AI in renewable energy forecasting

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Abstract

Accurate prediction of renewable energy generation is crucial to optimize resource allocation and Reduce energy waste, which helps support a stable and sustainable energy grid. Artificial Intelligence (AI) has been used to predict renewable energy generation to tackle the challenges of intrinsic variability of the data that is used for this task. With the increasing demand for Renewable Energy Sources like wind and solar, precise forecasting is essential for efficient planning of energy production and consumption. This paper surveys various methodologies that adopt different AI techniques to get accurate predictions. This study examines several researches that use sophisticated algorithms, including long short-term memory networks (LSTMs), recurrent neural networks (RNNs), and hybrid models that utilize both machine learning and statistical techniques. The results showcase how implementing AI for the task of predicting renewable energy generation could improve accuracy significantly and lower operating costs, making it easier to integrate into real-world scenarios.

Introduction

The transition to renewable energy sources is essential for addressing climate change and achieving a sustainable energy future. However, maintaining a steady energy supply is challenging due to the highly variable nature of renewable energy sources like wind and sun. These issues can be effectively addressed by data-driven artificial intelligence (AI) models, which use both historical and current data to produce precise, flexible predictions.

Machine Learning (ML) techniques such as ensemble learning and support vector machines predict the results by utilizing the patterns in the datasets. Deep Learning (DL) models such as Recurrent neural networks (RNNs) and convolutional neural networks (CNNs) are based on these ideas and enable automatic feature extraction and generalizability to non-linear data. These models have been widely used in the energy sector due to their robustness and ability to handle large and heterogeneous datasets to generate accurate forecasts.

However, data-driven models present certain limitations as they can be biased or lack explainability, and need large datasets. To address these challenges, various research have been conducted and explored the utilization of hybrid models that optimize the improve the model's performance.

In this study, we present the state of data-driven AI models for renewable energy forecasting, with an emphasis on DL and advanced ML techniques, and their potential enhancements to improve the forecasting accuracy. We survey different cutting-edge AI methods used in solar, wind, and other renewable energy source forecasting. Lastly, we propose an architecture to solve the common challenges in this task to enhance the robustness of the model and prove its usefulness in real-world applications.

II. Literature review

Saxena et al. [1] proposed a hybrid model by integrating K-Nearest Neighbors (KNN) with Support Vector Machine (SVM) to leverage the structural diversity of KNN and data diversity through SVM. This hybrid model showed high performance compared to conventional LSTM models, with notable improvements in the accuracy of 98% for forecasting PV power generation. The study used real-time series, one-year dataset from Jodhpur containing hourly average temperature, sunlight duration, Global Solar Irradiance (GSI) and PV energy generation. The model excels in real-time dataset by leveraging the mapping of non-linearly separable data to higher-dimensional spaces. The hybrid model showed lower RMSE values of 0.001, which is lower than RMSE of 0.14 for LSTM model during the training phase. When comparing accuracy, sensitivity, and specificity for specific parameters, the LSTM model marginally surpasses KNN-SVM in overall accuracy and specificity by 2.99% and 3.91%, respectively. However, KNN-SVM shows a higher sensitivity by 2.46% when used with Hourly Total Global Solar Radiation (HTGSR), which could indicate its effectiveness in correctly identifying positive cases, potentially useful in applications where sensitivity is crucial. However the model remains sensitive to the data preprocessing methods used as it gave higher sensitivity when used with HTGSR compared to using only Global Solar Irradiance.

Optimizing hyper-parameters is essential for increasing machine learning models' efficiency and forecast accuracy, particularly in intricate recurrent neural networks (RNNs). Model parameters are often adjusted using extensive simulations and empirical information, although this process may be resource- and time-intensive. Bayesian optimization (BO) uses probabilistic models to direct the search and enable exploration of the hyper-parameter space. Truncated-Newton BO

(BO-TNC) and BO with limit-BFGS-bound (BO-L-BFGS-B) depend on gradient-based methods, which increases the computational cost. This is addressed by Yaru Li et al. [2], where the BO-PSO (particle swarm optimization within the BO framework) approach was used to parallelizable particle motions instead of gradient computations. The research analyzed the models such as RNN-BO-PSO, the LSTM-BO-PSO, and the previously mentioned models on the normalized power load data with a sampling of 15 minutes. The three main parameters that were tuned using the algorithms include Feature length, Number of network units, and Batch size of training data. The models were analyzed on R-squared values where LSTM-BO-PSO showed the highest value with 0.9951. Though the research has obtained higher accuracies with the optimization techniques, it did not utilize the models on multiple variables, thus not providing results to prove the model to be robust for real-world applications. Another limitation can be pointed at the utilization of BO as the model can over-exploit, leading it to get stuck in local optima without fully exploring the other promising regions in the hyperparameter space.

The study conducted by M. Tortora et al. [3] introduced a Multi-Level Fusion Transformer-Based Model that combines the strength of both AI and physics-based methods. Forecasting methods typically fall into physics-based and data-driven approaches, with AI-based models demonstrating strong performance by capturing complex data patterns. However, these models tend to not capture the underlying principles of Photovoltaic (PV) generation. The proposed model aims to bridge this gap by leveraging self-attention transformer architecture with a multi-level fusion of historical PV and weather data to produce multivariate and multistep day-ahead forecasts. The authors used the Ausgrid benchmark dataset which includes data on solar capacity, total energy consumption, postal codes, solar conditions like Direct Normal Irradiance (DNI), Global Horizontal Irradiance (GHI), and Diffuse Horizontal Irradiance, along with the weather data like temperature, pressure, humidity, and wind speed. The results obtained in the research show the MATNet produces the best accurate results with the lowest RMSE score of 0.0460 and 0.0245 MAE score, compared to LSTM-based MATNet which gave 0.0495 and MAE score of 0.0267. However, the study fails to account for the adverse or variable nature of the weather data, since the utilized weather dataset didn't have such conditions to train the model in such scenarios.

Yahia Said et al. [4] proposed a hybrid forecasting model by combining LSTM with an autoencoder to enhance solar energy predictions. The LSTM captures temporal patterns in historical solar energy data, while the autoencoder extracts spatial features. The findings from this study demonstrate that extracting temporal features before spatial features would yield better performance. The data used include the historical time series of active power with weather conditions like temperature, humidity, wind speed, GHI, and DHI. The results show that the sequence-to-sequence LSTM-autoencoder model produced predictions with low MAE values of 0.217 and RMSE values of 0.602, compared with 0.312 MAE score and 0.645 RMSE score shown by sequence-to-sequence LSTM and 0.219 MAE score and 0.613 RMSE score shown by

LSTM-autoencoder model. However, the approach to extract temporal features before spatial features may not generalize well when geographical context is used in the data.

Shahram Hanifi et al [5] introduced a hybrid model between LSTM and CNN by combining with wavelet packet decomposition (WPD) to use in wind power forecasting. The data used include wind speed, and power generation along with the configuration of the wind turbine blades. WPD is utilized to decompose wind power data into various frequency sublayers. It works by applying both low-pass and high-pass filters to decompose a signal into low and high-frequency components to allow for a multi-level analysis of the frequency of the signal's components. The authors employed Sequential Model-Based Optimization (SMBO) with the Tree Parzen Estimator (TPE) for hyperparameter tuning, enhancing the efficiency of the model. The optimized LSTM captures both long-term and short-term dependencies in low-frequency sub-layers, while the CNN focuses on high-frequency sub-layers characterized by short-term dependencies. However, this research is limited to the use of non-geographical features. The proposed model has resulted in high accurate results considering the mentioned data with the respective MSE, RMSE, and R-square values being 0.633, 0.79, and 0.99.

Politecnico di Milano et al [6] proposed a Bayesian Hyperparameter Optimization (BHO) approach with a Gaussian process on the stacked Bidirectional LSTM (BiLSTM) model. BiLSTM captures dependencies from both past and future contexts in the sequence by processing sequence data in both forward and backward directions. By combining two LSTM layers, where one reads the sequence from start to end and another from end to start, BiLSTM can better understand complex temporal relationships. In the study, the method was validated using two public datasets with different time granularities, highlighting both accuracy and computational efficiency improvements over other state-of-the-art methods. Their analysis revealed that decreasing time granularity reduced model creation time without sacrificing accuracy, which was quantified using Floating-point Operations (FLOPs) as a metric for computational volume. The model gave the respective MAE% and RMSE% values as 1.306 and 1.696. However, the model showed a tradeoff between accuracy and computational load, emphasizing the importance of careful parameter selection for optimal performance. BiLSTM model also exhibits limitations when used with multivariate data since it is developed to capture the patterns based on historical sequences, but they struggle to model the relationships among the different variables effectively.

Dahmani et al. [7] investigated Single Neural Networks (SNN) and Bootstrap Aggregated Neural Networks (BANN) to predict hourly global radiation. The study used a dataset with 3,606 data points collected from Bouzareah, Algeria, which has weather conditions similar to that of Dubai. The features used include temporal features, mean temperature, daylight duration, wind speed, wind direction, relative humidity, rainfall, and daily worldwide solar radiation. To enhance model precision and robustness, they applied bootstrap aggregation, which generated multiple training datasets through bootstrap resampling with replacement. This approach helped mitigate limitations caused by an incomplete training dataset, allowing each SNN model to learn from diverse samples. The BANN was constructed by averaging the outputs of individual neural networks (INNs), creating a more resilient ensemble. The ANN is architectured using varying number of neurons ranging from three to twenty-five. Four activation functions were tested in the hidden layers like logistic sigmoid, hyperbolic tangent, sine, and exponential, with a pure-linear function for the output layer. Results showed that BANN achieved a lower root mean squared error (RMSE) of 62.49 Wh/m^2 compared to the SNN's 68.40 Wh/m^2, demonstrating greater accuracy and robustness in solar radiation prediction. SNN, INN and BNN showed respective R-squared values of 0.9620, 0.9618, and 0.9680, showing that BANN can accurately predict the diffused solar radiation using weather conditions that are similar to that of Dubai. However, the observations from the fit curves show that the model may suffer from systematic bias and it could consistently overestimate or underestimate the target values.

A. Verdone et al. [8] explored the application of Spatio-Temporal Graph Neural Networks (STGNNs) with 1D CNN for energy forecasting, leveraging their ability to integrate topological data related to the spatial distribution of energy plants and temporal data from time series. The study utilized synthetically produced time series data having features such as energy production data along with wind speed and temperature data, where the data was sampled for 1 hour. Each time step was normalized to stay in the interval between 0 and 1 given the minimum and maximum values of each time series. The proposed Graph Convolutional Network + 1D CNN (GCN1D) model avoids the vanishing gradient problem which is associated with RNN by utilizing a Graph Convolutional Network (GCN), which allows for the integration of both topological data, defined by the distribution of the plants in the territory, and temporal data of the time series. The model outperformed the LSTM and GCN-LSTM models with r-squared, MSE, MAE values of 0.984, 105, and 1245 respectively. The LSTM model gave the r-squared, MSE, MAE values of 0.952, 311, and 2430 respectively. GCN-LSTM gave 0.975, 162, and 1965 for r-squared, MSE, and MAE values respectively. The potential drawback in this model can be pointed at the absence of dropout layer, due to which the model may become overly reliant on specific neurons or layers, leading to overfitting.

Vartholomaios, A. et al. [9] employed a hybrid model combining Extra Trees (ExT) and Prophet model to predict one step ahead of solar and wind energy forecasting. The study used biseasonal features, temporal features such as sunrise, morning, noon, sunset and night times along with solar + wind energy source generation data. The study also experimented with features obtained from feature engineering where rolling window features were extracted from the energy generation data, based on key statistics like mean, minimum, maximum, standard deviation, and variance. 48 and 72 hours ahead energy values were also considered to train the model. The modeling process begins by first adding custom seasonalities and regressor to the Prophet model and then fitting the model to the training data, where the seasonal component is calculated. The seasonal component is subtracted and the deseasoned series is used as input to the ExT model, where the final forecast is produced by the residual forecasts along with the extrapolated seasonal patterns from the Prophet model. The proposed hybrid model with feature engineering performed showed the best MAE and RMSE values of 0.041 and 0.067 respectively when used with solar energy data, and 0.069 and 0.088 MAE and RMSE values when used with wind energy data, compared to only using the Prophet model which gave 0.055 and 0.08 MAE and RMSE values with solar generation data and 0.083 and 0.104 MAE and RMSE values with wind energy data. By combining the model to get the hybrid model, the resultant model can capture non-linear patterns in residual time series as well as estimate the seasonal and trend components of time series. These capabilities including the ease of use of the model makes the proposed method outperform the competition for time-dependent data having multiple seasonal effects. However, the random splitting threshold used in ExT can make the model depend on greater number of estimators, which can cause less efficient feature extraction.

Wang et al. [10] proposed a novel ensemble prediction model known as the Gradient Boosting Dendritic Network (GBDD), which leverages a gradient-boosting strategy combined with a dendritic network architecture to predict ultra-short-term PV power. The study utilizes the ability of Dendritic Network (DD), which employs Hadamard products to perform multiple logical operations, which proves to be efficient compared to mapping operation functions. The study also claims that DD operates as a white-box model, adding explainable capability to the hybrid model. The GBDD model has 5 inputs with a maximum epoch range set to 50 and the learning rate used is 0.006. The study used 9 days of historical weather data and PV power output data such as DHI, GHI, radiation diffuse tilted (RDT), radiation global tilted (RGT), daily rainfall, relative humidity, temperature, wind direction, and wind speed. The model was evaluated using MAE, MAPE, and RMSE scores, and was compared with LSTM, and GBLSTM. The proposed model gave 0.0771, 6.6027, and 0.1246 scores of MAE, MAPE, and RMSE, while LSTM gave 0.1207, 9.8891, and 0.1700 values of previously mentioned evaluation metrics in order. GBLSTM on the other hand gave improved scores with the scores as 0.0998, 9.2795, and 0.1544. These results showcase that the proposed model not only can outperform the models used for comparison, but also be used as a hybrid model for other prediction methods to improve the model predictions. The high performance of the model can be accounted to the use of the Maximum Information Coefficient (MIC) for variable selection, that allows the model to capture both linear and non-linear relationships between input features and PV output. The introduction of the Hampel filter to smooth the residuals allow the DD base learner to focus on broader trends rather than getting distracted by the noise in the the dataset. This helps in preventing overfitting in the initial model, which is DD in the proposed model. While the Hampel filter helps reduce noise in the dataset, it could potentially over-smoothen the data and diminish the model's ability to capture rapid fluctuations, which are commonly present in the data for PV generation. The model is proven to perform well with larger datasets, but the study failed to test the model with a real-time environment.

III. Problem Statement

The integration of renewable energy sources like solar and wind into energy grids demands highly accurate forecasting methods to ensure grid stability and efficient resource management. Traditional forecasting approaches often fail to capture the complexities and variabilities inherent in renewable energy generation, leading to unreliable predictions and suboptimal decision-making. This study aims to address these challenges by exploring advanced AI-driven methodologies, such as hybrid models and effective hyperparameter optimization techniques, to enhance the accuracy and robustness of forecasting for renewable energy systems.

IV. Dataset

The dataset was sourced from Kaggle which contains historical data filtered over three months (May, June, and July). The data used include Temperature, pressure, humidity, GHI, and Energy Delta. This comprehensive dataset serves as the foundation for training and testing the proposed models, enabling accurate forecasting of energy generation based on solar and environmental factors.

V. Methodology

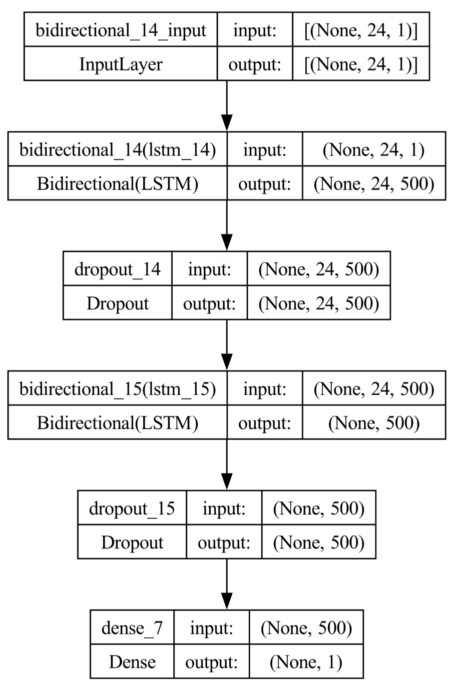

Figure 1. The model architecture of BiLSTM

This study employs a DL approach with a 5-layer architecture BiLSTM model as seen in Figure 1. The architecture includes two Bidirectional LSTM layers, each consisting of 250 neurons and utilizing the ReLU activation function. Two dropout layers are added to reduce overfitting, followed by the inclusion of a dense layer for final predictions.

The dropout layer is used as a regularization technique that randomly deactivates a subset of neurons during the training process. By this approach, the model is encouraged to learn more robust feature representations and reduce reliance on specific units of neurons.

The model is trained for 10 epochs with a batch size of 64, optimizing the learning process using the Mean Squared Error (MSE) loss function. The Adam optimizer is employed for hyperparameter tuning, ensuring efficient convergence during training.

In addition to the base BiLSTM model, hybrid algorithms are developed in this study by integrating the BiLSTM with gradient-boosting techniques. Models such as GBDT-BiLSTM, XGB-BiLSTM, CatBoost-BiLSTM, and LightGBM-BiLSTM are utilized to analyze and compare the performance of the models for the task of predicting energy delta for PV energy generation. By developing the hybrid models, we combine the BiLSTM's ability to capture long-term dependencies by retaining information over extended periods, and the gradient-boosting algorithm's ability to capture short-term dependencies by focusing on local patterns and interactions among features. By leveraging the strengths of both the BiLSTM's sequential modeling capabilities and the gradient boosting method, this study aims to present the robustness of the models in handling complex relationships within the data. This methodology aims to improve the overall forecasting performance for energy generation prediction.

VI. Results

Inorder to understand the effect of weather variables on prediction performance, this study initially trained the model using Global Horizontal Irradiance (GHI) data and tested it on the target variable, which is Energy Delta.

6.1 Evaluation scores

Table 1 presents the evaluation scores of the models using only Energy delta and Global Horizontal Irradiance (GHI) data. The BiLSTM model exhibits the highest Mean Absolute Error (MAE) at 179.2643, along with a Mean Squared Error (MSE) of 122170.6750 and a Root Mean

Squared Error (RMSE) of 349.5291, indicating a comparatively lower performance. Whereas, the hybrid models demonstrate significantly improved performance metrics, with GBDT-BiLSTM achieving an MAE of 15.6850, MSE of 669.6340, and RMSE of 25.8772. The XGBoost-BiLSTM further enhances predictive accuracy, giving the lowest MAE of 10.8162, MSE of 441.6858, and RMSE of 21.0163. Overall, the CatBoost-BiLSTM and LightGBM-BiLSTM models also show robust performance, with MAE values of 14.0843 and 11.0640, respectively, confirming that hybrid models significantly enhance prediction capabilities in this context.

Table 1 *Evaluation scores of the models using only Energy delta and GHI data*

Model	MAE	MSE	RMSE	R-square
BiLSTM	179.2643	122170.6750	349.5291	0.8996
GBDT-BiLSTM	15.6850	669.6340	25.8772	0.9263
XGBoost-BiLSTM	10.8162	441.6858	21.0163	0.9514
CatBoost-BiLSTM	14.0843	610.8645	24.7156	0.9309
LightGBM-BiLSTM	11.0640	447.2854	21.1491	0.9510

Table 2 *Normalized evaluation scores of the models using only Energy delta and GHI data*

Model	MAE	MSE	RMSE	R-square
BiLSTM	0.0384	26.2	0.0747	0.8996
GBDT-BiLSTM	0.0034	0.1437	0.0055	0.9263
XGBoost-BiLSTM	0.0023	0.0946	0.0044	0.9514
CatBoost-BiLSTM	0.0030	0.1310	0.0052	0.9309
LightGBM-BiLSTM	0.0024	0.0960	0.0045	0.9510

Table 3 summarizes the evaluation scores of the models incorporating weather data alongside Energy delta and GHI data. The BiLSTM model gave an MAE of 171.0345 and an MSE of 116048.3468, indicating a moderate performance in forecasting energy generation. The hybrid models show significant improvement in the predictive capabilities, where the GBDT-BiLSTM model achieved an impressive MAE of 14.4551 and an MSE of 633.9615. XGBoost-BiLSTM model outperformed with an MAE of 12.1961 and an MSE of 537.4874. The CatBoost-BiLSTM and LightGBM-BiLSTM models also show competitive performance, with MAE values of

11.2797 and 13.7744, respectively, along with R-square values indicating higher variability, for XGBoost-BiLSTM valued at 0.9514.

Table 3 *Evaluation scores of the models including weather data*

Model	MAE	MSE	RMSE	R-square
BiLSTM	171.0345	116048.3468	340.6586	0.8996
GBDT-BiLSTM	14.4551	633.9615	25.1785	0.9263
XGBoost-BiLSTM	12.1961	537.4874	23.1838	0.9514
CatBoost-BiLSTM	11.2797	468.5298	21.6455	0.9309
LightGBM-BiLSTM	13.7744	564.8327	23.7662	0.9510

Table 4 *Normalized evaluation scores of the models including weather data*

Model	MAE	MSE	RMSE	R-square
BiLSTM	0.0384	26.19	349.5292	0.8996
GBDT-BiLSTM	0.0031	0.1360	0.0054	0.9263
XGBoost-BiLSTM	0.0026	0.1153	0.0050	0.9514
CatBoost-BiLSTM	0.0024	0.1005	0.0046	0.9309
LightGBM-BiLSTM	0.0029	0.1211	0.0051	0.9510

6.2 Learning Curves Analysis

The learning curves obtained when weather data is included, as can be seen in Figure 2, give significant insights into the performance of the implemented models. The BiLSTM-only model showed a smooth decrease in loss, with minimal proof of overfitting, and the training and validation losses are effectively converged through the epochs. The LightGBM-BiLSTM model exhibits a rapid decline in training loss but has stable validation loss throughout, which suggests that the model has strong generalization capabilities with minimal fluctuations. The XGBoost-BiLSTM model also shows good convergence with consistent decrease in training loss. However, minor fluctuations can be seen between the epochs 6 and 8. We can see from the result from GBDT-BiLSTM that there is a huge spike in validation loss around epoch 8, suggesting that there is a potential case for overfitting. Finally, the CatBoost-BiLSTM model consistently improved in both training and validation losses as it maintains close alignment between both losses. This reflects the model exhibits strong generalization and stable performance. From the overall observations, we can conclude that CatBoost-BiLSTM outperforms the others due to its stability in validation loss, minimal overfitting and smooth convergence.

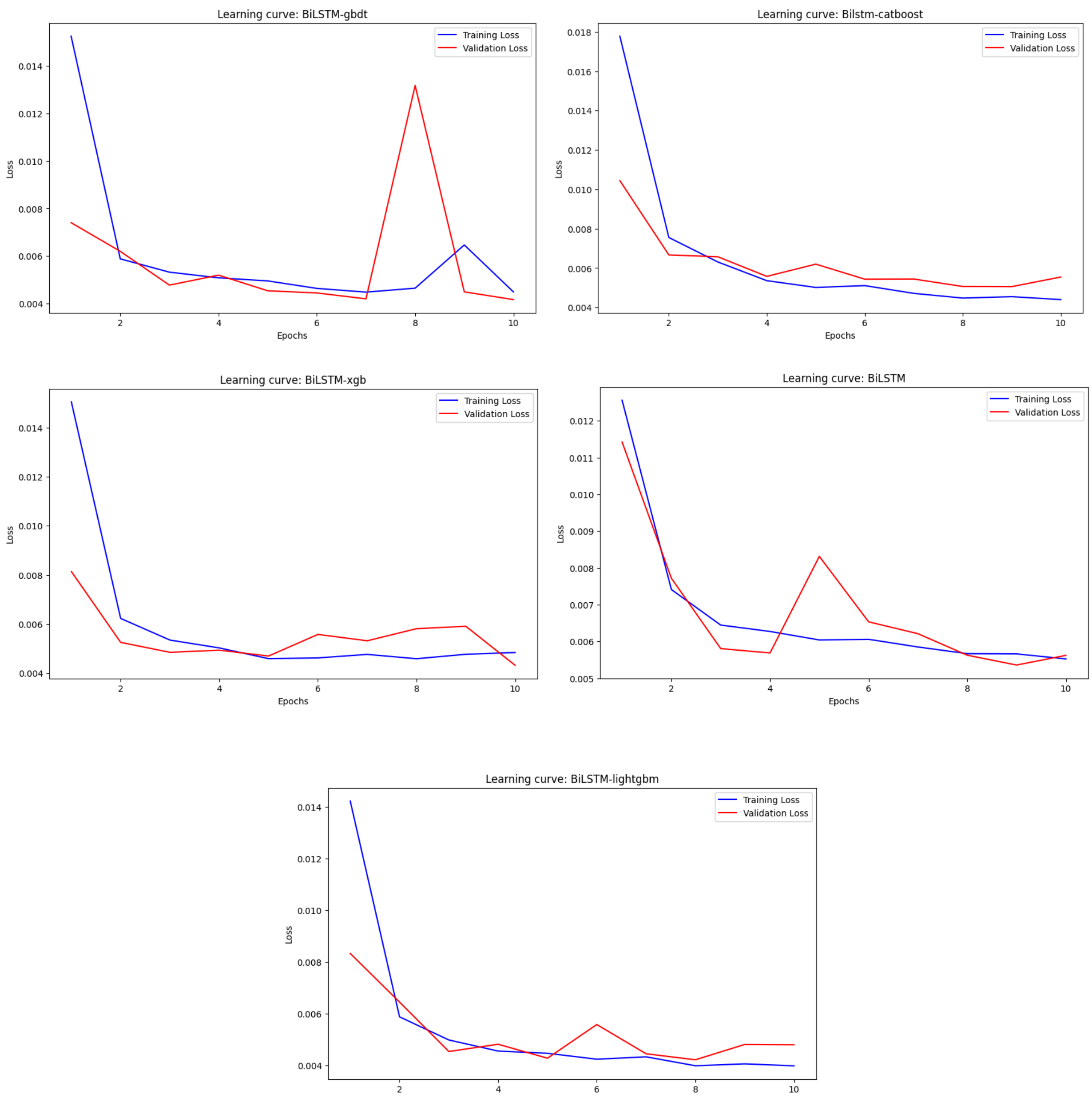

Figure 2. Learning Curves for Implemented Models

Figure 3 shows the actual versus predicted energy delta values obtained using the CatBoost-BiLSTM model. The graph demonstrates the model's performance in accurately capturing trends over the testing period, the predicted values closely align with the actual values. This indicates the high degree of accuracy of the model's forecasting capabilities.

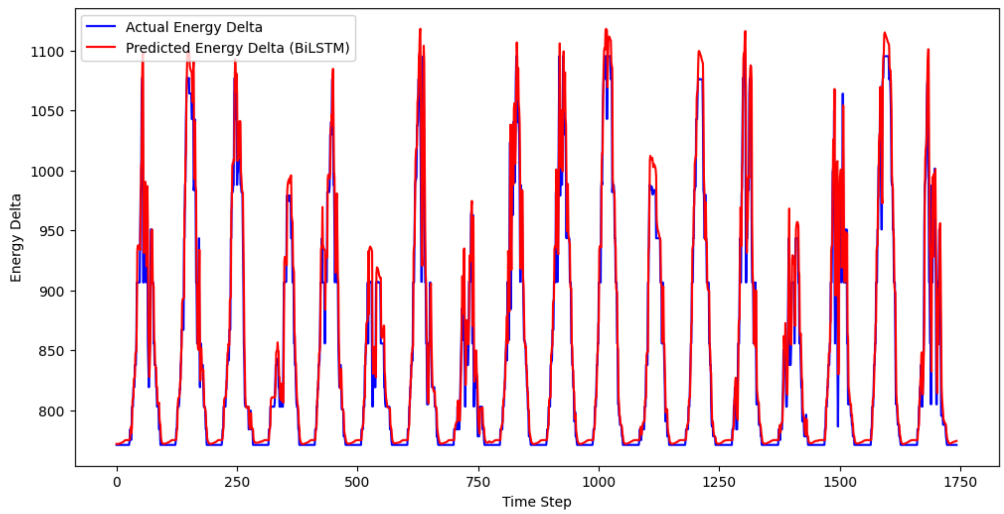

Figure 3. Actual vs. Predicted Energy Delta graph using CatBoost-BiLSTM model

VII. Conclusion

In this paper, we analyzed different AI techniques used for enhancing the accuracy and robustness of renewable energy forecasting. The analysis confirms that BiLSTM with gradient-boosting algorithms such as GBDT, XGBoost, CatBoost, and LightGBM effectively capture both long-term dependencies and local patterns in the data. Among the hybrid models that were implemented, XGBoost-BiLSTM showed best performance with the lowest MAE and RMSE values which suggests it can be used on real-time dataset and get better results.

The inclusion of additional weather variables further improved the model's predictive capability which is evident by the strong generalization observed in the learning curves, particularly for the CatBoost-BiLSTM model. Based on these findings, we can conclude that efficient prediction results can be obtained by combining the DL with boosting techniques.

Future work could explore increasing the complexity of the DL model by adding more hidden layers and also increasing the time frame of the dataset to use for training the model.

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