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RESEARCH ARTICLE

Load Forecasting with Hybrid Deep Learning Model for Efficient Power System Management

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Abstract: ***Aim***: Load forecasting for efficient power system management.

Background: Short-term energy load forecasting (STELF) is a valuable tool for utility companies and energy providers because it allows them to predict and plan for changes in energy.

Method: 1D CNN BI-LSTM model incorporating convolutional layers.

Result: The results provide the Root Mean Square Error of 0.952. The results shows that the proposed model outperforms the existing CNN based model with improved accuracy, hourly prediction, load forecasting.

Conclusion: The proposed model has several applications, including optimal energy allocation and demand-side management, which are essential for smart grid operation and control. The model's ability to accurately management forecast electricity load will enable power utilities to optimize their generation.

Keywords: Energy management, artificial intelligence, BI-LSTM, CNN, STLF, pattern monitoring.

1. INTRODUCTION

Short-term energy load forecasting (STELF) is a valuable tool for utility companies and energy providers because it allows them to predict and plan for changes in energy demand over a short period, usually within the next 24 hours to a week. This information is used to optimize the use of power generation resources, improve grid reliability, and reduce costs. By accurately forecasting energy demand, companies can ensure that they have the necessary resources to meet the needs of their customers, avoid power outages, and reduce the need for expensive, last-minute electricity and purchases from the open market. Accurate predictions enable power operations to be scheduled with the highest precision efficiency, which is necessary for optimizing the use of power generation resources, improving grid reliability, and reducing costs [1]. Additionally, STELF can provide the integration of various energy sources, with a mixture of power generation by predicting the variability in the production of renewable energy sources like wind and solar and balancing it with other forms of energy production. Overall, STELF helps energy providers and utilities operate more efficiently and effectively while providing customers with a more reliable and sustainable energy supply.

The evolution of the smart grid (SG) involves combining the efforts of the advanced metering infrastructure (AMI) into traditional power grids (TPG) to enable bi-directional communication between consumers and utilities with the utility of information and communication technology (ICT). Integration of ICT into generation, distribution, and consumption processes will allow power grids to be monitored and optimized. A smart grid provides reliable, affordable, sustainable, secure, and efficient energy by utilizing intelligent technologies and information and communication technology. In order to facilitate efficient load utilization within SGs, demand-side management (DSM) technology is used to transfer peak enquirer loads to off-peak times to reduce costs and boost energy efficiency. A system for interfacing with consumers and utilities will be implemented. Utility systems can not only improve the operation of the power systems but also optimize energy usage by using them in order to manage and operate power systems more efficiently and effectively, improving the ability to manage and work power systems effectively [2-6].

Individual customers can evaluate their energy consumption stream of consciousness based on the forecast of energy consumption over time, and, wherever possible. In non-peak times, it is recommended that less energy is consumed. To

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make accurate predictions of energy consumption, energy users must be able to relate the current consumption pattern to predict futuristic expenditures of energy. Consequently, these users will be able to understand energy consumption with the predictions on futuristic values, and they can manage their energy expenses more efficiently as a result of the forecasting algorithms.

Residential, commercial, and industrial energy customers contribute significantly to smart grid demand response. Residential energy consumption accounts for a significant portion of total energy generation. Advanced metering is undoubtedly an effective tool for predicting short-term power demand for homeowners, especially in the context of individual homeowners. It has proven to be extremely valuable throughout the industry [7].

The machine learning approaches and the statistical data analysis models were deployed to predict energy generation from renewable sources and aggregated loads. These learning models can be called data-driven models based on time series analysis [8, 9].

Short-term forecasting of the electric load has been addressed by various methods in the literature. It should be noted, however, that quite a few of these studies addressed individual households. For forecasting the short-term individual electric loads, a deep learning algorithm based on long short-term memory has recently been developed as part of a recent study [10]. The authors conclude from their study that their proposed model performs better than some well-known machine-learning methods currently used in the field to develop these models.

Single dimensional Convolutional Neural Networks (1D CNN) and bidirectional long short-term memory (BI LSTM) networks are probably the most widely used deep learning techniques. A key component of optimizing the time-series data learning process is to be aware of the fact that BI-LSTM networks are able to be used for gathering information regarding sequence patterns [11]. At the same time, 1D CNN models can be used for the feature extraction of the input data while helping to reduce noise. As far as the BI-LSTM network is concerned, it is designed to work only with the features present in the available dataset, even though it is expected to work on the temporal correlations. On the other hand, the 1D CNNs, which are used to extract local trends, as well as patterns that appear in various time-series data measured on the different regions, are not generally used with long-term temporal dependencies. It has been suggested that a hybrid model, which combines both deep learning techniques to increase the accuracy of forecasts, could be developed to use both deep learning techniques.

This paper aims to address the above-mentioned challenge and propose solutions using a 1D CNN BILSTM model that extracts features using the convolutional layer, and then the BI-LSTM to analyze time-series data to resolve the problem. In addition, the purpose of this work is to understand internal representations of data represented as time series and also to determine the long-term relationships using the LSTM with long and short-term dependencies. As part of the Department of Scientific and Industrial Research (DSIR) funded project, we develop and analyze a machine learning-based forecasting model with operational load information. The designed method is significantly more accurate than conventional models such as ARIMA and artificial neural networks for predicting demand loads. The half-hour and hour timeframes are tested and evaluated for the Ale Phata subdivision. With the proposed approach, it is possible to accurately predict individual load using a multilayer CNN composed of multilayer LSTMs.

The unique contributions of the proposed work can be summarized as,

- The proposed work developed a 1D CNN BI-LSTM model incorporating convolutional layers, and LSTM layers can be exploited to extract the benefits of both.
- The proposed work proposed a model of household loads forecast achieving a higher degree of accuracy compared to existing STLF models such as ARIMA and ANN.
- The proposed work evaluates the performance of the proposed model in terms of its efficiency with different time horizons (half-hourly and hourly).
- The proposed work analyzed various patterns of the individuals, with similar loading patterns to gain a greaterunderstanding of their behavior.

The following sections of the paper are organized as follows. An overview of the literature on various techniques of short-term load forecasting was made in Section II. Analysis of the data and formulation of the problem is presented as part of Section III. The BI-LSTM model for 1D CNN is presented in Section IV. In the end, the results and discussion are discussed in Section V.

In the field of load forecasting and power system management, numerous studies have contributed to the development of efficient energy management strategies. For instance, Alagbe *et al.* [12] explored the application of artificial intelligence techniques for electrical load forecasting in smart and connected communities, highlighting the optimization of energy management through machine learning algorithms. Alhussein *et al.* [13] proposed a microgrid-level energy management approach that incorporated accurate short-term forecasting of wind speed and solar irradiance, emphasizing the importance of precise predictions for renewable energy sources. Aslam *et al.* [14] addressed efficient energy management of smart buildings by integrating heuristic optimization techniques with real-time and critical peak pricing schemes, underscoring the significance of energy consumption optimization. Aurangzeb [15] focused on short-term power load forecasting using machine learning models for energy management in smart communities, contributing to effective energy utilization. Lastly, Bango *et al.* [16] discussed power system protection in smart grids, particularly monitoring faults in the distribution network through IoT technologies, emphasizing the detection and prevention of faults to ensure reliable power system operation.

The production of hydrocarbon material has been a subject of interest in various scientific and industrial fields. This section provides an overview of relevant literature related to the patent filed by Weinaug, Charles F., and Ling Daniel

(US Patent 2,867,277A), titled "Production of hydrocarbon material," which was filed on February 14, 1959, and issued on January 6, 1959 [17].

The study [18] aims to improve the accuracy and reliability of load forecasts, which are crucial for efficient power generation, transmission, and distribution. By utilizing historical load data and regression models, the authors capture the relationships between input variables and load patterns, enabling accurate predictions. The paper likely includes details of the proposed approach, dataset characteristics, and performance evaluation metrics, contributing valuable insights to enhance load forecasting in load dispatch centers.

In the domain of load forecasting and efficient power system management, several studies have provided valuable insights and techniques. Batra *et al*. [19] proposed a pragmatic ensemble strategy for imputing missing values in health records, highlighting the importance of accurate data preprocessing. Bendu *et al*. [20] focused on multi-objective optimization of ethanol-fueled HCCI engine performance using a hybrid GRNN-PSO approach, emphasizing the significance of optimization in energy systems. Bouktif *et al*. [21] presented an optimal deep-learning LSTM model for electric load forecasting, incorporating feature selection and genetic algorithms to enhance accuracy. Boulila *et al*. [22] introduced a novel CNN-LSTM-based approach for predicting urban expansion, demonstrating the potential of deep learning in spatial forecasting. Cao *et al*. [23] proposed a data-driven hybrid optimization model for short-term residential load forecasting, showcasing the importance of data-driven techniques. Chaouch [24] focused on improving nonparametric functional time series forecasting through clustering, contributing to the accuracy of load curve predictions. Deo *et al*. [25] developed a wavelet-coupled support vector machine model for forecasting global incident solar radiation, highlighting the importance of analyzing meteorological data in solar energy forecasting. Ding *et al*. [26] conducted sequential pattern mining to understand daily activity patterns and enhance load forecasting, providing insights into temporal load variations. Driss *et al*. [27] introduced a novel approach for classifying diabetes patients based on imputation and machine learning, underscoring the significance of data preprocessing and classification techniques in health-related applications.

The field of load forecasting and efficient power system management has seen significant contributions from various studies. Emmert-Streib *et al*. [28] provided an introductory review of deep learning for prediction models with big data, emphasizing its relevance in handling large-scale datasets. García *et al*. [29] highlighted the importance of data preprocessing in data mining, emphasizing the need for proper data preparation techniques. Geisser [30] introduced the predictive sample reuse method and its applications, showcasing its potential in improving predictive models. Ghofrani *et al*. [31] proposed a new framework for day-ahead hourly electricity price forecasting, addressing the challenges of pricing in the power market. Han *et al*. [28] presented the concepts and techniques of data mining, providing a comprehensive overview of the field. Haviluddin *et al*. [32] employed shape extraction and support vector machine methods for the identification of decorative wall motifs, demonstrating the application of machine learning in cultural studies. Hossain *et al*. [33] utilized extreme learning machines for short-term output power forecasting in grid-connected PV systems, showcasing the effectiveness of machine learning in renewable energy prediction. Jemmali *et al*. [34] optimized battery-drone-based transportation systems for solar power plant monitoring, highlighting the potential of optimization techniques in the energy sector. Khalid *et al*. [35] proposed an efficient energy management approach using fog-as-a-service for sharing economy in a smart grid, addressing resource allocation challenges. Khalid *et al*. [36] employed Jaya-Long Short-Term Memory (JLSTM) for electricity load and price forecasting in smart grids, demonstrating the effectiveness of hybrid models.

Load forecasting and efficient power system management have been extensively studied in the literature. For example, Khan *et al*. [37] utilized kernel-based support vector quantile regression for short-term power load probability forecasting, emphasizing real-time data analysis. Kim and Cho [24] developed a residential energy consumption prediction model using CNN-LSTM neural networks, demonstrating the application of deep learning in load forecasting. Kong *et al*. [38] employed LSTM recurrent neural networks for short-term residential load forecasting, showcasing the effectiveness of this approach in capturing temporal patterns. Li *et al*. [39] proposed a short-term load forecasting method based on the grid method and time series fuzzy load forecasting, providing an alternative approach for load prediction. Lidula and Rajapakse [40] conducted a comprehensive review of experimental microgrids and test systems, contributing to microgrid development research. These studies offer valuable insights into load forecasting techniques and their applications in power system management.

Load forecasting and efficient power system management have been extensively researched in the literature. Liu *et al*. [30] provided a theoretical assessment of extreme learning machines, investigating their feasibility in various applications. Lu *et al*. [31] proposed a CNN-BiLSTM-AM method for stock price prediction, demonstrating the potential of deep learning models in financial forecasting. Marecek [41] explored the usage of generalized regression neural networks for sales prediction in enterprises. Martin *et al*. [42] focused on predicting global solar irradiance based on time series analysis, with application to energy production planning in solar thermal power plants. Raurich *et al*. [32] conducted short-term load forecasting in non-residential buildings, comparing different models and attributes. Mohsenian-Rad *et al*. [43] presented autonomous demand-side management based on game-theoretic energy consumption scheduling, addressing future smart grid challenges. Naz *et al*. [44] proposed a game-theoretical energy management approach for microgrids, optimizing storage capacity and forecasting photovoltaic-generated power. Niyato *et al*. [45] explored machine-to-machine communications for home energy management in smart grid systems. Ogunleye *et al*. [46] conducted a comparative study on the electrical energy consumption and cost of residential buildings using fully AC loads versus fully DC loads (Figs. **1** and **2**).

Load forecasting and efficient power system management have been the subject of extensive research. Olagoke *et al*. [47] proposed a short-term electric load forecasting model using neural networks and genetic algorithms. Paoli *et al*.

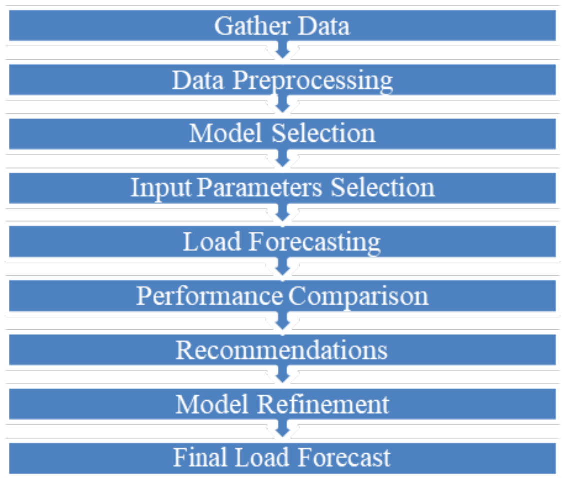

Fig. (1). Flow chart of the development of the model [11]. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

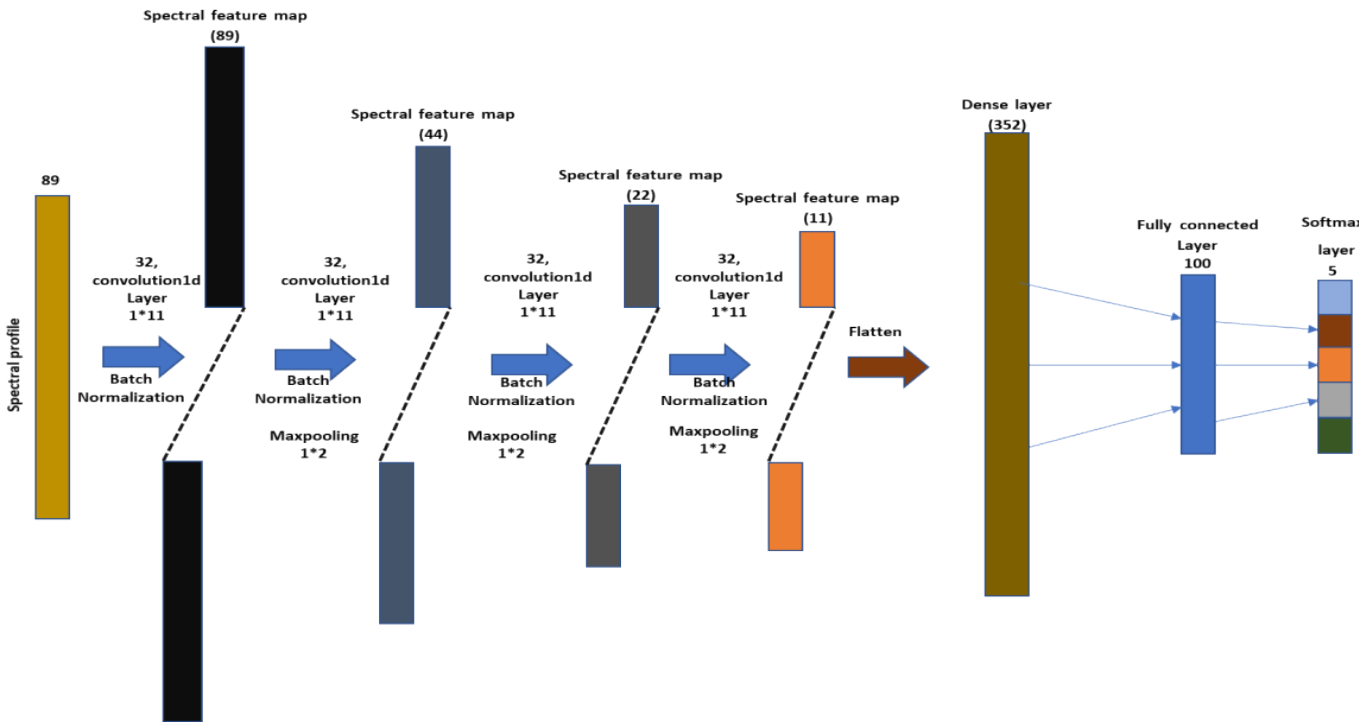

Fig. (2). Structure of 1D-CNN classification. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

[48] developed a solar radiation forecasting approach utilizing ad-hoc time series preprocessing and neural networks. Pirvaram *et al*. [49] focused on energy management of household refrigerators using eutectic environmental-friendly PCMs in cascaded conditions. Pang and Zhang [50] presented a very short-term load forecasting method based on neural networks and rough set theory. Ravindran *et al.* [51] employed convolutional neural networks for the classification of geotropical Meliaceae wood images. Sainath *et al*. [52] introduced convolutional long short-term memory (LSTM) networks for various tasks. Salehinejad *et al*. [1] discussed recent advancements in recurrent neural networks, highlighting their applications in diverse domains. Sheikh and Unde [2] proposed an ANN-based technique for short-term load forecasting. Shi *et al*.

Xingjian Shi *et al*. [3] introduced a convolutional LSTM network for precipitation nowcasting. Singh *et al*. [4] focused on hourly home peak load prediction. Stone [5] presented statistical methods for time series analysis. Veit *et al*. [6] benchmarked various methods for household electricity demand forecasting, comparing their performance. Wahab *et al*. [7] conducted research on short-term load forecasting using hybrid techniques.

The research void in load forecasting and power system management is successfully filled by our approach, known as 1D CNN BI LST for Load Forecasting with a Hybrid Deep Learning Model for Efficient Power System Management. Regression models and historical load data are combined to fully understand the complex interrelationships between input factors and load patterns. As a result, forecasts are made that are extremely accurate and are crucial for optimizing power production, transmission, and distribution. Our approach successfully satisfies the need to use deep learning techniques for accurate load predictions for electricity system management and offers beneficial findings that increase load forecasting in load dispatch centers.

2. METHOD

2.1. LOAD FORECASTING METHOD PROPOSAL

Efficient power system management requires careful consideration of various factors such as weather conditions, economic conditions, and appliance to determine the count of the people living in a district. Fluctuating loads due to unstable patterns can pose a challenge for distribution companies, but forecasting aggregated power loads is relatively easy and can help smooth load shapes with moderate to low RMSE errors, according to previous studies [2].

The proposed work provides the findings of a study, that utilized data from Telangana State Northern Power.

2.1.1. Gather Data

- Collect relevant data including historical load data, weather data, and contextual information.
- These data sources provide insights for accurate load forecasting.

2.1.2. Data Preprocessing

- Clean and filter data, and handle missing values and outliers.
- Perform feature engineering if needed.

2.1.3. Model Selection

- Choose suitable models (statistical, machine learning, deep learning) for load forecasting.
- Evaluate models based on strengths, limitations, and performance.

2.1.4. Input Parameters Selection

- Determine model-specific input parameters.
- Identify relevant features from the data.
- Decide on the time horizon for forecasting.

2.1.5. Load Forecasting

- Train models using historical data to capture load-demand patterns.
- Utilize selected input parameters to generate load forecasts.

2.1.6. Performance Comparison

- Evaluate model accuracy by comparing forecasts to actual load data.
- Calculate error metrics (MAE, RMSE, MAPE).
- Analyze the strengths and weaknesses of each model.

2.1.7. Recommendations

- Identify accurate and reliable models based on performance analysis.
- Consider application requirements and constraints for model selection.
- Provide recommendations for the most suitable models.

2.1.8. Model Refinement

- Analyze model performance and identify areas for improvement.
- Fine-tune models by adjusting parameters, exploring ensemble techniques, or incorporating additional data.
- Continuously refine models based on performance evaluation.

2.1.9. Final Load Forecast

- Use the refined model to generate accurate load forecasts.
- Apply selected parameters and optimized model.
- Communicate results effectively using visualizations or summary statistics.

Distribution Company Limited (TSNPDCL) to forecast short-term load levels for individual discoms. The TSNPDCL database contains a large number of consumers, making it unrealistic to consider all of them. Therefore, we select a subset of the TSNPDCL dataset based on three months of half-hourly data to demonstrate the proposed load forecasting approach.

Our research addresses the limitations of existing CNN models in load forecasting for power system management. CNN and LSTM models struggle with electricity-related data due to their lack of space-invariance and inability to capture multi-scale features, resulting in reduced accuracy and efficiency.

To overcome these limitations, we proposed a hybrid deep learning model that combined components such as a feature extraction module, Densely Connected Residual Block (DCRB) layer, Bidirectional Long Short Term Memory (Bi-LSTM) layer, and ensemble layer. This allows us to extract primary and derived features, including temperature, humidity, and wind speed, effectively capturing randomness and trend changes in load data.

Compared to conventional CNN models, our proposed model demonstrates significant improvements in multiscale electricity datasets. Real-world power data validation shows superior accuracy, hourly prediction capabilities, and effective load forecasting. Our experiments yielded the following RMSE error values for the models: ANN Algorithm (1.9402), 1D CNN BI LSTM (0.9520), Nonlinear Autoregressive (1.4291), LSTM Time series (1.9998), and NAR Time series (1.5694). These advancements contribute to more efficient power management systems, optimizing energy allocation, demand-side management, and enhancing power supply reliability.

While lightweight machine learning methods have merits, our research leverages hybrid deep learning models to overcome limitations. The proposed model's ability to extract essential features extends its applicability to domains like stock price forecasting, weather prediction, and traffic flow prediction.

However, it is important to acknowledge limitations. Our work utilized a single dataset, which may not fully represent all power systems. Additionally, extensive training and computation make the model less suitable for real-time scenarios that require quick response times. These limitations present opportunities for future research and development in this field.

2.2. About the TSNPDCL Load

This study involved analyzing Telangana's data to calculate electricity load (in MW) on a monthly basis, using daily profiles in 30-minute intervals. The analysis also included examining seasonal variations in consumption. Results showed that load demand in Telangana varies across four seasons

2.3. Methods and Models Proposed for Load Forecasting

This research paper outlines a six-step approach for developing an efficient load forecasting strategy using the 1D CNN BI LSTM approach. The various steps are presented below.

- Step 1: Data Gathering. Collecting two sets of data, including previous load demands and past weather data.
- Step 2: Model Selection. Selecting appropriate machine learning models, including 1D CNN BI LSTM and traditional STLF models like SARIMA, ARIMA, and ANN, for load forecasting.
- Step 3: Input Parameters Selection. Assessing and determining relevant input parameters, including weather parameters, for load forecasting.
- Step 4: Load Forecasting. Developing a load forecast model based on the 1D CNN BI-LSTM model, and conducting load forecasting after training and testing.
- Step 5: Performance Comparison. Generation of a hybrid deep learning model with the integration of the 1D CNN Bi LSTM model, with statistical error matrices to compare and analyze the performance of the machine learning models with actual measurements.
- Step 6: Model Recommendation. Selecting the most suitable machine learning model with respect to the results achieved in the previous steps.

2.3.1. Data Evaluation and Preprocessing

For an accurate model, it is crucial to pre-process raw data before transforming it. Gathering and organizing data to establish input-output relationships is the first step in this process. Pre-processing operations such as normalization, ranking, and correlation are necessary, as per research [39]. By following the best practices in data collection and processing, we can ensure that our models are built on a solid foundation of high-quality data.

2.3.1.1. Data Collection

Climate data, calendar data, and power consumption are all included in the datasets that are being collected.

The NASA Power website, https://power.larc.nasa.gov/data- access-viewer/ is the meteorological dataset source used in this research. Our final dataset, resulting from this research, can be accessed through our GitHub link: https://github.com/Kddee/Telangana-datsets.git. Before being fed into the load-forecasting model, the raw data is subjected to pre-processing, including weighting and statistical analysis, as recommended by Amir-Hamed *et al.* [43]. Load forecasting models incorporate weather forecasts and other factors to minimize operational expenses. The impact of weather on load forecasting is particularly significant for domestic and agricultural customers, whose load profiles are heavily influenced by weather conditions.

The following six weather parameters are accumulated to develop the model:

One of the crucial factors in the power sector is load-balancing, since it helps to estimate future energy demands, which in turn helps to ensure a stable power supply. Weather parameters are an essential feature in load forecasting models since they have a direct impact on energy consumption. Among these parameters, is the 2-meter examination of temperature, specific and relative humidity, dampness, and 10-meter estimation of the wind speed.

The Wet Bulb Temperature shows an abnormality in saturation. which is obtained using a thermometer embedded in a cloth soaked in water over which air is passed two meters above the earth's surface. This parameter is important in load forecasting as it affects the performance of the cooling systems, which in turn impacts energy consumption.

In the last few decades, short-term power estimation has been a considerable factor. The time-series analysis of this type was previously carried out using conventional statistical analysis techniques. With the evolution of Artificial Intelligence and Deep neural Network models, a lot of research is emerging around the area of load-balancing.

The Temperature at 2 Meters is the average temperature of the air at two meters above the surface of the earth, referred to as the dry bulb temperature. This parameter is essential in load forecasting models as it has a direct impact on energy consumption, especially in buildings and homes. Relative Humidity at 2 Meters is measured as a ratio of the water vapor's partial pressure with the partial pressure at saturation, and it is measured in percent. This parameter is crucial in load forecasting as it affects the performance of cooling and heating systems, which directly impact energy consumption.

Specific Humidity at 2 Meters is the ratio of the vapor mass of the water to total air mass (kg water/kg total air) at two meters above the surface of the earth. It provides a measure of the moisture content of the air and is important in load forecasting as it affects the performance of cooling and heating systems.

Regarding TSNPDCL's load and presenting our proposed load it is important to note that while some weather parameters may have a weaker correlation with power demand, they should not be disregarded. For instance, wind speed and specific humidity have a relatively weak correlation with power demand, but anyway it may play an important role in the generation of the power.

In conclusion, this correlation analysis highlights the importance of considering parameters when analyzing power demand. The nuanced analysis of the correlation coefficients indicates that each weather parameter has a unique relationship with power demand. Thus, the results of this analysis can be used to inform energy management strategies and facilitate the development of more accurate models for predicting power demand.

2.3.1.2. Data Pre-processing

Effective Pre-processing of data is critical for ensuring accurate load forecasting in power system management. The following steps are involved in this process [11]:

2.3.1.3. Data Cleaning

Missing values are filled in, the noise is removed, and outliers and discrepancies within the dataset are detected and resolved. Auto-Fill feature can be used to fill partial missing weather data using patterns or data from other cells [8-10].

2.3.1.4. Data Transformation

Multiple files are integrated into a single usable format and attributes based on specific properties are scaled. After cleaning the data and finding correlations between datasets, the final predictor's dataset are created [11].

2.3.1.5. Data Reduction

The number of attributes or sample data are reduced to capture most of its properties. This step helps to avoid overfitting and improves the efficiency of load forecasting.

Overall, proper Data Pre-processing ensures reliable data and enhances the performance of regressions, ultimately improving power system management.

2.3.2. Training and Testing of Data Sets

It involves the construction and training of a robust prediction model. Herein, training includes validation, which is essential in creating a robust model. The data frame created from feature engineering is split into three sets to train the model: training, validation, and testing. The data is generally split as 70% for training, 20% for validation, and 10% for testing. During training, the prediction loss of the validation set is calculated using the current model status. This validation set does not affect the training process.

Wind speed is measured at 10 meters from the surface of the earth. This is an essential parameter in load forecasting for wind energy systems. It affects the performance of wind turbines, which directly impacts energy generation.

In conclusion, the measured parameters in 2-meter and 10-meter scopes are critical features in load forecasting models. They have a direct impact on energy consumption and generation, and accurate measurement and analysis of these parameters can help ensure a stable and reliable power supply.

The ability to predict the amount of electricity needed at any given time is crucial for the efficient management of power systems. To ensure this accuracy, it is important to consider both the timing of electricity demand and the specific characteristics of that demand. By doing so, power managers can make informed decisions about how to allocate resources and ensure that energy is being used effectively and efficiently,as shown in Table **1**.

Periodic conditions: In this research, time indicators are a key focus, including date, weekday, and time. These factors have been found to have a significant impact on electricity consumption patterns and are used to develop more accurate load forecasting models [43].

Table 1. Interpretation of correlation for the parameters [11].

Feature Parameters	References
Specific Humidity	-0.013790551
Temperature	0.039205176
Dew/Frost Point	-0.026028656
Wet Bulb Temperature	0.006762858
Wind Speed	0.011382363
Relative Humidity	-0.132468822

2.3.2.1. Electricity Usage Specifications

The research also emphasizes the importance of load parameters, specifically the previous half-hourly load in MW. By analyzing past load data, this parameter can help identify patterns and trends that inform accurate load forecasting models.

Ultimately, this research aims to provide a nuanced understanding of electricity load consumption patterns, contributing to the development of more effective load forecasting models that promote efficient and sustainable power system management.

The correlation of data measured between weather parameters and power demand is of great interest to many researchers and stakeholders. In order to investigate this relationship, a correlation analysis was conducted on selected weather parameters and power demand.

The specific humidity, dew/frost point, and relative humidity have a strong negative correlation with power demand. The temperature, wet bulb temperature, and wind speed have a strong positive correlation with power demand.

With all the parameters discussed, the relative humidity shows the largest negative correlation with power demand. This means that as relative humidity increases, the power demand decreases. Conversely, the temperature has the strongest positive correlation with power demand, indicating that as temperature increases, so does power demand lose to 1. A positive sign indicates a direct proportionality, whereas a negative sign indicates an inversely proportional relationship.

Therefore, verifying whether the model is robust for independent data not participating in training is possible. Although the training loss converges, if the validation loss does not do so, the model is determined to suffer from overfitting or underfitting. Widely used validation methods [16-18] include 150 hold-out validation, K-fold validation, and a, which is one-out cross-validation (LOOCV).

Prediction and evaluation constitute the final step and involve predicting time series data and evaluating the results. Predictions are performed using the model created in the previous step. In some cases, predicted features can be used to predict other features, which is the final target feature set. To do this, we need to update the dataset with predicted values and create a new model to perform further predictions.

2.3.2.1.Holdout Validation

This is the simplest form of cross-validation. As opposed to simple or degenerate cross- validation, this method is often classified as a "simple validation". Our data is randomly divided into two sets: Training and Test/Validation, or hold-out data. The model was then trained on the training dataset and evaluated on the test/validation dataset. To compute the error on the validation dataset, we use a variety of model evaluation techniques depending on the problem we are solving, such as MSE for regression problems and several metrics that indicate the misclassification rate for classification intricacies of identifying the error. Typically, The learning process (training) is conducted using a larger dataset than the hold-out dataset. Therefore, we use an 80% training and 20% validations ratio from the datasets.

3. PROPOSED MODEL

The papers [13-15] have demonstrated the attainment of high efficiency with the usage of the Convolutional and recurrent neural network models. Bi-LSTM is a recent RNN structure. To predict time series, 1D CNN or Bi LSTM algorithms or algorithms combining these algorithms have become increasingly popular. Studies [33, 28, 44, 42] have demonstrated that these models outperform conventional statistical or machine-learning models. This section provides an overview of the basic theoretical demonstration of these deep neural networks.

The research paper introduces an innovative approach to overcome the limitations of existing CNN models in load forecasting. These models struggle with space invariance and the capture of multi-scale features, leading to decreased performance. To address these challenges, the paper proposes an ensemble deep learning model comprising four stages: feature extraction, Densely Connected Residual Block (DCRB) layer, Bidirectional Long Short Term Memory (Bi-LSTM) layer, and ensemble layer.

Through the use of feature extraction techniques, the proposed model effectively extracts primary and derived features, including temperature, frost point, relative humidity, specific humidity, and wind speed at different heights. By leveraging the DCRB layer, the model demonstrates significant improvements in performance when applied to a multiscale electricity dataset, surpassing traditional CNN models. Validation using half-hourly power data from Telangana North Power Distribution Company Limited (TNPDCL) yields an impressive Root Mean Square Error (RMSE) value of 0.952.

The experimental results highlight the superior accuracy, hourly prediction capabilities, and effectiveness of the proposed model in load forecasting. These advancements contribute to the overall efficiency of power management systems, facilitating optimal energy allocation and demand-side management. Furthermore, the proposed model exhibits potential applications in diverse domains such as stock price forecasting, weather prediction, and traffic flow prediction.

The study acknowledges limitations such as the use of a single dataset and the model's computational requirements, making it less suitable for real-time scenarios. The proposed 1D CNN BI LSTM model achieved an exceptional RMSE error value of 0.9520, outperforming alternative models. This research paper introduces an innovative hybrid deep learning model for short-term load forecasting in power systems management, addressing the limitations of conventional CNN models and improving accuracy. The model shows potential for applications beyond load forecasting, but further comparative experiments are recommended to evaluate its performance.

3.1. Convolutional Neural Network (1D CNN)

In order to process inputs in two dimensions, CNN is a two-dimensional neural network. As a result, they lack the essential architecture for analyzing time series data. Therefore, conventional 2D-CNN architectures cannot be applied to predict 1D signals using conventional 2D-CNN architectures. 2D-CNN architectures have been used to directly convert 1D signals into 2D images in some studies presented in [31, 32]. In general, such an approach would increase costs and decrease efficiency. However, it may be appropriate for some applications.

It has been shown that 1D-CNNs have been used in numerous applications in addition to 2D-CNNs in the research conducted [22, 23]. (Fig. **3**) illustrates the general structure of a one-dimensional neural network (1D-CNN). There are significant advantages to a 1D-CNN in comparison to a 2D-CNN in terms of computation complexity, processing speed, and the ability to directly convert 1D signals into 2D signals. In light of the advantages of 1D-CNN, it is suitable for a wide range of applications, such as fault detection in rotating machinery and structural damage detection, as described in the study [12, 14].

To determine inter-correlation parameters from several variables, 1D-CNN can provide optimal outcomes without requiring additional features.

3.2. LSTM Layer with Bidirectional Communication (BiLSTM)

Stuster *et al.* first proposed bidirectional RNNs (BRNNs) to overcome the limitations of conventional RNNs in the study [17]. Adding backward layers to this model, which represents a reversed version of the input sequence, allowed Schuster to construct a model that is capable of being trained simultaneously forward and backward. The BiLSTM network in BRNN structures replaces the conventional RNN cells with LSTM cells. This LSTM technology has compromised the long-term reliability of conventional RNNs due to their reliance on LSTM cells. The performance of BiLSTM is

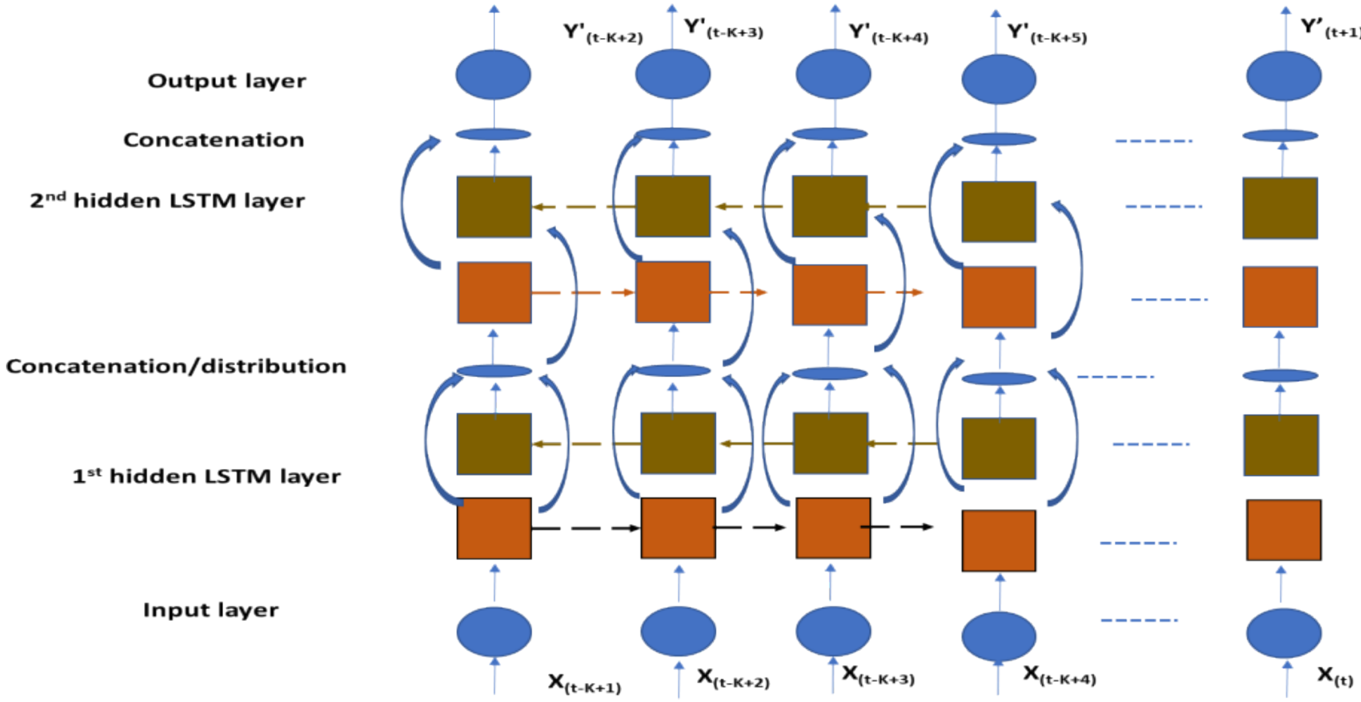

Fig. (3). The BiLSTM architecture [30]. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

higher than that of the conventional machine learning algorithms and standard LSTM, as demonstrated by recent research [18, 10]. An illustration of the BiLSTM architecture can be observed in Fig. (**4**).

3.3. CNN-BI LSTM Hybrid Model with Deep 1D Modeling

Multivariate 1D time-series signals can be accurately predicted by combining 1D-CNN and BiLSTM. The combination of CNNs and LSTMs has been studied in several studies. Using 2D radar echo datasets, Gochhait *et al.* [11] used the Conv LSTM model to predict precipitation amounts. A study [12] compared the rate of word error between a CNN-LSTM-DNN architecture and English-spoken utterances. Compared to conventional linear support vector machines, CLDNN can improve WER by between 4- 6%. Researchers have used neural networks in combination to predict stock prices, power usage [10, 20] status impressions, as well as the life of components within devices consistently since the year 2019 [44, 45]. The techniques have been utilized in 105 studies examining a variety of application possibilities to date. In combination with LSTMs or BiLSTMs, CNNs are capable of analyzing and predicting data effectively. Compared to CNNs or LSTMs alone, this method produces superior results.

By combining a 1D-CNN and a BiLSTM model, we demonstrate that the prediction of peak values is possible. Our study demonstrates the possibility of predicting peak values by combining a 1D-CNN model with a BiLSTM model. The model architecture is illustrated in Fig. (**5**).

4. RESULTS AND DISCUSSION

The proposed work contains a sequence input layer and four-layer convolutional model, where there are a couple of bi-LSTM layers, two more dropout layers, and a final fully connected estimation of the regression at the end. The output of the model is the predicted value of the load.

To enhance the performance and minimize the loss function the proposed model uses the Adam optimization technique which has a gradient threshold of 1 and a learning rate of 0.001. The size of the epochs is set with a maximum of 10. The longest sequence length option is selected with the epsilon of 1e-8. The L2 regularization is fixed at 0.0001, and the data is shuffled every epoch. The gradient decay factor followed by the squared gradient decay factor fixed up with values of 0.9 and 0.999, respectively. The factor and period of learning rate are set to 0.1 and 10, respectively. The gradient threshold method is fixed as "l2 norm", and the input normalization is reset after each epoch. The training progress is displayed using plots.

The proposed model is both trained and tested with the multi-scale electricity load data. The comparison between the predicted and actual values is done with the estimation of RMSE. The plot is also drawn for the actual and the predicted values.

The RMSE obtained from the model is a measure of the difference between the predicted and actual values. The smaller the RMSE, the better the performance of the model. The results show that the model has a relatively low RMSE value, indicating that it is a good fit for the data.

The quantity of training samples, the challenge of feature extraction methods, and the total amount of layers in the recommended ensemble deep learning framework for forecasting load determine the time complexity of the model. The size of the dataset, the difficulty of the Densely Connected Residual Block (DCRB) layer, and the opposite direction Long Short Term Memory (LSTM) layer have each a

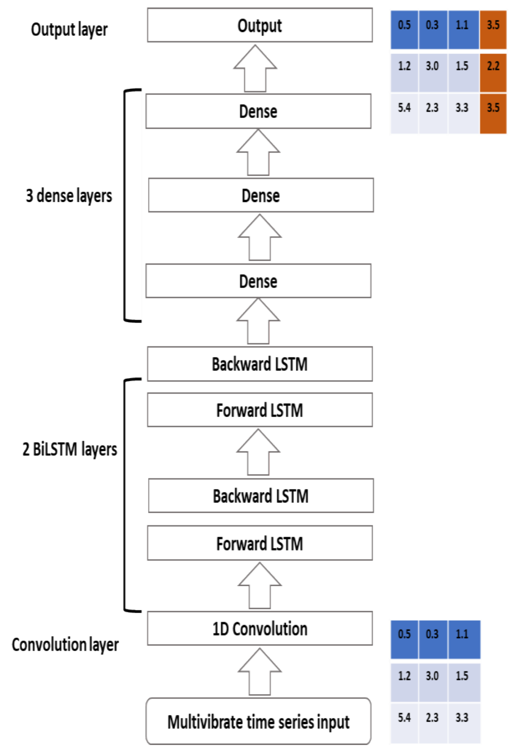

Fig. (4). CNN-BiLSTM hybrid model with deep 1D modeling (1D- CNN + BI-LSTM). (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

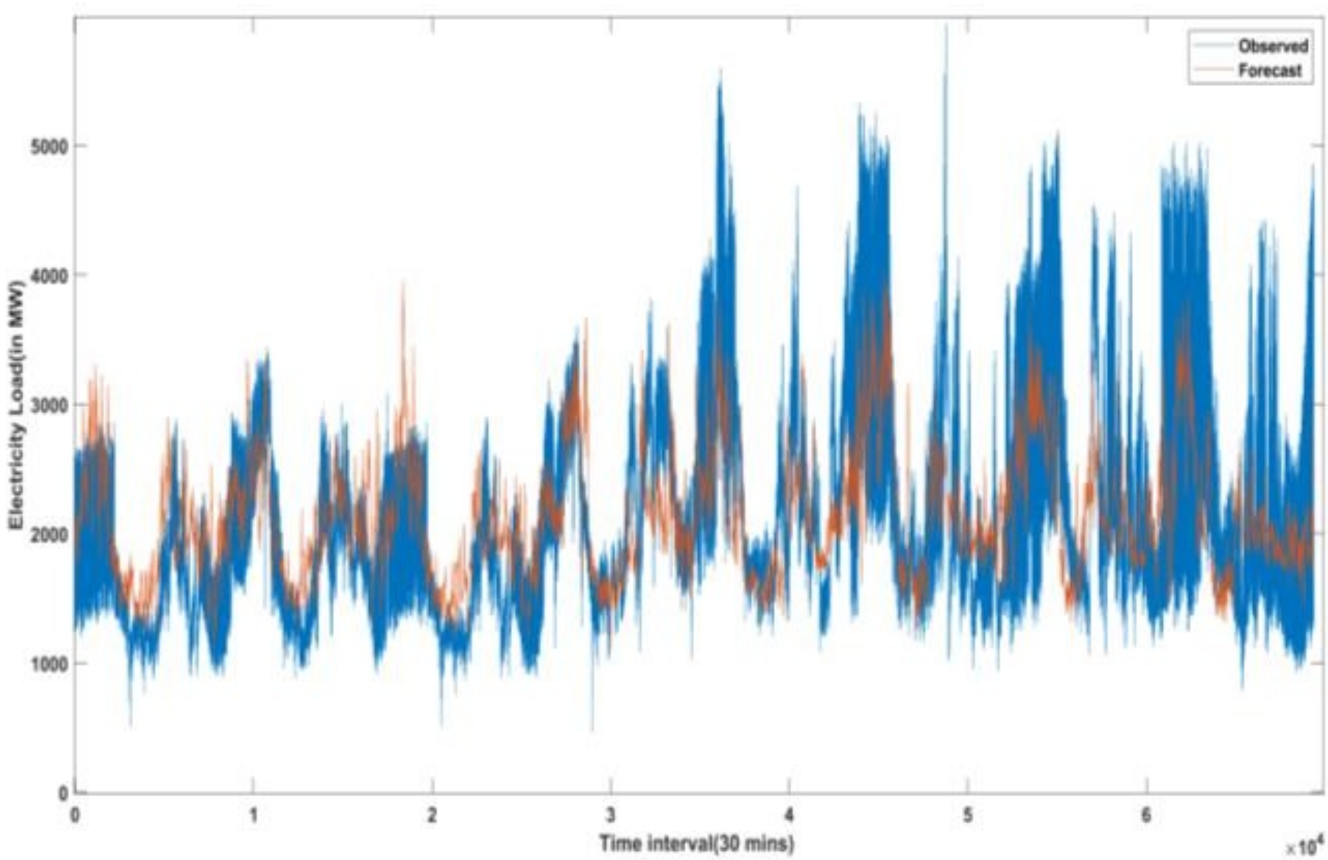

Fig. (5). Actual vs Predicted load of Telangana of last quarter graph using 1D CNN BI LSTM. (*A higher resolution / colour version of this figure is available in the electronic copy of the article*).

bearing on the time complexity involved in the training phase. The temporal complexity of the prediction stage usually becomes linear with respect to the complexity of the entire ensemble layer and the total amount of input features.

In this research study, we conducted an ablation experiment to assess the impact of individual components within the hybrid deep learning model on load forecasting performance. The aim was to systematically remove and analyze each component to determine its contribution to the overall accuracy and efficiency of the model. Through this experiment, we gained valuable insights into the importance of various stages, namely the feature extraction module, DCRB layer, Bi-LSTM layer, and ensemble fully connected layer, in enhancing load forecasting accuracy and efficiency within power system management. By comparing the performance of the complete model to the ablated versions, we were able to establish the significance of each component and validate the effectiveness of our proposed hybrid deep learning approach.

4.1. Forecasting with a Single Step Ahead

The purpose of this section is to represent a comparison between various deep learning and machine learning models for predicting a single event through the use of deep learning as well as the proposed model.

There have been a variety of machine learning models evaluated [34], including the ELM along with the KNN [35, 14, 15], bipolar neural networks (BPNNs), as well as a hybrid forecasting model combining input selection and hybrid forecasting [38]. Table **2** compares RMSE with the development of machine learning models that are applicable to a variety of situations, including LSTM [13] and hybrid models.

Table 2. Comparative analysis table in terms of RMSE error.

Used Model	RMSE Error Value
ANN Algorithm	1.9402
1D CNN BI LSTM	0.9520
Nonlinear Autoregressive	1.4291
LSTM Time series	1.9998
NAR Time series	1.5694

In Table **2**, a variety of the models of machine learning with the empirical methods have been compared to one another. As shown in Table **2** includes the RMSE values for these methods. (Fig. **5**) presents the load distribution of the predicted and actual performance of the TSNPDCL dataset of the last quarter graph using 1D CNN BI LSTM. Using a CNN BILSTM-based model, the 1D CNN BI LSTM model achieved an average RMSE of 0.952 for the Telangana state over a four-month period. As mentioned [41], the advantage of this deep learning model is that the RMSE value generated is lower than any of the other machine learning models or observed methods that are currently being used, which result from the use of a 1D CNN BI LSTM architecture. To determine the effectiveness of a CNN- LSTM hybrid model, a deep learning model based on CNN BI LSTM architecture is evaluated. We assessed its overall effectiveness using a CNN-LSTM hybrid model derived from a CNN-Bi-LSTM-based deep learning model. An average RMSE of 0.952 was achieved for the proposed model for the Telangana state, based on three months of half-hourly data. Compared to LSTM time series models as well as traditional STLF models, such as ARIMA and ANN-based models, the proposed method performed better.

Table 3. Parameters of the model.

Layer/Option	Value
Input features	QV2M,T2M,T2MDEW, T2MWET, WS10M,RH2M
Output	Load(Mw)
Number of features	6
Number of responses	1
Number of hidden units	256
Number of epochs	10
Optimizer	Adam
GradientThreshold	1
InitialLearnRate	0.001
L2 regularization	0.0001
LRDF	0.1
LRDP	10
SequenceLength	longest
Shuffle	every-epoch
GradientDecayFactor	0.9
SquaredGradientDecayFactor	0.999
GradientThresholdMethod	l2norm
ResetInputNormalization	True

*Table **3** analyzes the parameters of the model used while coding in MATLAB.

The research introduces an innovative approach to overcome the limitations of existing CNN models in load forecasting. These models struggle with space invariance and the capture of multi-scale features, leading to decreased performance. To address these challenges, the paper proposes an ensemble deep learning model comprising four stages: feature extraction, Densely Connected Residual Block (DCRB) layer, Bidirectional Long Short Term Memory (Bi-LSTM) layer, and ensemble layer.

Through the use of feature extraction techniques, the proposed model effectively extracts primary and derived features, including temperature, frost point, relative humidity, specific humidity, and wind speed at different heights. By leveraging the DCRB layer, the model demonstrates significant improvements in performance when applied to a multiscale electricity dataset, surpassing traditional CNN models. Validation using half-hourly power data from Telangana

North Power Distribution Company Limited (TNPDCL) yields an impressive Root Mean Square Error (RMSE) value of 0.952.

The experimental results highlight the superior accuracy, hourly prediction capabilities, and effectiveness of the proposed model in load forecasting. These advancements contribute to the overall efficiency of power management systems, facilitating optimal energy allocation and demand-side management. Furthermore, the proposed model exhibits potential applications in diverse domains such as stock price forecasting, weather prediction, and traffic flow prediction.

It is crucial to acknowledge the limitations of the study, including the use of a single dataset for model development and evaluation, which may not fully represent all power systems. Additionally, the proposed model requires extensive training and computation, making it less suitable for real-time scenarios that demand rapid response times.

In the comparative analysis, various models were evaluated based on the RMSE error value metric. The proposed 1D CNN BI LSTM model achieves an exceptional RMSE error value of 0.9520, outperforming alternative models such as ANN Algorithm (1.9402), Nonlinear Autoregressive (1.4291), LSTM Time series (1.9998), and NAR Time series (1.5694).

In conclusion, this research paper presents an innovative hybrid deep-learning model for short-term load forecasting in power systems management. The proposed model effectively addresses the limitations of conventional CNN models, resulting in enhanced accuracy and efficiency. Moreover, its potential applications extend beyond load forecasting, offering promising opportunities in various domains. However, conducting additional comparative experiments is highly recommended to further highlight the performance of the proposed work.

The proposed model is based on CNN-LSTM in comparison with the traditional LSTM and LTSF models, including ARIMA and ANN-based methods [35]. A deviation from normality is represented by the independent axis of this figure, whereas a deviation from the mean square error is represented by the dependent axis. This figure illustrates that the proposed hybrid model has a low RMSE compared to the LSTM time series and traditional STLF models comprising ARIMA and ANNs.

Based on the results of a review of four months' steps, the CNN-LSTM hybrid model performs optimally (lower RMSE). In order to forecast energy consumption, the LSTM-based model and the hybrid approach that was proposed become more challenging with the rise in outliers. As a result of the proposed model, the average RMSE for individual household energy consumption forecasting has been improved.

CONCLUSION

The research study presents a novel hybrid deep-learning model for predicting short-term loads in the management of power systems. A feature extraction module, DCRB, a Bi-LSTM layer, and an ensemble fully connected layer are all included in the model's four-stage structure. The suggested approach incorporates both random and trend characteristics in electrical load data by extracting crucial factors including temperature, humidity, and wind speed. When it comes to accuracy, payload, multi-scale data access, and efficiency, the model exceeds traditional CNN models. The suggested model achieves an RMSE value of 0.952 using half-hourly load data from TSNPDCL.

The suggested model also has important applications, such as demand-side management and optimal energy allocation, both of which are crucial for the operation and control of the smart grid. Power utilities are enabled to manage their resources, reduce the risk of blackouts, and improve the dependability of the power supply thanks to its accurate load forecasting capabilities. Other areas like stock price forecasting, weather forecasting, and traffic flow prediction can be added to the algorithm's feature extraction capabilities.

There are some restrictions to take into account, though. The model's development and evaluation rely on a single dataset, which may not adequately reflect all power systems. Moreover, the model is less effective in real-time applications where quick responses are essential due to the long training and computing complexity.

Future work ought to concentrate on enhancing the Bi-LSTM model's precision and effectiveness through additional advancements. The recommended model's generalizability and robustness will additionally be assessed through the examination of the variables affecting electrical demand and through the application of the proposed approach to other power systems and datasets.

In conclusion, our proposed hybrid deep learning model overcomes the shortcomings of existing CNN-based models by providing superior short-term load forecasting for effective power system management. The model offers a wide range of uses, and future work can increase its accuracy while broadening its possibilities.

LIST OF ABBREVIATIONS

MLR	=	Multiple Linear Regression
ANN	=	Artificial Neural Network
SVR	=	Support Vector Machine
ARMAX	=	Autoregressive Integrated Moving Average with Exogenous Variables
RF	=	Random Forest
GPR	=	Gaussian Process Regression
KWH	=	Kilowatt-Hour
RMSE	=	The Root Mean Square Error
LDC	=	Load Dispatch Center
MSEDCL	=	Maharashtra State Electricity Distribution Company Ltd load
AMR	=	Automatic Meter Reading
MRI	=	Meter Reading Instrument
KVARH	=	kilo Volt Ampere Hours
BU	=	billing unit

T2M	=	Temperature at 2 Meters (C)
RH2M	=	Relative Humidity at 2 Meters (%)
QV2M	=	Specific Humidity at 2 Meters (g/kg)s
WS10M	=	Wind Speed at 10 Meters (m/s)
T2MWET	=	Wet Bulb Temperature at 2 Meters (C)
T2MDEW	=	Dew/Frost Point at 2 Meters (C)
AI	=	Artificial Intelligence
LDRP	=	Learning Rate Drop Period
LDRF	=	Learning Rate Drop Factor

CONSENT FOR PUBLICATION

Not applicable.

AVAILABILITY OF DATA AND MATERIALS

The data and supportive information are available within the article.

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CONFLICT OF INTEREST

"The authors declare that they have no conflicts of interest toreport regarding the present study."

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