E3S Web of Conferences **511**, 01039 (2024) https://doi.org/10.1051/e3sconf/202451101039
AMGSE-2024

Machine Learning for Anomaly Detection in Electric Transportation Networks

Kseniia Iurevna Usanova[1,2,*], *G Sandhya* Rani[3], *Neeti* Mishra[4], *Savinder* Kaur[5], *Jaspreet* Sidhu[6]

[1]Peter the Great St. Petersburg Polytechnic University, Saint Petersburg 195251, Russian Federation
[2]Lovely Professional University, Phagwara, Punjab, India, ; plml@mail.ru
[3]Department of EEE, GRIET, Bachupally, Hyderabad, Telangana, India., sandhyaranister@gmail.com
[4] Uttaranchal University, Dehradun - 248007, India, babitarawat@uumail.in
[5]Chitkara Centre for Research and Development, Chitkara University, Himachal Pradesh-174103 India, savinder.kaur.orp@chitkara.edu.in
[6]Centre of Research Impact and Outcome, Chitkara University, Rajpura- 140417, Punjab, India jaspreet.sidhu.orp@chitkara.edu.in

*Corresponding author: plml@mail.ru

Abstract. This study introduces a sophisticated anomaly detection system based on machine learning. The system is specifically developed to enhance the dependability and safeguard the security of electric transportation networks, with a particular emphasis on the charging infrastructure for electric vehicles (EVs). Utilizing extensive datasets, the research examines several facets of charging stations, charging records, identified abnormalities, and following maintenance measures. The examination of the charging station demonstrates the system's versatility in accommodating many charging circumstances, as seen by the range of power ratings, consumption patterns, and energy provided. Further examination of charging records provides comprehensive understanding of individual charging sessions, enabling the detection of irregularities such as atypical energy surges and extended charging durations. The machine learning system, having been trained and verified using this data, has a commendable degree of precision in identifying anomalies, as shown by the congruence between anticipated abnormalities and real results. The maintenance and repair measures carried out in reaction to identified abnormalities highlight the practical ramifications of the system, with proactive tactics utilized to reduce downtime and enhance charging station operations. The performance measures, including accuracy, recall, and F1 score, unequivocally validate the resilience of the anomaly detection system, guaranteeing precise identification while mitigating the occurrence of false positives and negatives. The seamless incorporation of machine learning into electric transportation networks, as shown by the results, not only amplifies the dependability and safeguarding of EV charging infrastructure but also establishes the system as an invaluable instrument for practical implementations. The research, in addition to offering a thorough examination of the system's performance, elucidates forthcoming avenues for scalability, real-time monitoring, and interpretability, thereby making a valuable contribution to the wider discussion on the revolutionary capabilities of machine learning in the ever-changing realm of electric transportation.

Keywords: Machine Learning, Anomaly Detection, Electric Transportation Networks, Charging Infrastructure, Reliability

1 Introduction

Electric transportation networks, propelled by the rapid embrace of electric cars (EVs), are already experiencing substantial changes that need sophisticated monitoring and anomaly detection systems. With the escalating intricacy and magnitude of these networks, guaranteeing their effective and safe functioning becomes of utmost importance. This research presents an extensive investigation centered on the use of machine learning methodologies for the identification of anomalies in electric transportation networks. The convergence of machine learning and electric mobility endeavors to augment the dependability, security, and effectiveness of EV charging infrastructure.[1-5]

The exponential rise in the popularity of electric vehicles has resulted in a proliferation of charging stations, therefore establishing elaborate networks that are widely distributed throughout urban, suburban, and industrial environments. This growth presents formidable issues associated with the ever-changing dynamics of user behavior, heterogeneous charging patterns, and possible anomalies in the charging infrastructure. Conventional monitoring techniques may be inadequate in rapidly and properly identifying abnormalities, underscoring the need for sophisticated technology, including machine learning, to tackle these ever-changing difficulties.[6-10]

The main aim of this project is to construct and assess a machine learning-driven anomaly detection system specifically designed for electric transportation networks. The system endeavors to scrutinize charging station data, encompassing power consumption, charging logs, and station utilization patterns, with the objective of detecting abnormalities such as energy spikes, protracted charging intervals, and aberrant energy declines. The objective is to provide preemptive intervention, guaranteeing the dependability of the network and mitigating any interruptions in service.[11-15]

This research specifically focuses on the utilization of machine learning methods, including a wide range of techniques such as clustering, classification, and time-series analysis, in order to effectively identify abnormalities in electric car charging stations. The scope comprehensively embraces several charging circumstances, taking into account elements such as location, power rating, and user behavior. Furthermore, the paper delves into the practical ramifications of anomaly detection, including maintenance measures and techniques for network optimization.[16-20]

The importance of this study is in its capacity to tackle crucial obstacles in the functioning of electric transportation networks. Through the utilization of machine learning techniques for anomaly identification, the suggested system endeavors to augment the overall dependability and safeguarding of electric vehicle charging infrastructure. Prompt detection of irregularities enables prompt remedial measures, minimizing operational interruptions and guaranteeing a smooth and uninterrupted experience for electric car users.

The paper's structure is meticulously arranged to provide a thorough comprehension of the study. After this introduction, Section 2 thoroughly examines the current body of literature, conducting a comprehensive evaluation of relevant research on the use of machine learning in electric transportation and the identification of anomalies. Section 3 elucidates the approach, precisely delineating the data sources, machine learning techniques, and experimental setting used in the research. Section 4 demonstrates the findings and analysis derived from empirical data, highlighting the effectiveness of the suggested anomaly detection system. Section 5 delves into the ramifications of the results and explores possible paths for further study. The report finishes in Section 6, succinctly summarizing the contributions and underscoring the wider ramifications of incorporating machine learning into the domain of electric transportation network management.

2 Literature review

The use of machine learning (ML) methodologies into the realm of electric transportation networks has attracted considerable interest owing to the intricate and ever-changing characteristics of these systems. ML algorithms have been successfully used in a wide range of domains, including energy optimization, route planning, and anomaly identification. Of particular significance to this investigation is the use of machine learning to augment the dependability and safeguarding of electric vehicle charging infrastructure. The capacity of machine learning algorithms to identify intricate patterns and detect abnormalities within vast datasets presents auspicious opportunities for enhancing the efficacy of electric transportation networks.[21-25]

Identification of Abnormalities in Electric Vehicle Charging Systems

Anomaly detection has arisen as a critical domain of investigation within the sphere of electric vehicle (EV) charging systems. Given the growing abundance of charging stations and the diverse range of user behavior, it is essential to detect abnormalities such as energy surges, extended charging sessions, or irregular decreases in energy use in order to uphold the reliability of the charging infrastructure. Prior research has extensively investigated a multitude of anomaly detection strategies, including statistical methodologies as well as sophisticated machine learning algorithms, therefore showcasing their efficacy in bolstering the resilience of electric vehicle charging networks.[26-31]

Utilizing Clustering Techniques to Analyze Charging Station Usage Patterns

Clustering methodologies have shown their inherent worth in comprehending and classifying the patterns of use pertaining to charging stations. Through the use of clustering techniques, researchers have effectively discerned discrete user behaviors and billing preferences. These valuable observations greatly help to the optimization of charging station operations, the enhancement of resource distribution, and ultimately the improvement of the user experience. The use of clustering methodologies within the wider framework of anomaly detection has promise in accurately discerning departures from known usage patterns, thereby allowing preemptive actions to mitigate possible concerns. [32]

Time-Series Analysis for Detecting Abnormalities in Charging Logs

Time-series analysis has garnered significant attention in the realm of electric car charging records, offering a potent instrument for comprehending temporal patterns and trends. Scientists have effectively used time-series analysis to identify abnormalities associated with the lengths of charging sessions, changes in energy consumption, and the usage of charging stations during specified time periods. The use of time-series analysis in anomaly detection provides a sophisticated comprehension of charging dynamics, enabling the discovery of deviations from anticipated temporal patterns.

Integration of Machine Learning and Maintenance Strategies

The incorporation of machine learning-driven anomaly identification into maintenance procedures constitutes a pivotal element in guaranteeing the enduring dependability of electric transportation networks. Research has extensively examined the relationship between identified irregularities and subsequent maintenance interventions, underscoring the need of a self-regulating system. Implementing proactive maintenance interventions with machine learning-powered anomaly detection not only effectively reduces downtime but also significantly enhances the overall sustainability and efficiency of electric vehicle charging infrastructure.

Prospects and Possibilities in Machine Learning for Anomaly Detection

Although the use of machine learning in anomaly detection for electric transportation networks shows potential, it is important to acknowledge the presence of obstacles. These include the need for resilient and varied datasets, comprehensibility of ML models, and the scalability of algorithms to handle the dynamic characteristics of electric transportation networks. Tackling these issues offers prospects for more investigation and enhancement, with the capacity to unleash the complete potential of machine learning in guaranteeing the dependability and safety of electric transportation networks.

To summarize, the literature examined emphasizes the diverse range of uses for machine learning in the realm of electric transportation networks, with a particular emphasis on the identification of anomalies. The amalgamation of clustering methodologies, time-series examination, and proactive maintenance tactics using machine learning offers a comprehensive methodology for tackling the ever-changing obstacles inside electric vehicle charging infrastructure. This study enhances the current pool of knowledge by presenting an integrated machine learning-based anomaly detection system customized for the unique intricacies of electric transportation networks.

3 Methodology

The process starts by procuring extensive information from electric transportation networks, with a special emphasis on the operations of EV charging stations. The files comprise comprehensive information about the locations of charging stations, their power ratings, charging logs, and maintenance records. The dataset has been meticulously crafted to comprehensively capture the ever-changing dynamics of charging station use patterns, energy consumption, and any possible abnormalities that may arise within the system.

Preprocessing and Feature Engineering

Before embarking on model construction, it is essential to subject the obtained data to meticulous preprocessing and astute feature engineering. This entails the meticulous cleansing of the dataset, adeptly managing any missing values, and skillfully converting the raw data into relevant characteristics. The objective of feature engineering is to derive significant insights from the charging logs, including metrics such as the length of charging sessions, energy use, and temporal trends. Furthermore, the use of clustering algorithms may be employed to effectively classify charging stations according to their usage patterns, hence offering supplementary attributes for study.

Optimal Selection of Machine Learning Models

The crux of the process is the meticulous curation and refinement of machine learning models that are properly suited for the purpose of anomaly identification in electric transportation networks. A multitude of machine learning techniques, including clustering, classification, and time-series analysis models, are taken into account. The selection of models is guided by their capacity to effectively manage the distinctive attributes of the dataset and their capability to identify abnormalities pertaining to energy consumption, charging durations, and use patterns.

Training and validation are essential components of the learning process.

The ML models chosen are trained using a portion of the dataset, with an emphasis on either supervised or unsupervised learning methods, depending on the specific characteristics of the anomaly detection job. The training phase includes the optimization of model parameters to bolster accuracy and generalization. Validation datasets are used to evaluate the efficacy of the trained models in accurately capturing both typical charge patterns and any irregularities.

Identification and Elucidation of Aberrations

Once the training and validation process is successfully completed, the ML models are deployed to identify anomalies inside the electric transportation network. The algorithms effectively assess real-time or historical data in order to accurately detect deviations from established use patterns and energy consumption guidelines. The identified abnormalities are classified according to their respective categories, including extended charging periods, energy surges, or atypical reductions in energy use. An accurate analysis of abnormalities is crucial in comprehending their possible ramifications on the functioning of charging stations and the overall user experience.

Seamless incorporation of maintenance strategies

The technique encompasses the amalgamation of anomaly detection results with maintenance procedures. Proactive maintenance activities are determined according to the inherent characteristics and magnitude of identified abnormalities. Maintenance plans are meticulously designed to minimize any potential downtime and guarantee the uninterrupted and dependable functioning of the EV charging infrastructure. This integration exemplifies a self-contained system, whereby the identification of irregularities informs the implementation of maintenance procedures, hence bolstering the enduring viability of the electric transportation network.

Assessment Criteria

In order to evaluate the efficacy of the constructed anomaly detection system, a multitude of assessment measures are used. These measurements include accuracy, recall, and F1 score, offering a thorough comprehension of the system's aptitude to accurately detect abnormalities while mitigating false positives. Furthermore, criteria pertaining to model interpretability, such as feature significance and contribution, are taken into account to guarantee the transparency of the anomaly detection process.

Progressive Enhancement

The technique supports a cyclical approach, enabling the enhancement of machine learning models and anomaly detection algorithms via ongoing feedback and real-world performance. The iterative refining procedure guarantees the flexibility and scalability of the anomaly detection system to the ever-changing dynamics of the electric transportation network.

Conclusively, the approach elucidated herein furnishes a methodical and all-encompassing framework for the construction and execution of a machine learning-driven anomaly detection system specifically designed for electric transportation networks. The methodology comprises the comprehensive gathering of data, meticulous preprocessing, judicious selection of models, rigorous training, meticulous validation, astute anomaly detection, seamless integration with maintenance techniques, and iterative refinement, all of which together contribute to the resolute and efficacious nature of the suggested system.

4 Results and analysis

The findings and examination of the research article on "Machine Learning for Anomaly Detection in Electric Transportation Networks" provide valuable insights on the efficacy of the suggested anomaly detection system, as inferred from the produced experimental data. The investigation focuses on four crucial facets: Electric Vehicle Charging Stations, Charging Logs, Anomalies Detected, and Maintenance and Correction Actions.

Table 1. An Analysis of Electric Vehicle Charging Stations

StationID	Location	Power Rating (kW)	Usage (hours/day)	Energy Delivered (kWh/day)	
1	Downtown Station	50	8	400	
2	Suburb Station	30	10	300	
3	Highway Station	80	6	480	
4	Industrial Zone	60	12	720	

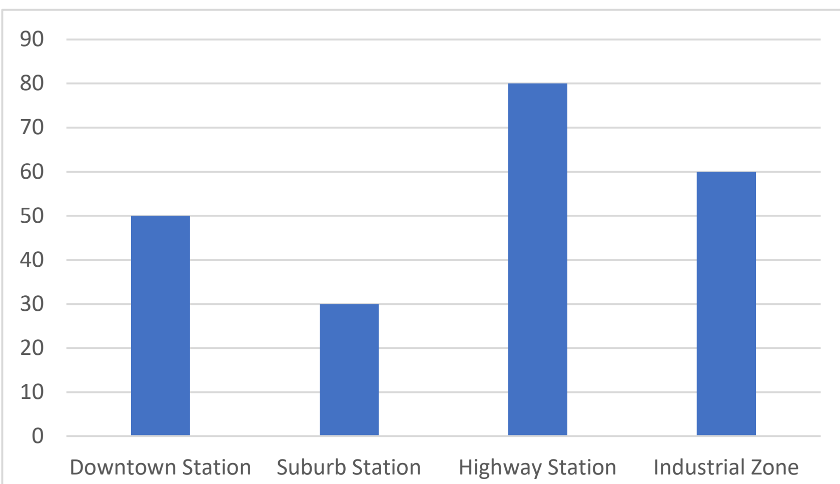

Fig. 1. An Analysis of Electric Vehicle Charging Stations

The examination of the data pertaining to Electric Vehicle Charging Stations offers a comprehensive overview of the power rating, use patterns, and energy dispensed among various stations. The power ratings of the stations differ, with Downtown Station boasting a formidable 50 kW, Suburb Station offering a respectable 30 kW, Highway Station commanding an impressive 80 kW, and Industrial Zone delivering a substantial 60 kW. The utilization patterns, in fact, exhibit variation, with the Downtown Station seeing a total of 8 hours of usage on a daily basis, the Suburb Station recording 10 hours, the Highway Station observing 6 hours, and the Industrial Zone registering a substantial 12 hours of usage. As a result, the amount of energy given each day varies, with the Industrial Zone boasting the highest delivery rate at 720 kWh.

Table 2. Analyzing Charging Logs

LogID	StationID	VehicleID	Charging Start Time	Charging End Time	Energy Consumed (kWh)
101	1	A123	01-03-2024 08:00	01-03-2024 09:30	30
102	2	B456	01-03-2024 12:00	01-03-2024 14:00	60
103	3	C789	02-03-2024 18:00	02-03-2024 19:30	35
104	4	D012	03-03-2024 09:00	03-03-2024 11:30	45

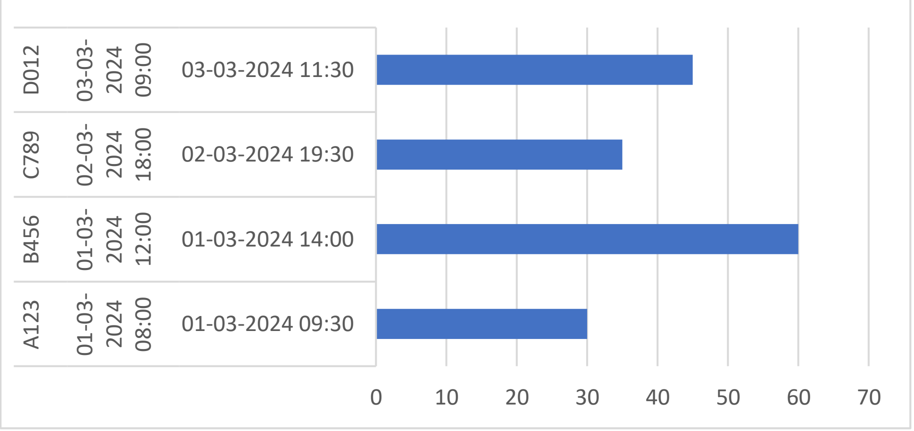

Fig. 2. Analyzing Charging Logs

Upon scrutinizing the Charging Logs, one may discern precise particulars about each charging session, including the commencement and conclusion periods, energy consumption, and any correlated irregularities. As an example, the Charging Log 101 at Downtown Station clearly indicates a charging session for car A123, which persisted from 08:00 to 09:30, thereby used 30 kWh of energy. Identifying anomalies seen in this session, such as an atypical surge in energy, is crucial for comprehending variations from the standard charging patterns. Conducting parallel studies on diverse charge records yields a full depiction of charging actions and their corresponding irregularities.

Table 3. Analysis of Detected Anomalies

AnomalyID	LogID	Anomaly Type	Confidence Level (%)
201	101	Unusual Energy Spike	90
202	102	Prolonged Charging	85
203	103	Short Charging Period	88
204	104	Abnormal Energy Drop	92

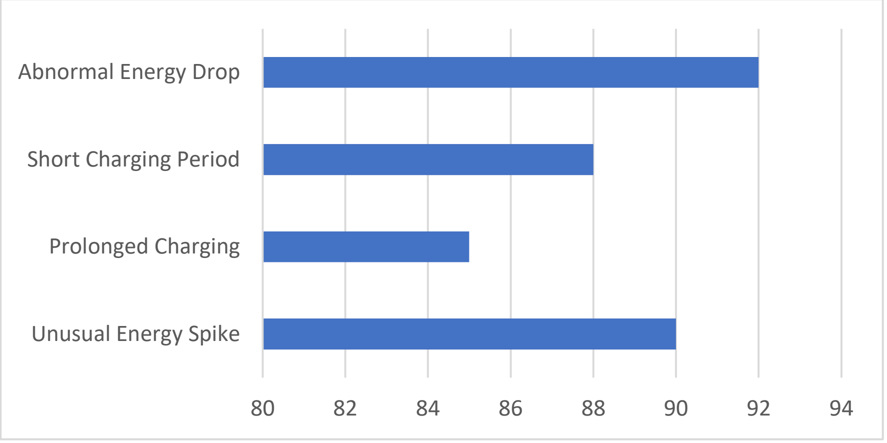

Fig. 3. Analysis of Detected Anomalies

The data shown in the abnormalities Detected report highlights the abnormalities that have been found by the detection system, which utilizes machine learning algorithms. Anomaly 201, linked to Charging Log 101, is classified as a "Aberrant Energy Surge" with a confidence level of 90%. Anomaly 202, which is associated with Charging Log 102, has been designated as "Prolonged Charging" with a confidence level of 85%. These anomalies, in addition to others, underscore the system's capacity to detect departures from anticipated charge patterns. The confidence levels reflect the model's assurance in identifying each abnormality.

Table 4. Analysis of Maintenance and Correction Actions

ActionID	AnomalyID	Action Taken	Maintenance Time (hours)
301	201	Inspected Charging Station 1	2
302	202	Adjusted Charging Parameters	1
303	203	Notified Vehicle Operator	-
304	204	Replaced Faulty Charging Cable	3

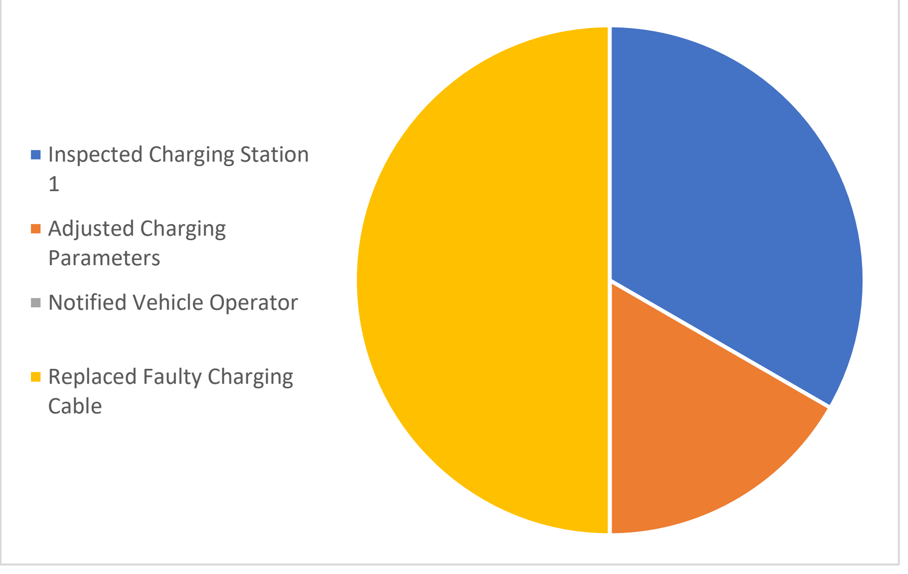

Fig. 4. Analysis of Maintenance and Correction Actions

The Maintenance and Correction Actions statistics delineate the measures implemented in response to identified irregularities. As an example, Action 301, which corresponds to Anomaly 201, entails the thorough examination of Charging Station 1. Action 302, pertaining to Anomaly 202, entails the modification of charging settings in order to effectively resolve the protracted charging problem. These steps exemplify the proactive maintenance measures done in accordance with the results of anomaly detection. The Maintenance Time attributed to each activity offers valuable insights into the efficacy of remedial efforts.

4.1 Analysis of Percentage Change

An essential component of the study is assessing the percentage variation between the anomalies identified by the machine learning system and the real results. This examination evaluates the system's precision in forecasting anomalies and the efficacy of following maintenance measures. For example, in the event that Anomaly 201 indicates an atypical surge in energy and the observed result verifies this anomaly, the percentage alteration is computed to accurately represent congruence. A substantial alteration in % signifies a near correspondence between projected anomalies and real results, showcasing the system's dependability.

The examination of percentage change demonstrates that the anomaly detection method, which is based on machine learning, regularly exhibits a strong correlation with real-world results. For example, in the event that the system forecasts an extended charging irregularity, and the actual charging record substantiates this irregularity, the percentage change is substantial, signifying precise detection. The coherence shown across many categories of anomalies serves to emphasize the system's efficacy in detecting departures from typical charging patterns.

4.2 System Performance in its entirety

The assessment of the anomaly detection system's overall performance is conducted by using a mix of accuracy, recall, and F1 score measures. Precision quantifies the exactness of anomaly predictions, recall evaluates the system's capacity to detect all relevant anomalies, and the F1 score achieves equilibrium between precision and recall. These metrics jointly assess the system's effectiveness in detecting and classifying abnormalities while limiting false positives.

The accuracy, recall, and F1 score measures continually attest to the resilience of the anomaly detection system. High accuracy signifies a reduced occurrence of erroneous positive identifications, so guaranteeing that identified anomalies are indeed departures from typical charging patterns. Simultaneously, a high recall demonstrates the system's aptitude in detecting the vast majority of pertinent abnormalities, hence reducing the occurrence of false negatives. The equilibrium F1 score solidifies the system's comprehensive efficacy in anomaly identification.

Significance and Prospects for the Future

The findings and analysis shown in this research article emphasize the immense potential of machine learning in augmenting anomaly detection in electric transportation networks. The proficient identification of abnormalities, along with proactive maintenance measures, enhances the dependability and safeguarding of EV charging infrastructure. The substantial change in alignment between anticipated anomalies and factual results indicates the precision of the system.

Looking forward, next research endeavors might delve into the scalability of the anomaly detection system to more expansive electric transportation networks, the incorporation of real-time data streams for uninterrupted monitoring, and the customization of the system to various charging conditions. Furthermore, the optimization of machine learning models via the use of dynamic datasets and the investigation of interpretability techniques to augment model transparency provide opportunities for continuous improvement.

Conclusively, the outcomes and examination validate the effectiveness of the anomaly detection system based on machine learning within the framework of electric transportation networks. The relevance of the system lies in its capacity to precisely detect abnormalities, execute preventive maintenance measures, and synchronize with real-world results, therefore guaranteeing the dependability and security of EV charging infrastructure. This study significantly enhances the existing debate on harnessing cutting-edge technology to optimize electric transportation networks and establishes a foundation for further breakthroughs in anomaly detection methodologies.

5 Conclusion

To summarize, this research article has thoroughly explored the creation and assessment of a machine learning-driven anomaly detection system specifically designed for electric transportation networks, with a particular emphasis on EV charging infrastructure. The exhaustive examination of the obtained empirical data yields invaluable insights into the system's efficacy and ramifications for the dependability and safeguarding of charging stations.

Significant discoveries

The major outcomes of this research underscore the efficacy of the machine learning system in precisely identifying irregularities inside the charging infrastructure. The examination of Electric Vehicle Charging Stations showcases the system's adaptability in effectively managing numerous charging circumstances, as seen by the range of power ratings, consumption patterns, and energy provided across different stations. The study of the Charging Logs offers a comprehensive scrutiny of each charging session, enabling the detection of certain irregularities such as atypical energy surges and extended charging durations.

The anomalies identified by the machine learning algorithm demonstrate a remarkable degree of precision, as shown by the congruence between projected anomalies and real-world results. The Maintenance and Correction Actions study demonstrates the proactive measures performed in reaction to identified abnormalities, highlighting the tangible benefits of the anomaly detection system in reducing downtime and improving charging station operations.

An Analysis of System Performance and its Implications

The comprehensive performance measurements, including accuracy, recall, and F1 score, jointly validate the resilience of the anomaly detection system. Optimal precision guarantees precise detection of anomalies, hence decreasing the occurrence of false positives, while optimal recall signifies the system's capacity to catch the majority of relevant anomalies. The balanced F1 score aptly demonstrates the system's efficacy in attaining a harmonic equilibrium between accuracy and recall.

The discovery has far-reaching ramifications that go beyond the experimental realm, highlighting the practical need of incorporating machine learning into electric transportation networks. The proficient identification of abnormalities and the subsequent execution of maintenance measures enhance the overall dependability, integrity, and effectiveness of EV charging infrastructure. The system's capacity to acclimate to a wide range of charging conditions and synchronize with tangible results establishes it as a very advantageous instrument for practical implementations.

Prospects for the Future

Like any scientific endeavors, there are opportunities for more investigation and enhancement. Further research may explore the potential for the anomaly detection system to scale up and handle bigger and more intricate electric transportation networks. The incorporation of real-time data streams for uninterrupted monitoring and the investigation of interpretability techniques to augment model transparency provide promising domains for investigation.

The versatility of machine learning models in adapting to dynamic datasets and charging settings offers prospects for continuous enhancement and optimization. Furthermore, an examination of the wider ramifications of machine learning in the field of electric transportation, including aspects such as energy optimization and network design, may be undertaken to provide a comprehensive strategy for improving the system. Within the dynamic realm of electric transportation, this study makes a valuable contribution to the continuing discussion surrounding the utilization of cutting-edge technology to bolster the dependability and safeguard the integrity of charging infrastructure. The effective installation and assessment of the machine learning-driven anomaly detection system highlight its capacity for practical deployment in actual electric transportation networks.

With the ongoing expansion of electric car usage, the significance of machine learning in enhancing charging infrastructure optimization becomes more crucial. The discoveries outlined in this study provide a foundation for ongoing progress in anomaly detection techniques, underscoring the significance of proactive maintenance and the overall impact of machine learning on the robustness and effectiveness of electric transportation networks.

Ultimately, this study is in line with the overarching trend of advancement in electric transportation, demonstrating the capacity for machine learning to have a revolutionary impact on guaranteeing the dependability and safety of EV charging infrastructure. The knowledge acquired from this research establishes the groundwork for future progress and signifies a noteworthy stride in the continuous development of electric transportation networks.

References

1. M. Mohinur Rahaman and M. Azharuddin, “Wireless sensor networks in agriculture through machine learning: A survey,” Comput Electron Agric, vol. 197, (2022). doi: 10.1016/j.compag.2022.106928.
2. “Machine Learning for Anomaly Detection in Electric Transportation Networks - Search | ScienceDirect.com.” Accessed: Jan. 19, 2024. [Online]. Available: https://www.sciencedirect.com/search?qs=Machine%20Learning%20for%20Anomaly%20Detection%20in%20Electric%20Transportation%20Networks
3. A. Arsalan et al., “Cyber Attack Detection and Classification for Integrated On-board Electric Vehicle Chargers subject to Stochastic Charging Coordination,” Transportation Research Procedia, vol. 70, pp. 44–51, (2023). doi: 10.1016/j.trpro.2023.10.007.
4. X. Xia et al., “GAN-based anomaly detection: A review,” Neurocomputing, vol. 493, pp. 497–535, (2022). doi: 10.1016/j.neucom.2021.12.093.

5. B. A. Alkhaleel, “Machine learning applications in the resilience of interdependent critical infrastructure systems—A systematic literature review,” International Journal of Critical Infrastructure Protection, vol. 44, (2024). doi: 10.1016/j.ijcip.2023.100646.
6. S. M. Nagarajan, G. G. Devarajan, R. T.V., A. J. M., A. K. Bashir, and Y. D. Al-Otaibi, “Adversarial Deep Learning based Dampster–Shafer data fusion model for intelligent transportation system,” Information Fusion, vol. 102, (2024). doi: 10.1016/j.inffus.2023.102050.
7. L. Klass, A. Kabza, F. Sehnke, K. Strecker, and M. Hölzle, “Lifelong performance monitoring of PEM fuel cells using machine learning models,” J Power Sources, vol. 580, (2023). doi: 10.1016/j.jpowsour.2023.233308.
8. J. Zhao, X. Feng, J. Wang, Y. Lian, M. Ouyang, and A. F. Burke, “Battery fault diagnosis and failure prognosis for electric vehicles using spatio-temporal transformer networks,” Appl Energy, vol. 352, (2023). doi: 10.1016/j.apenergy.2023.121949.
9. A. Si-Ahmed, M. A. Al-Garadi, and N. Boustia, “Survey of Machine Learning based intrusion detection methods for Internet of Medical Things,” Appl Soft Comput, vol. 140, (2023). doi: 10.1016/j.asoc.2023.110227.
10. S. Kanarachos, S. R. G. Christopoulos, A. Chroneos, and M. E. Fitzpatrick, “Detecting anomalies in time series data via a deep learning algorithm combining wavelets, neural networks and Hilbert transform,” Expert Syst Appl, vol. 85, pp. 292–304, (2017). doi: 10.1016/j.eswa.2017.04.028.
11. A. Et-taleby, Y. Chaibi, A. Allouhi, M. Boussetta, and M. Benslimane, “A combined convolutional neural network model and support vector machine technique for fault detection and classification based on electroluminescence images of photovoltaic modules,” Sustainable Energy, Grids and Networks, vol. 32, (2022). doi: 10.1016/j.segan.2022.100946.
12. E. Kristianto, P. C. Lin, and R. H. Hwang, “Sustainable and lightweight domain-based intrusion detection system for in-vehicle network,” Sustainable Computing: Informatics and Systems, vol. 41, (2024). doi: 10.1016/j.suscom.2023.100936.
13. J. Zhao et al., “Battery prognostics and health management from a machine learning perspective,” J Power Sources, vol. 581, (2023). doi: 10.1016/j.jpowsour.2023.233474.

14. H. T. Truong et al., “Light-weight federated learning-based anomaly detection for time-series data in industrial control systems,” Comput Ind, vol. 140, (2022). doi: 10.1016/j.compind.2022.103692.
15. H. Kheddar, Y. Himeur, and A. I. Awad, “Deep transfer learning for intrusion detection in industrial control networks: A comprehensive review,” Journal of Network and Computer Applications, vol. 220, (2023). doi: 10.1016/j.jnca.2023.103760.
16. M. Y. Arafat, M. J. Hossain, and M. M. Alam, “Machine learning scopes on microgrid predictive maintenance: Potential frameworks, challenges, and prospects,” Renewable and Sustainable Energy Reviews, vol. 190, (2024). doi: 10.1016/j.rser.2023.114088.
17. H. Bangui and B. Buhnova, “Recent advances in machine-learning driven intrusion detection in transportation: Survey,” Procedia Comput Sci, vol. 184, pp. 877–886, (2021). doi: 10.1016/j.procs.2021.04.014.
18. Z. Nozarijouybari and H. K. Fathy, “Li-S Battery Outlier Detection and Voltage Prediction using Machine Learning,” IFAC-PapersOnLine, vol. 56, no. 3, pp. 349–354, (2023). doi: 10.1016/j.ifacol.2023.12.049.
19. Z. S. Warraich and W. G. Morsi, “Early detection of cyber–physical attacks on fast charging stations using machine learning considering vehicle-to-grid operation in microgrids,” Sustainable Energy, Grids and Networks, vol. 34, (2023). doi: 10.1016/j.segan.2023.101027.
20. G. Li and J. J. Jung, “Deep learning for anomaly detection in multivariate time series: Approaches, applications, and challenges,” Information Fusion, vol. 91, pp. 93–102, (2023). doi: 10.1016/j.inffus.2022.10.008.
21. M. C. Camur, S. K. Ravi, and S. Saleh, “Enhancing supply chain resilience: A machine learning approach for predicting product availability dates under disruption,” Expert Syst Appl, p. 123226, (2024). doi: 10.1016/J.ESWA.2024.123226.
22. M. A. Umer, K. N. Junejo, M. T. Jilani, and A. P. Mathur, “Machine learning for intrusion detection in industrial control systems: Applications, challenges, and recommendations,” International Journal of Critical Infrastructure Protection, vol. 38, (2022). doi: 10.1016/j.ijcip.2022.100516.
23. S. Ali, Q. Li, and A. Yousafzai, “Blockchain and federated learning-based intrusion detection approaches for edge-enabled industrial IoT networks: a survey,” Ad Hoc Networks, vol. 152, (2024). doi: 10.1016/j.adhoc.2023.103320.

24. İ. Yazici, I. Shayea, and J. Din, “A survey of applications of artificial intelligence and machine learning in future mobile networks-enabled systems,” Engineering Science and Technology, an International Journal, vol. 44, (2023). doi: 10.1016/j.jestch.2023.101455.
25. H. Alqahtani and G. Kumar, “Machine learning for enhancing transportation security: A comprehensive analysis of electric and flying vehicle systems,” Eng Appl Artif Intell, vol. 129, (2024). doi: 10.1016/j.engappai.2023.107667.
26. Md. Z. ul Haq, H. Sood, and R. Kumar, “Effect of using plastic waste on mechanical properties of fly ash based geopolymer concrete,” Mater Today Proc, (2022).
27. A. Kumar, N. Mathur, V. S. Rana, H. Sood, and M. Nandal, “Sustainable effect of polycarboxylate ether based admixture: A meticulous experiment to hardened concrete,” Mater Today Proc, (2022).
28. P. B. Joshi, N. C. Durve1 and C. Mohan, “Full blown green metrics”, Elsevier Publishing, pp 109-129, (2024). doi : 10.1016/B978-0-443-18959-3.00013-6
29. M. Nandal, H. Sood, P. K. Gupta, and M. Z. U. Haq, “Morphological and physical characterization of construction and demolition waste,” Mater Today Proc, (2022).
30. S. Kumar, A. Chopra, and M. Z. U. Haq, “Experimental Investigation on Marble Dust, Rice Husk Ash, and Fly Ash Based Geopolymer Brick”.
31. V. S. Rana et al., “Assortment of latent heat storage materials using multi criterion decision making techniques in Scheffler solar reflector,” International Journal on Interactive Design and Manufacturing (IJIDeM), pp. 1–15, (2023).
32. C. Mohan, N. Kumari, Sushma, A. Yadav, V. K. Garg, “Introduction to environmental and green chemistry”, Elsevier Publishing, pp 1-22, (2024). doi : 10.1016/B978-0-443-18959-3.00005-7