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A systematic review and meta-analysis of machine learning, deep learning, and ensemble learning approaches in predicting EV charging behavior

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ABSTRACT

Machine learning (ML) and deep learning (DL) have enabled algorithms to autonomously acquire knowledge from data, facilitating predictive and decision-making capabilities without explicit programming. This transformative potential has reshaped industries by utilizing data-driven insights. ML and DL models have found extensive application within the domain of electric vehicle (EV) charging predictions. These techniques effectively forecast EV charging behavior, considering variables such as charging station location, time of day, battery state of charge, EV owner behavioral patterns, and weather conditions. This study aims to comprehensively evaluate ML and DL applications in forecasting EV charging behavior while introducing a systematic categorization, a notable gap in current literature. A comprehensive dataset, selected from both the Web of Science and the Scopus database, sourced from Elsevier Journal, was thoughtfully chosen to cover relevant research studies for the purpose of achieving this goal. Furthermore, our research emphasizes the significance of model evaluation and explores the usefulness of commonly employed ML and DL techniques within forecasting approaches, including Short-Term Load Forecasting (STLF), Medium-Term Load Forecasting (MTLF), and Long-Term Load Forecasting (LTLF) to ensure precise predictions. Within this framework, the selected publications are classified based on methodology, research focus, objectives, publication year, geographic origin, and research outcomes. While both ML and DL techniques exhibit substantial potential in predicting EV charging behavior and mitigating challenges posed by the rising adoption of EVs, our analysis demonstrates that ensemble learning techniques surpass them in terms of predictive performance.

1. Introduction

The advent of electric vehicles (EVs) represents an essential change and the beginning of a new phase in the evolution of the automotive industry (Emanovi et al., 2022). According to United Nations estimates, by 2050, two-thirds of the world's inhabitants will live in towns, increasing the need for transportation within cities and the use of fossil fuels and Greenhouse Gas (GHG) pollution (Shahriar et al., 2021; Aggarwal and Singh, 2021). The crucial need to decrease GHG emissions has led to a broader acceptance of eco-friendly transportation options (Dimitriadou et al., 2023). A Chinese study found that EVs are effective in reducing GHG emissions compared to internal combustion engine vehicles (ICEV) (Zhang et al). Now, EVs are more practical for commuting and short-distance traveling due to the developments in battery technology, making them leaders in offering clean transportation. Establishing fully prepared charging stations is a top priority for EVs, considering range anxiety, the availability of charging infrastructure, and the shortest possible charge time (Pillai and Bak--Jensen). However, the longer charging times of EVs compared to ICEV present a challenge. Besides, not only will managing the electrical power source (EPS) be difficult when the number of EVs increases in the system but also EVs will affect electricity market pricing and consumption; therefore, the main significant problem of EPS is forecasting EV charging demand accurately (Alquthami et al., 2022). In response to these challenges, scientists have started utilizing Machine Learning (ML) techniques to tackle problems related to charging infrastructure planning, including the placement of charging stations, predicting charging demand and scheduling charging (Deb). Furthermore, DL, a subfield of ML that aims to develop the capability of learning algorithms to handle complex data using artificial neural networks with multiple layers of

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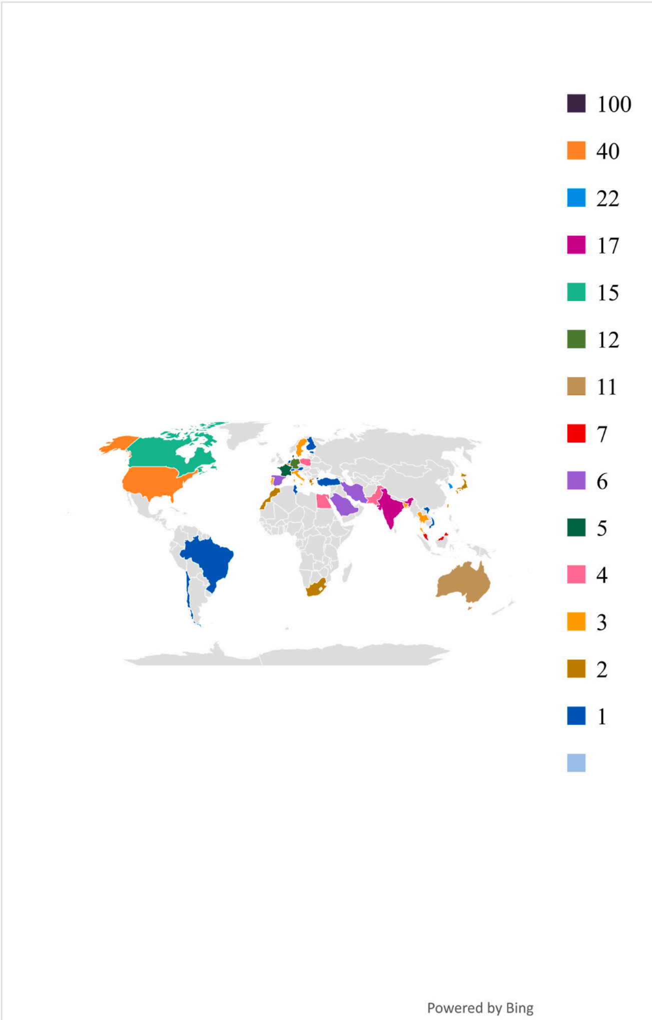

Fig. 1. Application of DL techniques in analyzing Ev charging behavior as reflected in total publications by country from the WOS database.

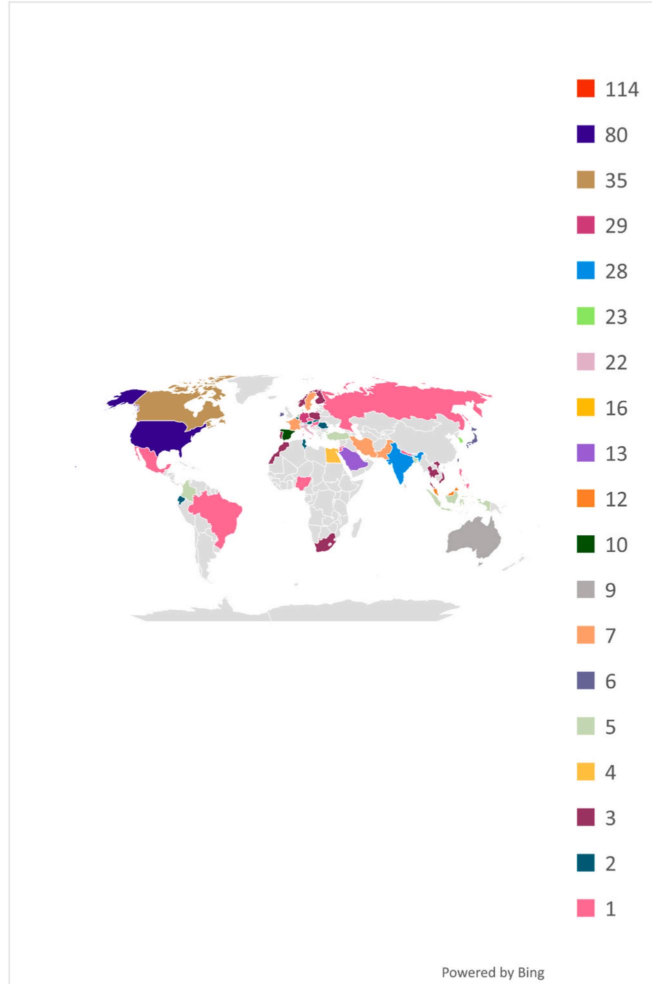

Fig. 2. Application of Ml techniques in analyzing Ev charging behavior as reflected in total publications by country from the WOS database.

interconnected nodes (P et al., 2023, Bao et al., 2022; Peixiao and Jun, 2022), has gained popularity in solving learning problems. Optimization of DL is currently a popular subject of study in artificial intelligence (Zhan et al., 2022; Yang et al., 2023). DL, like ML techniques, is used to forecast EV charging patterns. Figs. 1 and 2 show the total number of research publications using DL and ML technique for EV charging behavior in different countries from 2016 to 2023.

This research aims to utilize Machine Learning (ML) and Deep Learning (DL) techniques to address planning challenges related to EV charging, including the placement of charging stations, predicting charging demand, and scheduling charging. The performance optimization of DL in this context will also be explored. Aimed at providing insights into accurate EV charging demand forecasting, contributions will be made toward the efficient management of electrical power sources and the growth of eco-friendly transportation options. Table 1 provides vital references to assist readers in understanding critical terms within the paper. This table emphasizes important keywords and offers concise, informative explanations of the fundamental terminology in the article. Table 2 presents the limitations of previous review papers concerning various aspects within the domain of power systems and electric vehicle (EV) adoption.

These limitations include the identification of challenges and solutions in power systems with increasing EV adoption, analysis of charging behaviors and associated spatial and temporal charging profiles, planning and commissioning of power systems for electric transport delivery, the significance of gathering detailed information about EV charging behavior and characteristics, and the application of algorithms or techniques such as DL and ML for optimizing EV charging. Additionally, this table categorizes load forecast types into STLF, MTLF, and LTLF.

The keyword analysis, focusing on ML and DL techniques for EV charging, was carried out using data retrieved from the Scopus database and visualized using VOS Viewer. Fig. 3 illustrates the research trend spanning from 2016 to 2023, showcasing a consistent increase in annual article production following the initial database screening enhancements. Over the period from 2016 to 2023, a total of 1910 manuscripts were cumulatively published. Furthermore, keyword simultaneous appearance analysis was conducted using VOS Viewer and data sourced from the Scopus database (Miah et al., 2021).

2. Overview of EVs

Unlike the ICEV, which uses fossil fuels, the EV is a kind of vehicle that runs on electricity. EVs are designed to store electrical energy in batteries or use it to produce electricity through fuel cells (Kumar and Alok, 2020). As shown in Fig. 4, there are four categories of EVs, including battery electric vehicle (BEV), plug-in hybrid electric vehicle (PHEV), hybrid electric vehicle (HEV), and fuel cell electric vehicle (FCEV) (Foley et al., 2020).

According to the electric power research institute (EPRI) and society of automotive engineers (SAE) standard organizations, there are three EV charging modes and these charging levels refer to different power

Table 1
Explanations of abbreviations employed throughout the paper.

AI	Artificial Intelligence	DL	Deep Learning
SVM	Support Vector Machine	EV	Electric Vehicle
MLP	Multiplayer Perceptron	GHG	Greenhouse Gas
AE	Autoencoder	ICEV	Internal Combustion Engine Vehicles
GA	Genetic Algorithm	EPS	Electrical Power Source
BP	Backpropagation	BEV	Battery Electric Vehicle
PSO	Particle Swarm Optimization	PHEV	Plug-In Hybrid Electric Vehicle
BPNN	Backpropagation-Based Neural Network	HEV	Hybrid Electric Vehicle
ANN	Artificial Neural Network	FCEV	Fuel Cell Electric Vehicle
DNN	Deep Neural Network	EPRI	Electric Power Research Institute
CNN	Convolutional Neural Network	EVCS	Electric Vehicle Charging Stations
RF	Random Forest	DGs	Distributed Generations
LSTM	Long Short-Term Memory	SoC	State of Charge
RNN	Recurrent Neural Network	RMSE	Root Mean Squared Error
RBM	Restricted Boltzmann Machine	MAPE	Mean Absolute Percentage Error
DBN	Deep Belief Network	EPA	Ensemble Predicting Algorithm
SVR	Support Vector Regression	SMC-EV	Service And Management Center for EV
k-NN	K-Nearest Neighbors	SHAP	Shapley Additive Explanation
NN	Neural Networks	CNN	Convolutional Neural Network
ML	Machine Learning	VGG	Visual Geometry Group
RNN	Recurrent Neural Network	LSTM	Long Short-Term Memory
GRUs	Gated Recurrent Units	DBN	Deep Belief Network
DTL	Deep Transfer Learning	AEs	Autoencoders
STLF	Short-Term Load Forecasting	MTLF	Mid-Term Load Forecasting
GA	Genetic Algorithm	LSTF	Long-Term Load Forecasting
MPGA	Population Genetic Algorithm	ARIMA	Autoregressive Integrated Moving Average
DKDE	Diffusion-Based Kernel Density Estimator	CatBoost	Categorical Boosting
XGBoost	Extreme Gradient Boosting		

capabilities and charging speeds for EVs. AC Level 1 charging typically uses a standard household outlet, AC Level 2 charging requires a dedicated charging station, and DC Level 3 charging (also known as DC fast charging) offers the highest charging power and is typically found at public charging stations (Hall and Lutsey; Narasipuram and Mopidevi, 2021). Fig. 5 explains each level of EV charging modes.

3. EV charging challenges

Although using EVs has significant benefits in increasing energy efficiency (Challa et al., 2022; Shao et al., 2020; Zhou et al., 2018) such as reducing GHG pollution (Erickson, 2017; Requia et al., 2018) and providing grid services (David and Al-Anbagi, 2017; Sioshansi and Denholm, 2009; Gay et al., 2018; Wang et al., 2016a; Aziz and Budiman; Ortega-Vazquez, 2014; Almaghrebi et al.), the EPS encounters some challenges with adopting EVs. The sudden entry of a considerable number of EVs in the EPS can create pressure on the power grid infrastructure. This increased demand can result in peak load requirements and potential challenges such as power outages, reduced grid reliability, and a rise in costs. Charging of EVs in non-peak time can help to mitigate this problem and make load balances. Charging of EVs is essential for expanding EV adoption, but its charging behavior is unclear, making the uncertain charging power of electric vehicle charging stations (EVCSs) (Wang et al., 2016b; Machura and Li, 2019; Das et al., 2020; Khalid et al., 2019; Khan et al., 2019; Shi et al., 2018). This uncertainty can potentially jeopardize the secure operation of the EVCS and power systems (Li et al., 2020, 2021a; Nimalsiri et al., 2019; Kong et al., 2023; Mastoi et al., 2022; Chaudhari et al., 2018). Two approaches exist for charging power forecasting for EVCS: model-based and data-driven (Abdullah et al., 2021; Lebrouhi et al., 2021; Hafeez et al., 2023; Li et al., 2022a; Mathew et al., 2023).

Model-based approaches to predicting EV charging behavior offer accuracy and predictability through mathematical models. This makes them particularly effective in controlled environments like laboratories or test tracks. However, model-based approaches are also complex and require a deep understanding of the underlying physics of batteries. This can limit their adaptability to rapidly changing real-world conditions, such as those experienced by EVs in everyday use (Shahriar et al., 2020; Aggab et al., 2021; Zhang et al., 2020a; Oliva et al). Data-driven approaches, which utilize historical and real-time data to make predictions and decisions, offer superior real-world accuracy and adaptability in dynamic environments. However, these approaches are highly dependent on the quality of the data used to train them, and they may face challenges in generalizing beyond the training data. Additionally, data-driven models can be perceived as "black boxes," raising concerns about privacy and interoperability (Kalfarisi et al., 2022; Li et al., 2022b; Zhong et al., 2019; Tiong et al., 2023)

Table 2
Constraints of previous review articles.

Parameters	(Deb)	Sadeghian et al. (2022)	Patil et al. (2022)	Shah et al. (2022)	Abdullah et al. (2021)	Ganesh and Xu (2022)	Wu et al. (2022)	Shahriar et al. (2020)	Barman et al. (2023)	This Paper
Identify challenges and solutions in power systems with increasing EV adoption	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Analyze charging behaviors and determine spatiotemporal charging profiles	×	✓	✓	×	×	✓	✓	✓	✓	✓
Planning and operating the power system in the field of transportation electrification	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Emphasize the importance of collecting detailed information about EV charging behavior and profile	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Explore algorithms or techniques such as deep learning (DL) and machine learning (ML) for optimizing EV charging	✓	×	×	✓	✓	×	×	✓	×	✓
Load Prediction Categories (STLF, MTLF, and LTLF)	×	×	×	×	×	×	×	×	×	✓

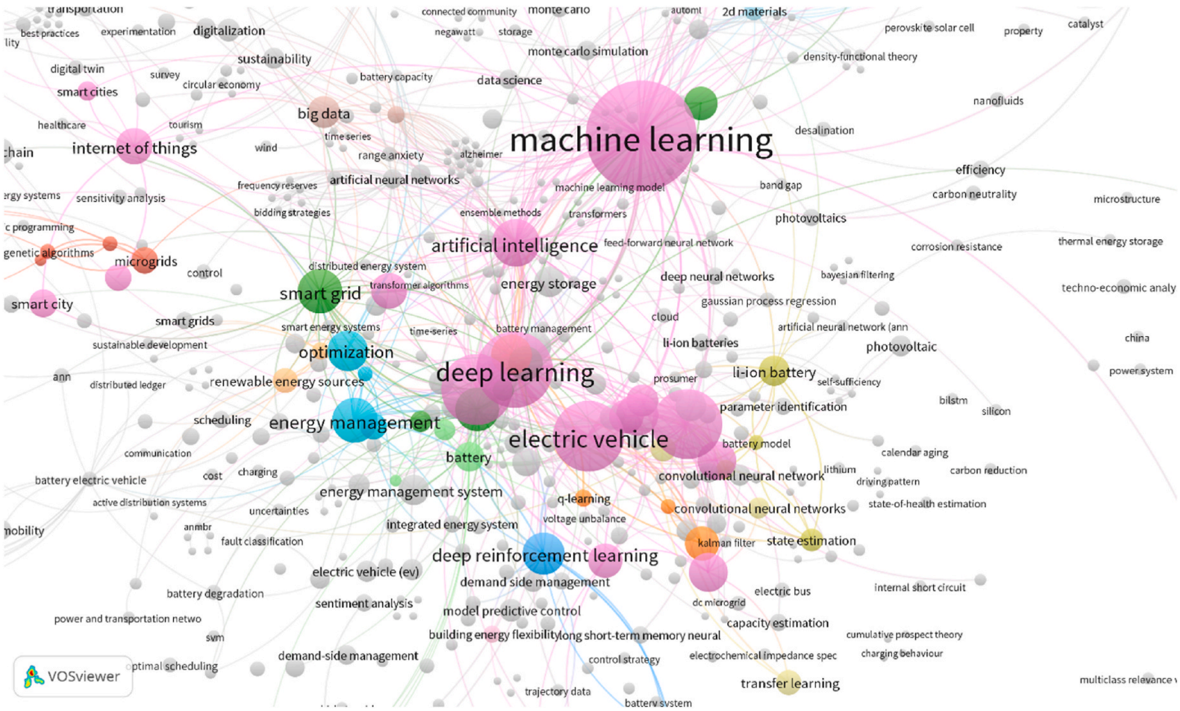

Fig. 3. Application of DL and Ml techniques in Ev charging as evidenced by total publications from the scopus database.

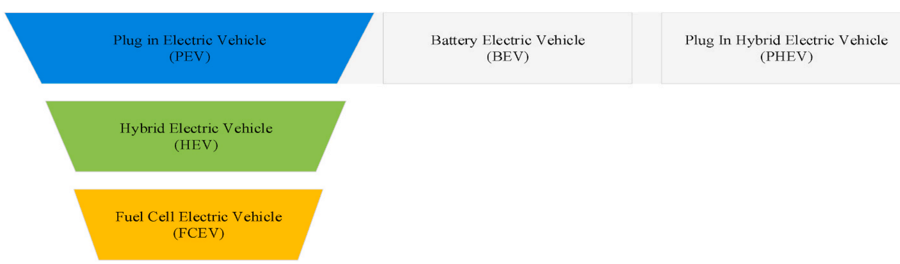

Fig. 4. The diagram of the EV categories.

Fig. 5. The type of EV charging modes.

As mentioned by (Cheng et al., 2020; Xu et al., 2021), using a model-based approach is useful for predicting EV user charging behavior. Moreover, data-driven algorithms have the potential to predict the power requirements for charging EVCS (Mathew et al., 2023; Loni and Asadi, 2023; Kezunovic et al., 2022; Feng et al.). The problems associated with EV charging can be resolved using scheduling, clustering, and forecasting methodologies (Shahriar et al., 2020; Al-et al., 2019; Zhu et al., 2016). These control algorithms consider both the demand for EV charging and the present condition of the EPS, increasing grid stability and efficiency while lowering operating costs and preventing peak loads (Patil and Kalkhambkar, 2020; Wang et al., 2019; Zhu et al., 2018). EV batteries may be incorporated into

Table 3
The disadvantages of EV charging to the power grid.

Ref	Negative Impact	Describe
KoundinyaSistlaPavanVenkat et al. (2021)	Voltage Stability	The negative effects of EVCS are mostly due to the risk of voltage stability. Rapid load growth is one of the main reasons for voltage instability. When charging EVs, a significant load increase causes voltage instability.
(Bayram)	Increased peak demand	Due to the loss of store edge, the network is under more peak load pressure due to the increased power needed for charging EVs.
Patel et al. (2021)	Power Efficiency	Power efficiency is a network's ability to distribute electricity to produce a constant, disorder-free output with voltage and frequency endurance. Due to the EV charging load's nonlinearity, power efficiency is in danger. Two of the most prevalent Power Efficiency issues are harmonics and voltage sag.
Tay et al. (2022)	Transformer Efficiency	The temperature of the welding point in the transformer rises as the load increases. EV charging raises the temperature of the welding point by increasing the load.

scheduling, clustering, and forecasting plans to ensure smooth load consumption (Al- et al., 2019; Cui et al., 2023; Caliwag and Lim, 2019). EV batteries are futuristic solutions for storing intermittent supplies (Hussain et al., 2021; Thompson, 2018; Lehtola). EVs have a positive impact on the EPS by reducing GHG pollution, providing grid services, lowering peak demand, and improving energy efficiency (Viswanath et al; Alamoush et al., 2020; Hoang et al., 2022; Hoehne and Chester, 2016). Conversely, it is crucial to consider the unfavorable effects of EV charging on the distributed generations (DGs) (Ahmad et al., 2022a; Arias et al., 2017; Colmenar et al., 2016; Luo et al., 2019). As indicated in (Li et al., 2021a; Chen et al., 2020; Karmaker et al.; Ghasemi--Marzbali, 2022; Ahmad et al., 2022b), the main challenges associated with integrating EV charging infrastructure into existing electrical power systems include voltage stability issues, peak load pressure, power efficiency, and transformer efficiency. Table 3 addresses the adverse effects of EV charging on the power grid, whereas Table 4 assesses the pros and cons of EV charging within the main grid, including the resulting outcomes.

4. Machine learning (ML) technique in EV charging

ML is a branch of artificial intelligence (AI) in which statistical methods are utilized to enable computer systems to acquire knowledge from data without explicit programming (Almaghrebi et al.). ML can be used to perform various tasks, such as prediction, classification, clustering, and optimization(Almaghrebi et al.), (Wang et al., 2016b). ML is classified into four different types of algorithms including:

- Supervised learning: Supervised learning is the process of training an algorithm using a labeled dataset, where each input characteristic corresponds to a known output. The algorithm learns to map the input properties to the desired output by examining these labeled samples (Mahesh, 2020; An et al., 2023; Sarker, 2021a; Coronnello and Francipane, 2022; Hsu, 2020; Zhang et al., 2022). This learning is divided into classification and regression (Nasteski, 2017; Criminisi et al., 2011; Osisanwo et al., 2017). Classification aims to categorize or label data into predefined classes or categories. The output is typically a discrete value representing a class or category (Nasteski, 2017; Kotsiantis et al., 2007; Linares-Vá et al., 2014). Regression is another type of supervised learning, but in this case, the goal is to predict a continuous numerical value (or a real number) rather than a discrete category. Regression models are used when the output is a quantity varying over a continuous range (Sarker, 2021a; Nasteski, 2017; Greener et al., 2022; Goldstein et al., 2018).
- Unsupervised learning: Unsupervised learning is the process of detecting patterns or structures in data without knowing what the result will be. The method is trained on an unlabeled dataset, to learn an input representation that captures the underlying structure of the data (Mahesh, 2020; An et al., 2023; Sarker, 2021a; Coronnello and Francipane, 2022; Hsu, 2020; Zhang et al., 2022). Unsupervised learning is divided into clustering, dimensionality reduction, density estimation, and anomaly detection (Alghanmi et al., 2022; Usmani et al; Nassif et al., 2021). Clustering is the process of grouping similar data points together based on certain features or similarities (Sarker, 2021a; Yuan et al., 2017; Kassambara, 2017). Dimensionality reduction techniques aim to reduce the number of features in a dataset while preserving important information (Zebari et al., 2020; Anowar et al., 2021; Sharma and Saroha; Gisbrecht and Hammer, 2015). Density estimation involves estimating the probability density function of a dataset (Nachman and Shih, 2020; Carleo et al., 2019; Wang and Scott, 2019). Anomaly detection identifies data points that deviate significantly from the expected or normal behavior (Usmani et al.; Lavin and Ahmad; Beggel et al.).
- Semi-supervised learning: A combination of supervised and unsupervised learning methods is called semi-supervised learning. The method is trained using both labeled and unlabeled instances from a dataset. The goal is to use the unlabeled instances to improve the model's performance on labeled examples (Mahesh, 2020; An et al., 2023; Sarker, 2021a; Coronnello and Francipane, 2022; Hsu, 2020; Zhang et al., 2022). This kind of learning is divided into self-training, graph-based methods, co-training, and multi-view learning (Reddy et al., 2018; Kostopoulos et al., 2018; Mustajab, 2020). Self-training is a simple semi-supervised learning algorithm where a model is trained on the initially labeled data and then used to label unlabeled instances with the highest predicted confidence. These newly labeled instances are then added to the labeled dataset, and the process iterates (Triguero et al., 2015; Sohn et al., 2020; Tanha et al., 2017). Graph-based semi-supervised learning techniques represent data points as nodes in a graph, with edges denoting similarity or relationships. These methods propagate labels through the graph to label unlabeled nodes (Song et al., 2022a; Subramanya and Talukdar, 2022; Chong et al., 2020). Co-training is an algorithm that involves training multiple models (usually two) on different subsets of features or views of the data. These models then exchange and label each other's unlabeled instances, combining their knowledge (Triguero et al., 2015; Van et al., 2020; Ma et al., 2020). In multi-view learning, the data is viewed from multiple perspectives, and models are trained on each view. These models then collaborate to improve overall performance (Gao et al.a; Bian et al.; Han et al., 2021).
- Reinforcement learning: Reinforcement learning involves training an agent to respond to its environment through feedback signals. For its activities, the agent is provided with rewards or penalties, and the objective is to acquire a policy that maximizes the anticipated reward (Mahesh, 2020; An et al., 2023; Sarker, 2021a; Coronnello and Francipane, 2022; Hsu, 2020; Zhang et al., 2022).

Reinforcement Learning is divided into value-based methods, policy-based methods, actor-critic methods, and model-based methods (Zhang and Yu, 2020; Perera and Kamalaruban, 2021; Zheng et al). Value-based methods involve the learning of value functions (Q-values or state values) and the selection of actions based on value estimates(Lu et al., 2018a; Rashid et al., 2020; Marchesini and Farinelli). Policy-based methods involve directly learning policies to select actions that maximize expected rewards (Pope et al.; Sharma et al; Wang et al). Actor-critic methods combine the estimation of value functions

Table 4
Analyzing the consequences of EV charging on the main grid.

Ref	Advantages of Charging EV	Disadvantages of the Consequences of Charging EV	Result
(Miah et al., 2021)	1) Decreased emissions of greenhouse gases 2) enhanced energy efficiency 3) Decreased operational costs 4) Noise reduction 5) Capability for incorporating renewable energy sources 6) Generation of employment opportunities.	1) Challenges in establishing charging infrastructure 2) Pressure on the main grid 3) Production and disposal of batteries 4) Cost of batteries 5) Range limitations	The embrace of electric vehicles offers many advantages to the environment, economy, and society. Balancing between these pros and cons is crucial to making well-informed choices regarding the widespread adoption of EVs, ultimately leading to decarbonization objectives and sustainable development milestones.
(Karmaker et al.)	1) Lower dependence on non-renewable energy sources 2) Decreased carbon pollution and 3) Potential cost savings for consumers.	1) Produce harmonics 2) Affect the voltage profile 3) Ultimately affect power quality.	The results suggest that integrating numerous EV charging stations could have notable effects on power quality, but proper mitigation techniques could reduce these disturbances.
Qiu et al. (2022)	1) EVs provide an environmentally friendly and efficient means of transportation. 2) Charging at home is convenient and eliminates the need for frequent visits to gas stations. 3) Incentives and subsidies for EVs and charging infrastructure can promote sustainable mobility and reduce dependence on fossil fuels.	1) EV charging can increase electricity demand during peak hours, potentially putting stress on the electric grid. 2) The construction of EV charging infrastructure may require significant upfront costs and resources. 3) The manufacturing and disposal of EV batteries may result in adverse environmental consequences.	The study found that in-home EV charging can increase electricity demand during peak hours in the summer, but households can shift charging to off-peak hours in response to pricing signals. Rebound effects in driving also led to a reduction in home-electricity consumption at certain times, and the difference between predicted and actual behaviors highlights the need for policy interventions that account for consumer behavior.
Khamis et al. (2023)	1) Potential technical 2) Environmental 3) Economic benefits.	lead to peak demand, which can negatively impact the distribution grid, especially in terms of maintaining voltage stability	The implementation of demand-side management in the suggested charging strategy decreases the negative effects of EV charger integration by adjusting the charging time to off-peak hours and decreasing peak active power losses by 2.2–3.2 percent. This approach adds value to the development of efficient EV charging strategies.
Alsharif et al. (2023)	1) The potential for reducing carbon emissions 2) Improving air quality 3) Enabling the incorporation of renewable energy sources 4) The feasibility of utilizing EVs as a distributed energy storage system to enhance the grid's stability and resilience.	1) The potential for creating new technical challenges for grid operators 2) The need for significant infrastructure investment 3) The possibility of causing peak demand and voltage instability.	The outcomes of the research indicated that energy management strategies including load shifting and peak shaving could significantly diminish the adverse effects of EV charging on residential power distribution. The use of a distributed energy storage system based on EVs could provide a cost-effective solution to support grid stability and reduce the need for significant infrastructure investment.
Baherifard et al. (2023)	1) The potential to reduce carbon emissions and facilitate the integration of RESs. 2) The possibility of using EVs as a flexible load to support demand response programs and help manage the variability and uncertainty of renewable energy generation.	1) The potential for creating new technical challenges for grid operators 2) The need for significant infrastructure investment to support widespread EV adoption.	The study showed that the suggested approach could remarkably reduce the disproportion index in an asymmetric distribution network. demand response and information retrieval methods could effectively manage EV charging patterns and improve the network's stability and resilience.
Xi et al. (2023)	1) The potential to reduce carbon emissions 2) Increase energy efficiency 3) Support the incorporation of renewable energy sources. 4) The role of EVs in supplying supplementary services to the power grid, such as regulating frequency and supporting voltage.	1) The potential for creating new technical challenges for grid operators 2) The need for significant infrastructure investment to support widespread EV adoption.	Based on the simulation outcomes, it was observed that the line carrying capacity and the load peak-valley attributes tend to restrict the hosting capacity of electric distribution networks for EVs, particularly as the quantity of EVs rises.
Hossain et al. (2022a)	1) Decreased carbon footprint 2) Improved energy efficiency 3) Lower operating costs 4) Enhanced energy reliability	1) Charging infrastructure challenges 2) Grid capacity constraints 3) Battery production and disposal 4) Initial cost of batteries 5) Range limitations	The article provides essential understanding of the changing patterns and obstacles in combining power electronics converters with energy storage in EVs, potentially propelling the adoption of EVs and aiding the automotive sector in achieving Sustainable Development Goals (SDGs) and reducing carbon emissions.
Lipu et al. (2022)	1) Enhanced operational efficiency and decreased carbon emissions actively contribute to addressing environmental issues. 2) EVs hold the potential to significantly contribute to the attainment of SDGs.	Challenges include battery health degradation, complexities in battery management, power electronics integration, and selecting appropriate charging strategies.	The study emphasizes the significance of EV technology in achieving sustainable development objectives, presenting valuable perspectives and suggestions for its improvement through continuous research and development efforts.

(performed by the critic) with policy optimization (performed by the actor) (Su et al., 2017; Kumar et al., 2023; Pfau and Vinyals, 2016). Model-based methods involve learning a model of the environment to plan and make decisions (Russek et al., 2017; Polydoros and Nalpantidis, 2017; Ayoub et al.).

Fig. 6 depicts an overall flowchart for the ML technique.

Fig. 7 compares the utilization of different ML algorithms in EV charging based on total publications from 2016 to 2023. The figure clearly shows that reinforcement learning has been the most extensively utilized algorithm in the field of EV charging.

The application of ML to EV charging faces a substantial obstacle due to the inadequacy and bias in available data. This challenge results from the relatively recent introduction of EV charging technology, resulting in a limited dataset (Shahriar et al., 2020).

As highlighted in (Shahriar et al., 2020; Panda et al., 2022; Gržani et al.; Azkue et al., 2023; Lahariya et al., 2020; Boikov et al., 2021; Ullah et al., 2023; Mavikumbure et al; Zhao et al., 2017), addressing this challenge involves considering several potential solutions:

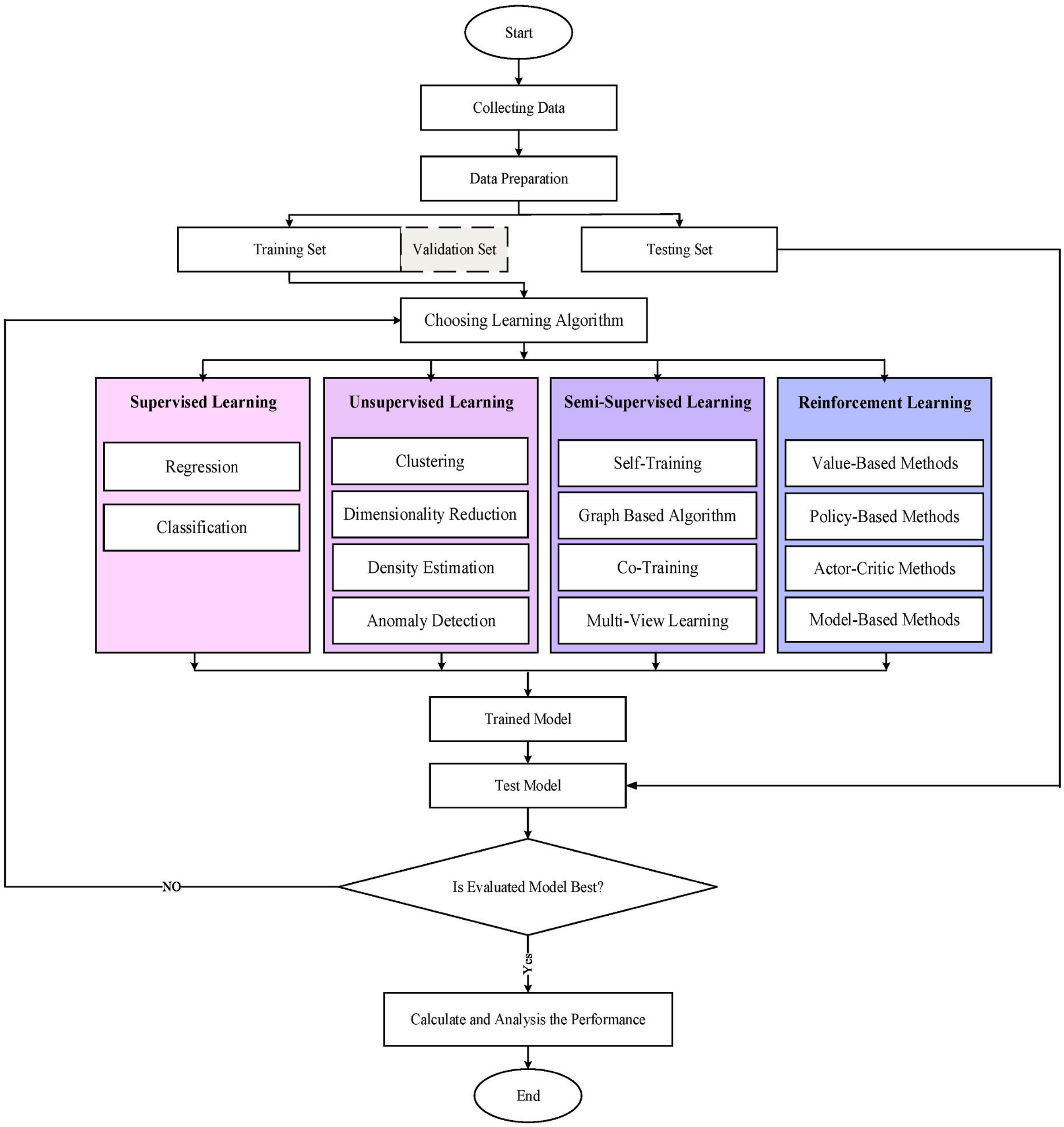

Fig. 6. An overall flowchart for the ML technique.

- Synthetic Data Generation: One approach to mitigate the limited real-world dataset is using synthetic data generated through computer models. This synthetic data can serve as a valuable resource for training ML models without relying solely on scarce real-world data.
- Diverse Data Collection: Expanding data collection efforts to encompass a wider range of EV users and scenarios is essential. By gathering data from a more diverse spectrum of EV users, a more comprehensive representation of the EV user population can be achieved, enhancing the robustness of ML models.
- Robust ML Algorithms: Researchers are actively developing resilient ML algorithms capable of effectively handling noisy and biased data. These algorithms reduce sensitivity to data quality issues, enabling meaningful insights and learning from smaller datasets with less-than-ideal data quality.

Implementing these solutions can significantly enhance the effectiveness of ML applications in EV charging despite the challenges posed by limited and skewed data.

Moreover, the SHAP (Shapley Additive Explanations) approach is valuable to ML techniques. The SHAP approach is applied to model electric vehicle (EV) energy consumption and charging behavior, including the behavior of EV users when selecting charging stations (Ullah et al., 2023; Nan et al., 2023). For EV energy consumption modeling, ML algorithms analyze historical data on EV usage, including driving patterns, time of charging, and external factors such as weather conditions. By processing this data, these models can make accurate predictions about when and how much energy an EV will consume, aiding in efficient charging planning and resource management (Shahriar et al., 2020). Moreover, ML techniques incorporate factors such as location, charging station availability, pricing, and user preferences when it comes to electric vehicle charging station choice behavior (Shahriar et al., 2020; Ullah et al., 2023). The SHAP approach, in particular, allows for the interpretation and quantification of the impact of each of these factors on the decision-making process of EV users. By understanding these influences, stakeholders can optimize charging infrastructure, improve station placement, and provide services that

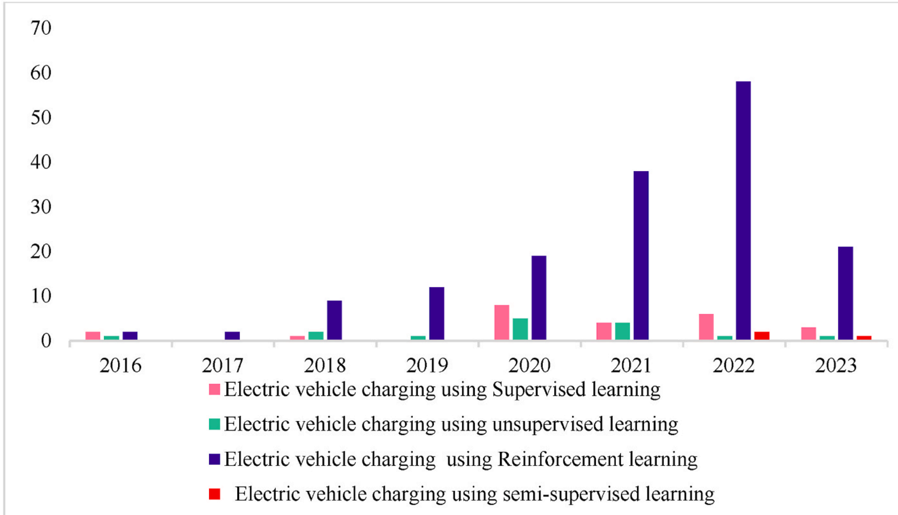

Fig. 7. The comparison of various Ml algorithms used in Ev charging based on the total number of publications from 2016 to 2023, using the WOS database.

align with the preferences and needs of EV owners, ultimately enhancing the electric vehicle charging experience and supporting the growth of sustainable transportation (Ullah et al., 2023)

Furthermore, data privacy and security emerge as substantial concerns and challenges within the domain of ML applications in EV charging. This is related to the training of ML models on sensitive user data, including location details and charging behavior, which, if mishandled, can potentially give rise to significant apprehensions related to privacy and security (Islam et al., 2022; Nasr et al., 2022; Nasr et al.; Girdhar et al)

Additionally, EV charging prediction is a significant challenge that can be tackled through ML methods. This prediction aims to estimate the power needed to charge an EV at a specific time, considering the time of day, weather, location of the EV, and state of charge (SoC) of battery (Hossain et al., 2022b). Table 5 presents the application of ML methods, specifically supervised learning and unsupervised learning, for forecasting EV charging. Finally, Fig. 8 provides an overview of the total number of research publications dedicated to EV charging using ML from 2016 to 2023.

5. Deep learning (DL) in EV charging

Over the recent years, DL has made significant progress and has been successful in different fields (Shen et al., 2021).

DL is a subfield of ML. It aims to develop algorithms that can learn increasingly complex representations of data. It employs neural networks with multiple linked layers of nodes. DL algorithms are commonly trained with abundant data, which enables them to learn from patterns and make predictions with high accuracy (Mathew et al., 2020; Qi et al., 2023). Fig. 9 depicts an overall flowchart for the DL technique.

There are several learning techniques for modeling DL at different levels which is advantageous for creating intricate data links (Deng and Yu, 2014; Yan, 2022). DL involves various methods that can be used for specific functions depending on the conditions. One such method is the multilayer perceptron (MLP) method, which provides the benefit of being able to learn non-linear models in real-time or online (Xu et al., 2022a). A convolutional neural network (CNN) is widely used in visual recognition, medical image analysis, image segmentation, natural language processing, and more, as they can automatically discover significant features (Yuan et al., 2023; Shamshad et al., 2023). Several variants of CNN exist, such as visual geometry group (VGG) (Veni and Manjula, 2022), AlexNet (Sohail, 2022; Luo et al., 2022), Xception, Inception (Hossain et al., 2022c), and ResNet (Baghbani et al., 2022), that can be applied to different domains based on their learning capabilities. A recurrent neural network (RNN) is built to deal with sequential data, with each input reliant on the preceding inputs in the sequence. RNN impacts the present input and output by utilizing data from prior inputs (Vamosi et al., 2022). Standard RNN encounters a common issue known as vanishing gradients, which can make learning from large data sequences challenging. Fortunately, several advanced types of RNNs, such as Long Short-Term Memory (LSTM), Bidirectional RNN/LSTM, and Gated Recurrent Units (GRUs), have been developed to address this issue. These advanced RNN variations have demonstrated significant utility in a variety of real-world applications, including prediction, machine translation, natural language processing, text summarization, and speech recognition (Gasparin et al., 2022; Li et al., 2019; Debus et al., 2021).

Moreover, a deep belief network (DBN) can create a layered representation of input data by utilizing its complex structure, allowing for the identification of deep patterns and the distinction between regular and anomalous data. The DBN method is used for unsupervised learning applications, such as feature extraction (Sohn, 2021; Rizk et al., 2019). Also, autoencoders (AEs) are neural networks used for unsupervised learning to learn representations of high-dimensional data and reduce dimensionality. Variants of AE such as sparse, denoising, and contractive are suitable for learning representations that can be used for classification tasks in the future, and variational autoencoders can be applied as generative models. These methods have been proven to be successful in various fields including healthcare, computer vision, speech recognition, cybersecurity, and natural language processing (Pratella et al., 2021; Yang et al., 2022; Sarker, 2021b). Deep transfer learning (DTL) transfers knowledge from a previously trained model to a new DL model, making deep neural networks easier to train with fewer data. DTL can be grouped into four categories based on the techniques utilized: instances-based, mapping-based, network-based, and adversarial-based deep transfer learning (Azizah and Adriani). Because of its great efficiency and practical utility, adversarial-based DTL has gained popularity in recent times, and DTL approaches are employed in a diversity of domains including natural language processing, sentiment classification, visual recognition, speech recognition, and spam filtering (Iman et al., 2023; Bhuiyan and Uddin, 2023). Other DL methods frequently combine and complement the methodologies outlined above to improve efficiency and overall effectiveness (Aslam et al., 2021).

CNN, RNN, and MLP are the most often used deep learning methods for forecasting EV charging behavior (Wang et al., 2022; Liu et al., 2022; Amara-et al., 2021). Fig. 10 indicates a steady increase in the utilization of DL techniques for EV charging according to overall research publications from 2016 to 2022.

Table 5
The use of ML-Based to forecast EV charging (supervised learning and unsupervised learning).

Ref	Location	Supervised	Unsupervised	Focuses	Result
Narasipuram and Mopidevi (2021)	FIfty-five electric taxis in Beijing city	✓	×	Regarding the real-time prediction of energy consumption for EVs in actual driving scenarios	The results of the real-world trip tests indicate that The model attained a root mean squared error (RMSE) of 0.159 (kWh) and a mean absolute percentage error (MAPE) of 12.68%, regarding its performance evaluation. These values represent a 32.05% reduction in RMSE and a 30.14% reduction in MAPE compared to the conventional method.
Zhu et al. (2016)	The data from the household's interactions and the EV was collected in approximately 20 days.	✓	×	Utilizing ML techniques to predict the timing of household EV charging and identify days when "no charge" is required enables the development of intelligent charging solutions at the household and neighborhood levels.	After analyzing the prediction outcomes, Proposed a hybrid stacking ensemble learning approach with two layers that combines various ML algorithms. The model was tested and showed significantly improved classification performance compared to both naive predictor and individual algorithms.
Caliwag and Lim (2019)	Nanjing, China	×	✓	Analysis of EV charging patterns through measured data and its potential application	The outcome of the research revealed that the charging patterns of EVs are complex and affected by various factors, including the type of EV, charging infrastructure, and user behavior. identified several charging patterns based on the analysis, such as regular charging, opportunistic charging, and long-duration charging.
Chung et al. (2019)	University of California(UCLA charging stations)	✓	×	Predicting the charging behavior of EVs and identifying the optimal approach to predict it, to optimize the scheduling of EV charging.	The findings indicate that integrating Ensemble Predicting Algorithm (EPA) prediction with charging scheduling can lead to a reduction of 27% in peak load, a 10% decrease in load variation, and a 4% reduction in costs, compared to uncoordinated charging.
Hong et al. (2020)	the Service and Management Center for EVs (SMC-EV) in Beijing	✓	×	development of a machine learning method for real-time multi-forward-step state of charge (SOC) prediction in battery systems of EVs	To simultaneously ensure the accuracy and prediction horizon of the model, a joint-prediction strategy based on LRLSTM was suggested. This strategy utilizes both LSTM and multiple linear regression algorithms to establish an accuracy baseline and allows the prediction stages of (LSTM)to be adjusted within an acceptable level of accuracy. prediction method improved Prediction accuracy for multistage forecasting
Lu et al. (2018b)	Shenzhen	✓	×	predicting EV charging load using an Enhanced random forest algorithm	Based on the simulation results, the suggested charging prediction algorithm for an individoal station can achieve an εMAPE of 9.76% and an εRMSE of 2.27 when making predictions every 15 min. Meanwhile, the prediction algorithm for a station group can reach an εMAPE of 10.83% and an εRMSE of 39.59.
Zhang et al. (2020b)	The US National Household Travel	✓	×	improving the simulation and estimating EV charging demand by taking into account the demographic and social characteristics of people, such as gender, age, and education level.	The findings indicate that the EV charging load profile is significantly impacted by the demographic and social characteristics of the user, particularly during workdays and at the workplace, affecting both the value and peak time. Also, the proposed probabilistic models provide better accuracy in data fitting and charging load simulation.
Sadeghi-Barzani et al. (2014)	Not Mentioned	✓	×	Applying supervised ML techniques to determine crucial factors influencing EV adoption and evaluating various ML approaches for classifying prospective EV buyers.	findings indicate that the use of algorithms that consider multiple factors related to users and their vehicles can accurately categorize them into distinct clusters, leading to better predictions and a competitive edge for those who use them. Additionally, identifying potential EV purchasers based on these factors can increase the effectiveness of policies aimed at promoting EV adoption.
Xiong et al. (2018)	UCLA campus and the city of Santa Monica	×	✓	the most effective approaches to control bi-directional charging of EVs, allowing them to function as distributed energy resources	The simulations conducted in the study indicate that the suggested charging controls can utilize EVs as a distributed energy resource to Take part in demand-

(continued on next page)

Table 5 (*continued*)

Ref	Location	Supervised	Unsupervised	Focuses	Result
				and participate in demand-response programs within the power grid	response initiatives. This approach can meet the energy requirements of the vehicles while also generating substantial energy cost savings.
Mao et al. (2017)	Not Mentioned	✓	×	utilizing ML algorithms to analyze historical EV charging data along with weather, traffic, and event data, to predict session duration and energy consumption.	Four widely used ML models were trained and combined with two EML to forecast charging behavior. The performance of the predictions was found to be superior to that of previous studies. The research also revealed a noteworthy enhancement in the forecasting of charging tendencies for the Adaptive Charging Network (ACN) dataset and indicated the possibility of integrating traffic and weather data for more accurate forecasting.
Mwasilu et al. (2014)	500 EVs in Japan's private and commercial vehicles	✓	×	Estimating the time required for EV charging to reduce range anxiety during traveling	The findings suggest that ensemble machine learning (EML) models showed good performance across different situations, with the XGBoost model achieving the highest precision. Additionally, utilized the Shapley additive explanation (SHAP) method, which is a recent development, to address the problem of non-interpretable outputs from the ML algorithm. By analyzing the SHAP value plots, the research demonstrated the non-linear association between input variables and the EV charging duration time.
Mortaz and Valenzuela (2018)	Data was collected between 2016 and 2018 from a heterogeneous EV fleet of 1001 EVs with 18 unique models	✓	×	A methodology was proposed to incorporate predictive models for charging EVs into smart charging algorithms to optimize charging processes and infrastructure usage.	The research evaluates ML techniques for forecasting charge patterns and concludes that XGBoost produces the most precise predictions, achieving an MAE of 126 W and a relative MAE of 0.06. using the XGBoost model for smart charging results in more efficient infrastructure utilization, allowing for up to 21% more energy than charging optimization without taking into account the charging patterns.

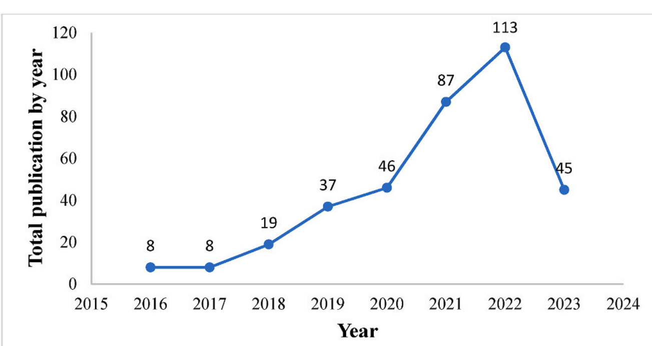

Fig. 8. Analysis of Ml application in Ev charging based on total publications per year, using the WOS database.

Additionally, the use of EV charging prediction strategies involves forecasting and estimating future EV charging demand in a specific area. This approach aids in managing charging load, optimizing the utilization of charging infrastructure, and preventing grid overload during peak demand periods (Al- et al., 2019; Chen and Folly, 2022).

These strategies are crucial for maintaining optimal efficient and reliable functioning of the power network and promoting the widespread adoption of EVs while reducing their negative influence on the grid (Li et al., 2021b). Correct load prediction decreases investment expenses and improves the ability to plan for the development of distribution and transmission networks (Aisyah et al., 2022).

As noted by (Xu et al., 2022b; Cho et al., 2022; Yoo et al., 2020; Yi et al., 2022); load forecasting can be categorized into three levels, each with its applications and methods. Short-term load forecasting predicts energy demand over a brief period and is used for optimizing network utilization in short-term planning. Mid-term load forecasting covers monthly or yearly forecasts and helps manage peak consumption during specific seasons. Lastly, long-term load forecasting predicts energy demand several years ahead and aids in long-term planning, including the construction of new power plants.

Table 6 shows the prediction methods for EV charging based on STLF, MTLF, and LTLF using DL techniques.

Meanwhile, utilizing DL models demands substantial quantities of labeled data for effective training. This demand can pose notable challenges, particularly when dealing with specific EV charging scenarios or unique geographical locations (Zhu et al., 2019; Liu et al., 2023; Ló et al., 2018). Additionally, DL places significant demands substantial computational power (Zhu et al., 2019; Qiu et al., 2020; Luo et al) and is time-consuming (Luo et al; Song et al., 2022b; D' et al., 2023), necessitating powerful hardware and substantial processing resources (Lane et al; Zhang et al., 2018) for EV charging.

6. Ensemble learning technique in EV charging

Ensemble learning involves the combination of several separate techniques to generate a more precise and resilient prediction model (Dong et al., 2020). An ensemble model aims to use the strengths of multiple techniques to create a more accurate and reliable prediction model, compared to using an individual learning model to resolve a specific task (Wang and Srinivasan, 2017). Ensemble learning techniques generate multiple hypotheses and combine them to solve a given

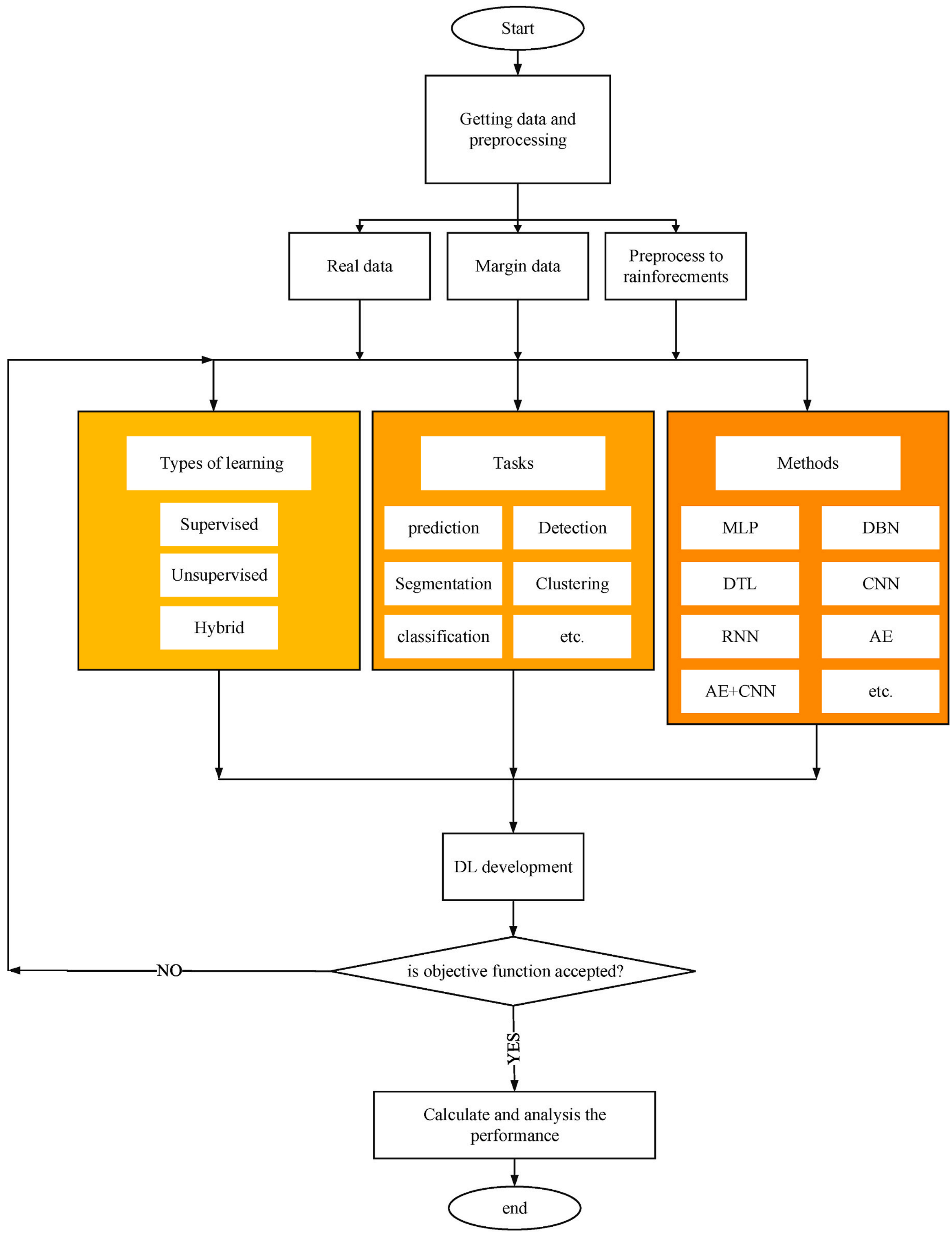

Fig. 9. An overall flowchart for the DL technique.

problem, unlike conventional machine learning techniques that aim to learn a hypothesis from training data. Ensemble models come in many varieties, including bagging, boosting, and stacking, which use different methods to combine individual models. Ensemble-based approaches are among the most popular methods utilized in classifying data streams (Heywood, 2015; Gomes et al., 2017). By combining multiple techniques, ensemble methods can reduce the risk of overfitting and improve generalization (Ganaie et al., 2022). Ensemble models provide a powerful tool for creating more accurate and robust predictive models in ML (Malhotra and Meena, 2023). Table 7 presents the ensemble techniques employed in the field of EVCS, specifically using both ML and DL approaches.

7. Discussion

As the deployment of EVs increases, the main grid faces additional

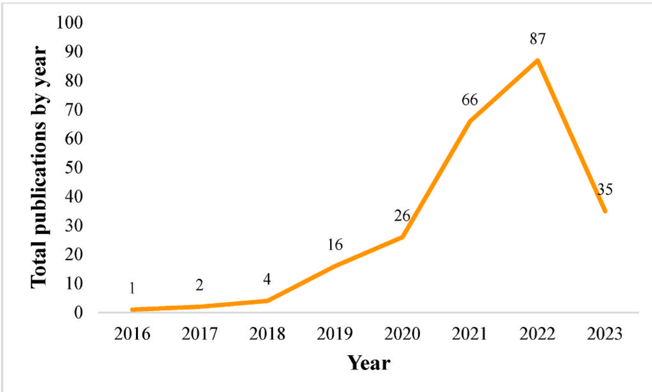

Fig. 10. Adoption rate of DL techniques in Ev charging over the years, based on total research publications, utilizing the WOS database.

challenges. The EPS is not designed to accommodate a sudden increase in EVs. One of the main challenges associated with EV charging within the EPS is the occurrence of peak demand (Li et al., 2022). This increase in demand puts considerable pressure on the main grid. This pressure can result in power outages, reduced reliability, and increased costs for companies and consumers. The adoption of EVs has significant implications for the EPS, particularly in terms of managing peak demand and ensuring reliability. As shown in Fig. 11, there is a rising interest among researchers in understanding the implications of integrating EV charging into the main grid from 2016 to 2021. However, since 2022, there has been a gradual decline in this trend.

One of the solutions to reduce the pressure on the main grid when EVs are present in the system is to charge the EVs during non-peak hours to balance the load. Besides, another solution is using the benefit of ML and DL techniques for forecasting EV charging behavior. These technologies can accurately predict EV charging behavior by analyzing historical data and identifying patterns and relationships between various parameters such as charging time, location, type of vehicle, and SoC of batteries. ML and DL techniques enable accurate prediction of EV charging behavior, optimizing the charging process and promoting efficient resource utilization for improved sustainability.

Load prediction based on ML and DL techniques is divided into three categories: STLF, MTLF, and LTLF. Each prediction period has its own accuracy and relevance in specific applications, making it difficult to determine the relative importance of one over the others. STLF is primarily used for optimizing the main grid, MTLF is applied for managing peak consumption in certain seasons, and LTLF holds great significance for electricity companies as it guides decisions regarding the construction of new power plants or expanding utilities.

When examining ML and DL approaches in the context of EV charging, based on data from the Scopus database sourced from the Elsevier Journal, it becomes evident that scholars have authored 4601 research papers on machine learning methods between 2016 and 2023, as depicted in Fig. 12. Furthermore, Fig. 12 illustrates co-occurring keywords related to machine learning techniques for EV charging, drawn from the most relevant articles identified in the selected database. In contrast, this database reveals that researchers specializing in DL methods have contributed 7279 research papers, as shown in Fig. 13. Fig. 13 presents the internal network of keywords associated with DL techniques for EV charging, constructed using VOS Viewer software. The size and label of each circle correspond to the significance of the respective keyword. Connecting lines indicate relationships between the keywords. Different colors denote distinct clusters based on their specific areas of expertise [19].

Although this study demonstrates the potential of both ML and DL techniques in predicting EV charging behavior and overcoming challenges linked to the growing adoption of EVs, the ensemble learning technique can achieve higher performance. This is due to its combination of several separate techniques and the utilization of their respective strengths together. As a result, the technique produces the most accurate and reliable forecasting model. As depicted in Fig. 14, ensemble learning is achieving rapid popularity among researchers due to its advantages and high-performance accuracy, despite being a relatively new technique.

All three techniques - ML, DL, and ensemble learning - have the potential to revolutionize the EV industry by enabling data-driven insights and paving the way for a more sustainable future in transportation. These techniques can generate accurate forecasts that relieve pressure on the main grid and effectively reduce costs associated with constructing and maintaining EV charging infrastructure. As a result, a sustainable and environmentally friendly transportation system can be established.

ML offers interpretability and efficiency for simpler problems but may struggle with complex, high-dimensional data in the context of EV charging. DL can be employed for more intricate tasks, such as image-

Table 6
Forecasting tactics for EV charging using DL techniques for STLF, MTLF, and LTLF.

REF	record	DL Model	Result
Xu et al. (2022b)	medium-term load forecasting (MTLF)	Restricted Boltzmann Machine (RBM), and the contrastive divergence algorithm	The outcomes show that the proposed model achieves a mean absolute percentage error (MAPE) for a load peak of less than 5% one year ahead, and a mean MAPE for all days of less than 5% for 24-h pattern forecasting
Salah et al. (2015)	short-term load forecasting (STLF)	(LSTM)	The numerical outcomes show that the LSTM model outperformed the traditional artificial neural network approach for predicting the power demand of EVs from the outlook of charging stations. This indicates that the LSTM model is a promising approach for STLF in power systems with the presence of EVs.
Ramadhani et al. (2021)	medium-term load forecasting (MTLF)	Conditional Restricted Boltzmann Machine (CRBM), discrete-time Markov chain, and adaptive k-means	The outcomes of the simulation indicate that the suggested model performs better than previously utilized by other existing models in accuracy, convergence, and execution time. the model achieves a mean absolute percentage error (MAPE) of 2.26% for the month-ahead hourly electrical load forecasting, which is better than the benchmark model. The Jaya algorithm used for optimizing the CRBM also improves the accuracy rate and convergence of the model.
Sokorai et al. (2018)	short-term load forecasting (STLF)	Markov chains	The results show that the algorithm offers significant stochastic insights into the electricity usage and annual revenues of an EV charging station and can be customized to suit various places with distinct characteristics.
Liu and Liu (2022)	long-term load forecasting (LSTF)	grey Verhulst model and Monte Carlo simulation	According to the analysis, as the number of EVs increases, their charging load will have significant effects on the power grid's stability, load characteristics, and power consumption. These effects should be taken into account when forecasting power demand and planning power systems.
(Zhu et al.)	short-term forecasting (STLF)	(LSTM)	The quantitative findings showed that the long short-term memory model outperformed other models and achieved higher accuracy in STLF of EV charging load compared to the traditional artificial neural networks

Table 7
Use of ensemble learning techniques for EVCS.

Ref	Location	Ensemble Model	Focus	Aims	Result
Shahriar et al. (2021)	Not Mentioned	Random Forest, Support Vector Machine (SVM), XGBoost, and deep neural networks	Improving the scheduling of public charging demand for EVs and highlighting the significance of considering weather and traffic information for accurate EV charging behavior predictions.	A solution to address the potential strain on power grid infrastructure resulting from the widespread deployment of EVs. based on utilizing smart scheduling algorithms to effectively manage the increasing public charging demand.	The EPA achieves the best predictive performance with SMAPE scores of 9.9% and 11.6% for session duration and energy consumption predictions, respectively. The paper demonstrates that incorporating weather and traffic information can significantly enhance the precision of predictions related to EV charging behavior.
Chung et al. (2019)	Data from 252 users	Support Vector Regression (SVR), Random Forest (RF) Regression, Diffusion-based Kernel Density Estimator (DKDE)	The paper is on discussing different ML algorithms that can be utilized to forecast the duration of stay and energy consumption through historical charging records	Identify the most effective technique for forecasting charging behavior to optimize the schedule for EV charging	The findings indicate that the integration of charging scheduling and EPA prediction yields promising outcomes, including a significant decrease of 27% in peak load, 10% in load variation, and 4% in cost reduction compared to uncoordinated charging. Additionally, the approach leads to a reduction of 11% in prediction errors for the duration and 22% for energy consumption.
Bollen (2000)	Orange County, California	Random Forests	Examine spatial disparities in the distribution of EVCS	Identifying areas lacking access to EVCS and directing infrastructure investments to ensure equitable and widespread EV adoption.	The study offers a replicable approach for evaluating disparities in the distribution of EVCS, allowing policymakers to pinpoint societies with insufficient infrastructure and implement specific investments to encourage universal EV adoption.
Francisco (2006)	A coastal city in South China	The Affinity Propagation method and the Binary Particle Swarm Optimization algorithm.	Propose a planning model for fast-charging stations for electric buses that considers both the bus operation network and distribution network.	The objective of minimizing costs and optimizing the layout of the charging stations	The outcomes suggest that the implemented approach is successful in maximizing the efficiency of electric bus fast-charging station placement in urban areas, resulting in a noteworthy decrease in costs when compared to alternative methods. Furthermore, the study affirms that the model effectively considers different operational and network constraints when locating bus charging stations.
(Gao et al.b)	The ride-hailing fleet of Haikou City and the charging information from the electric ride-hailing fleet in Shanghai City	Genetic Algorithm (GA), Multi-Population Genetic Algorithm (MPGA)	Maximize the efficiency of public charging station placement for electric ride-hailing services in a city, considering the investment costs of charging station operators and trip expenses of BEV users.	Not Mentioned	The outcomes show that the proposed methodology has the potential to decrease the overall expense of electric ride-hailing services by 7.6%. This indicates that the optimized placement of public charging stations can significantly reduce the operational costs of electric ride-hailing services, making them more affordable and accessible to customers.
Louie (2017)	Over 2400 charging stations in Washington State and San Diego, California	Autoregressive integrated moving average (ARIMA) model	The focus of the study is on identifying, evaluating, and proposing ARIMA models for the total charging load of all EV stations	Not Mentioned	In this study, seasonal ARIMA models are used to capture the patterns and trends in the aggregated EV charging station load data. The models are assessed and contrasted based on their precision in predicting future values of the time-series data.
(Lilhore et al.)	The Adaptive Charging Network (ACN) implemented at Caltech, USA.	Random Forest (RF), Support Vector Machine (SVM), and Extreme	improving the Prediction of EV charging behavior through the use of historical public	One way to address the challenges of increasing EV adoption and grid issues is to use smart charging schedules to	The paper presents an EML model for predicting energy consumption and session duration for EV charging. The

(continued on next page)

Table 7 (*continued*)

Ref	Location	Ensemble Model	Focus	Aims	Result
		Gradient Boosting (XGBoost)	charging data, weather data, and nearby events data.	efficiently manage the charging load.	achieved MAE for energy consumption and session duration are 1.45 kWh and 66.5 min, respectively. Additionally, the use of weather and event data enhances the reliability of forecasting.
Alshammari and Chabaan (2023)	Not Mentioned	Random Forest, Categorical Boosting (CatBoost), and Extreme Gradient Boosting (XGBoost) ,Ant Colony algorithm.	The research uses EML techniques to estimate EV charging times and enhance the sustainability factor of electric charging stations. also includes the development of a foreign object recognition system to raise the reliability and security of wireless charging for EVs	Reducing travel disruption for EV drivers by accurately predicting charging times, which can help end consumers plan their trips and minimize electricity waste. also highlights how these efforts can improve the stability of EVS and the security and dependability of wireless charging for EVs.	The study proposes an approach for synchronized charging of PV batteries that reduces charging costs and demand on the electric grid. It also preserves the efficient functioning of the distribution system and meets operational and priority limitations.

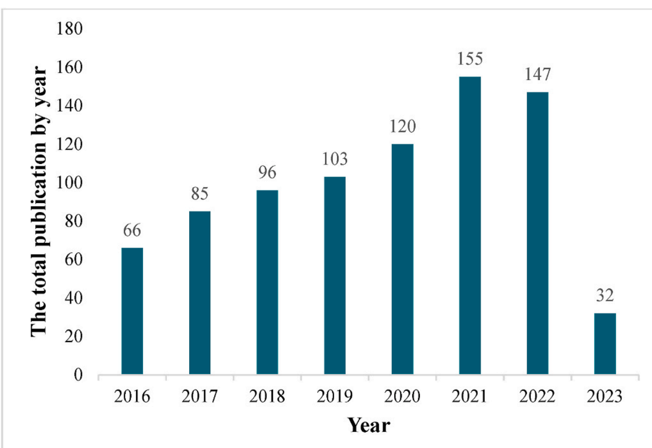

Fig. 11. The consequences of Ev charging on the main grid as reflected in total research studies conducted annually, utilizing the WOS database.

based EV charger recognition, charging station localization, and real-time demand forecasting using recurrent neural networks (RNNs).

On the other hand, ensemble learning can enhance prediction accuracy and robustness by combining multiple models, making it valuable for integrating various data sources in EV charging scenarios. this technique can be precious in scenarios where multiple data sources or models need to be integrated to make informed decisions about EV charging, such as combining weather data, user behavior, and charger availability. As the studies referenced in (Ullah et al., 2022; Huang et al.) highlighted, the ensemble learning approach demonstrated superior performance when contrasted with ML and DL techniques. Specifically, the ensemble learning-based model consistently outperformed its counterparts, boasting notably lower prediction errors across various evaluation metrics, including mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

ML techniques are a practical choice for shorter-term forecasting and grid management due to their efficiency and versatility. While DL and ensemble learning demonstrate greater potential for long-term research and adaptability to dynamic data challenges.

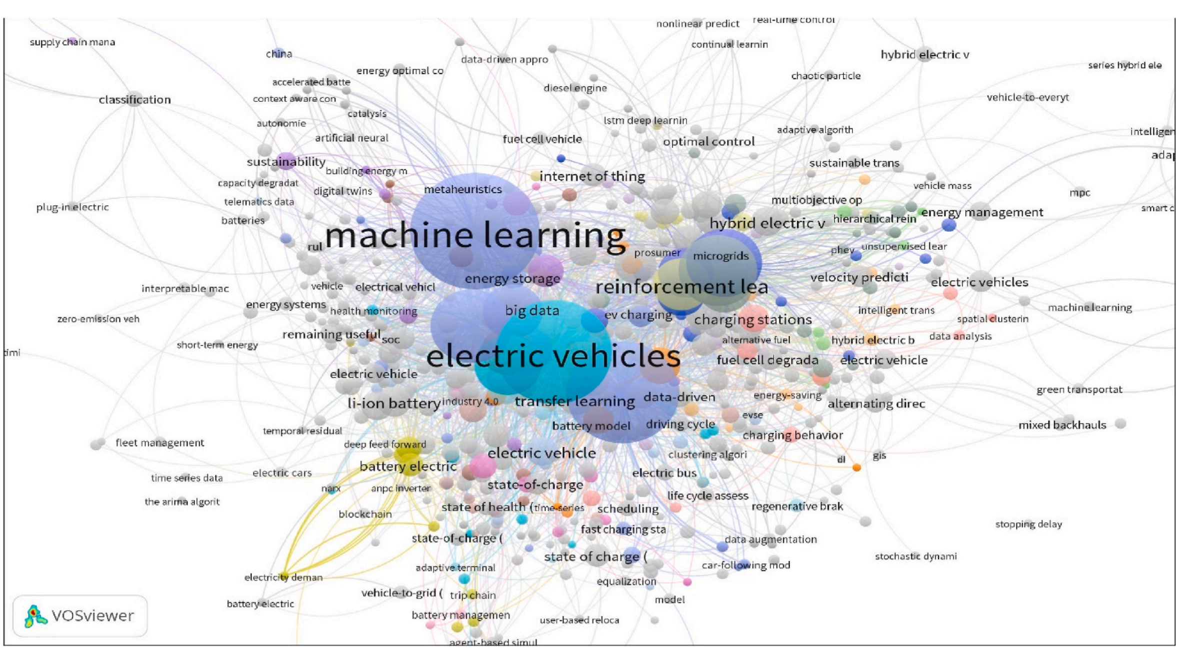

Fig. 12. Machine learning keywords for Ev charging from the scopus database.

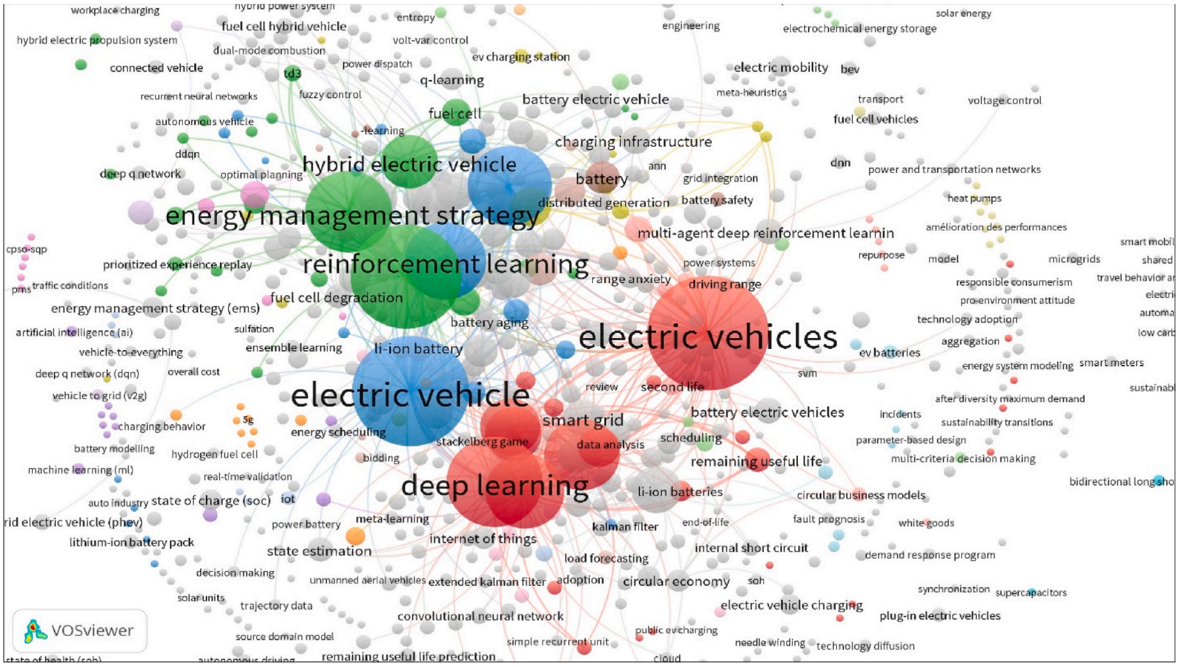

Fig. 13. Deep learning keywords for Ev charging from the scopus database.

8. Future research direction

Given their demonstrated effectiveness, future research in EV charging behavior should focus on Modification ensemble learning techniques. Integrating ML, DL, and ensemble methods with smart grid technology can optimize EV charging efficiency and reduce pressure on the main grid. Efforts should be directed towards real-time forecasting and control of EV charging, utilizing Internet of Thing (IoT) and advanced analytics. Dynamic pricing strategies can be incorporated to incentivize off-peak charging. Combining insights from behavioral economics can enhance understanding and prediction of EV owner behavior. Addressing data privacy and security concerns in extensive dataset usage is crucial, and expanding forecasting models to include various transportation modes can lead to a more comprehensive and sustainable system. Fig. 15 provides a visual representation of the key future research directions in the field of EV charging.

9. Conclusion

This study discusses the recent advancements in the application of ML, DL, and ensemble learning concepts in the field of EV charging.

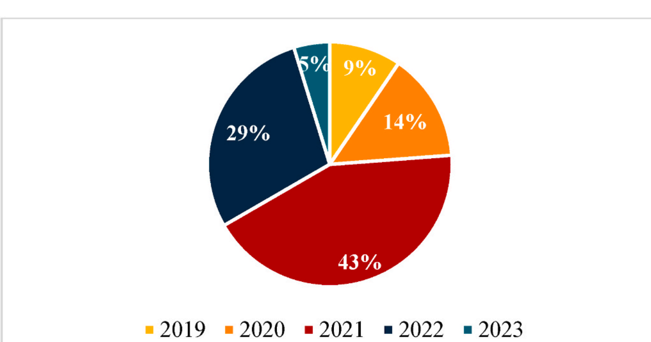

Fig. 14. The adoption rate of ensemble learning techniques in publications over the years, based on the WOS database.

Decreasing GHG pollution and improving energy efficiency are the main positive consequences of using EVs while adding a huge number of EVs in EPS for charging, puts lots of pressure on the main grid. using ML and DL techniques can forecast EV charging behavior; so, these techniques lead to better utilization of sources and improve the sustainability of EPS. Meanwhile, many studies have demonstrated that the ensemble learning technique enables precise forecasting for EV charging behavior by leveraging the strengths of multiple techniques simultaneously, resulting in superior performance compared to ML and DL. Furthermore, the findings indicate that ML, DL, and ensemble learning techniques show promising potential in predicting EV charging behavior and addressing the challenges arising from the growing adoption of EVs. These techniques contribute to the development of a more sustainable transportation system. In addition to exploring research areas, the objective of this study was to conduct a thorough assessment of these applications and classify the articles based on their methodology, focus, aim, year of publication, countries, and results.

CRediT authorship contribution statement

Elaheh Yaghoubi: Writing – review & editing, Writing – original draft, Conceptualization. **Elnaz Yaghoubi:** Investigation, Conceptualization. **Ahmed Khamees:** Writing – review & editing, Methodology. **Darioush Razmi:** Investigation. **Tianguang Lu:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

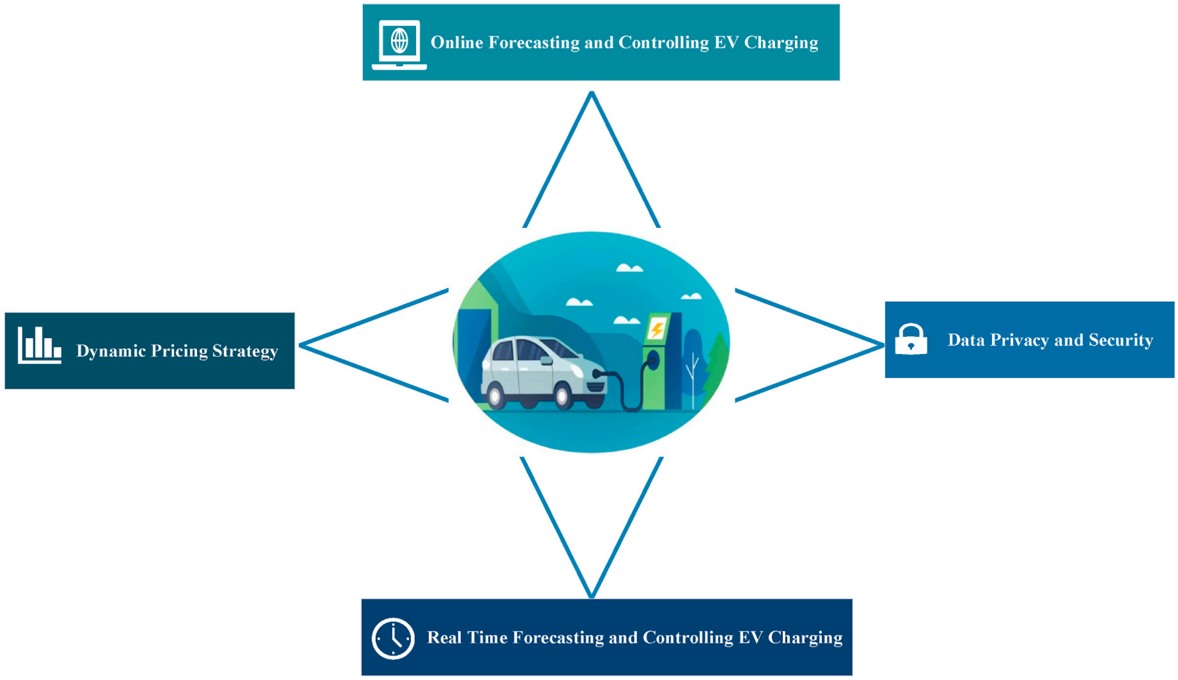

Fig. 15. A visual overview of key future research directions in Ev charging.

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