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Multi-Horizon Energy Forecasting Using a Hybrid CNN-BiLSTM LSTM Deep Learning Framework

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Abstract
Energy forecasting plays an important role in energy management. The fluctuations in the consumption of energy at different time intervals lead to the difficulty in making accurate predictions about future energy usage. In Multi-Horizon Energy Forecasting Using a Hybrid CNN-BiLSTM LSTM Deep Learning Framework, deep learning methods have been used to identify spatiotemporal characteristics within the data for forecasting purposes. The combination of CNN, Bi-LSTM, and LSTM helps the model learn about the complexities and inter relationships in the data better.The use of XAI increases the transparency of the process. The performance of the model has been evaluated based on the Individual Household Electric Power Consumption dataset which consists of over two million records. The mean squared error obtained was 0.01605 whereas the mean absolute error was 0.010389. This framework outperforms others in terms of predictive power making the study highly relevant and superior to other approaches.

Keywords: *BiLSTM; CNN; Deep Learning; Energy Forecasting; Hybrid Model; LSTM; XAI*

1. Introduction
The increased demand for energy around the world, due to factors like urbanization and increased usage of appliances, has heightened the importance of energy management systems [8]. Energy consumption forecasting is important to optimize the allocation of resources and to make the system more efficient [12]. Accurate forecasting results can increase the sustainability of the energy supply system. Conventional forecasting techniques have been found to be inadequate to handle the non-linear patterns found in energy consumption data [8].es in the energy consumption time series. The recent developments in deep learning improved the modeling efficiency of complex temporal dependencies observed in energy consumption data [4]. This paper proposes a hybrid model with DL framework upon integration of CNN, LSTM, and Bi-LSTM models using Explainable Artificial Intelligence (XAI) for efficient results.

2. Related Work
Energy consumption prediction is key operations in the management of the smart grid in an efficient manner. The first strategy statistical model like ARIMA was used in the energy load forecasting domain. It was found that it performs poorly in handling non-linear relationships [8]. Although the application of these models is quite efficient, the models still face problems while facing non-linear relationships, especially in large datasets. Later, Data-driven models have shown improved accuracy in terms of forecasting. However, there are issues with feature engineering and handling long dependencies [12]. Although these models can handle non-linear relationships efficiently, they still face problems in feature engineering as well as the handling of long-term dependencies. Recently, deep learning models have been used in the process. Better performance is shown by LSTM models in handling sequential dependencies in time series data due to the inclusion of memory cells in the model [2]. Better performance is shown by CNN models in handling spatial features in structured data [5]. Hybrid approaches like Combining CNN along with LSTM models has shown consistent performance in

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improving the accuracy of models [6]. Despite showing better accuracy in terms of forecasting, deep learning models have faced criticism for being less interpretable, known as the "black box" problem [9]. Explainable AI (XAI) is being used in the process. However, it is still considered that there is an ongoing trade-off between high accuracy and interpretability [9, 10].

3. Existing Methods

3.1. Statistical Methods

Statistical methods like (ARIMA) "Autoregressive Integrated Moving Average and linear regression models have been used for load forecasting" [8]. Such approaches are easy and computationally inexpensive but limited in their capacity to handle complex nonlinear data relationships [8], efficient, and can be applied for short-term load forecasting. But the drawback of these methods is that they cannot handle non-linear relationships.

3.2. Machine Learning Methods

ML algorithms like SVM and Random Forests can be employed to increase the accuracy of the model by handling nonlinear data relationships [12], Decision Trees, and RandomForests can be used to improve the accuracy of load forecasting. These models can handle non-linear relationships. They can handle multiple feature inputs like weather, time, and user behavior. However, these models are featuring engineering intensive. Feature engineering can be a tedious task. These models face challenges in handling long-term temporal dependencies.

3.3. Deep Learning Methods

DL algorithms can automatically learn complex patterns in large amounts of data for load forecasting because they can automatically learn the patterns from the large dataset [2]. Long Short-Term Memory can handle the dependencies in the load consumption pattern. Convolutional Neural Networks can be used to learn the essential features from the structured data. The combination of CNN and LSTM can be used to improve the results and accuracy of the load forecasting model.

4. Proposed Method

The proposed framework provides a framework based on a hybrid model of deep learning. This framework is useful for improving the accuracy and interpretability of energy consumption forecasting for various horizons. For example, it combines (CNN) Convolutional Neural Networks ,(LSTM) Long Short-Term Memory , and (BiLSTM) Bi-directional Long Short-Term Memory networks. These networks will be effective in handling spatial and temporal dependencies in energy consumption. The framework will also incorporate Explainable Artificial Intelligence (XAI) to improve its interpretability and transparency.

4.1. Data Preprocessing

The energy usage dataset will be subjected to various preprocessing activities to improve its quality and compatibility. For example, the dataset will be preprocessed to handle missing values. Interpolation methods will be applied to handle missing values. The dataset will also be preprocessed to smooth the outliers. The smoothing of outliers will improve the quality of the dataset by reducing noise. The dataset will be normalized using Min-Max normalization. Time-based features will be included to improve the accuracy of the model. The dataset is partitioned into training and testing datasets to evaluate its accuracy.

4.2. CNN Feature Extraction

The CNN layers will be used in the proposed architecture to extract spatial patterns in the data related to energy consumption.This involves the use of appliance usage patterns and occupancy patterns. The convolutional layers employ various filters to obtain feature representations. These feature representations are then reduced through the pooling layers. This feature extraction enables the model to learn patterns, which is essential to learn about energy consumption.

4.3. Temporal Modeling using LSTM and Bi-LSTM

After feature extraction, an LSTM and Bi-LSTM layer is employed. This is to ensure that the model is able to learn about temporal dependencies. The LSTM layers will be used in the proposed architecture to extract temporal dependencies in the data related to sequential energy usage.This is because the LSTM network is composed of memory cells. This enables the model to store information. The Bi-LSTM layer learns features. This is because the Bi-LSTM layer is employed to process the input data from both ends. This ensures model to pursue contextual information from the future and past.

4.4. Fully Connected and Output Layer

The features are then passed on to the fully connected dense layer for the predictions to be made on the energy consumption. Finally, the output layer is added for the predictions to be made on the amount of energy consumption that is to be expected in a particular time period in the future.

4.5. Explainable AI Integration

In this section, explainable AI is integrated into the framework for addressing the black box problem, which is inherent in deep learning methods. In this regard, the feature importance analysis is used for determining the features that have the maximum impact on the predictions made by the model. This will ensure transparency in terms of the results obtained by the model. The proposed model is useful for multi-horizon forecasting since it can forecast energy consumption over various periods of time in the future. Furthermore, it can be extended to accommodate smart meter systems, whereby energy consumption prediction can be useful for planning energy recharge.

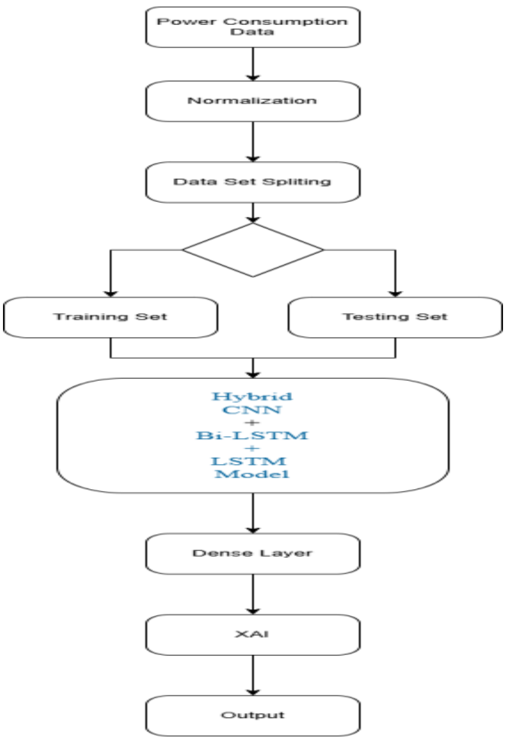

Figure 1 Architectural Workflow of the Model

5. Result Analysis

5.1. Training & Validation Loss Dynamics

The training/validation loss curve can be used in the context of determining the extent of convergence that is achieved in the context of the proposed hybrid model. It can be clearly seen from the training loss curve that there is indeed a reduction in the loss with regard to the training set with the increase in the number of epochs. It can be seen that the training loss is around an approximate value of 0.0195. It is observed that the training loss reduces steadily with the increase in the number of epochs. Towards the end, it reduces in value to an approximate value of 0.0125. The validation loss curve is seen to be fluctuating moderately between the range of 0.017 and 0.042. It is observed that spikes are present in the validation loss curve towards the end. It is observed that the validation loss is not fluctuating too much. variance and overfitting. The trend indicates stable convergence of the model and the effectiveness of the training dynamics in learning the complex dependencies. The model has shown consistent learning behavior.

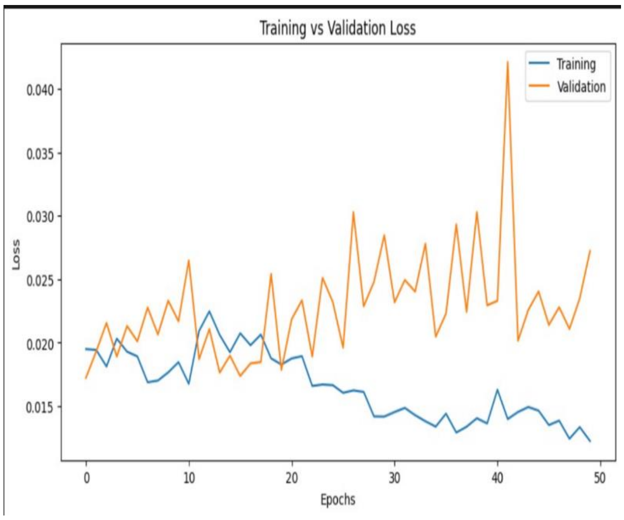

Figure 2 Visualization of Training and Validation Loss

5.2. Weekly Consumption Forecasting Performance

The performance of model in the weekly prediction task shows the effectiveness of the model in pursuing the dependencies. The values show the trend of the

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actual values' consumption curve. The results show strong performance of the model in learning the long-range dependencies in the actual consumption values. Smoothness in the values shows the effectiveness of the model in the task of predicting the medium-term energy consumption.

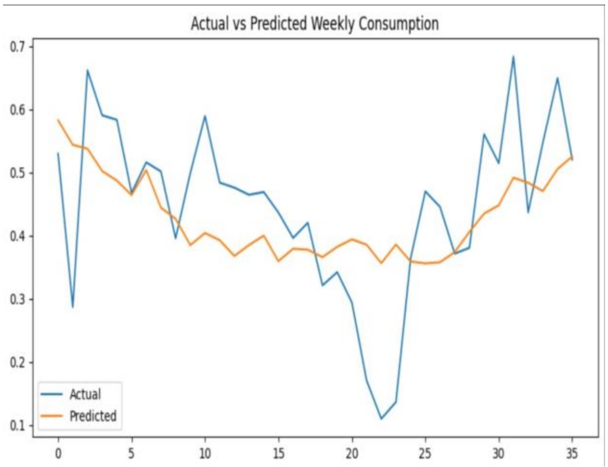

Figure 3 **Visualization of actual and Predicted Weekly Consumption**

5.3. Hourly Consumption Forecasting Performance

The prediction result in the performance of the model in terms of hourly consumption forecasting shows the effectiveness of the model in the forecasting of the patterns of consumption. From the above figure, it is clear that the prediction values of the model successfully follow the pattern of the baseline consumption while at the same time being stable at different time steps[1]. There is the presence of some differences in the process at unexpected peaks in the consumption patterns, which are stochastically distributed; however, the model is able to successfully retain the trends of the consumption pattern. The results show strong performance of the model's architecture in successfully striking the perfect balance between sensitivity and forecasting.

5.4. Correlation Analysis

From the correlation heatmap, we can see that there is significant information about the features' importance and their correlation to energy consumption. The correlation between daily consumption and hourly consumption is perfect since their correlation is equal to 1.The correlation between Energy_kWh_min, global active power, and global intensity is high since their correlation is about 0.88. These features are very important and efficient in influencing energy consumption[3]. The correlation between sub_metering_3 and weekly consumption is moderate since their correlation is between 0.49 and 0.50. These features are relevant in terms of learning the model. The correlation between sub_metering_2 and global reactive power is low since their correlation is 0.19. The correlation between voltage and energy consumption patterns is very low since their correlation is ~ 0.21.

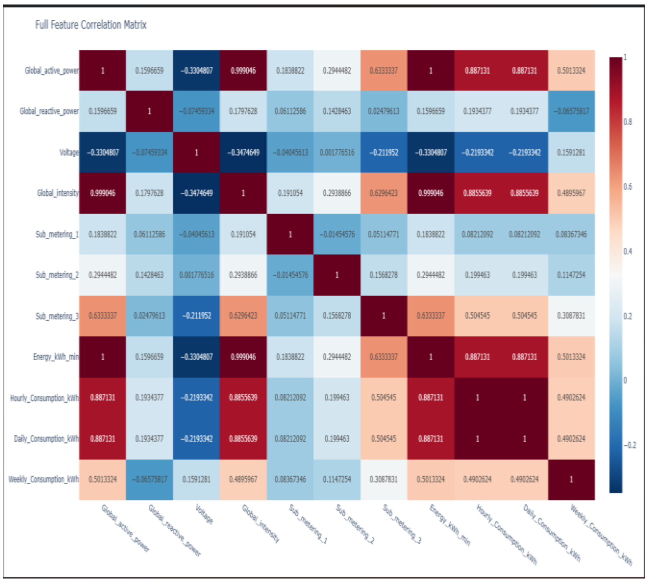

Figure 4 **Visualization of Correlation Analysis**

5.5.Overall Performance of Model

Overall, the results indicate that the hybrid model is effective in learning spatial relationships as well as temporal relationships for different forecast horizons. The training behavior indicates convergence, while the prediction plots show that the model is effective in learning consumption patterns for different scales, such as weeks and hours. Moreover, the results for correlation verified the importance of features selected for the model and are consistent with the concept of interpretability in Explainable AI[7]. Overall, these results prove that the proposed model is robust and consistent for effective energy consumption forecasts. The results for the experiment

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have shown that deep learning and Explainable AI can be used for high accuracy and interpretability for effective intelligent management systems. The Model performance is evaluated using Mean Square Error (MSE), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

$$\text{MSE}=\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i|$$

Table 1 Comparison of Proposed Hybrid Model with Base Model

S.NO	MODEL	MSE	RMSE	MAE
1	LSTM-attention layer[13]	0.40225	0.59925	0.45275
2	Linear Regression [13]	0.30775	0.544	0.408
3	Decision tree[15]	0.59	0.77	0.54
4	Bi-LSTM [16]	0.104	0.322	0.257
5	EECP-CBL [13]	0.11575	0.3115	0.2145
6	CNN-LSTM [14]	0.232	0.4595	0.294
7	CNN-GRU [15]	0.22	0.47	0.33
8	CNN-Attention layer [15]	0.37	0.67	0.47
9	SVR [15]	0.59	0.77	0.49
10	Proposed Model	0.01605	0.1267	0.010389

Conclusion

This paper proposed a hybrid DL approach that incorporates CNN, LSTM & BiLSTM architectures in the prediction of multi-horizon energy consumption. The proposed model was able to adequately capture the spatial and intricate temporal dependencies present in large energy consumption datasets. Experimental results using the Individual Household Electric Power Consumption dataset showed the proposed model's stable convergence and prediction capabilities, as proven by the low error values and the similarity in actual and predicted energy consumption patterns. The analysis of the training and validation loss curves showed the model's effectiveness in learning from the dataset with little generalization gap. The prediction results showed the model's capacity to recognize the actual energy consumption trends despite the short-term fluctuations. Incorporating interpretability with feature correlation analysis helps to improve transparency by identifying major consumption factors such as global active power, energy minimum values, and global intensity. This helps to improve the trustworthiness of the model in energy management systems. In conclusion, it is evident that the proposed model has shown high scalability and reliability in terms of multi-horizon forecasting, and interpretable in solving advanced energy forecast problems. The study demonstrates the potential of the proposed model in its application to intelligent grid systems, where demand prediction is critical in resource management. Improvements to be made in the future

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involve integrating real-time data from smart meters to improve the proposed model. The proposed model can be applied in the development of prepaid energy management systems, where forecast is critical in planning energy recharge. The proposed model can be improved through advanced interpretability to enhance the accuracy of forecast in dynamic energy consumption.

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