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Grey Wolf Optimization Based CNN-LSTM Network for the Prediction of Energy Consumption in Smart Home Environment

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ABSTRACT In smart homes, the management of energy is gaining huge significance among researchers in recent times. This paper presents a system for predicting power utilization and scheduling household appliances in smart homes. The system utilizes a combination of Grey Wolf optimization (GWO), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) to improve energy management. The GWO algorithm is used to enhance the performance of the CNN-LSTM model. GWO is an optimization algorithm inspired by the hunting behaviour of grey wolves. It helps in finding optimal solutions for complex problems by mimicking the social hierarchy and hunting mechanisms of wolves. The fusion of CNN and LSTM serves as a pattern finding strategy for energy management. CNN is effective in extracting spatial features from data, while LSTM can capture temporal dependencies. By combining these two approaches, the model can analyze energy consumption patterns and make accurate predictions. To evaluate the performance of the proposed model, the paper uses three error metrics: Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE). The reported values of RMSE, MSE, and MAE are 0.6213, 0.3860, and 0.2808, respectively. These metrics indicate the accuracy of the model's predictions, with lower values indicating better performance. Furthermore, this paper compares the proposed approach with the existing baseline models to access its superiority. According to the results, the proposed model outperforms the existing approaches in terms of prediction accuracy, as it achieves lower errors, compared to the baseline models. In summary, the proposed GWO-based CNN-LSTM network demonstrates improved prediction accuracy compared to the existing approaches, as indicated by the evolution metrics.

INDEX TERMS Smart Homes, Energy Management, Grey Wolf Optimization, Convolutional Neural Network, Long Short-Term Memory, Internet of Things

I. INTRODUCTION

There has been considerable attention among the researchers to improve energy efficiency in household applications. Several techniques have been introduced to improve energy consumption in residential buildings and one among them is the design of Internet of Things (IoT) based smart homes [1]. The emergence of IoT has simplified the design of smart homes which reduces the carbon footprint and improve the sustainability of energy management systems (EMS). In this context, there is a great demand for smart energy management techniques for smart homes [2]. IoT technologies enable the conventional EMS to sense the data collected across different sensors and helps in the monitoring and controlling of energy consumption by household appliances. Different sensors are installed in the residential buildings and the energy consumption data is collected from these sensors for estimating the energy utilization. Due to the simplicity and feasibility of energy management, IoT based smart homes has become one of the emerging research topics in recent times [3][4].

Most of the existing smart homes focuses on establishing a stable communication system, high speed wireless communication, reliability of power transmission, secure data storage, and robust system architecture [5][6][7]. The existing works also state prominence of IoT technologies for the design and development of next generation smart homes [8][9][10]. However, the implementation of IoT technology for smart homes involves a lot of complexities such as high installation cost, high maintenance, lack of storage etc. [11]. These limitations restrict the large-scale deployment of such systems. In general, IoT devices collect huge volume of data from multiple sensors and it is challenging to process and analyze such large-scale data. AI based ML and DL models are considered as a potential tool to analyze IoT data for smart homes [12][13]. These models can make decisions automatically based on the energy minimization of the EMS deployed in smart homes. The ML and DL models extract relevant features and identify suitable data patterns for generating an optimized solution. The optimized solutions incorporate different environmental conditions and energy constraints which makes EMS in smart homes a self-learning system [51][52].

This paper presents a self-learning EMS for smart homes which predicts the energy utilization by household appliances. The proposed model incorporates a hybrid CNN-LSTM model for making appropriate decisions with respect to forecasting energy consumption and improving energy efficiency [49][50]. Grey Wolf Optimization (GWO) algorithm is being used in this paper to optimize the results of the hybrid CNN-LSTM network to improve the performance. GWO is a nature inspired optimization algorithm which is based on the social hierarchy and hunting behavior of the grey wolves. This algorithm has several characteristics like; GWO exhibits a good balance between searching for a new solution and exploiting the current best solution. This feature is very crucial in energy optimization problems because it allows the algorithm to search for both global and local optima in the solution space. Energy optimization often requires finding the best configuration or allocation of resources, and GWO's exploration-exploitation balance can help in achieving the best solution. This algorithm is a population-based algorithm that simulates the social hierarchy and cooperation among wolves and maintains the population of candidate solutions (wolves) and updates their positions based on their fitness values. This aspect of WO can help in exploring the solution space more effectively, especially in complex energy optimization problems where there may be multiple conflicting constraints. This algorithm has more convergence speed which is advantageous for energy optimization problems, as they often involve large scale systems with multiple variables and constraints. Faster convergence allows GWO to find good solutions within a reasonable time frame. GWO is scalable for high-dimensional optimization problems.

This paper is further organized as follows: Section 1 describes this area and proposed research. Section II discusses the review of existing works related to energy management in smart homes. Section III provides a brief description of the proposed work in the paper. Section IV presents the simulation of the GWO based CNN-LSTM architecture. Section V discusses the simulation results and the complete performance evaluation of the proposed work, and Section VI concludes the paper with prominent research observations with the future work.

II. Related Works

In 2016 Zhou et al., In 2018 Nilsson et al., In 2019 Khalid et al. emphasized their attention towards smart EMS for smart homes has gained vast significance in the past decades [14][15][16]. The overall performance of EMS has seen a great improvement with the emergence of different energy management strategies and efficient controlling techniques.

In 2019 according to Pallonetto et al., the households and residential buildings are responsible for consuming 39% of energy which often creates issues related to the shortage of energy and high pollution levels. The high consumption of energy also increases the cost of individuals and reduces their saving and spending power on other durables. To eliminate the issues that are faced by energy users and increase its usability, several measures have been proposed by scholars and researchers [17].

In 2020, according to Khan et al., the EMS are efficient in terms of energy consumption, there are certain drawbacks such as low density, low efficiency, and challenges to forecast energy consumption and scheduling household appliances. To overcome this limitation and to design an efficient EMS, the data aggregated from smart home appliances are categorized into different groups. Data classification helps in minimizing the computation time required for processing the data using ML models. However, conventional ML models underperform in terms of achieving high classification accuracy. This is mainly due to the inability of ML models to perform real time analysis of collected data and categorize the home appliances based on their energy consumption [18].

In 2020 Aurangzeb et al. and 2022 Alden et al. proposed that DL algorithms can be considered as a potential tool to overcome the problems associated with ML models. DL algorithm such as CNN, RNN such as LSTM models extract important and relevant features from the collected data and identify suitable data patterns to accurately forecast energy usage in household appliances [19][20]. However, these techniques require larger dataset for training, which increases the computational time and increases the work load. Hence it is required to optimize the performance of DL models using intelligent and metaheuristic algorithms.

Several researchers have done their research work in the domain of the power utilization. In 2016, A. Bogomolov et al. [33] used random forest regressing and described about electricity utilization forecasting using social activity examination. In 2016, D. L. Marino et al. [38] utilized sequence to sequence approach and described the implementation of the given model with LSTM. In 2017, C. Li et al. [36], utilized stacked autoencoders, and described that the given technique is being utilized to select and acquire the useful features out of the dataset. In 2021, Çetiner et al. [33] utilized the regression, Xgboost, and LSTM on the power consumption dataset and described that the given and popular algorithms are being implemented and compared the obtained results. In 2022, Maghraoui et al. [34] utilized ANN, SVM, DT and RF and described that the model which is producing the results with the better results is RF and stated that this is the most effective technique also to implement in such types of problems.

In general, there are two main categories for EMS which are rule based EMS (Jithish & Sankaran, 2017) [21] and optimization-based EMS (Molla et al., 2019) [22]. Rule based EMS are mainly dependent on the outcome of the detailed experimental analysis without having the preliminary knowledge about the energy demand and utilization. On the other hand, various optimization algorithms such as Genetic Algorithm (GA) (Molla et al., 2018) [23], Particle Swarm Optimization (PSO) (Abid et al., 2017) [24], and ant colony optimization (ACO) (Okonta et al., 2016) [25] were used to improve the performance of EMS. Despite the availability of different optimization algorithms, there is a great demand for the implementation of computationally light optimization algorithms and a deeper investigation is required in this context.

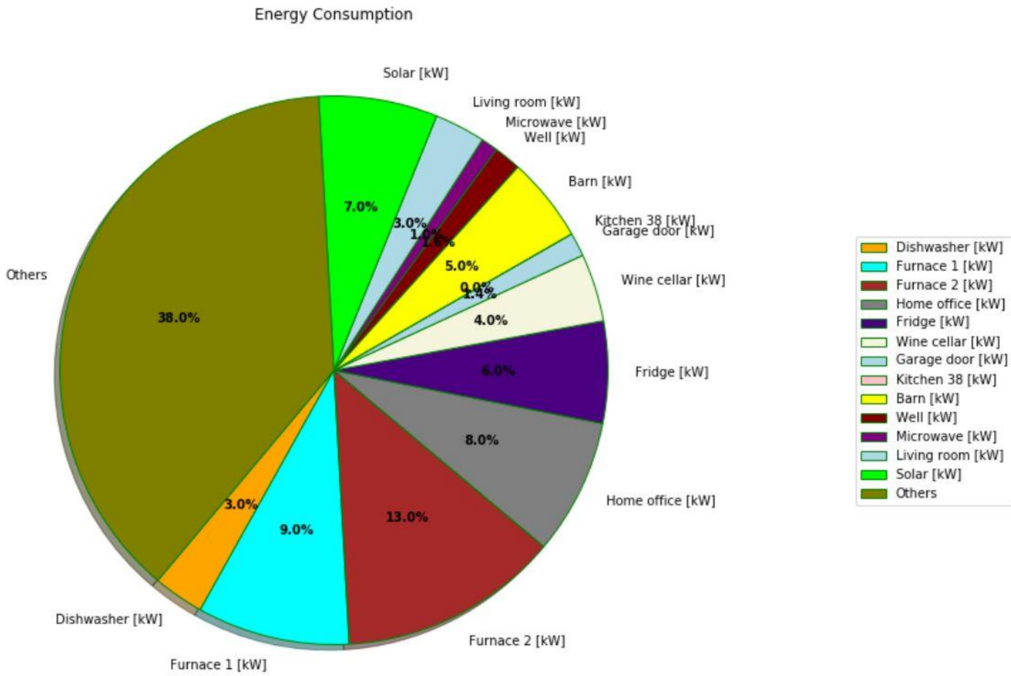

FIGURE 1. Different parameters in the dataset

In energy optimization, there can be many variables and parameters to optimize, such as energy generation, consumption, storage, and distribution. GWO's ability to handle high-dimensional spaces can be beneficial in tackling the complexity of energy optimization problems. This work is implemented using the smart home energy consumption dataset which is available online [32]. The dataset is having different parameters and different type of energy consumption represented in figure 1.

III. Material and Methods

In this section of this paper, the dataset that is used to implement the proposed techniques is being discussed followed by the preprocessing of the dataset.

A. Power Utilization Dataset of the Smart Home

The Smart Home Dataset is extracted from online repository for the data for the experimental analysis. This data is gathered every minute for 350 days in a smart home setting from the smart appliances in kW and the local weather conditions [32]. Table 1 represents different parameters present in the data collected from the smart home.

TABLE 1
PARAMETERS IN THE DATASET

Parameters	Data Type	Non-Null Count
use [kW]	Int64	503910
gen [kW]	float64	503910
House overall [kW]	float64	503910
Dishwasher [kW]	float64	503910
Furnace [kW]	float64	503910
Home office [kW]	float64	503910
Fridge [kW]	float64	503910
Wine cellar [kW]	float64	503910
Garage door [kW]	float64	503910
Kitchen [kW]	float64	503910
Barn [kW]	float64	503910
Well [kW]	float64	503910
Microwave [kW]	float64	503910

Living room [kW]	float64	503910
Solar [kW]	float64	503910

The data acquired using different devices like; sensors are subjected for preprocessing to filter out uncertainties such as outliers, missing values, null values etc. from the input data. Preprocessing has a significant role in enhancing the working of CNN-LSTM algorithms in the form of prediction accuracy. Preprocessing also involves data normalization wherein the data is logically grouped within the same range (usually the range is between 0 and 1). Here, the data is normalized by determining the distance between minimum and maximum values of each feature. In this stage, the string columns are converted into integer type and the correlation between the features are calculated by eliminating highly correlated features. In this stage, appropriate features are being extracted from the obtained data which are being used for finding suitable data patterns. Figure 2 is the visual representation of the dataset collected from the smart home environment.

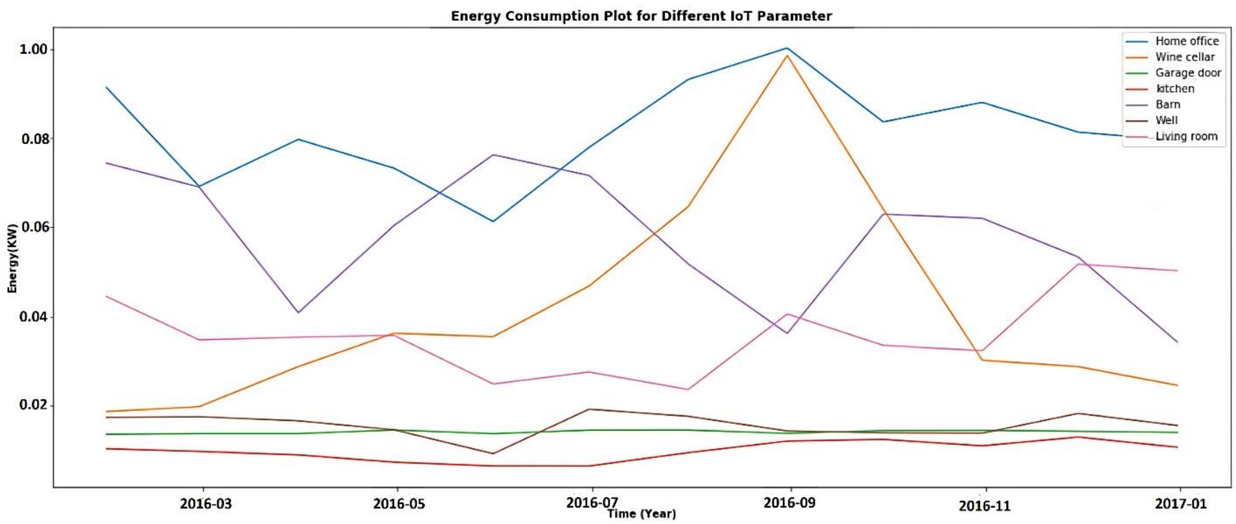

FIGURE 2. **Visualization of the Data Collected from a Smart Home**

Here, the proposed CNN-LSTM can perform both feature extraction and selection and hence it eliminates the necessity of using any additional techniques for feature selection. This allows fast and quick operation and thereby speed up the execution process. Table 2 represents the quantitative description of the IoT data collected using different smart devices like dishwasher, furnace, home office, fridge, kitchen, microwave, etc. The total energy consumption, minimum, maximum, and average energy consumption values are given in table 3.

TABLE 2
QUANTITATIVE ANALYSIS OF THE IOT DATA COLLECTED IN SMART HOME

Parameters	Total	Max	Min	Avg
Use	432839.74	14.7145	0	0.8589
Gen	38412.76	0.6138	0	0.0762
Dishwasher	15806.40	1.4017	0	0.0313
Furnace	49993.06	1.9340	0.0000167	0.0992
Home office	40961.27	0.9717	0.0000833	0.0812
Fridge	32026.71	0.8512	0.0000667	0.0635
Wine Cellar	21233.07	1.2739	0.0000167	0.0421

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Garage Door	7124.84	1.0889	0.0000167	0.0141
Kitchen	1388.44	1.1665	0	0.0027
Microwave	5534.44	1.9298	0	0.0109
Living Room	17794.47	0.4652	0	0.0353
Solar	38412.76	0.6138	0	0.0762

In the proposed work, one feature is selected from the dataset and the feature is labelled as the "use" column and this feature helps in finding all energy usage patterns. Once all the features are selected and extracted, they are converted into time series data format. The extracted features are further used by the CNN-LSTM model for forecasting the power utilization by household appliances.

A. PREPROCESSING OF THE DATASET

In this section of the paper, preprocessing of the datase t is being discussed. The dataset is being obtained from the online repository. There are number of parameters under the dataset given in table 1. The whole dataset ha s two different types of parameters in the dataset i.e., th e IoT parameters, and the weather conditions paramete rs. The objective of this papers is to predict the energ y consumption, so only IoT parameters are being obtai ned out of the whole dataset. Following steps are being carried out to perform the preprocessing of the dataset.

Step 1: Importing Data

Step 2: Checking for the overall parameters from the d ataset.

Step 3: Converting the Unix time to the date and time f ormat.

Step 4: Extracting the IoT parameters out of the data.

Step 5: Removing "[kW]" from all the parameters.

Step 6: Identifying and dropping the NULL and outlie rs.

Step 7: Converting the data into time series.

On the implementation of the above steps for the prepr ocessing of the dataset, the data is divided into the train ing and testing sets to implement the proposed method ology and to generate the energy predictions.

IV. Proposed Work: GWO Based CNN-LSTM Network

This section of this paper discusses the methodology of the proposed work, CNN-LSTM network designing, Grey Wolf Optimization, Architecture, process flow, Algorithm of the proposed work.

A. METHODOLOGY OF THE PROPOSED WORK

The methodology which is being adopted to implement the proposed methods is given in the following steps;

Step 1: IoT data collection from smart environment i.e., Smart Home.

Step 2: Data preprocessing to formulate the data for implementing the algorithm on the dataset.

Step 3: Designing the CNN-LSTM network to generate the energy predictions.

Step 4: Implementation of the GWO algorithm on the predictions obtained in step 3 to obtain the best optimized results.

Step 5: Visual representation and analytical study of the results obtained.

Step 6: Analyzing the proposed work in comparison to the current work.

Step 7: Obtaining the best optimized results.

B. CNN-LSTM NETWORK

Electrical energy consumption is predicted using the CNN-LSTM approach using several CNN and LSTM layers. When collecting sensor data for energy demand assessments, CNN-LSTM can extract complex attributes and retain complex irregular patterns. First, CNN makes top most layer of CNN-LSTM. The input, output, and sub measurement, et. variables may indeed be sent to the CNN layer and have an impact on the amount of power is used. Additionally, the CNN layer's meta information may be used to represent domestic features like date, time, resident behavior, family profession, etc. The input layer makes up the CNN. As the extraction function and output layer of certain hidden layers of LSTM, the input layer receives a sensor variable. The function and the pooling layer are often active by reviewing, and the hidden layer is typically made up of a convolution layer. The convolution layer applies the introduced series of different sequences and transmits the outcomes to the subsequent layers. The CNN operation mimics the response of a single neuron to sensory input. Essentially the storage area is handled by each convolution neuron, which only processes energy data. Convolutional operation may expand the CNN-LSTM network and lower the number of parameters.

If the energy consumption participation vector $x_i^0 = \{x_1, x_2, \dots, x_n\}$ and the number of standard one unit per window (n) are both present. Equation (1) represents the result of the vector y_{ij}^1 generated from the first convolutional layer, where y_{ij}^1 is designed by the vector x_{ij}^1 generated from the previous layer, where b_j^1 characterises the bias for the j^th^ feature map, where w is the weight of the kernel, m is the catalogue value of the filter, and σ is the initiation feature similar to ReLU. The vector y_{ij}^1 generated by the lth convolutional layer is the result in equation (2).

$$y_{ij}^1 = \sigma\,(b_j^1 + \sum_{m=1}^{M} w_{m,j}^1\, x_{i+m-1,j}^0\,) \tag{1}$$

$$y_{ij}^1 = \sigma\,(b_j^1 + \sum_{m=1}^{M} w_{m,j}^1\, x_{i+m-1,j}^0\,) \tag{2}$$

Pooling layers are used in convolutional layers to combine the output of a group of neurons in one layer into a single neuron in the next layer. To reduce the computational cost and attribute count of the network, a pooling layer compresses the data. The max pooling approach predicts the energy usage using the maximum value of each set of neurons in the previous layer. Additionally, bias is modified appropriately. Equation (3) illustrates the max pooling layer's performance. T indicates how far the input data area should be moved, and R is the cluster size, which is less than the input y's size.

$$p_{ij}^l = \max_{r\,\epsilon\,R} y_{i\times T+r,j}^l \tag{3}$$

The CNN-LSTM's lower layer, LSTM, maintains temporal data concerning significant power demand features that were obtained using CNN. The LSTM groups memory units that can update the previously hidden state in order to maintain long-term memory. This function makes it easy to understand the temporal links of long-term sequences. A gate unit receives the output values from the previous CNN layer. Since gating units can handle them, the output values from the previous CNN layer are transmitted to the gating unit. LSTM networks are well suited for power estimation because they can handle the problem of rapidly decreasing gradients that can arise when training conventional RNNs. Multiplication uses three gate cells to determine the state of individual memory cells. Depending on their function, door units include entry, exit and oblivion doors. Each time a gate cell is engaged, the memory cells that make up the LSTM update their state, which is set to a continuous value between 0 and 1. LSTM networks are more appropriate for energy use estimation than typical RNNs, which may experience the quickly fading gradient issue during training. Three gate cells are used through combination to determine the state of each memory cell. Entry, exit, and forgetting gates are some of the many gateway units, depending on their purpose. Each time a gate cell is engaged, the memory cells that make up the LSTM update their state, which is set to a continuous value between 0 and 1. Every t step, the LSTM cell's concealed state, h_t, is updated.

$$i_t = \sigma\left(W_{pi}p_t + W_{hi}h_{t-1} + W_{ci}\;o\;C_{t-1} + b_i\right) \tag{4}$$

$$f_t = \sigma\left(W_{pf}p_t + W_{hf}h_{t-1} + W_{cf}\;o\;C_{t-1} + b_f\right) \tag{5}$$

$$o_t = \sigma\left(W_{po}p_t + W_{ho}h_{t-1} + W_{co}\;o\;C_{t-1} + b_o\right) \tag{6}$$

The functions of the input, forget, and output gates to make up the LSTM are shown in equations (4) and (6). The symbols i, f, and o represent every gate's outputs. The hidden layer and unit levels generated by the input, forgot, and output are described using symbol c, and h in Equations (7) and (8), respectively. The activation mechanism is the same as tanh. Equivalent compression is used for the input to this nonlinear activation function throughout the range [-1, 1]. Each gate unit has a bias vector called b and the weight matrix called W. The basic characteristics of the power utilization of the pooling layer at the output at time t are included in the input p_t of the LSTM memory cell. CNN-LSTM networks using LSTM cells modeled with signal timing information improve performance and provide state-of-the-art results in predicting household energy consumption.

$$c_t = f_t \, o \, c_{t-1} + i_t \, o \, \sigma \left(W_{pc} p_t + W_{hc} h_{t-1} + b_c \right) \quad (7)$$

$$h_t = o_t \, o \, \sigma(c_t) \quad (8)$$

Fully - connected layers make up the CNN-LSTM's last layer. This may be used to calculate the amount of energy utilized over a certain time frame. A feature vector is created using the output of an LSTM unit. $h^l = \{h_1, h_2, h_3, \dots, h_l\}$, while l is the overall number of components in the LSTM. The fully linked layer receives its input from the LSTM's output. For a 60-minute prediction of energy usage CNN-LSTM is being utilized. The equation employed in this layer is shown in equation (9). The bias is represented by b i(l-1), where w is the weight of the i^{th} and j^{th} nodes in layer l - 1. The nonlinear activation function is written as σ.

$$d_i^l = \sum_j w_{ji}^{l-1} \left(\sigma\left(h_i^{l-1}\right) + b_i^{l-1} \right) \quad (9)$$

In this paper, CNN-LSTM network is designed and implemented on the power utilization dataset to obtain the prediction of the power utilization in the smart home environment. Different layers like; one layer of 1D Convolution with relu activation function, two layers of LSTM with tanh activation function, and three dense layers with relu activation function are being included in the network. The energy consumption data is first converted into the time series and then passed to the network. The CNN-LSTM network uses the time series data to produce the prediction of the power utilization based on the actual power utilization patterns. Further, to optimize the results of the network, a meta heuristic algorithm i.e., Grey Wolf Optimization is being implemented on the obtained results. This algorithm helps to obtain the batter prediction of the energy consumption. This algorithm is being discussed in section 3.2.

C. GREY WOLF OPTIMIZATION

The GWO is a metaheuristic algorithm encouraged by the hierarchical process of management and hunting in gray wolves. Four species of gray wolves, alpha, beta, delta, and omega, are thought to model leadership hierarchies. For analysis purposes, male and female wolves were considered pack leaders known as alpha (α), and secondary gray wolves were represented by beta (β). Beta Wolves help Alpha Wolves make the right decisions to reach the optimal solution. Another pack of wolves known as delta (δ) are considered as the third level wolves and the lowest rank of wolves are represented as omega (ω). This represents the hierarchy of the leadership in figure 3. This section begins by talking about where the suggested technique got its ideas [43]. The mathematical model is then presented in this section.

FIGURE 3. Social hierarchy of the Grey Wolfs

The grey wolf works in a group to hunt their prey and follow a particular hierarchy to accomplish the task represented in figure 4. Few steps are being carried out to by the grey wolfs for the hunting of the prey. All these steps are searching for the prey, when the prey is found then pursuing it. When the wolves get their prey or target, they encircle it until the prey stops movement. As soon as the target gets still and have no movement, the grey wolves attack it and start feeding by following the hierarchy of dominance. The outline of these key steps of the hunting procedure of the grey wolves is represented in figure 4.

FIGURE 4. Different phases of Hunting

This section provides the mathematical modelling for grey wolf hunting behavior. The greatest option is believed to be alpha (α), followed by beta (β) and delta (δ) as the next best options. It is expected that the remaining possible solutions are omega (γ). α, β, and δ serve as the hunting (or optimization) indications in the GWO algorithm. These three wolves are followed by the γ wolves. In the section, the grey wolves' hunting strategy is described.

Step 1: In this step, the whole pack of grey wolfs works together for the searching of the prey or target. If any target like, deer, goat, moose etc., enters the territory, the wolves chase the target to hunt it down. The figure 7 (b) represents the searching of the prey.

Step 2: The pack of the grey wolves select the bigger target for hunting. They chase the target and make it kill. The participants in this stage are several wolves, such as alpha, which is the best option, beta, which ranks second, delta, which comes in third, and omega, which takes the lead from the other three wolves.

Step 3: When hunting, the grey wolves circle their prey or target until it stops moving. Equation (10) and equation (11) are used in mathematics to represent the encircling approach of grey wolves. According on the location of the prey, these equations are employed to update the grey wolf's position. Figure 5 illustrates various potential locations for the grey wolf and the subsequent position.

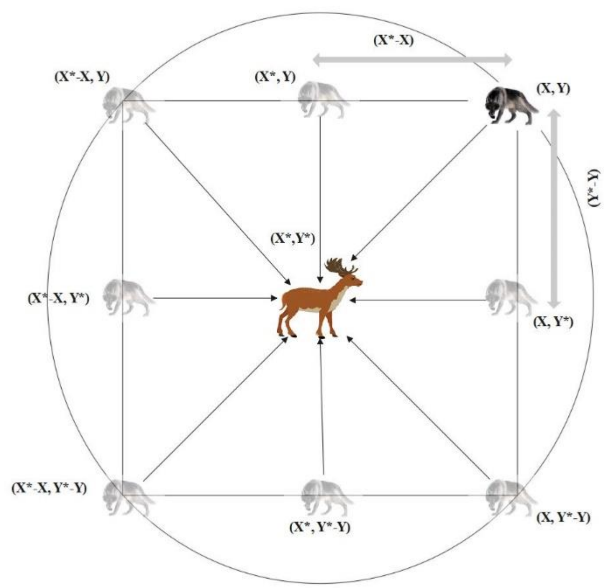

FIGURE 5. Position vector of the Grey Wolf and possible next Location

By adjusting the values of B and D, it is possible to achieve the various locations around the best seeking agent or the grey wolf about the present position. Equations 12 and 13 are used to derive B and D. Figure 6 illustrates the position update. Finding the prey is the first step in the grey wolves' hunting strategy. Once the prey is entered into the territory, the wolves start chasing the prey and if the prey confronts, it starts moving i.e., getting away from the wolves.

The alpha wolf mathematically controls the grey wolf pack's hunting strategy. It is obvious that the alpha, beta, and delta have a better understanding of where the prey is located or the optimal solution.

The other wolves' locations is being altered in accordance with the positions of alpha, beta, and delta. The update in the position is being calculated using equation (14), (15) and (16), also represented in figure 6.

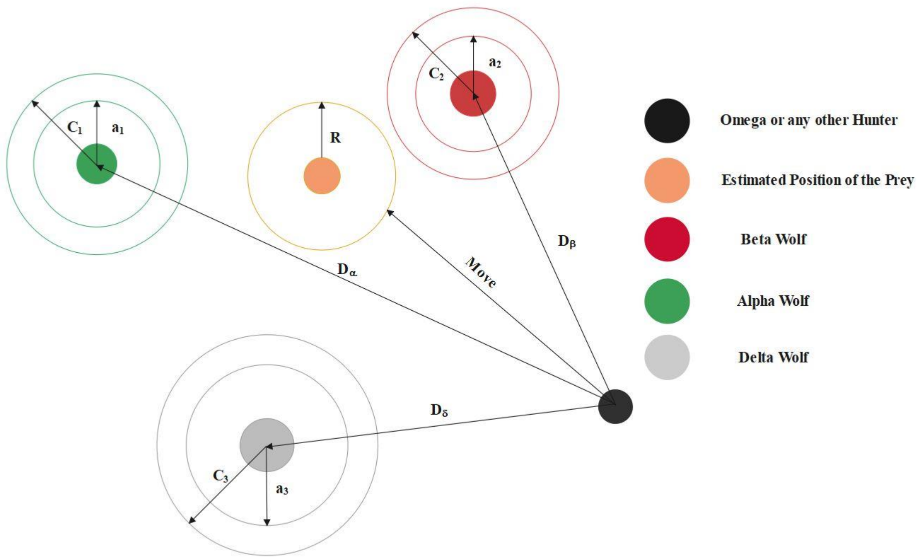

FIGURE 6. **Position updates of GWO**

Step 4: Alpha wolf finishes the hunt by attacking the prey. The wolf attacks its victim to complete the hunt after the animal stops moving. According to the grey wolves' leadership order, the alpha wolf can consume the prey first when the hunt is over. The process of hunting is modelled by decreasing the value of $\vec{b}$ from 20 to 0 during the iteration. As the $\vec{b}$ is decreased $\vec{B}$ also decreases. Figure 7 (a) represents the attacking condition of the grey wolf.

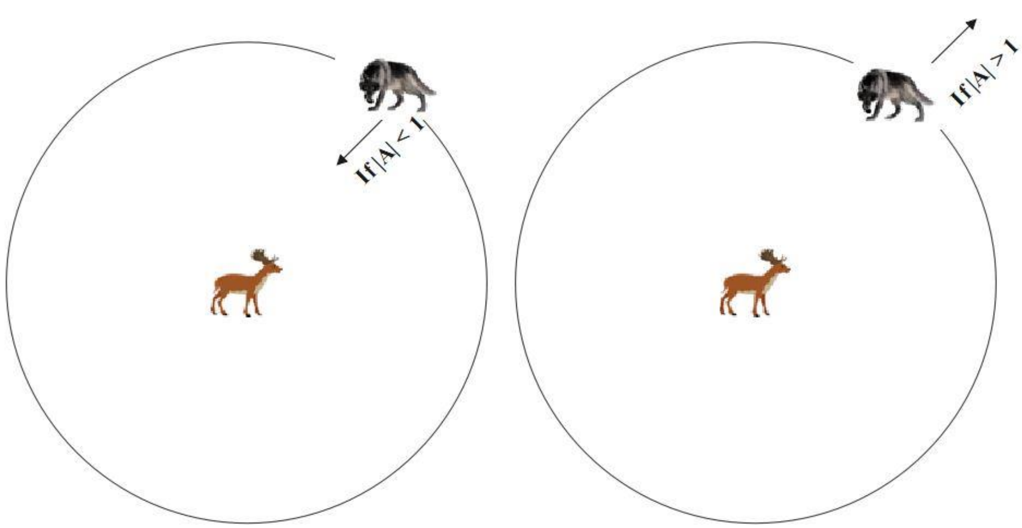

FIGURE 7(a, b). **Attacking and Searching for the Prey**

To summarize GWO, as an initial phase in the search procedure, the GWO algorithm creates a random population of grey wolves (potential solutions). Within a few rounds, alpha, beta, and delta wolves determine possible prey locations. Each potential response changes the distance to the prey. Change the value from 2 to 0 to emphasize exploration and

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exploitation. When $|\vec{B}| > 1$ and when $|\vec{B}| < 1$, candidate solutions often diverge from the prey and converge on it, respectively. Finally, the GWO algorithm is ended when an end criterion is satisfied. In this paper, GWO is being used for finding out the optimized energy consumption. Following few steps are being performed to implement the GWO in this paper;

Step 1: Initialize the wolf population

Step 2: Generate the wolf; The result which is obtained from the CNN-LSTM network is used to initialized the wolf population.

Step 3: Train the generation using CNN-LSTM network

Step 4: Predict the energy.

Step 5: Checking the fitness of the solution.

Step 6: Using the locations of all the grey wolves to determine the new weights.

Step 7: Searching and attacking the prey (i.e., accuracy) based on the wolf weight.

Step 8: Running the evolution to obtain the optimized energy prediction.

On the implementation of all the eight steps, optimized prediction of the energy consumption is obtained using the proposed technique.

D. ARCHITECTURE OF THE PROPOSED WORK

Figure 8 displays a thorough design that employs the CNN-LSTM model to calculate the household energy usage. The acquisition of electricity utilization data, the development of the CNN-LSTM network, and the implementation of the grey wolf optimization algorithm comprise are three modules that comprised in the proposed architecture. The suggested study uses actual energy usage data that includes several housing-related characteristics. The CNN-LSTM model learns from preprocessed input data using a variety of approaches. The CNN-LSTM network receives the data after it has been transformed into time-series data. From the CNN layer, it separates different attributes of multiple time sequential variables and delivers them to the LSTM layer.

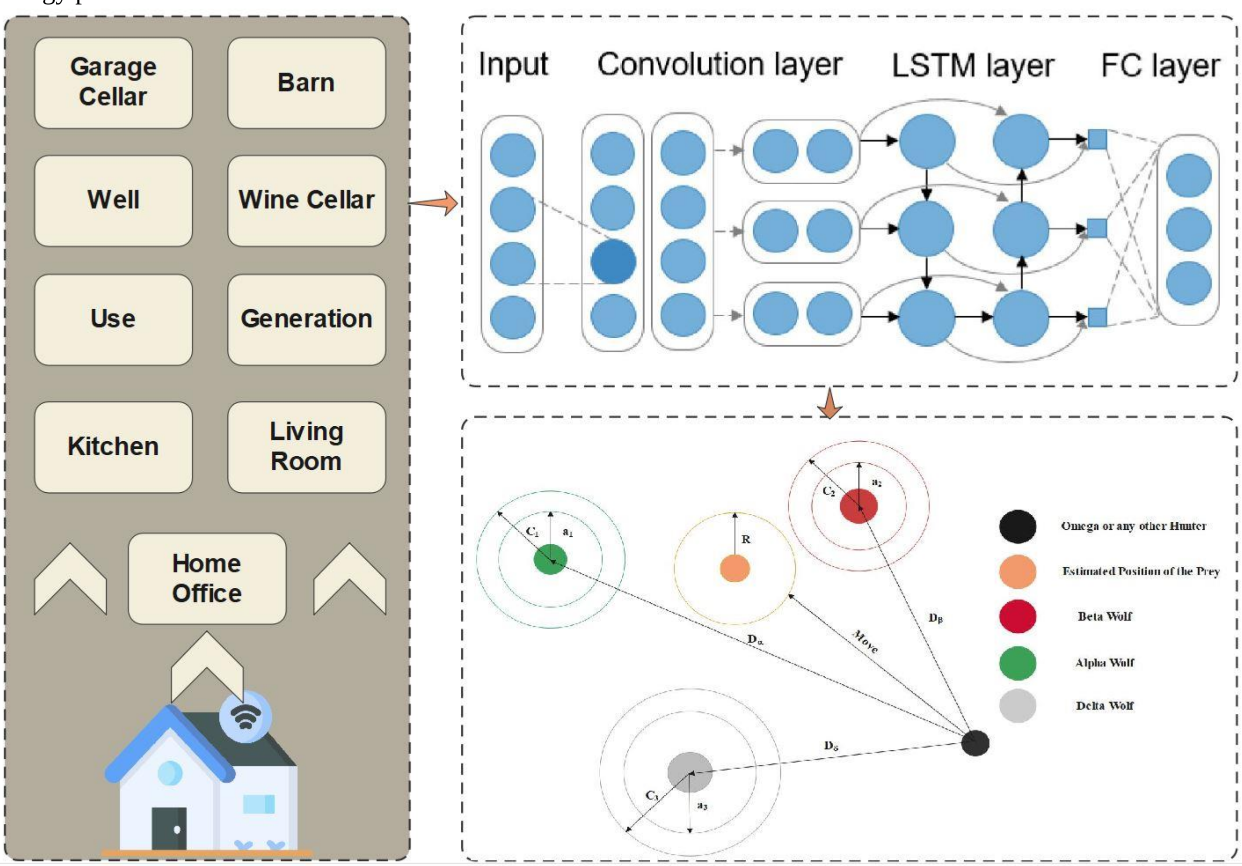

FIGURE 8. **Architecture of the GWO based CNN-LSTM Network**

Finally, the CNN-LSTM approach can provide power consumption predictions with a fully - connected hierarchical structure. Various error matrices, including RMSE, MSE, and MAE, are used to determine error in the energy consumption predictions.

The novelty of the proposed GWO-based CNN-LSTM network is that the 1D CNNs are commonly used for data analysis tasks, while LSTMs are effective in capturing long-term dependencies in sequential data. The novelty arises from the combination of CNN and LSTM networks, which enables the network to extract spatial and temporal features from the energy consumption data in smart homes. This integration allows the network to learn patterns and make accurate predictions, leading to more effective energy optimization strategies. The novelty lies in the utilization of GWO as an optimization technique for energy optimization in smart homes. GWO helps in finding optimal solutions for energy management problems, such as scheduling appliances and controlling energy consumption. Smart homes are equipped with various energy-consuming devices and appliances. The novelty lies in using the GWO-based CNN-LSTM network to optimize the energy consumption within smart homes. The network can learn from historical energy data, weather patterns, and user preferences to make intelligent decisions on appliance scheduling, load balancing, and energy management. This approach can help reduce energy waste, improve efficiency, and lower energy costs for residents. Another major point of the GWO-based CNN-LSTM network is its adaptability to changing conditions in smart homes. The network can dynamically adjust its optimization strategy based on real-time data, such as changes in occupancy, weather conditions, or energy prices. This adaptability ensures that the energy optimization system remains effective and responsive to the dynamic nature of smart home environments.

Basically, the GWO-based CNN-LSTM network for energy optimization in smart homes lies in the combination of the GWO optimization algorithm with CNN and LSTM networks, along with its adaptability to changing conditions. This integrated approach enables more accurate predictions, efficient energy management, and improved energy optimization in smart homes.

E. PROCESS FLOW OF THE PROPOSED WORK

The proposed work's process flow is shown in Figure 9. The whole implementation is split into two segments. The design of the CNN-LSTM network comes first, and the application of the optimization technique to obtain optimum results comes second. The CNN-LSTM architecture can be altered in several ways depending on the kind and extent of parameter modification of the network's layers. The CNN-LSTM is composed of three types of layers: the Convolutional, LSTM, and Dense layers. Each layer can change the number of filters, kernel size, and strides shown in table 3.

TABLE 3
DESCRIPTION OF THE PROPOSED CNN-LSTM ARCHITECTURE

Layer	#Layers	Activation Function	Filter	Kernel Size
Convolution	1	Relu	60	5
LSTM	2	Tanh	60	-
Dense	3	Relu	60	-

Depending on the features of the learning data, changing these factors may have an impact on learning efficiency and effectiveness. The performance difference can be verified by changing the parameter's value. Understanding the features of the input data is necessary in order to modify the parameters and create the best architecture for energy consumption prediction. Data on energy use is multivariate and is formatted in Unix time. 60 datapoints from 7 variables from a dataset with a time-series of 60 seconds make up CNN-input. LSTM's The convolution layer, LSTM layer, and denser layer are all applied after the convolution layer.

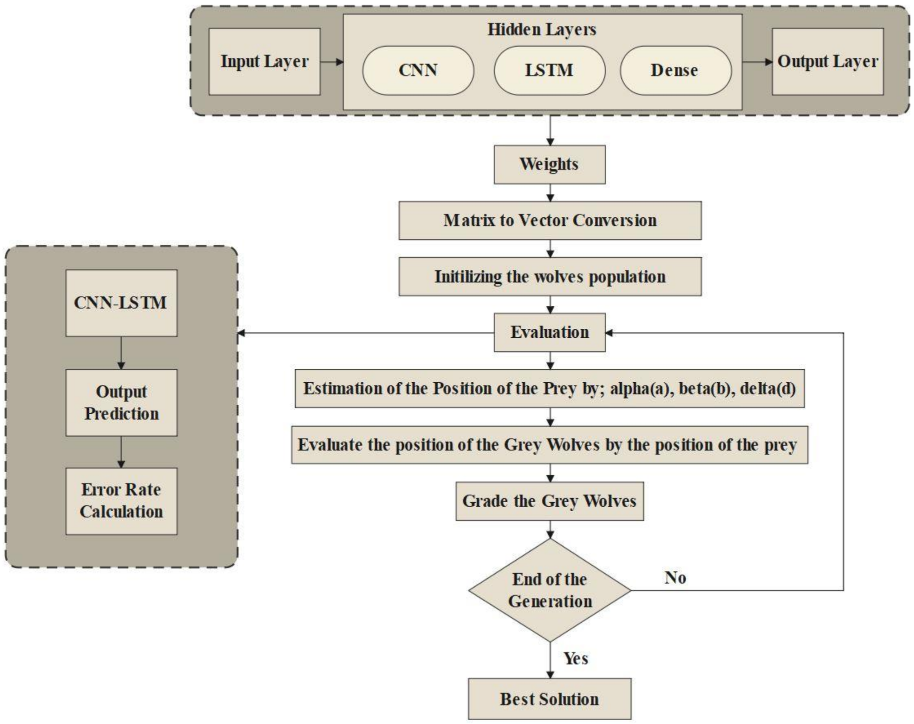

FIGURE 9. **Process flow of the proposed work**

In the whole work is divided into two sub sections i.e., Designing of CNN-LSTM Network, and Implementation of GWO algorithm to obtain the optimized results. So, in this section Algorithm and pseudo code is given.

F. ALGORITHM OF THE PROPOSED WORK

The proposed work is separated into two segments i.e., Design and implementation of CNN-LSTM network and implementation of GWO algorithm to obtain the optimized energy consumption prediction. So, the following algorithm can forecast the optimized energy utilization in smart home, also to implement the proposed work.

Algorithm: GWO based CNN-LSTM Network

Step 1: Collection of energy consumption Data using IoT devices

Step 2: Preprocessing of the Energy Data

Step 3: Conversion of the data into time-series

Step 4: Design of CNN-LSTM network

  Layer 1 — Conv1D (filter = 60, kernel_size = 5, stride = 1, activation = "relu")
  Layer 2 — LSTM (filter = 60, activation = "tanh")
  Layer 3 — LSTM (filter = 60, activation = "tanh")
  Layer 4 — Dense (filter = 30, activation = "relu")
  Layer 5 — Dense (filter = 10, activation = "relu")
  Layer 6 — Dense (1)
  Layer 7 — Lambda (lambda x: x*100)

train_neural_network()
  batch_size = 32, epoch = 25, split = 0.10

test_neural_network()
  prediction of energy consumption using the proposed model

Step 5: Implementing Grey Wolf Optimization

Initialize the grey wolf population using the output of the CNN-LSTM network P_i (i = 1, 2,..., n)

Searching of the prey.

Chasing and Encircling the Prey

$$\overrightarrow{G_d} = |\vec{C}.\overrightarrow{P_p}(c) - \overrightarrow{P_g}(c)| \tag{10}$$

$$\overrightarrow{P_g}(c+1) = \overrightarrow{P_p}(c) - \vec{A}.\overrightarrow{G_d}| \tag{11}$$

Where c = current iterations, $\overrightarrow{G_d}$ = distance vector, $\overrightarrow{P_p}$ = position of the prey, $\overrightarrow{P_g}$ = position of the grey wolf

Initialize b, B, and D coefficient vectors

$$\vec{B} = 2\vec{b}.\overrightarrow{a_1} - \vec{b} \tag{12}$$

$$\vec{D} = 2.\overrightarrow{a_2} \tag{13}$$

Where, $\overrightarrow{a_1}, \overrightarrow{a_2}$ are random vectors from [0, 1], $\vec{b}$ linearly decreasing from 2 to 0 over the iterations

Calculate the fitness of the grey wolves; $P_\alpha, P_\beta, P_\delta,$ using the following equation

$$\text{Fitness} = \frac{1.0}{|\sum(\text{solution}*\text{function\_inputs}) - \text{desired\_output}|}$$

while (t < max number of iterations)

for each grey wolf

Update the position of the current grey wolves using the distance vector and the position vectors

$$\overrightarrow{G_{d_\alpha}} = |\overrightarrow{G_{d_1}}.\vec{X}_\alpha - \vec{X}\,|, \overrightarrow{G_{d_\beta}} = |\overrightarrow{G_{d_2}}.\vec{X}_\beta - \vec{X}\,|, \overrightarrow{G_{d_\delta}} = |\overrightarrow{G_{d_3}}.\vec{X}_\delta - \vec{X}\,| \tag{14}$$

$$\vec{P}_1 = |\vec{P}_\alpha - \overrightarrow{B_1}.(\overrightarrow{G_{d_\alpha}})|, \vec{P}_2 = \left|\vec{P}_\beta - \overrightarrow{B_2}.\left(\overrightarrow{G_{d_\beta}}\right)\right|, \vec{P}_3 = |\vec{P}_\delta - \overrightarrow{B_3}.(\overrightarrow{G_{d_\delta}})| \tag{15}$$

$$\vec{P}_{(c+1)} = \frac{\vec{P}_1+\vec{P}_2+\vec{P}_3}{3} \tag{16}$$

End for

Update b, B, D

Calculate the fitness of all the grey wolfs

Update $P_\alpha, P_\beta, P_\delta$

c = c + 1

end while

return P_α (Best Solution)

V. Experimentation and Results

This section of this paper discusses the complete setup for the execution of the proposed methodology followed by the analytical study of the results obtained on the execution of the proposed technique.

A. EXPERIMENTAL SETUP

The proposed approach is being executed on the system with following hardware and software specifications;

1) HARDWARE SYSTEM SPECIFICATIONS

System Type: 64-bit operating system, x64-based processor,

Processor: Intel(R) Core (TM) i7

RAM: 32 GB

System Type: 64-bit operating system, x64-based processor

2) SOFTWARE SYSTEM SPECIFICATIONS

The proposed approach is being implemented in Python 3.7.3, on Jupyter Notebook.

B. ANALYTICAL STUDY OF THE RESULTS

Various performance measures, including RMSE and MAE, are used to assess the proposed GWO-based CNN-performance. LSTM's Training and test sets of the data have been created. Training data is 90%, 80%, 70%, 60% and the test data is 10%, 20%, 30%, and 40% respectively. The training subset is further provided to train the data using the grey wolf optimization-based CNN using LSTM, while the remaining test dataset is used to validate the results. The training and validation accuracy and training and validation loss of RMSE values are shown in Figure. 10(a, b) respectively. Different error matrices are also being utilized to evaluate the error in the energy prediction. Equation (17) is used to evaluate the root mean square error in the predictions. Equation (18) is utilized to evaluate the mean squared error and equation 19 is used to evaluate the mean absolute error of the proposed work.

1) ROOT MEAN SQUARE ERROR

RMSE is obtained by taking the root of the squared difference of the actual and predicted values followed by taking the mean of the obtained value [43][44] given in equation (17).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(pred_i - actual_i)^2}{N}} \quad (17)$$

2) MEAN SQAURE ERROR

MSE is obtained by squaring the difference of the actual and predicted values followed by taking the mean of the obtained value [45][46] given in equation (18).

$$\mathrm{MSE} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(actual_{\mathrm{i}} - \mathrm{pred}_{\mathrm{i}})^2}{\mathrm{N}} \quad (18)$$

3) MEAN ABSOLUTE ERROR

MAE is obtained by taking the root of the squared difference of the actual and predicted values followed by taking the mean of the obtained value [47][48] given in equation (19).

$$\mathrm{MAE} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}|\mathrm{actual}_{\mathrm{i}} - pred_{\mathrm{i}}|}{\mathrm{N}} \quad (19)$$

TABLE 4
TRAINING AND VALIDATION LOSS OF GWO BASED LSTM-CNN NETWORK

Epoch	Loss	RMSE	Validation Loss	Validation RMSE
1	0.5925	0.7698	0.6493	0.8058
2	0.5327	0.7299	0.5784	0.7605
3	0.5066	0.7118	0.5197	0.7209
4	0.4911	0.7008	0.4884	0.6988
5	0.4764	0.6902	0.4768	0.6905
6	0.4620	0.6797	0.4763	0.6902
7	0.4517	0.6721	0.4809	0.6935
8	0.4404	0.6636	0.4926	0.7018
9	0.4287	0.6548	0.4957	0.7041
10	0.4190	0.6473	0.4393	0.6628
11	0.4088	0.6394	0.4551	0.6746
12	0.4004	0.6327	0.4335	0.6584
13	0.3907	0.6251	0.4409	0.6640
14	0.3853	0.6207	0.4210	0.6488
15	0.3755	0.6128	0.4672	0.6835
16	0.3685	0.6070	0.4154	0.6445
17	0.3624	0.6020	0.4104	0.6406
18	0.3544	0.5953	0.4438	0.6662
19	0.3469	0.5890	0.4179	0.6464
20	0.3404	0.5834	0.4217	0.6494
21	0.3357	0.5794	0.4141	0.6435
22	0.3323	0.5765	0.3988	0.6315
23	0.3279	0.5727	0.3994	0.6320
24	0.3227	0.5681	0.3880	0.6229
25	0.3195	0.5652	0.3782	0.6150

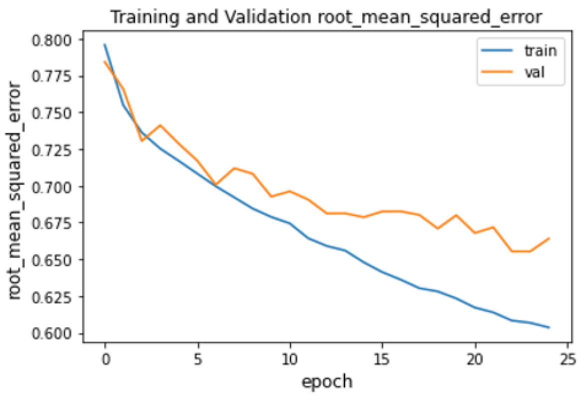

FIGURE 10 (a). Training and validation accuracy of RMSE

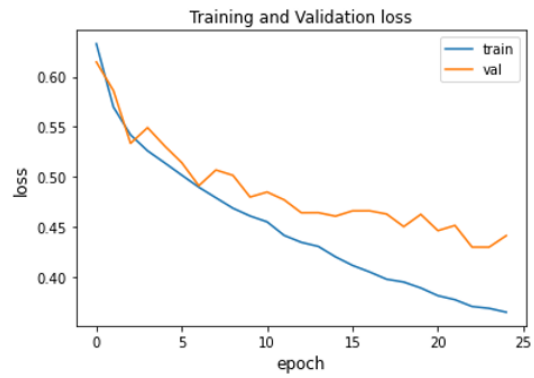

FIGURE 10 (b). Training and validation loss of RMSE

FIGURE 10 (a, b). Training and validation accuracy of RMSE and loss of RMSE

It can be observed from Graph 10(a, b) that the accuracy of the CNN-LSTM model for determining the RMSE values is based on the epochs. Here the epochs level is 25 and based on that the accuracy of RMSE is determined and is denoted using a blue line. Similarly, the orange line shows the validation accuracy which is lower than training accuracy. Correspondingly figure 10(b) shows the amount of data loss (training and validation loss) based on the epochs. As observed from the figure, the training loss is lesser than the validation loss. The graphs illustrated in figures 10(b) determine the accuracy of the proposed CNN-LSTM model for the RMSE considered for experimental evaluation based on the epochs. Table 4 represents all the values of RMSE and Loss for training and validation.

In figure 11, the forecasting effectiveness of the suggested model for forecasting energy usage is shown. The expected and actual energy use for each interval of ten minutes is shown in this graph. In this graph red line represents the original data which is obtained from the smart home environment. The blue line in the same graph represents the prediction of the power utilization using the proposed model. X-axis of the graph contains the Time in minutes and the Y-axis contains the Energy in kw. The visualization of the graph is showing that the prediction of the proposed model is having only slight variation from the original data which is represented in table 5. This variation in the prediction values is because of the error the proposed model is having. The error values of the model are evaluated using different error matrices like; RMSE, MSE, and MAE.

TABLE 5
ACTUAL AND PREDICTED DATA OF SMART HOME ENERGY CONSUMPTION USING GWO BASED LSTM-CNN NETWORK

Date	Time	Actual Data	Predicted Data
2016-01-14	16:16:00	0.086267	0.36167568
2016-05-24	16:27:00	0.251950	0.6151967
2016-09-05	13:56:00	0.221550	0.4170033
2016-08-04	12:00:00	0.769283	1.0075793
2016-07-19	20:50:00	0.464783	0.7823252
2016-05-15	14:25:00	0.584383	0.8434061
2016-08-18	19:38:00	0.756033	1.946157
2016-12-04	18:52:00	1.709767	0.47624287
2016-08-03	01:08:00	0.561617	0.31924936
2016-01-08	08:57:00	1.620433	0.8603161
2016-06-28	15:04:00	0.320767	0.48148233
2016-08-12	17:16:00	0.423567	0.46342388
2016-03-27	21:30:00	1.159867	0.6915341
2016-01-20	20:19:00	0.328900	0.25268942

2016-12-02	03:09:00	0.724283	0.7877499
2016-05-14	04:48:00	0.328150	1.2156434
2016-04-11	11:09:00	2.004117	0.28380725
2016-12-13	09:53:00	1.616383	0.15216284
2016-11-09	09:54:00	0.317017	0.3211606
2016-10-23	16:54:00	2.113417	0.92494935
2016-08-19	15:37:00	0.363300	0.50532657
2016-06-15	17:54:00	0.122967	0.6972247
2016-11-24	21:59:00	1.595567	0.5011479
…	…	…	…

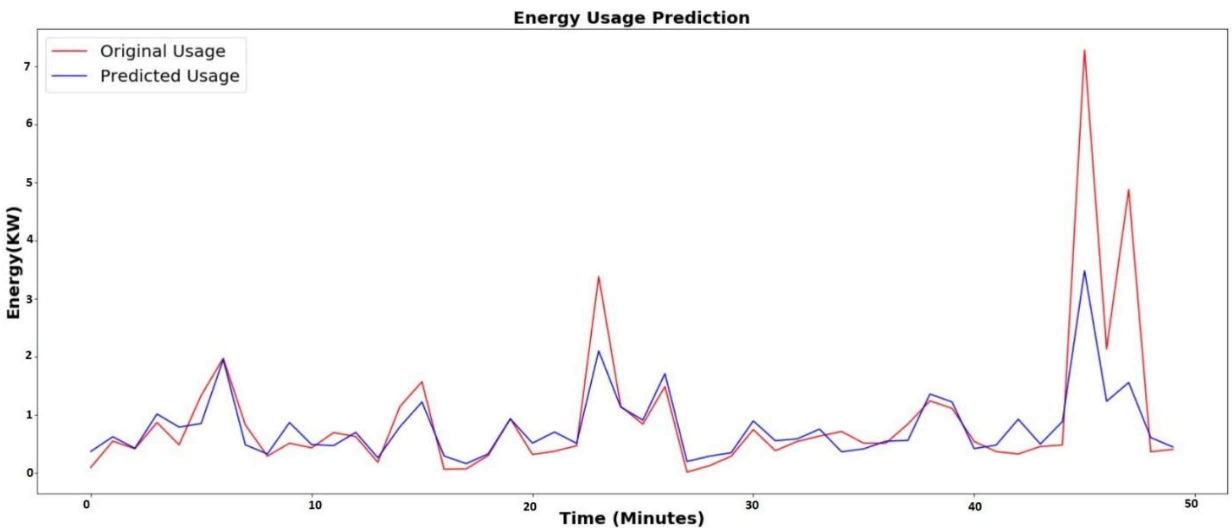

FIGURE 11. Energy usage prediction using GWO based CNN-LSTM model

The performance of the proposed approach is validated by comparing the RMSE, MSE and MAE values with other existing baseline models. The significance of RMSE value is error in the prediction is if lesser the value of RMSE more accurately the model is predicting. To validate the performance of our model, it is being checked on different split ratios and different epoch. The lowest RMSE value is achieved on 90-10% split ration and 25 epochs. The results are represented in table 6 are visualization is given in figure 12.

TABLE 6
RMSE VALUES OF THE PROPOSED GWO BASED CNN-LSTM NETWORK ON DIFFERENT TRAINING AND TESTING SPLIT RATIONS AND EPOCH

Split Ratio/ Epoch	10	15	20	25
90-10%	0.6817	0.6586	0.6468	**0.6213**
80-20%	0.6974	0.6695	0.6624	0.6391
70-30%	0.6853	0.6750	0.6731	0.6487
60-40%	0.6989	0.6627	0.6586	0.6611

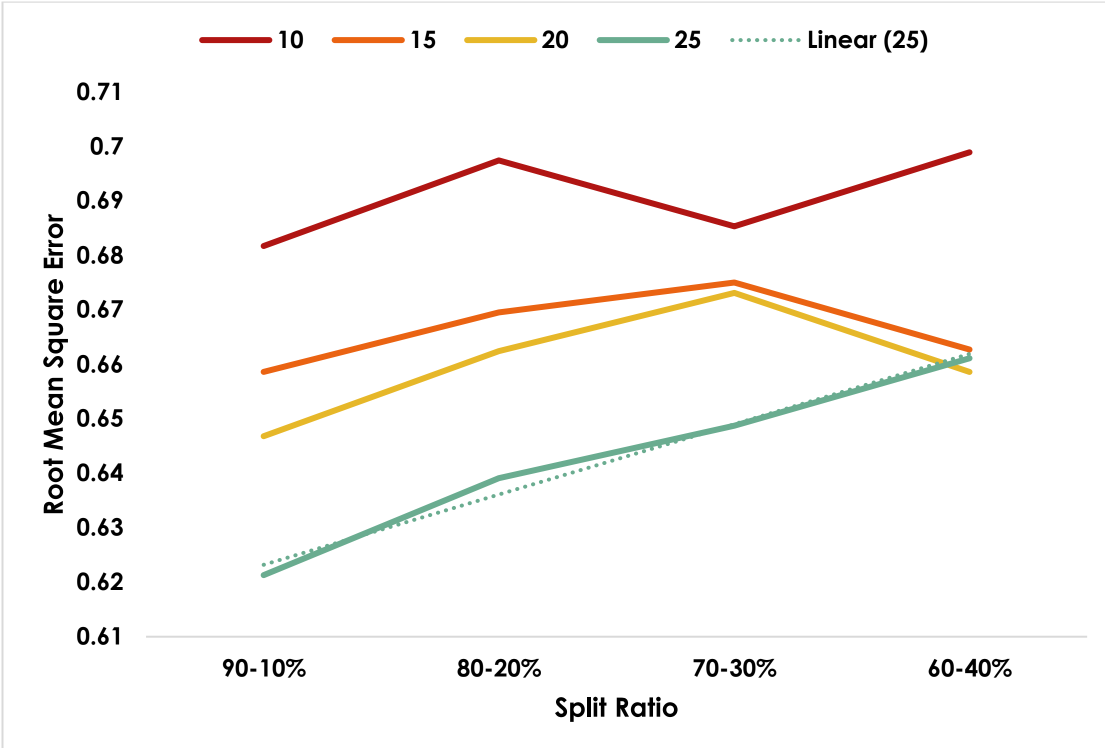

FIGURE 12. RMSE values on different epoch and split ratios

On achieving the lowest RMSE value on 90-10% split ratio and 25 epochs, the model is further tested on few higher numbers of epochs and the RMSE value of the proposed model is increasing, which shows that if the number of epochs is increase then the performance of the model is decreasing. These results are represented in table 7 which contains the RMSE values on different epoch. The lowest RMSE is obtained on 25^{th} epoch i.e., 0.6213. The obtained results are visualized in figure 13.

TABLE 7
RMSE VALUES FOR 90-10% SPLIT RATIO ON DIFFERENT EPOCH

Epoch	RMSE
10	0.6817
15	0.6586
20	0.6468
25	0.6213
30	0.6224
35	0.6281
40	0.6365

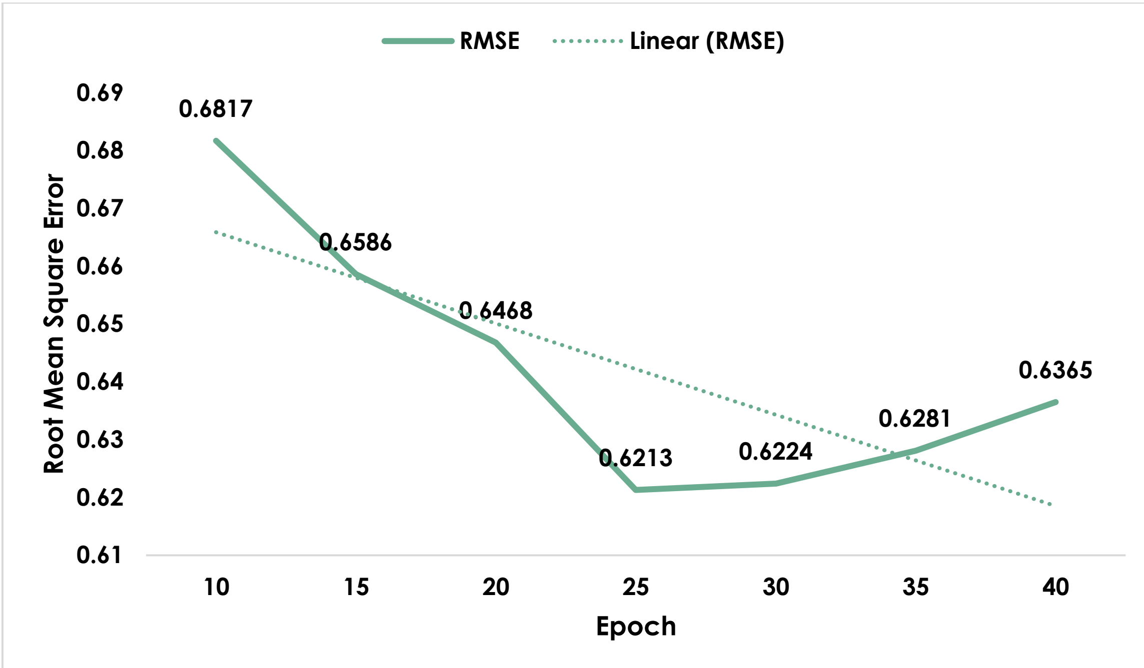

FIGURE 13. Visualization of the RMSE trend on different epoch

VI. Analysis of the Results

In this section of this paper, a comparative analysis is being performed to check the performance of the proposed model with respect to the existing models. Different ML and DL models are being implemented on the same dataset to perform the energy prediction. In table 4, the RMSE, MSE and MAE values are being represented which are obtained using different existing and the proposed model [42].

Graph 14 is presenting the comparative analysis of the proposed approach with the different ML algorithms and proposed approach is achieving the better performance compared to other existing models. Table 8 represents the RMSE, MSE, and MAE values obtained using different ML algorithms. The proposed model is obtaining the lowest error in prediction in comparison with the other ML and DL models i.e. RMSE is 0.6213, MSE is 0.3860, MAE is 0.2808 respectively. As the values given in the table 4 and graph 6 the RMSE value is 0.6213, MSE value is 0.3860, and the MAE value is 0.2808 for the proposed model. The rest of the existing models are having the higher error values than the proposed models.

TABLE 8
RMSE, MSE, AND MAE VALUES OBTAINED FROM THE PROPOSED AND EXISTING MODELS

Algorithm	RMSE	MSE	MAE
Random Forest	0.9723	0.9340	0.4178
Decision Tree	0.9295	0.5634	0.3980
LSTM	0.7834	0.6328	0.3816
XGBoost	0.7506	0.8382	0.3515
Simple Linear Regression	0.7465	0.5573	0.3661
Support Vector Machine	0.7217	0.5108	0.3017
K – Nearest Neighbor	0.7024	0.4934	0.3309
Ridge Regression	0.7024	0.5573	0.3661
Proposed Model	0.6213	0.3860	0.2808

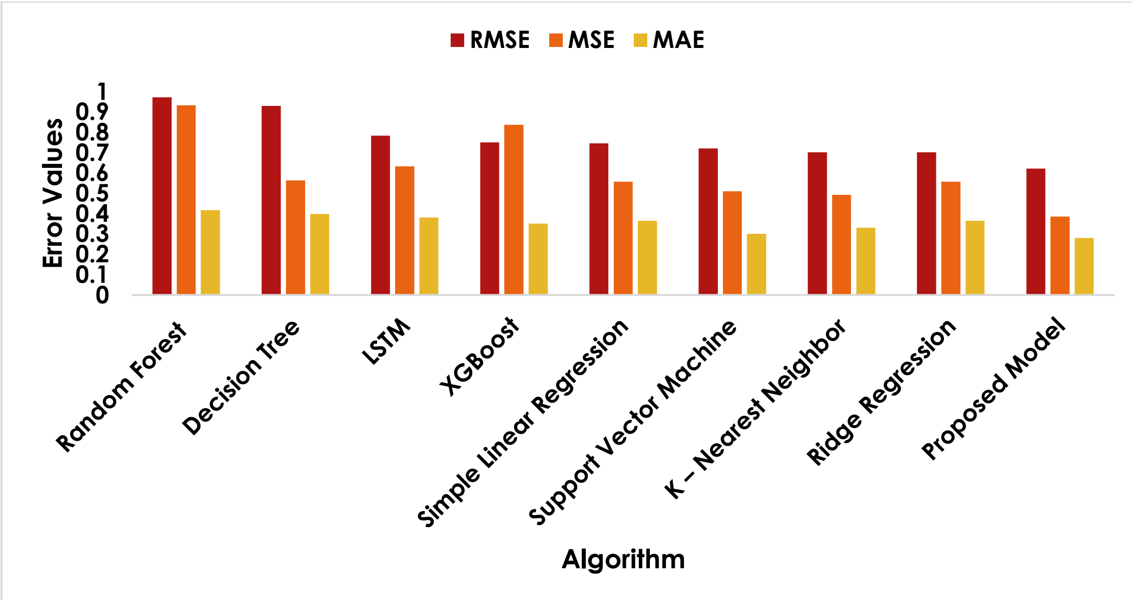

FIGURE 14. Comparative visualization of the RMSE, MSE, and MAE of the Proposed and the existing Models

Graph 14 is the conclusive analysis of the proposed and the existing models. The graph is clearly visualizing that the proposed model can produce the better prediction than the other ML algorithms. As the proposed model is achieving the lowest error in prediction.

TABLE 9
PREDICTION OF ENERGY CONSUMPTION USING DIFFERENT ML AND DL ALGORITHMS

Date	Time	Actual Data	Predicted Data	LSTM	XGBoost	Simple Linear Regression
2016-01-14	16:16:00	0.086267	0.36167568	0.49878213	0.40658742	0.49782627
2016-05-24	16:27:00	0.251950	0.6151967	1.4744353	0.83633304	1.35856581
2016-09-05	13:56:00	0.221550	0.4170033	0.23339587	0.40658742	0.28635358
2016-08-04	12:00:00	0.769283	1.0075793	0.2482034	0.40658742	0.31338055
2016-07-19	20:50:00	0.464783	0.7823252	0.9490794	0.6970979	1.11301944
2016-05-15	14:25:00	0.584383	0.8434061	0.54463243	0.5917204	0.5519076
2016-08-18	19:38:00	0.756033	1.946157	0.7486178	0.4675787	0.65053001
2016-12-04	18:52:00	1.709767	0.47624287	3.0352354	1.3343077	3.49775464
2016-08-03	01:08:00	0.561617	0.31924936	1.4707663	0.83633304	1.88552491
2016-01-08	08:57:00	1.620433	0.8603161	1.0090871	0.6379342	0.76302381
2016-06-28	15:04:00	0.320767	0.48148233	0.1472401	0.4675787	0.26232923
2016-08-12	17:16:00	0.423567	0.46342388	1.3831865	0.7626283	1.28374625
2016-03-27	21:30:00	1.159867	0.6915341	0.78779364	0.6379342	0.81727189
2016-01-20	20:19:00	0.328900	0.25268942	0.17842877	0.40658742	0.2744723
2016-12-02	03:09:00	0.724283	0.7877499	1.30615	0.83633304	1.08737714
2016-05-14	04:48:00	0.328150	1.2156434	1.2970529	0.83633304	1.33004044
2016-04-11	11:09:00	2.004117	0.28380725	0.6941341	0.51646477	0.65531796
2016-12-13	09:53:00	1.616383	0.15216284	0.54409355	0.51646477	0.53114264
2016-11-09	09:54:00	0.317017	0.3211606	0.47610745	0.51646477	0.48757852
2016-10-23	16:54:00	2.113417	0.92494935	1.0852661	0.6970979	1.15051683
2016-08-19	15:37:00	0.363300	0.50532657	0.8038213	0.5917204	0.79152845
2016-06-15	17:54:00	0.122967	0.6972247	0.08088931	0.40658742	0.11386859
2016-11-24	21:59:00	1.595567	0.5011479	1.1407225	0.6379342	1.11954841
…	…	…	…	…	…	…

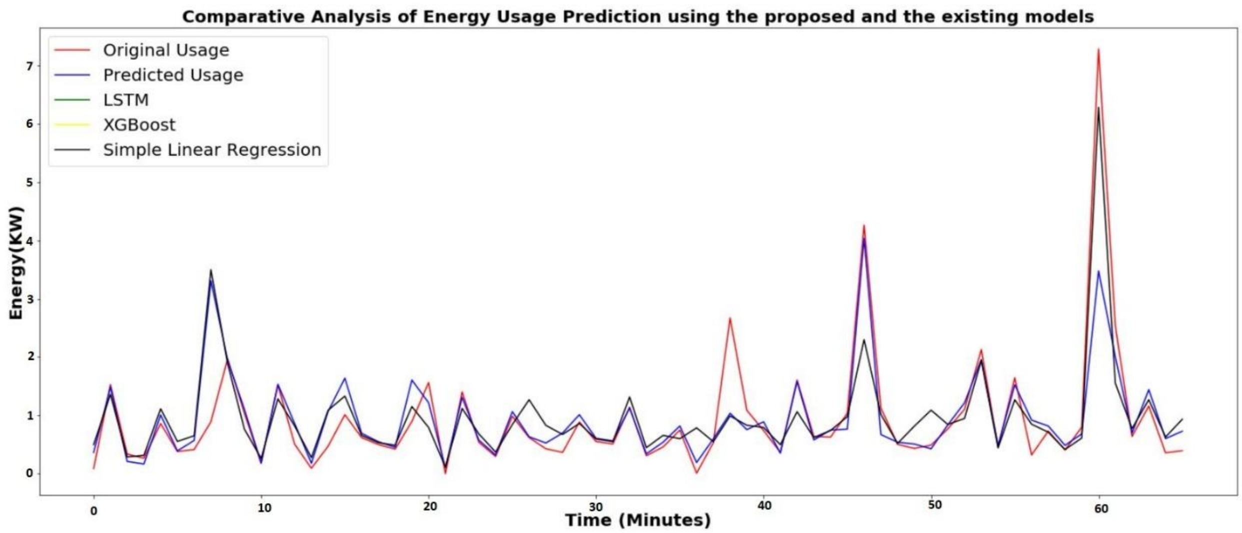

FIGURE 15. **Comparative analysis of the prediction of energy consumption data using the proposed and the existing models.**

Figure 15 visualizes the prediction of the energy consumption data using different existing ML and DL models [64] and the proposed GWO based CNN-LSTM model. Table 9 represents the actual energy prediction values in comparison with the already existing ML and DL models. The graph is clearly visualizing that the proposed model is predicting the energy consumption with less errors.

VII. Comparison with Existing Work

Different algorithms are being simulated on the dataset to compare with the GWO based CNN-LSTM network, considering few conditions. Selection of the dataset, preprocessing to ensure the quality and compatibility of the dataset for the comparison. Choice of the set of algorithms to compare, Implementation of each algorithm to solve the same problem including the proposed algorithm. Hyperparameter tuning like; learning rate, batch size, number of layers, number of filters, optimizer, activation functions, etc. Training, Evaluation Metrics, Experimental Design, Performance Comparison are some other conditions to analyze the proposed algorithm. The proposed work is compared with different machine learning, deep learning and soft computing techniques as shown in table 10. Based on the provided information, it appears that the comparison of the performance of various models using different evaluation metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) [61][62][64]. The values that have been listed are the RMSE and MAE values for different models, including PSO, GSA, FPA, CSO, Fuzzy GWO, FCBRM, Seq2Seq, CNN-LSTM, and the proposed model.

TABLE 10
COMPARISON OF THE PROPOSED MODEL WITH EXISTING ML, DL, AND SOFT COMPUTING TECHNIQUES

Algorithm	RMSE	MSE
PSO [53]	0.681	-
GSA [54]	0.666	-
FPA [55]	0.772	-
CSO [56]	0.690	-
Fuzzy GWO [57]	0.724	-
FCBRM [58]	0.6663	-
Seq2Seq [59]	0.742	-
CNN-LSTM [60]	0.733	-
Proposed Model	0.6213	0.3860

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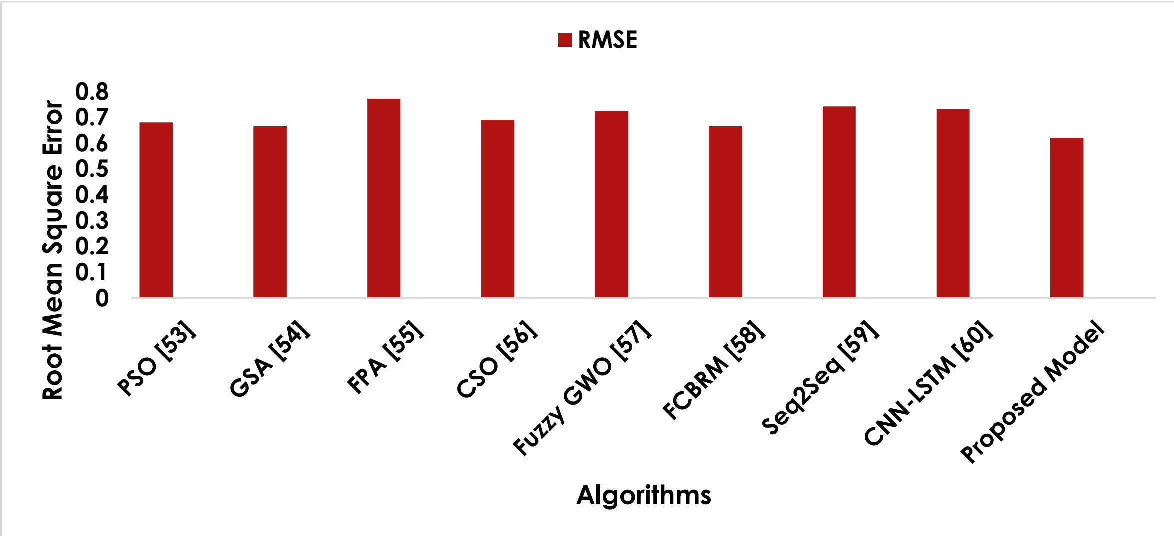

FIGURE 16. Visual Representation of Comparative analysis of the prediction of energy consumption data using the proposed and the existing models.

Based on the RMSE values, it seems that the proposed model has an RMSE of 0.6213, which is lower than the RMSE values of PSO (0.681), GSA (0.666), FPA (0.772), CSO (0.690), Fuzzy GWO (0.724), FCBRM (0.666), Seq2Seq (0.742), and CNN-LSTM (0.716) represented in figure 16. A lower RMSE indicates better performance in terms of the model's ability to minimize the differences between predicted values and actual values. Similarly, based on the MAE values, the proposed model has an MAE of 0.2808, which is lower than the MAE values of PSO (0.420), GSA (0.438), FPA (0.537), CSO (0.448), Fuzzy GWO (0.526), and CNN-LSTM (0.489). Again, a lower MAE signifies better performance in terms of the model's ability to minimize the absolute differences between predicted values and actual values.

Therefore, based on the provided evaluation metrics, it can be concluded that the proposed model outperforms the state-of-the-art models (PSO, GSA, FPA, CSO, Fuzzy GWO, Seq2Seq, CNN-LSTM) in terms of RMSE and MAE values, indicating better predictive performance.

VIII. Conclusion and Future Work

This paper introduces a novel framework that combines Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) for estimating energy utilization by household appliances. The aim of this study is to address the limitations of existing conventional Energy Management System (EMS) models by employing a data pattern finding approach. The proposed framework leverages the architecture of CNN integrated with LSTM to improve the classification and prediction accuracy of the model. By combining the capabilities of CNN in extracting spatial features and LSTM in capturing temporal dependencies, the model can effectively analyze energy consumption patterns and make accurate predictions. To optimize the performance of the CNN-LSTM model, the study employs a metaheuristic algorithm called Grey Wolf Optimization (GWO). The GWO algorithm helps fine-tune the model and improve its training performance and accuracy. The performance of the GWO-based CNN-LSTM model is evaluated using the Root Mean Square Error (RMSE), Mean Square Error (MSE), and Mean Absolute Error (MAE) metrics. The reported results show that the proposed approach achieves an RMSE of 0.6313, MSE of 0.3860, and MAE of 0.2808. These results indicate improved accuracy compared to existing approaches. In future work, the study plans to enhance the computational speed of the proposed approach by reducing the number of layers. Additionally, the researchers intend to extend the application of the model to a recommendation system for energy management. This extension aims to provide energy-saving recommendations in smart environments. To summarize, the paper presents a novel CNN-LSTM framework for estimating energy utilization in household appliances. The proposed approach improves upon existing models by utilizing a data pattern finding approach and optimizing performance using the GWO algorithm. The reported results demonstrate improved accuracy and future work aims to enhance computational speed and extend the model to energy-saving recommendations.

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