Journal of Computer Science

Research Paper

Enhancing Electric Vehicle Charging Demand Prediction Using a Novel SAE-DNN Neural Network Model for Probabilistic Forecasting

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Article history
Received: 21 September 2024
Revised: 11 December 2024
Accepted: 7 April 2025

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Abstract: The rapid growth and widespread adoption of Electric Vehicles (EVs) play a crucial role in the progress of intelligent transportation systems, resulting in a significant decrease in environmentally damaging greenhouse gas emissions. The increase in EV usage has made it crucial to develop charging infrastructure to keep up with the growing demand. Precisely predicting EV charging demand is crucial to relieve pressure on electricity systems and offer economical charging options. Simply increasing the number of charging stations is insufficient, as it puts pressure on power infrastructure and is constrained by spatial limits. Researchers are currently working on creating Smart Scheduling Algorithm (SSA) to handle public charging demand using modeling and optimization methods. There is a growing interest in using data-driven methods to model EV charging behaviors. The proposed approach includes preprocessing through normalization, feature extraction using Independent Component Analysis (ICA), and performance assessment with the SAE-DNN framework. The proposed approach compared the method with other two conventional techniques, DNN and SAE-CNN, to show its effectiveness.

Keywords: Electric Vehicle (EV), Stacked Auto Encoder (SAE), Dense Neural Network (DNN), State-Of-Charge (SOC), Independent Component Analysis (ICA), Smart Scheduling Algorithm (SSA)

Introduction

Many governments have established ambitious goals to combat urban environmental pollution and the worldwide energy problem, and one direct result of these goals is the fast growth of EVs around the world. Several studies have demonstrated that charging a large number of EVs would result in high power consumption. This, in turn, increases peak demand and demand unpredictability, which further pushes distribution networks to their limits and increases expenditures on capacity expansion. In order to overcome these obstacles, accurate modelling and forecasting of the EV charging load is essential. For the most part, the prediction and simulation models in earlier work have relied on a handful of data mining algorithms and three primary kinds of datasets.

(1) Information about previous charges from public and private charging infrastructure, including kilowatt-

hours (kW), state-of-charge (SOC), and other metrics and respectively.

(2) Data from traffic networks, geographic information systems, closed-circuit television, and information on traffic and travel trajectories, including congestion index and volume (Alam et al., 2022).

Electric cars (EVs) have seen a meteoric rise in popularity over the last decade, thanks to lowering CO_2 emissions and lower running costs compared to internal combustion engine (ICE) vehicles. According to research, EV might reduce carbon dioxide emissions by 29%. The public may encounter two main challenges while transitioning to EV: the high price tag and an absence of accessible charging stations. Among the primary issues brought up by the researchers is the fact that there is currently no dependable mechanism in place for charging electric automobiles. The ever-increasing global population of EVs poses a new challenge to the infrastructure that supports distribution network operators (DNOs). Integration of EVs, bus voltages, power loss, stability, harmonic distortion, voltage mismatch, and power efficiency are only a few of the issues that could lead to high electrical power demands, which could affect the distribution network negatively. Furthermore, to support the growing fleet of EVs, more efficient and reliable EVCS networks are required (Hasan et al., 2022). Concerns about carbon dioxide emissions, greenhouse effects, and the rapid depletion of fossil resources have accelerated the pressing need to find sustainable, ecologically friendly alternatives to cars powered by ICEs. EV have been more popular over the last decade due to their reduced oil usage and absence of dangerous fume gas emissions. Damage to lines increases, distortion occurs, fault currents, distribution transformer downturns, and power quality declines as a result of this strain. One efficient approach to reducing the impact is to integrate renewable energy sources (RES) and other forms of local power generation into the EV charging infrastructure. When charging batteries, have two options: conductive and inductive methods. An inductive charger is what makes up a wireless charging system, or WCS. Can use a static WCS only when the vehicle is at a complete stop, such as at a traffic light, in a garage, or in a parking lot, and a dynamic WCS can be utilized anytime the vehicle is in motion. The second choice allows charging the batteries while the vehicle is in motion. Aesthetics, reliability, durability, and ease of use are a few of WCS's possible advantages. The forecasting algorithm is fed the combined hourly intervals of power demand for EV charging as measured by fast chargers. Data normalization and cleansing are part of the preprocessing phase (Hasan & Alam, 2023). Finding missing data and dealing with outliers is the first step that significantly depart from the typical range. Following data cleansing, it is important to normalize the data within a certain range to ensure the stability of the gradient-based optimization process. Choosing appropriate network settings is crucial for optimizing predicting accuracy. The ideal parameters set is determined by comparing each experimental configuration using three evaluation matrices. The cumulative EV fast-charging power demand is predicted using three separate deep learning algorithms: SAE-DNN, SAE-CNN, and DNN.

Related Work

Electric vehicle (EV) adoption is accelerating in response to climate change concerns, yet several barriers hinder widespread deployment. While the cost gap between EVs and internal combustion engine vehicles is narrowing, accurate charging demand forecasting remains a critical challenge for grid integration and infrastructure planning. This section reviews existing approaches to EV charging load forecasting, organized by methodological approach.

Traditional Machine Learning Approaches

Early work in EV charging demand forecasting primarily employed classical machine learning techniques. K. Kumar et al. (2023) developed a charging load forecasting system using Support Vector Regression (SVR), demonstrating competitive accuracy for short-term predictions. Similarly, Mao et al. (2019) proposed a model for EV charging station short-term load forecasting that optimized Support Vector Machine (SVM) parameters using Particle Swarm Optimization (PSO), achieving improved prediction accuracy. Moorthi et al. (2023) employed supervised learning to forecast EV energy consumption using statistical data collected from vehicle sensors.

Tree-based ensemble methods have also shown promise for this application. Raghavan (2016) applied Random Forest (RF) to predict electricity demand from smart EVs, achieving a mean absolute percentage error of 16%. The study highlighted RF's balance between prediction accuracy and computational efficiency. Ahmad et al. (2022) and Wan et al. (2018) explored Bayesian approaches for handling uncertainties in charging demand forecasting, with Wan et al. specifically addressing smart charging issues such as equipment failures.

Deep Learning Methods

More recent studies have demonstrated that Deep Learning (DL) models can outperform conventional approaches for load prediction tasks. Li et al. (2018) applied Convolutional Neural Networks (CNN) combined with the Niche Immunity Lion optimization technique for one-step, short-term EV charging demand forecasting, obtaining competitive accuracy. Gandhi et al. (2023) incorporated short-term projections into a hybrid EV energy management system using deep learning, demonstrating potential energy efficiency improvements.

Transfer learning has emerged as an effective strategy when training data is limited. Fukushima et al. (2018) proposed a transfer learning approach that leverages data from multiple EV models to construct more robust prediction models. This technique addresses the challenge of limited data availability for specific vehicle types.

Ensemble Learning Approaches

Recognizing that individual models have complementary strengths, several studies have explored ensemble learning for improved forecasting performance. Majidpour et al. (2016) combined three neural network architectures: an Artificial Neural Network (ANN), a Recurrent Neural Network (RNN), and a Long Short-Term Memory (LSTM) network; to forecast demand at EV charging stations. J. Kumar et al. (2023) compared four machine learning techniques across two independent datasets to identify optimal model combinations for EV charging load prediction.

Sun et al. (2016) proposed using quantile regression methods, including Quantile Regression Neural Networks, quantile regression forests, and gradient boosted regression trees, to predict charging demand at various locations. Ramkumar et al. (2023) demonstrated that correlation regularization can improve Neural Network (NN) load predictor performance by reducing overfitting.

Reinforcement Learning Applications

Reinforcement Learning (RL) represents a newer paradigm that can generate control policies without requiring extensive historical data. This approach is particularly valuable for decision-making under uncertainty. Huang et al. (2020) applied the Q-learning algorithm to optimize fast EV charging station operations, demonstrating potential cost reductions for EV users. Prasanna Kumara et al. (2023) used RL to determine optimal charging schedules for EV fleets based on next-day consumption forecasts.

However, traditional Q-learning faces limitations when dealing with high-dimensional state and action spaces, as the action-value matrix becomes computationally intractable (Buzna et al., 2021). To address this challenge, researchers have turned to Deep Reinforcement Learning (DRL), which approximates the action-value function using deep neural networks. This approach helps overcome the curse of dimensionality and eliminates the need for explicit system identification, which can be difficult in practice (Yadav et al., 2023).

Vandael et al. (2015) employed a data-driven Deep Q-Network (DQN) approach to develop charging strategies that account for variable electricity pricing and commuting patterns, demonstrating effective cost reduction without requiring explicit system models. Shaarbaf & Ghayeni (2018) reviewed DRL-based methods for optimizing EV charging schedules, power electronic controllers, and emergency control under conditions such as wind power forecast uncertainty.

Research Gaps and Opportunities

Despite these advances, several challenges remain. Conventional and regular machine learning techniques may encounter accuracy limitations when forecasting high-resolution, extremely short-term individual EV charging loads due to large-scale data requirements, parameter sensitivity, and substantial uncertainty. Most existing studies focus on aggregated load forecasting rather than individual vehicle predictions, and few address real-time adaptation to rapidly changing conditions.

Furthermore, the integration of renewable energy sources with EV charging infrastructure introduces additional forecasting complexities that current methods do not fully address. Most existing approaches focus on deterministic forecasting and do not adequately capture the temporal patterns and variability in individual vehicle charging behavior.

To address these limitations, we propose a novel approach that combines Independent Component Analysis (ICA) with deep learning for EV charging load (EVCL) pattern extraction and forecasting. Unlike previous methods that treat charging load as aggregated demand, our approach identifies and extracts individual charging patterns at multiple temporal resolutions. The following sections present our methodology, including the theoretical foundation of ICA-based preprocessing, the pattern extraction algorithm, and experimental validation on multiple real-world datasets.

Proposed System

The core function of this proposed system is the precise prediction of Electric Vehicle (EV) charging demand, which is essential for optimizing the power grid and facilitating future infrastructure expansions.

Forecasting demand in the short and long term enables more efficient utilization of existing power resources.

To achieve this, the system utilizes a publicly accessible dataset to predict EV charging demand. This dataset, which can be found on Kaggle, is based on a field experiment conducted by Omar Asensio, tracking 3,395 EV charging sessions from 85 drivers using 105 stations spread over 25 sites (Gholizadeh, 2024). The details captured include the total energy utilized, cost, date, and duration of each session. The use of this public data allows for reproducible research and validation against real-world charging behaviors.

```
Algorithm 1 : Ev CHarging Algorithm with SAE and DNN
   Input: Training and Testing dataset
   Output: Classification results : Accuracy, Precision, recall and F1-Score.
```

1. **Step 1:** Preprocessing of data
2. $d_t' = \text{normalization}(d)$
3. **End Step**
4. **Step 2:** Feature Extraction
5. Train the ICA using Train dataset and minimize the reconstruction error
6. **End Step**
7. **Step 3:** Classification
8. The Weights of the latent layer of trained Stacked AutoEncoder is used to initialize the weight of DNN
9. Train the DNN classifier
10. Testing dataset are input into the trained DNN classifier
11. **End Step**
12. Return the classification results

Fig. 1. Algorithm 1-EV Charging Algorithm.

The Proposed Model utilizes DNN for EV charging. The SAE encoder automatically extracts features and its weights are utilized to initialize the weights of the hidden layer in the DNN. The activation function employed in the output layer of the DNN is softmax (Tang et al., 2020). The test samples are sent into the trained SAE-DNN classifier to identify EV Charging. Refer to Fig. 1 for more information.

Charging Behaviour of Electric Vehicles

Let i_{con} represent the time when the initially car plugs in, i_{discon} represent the time when the car plugs out and departs the station, and a represent the amount of energy given to the car during the session(Shahriar et al., 2021). The proposed approach defines the charging session behaviour $B_{session}$ as follows:

$$B_{session} \triangleq (i_{con}, i_{discon}, a) \tag{1}$$

According to the information provided above, it is to define the length of a session charging, or the duration of session, S_{dur}, in the following manner:

$$S_{dur} = i_{discon} - i_{con} \tag{2}$$

This system aims to forecast the consumption of energy and duration of a charging session based on an individual charging record, assuming that the time for connection is already known.

Fig. 2 displays the flow chart of the suggested methods. The data set is initially partitioned into a training set and a testing set in a random manner. The training set is utilized to train the deep learning algorithms. The DL algorithm parameters are optimized using three metaheuristic strategies. Next, the analysis to determine the ideal number of neurons in the hidden layer is provided. The suggested models' predictive performance is demonstrated using several statistical indices and visual graphics.

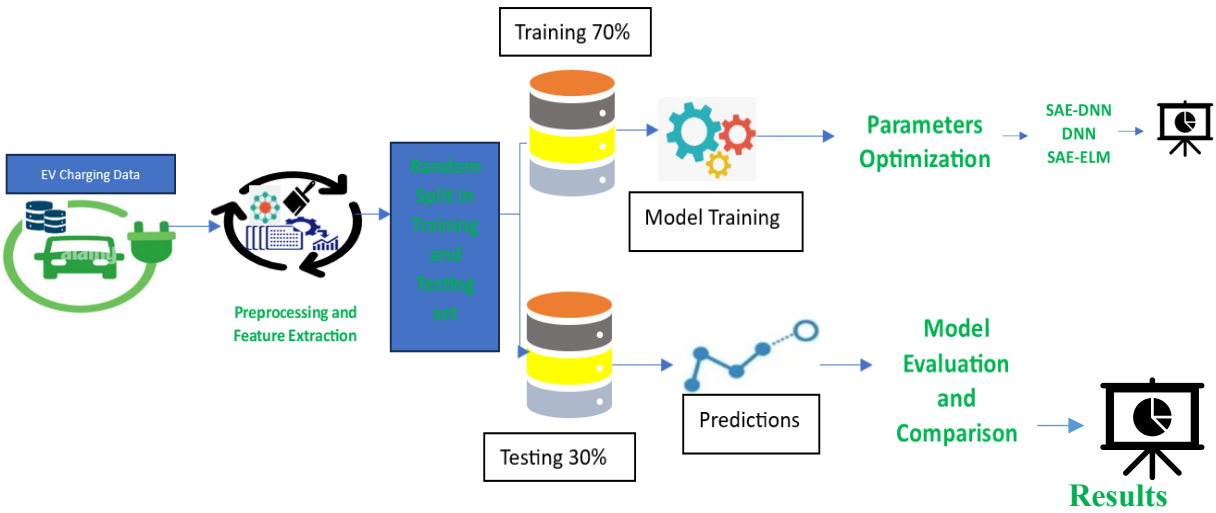

Fig. 2. Proposed Architecture of Electric Vehicle Charging.

Preprocessing

Normalization

The normalization approach is essential for predicting problems since it ensures the stability of the training period optimization procedure. Shortening the time, it takes to train neural networks and allowing them to converge optimally are the two main goals of normalization. The non-convex error surface is kept in a more spherical form by using an appropriate scaling strategy, which improves the convergence of gradient-based optimization algorithms. Without a doubt, the original dataset could be simply normalized using the min-max method. And can split the dataset used for this method into three parts: the training set, the test set, and the overall dataset (Chang et al., 2021). Additionally, the dataset can be rescaled to fit within the range of [0, 1], while still preserving its original scale invariance as described by equation (3). Due to the vulnerability of the SAE-DNN recurrent network to data scale, several research that have focused on time series forecasting using SAE-DNN have utilized min-max normalization.

$$d_{norm} = \frac{d_t - \min(d)}{\max(d) - \min(d)} \quad (3)$$

The variable xnorm represents the normalized output of the supplied sequence d, while d; refers to the t-th instance of d_t . $\min(d)$ and $\max(d)$ represent the minimum and maximum values of d, respectively. This proposed system introduces a novel method called window sliding min-max normalization, also referred to as window normalization, as a secondary approach for estimating charger power consumption for EV. By utilizing a predetermined window length, window normalization aims to transform the input data. Because of this quality, changes to the original data can be made in short amounts of time.

Feature Extraction

This section presents the general independent component analysis (ICA) approach. Additionally, an explanation is provided on how the ICA can be utilized to extract the stage 2 EVCLs.

Independent Component Analysis (ICA)

Independent Component Analysis (ICA) is a signal processing technique utilized primarily for blind source separation. Its goal is to represent a group of observed random variables as a linear combination of statistically independent component variables.

In the standard ICA model, the observed signal vector $d = [d_1, \ldots, d_h]$ is assumed to be a linear mixture of \$m\$ independent random vectors $w = [w_1, \ldots, w_h]$. This relationship is defined by:

$$d = Ew \quad (4)$$

Where E is the unknown $h \times j$ mixing matrix. The statistical model shown in Equation (4) is referred to as the ICA model. The independent components (w) are latent variables that cannot be observed directly. Given only the random vector d, the method must estimate the best-case matrices for E and w. This is achieved by assuming that w consists of non-Gaussian, statistically independent components.

Assuming the unknown mixing matrix (E) is a square matrix, the independent components can be recovered by estimating the de-mixing inverse matrix (S):

$$w = Sd \quad (5)$$

To simplify and improve the estimation of the ICA problem, preprocessing steps such as centering and whitening are first applied to the data. A key limitation of the ICA approach is its inability to determine the order or scale (amplitude and polarity) of the extracted independent components.

ICA for ECVL Extraction

In this research, the aggregated signal (x) is a combination of two mixed signals: the combined signal without the EVCL and the EVCL signal itself. Our goal is to use the ICA model on the aggregated signal (x) to determine the EVCL distribution pattern.

While the ICA approach is capable of extracting the EVCL from the combined load signal, it is not possible to accurately determine the sign and magnitude of the retrieved EVCL. This is a result of the uncertainties inherent in the ICA approach. To achieve this objective, the classification of EV into certain categories will be used to determine the magnitude of the extracted EVCL load signal.

Classification of the Model

Unsupervised feature learning can acquire discerning and efficient features from a substantial quantity of unlabeled input. Acquiring labelled vibration signals in the field of EV charging is challenging due to the requirement for particular and extensive experimental settings. Hence, unsupervised feature learning can offer a viable resolution for defect diagnostics. In this system, the proposed approach examines one of the common unsupervised feature learning methods, known as SAE. The suggested framework utilizes the SAE in conjunction with a denoising module to extract features from the vibration signals. Next, the acquired features are inputted into a neural network classifier that incorporates dropout. The intricacies of the framework are depicted in the subsequent sections. The hybrid model of SAE-DNN processes feature inputs from EV data providers to

estimate the cost of healthcare providers. Hyper-parameter values are crucial in deep learning models as the system significantly impact the training process and ultimately determine the model's learning efficiency and performance. The hyper-parameters for SAE-DNN are epoch, function of activation, optimizer, batch size, and function of loss. The number of epochs is set to 70 and the batch size is 32. ReLU function activation, Optimizer of Adam, and MSE loss metric are utilized for SAE-DNN. Following the SAE process, DNN is employed to forecast the cost estimation of EV providers(Bhatti et al., 2023). A DNN is composed of numerous layer of hidden and layer of dense that utilize backpropagation to adjust the weights, enhancing the accuracy of predicting healthcare providers. Algorithm 2 outlines the operation of hybrid SAE-DNN.

Hybrid SAE-DNN
Input: Input data as $D = D^{\wedge}1, D^{\wedge}2 \ldots D^{\wedge}R$
Output: The output L of hybrid SAE-DNN.

1. Take D and L from Electric Vehicle Charging dataset
2. Apply Imputation mode on D and L
3. Apply standard scalar normalization on D and L
4. Split the D and L into train and test
5. **SAE Working Mechanism**
6. Input Layer W_t =D_{train} and L_{train}
7. Encoded Layer $A_t = W_t$
8. Decoded Layer $X_t = A_t$
9. Train the EV using SAE and DNN
10. Pass the output of X_t to DNN
11. **DNN Working Mechanism**
12. Input layer $l_t = X_t$
13. Hidden layer $m_t = Relu(x_t s_v^l)$
14. $s_t = Parameter(Size = [x_v, x_d])$
15. output layer $\hat{l} = ||\hat{l} - l||^2 LossFunction$
16. **Hybrid SAE-DNN Mechanism**
17. Concatenate the output of SAE and DNN
18. $Concat = (SAE_{output}, DNN_{output})$
19. Train the Hybrid model using SAE and DNN
20. **Performance Evaluation**
21. $Accuracy \leftarrow Accuracy(l_{test}, l_{pred})$
22. $Precision \leftarrow Precision(l_{test}, l_{pred})$
23. $Recall \leftarrow Recall(l_{test}, l_{pred})$
24. $F_1 - Score \leftarrow F_1 - Score(l_{test}, l_{pred})$

Fig. 3. Algorithm 2 - Flowchart for proposed SAE-DNN Model.

Smooth l1 regularization with Sparse AutoEncoder (SAE)

Unsupervised feature learning can acquire discerning and efficient features from a substantial quantity of unlabeled input. Acquiring labelled vibration signals in the field of EV charging is challenging due to the requirement for particular and extensive experimental settings. Hence, unsupervised feature learning can offer a viable resolution for defect diagnostics. In this system, the proposed approach examines one of the common unsupervised feature learning methods, known as SAE. The suggested framework utilizes the SAE in conjunction with a denoising module to extract features from the vibration signals. Next, the acquired features are inputted into a neural network classifier that incorporates dropout. The intricacies of the framework are depicted in the subsequent sections.

In the SAE with smoothed $y1$ regularisation methods, the proposed approach are provided with a labelled training set of m records, which is represented as $\left\{\left(d_y^{(1)}, l^{(1)}\right), \left(d_y^{(2)}, l^{(2)}\right), \ldots, \left(d_y^{(h)}, l^{(h)}\right)\right\}$. The input feature vector, $d(t)$, is a real number that belongs to the set K^j. Every record can be labelled with either a binary classification $l^t \in \{+1, -1\}$ or a multi-classification $l^t \in \{1,2,3, \ldots, G\}$, represented $'y'$. Assumingly, As a train set, the labels are removed to yield $d_z^{(1)}, d_z^{(2)}, d_z^{(3)}, \ldots d_z^{(h)}$ which are unlabeled samples in K^j. In order to reduce the dimensionality of the input training set and produce a suitable representation, the proposed approach feed unlabeled training samples $d_y^{(1)}, d_y^{(2)}, d_y^{(3)}, \ldots d_y^{(h)} \in K^j$ into the proposed sparse autoencoder model. Using it, may replicate the training input dataset and learn from it. Using Sparse autoencoder on unlabeled data xb allowed us to determine the optimal values for W and b. The system needs to learn and duplicate its output values $\hat{d}_z^{(1)}, \hat{d}_z^{(2)}, \hat{d}_z^{(3)}, \ldots \hat{d}_z^{(h)} \in K^j$ so that the system match its input samples $d_z^{(1)}, d_z^{(2)}, d_z^{(3)}, \ldots d_z^{(h)}$.

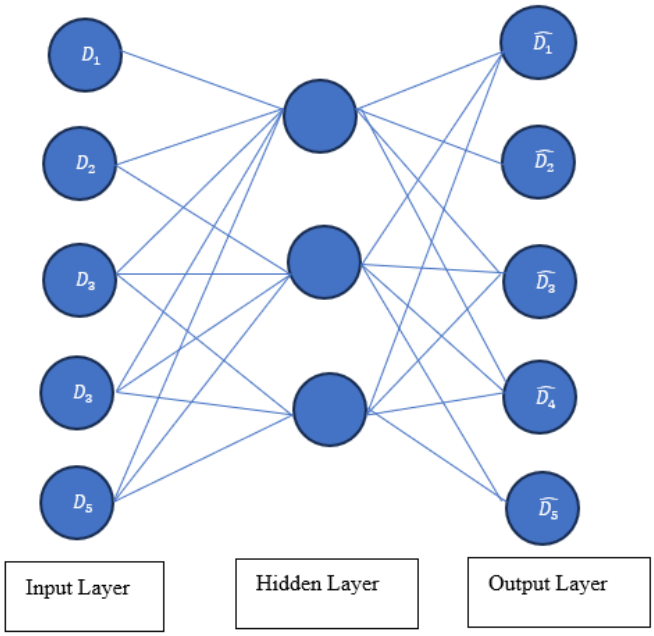

Fig. 4. Illustration of SAE Model

The result will be a new representation with fewer dimensions, as follows:

$$\left\{\left(m_y^{(1)}, l^{(1)}\right), \left(m_y^{(2)}, l^{(2)}\right), \ldots, \left(m_y^{(h)}, l^{(h)}\right)\right\}$$

The initial input samples are obtained using activation samples of m that are similar. There is just one procedure that does both dimensionality reduction and feature extraction (Jia et al., 2019). During the encoding phase, the input data d_t is converted into the representation of the hidden components, as demonstrated in Fig. 4.

$$U = m(SD + p) \quad (6)$$

$$\widehat{D} = c(S'u + p') \quad (7)$$

In the given equations, the input data is represented as a high-dimensional vector $D = (d_1, d_2, d_3, \ldots, d_h)$. The reconstructed vector of the input data is denoted as $\widehat{D} = \left(\hat{d}_1, \hat{d}_2, \hat{d}_3, \ldots, \hat{d}_h\right)$. The output from the hidden layer is a low-dimensional vector $U = (m_1, m_2, m_3, \ldots, m_h)$ .. In the above formulation, c . represents the activation function of the neurons in the hidden layers, whereas h represents the activation function of the neurons in the output layer. The weight matrices S and S' correspond to the encoder and decoder, whereas the bias vectors p and p' correspond to the receiver and the transmitter, correspondingly. Input d minus the reconstructed input A is the reconstruction error function $\hat{d}$ is calculated using the Mean Squared Error (MSE) function.

$$A = \frac{1}{J}\sum_{t=1}^{J} d_t + d_t'^2 \quad (8)$$

The incorporation of smoothed $y1$ regularization where ML is concerned. It is difficult to optimize the $y1$ regularization since it is non-differentiable. The inf-conv (infimal convolution) method is a new approach to smoothing data (Narayana Rao et al., 2021). The term of regularization in maximum penalized likelihood reconstruction is defined as the infimal convolution of the first and second-order total variation. An application of a novel methodology is provided as follows:

$$c_z(i) = \begin{cases} \frac{i^2}{2\tau}, \ if\ |i| \le \tau \\ |i| - \frac{\tau}{2}, \ otherwise \end{cases} \quad (9)$$

The parameter τ, which is greater than zero, regulates the similarities between $y1$ and smoothed $y1$ regularization. When the value of τ is set to 0, it transforms into $y1$ regularization. The SAE employs backpropagation to minimize the cost function, as defined in Equation (10).

$$N_{spare}(S, p) = \left[\frac{1}{J}\sum_{t=1}^{J}\frac{1}{2}\left\|m_{S,p}(d_t) - \widehat{d_t}\right\|^2\right] + \frac{\delta}{2} \quad (10)$$

$$\sum_{y=1}^{j_y-1}\sum_{t=1}^{w_y}\sum_{n=1}^{w_y+1}\left(S_{nt}^{(y)}\right)^2 + \alpha\sum_{n=1}^{j} W(i_n) \quad (11)$$

In Equation (11), $W(.)$ represents the function that can cause sparsity. The mean value of the jth hidden unit's output is denoted as i_n.

$$i_n = \frac{1}{h}\sum_{t=1}^{h} e_n^{(t)} \quad (12)$$

In equation (12), n denotes the output of the nth hidden unit for the t th input sample. In the aforementioned sparsity function, the proposed approach is employing smoothed $y1$ regularization as an alternative to the often-utilized KL divergence. Nevertheless, the proposed system opts for the ReLU (rectified linear unit) activation function.

$$q(d) = \max(0, d) \quad (13)$$

The variable $e_n^{(t)}$ can only take values between 0 and 1, inclusive. On the entire training set, the average activation i_n of hidden unit n falls within the range of 0 to 1. However, it is important to take into account the possibility of i being greater than 0. In SAE, sparsity restrictions are used to control the process of the buried layer neurons. The sparsity constraints change the error criterion by inserting a penalty term that quantifies the divergence from the intended sparsity. This modified criterion is then used in the backpropagation algorithm, which also takes into account the sparsity penalty. Empirical evidence from varying degrees of sparsity suggests that there is a negative correlation between the level of sparsity and the types of correlations that can be recorded pertaining to the data used for training. A higher level of dispersion has a tendency to capture more valuable traits.

Deep Neural Network (DNN)

To properly classify multi-class assaults in IDS, the suggested hybrid approach employs DNN (Deep Neural Network). One subset of FFNs, called a Multilayer Perceptron (MLP), is a Deep Neural Network (DNN). There are more than two levels in a DNN, as opposed to a standard FFN, which consists of an input layer, an output layer, and perhaps more hidden layers. Numerous neurons that are completely linked with neurons in the forward direction make up each layer. In technical terms, the model is defined as $V: K^h \times K^j$. There are z elements in the input vector d , which are represented as$d_1, d_2, d_3, \ldots, d_h$. Included in the output vector $V(d)$ are j entries. The following is the calculation for the mathematical definition of each hidden layer p:

$$m_n\left(d_n^{y+1}\right) = q\left(u_{tn} + p_n^{(y+1)}\right) \quad (14)$$

$$u_{tn} = d_t^y s_{tn}^{(y,y+1)} \quad (15)$$

All the neurons in the bottom layer that are linked to neuron n. In equations (8) and (9), d_t^y represents the function for activation of neuron t at layer y, and u_{tn}

represents the contribution of neuron t at layer y to the neuron activation of n at layer $y+1$. The function q represents the non-linear function activation, whereas $s_{tn}^{(y,y+1)}$ denotes the weight and $p_n^{(y+1)}$ represents the bias of neuron n. The softmax function is utilized in the proposed model in order to accomplish multi-class classification using a non-linear activation function. A DNN is sometimes referred to as a MLP with several hidden layers. A DNN often consists of multiple hidden layers, which can be expressed in the following manner.

$$M_y(d) = M_y\left(M_{y-1}\left(M_{y-2}\left(\ldots\left(M_y(d)\right)\right)\right)\right) \quad (16)$$

Two hidden layers make up the DNN architecture. The outputs $v = v_1, v_2, v_3, \ldots, v_{g-1}, v_g$ are produced by the function from the inputs $d = d_1, d_2, d_3, \ldots, d_h$. It makes use of a DNN, a traditional FFN that is more sophisticated. In a DNN, the non-linear function for activation for each layer of hidden is a ReLU. This non-linear activation function helps reduce the frequency of disappearing and exploding gradient problems as compared to others. Training models with several hidden layers is made easier by the ReLU function for activation, which is also more efficient. One of the most important parameters for getting the best performance is the loss function. Using a loss function, one can find the difference between the target and anticipated values. This can be stated in its simplest form as:

$$x(i,b) = \|i-b\|_2^2 \quad (17)$$

The goal is to figure out a close approximation to the identity of a function. As seen in Equation (11) above, this learning process entails minimizing the reconstruction error. In this case, p stands for the desired values and b for the expected values. The loss function measures how much the target value differs from the expected value. In order to determine the loss function and the type of attack, the model uses the target and the features as inputs. For the target class, the proposed approach uses the negative logarithm of the probability, b, and for the predicted classes, the proposed system uses the probability distribution, $b(bx)$. The illustration looks like this:

$$x\big(i,b(b,x)\big) = -logb(bx)_i \quad (18)$$

The hybrid EVC system comprises two techniques, namely deep neural networks and sparse auto encoders can be used. When learning about data representation, the SAE is used to extract attributes. Convolutional neural networks then utilize these derived features to do multi-attack classification.

Result and Discussion

Electric vehicles pose a significant and complex issue for electricity distribution networks and the overall energy system. The study explores a new technique that uses a Sparse AE-DNN model and predict the spatial distribution of EV. The proposed model utilizes multilayer socioeconomic input raster data to extract features, which are then sequenced in strides. The model's output is a geographical estimation of EV distribution. Real-world applications like smart grid systems and EV management software can incorporate the suggested SAE-DNN paradigm. It allows smart grid systems to efficiently balance energy loads, optimise resource distribution, and lessen peak load pressures by accurately predicting EV charging requests. The model can help EV management software schedule and route EVs to charging stations, increasing station utilisation and user convenience. In order to encourage grid stability and lower customer prices, the model can also include dynamic pricing schemes and energy-saving incentives.

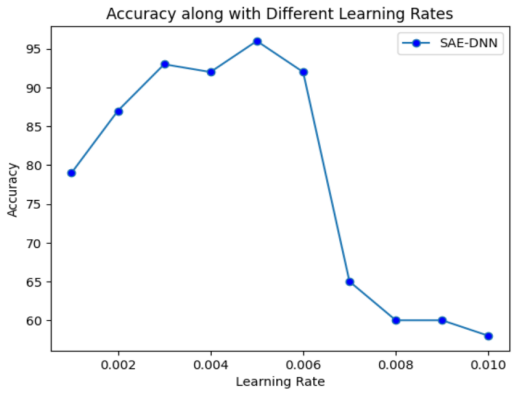

Fig. 5. The accuracy of SAE-softmax varies depending on the learning rates applied.

The training set is partitioned into five equal segments, and the optimum parameters are determined using five-fold cross-validation. For SAE-DNN, the accuracy reaches its peak at 96.48% when the learning rate is set at 0.05, as shown in Fig. 5.

Fig. 6. Training Loss shown in MSE

Fig. 6 displays two crucial curves for every neural network. The curves show if the training of the neural networks successfully converges to a minimum Mean Squared Error (MSE). A noteworthy distinction can be noted in the minimum Mean Squared Error (MSE) between the SAE-DNN and the two new neural networks. DNN and SAE-CNN achieve reduced Mean Squared Error (MSE) values compared to SAE-DNN. The distinction between DNN and SAE-CNN is minimal. The figures demonstrate that all three neural networks converge correctly for both training and validation losses without experiencing overfitting or oscillation problems.

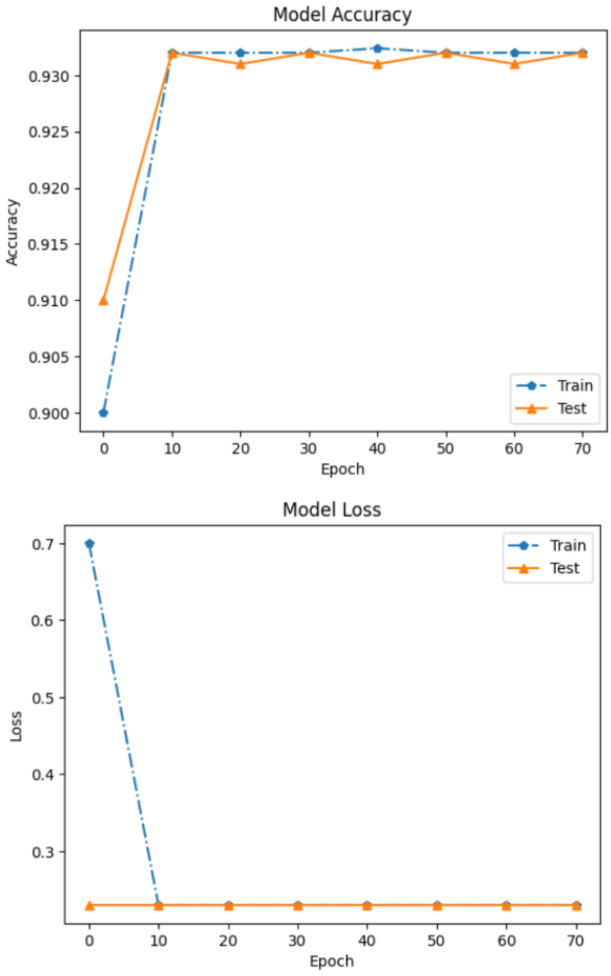

Fig. 7. Model Accuracy and Model Loss for the Classification using SAE-CNN

Fig. 7 illustrates the comparison of training and testing accuracy and loss for binary data categorization using the SAE-CNN approach. The SAE-CNN algorithm attained a training accuracy of 0.96 and a testing accuracy of 0.93.

Fig. 8 displays the training and testing accuracy and loss comparison for binary categorization of the data using the DNN method. The DNN algorithm achieved a training accuracy of 0.89 and a testing accuracy of 0.82.

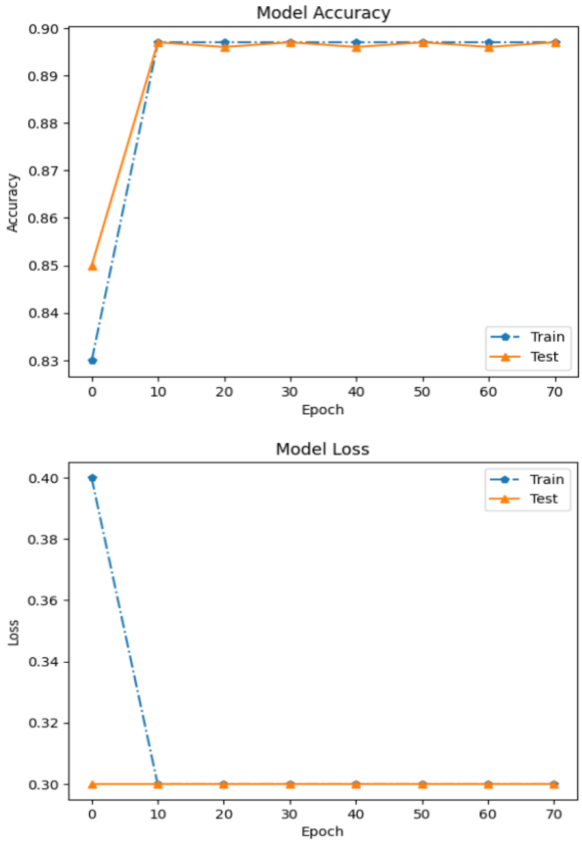

Fig. 8. Model Accuracy and Model Loss for the Classification using DNN

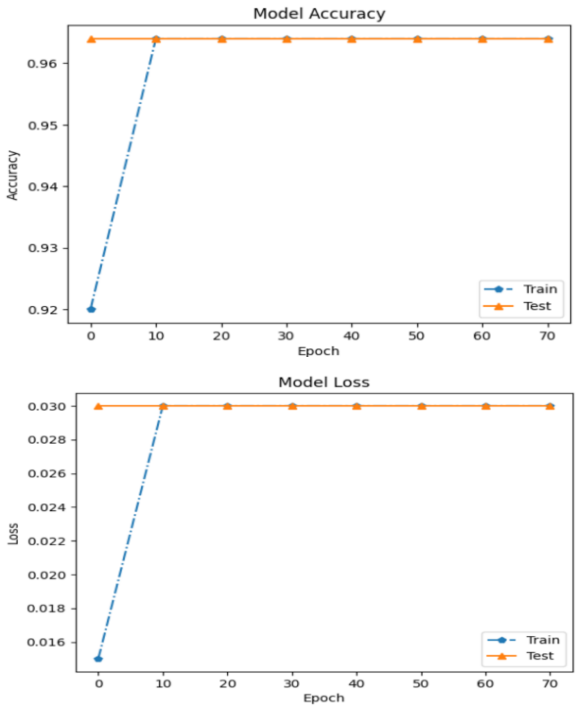

Fig. 9. Model Accuracy and Model Loss for the Classification using SAE-DNN

Fig. 9 displays the training and testing accuracy and loss for the binary classification of the data using the SAE-DNN. The training and testing accuracy of SAE-CNN are 0.96 and 0.69 higher than DNN and SAE-CNN, respectively.

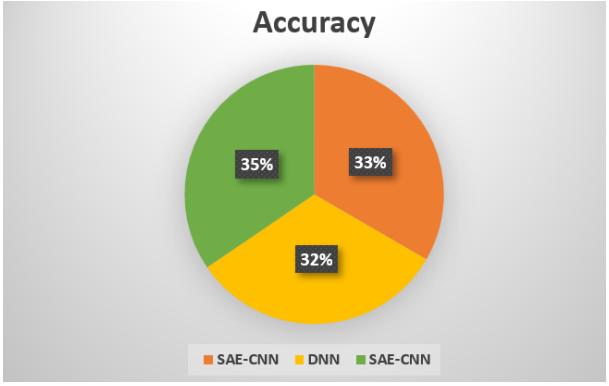

Fig. 10. Classification Accuracy for the Models

Various solutions need to be created to address issues such as surpluses and strain when EV are linked to a smart grid. This occurs only after obtaining the most cost-effective energy. EV can qualify for discounted electricity rates based on certain requirements in a particular location. Price signals are being utilized to deter vehicle charging in congested areas and generate revenue from electric car sharing. EV software employs a range of deep learning algorithms. Fig. 10 displays the classification accuracy of a Deep Learning classifier.

	Accuracy	Precision	Recall	F-Score
SAE-CNN	93.25	92.77	90.68	93.78
DNN	89.77	86.43	84.72	90.28
SAE-DNN	96.48	94.39	92.83	96.64

Fig. 11. Classification Results for the Models

Fig. 11 display the assessment outcomes of SAE-CNN, DNN, and SAE-DNN on n test sets, analysing the classification results using four evaluation metrics: accuracy, precision, recall, and F1-score. SAE-DNN demonstrates an accuracy that is 3.23% and 6.71% greater than SAE-CNN and DNN, respectively, in the classifications. The precision, recall rate, and F1-score have increased by 1.62%, 7.96%, 1.8%, 7.76%, and 2.86%, 6.36%, respectively.

The algorithm might have trouble scaling to bigger datasets or adjusting to different geographic areas with different rates of EV adoption and charging habits. Normalisation and optimisation approaches were employed to solve computational problems during training, including managing substantial amounts of high-dimensional data. However, there may be drawbacks due to the dependence on preprocessed data and the possible requirement for retraining on a regular basis to preserve accuracy. Extending the model's efficiency and generalisability in other real-world scenarios may be the focus of future research.

Conclusion

Accurately forecasting the Electric Vehicle Charging Load (EVCL) has significant implications for improving power grid stability, optimizing traffic management, and promoting urban economic development. Forecasting this demand is challenging due to the intricate layout of charging infrastructure in metropolitan areas and the temporally changing nature of charging patterns.

The methodology proposed in this paper successfully addresses this difficulty by utilizing a robust, data-driven framework encompassing preprocessing, feature extraction, and comparative deep learning model training. The preprocessing stage employs data cleaning and normalization to ensure the quality and consistency of input data. Independent Component Analysis (ICA) is then used for feature extraction, allowing the model to identify and isolate important underlying patterns and features from the raw data.

The methodology is centered on the Stacked Autoencoder-Deep Neural Network (SAE-DNN) framework, which is rigorously compared against two conventional deep learning methods: the standard Deep Neural Network (DNN) and the Stacked Autoencoder-Convolutional Neural Network (SAE-CNN). The proposed SAE-DNN strategy demonstrated superior performance, achieving a high accuracy rate of approximately 96.48%.

This high accuracy provides precise long-term projections of the EV charging load. Such projections are vital for Distribution Network Operators to strategically plan energy provision and infrastructure expansion. Furthermore, this forecasting capability supports intelligent transportation systems by offering reliable insights into network usage, allowing drivers to strategically plan their charging operations, alleviating concerns about battery depletion, and enhancing urban traffic flow.

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