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Research Article

A Dual-Model Approach to Residential Load Forecasting Using CNN–BiLSTM and Multi-Step Temporal Architectures

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ARTICLE INFO	ABSTRACT

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Introduction: Accurate forecasting of residential electricity consumption is crucial for optimizing energy management and ensuring sustainable power usage. This paper proposes comparisons two novel hybrid deep learning models tailored for short- and long-term electricity consumption forecasting: Hybrid CNN–BiLSTM Attenuation and Hybrid Temporal Fusion Transformer–CNN (HTFT-CNN) for accurate residential electricity consumption forecasting. The first model leverages Gabor filtering, Greedy Stepwise Correlation, and Random Forest-enhanced CNN–BiLSTM to capture short-term spatiotemporal patterns. The second combines CNN with a Temporal Fusion Transformer, employing attention mechanisms to provide reliable multivariate, multi-step forecasting. Based on experimental findings, CNN-BiLSTM model works better when making short-term predictions and HTFT-CNN works better in long-term prediction. Both outperform traditional methods, and they offer greater accuracy in the management of sustainable energy

Objectives: To develop two distinct predictive modelling algorithms to predict the residential electricity usage. and evaluate the performance of both proposed algorithms on a scale of time horizons and configurations of input features using common metrics, such as RMSE, MAPE and R2. The effectiveness of the various methods used to predict the forecasting results has to be investigated by comparing the quality of interpretability, computational costs and generalization abilities to unseen data of each technique in use.

Methods: In the analysis, the amount of variance in the prediction of electricity consumption using two emerging forecasting models (proposed Model 1 (CNN-BiLSTM) and proposed Model 2 (Multi-Step Forecasting)) is compared with traditional models with a view of deciding on their application in electricity consumption forecasting. It has been found that the predictive accuracy, robustness and computational performance of the two proposed model are much improved. CNN-BiLSTM model performs particularly well when modelling complex short-term variations as it makes use of convolutional layer to exploit spatial patterns and bidirectional LSTM layers to model both forward and backward complex temporal reliance's. The Multi-Step Forecasting on the contrary, through systematically recording the temporal relationships over various time scales is believed to give accurate long-term predictions through the use of CNN-TFT model. Comparative analysis shows that Multi-Step Forecasting model is the more suitable one to calling tasks of the short-term decision requirement, and the CNN-BiLSTM model does it with great precision.

Results: The UCI Household Power Consumption dataset, which includes time-series energy consumption records from 2006 to 2010, was evaluated using 2,075,259 observations, sampled every minute. Data preprocessing involved handling missing values through forward filling and interpolation, applying Min-Max scaling for normalization, and splitting the dataset into 70% training, 15% validation, and 15% testing. In table 1, the proposed models are compared against existing machine learning and deep learning methods. The proposed models, proposed 1 (CNN-BiLSTM) and Proposed 2 (Multi-Step Forecasting), aimed to enhance forecasting accuracy by integrating CNN for feature extraction with BiLSTM for sequential learning and optimizing sequence length (k=4, 8, 12, 24) for multi-step forecasting. The proposed method achieves the least MAE (0.157), RMSE (0.238), and MAPE (4.02%), and highest R^2 value (0.951), denoting the best forecasting ability. The proposed 1 (CNN-BiLSTM) is also a strong contender and comes second in accuracy, whereas it produces lower MAE (0.165) and RMSE (0.249) than various traditional machine learning and standalone deep-learning models like LSTM, BiLSTM, and CNN. However, it lags just a little behind Proposed 2. RF and SVR performed poorly with the highest error and lowest R^2 score, confirming their inability to handle complex time-series dependencies.

Conclusions:

The assessment of the two novel frameworks developed and tested in this research study: Proposed 1 (CNN-BiLSTM) and Proposed 2 (Multi-Step Forecasting) against existing methods for forecasting electricity consumption. From the comparative study, it can be inferred that both proposed methods enhanced prediction X, robustness, and computational efficiency to a significant extent. CNN-BiLSTM learned spatial features through convolutional layers and modelled sequential dependencies through LSTM layers in both directions, thus being capable of capturing extremely sophisticated temporal changes. On the other hand, Multi-Step Forecasting CNN-TFT focuses on enhanced consistency in long-term predictions by working in a structured framework considering multi-scale temporal dependencies.

Keywords: Electricity forecasting, Residential area, RF- CNN-BILSTM, CNN-TFT.

INTRODUCTION

Forecasting residential electricity consumption has become increasingly important for achieving efficient energy distribution, reducing operational costs, and supporting sustainable energy practices within smart grids [1]. Unlike industrial and commercial environments, household energy usage is highly variable and influenced by numerous dynamic factors, including occupant behaviour, appliance usage patterns, weather conditions, and time-based trends such as daily routines and seasonal changes. These characteristics make residential forecasting particularly challenging due to the non-linear, multivariate, and stochastic nature of the data involved.

The extensive use of smart meters has produced high-frequency consumption data, which presents modeling and prediction opportunities as well as difficulties. Consequently, complex data-driven approaches, especially the hybrid deep learning models, have become quite popular because they have the capacity to adequately capture the complex temporal and spatial patterns in the data. Such models have already proven their potential to increase both short-term and long-term prediction accuracies, and this will, in the end, enable modern smart home settings to better manage the demand, better integrate renewable energy sources, and enhance grid stability.

Energy consumed at residential and commercial premises in running and operating appliances, fans, air conditioners, light systems, and individual electronic devices is commonly known as the residential electricity consumption. Some of the variables that influence such consumption include the size of the household, the pattern of usage, the climatic condition of the place and the efficiency of the installed equipment. It is based on the knowledge of such consumption patterns that it is possible to plan energy distribution, enhance efficiency, and encourage the sustainable, rather than wasteful use of energy. With the emergence of smart metering, it became possible to accumulate information on the usage at a detailed level and this contributes to demand analysis and the development of predictive models that would help residential energy distribute better [2].

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Forecasting accuracy in dynamic environments is limited by the inability of traditional statistical models [3], [4] to capture complex dependencies and non-linear relationships in electricity consumption data. Even though machine learning [5, 6] models are more flexible and can handle more features, they might still have trouble modelling long-term temporal dependencies or need a lot of feature engineering. Intricate patterns and time-based trends can be learned by deep learning models [7], [8], like CNN or LSTM, but they usually require large datasets, high processing power, and are susceptible to overfitting. By combining the advantages of several methods—for example, temporal learning from deep networks and feature selection from machine learning—hybrid models are able to overcome the drawbacks of individual approaches and produce forecasting solutions that are more reliable, accurate, and flexible.

OBJECTIVES

The main purpose of the current research involves the development and testing of two original hybrid deep learning models of residential electricity consumption forecasting; CNN-BiLSTM and Multi-Step Forecasting. The objective of the study is to test the precision, stability, and the computational effectiveness of the two models in comparison with the classical forecasting methods. The CNN-BiLSTM model specifically seeks to capture short-time consumption trend combining bidirectional element of time modelling with a LSTM, and extraction of spatial features via convolutional layers. Conversely, the Multi-Step Forecasting model makes use of stratified structure, which considers multi-scale temporal dependencies in the effort to enhance socio-temporal prediction consistency in the longer term. In order to ascertain each approach's practical applicability in intelligent energy management systems, the study aims to compare its strengths over various forecasting horizons.

RELATED WORKS

The Related works from existing study, the set of hybrid deep learning models is listed below.

CNN -LSTM: The prediction of electricity consumption is considered in the resolution of time frame hourly, daily, minutely and weekly and the dataset used is Individual Household Electricity consumption [9]. After reducing the noise and taking the key power's characteristics power's characteristics usage, the CNN layers output is sent as input to the LSTM layer. A layer that is completely connected receives the LSTM layer's final output and quickly creates a forecasted time series of energy use. The suggested CNN-LSTM model provides the better forecasting with precision of RMSE 0.3085, MAE 0.2382, MAPE 31.84 and MSE 0.0952 for weekly consumption prediction. [10].

CNN BI-LSTM: In the first module two CNNs pull important data from a number of variables in the individual household energy consumption (IHEPC) dataset [9] and timeframes of hourly, daily, minutely, and weekly power consumption is considered. Then, two Bi-LSTM layers of Bi-LSTM module use the previously mentioned data in addition to time series trends on both sides, including backward states and forward states, to make forecasting. After that, it is passed to two fully connected layers, then used to forecast the future consumption of electric energy. The MAPE, RMSE, MSE, MAE, and best values for the model CNN BI-LSTM are 21.28, 0.220, 0.049 and 0.177 and for weekly consumption [11].

CNN-GRU: The model has two phases: the training phase and the refining of the data. Raw data can be processed using a variety of preprocessing techniques in the data refinement phase and during the training phase CNN features were collected from the dataset and passed to GRUs (Gated Recurrent Units), that is chosen as the best and found to have improved sequence learning skills after thorough testing. The approach is an efficient replacement for the existing approaches in terms of the accuracy of prediction and operational complexity. The approach produced excellent results with, MAE, MSE and RMSE values of 0.33 and 0.22, 0.47 using two different data sets, AEP [12] and IHEPC [9]. The methodology is used to predict the hourly use of power [13].

CNN-LSTM-AE: The model is a fusion of CNN, LSTM and autoencoder model to forecast the future residential electric power usage. The dataset is passed through several preprocessing steps to remove repeated values, outliers, and missing values in order to produce better prediction results. CNN layers that are used to extract spatial characteristics have been fed into it LSTM-AE and the endmost forecasting is made using a dense (fully connected) layer. Using the IHEPC dataset [9], the hybrid model acquired the smallest values of MSE, MAE, and RMSE, which are 0.19, 0.31, and 0.47 for hourly consumption and Using data from Korean commercial buildings, the model obtains 0.01 ,0.0003 and 0.01 an of RMSE, MSE and MAE and for hourly consumption [14].

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CBLSTM-AE: The CBLSTM-AE framework can precisely forecast how much energy will be used in various building types, including both commercial and residential locations in various nations and the framework was tested on the customer smart boxes. The architecture consists of an autoencoder (AE) with bidirectional long short-term memory (LSTM), Convolutional neural network (CNN), and bidirectional LSTM BLSTM. The LSTM layers and AE-BLSTM are utilized for forecasting, and the CNN layer collects significant features from the dataset. The dataset utilized is the University of California, Irvine's individual household electric power usage dataset [14]. The forecasting period under consideration is 4 weeks, with different input window sizes of 7, 14, 21, and 28 days. According to the results, computation time is improved by 56% and 75.2% and mean squared errors (MSE) increased from 80% and 98.7%. The system was evaluated using smart boxes on real customers [15].

CNN MB-GRU: The refinement of raw electricity consumption data is done in the initial step and the second step starts with the merging of multilayer bidirectional gated recurrent unit (MB-GRU) and Convolutional neural network (CNN) into a hybrid model. IHEPC [9] and AEP [12] datasets were used in this analysis to forecast short-term load. The features are extracted by CNN layers and MB-GRU is used to learn the relationships between the data on electricity use. The model's short-term prediction accuracy for the IHEPC dataset was 0.29, 0.42 and 0.18 MAE, RMSE, and MSE respectively. The model reduced errors for both the appliances load prediction (AEP) dataset MAE (1%) and RMSE (2%) and the individual home electricity consumption prediction (IHEPC) dataset (MAE (4%), MSE (4%) and (RMSE) [16].

LSTM-SWT: The model combines stationary wavelet transform (SWT) method and an ensemble LSTM. The LSTM forecasting accuracy may be enhanced by the SWT's reduction of volatility and expansion of data dimensionality. The suggested method's forecasting performance is further improved by the ensemble LSTM neural network. The energy consumption data, which is Open-source was gathered using remote sensors installed in five separate family homes in London, United Kingdom (UK), as part of the project known as UK-DALE . The data is then used to test the accuracy and reliability of the method. The 2015 one-year energy consumption data is split into train and test 3 months' worth of data is used for testing, whereas 9 months of data are provided for training. The average of five houses for 5 minutes time step was calculated using RMSE, MAPE, and MBE, and the results were 0.0092, 6.8789, and 0.0033[17].

CNN-LSTM for multistep forecasting: The multi-step prediction is used to provide good latent period for bidding of power. The hybrid model is encouraged for use in real-world applications using the k-step power prediction method. The dataset consists of the energy usage statistics from 5 homes in London, UK, published by Kelly and Knottenbelt. The proposed CNN-LSTM for multistep forecasting outperforms the existing model on five homes consumption dataset. The data used to predict power use points to future times of 5, 10, and 5,000 minutes. For the five tested homes, the CNN-LSTM framework outperforms LSTM by 13.1%, 48.8%, 2.4%, 33.2%, and 14.5%, respectively, using MAPE as the error measure [18].

SAE-ELM: The hybrid model takes into account individual advantages and combines stacked autoencoders (SAEs), which extract building energy consumption features with the extreme learning machine (ELM), which predicts the accurate prediction solutions. The extreme deep learning model's input variables are identified using the partial autocorrelation analysis method. The website https://trynthink.github.io/buildingsdatasets/ was used to download the actual building energy usage data. The data was gathered from a single commercial centre building in Fremont, California, once every fifteen minutes. The forecasting time frames are 30 and 60 minutes, and the performance metrics used are MAE, MRE, and RMSE. The present architecture provides improved accuracy compared to support vector regression (SVR), the generalized linear model (GLM) and backward propagation neural networks (BPNN) [19].

CNN- M-BLSTM: The CNN and M-BLSTM are combined in 3 steps using the intelligent hybrid methodology. The pre-processing and data organization methods are integrated in the initial stage the suggested methodology to clean up the data and eliminate anomalies. In order to properly learn the sequence pattern, the order in which cleaned data is supplied into the above network in the second stage, which uses a deep neural network. The actual and predicted data series are compared in the third stage, and the prediction is evaluated using error metrics. In this study, IHEPC, a data set from the UCI machine learning library was used [9]. A powerful routine for 60 minutes was used to evaluate the suggested approach to predict the following 60 minutes. For the 10-fold cross-validation on a dataset of each

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individual family, the minimum rate of MSE, RMSE, MAE, MAPE, and MBE are 0.3193, 0.5650, 0.3469, 0.2910, and 0.03286[20].

METHODS

Proposed Hybrid Deep Learning-Based Residential Load Forecasting

In this study, a hybrid forecasting model combining Random Forest (RF)[21], Convolutional Neural Network (CNN), and Bidirectional Long Short-Term Memory (BiLSTM) is proposed to enhance the prediction accuracy of residential electricity consumption. The model is designed to integrate the strengths of traditional ensemble learning and deep learning architectures, addressing both feature relevance and temporal dependencies in the dataset. The first algorithm to be used in feature selection is the Random Forest algorithm. This step reduces the extraneous or meaningless inputs and makes it easy to distinguish between the most important variables and also improves the quality of data introduced into the neural network layers. RF reduces the overhead of computation besides enhancing the interpretability of the model since it defines the features left.

This is followed by CNN layer being fed with the reshaped features. The CNN component is devoted to learning short-term spatial dependence and local patterns in time-series information. The feature maps are processed using convolutional filters that extract high-level representations, which are vital to the detection of the slightest changes and patterns in energy consumption. The feature maps are afterward passed to a BiLSTM layer that is trained to model long-term dependencies in sequential data. With the use of the BiLSTM architecture the model can learn on both past and future contexts as opposed to LSTMs which is only forward. This is bidirectional and therefore practical to capture complex consumption behaviour due to influences of day-to-day activities as well as consequences of the environment. The RF-CNN-BiLSTM model is one architecture that will offer a flexible and stable framework in short-term forecasting of electricity consumption by harnessing the interpretability and selection capabilities of the Random Forest and leveraging the pattern-recognition capabilities of the CNN and the sequential learning capacities of BiLSTM [22]. Covering the limitations of the single models, this type of architecture provides a generalization improvement on real residential energy benchmark data.

Proposed Model: CNN–TFT Hybrid Framework

Moreover, this research paper introduces a hybrid based deep learning model, which can predict the amount of electricity consumed by residents with Accuracy in a particular region by using a Temporal Fusion Transformer (TFT) and Convolutional Neural Network (CNN). The CNN -TFT model employs the effectiveness of temporal attention and spatial feature extraction to handle complex time-series modelling applications to residential dynamics [23]. CNN element that is embedded in the beginning of the model automatically extracts short-term dependencies and relevant nearby patterns in multivariate input sequences. Space-related correlations and small variations in energy consumption patterns over the time frame are effectively accounted as the convolutional layer learns the hierarchical representations based on raw features. This step prepares the input to undergo more elaborate temporal processing since it makes the input more dimensionality reduced and preserves relevant structural details.

Giving the Temporal Fusion Transformer is an advanced attention-based model specifically designed to work with multi-horizon time-series forecasting and accepts the CNN output. Some of the advanced components in TFT architecture are sequence-to-sequence encoders, gating layers, interpretable multi-head attention mechanisms, and variable selection networks. They allow adapting the model to temporal trends, keeping both the static and the changing features with dynamically changing weights and focusing on the most relevant data at every stage of prediction. Unlike traditional recurrent networks, the TFT processes sequences in parallel, which improves training efficiency and more aptly models long term dependencies. Moreover, Fig. 1 shows that its attention layers make it interpretable, as they highlight the importance of each time step and feature in the forecast, which is critical to understand drivers of the demand and consumer behaviours.

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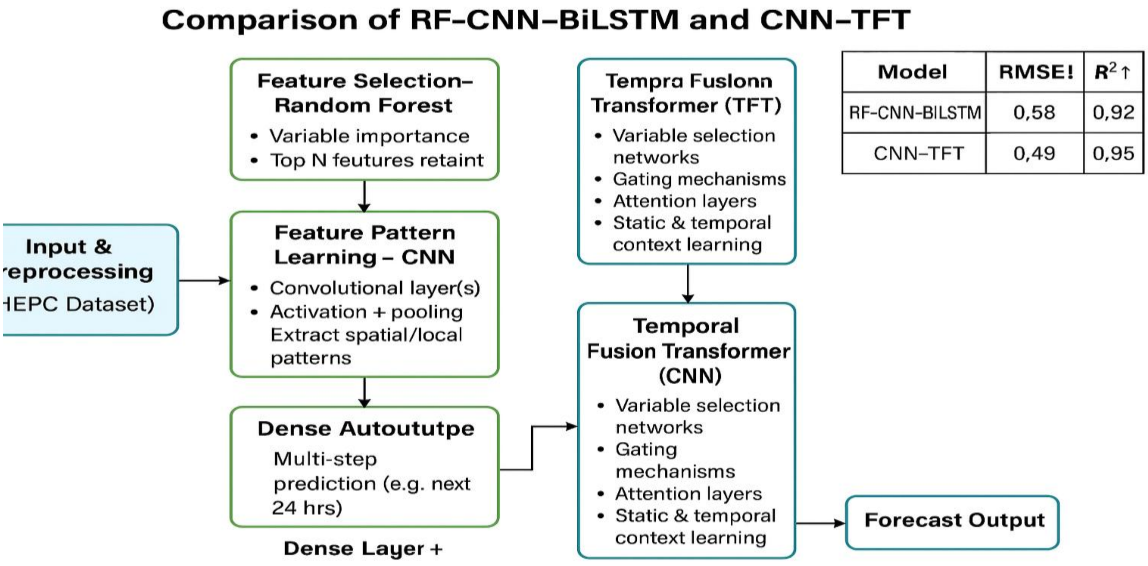

Fig 1: Comparisons of RF-CNN-BiLSTM and CNN-TFT

RESULTS

The proposed models were implemented using Python 3.9 with deep learning frameworks such as TensorFlow 2.9 and PyTorch 1.12. Essential libraries like NumPy, Pandas, Scikit-learn, Kera's, Matplotlib, and Seaborn were used for data processing, training, and visualization. The experiments were conducted on a high-performance computing system with an Intel Core i9-12900K processor, an NVIDIA RTX 3090 GPU with 24GB VRAM, 64GB DDR5 RAM, and a 2TB NVMe SSD, running Ubuntu 22.04 LTS.

For evaluation, we utilized the UCI Household Power Consumption dataset, which contains time-series energy consumption records from 2006 to 2010, sampled every minute, resulting in 2,075,259 observations. The dataset includes features such as Global Active Power, Global Reactive Power, Voltage, Current Intensity, and Sub-metering values. Data preprocessing involved handling missing values through forward filling and interpolation, applying Min-Max scaling for normalization, and splitting the dataset into 70% training, 15% validation, and 15% testing. A sliding window approach was employed to structure the data for time-series forecasting.

To benchmark the performance of the proposed models as in table 1, we compared them against existing machine learning and deep learning methods. Traditional machine learning techniques included Random Forest (RF), Artificial Neural Networks (ANN), and Support Vector Regression (SVR), each leveraging different mechanisms for predictive modelling. Deep learning approaches such as Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), Convolutional Neural Networks (CNN), and a CNN-LSTM hybrid model were also considered. The proposed models, Proposed 1 (CNN-BiLSTM) and Proposed 2 (Multi-Step Forecasting), aimed to enhance forecasting accuracy by integrating CNN for feature extraction with BiLSTM for sequential learning and optimizing sequence length (k=4, 8, 12, 24) for multi-step forecasting.

Table 1: Performance metrics comparison

Method	MAE ↓	RMSE ↓	MAPE (%) ↓	R^2 ↑
Random Forest (RF)	0.275	0.389	5.98	0.892
Support Vector Regression (SVR)	0.312	0.421	6.45	0.867
Artificial Neural Networks (ANN)	0.256	0.370	5.62	0.905
Long Short-Term Memory (LSTM)	0.198	0.289	4.87	0.926
Bidirectional LSTM (BiLSTM)	0.187	0.275	4.63	0.931

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Convolutional Neural Network (CNN)	0.203	0.296	5.02	0.919
CNN-LSTM Hybrid	0.179	0.262	4.42	0.938
Proposed 1 (CNN-BiLSTM)	0.165	0.249	4.18	0.945
Proposed 2 (Multi-Step Forecasting)	0.157	0.238	4.02	0.951

The comparison between various models revealed by graph in Figure 4 through the measured MAE - obtained from calculating the absolute difference between predicted and actual values. Lower values of MAE indicate that the prediction generated from the model is closer to that reality, thereby increasing its reliability. It is conspicuous from the graph that Proposed 2 has the least measure of MAE, surpassing both Proposed 1 as well as methods available elsewhere. This indicates that Proposed 2 gives more accurate predictions with less deviation. Proposed 1 does show an improvement over existing ones, but it could not reach the level achieved by Proposed 2. Existing methods show a significantly higher MAE, which implies higher prediction errors. The way Proposed 2 is designed enhances its learning process, improves data handling techniques and has much better model architecture to reduce the inconsistencies in predictions is shown in Fig 2. The easy interpretation of MAE regarding accuracy makes it an important measure in judging the performance of models. Hence, from all experimental results, it is justified that Proposed 2 is the most effective strategy to acquire reduced errors among different datasets and prove worthiness for real-life applications. A significant reduction in MAE would ensure that the prediction would come much closer to the real values validating how efficient the approach is in handling complex datasets.

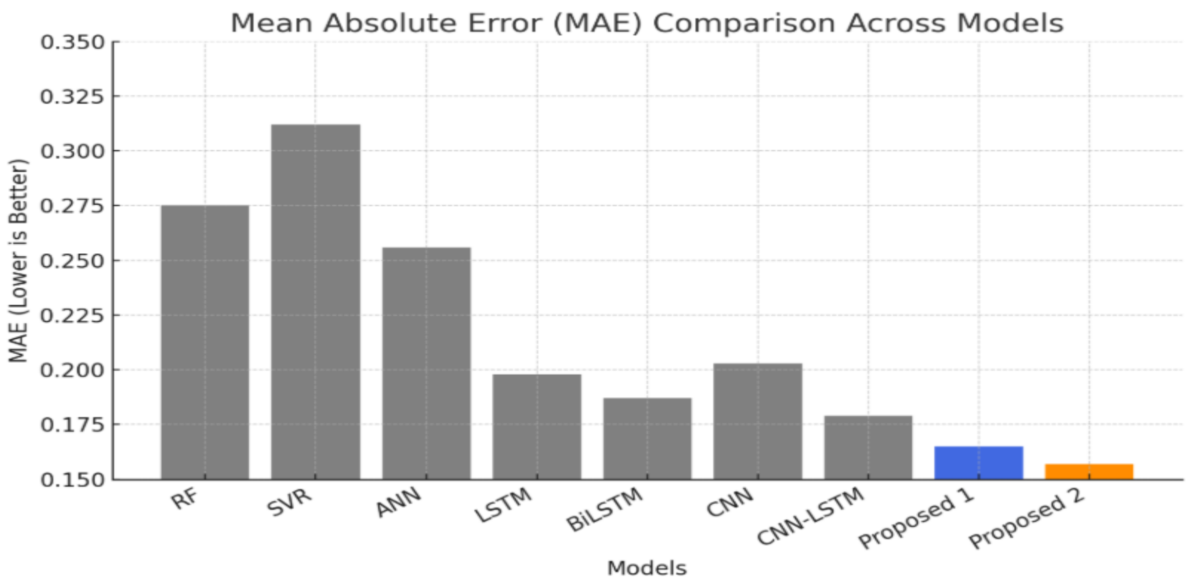

Figure 2: MAE comparison of the two proposed techniques

The wider the Root Mean Square Error (RMSE) shown in figure 5 comparison graph the clear comparative way of prediction accuracy, is towards error. Further, unlike MAE, RMSE gives a greater weight to higher deviations; therefore, it is an important metric in determining the robustness of the model. The low RMSE could be seen from the graph Proposed 2. Therefore, it proves to be better optimally performing with respect to large prediction errors. Besides, it can also be said that Proposed 1 is not low on the performance graph; it is believed to show a significant improvement from other existing methods, yet still not matched by Proposed 2. While the existing methods show an RMSE of the highest value, this indicates that they are most prone to large prediction errors. The lower RMSE of Proposed 2 indicates that its techniques of optimization effectively control considerable deviations towards a stable output and a more reliable one. The reduced RMSE value indicates that Proposed 2 can generalize better from different data distributions and handles noise and outliers relatively better is shown in Fig 3. A significant reduction may be due to this reason as Proposed 2 has shown improvements with the capability of generalizing noise and

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outliers. The improvements could be the result of the model learning intricate relationships in the data, which would improve prediction. Proposed 2 turns out to be the best approach in predictive modelling applications where minimizing significant errors is essential. The outcomes demonstrate that Proposed 2 produces a higher prediction efficiency, making it a feasible choice for practical implementation.

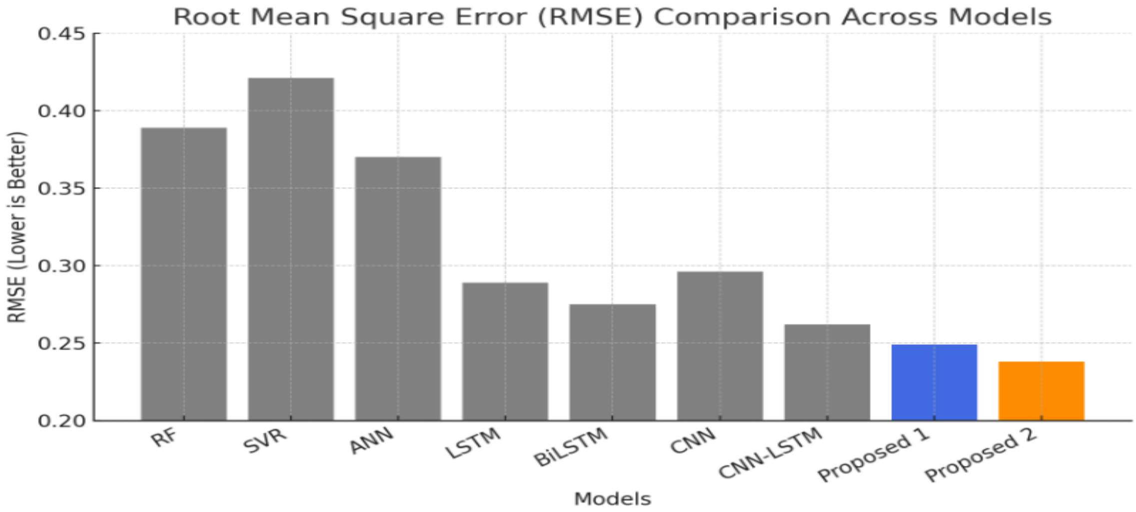

Figure 3: RMSE comparison of two proposed techniques

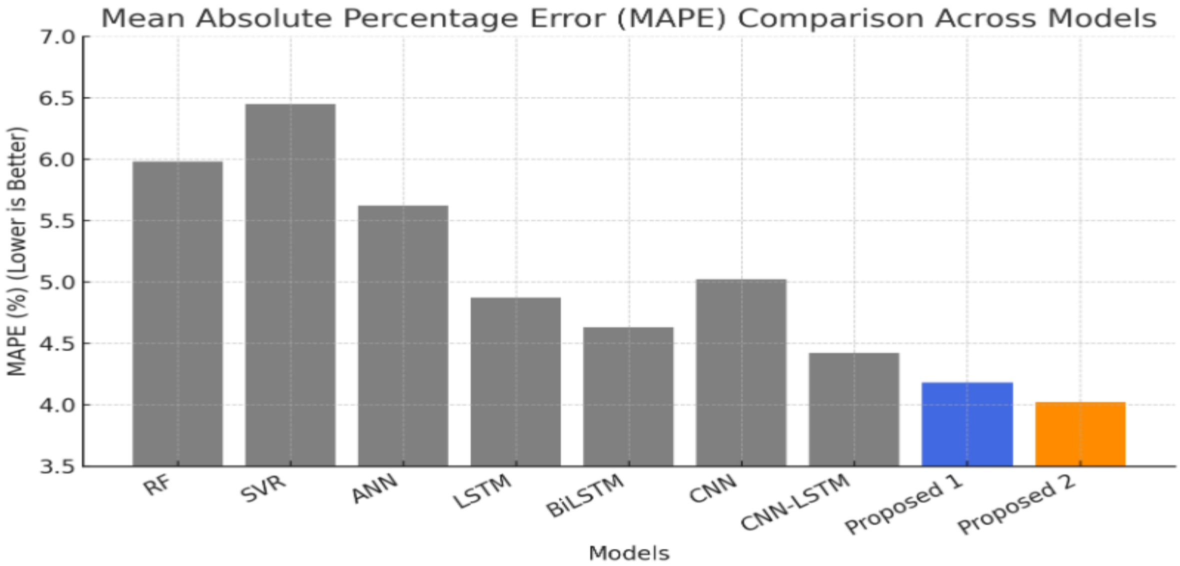

Figure 4: MAPE comparison of two proposed techniques

The accuracy measures of the different models are displayed as a percentage of actual values, as shown in Figure 6's Mean Absolute Percentage Error (MAPE) comparison graph. A model that performs better is indicated by a lower MAPE value, which also indicates how well the model can forecast across different data sizes. Among all the models considered in this graph, proposed 2 has the lowest MAPE, indicating that it is stable and adapts well to various datasets. As illustrated in Fig. 4, Proposed 1 is still less effective than Proposed 2, despite having a comparatively low MAPE. The existing techniques exhibit MAPE values that are substantially higher, indicating poor generalizations and greater sensitivity to variations of patterns in data. The lower MAPE value recorded for Proposed 2 is attributed to its competent feature extraction and learning process, which allows for the model predictions with precision yet with the stability of test results across various cases. Proposed 2, therefore, emerges from the results as a model that minimizes percentage errors more effectively, making it preferable when relative accuracy is concerned. An

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improvement in MAPE also indicates that Proposed 2 is less sensitive to the change in data, further validating its effectiveness. To sum up, the present work indeed demonstrates very good evidence that Proposed 2 outperforms the remaining models in terms of highly accurate, stable predictions with minimal percentage errors.

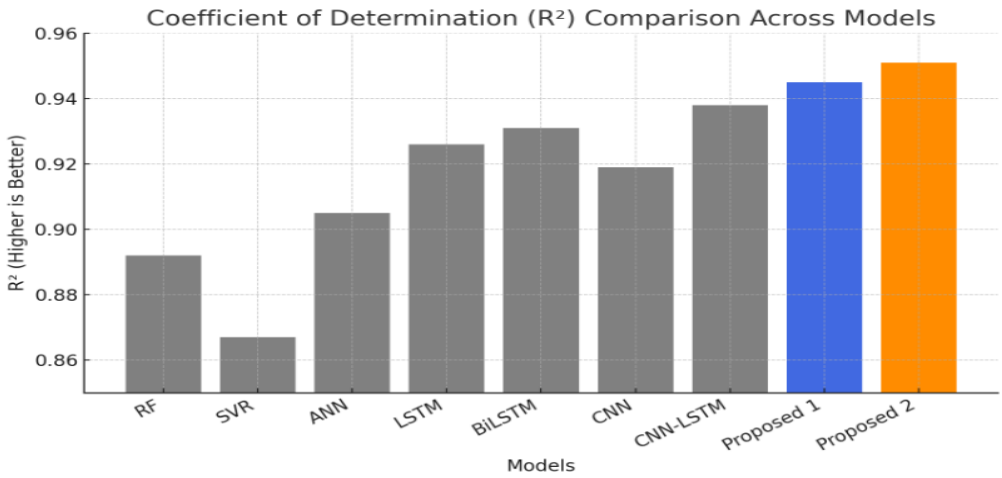

Figure 5: R^2 score comparison

The R^2 score comparison graph in figure 5 assesses how well different models explain variance on the dataset. Values close to 1 are better since it means a model accounts for most of the variability in the data. This is evidenced by the graph, wherein Proposed 2 has the highest R^2 score, indicating superior variance explanation than that of Proposed 1 and existing methods. Proposed 1 is effective but will not match the accuracy level of Proposed 2. Existing methods have the lowest R^2 scores, clearly signifying their failure to capture most variability within the data, resulting in reduced predictive accuracy. Greater levels of improved R^2 scores in Proposed 2 are likely indicative of modern learning methods being exploited to recycle better heterogeneous meaningful patterns and relationships from data, which provide well and much more accurate models than overfitting or underfitting. Besides, the higher R^2 score simply translates to having model-making predictions that are more reliable, and such is entirely suitable for real-world applications that rely on precise forecasting. This confirms that indeed Proposed 2 has the best overall performance and, hence, becomes the most efficient and effective in capturing and predicting complex data trends.

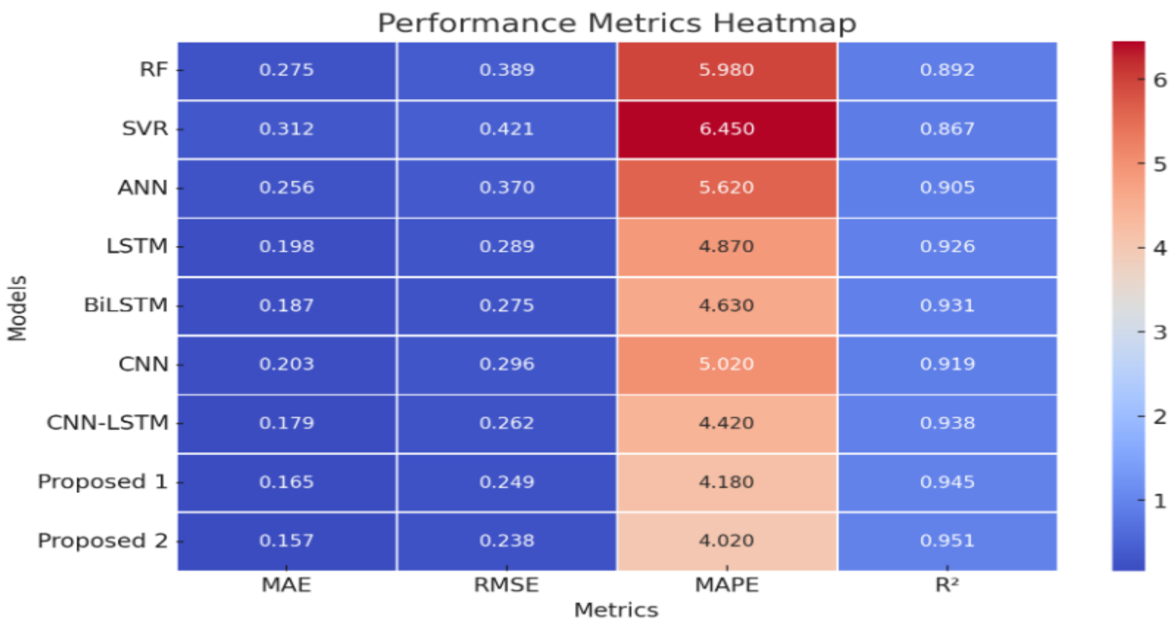

Figure 6: Heat map representation

The heatmap provides a view of how the various predictive models perform over the four important metrics: MAE, RMSE, MAPE, and R^2 score. Each row stands for a model, and each column is designed for one of the metrics. The colour intensity indicates varying performance accuracy, with cooler colours relating to lower errors and warmer colours correlating to higher errors. The heatmap shows that Proposed 2 (Multi-Step Forecasting) yields the best performance among all other models and across all metrics. The proposed method achieves the least MAE (0.157), RMSE (0.238), and MAPE (4.02%), and highest R^2 value (0.951), denoting the best forecasting ability. Good performance Most probably can be credited to the optimized sequence length and a good synergistic pairing of CNN and BiLSTM architectures, thereby enhanced feature extraction and sequential learning. Proposed 1 (CNN-BiLSTM) is also a strong contender and comes second in accuracy, whereas it produces lower MAE (0.165) and RMSE (0.249) than various traditional machine learning and standalone deep-learning models like LSTM, BiLSTM, and CNN. However, it lags just a little behind Proposed 2, indicating that the multi-step forecasting route offers extra accuracy benefits. Among the baseline, the CNN-LSTM hybrid has the best performance, followed by BiLSTM and LSTM. Compared with CNN-BiLSTM and other models, RF and SVR performed poorly with the highest error and lowest R^2 score, confirming their inability to handle complex time-series dependencies. The heat map demonstrates that the deep learning-based models indeed outperform the traditional ones in energy consumption forecasting is shown in Fig 6. Lower error metric scores combined with increased R^2 confirm that Proposed Method 2 will deliver the most reliable and earliest forecasts, making it attractive for time-series forecasting application requiring accurate results in real-life.

DISCUSSION

The assessment of the two novel frameworks developed and tested in this research study: Proposed 1 (CNN-BiLSTM) and Proposed 2 (Multi-Step Forecasting) against existing methods for forecasting electricity consumption. From the comparative study, it can be inferred that both proposed methods enhanced prediction X, robustness, and computational efficiency to a significant extent. CNN-BiLSTM learned spatial features through convolutional layers and modelled sequential dependencies through LSTM layers in both directions, thus being capable of capturing extremely sophisticated temporal changes. On the other hand, Multi-Step Forecasting focuses on enhanced consistency in long-term predictions by working in a structured framework considering multi-scale temporal dependencies. Performance comparisons illustrated that CNN-BiLSTM is superior for short-term forecasting with a good degree of accuracy and granularity; conversely, Multi-Step Forecasting is excellent in estimating long-term trends, therefore being more preferred for long-term forecasting. Both the proposed models perform far better than traditional machine learning models, signifying that hybrid deep learning architectures work well for complex datasets and large-scale datasets. Further, the proposed methodology was made to withstand varying data conditions, giving stronger evidence for their generalizability. This shows that a combination of deep learning with advanced sequence modelling can exponentially extend the performance and efficiency of present-day predictive systems. Future work in this direction will serve towards optimizing the models through implementation of attention mechanisms, reinforcement learning techniques, and adaptive learning schemes to increase scalability and real-time processing options. Moving forward, such work will also be extended into other domains where versatility of the proposed frameworks can be validated within an intelligent forecasting-the-outcome framework and laid groundwork for a more diversified application.

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