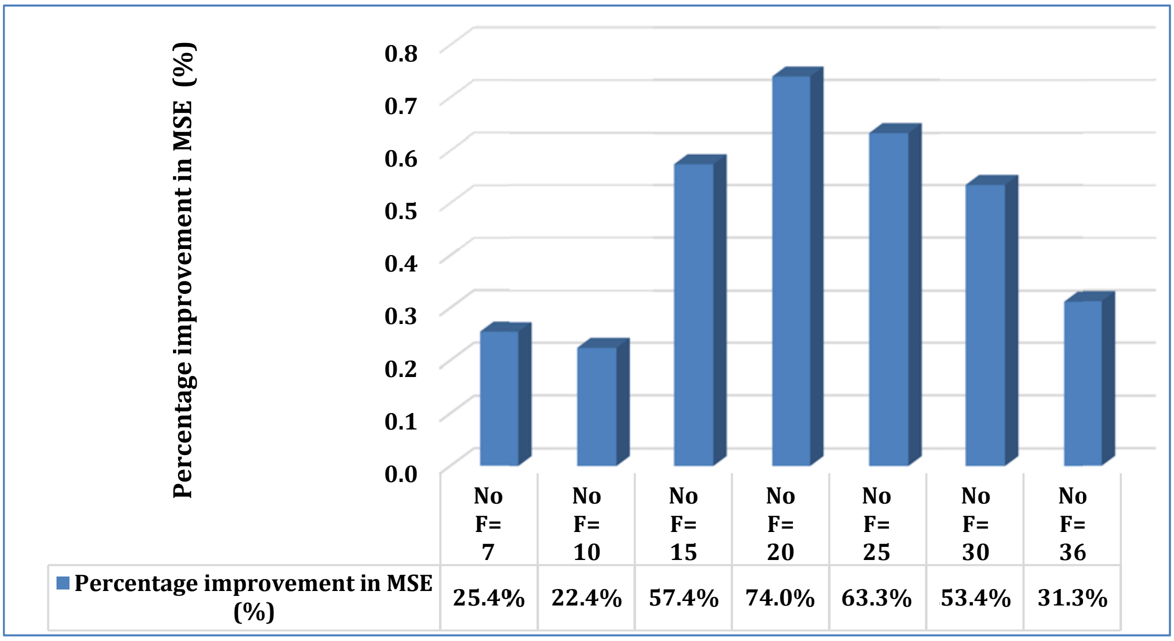


Figure 5: The bar chart of the percentage improvement in MSE for the application of different features in SHAP values-based feature selection to the CNN model (where NoF means number of features)

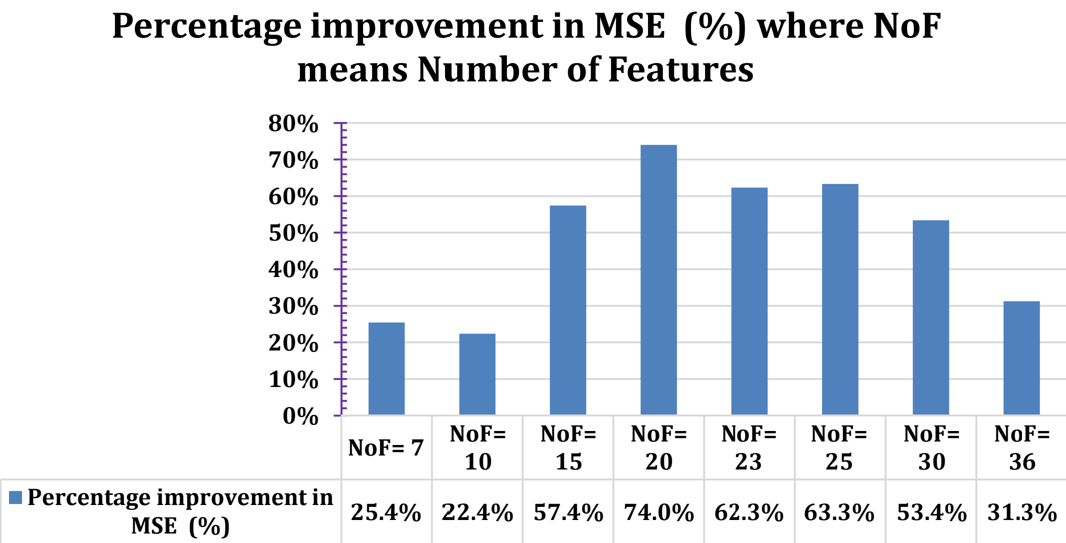


Figure 6: The bar chart of the percentage improvement in RMSE for the application of different features in SHAP values-based feature selection to the CNN model (where NoF means number of features)

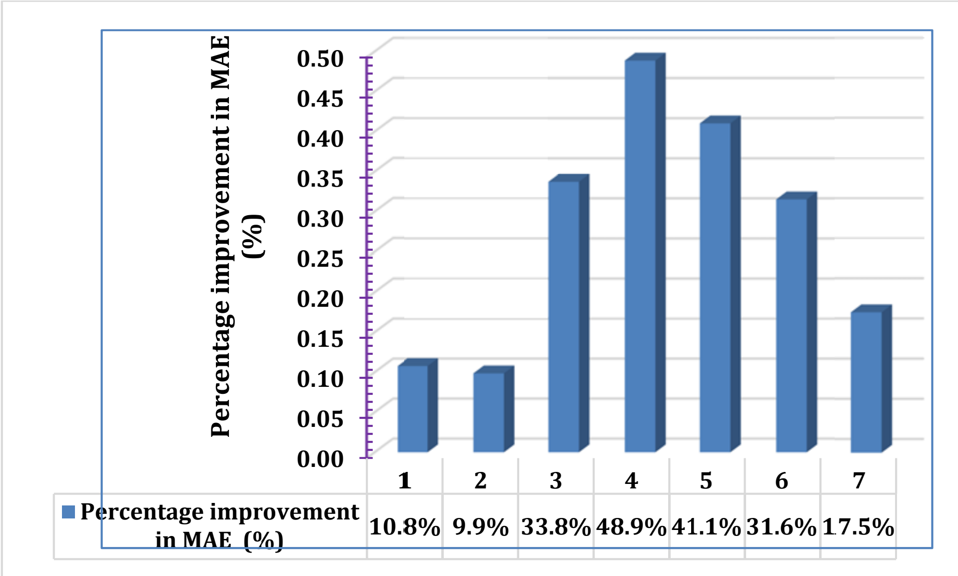


Figure 7: The bar chart of the percentage improvement in MAE for the application of different features in SHAP values-based feature selection to the CNN model (where NoF means number of features)

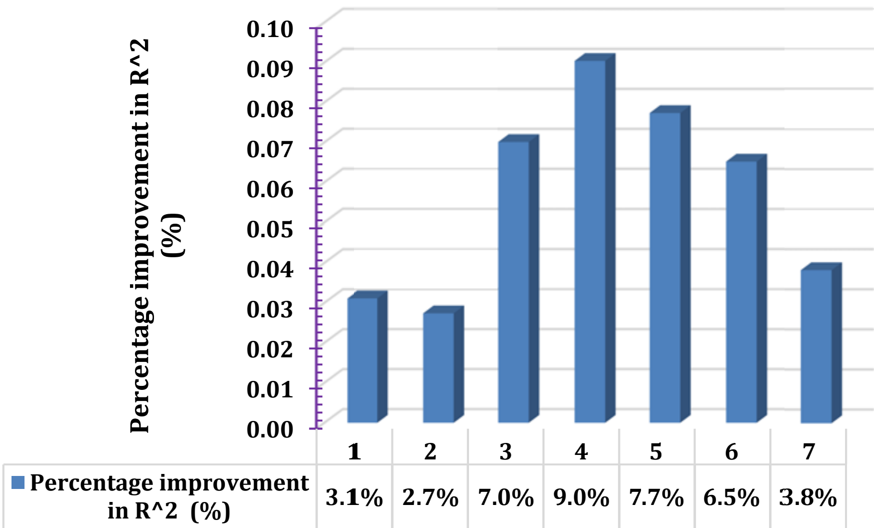


Figure 8: The bar chart of the percentage improvement in R^2 for the application of different features in SHAP values-based feature selection to the CNN model (where NoF means number of features)

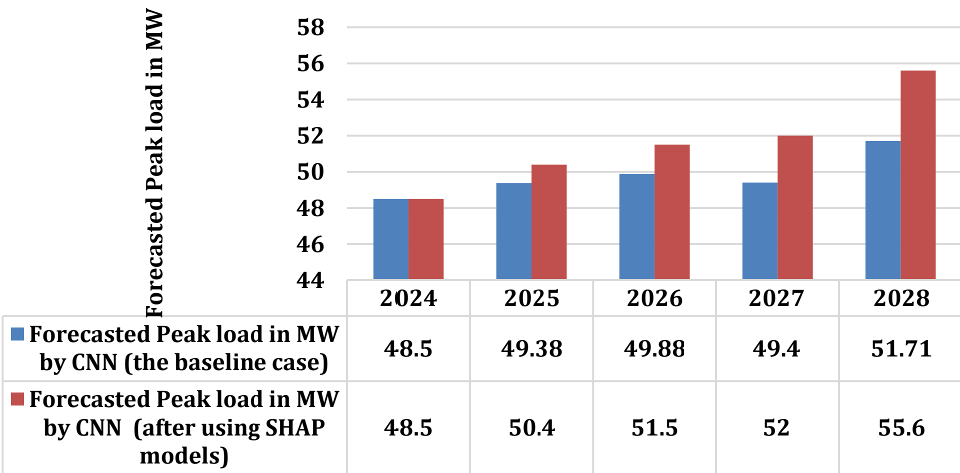


Figure 9 The bar chart for the CNN model forecast of the peak load the for the baseline case after the CNN model was enhanced using the SHAP value

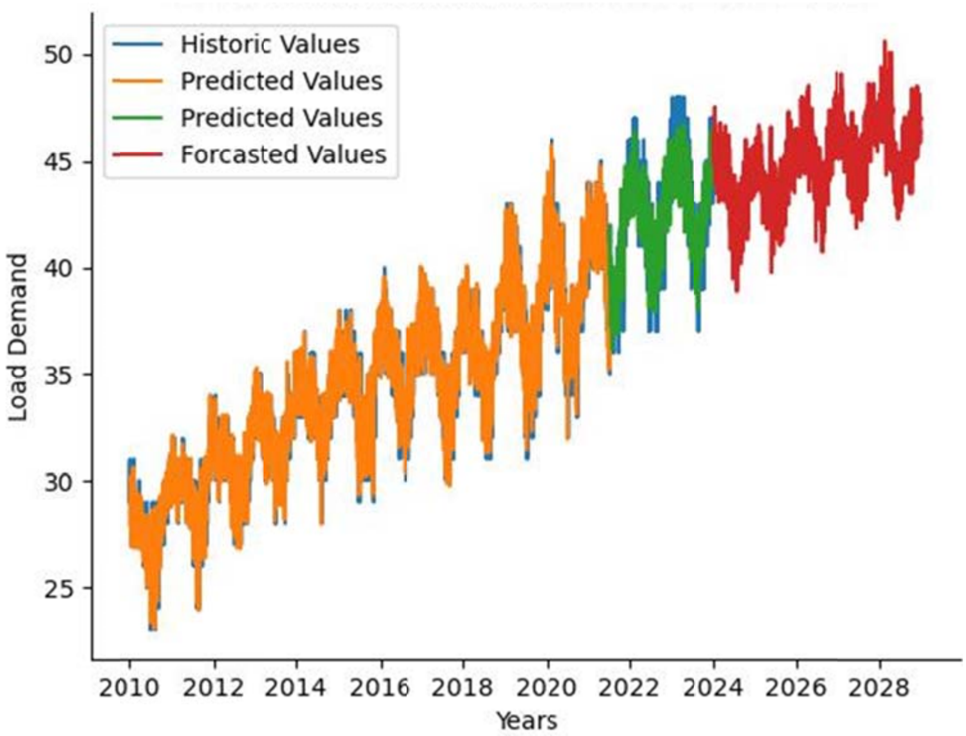


Figure 10: Plot of Load Demand Forecast with the CNN model that was enhanced using the SHAP values

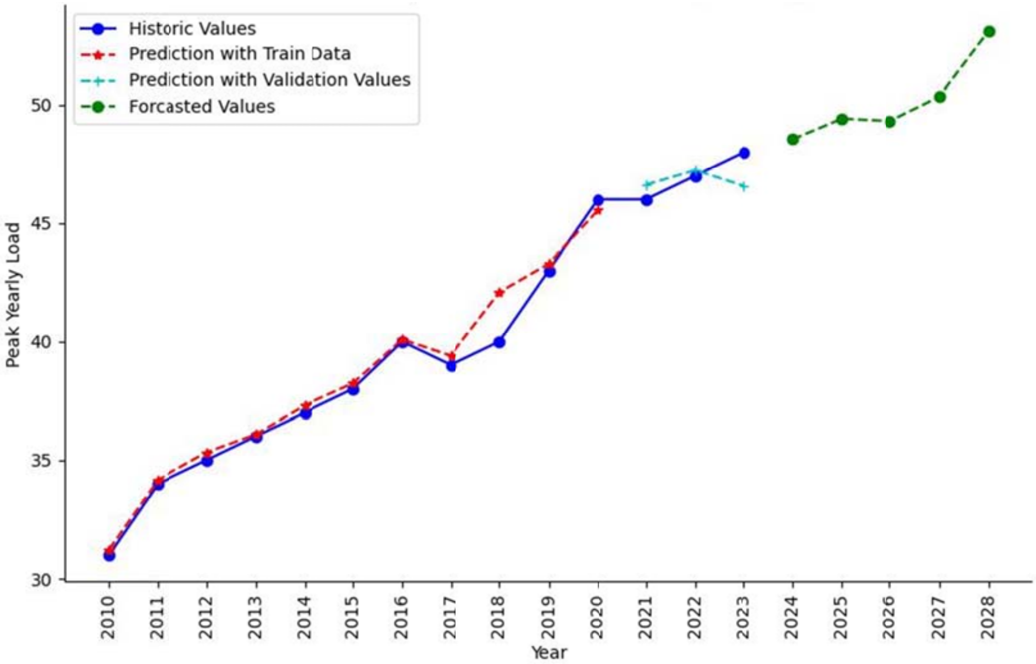


Figure 11: Plot of Yearly Peak Load Forecast with the CNN model that was enhanced using the SHAP values

4. Conclusion

The Convolutional Neural Networks (CNN) model is considered in this study. The CNN model was used to model and then forecast the peak electric load demand for a metropolis in Akwa Ibom State. The model was trained using some weather data parameters, as well as some macro-economic parameters and previous years' peak load demand datasets. Again, the CNN model prediction performance was assessed and enhanced using SHAP values for feature selection. The results showed that optimal selection of the features through the use of the SHAP values significantly enhanced the prediction performance of the CNN model.

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