International Journal of Applied Power Engineering (IJAPE)
Vol. 15, No. 3, September 2026, pp. 1375~1385
ISSN: 2252-8792, DOI: 10.11591/ijape.v15.i3.pp1375-1385

A deep learning approach for electric vehicle battery charging duration estimation using IoT

Tumuluri Kanthimathi[1], Adhimoolam Sairam[2], Durairaj Chandrakala[3], Moorthy Radhika[4], Bichagal Shadaksharappa[5], Pitchai John Britto[6], Minakshi Sanadhya[7], Balasubramanian Suganya[8], Chelliah Srinivasan[9]

[1]Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation, Guntur, India
[2]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India
[3]Department of Electrical and Electronics Engineering, Easwari Engineering College, Chennai, India
[4]Department of Information Technology, R.M.D. Engineering College, Chennai, India
[5]Department of Computer Science and Engineering, Sri Sairam College of Engineering, Bengaluru, India
[6]Department of Electrical and Electronics Engineering, J.J. College of Engineering and Technology, Tiruchirappalli, India
[7]Department of Electronics and Communication Engineering, Faculty of Engineering and Technology, SRM Institute of Science and Technology, Delhi-NCR Campus, Ghaziabad, India
[8]Department of Computer Science and Engineering, School of Computing, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India
[9]Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India

Article Info

Article history:

Received Dec 3, 2025
Revised Jul 10, 2026
Accepted Aug 15, 2026

Keywords:

Charging duration estimation
Deep learning
Electric vehicles
Energy management
Internet of things
Smart mobility

ABSTRACT

The rapid development of electric vehicles (EVs) has increased the desire for precise charging duration estimate to enhance charging station administration and elevate customer experience. This research presents a deep learning (DL) architecture that uses internet of things (IoT)-enabled data to categorise charging duration into short, medium, and long classifications. The assessment dataset comprises many numerical and categorical variables affecting battery performance and charging behaviour, providing a thorough foundation for prediction. The system utilises a deep neural network (DNN) architecture with nonlinear transformations and regularisation techniques, trained with adaptive optimisation to provide durable convergence. Extensive experiments indicate that the proposed model achieves an overall accuracy of 99.26%, markedly improving traditional machine learning (ML) techniques. These results highlight the potential of DL to adeptly discern complex linkages in charging dynamics, providing dependable predictions for duration classification. The framework provides an advanced basis for implementation in smart charging infrastructures, facilitating effective scheduling, minimizing waiting times, and endorsing predictive maintenance measures. It enhances the reliability and efficiency of EV charging ecosystems with data-driven, IoT-enabled DL technologies.

Corresponding Author:

Tumuluri Kanthimathi
Department of Mechanical Engineering, Koneru Lakshmaiah Education Foundation
Vaddeswaram, Guntur, Andhra Pradesh, India
Email: pkanthi1978@gmail.com

1. INTRODUCTION

EVs are seeing tremendous growth owing to environmental considerations and advancements in battery technology. Effective billing management is essential to minimise waiting times and enhance customer experience. Conventional machine learning methods, such as KNN and Naive Bayes, often struggle to identify intricate patterns within IoT-enabled information. IoT devices provide real-time battery and environmental information, enabling predictive analytics for enhanced charging efficiency. Precisely calculating charging period is difficult owing to several dynamic elements, including battery state-of-charge, temperature, battery age, and charger type. Conventional machine learning models often exhibit restricted accuracy and generalisation, which impairs effective scheduling and predictive maintenance. The primary contributions of this study are:

i) Integration of IoT data: Employing real-time data from various sensors monitoring battery and ambient conditions.
ii) Deep learning architecture: Utilizing DNN to simulate intricate relationships among diverse features.
iii) Enhanced predictive precision: Attaining superior accuracy and an elevated F1-score, beyond conventional machine learning methodologies.
iv) Practical applicability: Establishing a framework for intelligent charge scheduling and anticipatory maintenance.

The following parts of this paper are organised as follows. Section 2 examines relevant studies on EV charging estimates and IoT solutions. Section 3 outlines the proposed DL framework and preprocessing methodologies. Section 4 delineates the dataset and experimental technique, highlighting the framework's efficacy. Section 5 concludes the work and proposes future research directions in smart charging systems.

To enhance pack performance, this work introduces an active cell balancing strategy for EVs that reduces capacity and accelerates deterioration [1]. The method involves dispersing surplus charge from high-SOC cells and increasing discharge time from low-SOC cells. To address the challenge of controlling the online charging of numerous EV at once in an unpredictable charging environment with erratic EV arrivals and departures, this proposes a multi-agent deep reinforcement learning-based charging scheduling approach for EV charging stations [2]. By lowering capacity and speeding up degradation, this work introduces an active cell balancing strategy for EV that improves pack performance by spreading surplus charge from high-SOC cells and extending discharge duration from low-SOC cells [1]. Examining aspects such as precision, testing conditions, input/output, and data quality, this research assesses feed-forward neural networks (FFNNs) for ML-based EV state of charge and health estimate [3]. A new ML algorithm for estimating the RUL of EV lithium-ion batteries [4]. Random forest, K-Nearest neighbours, and gradient boosting decision tree are some of the artificial neural networks (ANNs) used in the framework, which also incorporates ANNs for feature extraction and ensemble modelling. Focussing on aspects such EV battery health, function, and remaining usable life, the article explains how to optimise EV battery performance using predictive ML approaches [5]. Because of their rapid depletion cost, technical developments, high energy and power density, and suitability for electric mobility, lithium-ion batteries are perfect [6]. Without taking electrochemical properties into account, an ML system is created to estimate the state of health from voltage, current, and temperature utilizing KNN, SVR, DT, and RF regressors. By constructing a smart charging hub network utilising dynamic K-means clustering, this research introduces a new method for charging EVs [7]. Static clustering systems are inefficient and cause charging station loads since EV use patterns are unpredictable. A charge scheduling system for EV fleets that maximizes remaining useful life (RUL) for all batteries and reduces greenhouse gas emissions [8]. Making sure that charging one car as late as feasible maximizes RUL, the strategy utilizes two optimization methods and an ML model.

Optimization approaches for lithium-ion battery management in EVs are investigated in this comprehensive mapping research [9]. Improving battery dependability, prolonging longevity, and optimizing energy management requires combining advanced filtering techniques, ML, and optimization algorithms. Improving efficiency, reducing energy consumption, and extending battery longevity are some of the goals of this paper's exploration of artificial intelligence (AI) and ML approaches to optimising EV battery charging operations [10]. A more efficient approach for managing EV batteries is developed by the research team using IoT, ML, and blockchain technology [11]. Databases, the lightGBM classifier, and a power scheduling method are used to process data collected by IoT sensors, which include information on the vehicle's position, charge level, and distance travel. This study introduces a fuzzy approach for controlling the charging and discharging of lithium-ion batteries used in EVs [12]. The purpose of this study was to examine the true energy consumption of commercial BEVs in Thailand by testing them in real-world scenarios on several routes, including urban and rural ones [13]. The data was collected using onboard diagnostics and GPS equipment. To help with mission planning and uncover the reasons for rapid ageing, this research study employs a customised neural network to assess the state of health (SOH) of an EV fleet using field data [14]. To mitigate uncertainty and prioritise the needs of the client, this study introduces a fuzzy multi-criteria decision-making approach for choosing a sustainable battery provider for BSS. The approach makes use of triangular fuzzy numbers (TFN) and quality function deployment (QFD) [15]. To charge EV batteries more efficiently, our study suggests a novel approach [16]. By regulating the current that flows from the PV array to the EV battery and back to the grid, the bidirectional converter's fuzzy logic controller (FLC) makes charging and discharging processes as efficient as possible. Focusing on state-of-the-art ML regression models, this work investigates the shortcomings of conventional approaches to EV battery state-of-charge estimation [17]. For managing power grid congestion in Europe, this study suggests an intelligently regulated BEV charging strategy [18]. This paper examines EVs and evaluates current charging methods, with an emphasis on hybrid car designs and recharging infrastructure [19]. To help infrastructure operators optimize EV charging methods examines the durations of EV charge events in Greater Manchester, exposing the effects of weather and seasons on charging behavior [20]. This study suggests a service mode architecture to provide grid-friendly electric vehicle charging for users [21]. Use optimization methods based on stochastic variables to control the flow of EV charging and discharging in car parks [22]. The purpose of this research is to find the best deep learning model for predicting when EVs will arrive at charging stations and how long it will take them to charge [23]. The development of electric vehicle technology enables independent wheel torque control, offering a unique opportunity to improve vehicle stability and manage through torque vectoring [24].

2. METHOD

The proposed system for estimating EV charging duration functions as a comprehensive view that incorporates IoT-enabled data acquisition, data preprocessing, DNN modelling, training with adaptive optimization, and the ultimate classification of charging duration into short, medium, and long categories. The research employs lithium-ion (Li-ion) batteries, represented by a simplified equivalent circuit model (ECM). The voltage of the battery when charging is denoted as (1).

$$V(t) = V_{\text{OCV}} - I(t) \cdot R \tag{1}$$

Where V_{OCV} is the open-circuit voltage, $I(t)$ is the charging current, and R is the internal resistance. These features, along with environmental parameters, were used to train the DNN for classifying charging duration. Figure 1 illustrates the proposed system, which begins with IoT-enabled data collection from charging stations, collecting key operational information on EV. The raw data is processed to preprocessing, which includes cleaning, normalization, and encoding, to guarantee quality and consistency. The processed data is further analyzed by a DNN, which identifies hidden relationships and categorises charging time into short, medium, or long categories. The predicted outputs facilitate applications such as real-time user assistance, intelligent scheduling, and predictive maintenance within EV charging infrastructure.

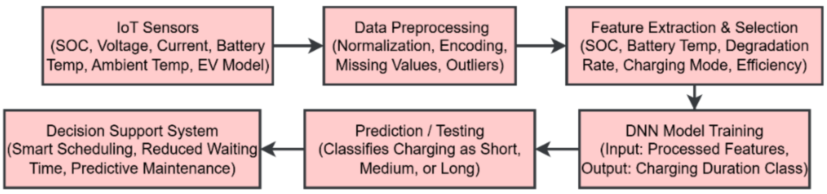

Figure 1. Workflow of the IoT-enabled charging duration prediction system

The process begins with IoT devices integrated into the charging infrastructure, which incessantly monitor diverse operational and contextual aspects throughout the charging procedure. The raw measurements are sent to a centralised compute unit, either in the cloud or at the edge, where preprocessing occurs to ensure the dataset is clean, standardised, and appropriate for input into the DL model. Preprocessing encompasses many stages, first with data cleaning to address absent or inconsistent values using imputation or filtering methods, succeeded by normalisation to adjust continuous values into a uniform numerical range. A conventional normalisation method, such as min–max scaling, is expressed as (2).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{2}$$

Where x is the original feature value, x_{max} and x_{min} denote the lowest and maximum values for that feature, whereas x' represents the normalized output. This guarantees that all numerical characteristics contribute equitably during model training. One-hot encoding is utilized for category information like car kind or charging mode, transforming symbolic categories into binary vectors that remove undesired ordinal correlations. Resampling procedures are employed to rectify the imbalance across target classes, ensuring a more consistent distribution of short, medium, and long charging durations, thereby enhancing the model's generalization. Upon completion of preprocessing, the dataset is divided into training, validation, and test subsets, guaranteeing stratification across duration categories. The predictive foundation of the framework is a feed-forward DNN with numerous hidden layers, engineered to identify nonlinear relationships between input parameters and charging duration categories. Every concealed layer does a linear translation of its inputs, subsequently applying a nonlinear activation function. The output of a hidden layer is calculated mathematically as (3).

$$z^{(l)} = W^{(l)}x^{(l-1)} + b^{(l)}\,,\ a^{(l)} = f\left(z^{(l)}\right) \tag{3}$$

Where $W^{(l)}$ is the weight matrix of layer l, $b^{(l)}$ is the bias vector, and $x^{(l-1)}$ is the input from the preceding layer, $z^{(l)}$ represents the pre-activation linear combination, whereas $a^{(l)}$ denotes the post-activation output. The selected activation function for the hidden layers is the rectified linear unit (ReLU), defined as (4).

$$f(z) = max(0, z) \tag{4}$$

Figure 2 shows that the DNN processes pre-processed IoT data via many fully linked hidden layers utilising ReLU activation, batch normalization, and dropout techniques to discern complex patterns. The final output layer uses softmax activation to classify charging duration into short, medium, or long classifications, facilitating precise predictions for EV charging management.

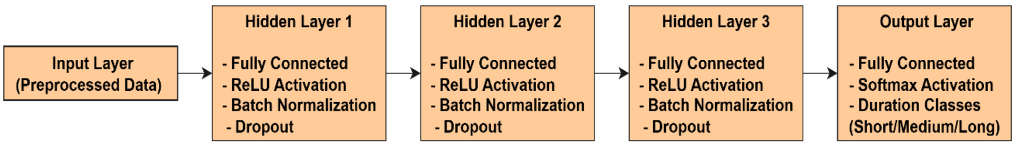

Figure 2. DNN architecture for charging duration prediction

It integrates nonlinearity and mitigates saturation problems prevalent with sigmoid or hyperbolic tangent functions. To enhance stability and convergence, batch normalization may be implemented after each linear transformation, standardizing intermediate outputs prior to activation. To prevent overfitting, dropout regularisation is utilized, randomly disabling a percentage of neurones during training to enable the network to acquire more generalisable representations. In the final stage of the network, a softmax layer is used to provide a probability distribution over the three potential classes of charging duration. The softmax function is defined as (5).

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \tag{5}$$

Where z_i is the logit associated with class i, where K is the total number of classes. This guarantees that the total of probabilities equals one and that each anticipated output may be understood as the probability of belonging to a certain class. The aim of the proposed training framework is to minimize the categorical cross-entropy loss function, which measures the disparity between predicted class probabilities and the actual one-hot encoded labels. The loss function is represented as (6).

$$L = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \tag{6}$$

Where y_i represents the ground truth label for class i and $\hat{y}_i$ denotes the predicted probability for that category. By optimizing this function, the network acquires the capacity to enhance the likelihood of the accurate duration class. The adaptive moment estimation (Adam) technique is utilized to optimise the network parameters. Adam integrates the advantages of momentum and RMSProp by sustaining running averages of both the first instant (mean) and the second moment (uncentered variance) of gradients. The parameter updating rule for Adam is presented as (7).

$$\theta_{t+1} = \theta_t - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}} \tag{7}$$

Where θ_t denotes the model parameters at time step t, α represents the learning rate, and $\widehat{m}_t$ signifies the variable $\widehat{m}_t$ time step t, $\hat{v}_t$ is the bias-corrected first moment estimation. It is the bias-corrected second moment estimate, and ϵ is a negligible constant to prevent division by zero. This adaptive technique enhances convergence velocity and stability relative to conventional stochastic gradient descent.

Training is conducted by mini-batch learning, wherein the dataset is partitioned into smaller batches to achieve a compromise between computing efficiency and convergence stability. Backpropagation is employed during training to calculate the gradient of the loss function concerning each parameter. The chain rule of differentiation is utilized sequentially, transmitting the mistake backward through the network to facilitate the adjustment of weights and biases in accordance with the Adam optimisation algorithm. Early stopping serves as a precautionary measure, halting training when validation loss does not improve over a certain number of epochs, thereby averting overfitting.

After completion of training, the deployed model may receive real-time IoT data from charging stations. The data is subjected to the identical preparation procedure as the training data before being input into the trained neural network. The model generates probability values for each duration class, and the class with the highest probability is designated as the projected category. These forecasts are conveyed to both EV drivers and charging station owners. The solution offers customers accurate charging time estimations to enhance planning and convenience, while enabling operators to intelligently schedule charging slots, optimize resource allocation, and forecast infrastructure demand. Furthermore, discrepancies between predicted and actual durations can be examined to identify abnormalities, potentially indicating battery deterioration, inefficiencies, or equipment failures, thereby facilitating predictive maintenance approaches. Table 1 illustrates the proposed DNN, detailing the units, activation functions, and regularisation procedures for each layer, illustrating the network's transformation of input data to predict short, medium, or long charging periods. Table 2 shows essential battery metrics gathered from IoT sensors, used for training and testing the DNN for duration prediction.

Table 1. Proposed DNN architecture parameters

Layer	Units	Activation	Regularization
Input	64	–	–
Hidden 1	128	ReLU	Dropout, BatchNorm
Hidden 2	128	ReLU	Dropout, BatchNorm
Hidden 3	64	ReLU	Dropout, BatchNorm
Output	3	Softmax	–

Table 2. EV battery parameters used for DNN training and testing

Parameter	Description/Units	Values
Battery type	Chemistry of the battery	Li-ion, LiFePO4
Capacity	Maximum energy storage	50–100 Ah
Nominal voltage	Rated voltage	3.7 V
State-of-charge (SOC)	Current charge level	0–100%
Charging cycles	Number of full charge-discharge cycles	50–500
Battery temp	Temperature during charging	20–45 °C
Degradation rate	Battery aging effect (%)	0–5%
Efficiency	Energy efficiency (%)	85–98%
EV model	Vehicle model	Model A, B, C

3. RESULTS AND DISCUSSION

This dataset [25] contains information related to the charging characteristics of EV batteries. The dataset includes several aspects influencing battery performance, deterioration, and charging duration, as well as the objective variable denoting the categorisation of optimal charging duration. The dataset has both numerical and category attributes, designed for analytical or predictive purposes. Optimal charging duration class are:

- 0 → Short (≤40 min)
- 1 → Medium (≤80 min)
- 2 → Long (>80 min)

Figure 3 shows the correlation between battery state-of-charge (SOC) and efficiency, demonstrating that efficiency stays continuously elevated throughout diverse SOC levels, signifying steady performance over varied charge levels. Figure 4 illustrates the relationship between battery SOC and charging cycles, emphasizing the variety in usage patterns and demonstrating how various SOC levels relate to a spectrum of battery cycles. Table 3 illustrates the distribution of charging duration classes, showing a slight imbalance, with medium and long durations occurring more frequently than short-duration data.

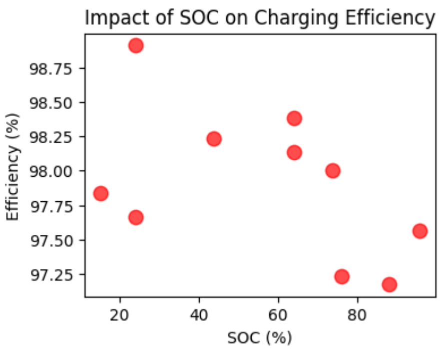

Figure 3. Battery efficiency

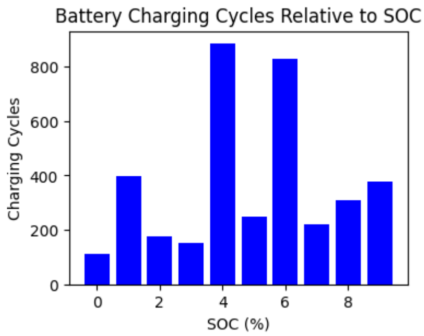

Figure 4. Charging cycles

Table 3. Sample count per charging duration class

Class	Count	Percentage (%)
Short (0)	201	20.1
Medium (1)	404	40.4
Long (2)	395	39.5
Total	1000	100

In this approach, random oversampling is utilized to address class imbalance in optimal charging duration categories. The dataset initially had a fewer number of samples in the "Short" class relative to the "Medium" and "Long" classes, potentially biasing the DNN towards the majority classes. By equalizing the numbers across all categories, the model acquires patterns uniformly across all classes. This ensures dependable classification of short, medium, and long charging intervals, improves equity, reduces bias, and enhances the overall robustness of the proposed DNN-based predictive system. Table 4 shows the method in which random oversampling equilibrates class distribution to 404 for each category. Data is constantly divided into training, validation, and testing sets using 70:15:15 split. This equitable division enables the DNN to learn equally from all classes, mitigates bias towards any certain length, and facilitates dependable assessment of model efficacy on novel data while preserving class consistency across all subsets.

Table 4. Balanced dataset split using random oversampling

Class	Original count	After random oversampling count	Train (70%)	Validation (15%)	Test (15%)
Short (0)	201	404	283	61	60
Medium (1)	404	404	283	61	60
Long (2)	395	404	283	61	60
Total	1000	1212	849	183	180

Figure 5 illustrates the DNN confusion matrix, which indicates a high level of accuracy in classifying EV charging periods. Among 60 samples per test class, only a limited number of misclassifications were observed: two short sessions were predicted as medium or lengthy, while one medium session was forecasted as short. This suggests that overlapping battery states or analogous environmental factors intermittently influence class difference. The model accurately predicted long-duration sessions, demonstrating its resilience and dependability in differentiating charging time groups.

The DNN confusion matrix demonstrates exceptional classification accuracy, with 177 of 180 samples accurately predicted. There were only three misclassifications: two in the short category and one in the medium category, whilst the long durations attained flawless accuracy. This illustrates the model's stability, high generalisation, and dependable performance in forecasting optimal EV battery charging periods across all categories. Figure 6 illustrates the DNN accuracy graph, which demonstrates a consistent rise in training accuracy throughout epochs, with validation accuracy closely aligning, signifying robust learning, convergence, and minimal overfitting. Figure 7 illustrates the loss graph, demonstrating a continuous decrease in both training and validation loss across the epochs, signifying successful learning, high convergence, low overfitting, and robust generalisation of the DNN model.

The DNN accuracy graph indicates a continuous increase in training accuracy, achieving 98.89% at epoch 100, while validation accuracy stands at 98.3%. This signifies efficient learning, robust convergence, and minimal overfitting, illustrating the model's capacity to generalise effectively and accurately categorize EV charging durations across all categories. The DNN loss graph indicates that the training loss decreases to 0.011 and the validation loss to 0.017 at the 100th epoch. This consistent reduction signifies excellent learning, high convergence, and small overfitting, validating the model's stability and dependable generalization for precise categorization of EV battery charging times. Figure 8 illustrates a comparison across KNN, Naive Bayes [26], and DNN, indicating that the proposed DNN achieves the highest accuracy in addition to balanced precision, recall, and F1-score.

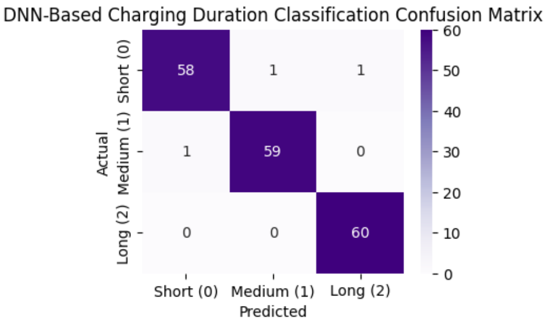

Figure 5. DNN confusion matrix for EV charging classification

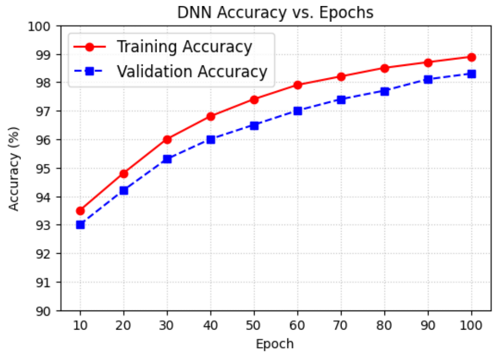

Figure 6. Accuracy of DNN over epochs

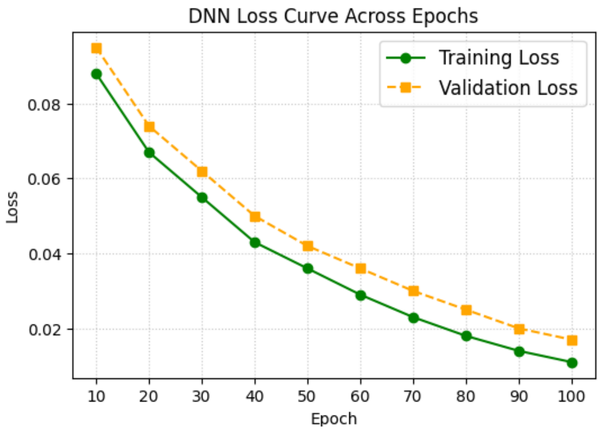

Figure 7. DNN model loss convergence

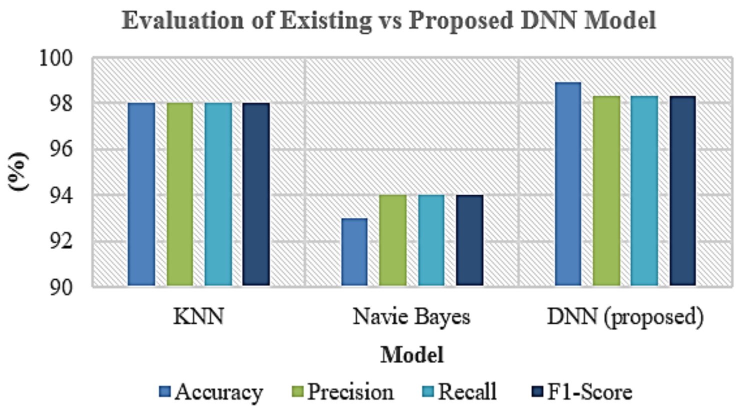

Figure 8. Comparison of ML models performance

The DNN model attains an overall accuracy of 98.89%, with precision, recall, and F1-score at 98.33%, exceeding classic machine learning techniques include KNN (98% accuracy) and naive bayes (93% accuracy). This illustrates the DNN's exceptional capacity to discern nonlinear and intricate correlations among several IoT-enabled factors influencing battery performance. Short charging sessions show minimal prediction errors, but medium and extended sessions demonstrate considerable variability attributable to user behaviour. The integration of IoT data improves performance. This platform enhances scheduling, minimises wait times, and facilitates predictive maintenance for effective EV charging systems. The research utilizes data from a single source (Kaggle), which may not include all electric vehicle types or actual environmental conditions. This may generate bias in forecasts in unrepresented circumstances.

4. CONCLUSION

This paper presents a DL framework using IoT and DNN to forecast optimal charging times for EV batteries. The system efficiently combines preprocessing, feature analysis, and balanced dataset management using random oversampling, providing equal representation of each class. DNN has enhanced performance relative to conventional ML models such KNN and Naive Bayes, with a training accuracy of 98.89%, with precision, recall, and F1-score over 98.33%. The training and validation accuracy and loss curves demonstrate significant convergence, little overfitting, and high generalization to unseen data. The study of the confusion matrix further substantiates the model's dependability, revealing only a limited number of misclassifications among the short, medium, and long charging time categories. The proposed framework's capacity to identify complex nonlinear correlations in EV battery data facilitates precise and reliable predictions of charging times, hence improving battery efficiency and user experience. The IoT-enabled DNN delivers precise forecasts of charge durations, enabling efficient scheduling and predictive maintenance. Future research should use multi-source information, investigate adaptive charging techniques, and account for grid and renewable energy limitations to develop more intelligent EV charging systems.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Tumuluri Kanthimathi	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Adhimoolam Sairam				✓	✓					✓		✓		
Durairaj Chandrakala	✓								✓					
Moorthy Radhika		✓				✓			✓					
Bichagal Shadaksharappa	✓					✓				✓	✓			
Pitchai John Britto		✓			✓				✓				✓	
Minakshi Sanadhya						✓				✓				
Balasubramanian Suganya					✓					✓		✓		
Chelliah Srinivasan		✓				✓				✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [TK], upon reasonable request.

REFERENCES

[1] Y. A. Sultan, A. A. Eladl, M. A. Hassan, and S. A. Gamel, “Enhancing electric vehicle battery lifespan: integrating active balancing and machine learning for precise RUL estimation,” *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-024-82778-w.

[2] Y. Li, Z. Zhang, and Q. Xing, “Real-time online charging control of electric vehicle charging station based on a multi-agent deep reinforcement learning,” *Energy*, vol. 319, p. 135095, Mar. 2025, doi: 10.1016/j.energy.2025.135095.

[3] G. Anilkumar, N. Ramakrishna, K. Suresh, S. Sreedevi, G. Jaswanthkumar, and P. S. Brahmanandam, “Revolutionizing EV battery management through machine learning approach-a case study,” *AIP Conference Proceedings*, vol. 3298, no. 1, 2025, doi: 10.1063/5.0279357.

[4] W. Huang, T. Zhou, J. Ma, and X. Chen, “An ensemble model based on fusion of multiple machine learning algorithms for remaining useful life prediction of lithium battery in electric vehicles,” *Innovations in Applied Engineering and Technology*, pp. 1–12, Mar. 2025, doi: 10.62836/iaet.v4i1.319.

[5] V. S. Naresh, G. V. N. S. R. Ratnakara Rao, and D. V. N. Prabhakar, “Predictive machine learning in optimizing the performance of electric vehicle batteries: techniques, challenges, and solutions,” *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 14, no. 5, 2024, doi: 10.1002/widm.1539.

[6] K. Das, R. Kumar, and A. Krishna, “Analyzing electric vehicle battery health performance using supervised machine learning,” *Renewable and Sustainable Energy Reviews*, vol. 189, p. 113967, Jan. 2024, doi: 10.1016/j.rser.2023.113967.

[7] V. Srividhya, S. Gowriswari, N. V. Antony, S. Murugan, K. Anitha, and M. Rajmohan, “Optimizing electric vehicle charging networks using clustering technique,” in *2024 2nd International Conference on Computer, Communication and Control (IC4)*, IEEE, Feb. 2024, pp. 1–5, doi: 10.1109/IC457434.2024.10486422.

[8] N. Naveenkumar, V. Sridevi, R. Bharathi, N. Mishra, S. Murugan, and S. Velmurugan, “Cloud-integrated clean fuel generation for solar-hydrogen production with wireless sensor networks,” in *7th International Conference on Inventive Computation Technologies, ICICT 2024*, 2024, pp. 1617–1622, doi: 10.1109/ICICT60155.2024.10544659.

[9] C. Tripp-Barba, J. A. Aguilar-Calderón, L. Urquiza-Aguiar, A. Zaldívar-Colado, and A. Ramírez-Noriega, “A systematic mapping study on state estimation techniques for lithium-ion batteries in electric vehicles,” *World Electric Vehicle Journal*, vol. 16, no. 2, 2025, doi: 10.3390/wevj16020057.

[10] H. P. Bhupathi and S. Chinta, “AI-powered efficiency machine learning techniques for EV battery charging,” *Article in ESP Journal of Engineering & Technology Advancements*, 2025, doi: 10.56472/25839233/IJAST-V2I3P107.

[11] K. Sujit, K. C. Ramaswamy, S. R. Mathiyalagan, J. Giri, and M. Kanan, “An efficient battery management system for electric vehicles using IoT & blockchain,” *Results in Engineering*, vol. 27, p. 106284, Sep. 2025, doi: 10.1016/j.rineng.2025.106284.

[12] A. Zaineb, M. Vijayasanthi, and P. N. Mandadi, “Fuzzy logic controller based charging and discharging control for battery in EV applications,” *International Journal of Electrical and Electronics Research*, vol. 12, no. 1, pp. 1–7, Jan. 2024, doi: 10.37391/ijeer.120101.

[13] W. Achariyaviriya *et al.*, “Estimating energy consumption of battery electric vehicles using vehicle sensor data and machine learning approaches,” *Energies*, vol. 16, no. 17, p. 6351, Sep. 2023, doi: 10.3390/en16176351.

[14] T. Lehmann and F. Weiß, “Lithium-ion battery aging analysis of an electric vehicle fleet using a tailored neural network structure,” *Applied Sciences*, vol. 13, no. 7, p. 4448, Mar. 2023, doi: 10.3390/app13074448.

[15] K. Koirala and Shabbiruddin, “Optimal selection of sustainable battery supplier for electric vehicle battery swapping station,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 45, no. 1, pp. 2206–2227, Apr. 2023, doi: 10.1080/15567036.2023.2185702.

[16] A. Karthikeyan, N. S. Vanitha, T. Meenakshi, R. Ramani, and S. Murugan, “Electric vehicle battery charging in grid system using fuzzy based bidirectional converter,” in *2023 3rd International Conference on Innovative Mechanisms for Industry Applications (ICIMIA)*, IEEE, Dec. 2023, pp. 1447–1452, doi: 10.1109/ICIMIA60377.2023.10426581.

[17] H. Gaikwad, J. R. Saini, and H. Gaikwad, “Predictive modeling of Li-ion battery state of charge in electric vehicles: study of modern machine learning regressors,” *Smart Innovation, Systems and Technologies*, vol. 395 SIST, pp. 441–455, 2024, doi: 10.1007/978-981-97-5081-8_34.

[18] R. Raman, S. Muthumarilakshmi, G. Jethava, R. Jagtap, M. Lalitha, and S. Murugan, “Energy monitoring in solar-powered buildings using internet of things,” in *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, 2023, pp. 318–322, doi: 10.1109/SmartTechCon57526.2023.10391826.

[19] M. Naoui, A. Flah, L. Sbita, M. Ben Hamed, and A. T. Azar, “Intelligent control system for hybrid electric vehicle with autonomous charging,” *Studies in Computational Intelligence*, vol. 1093, pp. 405–437, 2023, doi: 10.1007/978-3-031-28715-2_13.

[20] Y. Ali, F. Monsuur, C. Morton, and C. K. Man, “Modelling electric vehicle charging events using a random parameter duration approach,” *Travel Behaviour and Society*, vol. 39, 2025, doi: 10.1016/j.tbs.2025.100989.

[21] Z. Fu, X. Liu, J. Zhang, T. Zhang, X. Liu, and Y. Jiang, “Orderly solar charging of electric vehicles and its impact on charging behavior: a year-round field experiment,” *Applied Energy*, vol. 381, 2025, doi: 10.1016/j.apenergy.2024.125211.

[22] M. Nikzad and A. Samimi, “Assessment of time-based demand response programs for electric vehicle charging facilities,” *Renewable Energy Focus*, vol. 53, p. 100693, Jun. 2025, doi: 10.1016/j.ref.2025.100693.

[23] A. T. Yapıcı, N. Abut, and T. Erfidan, “Comparing the effectiveness of deep learning approaches for charging time prediction in electric vehicles: Kocaeli example,” *Energies*, vol. 18, no. 8, 2025, doi: 10.3390/en18081961.

[24] R. Sudharsan *et al.*, “Modelling and simulation of torque vectoring in electric vehicles for enhanced stability,” *International Journal of Advances in Signal and Image Sciences*, vol. 12, no. 1s, pp. 483–495, Jan. 2026, doi: 10.29284/ijasis.12.1s.2026.483-495.

[25] Ziya, “EV_battery_charging_data.” 2025. [Online]. Available: https://www.kaggle.com/datasets/ziya07/ev-battery-charging-data

[26] A. V. Panchbhai, R. Raman, C. B. Thacker, S. Muthumarilakshmi, and S. Murugan, “Residential electric vehicle charging station using the internet of things,” in *2023 International Conference on Power Energy, Environment and Intelligent Control, PEEIC 2023*, 2023, pp. 987–991, doi: 10.1109/PEEIC59336.2023.10450569.

BIOGRAPHIES OF AUTHORS

Dr. Tumuluri Kanthimathi is an assistant professor in the Department of Mechanical Engineering and professor-in-charge (Academics at Koneru Lakshmaiah Education Foundation (KLEF), Vaddeswaram, Guntur Dist., Andhra Pradesh, India. She obtained B.E. in mechanical engineering in the year 2000 from Sir C.R.R College of Engineering, Eluru, affiliated to Andhra University, M.Tech. in thermal engineering in the year 2011 from JNTU Hyderabad, and Ph.D. in the year 2024 from JNTU Hyderabad in the area of heat transfer. She has 18 years of teaching experience in both undergraduate and postgraduate levels. She has guided many B.E. and M.E. projects. She has published 25 articles in various national and international journals. She has expertise in the subjects like thermodynamics, fluid mechanics, heat transfer, and applied thermodynamics. She has memberships in ISHRAE and SAE professional bodies. She can be contacted at email: pkanthi1978@gmail.com.

Dr. Adhimoolam Sairam completed his B.E., M.E., and Ph.D. in computer science and engineering and is currently serving as a professor in the Department of Computer Science and Engineering, SIMATS Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, India. He has 18 years of teaching experience in higher education and has been actively involved in teaching, research, curriculum development, and mentoring undergraduate and postgraduate students. His academic interests include computer science and engineering, web technologies, artificial intelligence, machine learning, data science, cybersecurity, IoT, and cloud computing. He has made significant research contributions, having published more than 30 research papers in reputed international journals and international conference proceedings. He has also guided numerous student projects, participated in faculty development programs, and contributed to various academic and research activities. He can be contacted at email: dr.a.sairaam@gmail.com.

Durairaj Chandrakala is working as an assistant professor in Easwari Engineering College, Chennai, Tamil Nadu. She awarded B.E. degree in electrical and electronics engineering from Arulmigu Kalasalingam College of Engineering, Krishnankoil, Virudhunagar District, Tamil Nadu, in the year 2000 and M.E. degree in applied electronics from Coimbatore Institute of Technology, Coimbatore, Tamil Nadu, in the year 2007. She has 20+ years of teaching experience. Also, she is currently doing part time - Ph.D. degree in Faculty of Electronics and Communication Engineering, Anna University, Chennai, Tamil Nadu, India. She has published 14 patents and presented/published around 50+ papers in Journals and conferences. Her research interests include cybersecurity, smart grid, and implementation of optimization techniques in power system engineering. She can be contacted at email: chandrakala.d.eee@gmail.com.

Moorthy Radhika is an assistant professor in Department of Information Technology at R.M.D. Engineering College. She obtained her Bachelor's of Technology degree in information technology from Bhajarang Engineering College and Master of Engineering degree in computer science and engineering from Velammal Engineering College. She is currently pursuing her Ph.D. degree from Anna University. Her areas of interest include big data, machine learning, database management system, and data structure. She has published 5 papers in international journals and conferences. She can be contacted at email: radikamoorthi@gmail.com.

Dr. Bichagal Shadaksharappa currently working as the principal of Sri Sairam College of Engineering (Formerly Shirdi Sai Engineering College), Anekal, Bangalore. He has obtained his under graduation in CSE, master of science in software systems, and Ph.D. in CSE. He has rich academic and research experience for about 27 years. He is actively involved in guiding Ph.D. candidates in the field of CSE. He has published and presented many research papers in national and international conferences and reputed journals. He has many patents to his credit. He has published more than 60 papers in reputed national and international journals and he has published 17 books for VTU students as well; he has filed 17 patents. As an academician, he has served in different capacities as lecturer, senior lecturer, asst. professor, and HOD spanning about 20 years. He has administrative experience as vice principal for 9 years and as principal for 6 years. He can be contacted at email: shadbichagal@gmail.com.

Pitchai John Britto is an assistant professor in Department of Electrical and Electronics Engineering at J. J. College of Engineering and Technology. He obtained his Bachelors of Technology degree in electrical and electronics engineering at National Institute of Technology-Tiruchirapalli and Master of Engineering degree in power electronics and drives at J. J. College of Engineering and Technology, Anna University. His area of interest is power electronics. He has published 1 international journal and 05 national conferences. He can be contacted at email: johnbritto15061980@gmail.com.

Dr. Minakshi Sanadhya received her B.Tech. in applied electronics and instrumentation from M.I.T. Engineering College, Kota in 2008 and her M.Tech. degree from SRM University, Chennai in 2010. She completed her Ph.D. in 2023. Her research interests include digital circuit design and VLSI. Currently, she is working as an assistant professor at SRM Institute of Science and Technology, Delhi NCR Campus, Ghaziabad, India. She can be contacted at email: minakshisanadhya@gmail.com.

Dr. Balasubramanian Suganya is an assistant professor in the Department of Computer Science and Engineering at Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India. She received her bachelor's degree in computer science and engineering from Anna University, Chennai, India. She then obtained her master's degree in computer science and engineering from Vinayaga Missions University, Salem, India. She received her Ph.D. in the Faculty of Information and Communication Engineering from Anna University, Chennai, India. Her areas of interest include blockchain technology, internet of things, and data analytics. She has published few journal papers and conference proceedings. She is an IEEE member. She can be contacted at email: drsuganyab@veltech.edu.in.

Chelliah Srinivasan is an adjunct professor at the Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India. His research areas include image processing, signal processing, pattern recognition, and deep learning. He published a book 'Digital Image Processing' by Dipti Press OPC Private Limited. He published his research articles in many international and national conferences and journals. He can be contacted at email: srinivasanchelliah@gmail.com.