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RESEARCH ARTICLE

# Improving the Efficiency of Deep Learning Models Using Supervised Approach for Load Forecasting of Electric Vehicles

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**ABSTRACT** This research work proposes an Improved Supervised Learning (ISL)-based Deep Neural Network (DNN) for accurately forecasting the load demand of Electric Vehicles (EVs). This work incorporates Gated Recurrent Unit (GRU), Long Short Term Memory (LSTM), Recurrent Neural Network (RNN), Fully Connected (FC), and Convolutional Neural Network (CNN) architectures. The proposed ISL technique enhances prediction performance by refining the training process with additional features and information. Using a real-world EV charging dataset from Boulder City, USA, the simulations demonstrate consistent improvements in the GRU, LSTM, RNN, FC, and CNN models with the proposed ISL technique. Further, the proposed technique reduces the Normalised Root Mean Square Error (NRMSE) and Normalised Mean Absolute Error (NMAE) values. The accurate load demand predictions facilitated by the proposed models with ISL have significant implications for the planning and management of EV charging stations. This enables stakeholders to optimize resource allocation, effectively plan infrastructure capacity, and ensure the sustainable and reliable operation of grids in the face of increasing EV adoption. By leveraging deep learning architectures and incorporating the ISL technique, this research contributes to advancing load forecasting models for EVs, providing practical solutions for efficient management and planning in the evolving electric mobility landscape.

**INDEX TERMS** Artificial neural network, deep learning, electric vehicles (EV), load forecasting, supervised learning.

## I. INTRODUCTION

Fossil fuels are hard to quit as the economy of the world heavily relies on these due to their real-world applications such as producing energy, electricity, and transportation. Oil price increases have a great impact on society that is generally thought to increase inflation and reduce economic growth [1]. EVs are fossil fuels free that are gaining popularity by capturing the market share. This replacement assists the modern world in the reduction of carbon emissions and environmental contamination due to the burning of fossil fuels. Clean energy and improved performance due to technological advancements are driving vehicle owners to switch to EVs. With the increase in the EVs infiltration, their charging is anticipated to have a remarkable impact on the grid. Also, the need for a steady supply of electricity is a critical factor to charge EVs [2]. With the increasing number of EVs and the lack of public charging stations, the demand has risen to enhance the number of charging stations with fast charging [3].

Due to the uncertainty of EV charging loads, Electric Vehicles Load Forecasting (EVLF) becomes vital for the operation of charging stations. The EVLF has been extensively studied in the literature. Traditionally the methods used for EVLF to predict various scenarios are greyscale prediction methods, time series methods, and regression analysis methods [4], [5].

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The input load data for these models normally vary in a small range and depend on various environmental factors [6], [7]. Therefore, it is necessary to form a logical relationship between input features and the target variable. This relationship can be formulated through artificial intelligence models [8]. Owing to the availability of actual charging data, the researchers paid attention to building forecasting models for energy consumption [9] and state of charge [10]. In [10], a day ahead charging load of the workplace is predicted through the State of Charge (SOC). The demand of load for PHEVs is predicted by mathematical consumption modeling presented in [9]. The EV energy consumption has been forecasted by Monte Carlo simulations in [11] and [12].

Despite many promising improvements, there are a few challenges in promoting EVs among users. A long charging time is one of them which causes inconvenience to the users. In addition, EV owners have no sufficient capacity available to charge their EVs at home and depend on public charging stations. The requirement for high power to charge EVs causes huge constraints on the grid. Therefore, the optimal way is to manage the charging of EVs at charging stations by proper scheduling. Thus, the researchers are investigating the influence of charging behavior [13], [14] on EVs. For this purpose, the need has risen to accurately forecast the charging load of EVs. This will help the grid operators to properly manage the electricity distribution and start appropriate measures. The grid operators and charging station owners can also integrate renewable energy sources with power grids to enhance the production of electricity [15].

This motivation impulses to introduce the novel EVLF based on DL models. Deep Learning is an emerging technique, but firstly it was used in the 1940s [41]. There are immense benefits of machine learning (ML) approaches in the field of image processing, natural language processing, and video and audio recognition. Presently, the focus has shifted towards data driven approaches to solve the charging framework problems, to charge a fleet of EVs simultaneously [16]. DL is a type of ML that utilizes larger datasets for self learning based on algorithms [17]. There are different types of DL approaches, some of which are, Multilayer Perceptron (MLP) also called Fully Connected (FC) network, RNN, LSTM, and GRU are presented in [18]. For time series data in which output is dependent on time, RNN, LSTM, and GRU are most suitable. RNN based models consider the previous predictions and process short term dependencies. To reflect long term dependencies, LSTM can be used [19]. The hybrid DL models with Convolution LSTM and Bi-Convolution LSTM are also introduced in the recent literature, for energy demand forecasting of EVs [46]. As the dataset for load prediction of EVs is time series data, the RNN, LSTM, and GRU models have been considered in this work. In addition to validating the results, CNN and FC have also been used to predict the EV load with the ISL technique. These approaches were first used in 1997 for speech recognition. Recently researchers are using these models for time series prediction, sentiment analysis, and pattern recognition [42]. If the dataset contains input and output variables, such kind of ML approach is called Supervised Learning (SL) [16]. A generic DL algorithm with Supervised Learning was announced in 1965 by Iapa and Alexey Ivakhnenko [43]. Now, Supervised Learning is gaining popularity for the prediction of energy and load [43], [45]. In the dataset of EVLF, available inputs are the time of charging, session duration, station ID and electricity consumption, etc. and the target variable is EVs load. The ISL approach, in which dependency of features on previous timesteps, is considered with DL models in this work. This methodology has been used to improve the prediction abilities of all DL models and reduce prediction errors.

## II. LOAD FORECASTING MODELS USING DEEP LEARNING

The DL models considered for LF are RNN, LSTM, GRU, Convolutional Neural Network (CNN) and Fully Connected (FC) Network. The applications and featured based methods of DL models are critically reviewed in [20] and it shows that RNN and CNN are the most powerful models for solving problems related to time series and image processing, respectively. RNN does not perform well when the long sequence dataset is used as it cannot store the information of long sequences. According to the RNN model, it only focuses on current information, and this kind of problem is called vanishing gradients [21]. To overcome this problem, the RNN can be recreated as LSTM and GRU [18]. Further, FC networks are widely used for their ability to learn complex relationships between input features and target variables. They can handle both temporal and spatial features by processing them in a fully connected manner. FC networks are particularly useful for load forecasting when the data does not have explicit temporal or spatial dependencies but requires a more flexible and adaptable modeling approach. Therefore all of these models RNN, LSTM, GRU, CNN, and FC are used for load prediction of EVs with the ISL approach.

### 1) RNN MODEL

In traditional ANN, it is assumed that input and output are not dependent and RNN predicts the target variable based on previous input features.

In traditional ANN, it is assumed that input and output are not dependent and RNN predicts the target variable based on previous input features.

$$h_t = \sigma_h(X_t U_h + h_{t-1} W_h + b_h) \tag{1}$$
$$o_t = \sigma_h(V_h h_t + b_h) \tag{2}$$
$$y_t = \sigma(o_t) \tag{3}$$

The activation functions are *tanh*, $\sigma$ which are used to activate the nodes of the DL network, $o_t$ is the output and, $h_t$, $h_{t-1}$ and $h_{t+1}$ are the hidden units at $t$, $t-1$ and $t+1$ respectively in (1), (2) and (3). These hidden units act as a memory of the network, depending on the current input and

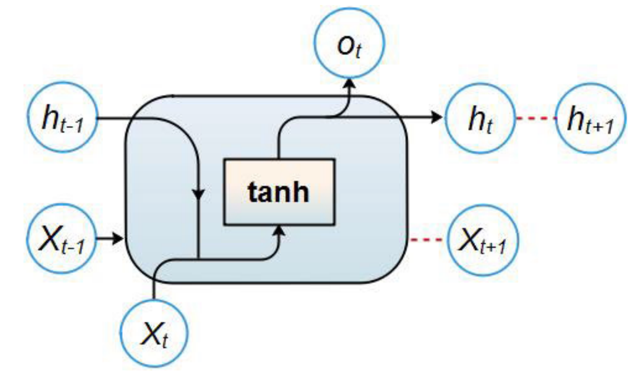



**FIGURE 1.** RNN model.

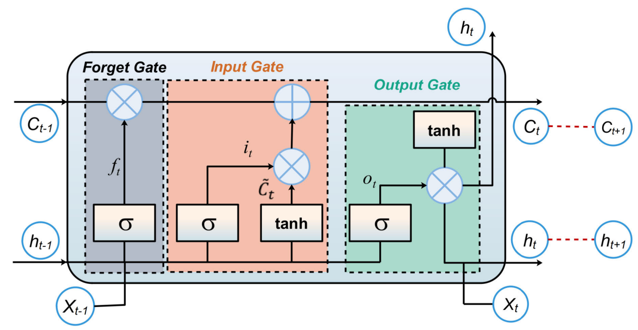



**FIGURE 2.** LSTM model.

previous time-steps hidden state). The internal connections of the network are parameterized by weight matrices. The weights of the network are denoted by $U_h$, $V_h$ and $W_h$ which shows input to hidden connections, hidden to hidden connections, and hidden to output connections respectively [23].

### 2) LSTM MODEL

The LSTM model can learn long sequences with its gated mechanism. The process of LSTM is complex as it introduces a short term memory cell to store the previous state and long term memory cell to store long term information as shown in Figure 2.

It has three gates, an input gate $i_t$, forget gate $f_t$ and output gate $O_t$ to regulate the information in short term and long term memory cells. In the first step, the forget gate $f_t$ decides how much information to be stored or ignored that is given by the output of the neural network. The input Gate $i_t$ finds the updated information on hidden layers. The output Gate $O_t$ selects the important information for prediction [24].

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{4}$$

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{5}$$

$$O_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{6}$$

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{7}$$

$$C_t = \sigma(f_t * C_{t-1} + i_t * \tilde{C}_t) \tag{8}$$

$$h_t = \tanh(C_t) * O_t \tag{9}$$

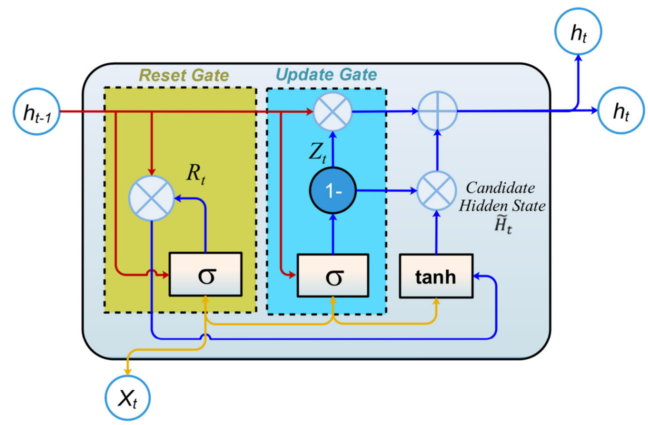



**FIGURE 3.** GRU model.

Here $h_{t-1}$ is the output at $t-1$ and $x_t$ is input at the current state. $\tilde{C}_t$ is the new value from the memory block at time $t$ and $\tilde{C}_t$ is the memory from the previous block. The weight of nodes is given by $W$, bias is shown by $b$ and the $*$ symbol is used to show element wise multiplier and, $\sigma$ and tanh are activation functions as shown below in (10), (11).

$$\sigma(x) = \frac{1}{(1 + e^{-x})} \tag{10}$$

$$\tanh(x) = \frac{(e^x - e^{-x})}{(e^x + e^{-x})} \tag{11}$$

### 3) GRU MODEL

The working of GRU is similar to RNN but it introduces two gates, an update gate, and a reset gate as shown in Figure 3. The update gate decides how much information from the previous state needs to be passed to the next state and it can copy all the previous information. In this way, the vanishing gradient problem of RNN can be removed. The reset gate is used to determine the amount of past information that needs to be neglected [25]. The parameters of GRU are fewer than LSTM and therefore it has a faster speed of training than LSTM.

$$R_t = \sigma(W_r.[h_{t-1}, x_t] + b_r) \tag{12}$$

$$Z_t = \sigma(W_z.[h_{t-1}, x_t] + b_z) \tag{13}$$

$$\tilde{C}_t = tanh(W_h.[r_t * h_{t-1}, x_t] + b_z) \tag{14}$$

$$C_t = (1 - z_t) * h_{t-1} + z_t * \tilde{C}_t \tag{15}$$

It has reset gate $R_t$ and update gate $Z_t$. All other parameters are same as described for LSTM network previously.

## III. METHODOLOGY

For the applications of deep learning methods, the dataset of EV charging sessions should be sufficient [26]. In this work, the open dataset from Boulder City USA has been used. There is a total of 288 charging stations in Boulder City out of which 27% are free [27].

The estimated infrastructure for charging stations in Boulder City, USA is shown in Figure 4. This dataset of charging stations is easily available and deals with complete information about historical charging sessions in all the charging stations of Boulder City. The dataset is available for the duration of $1^{st}$ Jan 2018 to $19^{th}$ Aug 2022 and is updated monthly. The dataset used in this work is for the duration from $1^{st}$ Jan 2021 to $31^{st}$ Dec 2021. The available fields in the dataset are station ID, address of charging station, start time, end time, charging time, gasoline saving, port type, and utilized energy in kWh for charging. 95% of charging stations are of level 2, 4% are of level 3 and 1% are of level 1 [27] as shown in Figure. 4. The proposed methodology consists of three different steps

- Data Pre-processing
- Improved Supervised Learning
- LF for EV with DL models

### A. DATA PRE-PROCESSING

The data pre-processing is unavoidable due to interference factors in the raw data [28]. There were no missing or null values in the dataset. The data pre-processing is done in time intervals and normalization.

#### 1) TIME INTERVAL PRE-PROCESSING

The data analysis task in Python is carried out by Pandas Library with Version 3.9.7. It is used to process large scale datasets efficiently. In this article, the dataset is split into 24 points (1-hour intervals), 96 points (15-minute intervals), and 1440 points (1-minute intervals) for each day. These kinds of dataset splitting are used to check three scenarios as given in [18], [29], and [30] to make an effective comparison with ISL.

Among the available fields in the dataset, charging time and date/time are used to predict the Energy (KWh) for EV charging. Three different kinds of scenarios are used to compare the proposed methodology with [18], [29], and [30]. In the first scenario, from date/time, weekdays, weekends, and public holidays are extracted as new fields to make the proposed methodology comparable with [29]. The charging of EVs is highly dependent on driving behaviors. During Public holidays, people are united at home so the charging load will be low. People also prefer to charge EVs on weekends mostly. The effect of weekdays, weekends, and public holidays is given in [29]. Therefore, the used fields as input to DL models are,

1) The hourly mapping of data fields is done by using 24 points per day of Charging Load denoted as CL sequence, which is taken from $1^{st}$ January 2020 to $28^{th}$ November 2021.
2) The 24 points per day for Charging Time represented as CT, is taken from $1^{st}$ January 2020 to $28^{th}$ November 2021.
3) The weekends and weekdays are considered as a separate field which is shown by BH (Binary Holiday). The weekday is given by '1' and the weekend by '0' in BH.
4) The Public Holidays are considered as PH. The normal day is given by '0' and the public holiday by '1' in PH.

The above first two fields CL and CT are used in [18] for comparison with an ISL model as a second scenario with 1-minute intervals data points. In [30] all the four fields as above, CL, CT, BH, and PH are used for prediction through LSTM as a third scenario for comparison with the proposed scheme.

#### 2) NORMALIZATION

In deep learning models, normalization is important to get all features on the same scale [31]. For normalization, in this work, min-max scaling is used which scaled the dataset in the range of [0, 1]. The training process of the DL models is accelerated by normalizing the dataset. After normalization, the dataset is divided into a training set to train the model and a testing set to predict the load of EVs. The formula for normalizing the data for DL models is given as [32],

$$y = \frac{(x - x_{min})}{(x_{max} - x_{min})} \tag{16}$$

### B. IMPROVED SUPERVISED LEARNING (ISL)

In time series analysis, supervised learning can be used when the dataset is dependent on time. Such a type of dataset is called time series data. The dataset of EVs for LF is time series data as the load is highly dependent on time [33]. Therefore it is proposed to reframe the dataset as an ISL problem. An ISL finds the relationship between input and output variables by observing the lag intervals at a previous time [34]. In this way, the DL models will be able to predict unseen data with high accuracy.

ISL can be applied by the feature engineering method. In feature engineering, different important features of input are extracted on which output is dependent [35]. In this way, a new dataset is made based on important features. The time series based features have four classes, Lag features extraction, date-time features extraction, windows feature extraction, and time until the next event/ time since the last event extraction. Here in the proposed model the date-time feature extraction and the lag feature extraction classes are used. With date-time feature extraction, two new variables called Binary Holiday (BH) and Public Holiday (PH) are extracted. These variables are important as drivers normally charge on weekends. People also travel a lot during Public Holidays or stay at home. In both cases, the charging Load is dependent on public holidays. With lag feature extraction, the dependency of input features on previous timesteps is extracted. In lag feature extraction, prior time-step values are used to predict future values. The Charging Load on the previous day is important for predicting the charging load on the next day [33]. Therefore the past values known as lags are considered for predicting the charging load. Figure 5 presents the proposed structure of an ISL approach with DL models. The dataset is divided into four input features: CL, CT, BH, and PH. The CL and CT represent different time intervals

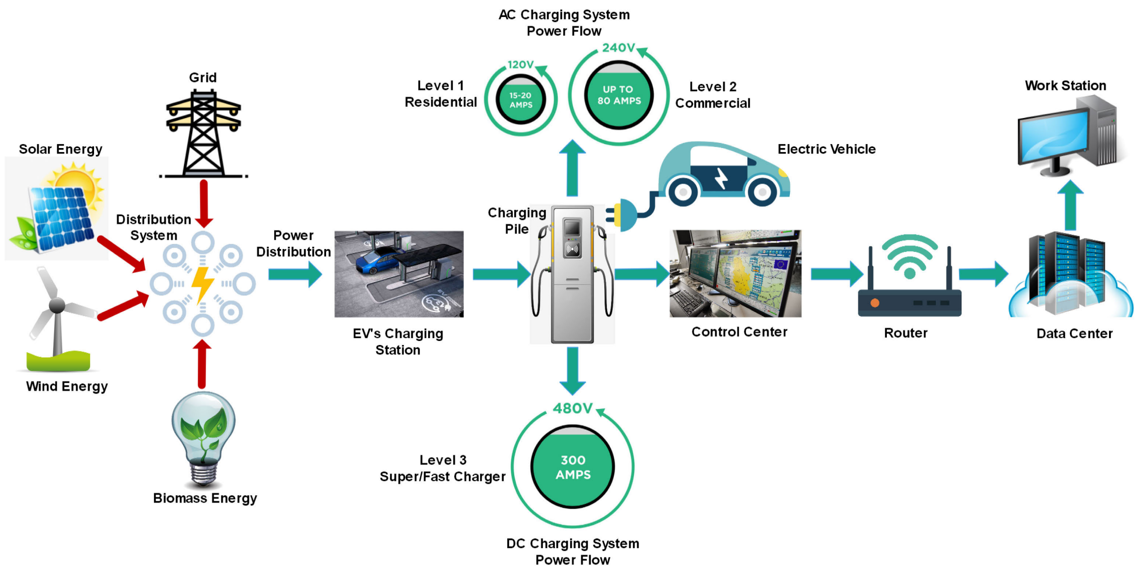



**FIGURE 4.** Infrastructure for charging station.

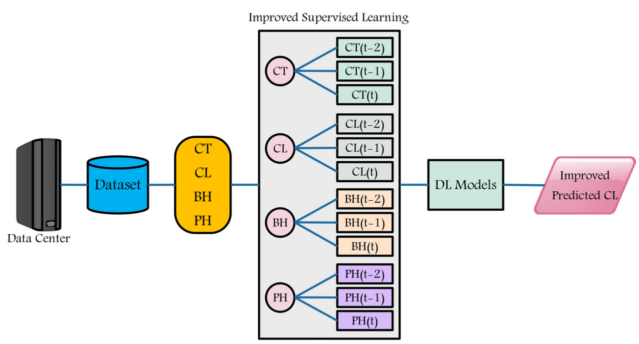



**FIGURE 5.** An ISL approach for deep learning models.

**TABLE 1.** System parameters.

| Parameters | As in [18] | As in [29] | As in [30] |
|---|---|---|---|
| Epochs | 30 | 100 | 50 |
| Hidden Layers | 2 | 2 | 1 |
| Hidden Layer Units | 16 units each | 64 units each | 128 units |
| Batch Size | 512 | 64 | 32 |
| Optimizer | adam | adam | adam |

(hourly, 15 minutes, and 1 minute) obtained using a date-time feature extraction technique. Additionally, BH and PH variables indicate weekends/weekdays and public holidays, respectively. Lag variables from the previous two time steps are also included. All these input features are utilized by DL models to generate improved predictions, as demonstrated in the Simulation Results section.

According to [36], there is no prior rule to consider the length of lag. In [37] it is mentioned that the number of lags should be typically small. 1 or 2 lags can be considered to keep the degree of freedom in the dataset. Hence, two lag features are considered in this work for prediction.

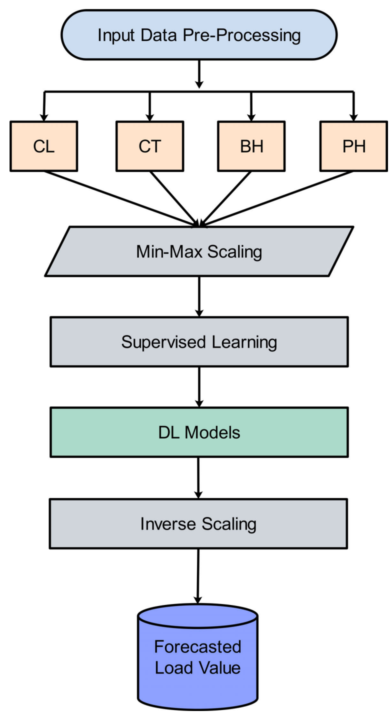
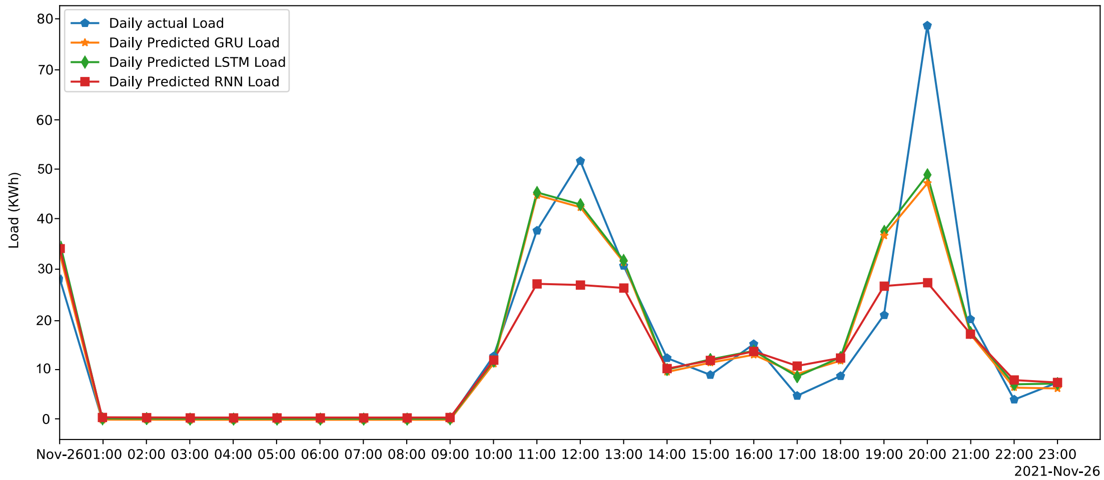
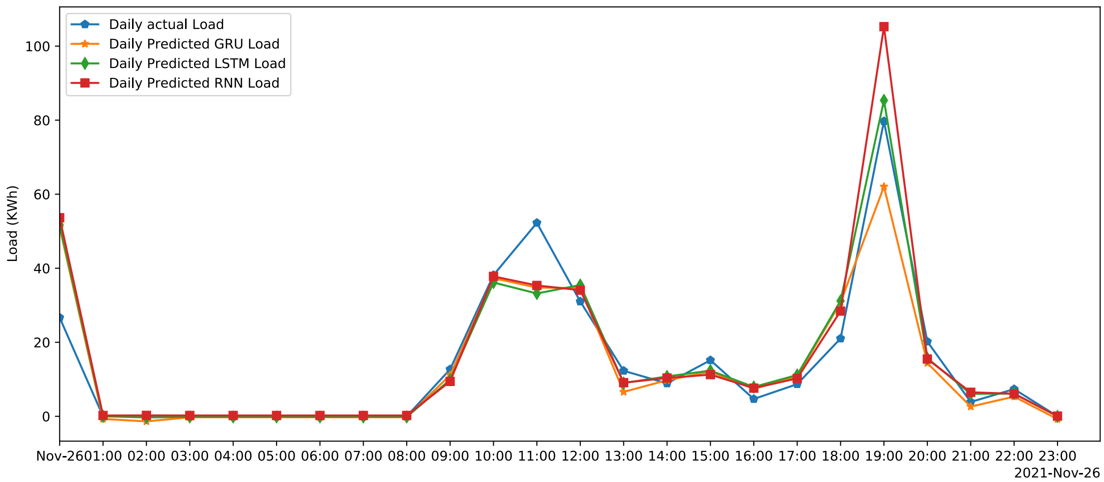



**FIGURE 6.** Block diagram of LF with improved supervised learning.

In Figure. 5, the dataset is divided into features CT, CL, BH, and PH as mentioned earlier. Further, by applying ISL, the lag variables are formed at $t-2$, $t-1$, and $t$. Then, the features are fed to DL models. Finally, the charging load of EVs is predicted at time $t$. The proposed technique showcased enhanced predictive capabilities of DL models, as demonstrated by the Results and Discussion section, where reduction in NRMSE and NMAE values is observed. This technique proves beneficial for handling nonlinearities, incorporating multivariate




(a) Daily Actual vs Predicted Load without ISL for 1 Hour Data interval




(b) Daily Actual vs Predicted Load with ISL for 1 Hour Data interval

**FIGURE 7. 1 Hour ahead prediction of daily EVs load (a) Without ISL (b) With ISL.**

**TABLE 2. Comparison of ISL with [29].**

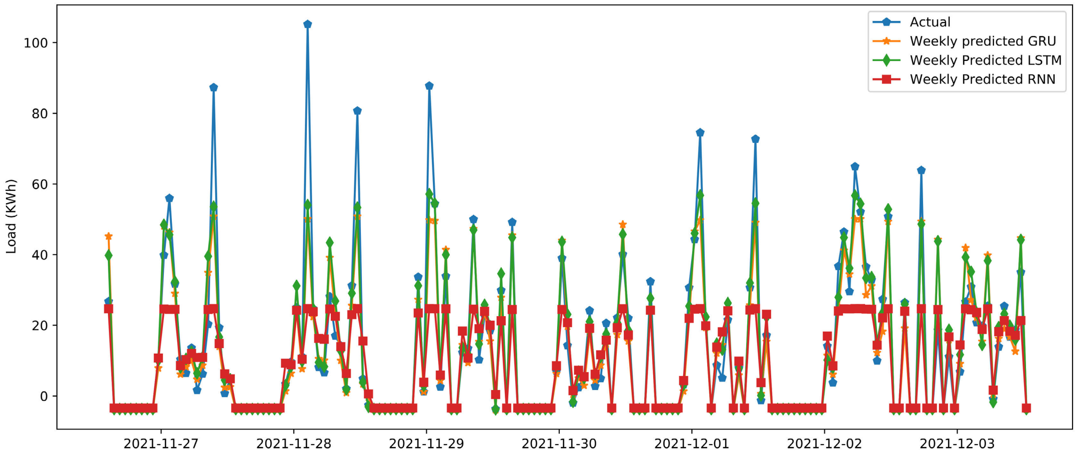
| Models | NMAE | | | NRMSE | | |
|---|---|---|---|---|---|---|
| | In [29] | With ISL | (%) Improvement | In [29] | With ISL | (%) Improvement |
| GRU | 0.77 | 0.171 | 77.79 | 2.89 | 0.028 | 99 |
| LSTM | 0.90 | 0.168 | 81.33 | 3.36 | 0.029 | 99.13 |
| RNN | 0.91 | 0.169 | 81.42 | 2.91 | 0.028 | 98.72 |

inputs, and learning from big data. These advantages contribute to more effective load forecasting, enabling efficient planning, resource allocation, and management of electric vehicle charging infrastructure.

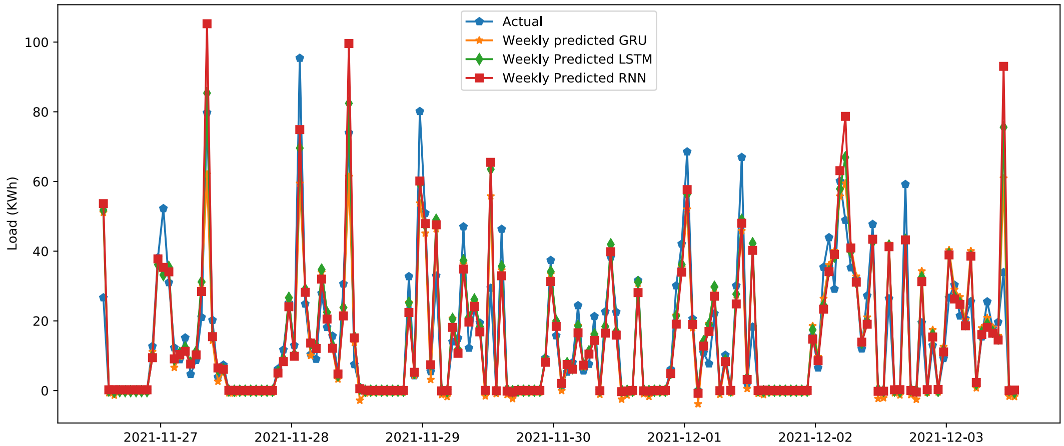
The method of feature engineering for the ISL approach depends on the dataset as well as ML algorithms. That's why the selected and created features have a great impact on the performance of ML models. Features should be relevant at hand and compatible with the model. Furthermore, comprehensive data pre-processing is required for feature engineering, which makes it complex to use. For the above listed reasons, feature selection for ISL is very challenging and time consuming.

### C. LOAD FORECASTING OF EV WITH DL MODELS

The framework of EV for LF is shown in Figure 6. The deep learning models used to predict load is RNN, LSTM, and GRU as described earlier. The dataset used for training and testing of models is charging load with 1-minute intervals, 1-hour intervals and 15-minute intervals for comparing the




(a) Weekly Actual vs Predicted Load without ISL for 1 Hour Data interval




(b) Weekly Actual vs Predicted Load with ISL for 1 Hour Data interval

**FIGURE 8.** 1 Hour ahead prediction of weekly EVs load (a) Without ISL (b) With ISL.

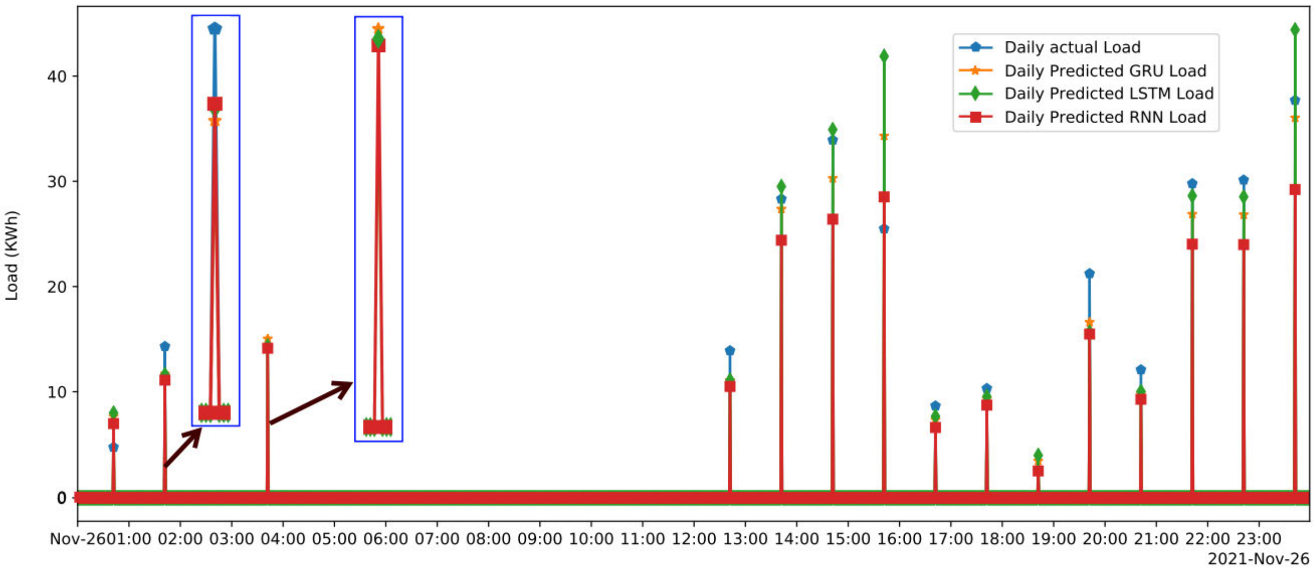
**TABLE 3.** Comparison of NMAE and NRMSE with and without ISL for 1 hour data interval.

| Models | NMAE | | | NRMSE | | |
|---|---|---|---|---|---|---|
| | Without ISL | With ISL | (%) Improvement | Without ISL | With ISL | (%) Improvement |
| GRU | 0.223 | 0.171 | 23 | 0.044 | 0.028 | 36.36 |
| LSTM | 0.198 | 0.168 | 15 | 0.042 | 0.029 | 30.95 |
| RNN | 0.394 | 0.169 | 57 | 0.078 | 0.028 | 64.10 |

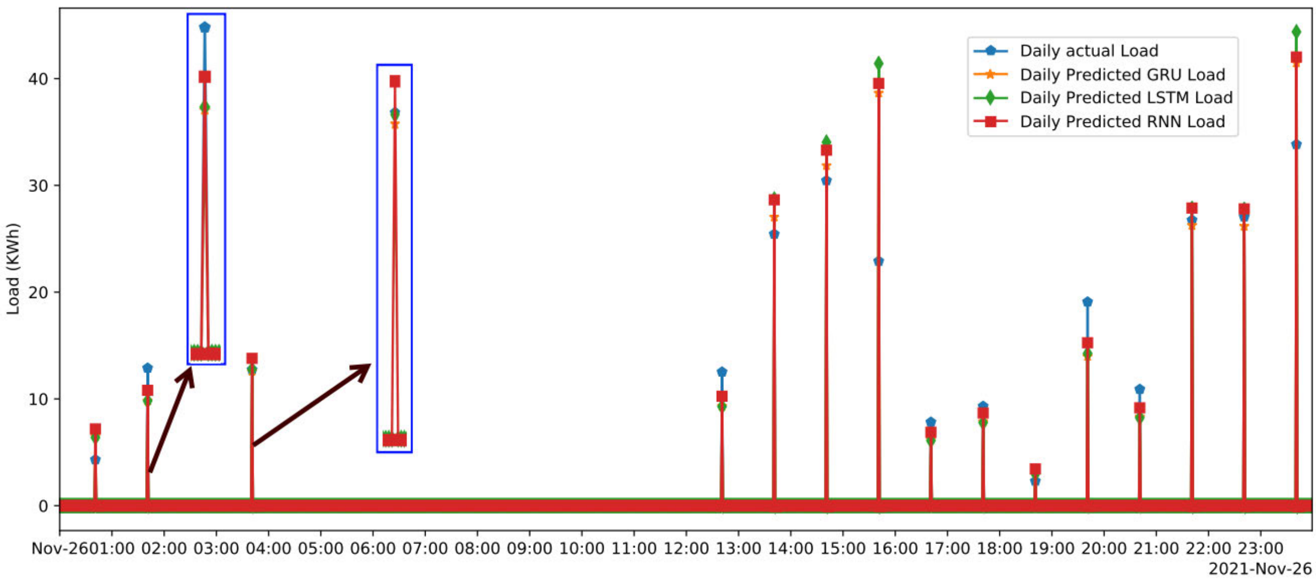
**TABLE 4.** Comparison of NMAE and NRMSE with and without ISL for 1 minute data interval.

| Models | NMAE | | | NRMSE | | |
|---|---|---|---|---|---|---|
| | Without ISL | With ISL | (%) Improvement | Without ISL | With ISL | (%) Imrovement |
| GRU | 0.380 | 0.345 | 10 | 0.005 | 0.003 | 40 |
| LSTM | 0.523 | 0.207 | 60 | 0.005 | 0.003 | 40 |
| RNN | 0.370 | 0.321 | 13 | 0.007 | 0.004 | 42 |

models in [18], [29], and [30], respectively. After the time interval pre-processing, ISL is applied and lag features are extracted at $(t-2)$, $(t-1)$ to predict the load at time $t$. The dataset was pre-processed as mentioned above and converted into features, time steps, and output format. The features used in the DL models (CT, CL, BH, and PH) with time step considered as 1 [29]. Further, the pre-processed dataset is fed to RNN, LSTM, and GRU models. In every block




(a) Daily Actual vs Predicted Load without ISL for 1 Minute Data Interval



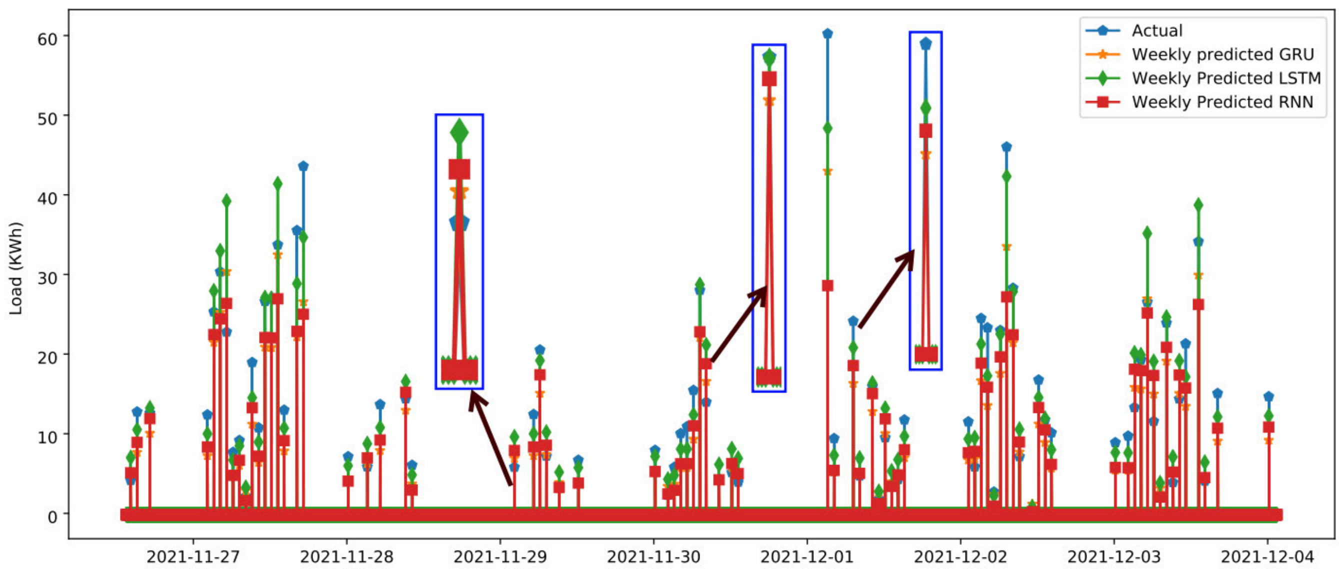

(b) Daily Actual vs Predicted Load with ISL for 1 Minute Data Interval

**FIGURE 9.** **1 Minute ahead prediction of daily EVs load (a) Without ISL (b) With ISL.**

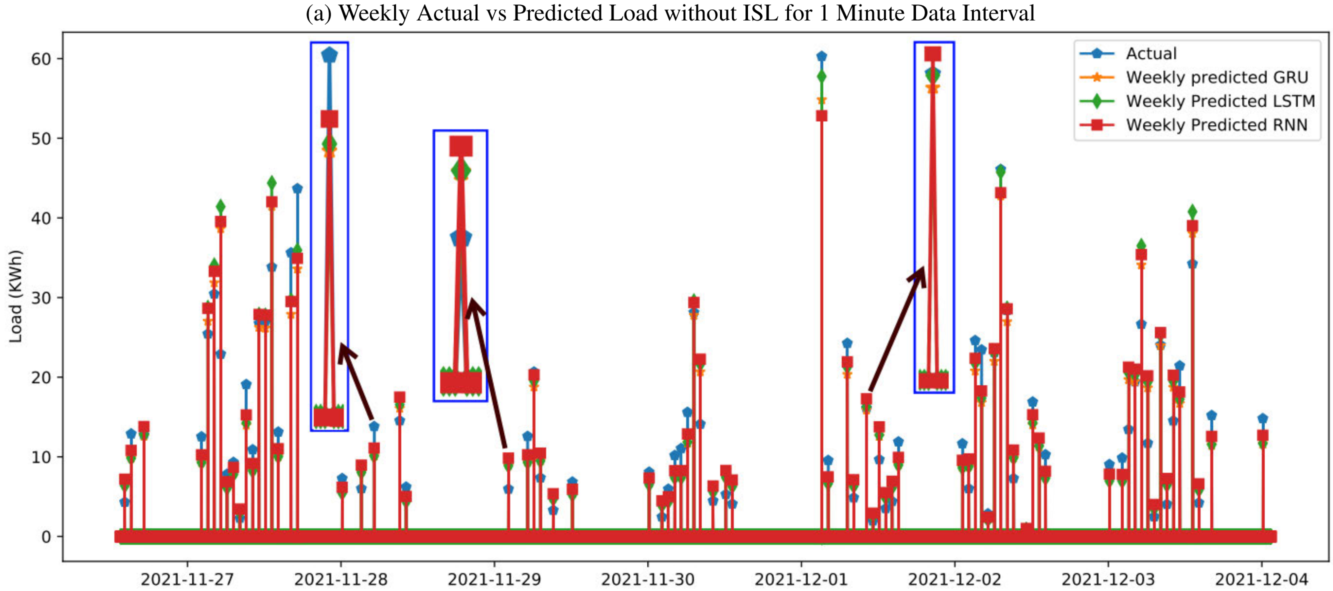
**TABLE 5.** **Comparison of MAE and RMSE with and without ISL for 1 minute data interval.**

| Models | MAE | | | RMSE | | |
|---|---|---|---|---|---|---|
| | In [18] | With ISL | (%) Improvement | In [18] | With ISL | (%) Improvement |
| GRU | 1.9116 | 0.072 | 96 | 2.4333 | 0.378 | 84 |
| LSTM | 0.4782 | 0.047 | 90 | 0.9546 | 0.411 | 57 |
| RNN | 3.2397 | 0.030 | 99 | 3.7915 | 0.378 | 90 |

of RNN, LSTM, and GRU, there is a block of the dense layer at the end which maps the output to a single value. After predicting the load from these DL models, the final forecasted load is obtained by inverse normalization of predicted data from RNN, LSTM, and GRU blocks as shown in Figure. 5.




(a) Weekly Actual vs Predicted Load without ISL for 1 Minute Data Interval



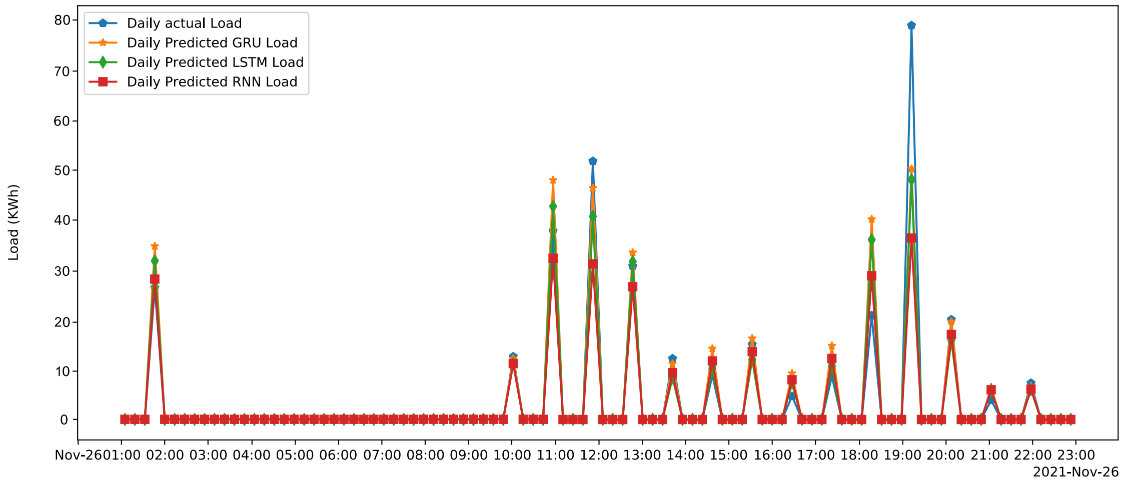

(b) Weekly Actual vs Predicted Load with ISL for 1 Minute Data Interval

**FIGURE 10.** 1 Minute ahead prediction of weekly EVs load (a) Without ISL (b) With ISL.

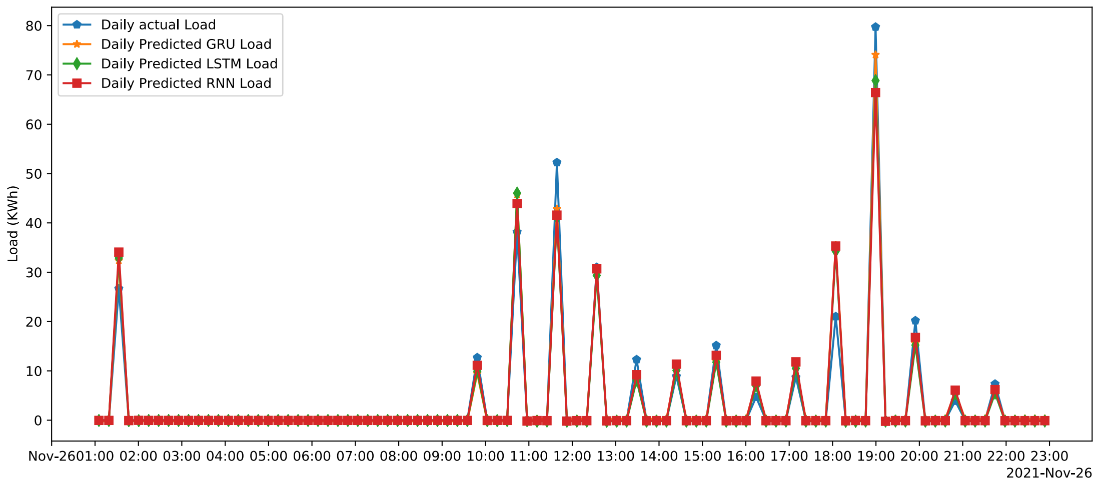
**TABLE 6.** Comparison of NMAE and NRMSE with and without ISL for 15 minute data interval.

| Models | NMAE | | | NRMSE | | |
|---|---|---|---|---|---|---|
| | Without ISL | With ISL | (%) Improvement | Without ISL | With ISL | (%) Improvement |
| GRU | 0.288 | 0.213 | 26 | 0.020 | 0.014 | 30 |
| LSTM | 0.198 | 0.186 | 6 | 0.020 | 0.014 | 30 |
| RNN | 0.261 | 0.197 | 24 | 0.026 | 0.015 | 42 |

The adjustment of hyper-parameters is very important for DL models which are dependent on repeated experimentation [38]. For comparison of the proposed methodology with [18], two hidden layers are considered with 16 nodes in each. The batch size and epochs should be considered according to the dataset size [39]. In this work, the batch




(a) Daily Actual vs Predicted Load without ISL for 15 Minutes Data Interval




(b) Daily Actual vs Predicted Load with ISL for 15 Minutes Data Interval

**FIGURE 11.** 15 Minutes ahead prediction of daily EVs load (a) Without ISL (b) With ISL.

**TABLE 7.** Comparison of NMAE and NRMSE with and without ISL for 1 hour data interval with CNN, FC.

| Models | NMAE | | | NRMSE | | |
|---|---|---|---|---|---|---|
| | Without ISL | With ISL | (%) Improvement | Without ISL | With ISL | (%) Improvement |
| CNN | 0.283 | 0.177 | 37 | 0.049 | 0.033 | 33 |
| FC | 0.300 | 0.188 | 38 | 0.049 | 0.032 | 34 |

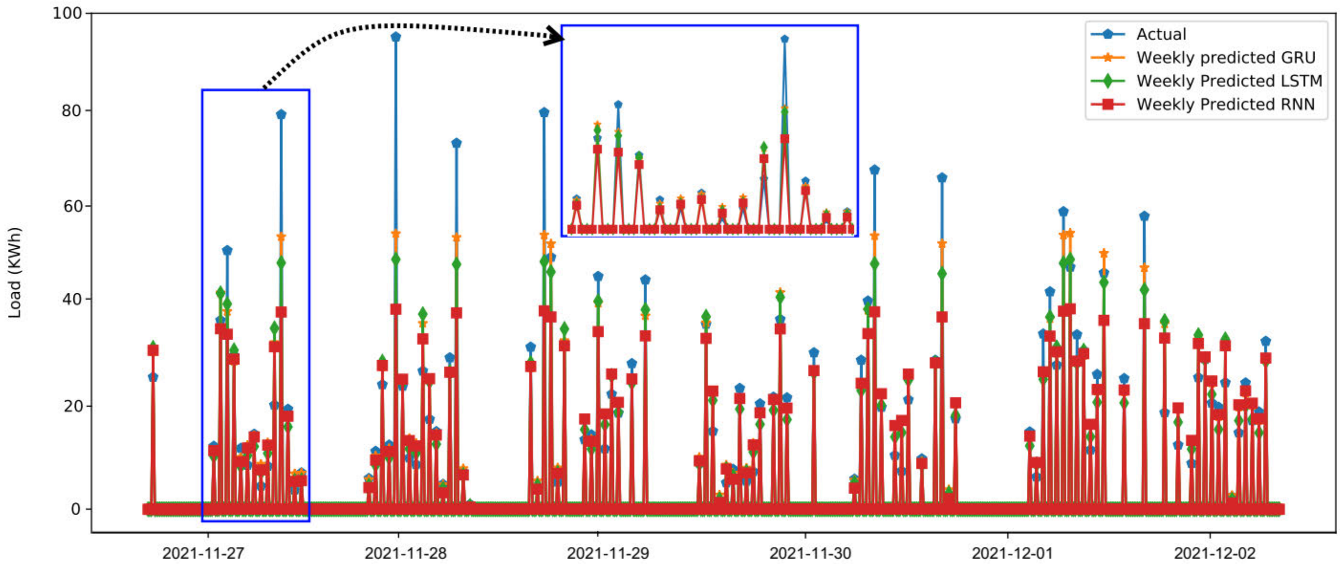
size and epochs considered are 512 and 30, respectively. For comparison of results with [29], 2 hidden layers with 64 units each, 100 epochs, and 64 batch sizes are considered. Furthermore, the proposed scheme is modeled as [30] in which, 1 hidden layer with 128 units, 50 epochs, and 32 batch sizes are considered for the comparison. All the used parameters are given in Table 1

## IV. RESULTS AND DISCUSSIONS

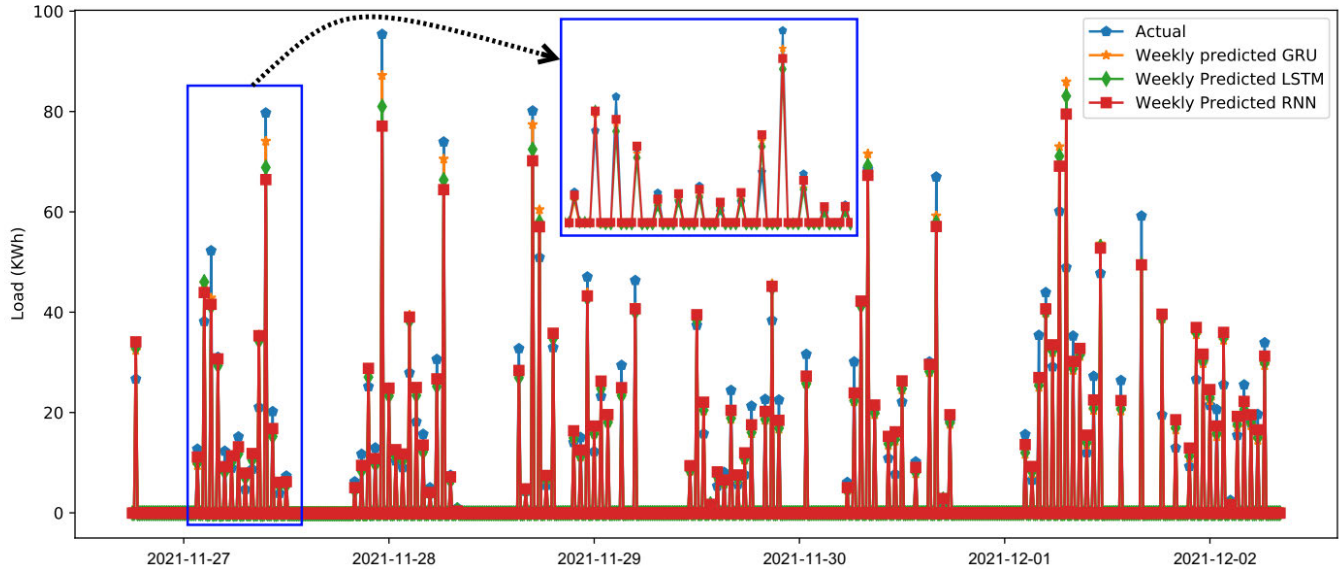
The pre-processing data has been fed into the three DL models. The performance of all the models was evaluated with and without ISL. To obtain the results, the simulations have been carried out with Tensorflow in Python version 3.9.7.

### A. MODEL EVALUATION

The matrices used to evaluate the models are Normalized Root Mean Square Error (NRMSE) and Normalized Mean Absolute Error (NMAE). The fluctuations in the charging load are always high, therefore normalized indicators




(a) Weekly Actual vs Predicted Load without ISL for 15 Minutes Data Interval




(b) Weekly Actual vs Predicted Load with ISL for 15 Minutes Data Interval

**FIGURE 12. 15 Minutes ahead prediction of weekly EVs load (a) Without ISL (b) With ISL.**

are used [29].

$$NRMSE = \frac{\sqrt{(1/N\,\Sigma_{i=1}^{n}(y'-y)^2)}}{(y_{max}-y_{min})} \tag{17}$$

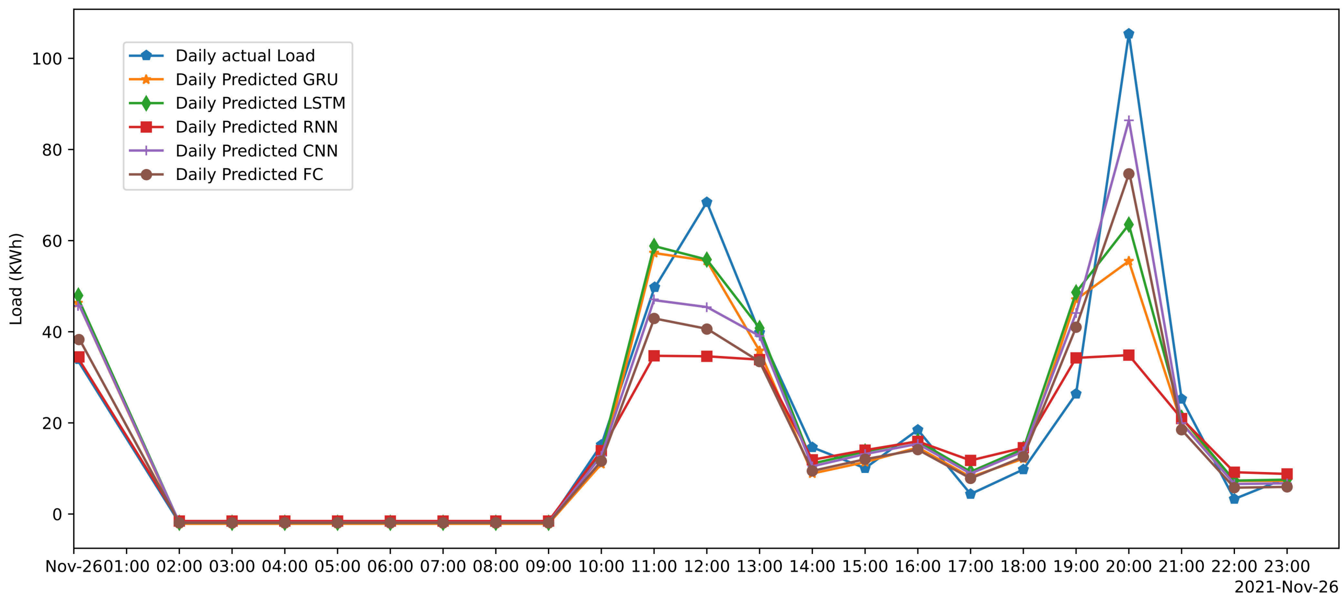
$$NMAE = \frac{(1/N\,\Sigma_{i=1}^{n}|y'-y|)}{(y_{max}-y_{min})} \tag{18}$$

These matrices are very important to evaluate the DL models. The NRMSE is an absolute value with normalization, which shows the difference between actual and predicted values. The NMAE is the normalized average variance between actual and predicted values. The simulation results of the proposed ISL scheme have shown lower error values for the DL models as given in the Simulation Results section.

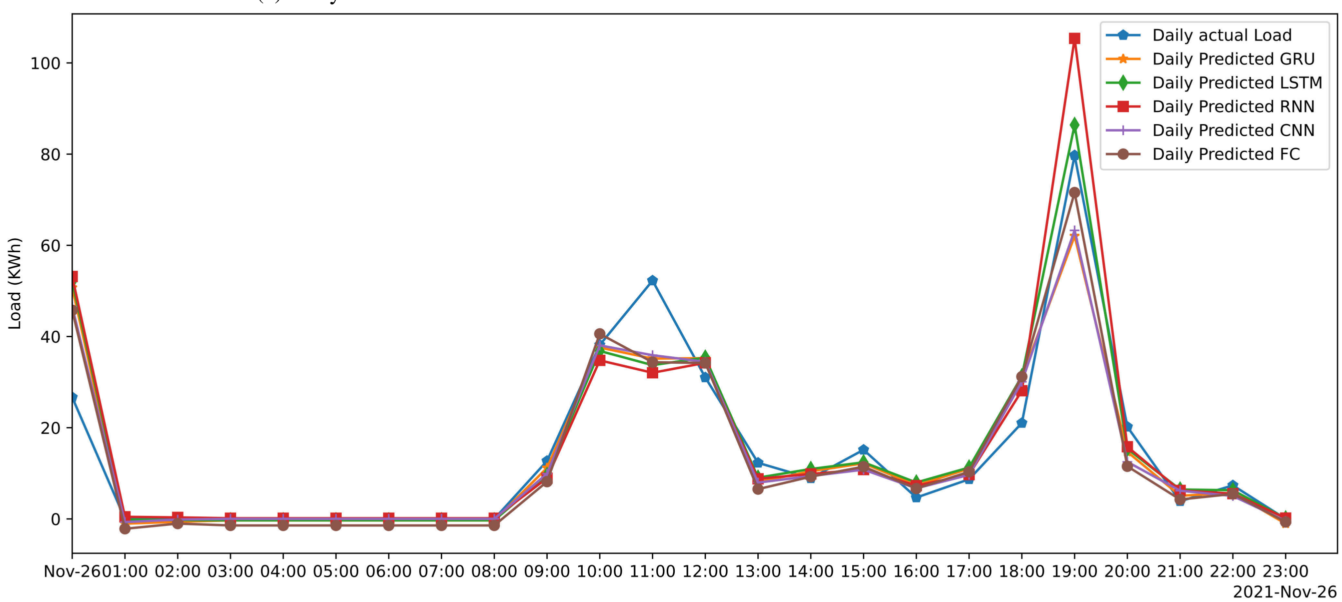
The Percentage Improvement in the NRMSE and NMAE values of the Proposed Scheme (ISL) is given by the following equation, (19).

$$Reductionin(Error)_{ISL} = \frac{(Error)_{ISL}-(Error)_{ET}}{(Error)_{ET}} \tag{19}$$

Here $(Error)_{ISL}$ is the Errors (NRMSE and NMAE) through ISL and, $(Error)_{ET}$ Errors through Existing Techniques or Existing Literature. The improvement in the proposed technique is given in Table 2, Table 3, Table 4, Table 5, Table 6 and Table 7. All these values are calculated




(a) Daily Actual vs Predicted Load without ISL for 1 Hour Data interval with CNN FC




(b) Daily Actual vs Predicted Load with ISL for 1 Hour Data interval with CNN FC

**FIGURE 13. 1 Hour ahead prediction of daily EVs load (a) Without ISL (CNN, FC) (b) With ISL (CNN, FC).**

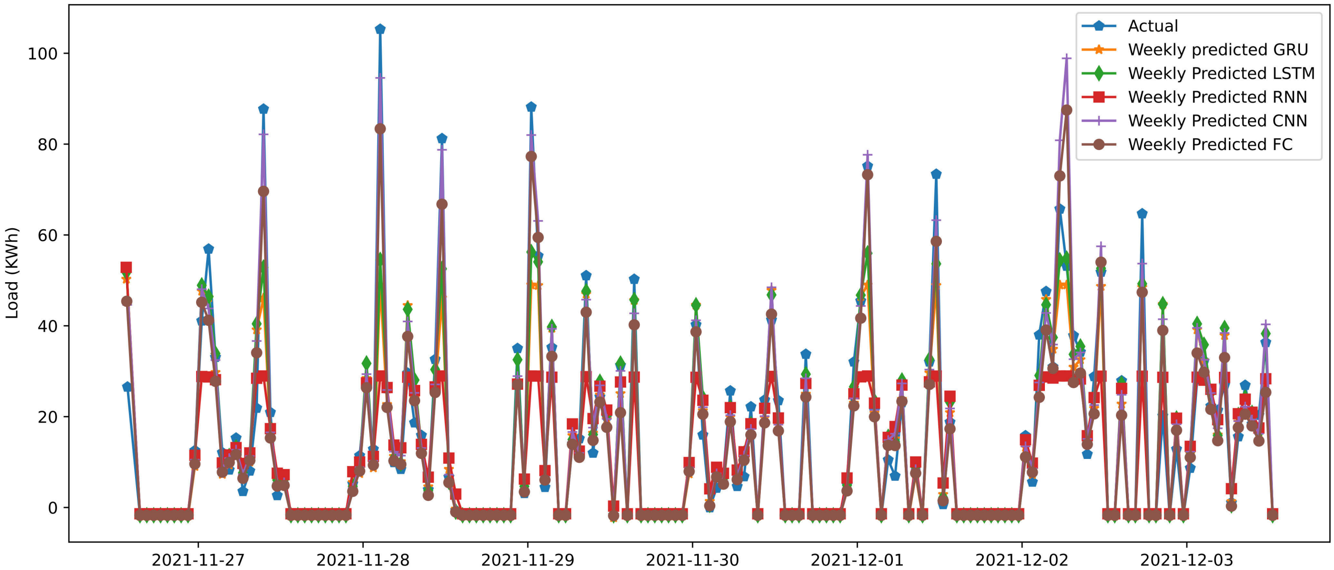
through the equation, (19). These tables show the reduction in NRMSE and NMAE values with the proposed ISL approach.

### B. SIMULATION RESULTS

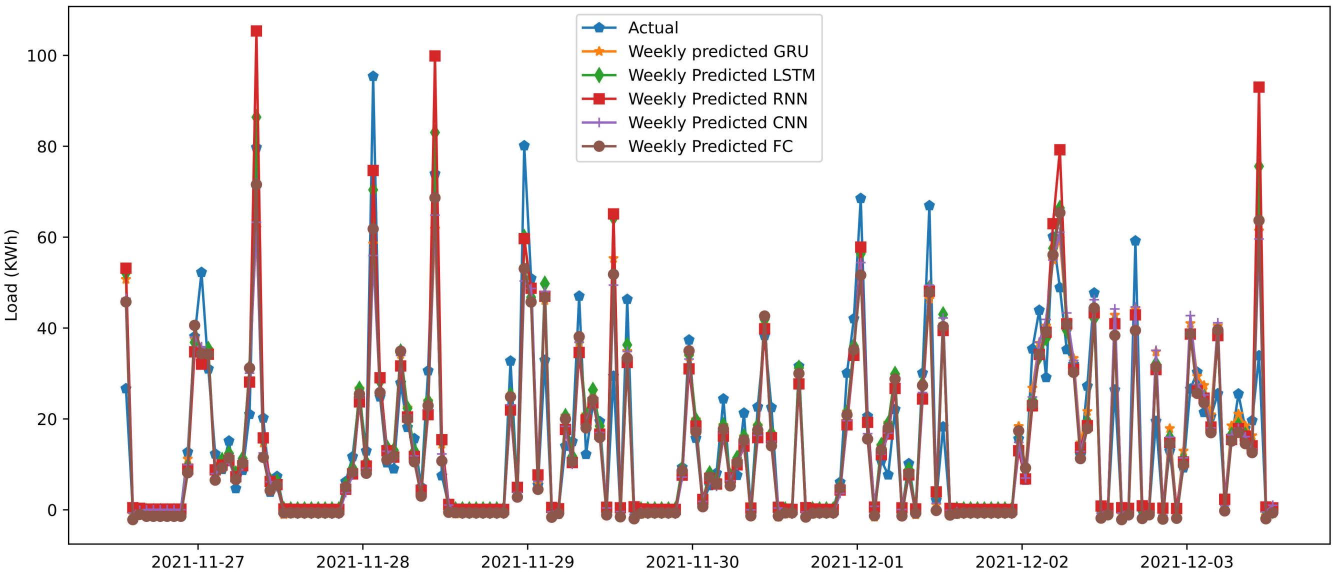
During the Process of Training, 70% of the dataset is used as a Training set and 30% as Testing Set. The comparison between the actual values and predicted values of three models without ISL as in [29] is shown in Figure. 7 and with ISL is shown in Figure 7b. The predicted values of LSTM and GRU are close to actual values while that of RNN is not predicting well without ISL. It is shown that there is no charging load at night in the charging station. Consumers normally charge during the daytime, so peak loads are around 12 pm and 8 pm. The highest peak in the day is at 8 pm as most consumers charge after working hours.

The predicting accuracy of deep learning models has been enhanced with ISL as shown in Figure 7. The RNN, LSTM, and GRU, all models are predicting the load very close to actual values.

In Figure 8a GRU and LSTM are shown good predictive capabilities than the RNN model without ISL. The highest peak of the load is shown on Sunday, 28th November 2021. The consumers fully charged the EVs on Sunday for the next working day. The GRU has shown the highest




(a) Weekly Actual vs Predicted Load without ISL for 1 Hour Data interval with CNN FC




(b) Weekly Actual vs Predicted Load with ISL for 1 Hour Data interval with CNN FC

**FIGURE 14. 1 Hour ahead prediction of weekly EVs load (a) Without ISL (CNN, FC) (b) With ISL (CNN, FC).**

predicting ability in Figure 8a. The predicting ability of RNN is not good without ISL. The improved results with the proposed technique for the whole week are shown in Figure 8b and it is observed that the predicting capability of RNN has increased the most. Table 2 shows the improvement in NMAE and NRMSE of the proposed model than in [29]. It is clearly shown that the proposed model is more efficient than the existing one in Figure 7 and Figure 8. The percentage decrease in the error of the proposed model in terms of NMAE is 77.79% for GRU, 81.33% for LSTM, and 81.42% for RNN. In terms of NRMSE, it is 99% for GRU, 99.13% for LSTM, and 98.72% for RNN. In Table 3, the reduction in prediction error for DL models is shown, in terms of NMAE and NRMSE. It is seen that the deep learning models perform well with ISL. The percentage decrease in NMAE is 23%, 15%, and 57% with GRU, LSTM, and RNN, respectively. The percentage reduction in NRMSE with GRU, LSTM, and RNN is 36.36%, 30.95% and, 64.10% respectively.

The DL models perform well with ISL which is clearly shown by the decrease in NMAE and NRMSE values in Table 2 and Table 3. The decrease in NMAE and NRMSE for LSTM is low as its predicting accuracy is good without ISL as well, shown in Figure. 7 and Figure. 8.

To authenticate the results further, the input features for DL models have changed as in [18] and the CT and CL have been used with 1-minute time intervals. The LSTM has shown the highest predicting ability without ISL as well in Figure 9a for one day. The predicting accuracy of RNN has increased with ISL, which is shown in Figure 9b. The predictions of GRU and LSTM models have also increased by applying the proposed methodology as shown in Figure 9b. The predictions of DL models for a whole week with 1-minute intervals are shown in Figure 10. The GRU model has shown the highest predicting accuracy without ISL in Figure 10a. Once again the predictions of RNN are not good without ISL. The increased prediction accuracy of all the models is shown in Figure 10b with ISL which proves the authentication of the proposed methodology. Some of the peaks are highlighted in Figure 9 and Figure 10, to show the charging interval.

The proposed scheme is modeled as [18] and its comparison with and without ISL is given in Table 4. It shows the comparison of NMAE and NRMSE values with and without ISL. The value of NMAE has been reduced by 10%, 60%, and 13% for GRU, LSTM, and RNN models, respectively. Similarly, the percentage decrease in NRMSE value is 40% for GRU and LSTM and, 42% for RNN models. These values show a percentage decrease in error values and an increase in the predicting accuracy of the proposed model.

The evaluation matrices used in [18] are MAE and RMSE values for RNN, GRU, and, LSTM models. For comparative analysis of the proposed technique with [18], MAE and RMSE values are considered in Table 5. The reduction in MAE for GRU, LSTM, and RNN, is 96%, 90%, and 99% respectively, when compared with MAE for GRU, LSTM, and RNN in [18]. The RMSE values are reduced by 84%, 57%, and 90% for GRU, LSTM, and RNN models, respectively, with the proposed technique as given in Table 5.

In Figure 11, the comparison of the forecasted load with the actual load is shown with DL models considering 15-minute data intervals as in [30]. The prediction accuracy of LSTM, as well as GRU and RNN, has increased, as shown in Figure 11b for one-day intervals with ISL. The predicting capability of RNN is very low without ISL in Figure 11b. It has increased along with the prediction of LSTM and GRU with ISL as shown in Figure 12b.

The predictions of DL models with and without ISL for a whole week with 15-minute data intervals are shown in Figure 12. Consistent with the results presented in Figure 8b and Figure 10b, which shows that the predictions of all the models have increased with ISL during the whole week.

A comparison of NMAE and NRMSE errors for 15-minute data intervals as in [30] is given in Table 6 with the proposed scheme. The NMAE values are reduced by 26.6% for GRU, 6% for LSTM, and, 24% for RNN as given in Table 6. The reduction in NRMSE values is 30% for GRU and LSTM and 42% in the case of RNN.

To further validate the results with more techniques, Convolutional Neural Network (CNN) and Fully Connected (FC) Neural Networks have been implemented. These networks have great importance as it allows for comprehensive validation and comparison of different DL techniques in the context of EV load prediction.

The results show that by applying the ISL techniques, predictions of CNN and FC models have also been increased along with RNN, LSTM, and GRU models. Figure 13b and Figure 14b show the weekly and daily improved load predictions of DL models with the ISL approach, respectively. Similarly, the reduction in NRMSE and NMAE with CNN, FC are given in Table 7.

This comparative analysis helps to identify the most effective models and provides valuable insights into the strengths and limitations of each approach, contributing to the advancement of accurate and robust load forecasting techniques for EVs.

## V. CONCLUSION AND FUTURE WORK

An Improved Supervised Learning Technique is proposed for Deep Learning models to predict the EV's Load for precisly meeting the charging need. The proposed technique is applied to different DL models namely, RNN, LSTM, and GRU. The simulation results have shown the enhanced predicting capabilities of these models by applying proposed ISL approach. The results are also compared with existing literature which shows the credibility of the proposed technique. The NRMSE and, NMAE values are used for model evaluation. Based on this evaluation, the prominent reduction for NRMSE is found as 99%, 99.13%, and 98.72% for GRU, LSTM, and, RNN respectively. In addition, the NMAE values are reduced for GRU, LSTM, and, RNN by 77.79%, 81.33%, and 81.42% respectively, with ISL as compared to these models without ISL. The minimum improvement in NRMSE value is 30% for LSTM, 30% for GRU, and 42% for RNN. Finally, the resulted reduction in NMAE values is 26%, 6%, and 24% for GRU, LSTM, and RNN respectively. In every case, the remarkable increase in predicting ability is shown by the RNN model. The inclusion of fully connected (FC) and convolutional neural network (CNN) architectures in this work further validates the results. The substantial reductions in the normalized root mean square error (NRMSE) and normalized mean absolute error (NMAE) values were found with the incorporation of the ISL technique. Specifically, the NRMSE for the FC model decreased by 34% and for the CNN model the error was decreased to 33% when compared to their respective baselines. Additionally, the NMAE values demonstrated a reduction of 38% for the FC model and 37% for the CNN model when ISL was applied. These improvements highlight the efficacy of the ISL technique in enhancing the accuracy and precision of load forecasting for electric vehicles using FC and CNN architectures. The significant increase in predicting capability of the proposed model proves its capability to predict load for EVs at charging stations.

In the future, researchers can focus on combining ISL based Deep Learning models with optimization and control algorithms to improve the prediction of Electric Vehicle load. This integration will allow the development of smart charging strategies that take into account factors like grid limitations, pricing, and user preferences. By optimizing the charging process, the efficient use of resources and better management of electric vehicle charging infrastructure can be ensured.

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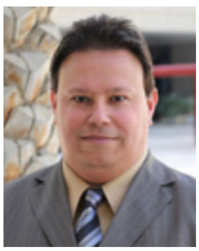

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