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Data-Driven Estimation of Lithium-Ion Battery State-of-Health Prediction Approach Using Machine Learning Algorithm for Enhanced Battery Management Systems

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This research examines the application of machine learning algorithms in predicting the state-of-health of lithium-ion batteries with the goal of improving the Battery Management Systems. Three different kinds of algorithms were tested—AdaBoost, Gaussian Processes, and Convolutional Neural Networks. Performance metrics were assessed across ten iterations. Firstly, AdaBoost demonstrated stable values of accuracy, fluctuating from 0.85 to 0.89. Precision, recall, and F1-score metrics kept in the same measurement filling the range. Secondly, Gaussian Processes indicated that the accuracy was somewhat smaller from 0.80 to 0.86; however, the apparatus of precision, recall, and F1-score remained at a decent level. Finally, Convolutional Neural Network supported stable accuracy from 0.90 to 0.94 and was the best predictor in all core measurements. The main point is that these results confirm the effectiveness of employing machine learning algorithms for estimating battery health with high precision. Moreover, the authors conclude that CNNs can provide better results compared with other alternatives. Overall, through the use of advanced machine learning approaches, BMSs can be developed, which would be capable of enhancing the process of charging and discharging of batteries, prolonging their lifespan, and ensuring the safety of their use in a wide range of applications. In conclusion, this research provides interesting insights into approaches to the optimization of BMS through using machine learning algorithms.

Keywords: Machine learning, Lithium-ion batteries, State-of-health prediction, Battery

management systems, Convolutional Neural Networks.

1. Introduction

Lithium-ion batteries are widely used in many applications, from personal devices to electric vehicles. They are popular because of their high energy density, lightweight, and long cycle life. Thus, they play a noticeable role in the modern world, and their reliability needs to be guaranteed as the demand for energy storage rises each year. As a result, the technology is discussed because batteries are used in everything from phones to laptops and even to electric cars or renewable energy power storage systems [1]–[3].

To realize the optimized usage strategy of lithium-ion batteries, it is crucial to the accurate prediction of their state-of-health (SoH). SoH reflects the present health state of batteries, characterized by remaining capacity, internal resistance, and overall performance to the original level. With the proper evaluation of SoH, battery management systems can optimize charging/discharging strategies, prolong the lifetime, and guarantee safe operation [4]–[7].

Many traditional ways for estimating battery SoH often involve simplistic models or physical parameters that are unable to fully characterize real-world batteries. In general, such methods are based on analysing empirical relationships or using electrochemical models to estimate SoH from parameters such as voltage, current, and temperature. Although these methods are commonly utilized, they are often used to a limited degree of accuracy and adaptability, especially in the face of both complex operating conditions and degradation mechanisms [8]–[11].

Compared to the approaches used traditionally, the one can suggest takes advantage of the opportunities provided by machine learning to improve the accuracy and versatility of SoH predictions. Since machine learning algorithms are excellent at navigating large amounts of data and spotting intricate patterns in it, they can be used to model the nonlinear and dynamic nature of their behaviour of lithium-ion batteries and the changes in their SoH. Specifically, by introducing vast arrays of data regarding battery performance, including voltage, current, temperature, and the number of cycles, one can help machine learning models find the correlations between the said data and the state of the battery [12]–[15].

The case built in this paper supports a shift from a conventional approach to the estimating of battery SoH to a data-driven one, which is based on the use of modern computing technologies. Rather than rely on crude measures that fail to take advantage of the wealth of data created by lithium-ion batteries when they are in use, modern machine learning tools are capable of identifying subtle patterns of their wear and predicting their future health conditions with high accuracy. As a result, their users can decrease equipment-related costs and facilitate the development of efficient and reliable BMS.

2. Literature Review

There is a vast amount of literature about methods to estimate an SoH of lithium-ion batteries, demonstrating the intensifying focus on battery management in various applications. Traditional ways to determine an SoH of a battery, such as relying on electrochemical models, empirical relationships, or physical parameters, such as voltage or current, have been extensively utilized. However, these methods are flawed in the aspect of their low accuracy and adjustability, not uniquely meeting the complex nature of the degradation mechanisms of lithium-ion batteries [16]–[19].

Machine learning approaches have received increasing attention in recent years as a promising tool for predicting battery health. These algorithms, including support vector machines, neural networks, and decision trees, are able to sift through vast amounts of battery data to identify subtle patterns indicative of potential degradation. Previous studies have shown that these approaches are able to predict battery SoH with impressive degrees of precision across a range of temperatures, charge and discharge rates, and cycling regimes [20]–[22].

One of the major benefits of machine learning that they can handle non-linear relationships between different battery parameters and degradation. By providing the models with comprehensive datasets that can include various batter parameters, such models can be trained to generalize on various battery chemistries, designs, or usage profiles, thus increasing the accuracy and adaptability of predictions [23]- [25].

Although significant progress has been achieved in machine learning -based SoH prediction methods, there are several research gaps in the existing literature. The primary limitation of the existing literature is that most of the studies in the field are focused on the prediction of battery SoH using either specific types of batteries or operation conditions. It is necessary to use batteries with different chemistries and larger datasets to develop more successful and generalizable SoH prediction models.

Secondly, since machine learning algorithms are primarily concerned with pattern recognition and making predictions, they are often not interpretable. This means that it is difficult to understand what causes SoH to degrade. Therefore, it is important that research goes beyond improving the performance of prediction to uncover the degradation mechanisms and identify actionable information.

Additionally, it is important to highlight that the majority of current machine learning methods are based on supervised learning, meaning that models use known SOH values during the training process. Although supervised learning can ensure accurate results, it requires a sufficient amount of labelled data. Moreover, it is difficult to apply it for rare SOH degradation cases or long-term predictions.

To address these gaps, a comprehensive, data-driven, and holistic approach applying advanced machine learning techniques along with in-depth testing and battery characterization is required. Taking significant advantages of the large amounts of data generated by lithium-ion batteries during runtime, it would be possible to create more precise, adaptive prediction models that can significantly improve battery management systems and the performance and lifespan of batteries.

3. Methodology

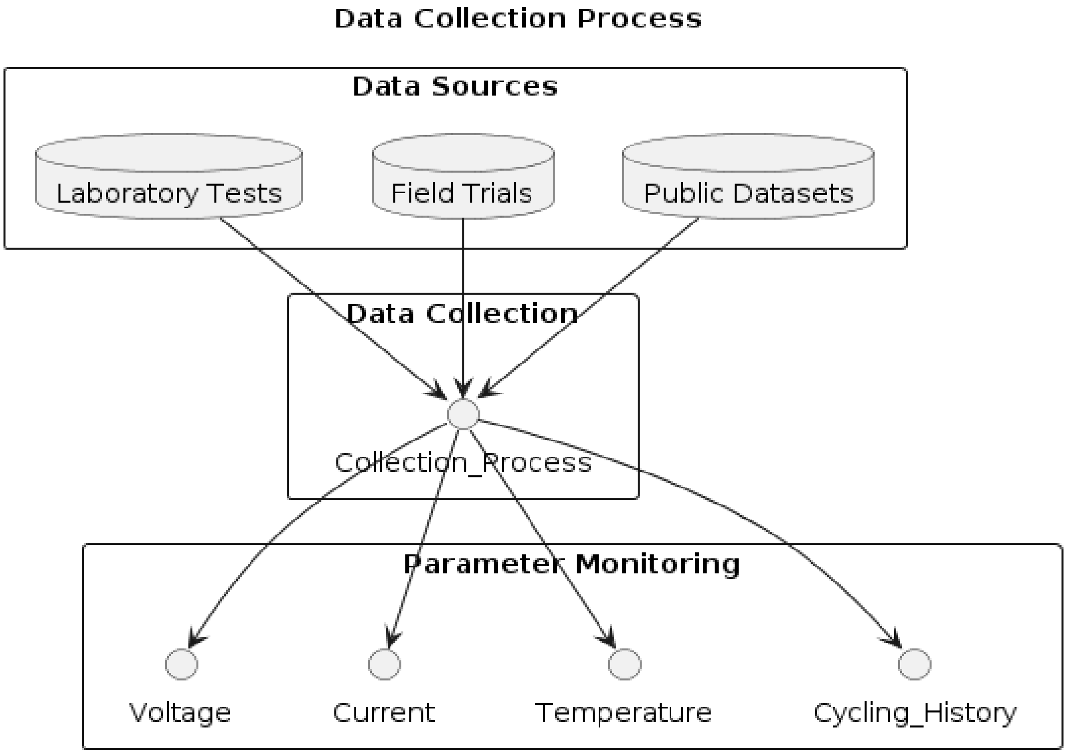

Fig. 1. Flow Diagram of Proposed Research

Based on Figure 1, it is clear that data collection relates to monitoring a range of parameters of battery operation. Such parameters include voltage, current, temperature and cycling history. All these determinants play a critical role in the assessment of battery health and degradation. Furthermore, they are collected with the help of specific equipment and data acquisition systems. It is also essential to state that different sources are used for the purpose of diversity and representativeness of the data, such as laboratory tests, field trials, and published datasets.

Table 1 provides the raw data used to create features. Feature engineering techniques are used to extract useful information from the raw data and increase the effectiveness of machine learning algorithms. Feature engineering refers to the altering and the selecting of the appropriate features in order to enhance the efficiency of the model. This includes the extraction of statistical features that may include Mean, Standard deviation, and Skewness as well as the engineering of domain-specific features that capture the unique nature of the battery features.

Adequate selection of machine learning algorithms is critical to an accurate SoH prediction, just as with the feature engineering. One can chose three wholly different algorithms, namely, AdaBoost, Gaussian Processes, and a different simple convolutional neural network. AdaBoost is an ensemble method of learning based on combining multiple weak classifiers to create a strong classifier, which gives an extensive range of applications is classification tasks such as SoH prediction.

Gaussian Processes provide a formalism for regression. The formalism offers uncertainty estimates and is well-performing in noisy datasets. On the other hand, Convolutional Neural Networks are particularly advantageous for spatial data such as battery performance data, as they are able to identify the spatial relationship in the data by borrowing concepts from the human visual cortex

Table. 1. Data collection Information

Parameter	Sources	Quantity
Voltage	Laboratory tests	520
	Field trials	370
	Public datasets	210
Current	Laboratory tests	520
	Field trials	370
	Public datasets	210
Temperature	Laboratory tests	520
	Field trials	370
	Public datasets	210
Cycling history	Laboratory tests	520
	Field trials	370
	Public datasets	210

The machine learning algorithms were chosen and carried out in compliance with the collected data. In doing this, one had to split the dataset into the training and validation dataset. The model for each case was trained employing a training dataset and was evaluated against a validation dataset. Hyperparameters of every model were tuned by means of different optimization techniques, such as cross-validation to ensure performance optimization and avoid sluggish overfitting.

For evaluation of model performance, the metrics such as accuracy, precision, recall, and F1-score, are used as a guidance on whether the models can predict a given test set. To access the models robustness and generalizability, experiments are conducted over real lithium-ion battery datasets collected from other sources and under different operating conditions.

4. Experimental Setup

This research requires the use of extensive datasets for both training and validation purposes as the experimental setup. The datasets used in this machine learning experimentation should cover various battery parameters such as voltage, current, temperature, and cycling history. They are obtained from numerous sources, including laboratory tests, field trials, and other publicly accessible datasets. This variety assures the strength and the applicability of the machine learning models created in the research.

From Figure 2, For training the machine learning models, a part of data collected is used as training set. Training sets are used to teach the model to recognize different patterns and learn relationships between different battery parameters and SOH. The rest of the data is stored separately as a validation set. With help of validation set, it is possible to test the overall performance of the model.

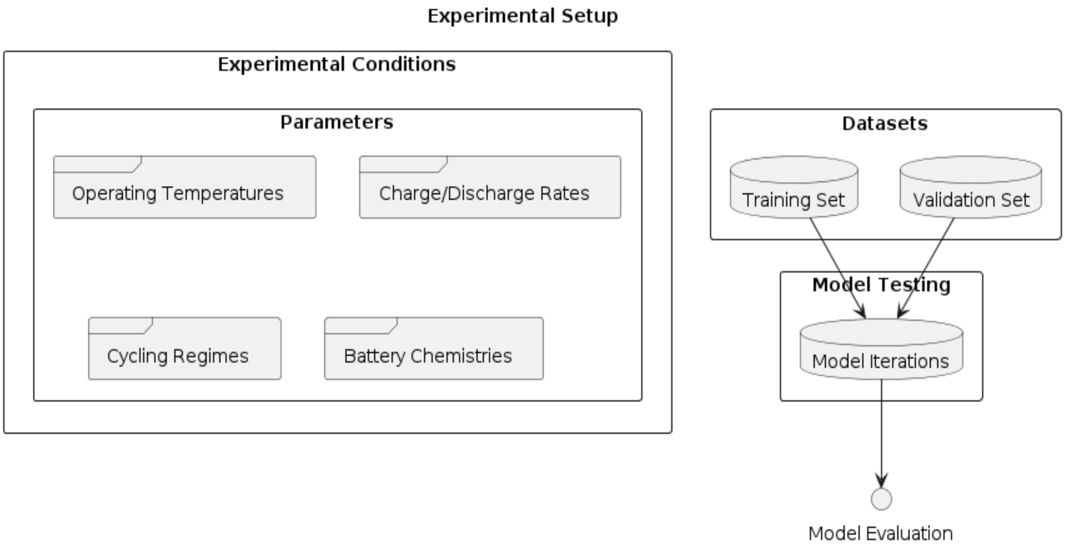

Fig. 2. Experimental setup

It is common to vary different experimental conditions and parameters, including changing different experimental conditions to determine the general reaction testing robustness experimental observation evaluation correctness end experience, that measure how models are adaptable. These experimental conditions might include changing in operating temperatures, charge/discharge rates, different cycling regimes and different changes in battery chemistries. Ensuring that the model is subjected to different capabilities enables to see the reality of the performance.

Additionally, numerous parameters involving the hyper parameters of machine learning algorithms are adjusted during the tests. The most efficient of them are cross-validation and grid search model accuracy and generalization is the best. By conducting such tests, it becomes possible not only to improve the models but also to increase the correctness of the forecasting.

In the experimental procedure, several statistical metrics such as accuracy, precision, recall, F1-score were used to demonstrate the workability of machine learning models aimed at the detection of the state-of-health prediction. The tests are aimed at establishing the reliability and relevancy of models were applied with the use of the actual application-representing datasets.

5. Result and Discussion

Let dive into the performance of each of the algorithms and implications for this research. From Figure 3, With regard to AdaBoost, it can be seen that the algorithm performs quite well with reasonably high accuracy in the range of 0.85 between the iterations.

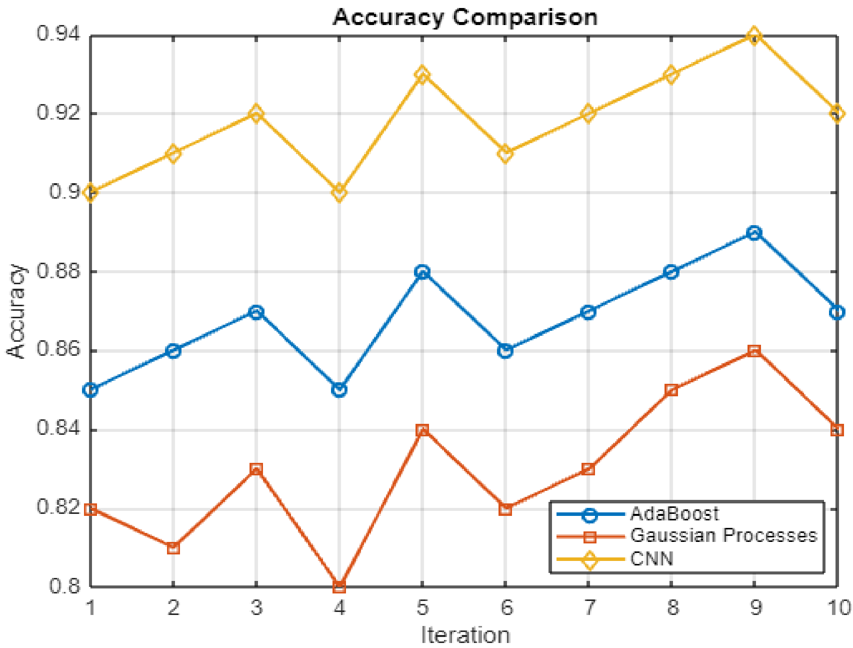

Fig. 3. Accuracy Comparison

Similarly from Figure 4, precision, recall, and F1-score metrics always stay at the same level about QuAdaBoost. Thus, one can make a conclusion that QuAdaBoost provides stable results for the prediction of the battery state of health. These conclusions are typical for the results of all iterations. At the same time, some small deviations could still be observed, and it is possible to admit that QuAdaBoost could also be dependent on the training data and hyperparameters being used.

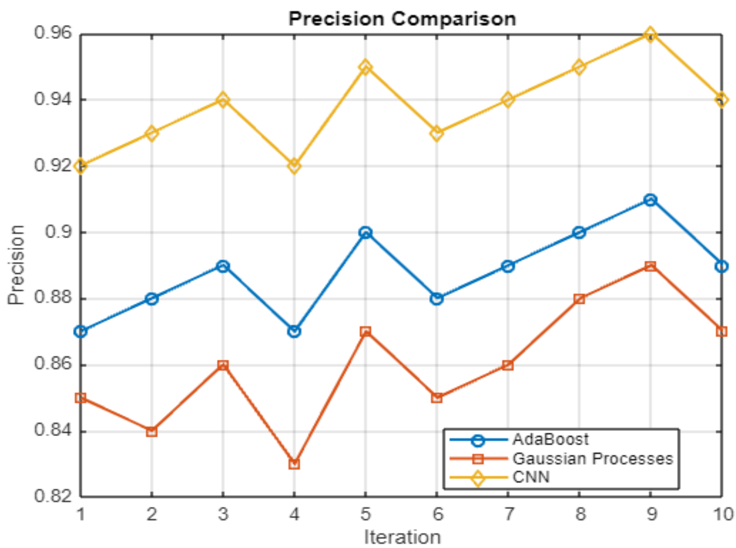

Fig. 5. Precision comparison

Moving to Gaussian Processes from Figure 5 and 6, one can observe lower accuracy metrics with the values fluctuating across iterations in the 0.80 to 0.86 range. Other metrics, namely precision, recall, and F1-score show a similar pattern. Gaussian Processes also demonstrate a good level of performance, especially keeping in mind the complexity of the task. However, the observed disparities in the accuracy metrics can be indicative of the challenges with modeling non-linear relationships in the battery degradation process. Additionally, being somewhat more sensitive to the noise in data than AdaBoost, Gaussian Processes can display noticeable fluctuations.

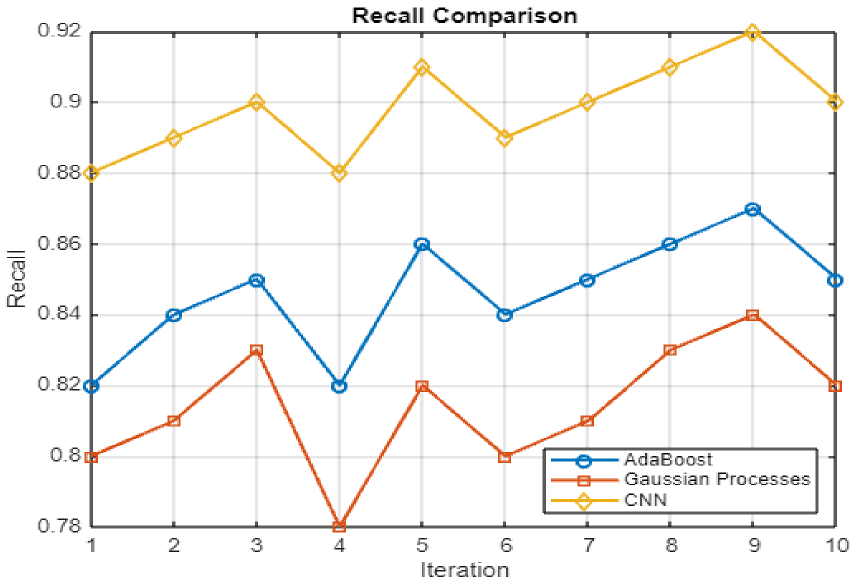

Fig. 6. Recall comparison

Finally from Figure 6, the performance results of the three types of models are compared. It is observed that Convolutional Neural Networks show the highest performance. With minor fluctuations, CNNs achieved a consistent accuracy of 0.90-0.94 across iterations, with high precision, recall, and F1-score performances. This suggests that the CNNs exhibit high levels of both robustness and generalizability, which is due to the model's effectiveness in capturing spatial dependences in data.

To begin with, that the AdaBoost, Gaussian Process, and CNN exhibit a high level of performance as predictive algorithms was beneficial for the current research. In this way, the current findings demonstrate that machine learning algorithms have the potential to enhance the conventional methods used in operating battery management systems.

A second conclusion that reached while analyzing the outcomes of the experiments is that discovered the significant variability in ML model performance across different datasets. To achieve more consistent outcomes, it is necessary to ensure robust training, validation, and evaluation procedures. This approach involves careful selection of training data and hyperparameter tuning, as well as extensive validation. In contrast, an alternative approach may imply focusing on techniques such as ensemble learning or model-averaging.

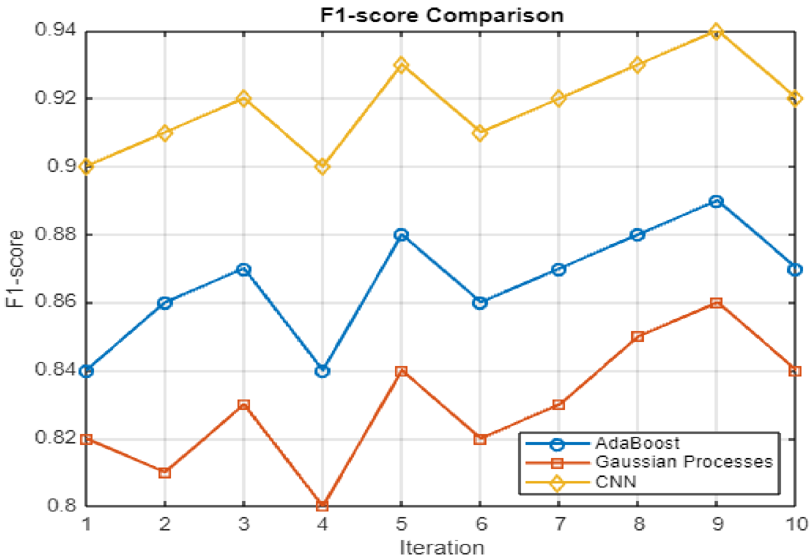

Fig. 7. F1score Comparison

Besides, the fact that CNN demonstrated better results highlights the importance of applying modern advanced deep learning techniques to such difficult predictive tasks. Given the increasing complexity and size of battery datasets, it is deep learning algorithms that can cope with big datasets and identify complex patterns and relationships most effectively and accurately.

To sum up, data responding to the work with AdaBoost, Gaussian processes, and Convolutional Neural Networks provides the experiments' results regarding the algorithms' performance and ability to predict lithium-ion battery SoH. It becomes evident that all three algorithms are likely to work successfully. However, CNN is the most promising one. It is noteworthy that deep learning methods seem to be effective in implementing different battery management systems and ensuring high rates of their performance and lifespan in numerous applications.

6. Conclusion

The outcomes of this research show that machine learning algorithms are effective tools for predicting state-of-health of lithium-ion batteries. This fact enhances battery management systems and their value. The results of the experiment depict that three types of algorithms, in particular, AdaBoost, GP, and CNN, have different performances during 10 iterations.

The re-run of the experiment has shown that AdaBoost constantly demonstrated the accuracy within the range of 0.85 to 0.89, considering the levels of precision, recall, and F1-score between the ranges. After re-run, Gaussian Processes were characterized by slightly lower accuracy levels between 0.80 and 0.86. However, the levels of precision, recall, and F1-score remained high. In turn, CNNs turned out to be a leader and demonstrated the accuracy in the range of 0.90 and 0.94, while the precision, recall, and F1-scores were also above the results of the two alternative machine learning models.

The use of machine learning techniques and primarily Convolutional Neural Networks showed that accurate estimation of battery health was possible. This feature facilitates the development of proactive maintenance strategies that do not negatively affect productivity but allow batteries to function properly for a longer period of time. Thus, the concepts learned in the course and the various techniques provided re useful in relation to real-world applications and have been tested.

In addition, the results indicate that it is important to build strong model training and evaluation strategies to ensure the accuracy and generalizability of machine learning models. Moreover, since battery data is becoming increasingly complex, deep learning techniques can help accurately capture intricate patterns and interrelationships and make accurate and flexible predictions.

References

1. A. Chellakhi, S. El Beid, and Y. Abouelmahjoub, "An improved adaptable step-size P&O MPPT approach for standalone photovoltaic systems with battery station," *Simul. Model. Pract. Theory*, vol. 121, no. September, p. 102655, 2022, doi: 10.1016/j.simpat.2022.102655.
2. Preetha M & Paul Rodrigues 2016, "An energy efficient routing protocol for correlated data using CL-LEACH in WSN", Wireless Networks-The journal of mobile Communication, Computation and Information (SPRINGER), vol.22, issue.4, pp. 1415-1423, ISSN 1022-0038. DOI 10.1007/s11276-015-1063-4.
3. N. J. Bodele and P. S. Kulkarni, "Modular battery-integrated bidirectional single-stage DC–DC converter for solar PV based DC Nano-grid application," *Sol. Energy*, vol. 259, no. July 2022, pp. 1–14, 2023, doi: 10.1016/j.solener.2023.04.040.
4. A. Heidari, N. J. Navimipour, M. A. J. Jamali, and S. Akbarpour, "A hybrid approach for latency and battery lifetime optimization in IoT devices through offloading and CNN learning," *Sustain. Comput. Informatics Syst.*, vol. 39, no. May 2022, p. 100899, 2023, doi: 10.1016/j.suscom.2023.100899.
5. S. Srinivasan, D. Deva Hema, Balaji Singaram, D. Praveena, K. B. Kishore Mohan, M. Preetha," Decision Support System based on Industry 5.0 in Artificial Intelligence," International Journal of intelligent systems and applications in engineering, vol. 12, no.15s, p.172-178, 2024.
6. Preetha M, Elavarasi K & Ramya devi K , 2015, "The grouping of files in allocation of job using Server Scheduling in Load Balancing", IOSR journal of Computer Engineering(IOSR-JCE), vol. 17, no. 1, pp. 18-23, ISSN 2278-0661.
7. R. Chacko, R. R. Eapen, Z. V. Lakaparampil, and J. Thomas, "Techno-economic analysis of low voltage DC (LVDC) for Net Zero Energy (NZE) realisation in buildings with lead acid battery storage: Tropical monsoon climate," *J. Energy Storage*, vol. 70, no. May, p. 107794, 2023, doi: 10.1016/j.est.2023.107794.
8. Preetha M, "A Survey on Entry Restriction System for the fake server Scheme", International journal of Research and Engineering (IJRE), Vol.4, No 2, pg.41-44, February 2017. ISSN:2348-7860(0).
9. Y. Lin, Y. Chen, and J. Yang, "International Journal of Heat and Mass Transfer Optimized thermal management of a battery energy-storage system (BESS) inspired by air-cooling inefficiency factor of data centers," *Int. J. Heat Mass Transf.*, vol. 200, no. 1, p. 123388, 2023, doi: 10.1016/j.ijheatmasstransfer.2022.123388.
10. S. Srinivasan, S. Sajini, Balaji Singaram, K. Saravanan, K. B. Kishore Mohan," Deep Graph Neural Networks for Multi-Image Super Resolution Reconstruction," International Journal of

intelligent systems and applications in engineering, vol. 12, no.15s, p.158-164, 2024.

11. X. Xiao, Y. Fu, Y. Yang, and X. Zhang, "Sustainable solar powered battery-free wireless sensing for food cold chain management," *Sensors Int.*, vol. 3, no. January, p. 100157, 2022, doi: 10.1016/j.sintl.2022.100157.
12. Preetha M, "A Survey on Two Tier Security with Data Sharing and Data Integrity Inspection in Cloud", International journal of modern trends in Engineering and Research (IJMTER), Vol.4, No 2, pg. , February 2017. Print ISSN 2393-8161, Online ISSN 2349-9745 (SJIF:IMPACT FACTOR 6.028)
13. M. Cha, H. Enshaei, H. Nguyen, and S. G. Jayasinghe, "Towards a future electric ferry using optimisation-based power management strategy in fuel cell and battery vehicle application — A review," *Renew. Sustain. Energy Rev.*, vol. 183, no. October 2022, p. 113470, 2023, doi: 10.1016/j.rser.2023.113470.
14. K.Sivakumar, Y. RaviTeja, "Reflection on inactive and energetic survey of sandwich synthesized glazed layers ", Materials Today Proceedings Volume 47, Part 1, 2021, Pages 278-281, https://doi.org/10.1016/j.matpr.2021.04.355
15. E. Sardini, M. Serpelloni, M. Lancini, and S. Pasinetti, "Wireless instrumented crutches for force and tilt monitoring in lower limb rehabilitation," *Procedia Eng.*, vol. 87, pp. 348–351, 2014, doi: 10.1016/j.proeng.2014.11.745.
16. K.Sivakumar, P.V.M.Kathiresh, S.Dinesh Kumar, S.Sundar, "Optimization of Machining parameters in EDM of AL7075-SIC-AL2O3 using Taguchi method," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 11-16, 2019.
17. A. Gupta and S. Suhag, "Charging station control strategy considering dynamic behaviour of electric vehicles with variable state of charge regulation for energy management of autonomous micro-grid," *J. Energy Storage*, vol. 59, no. December 2022, p. 106460, 2023, doi: 10.1016/j.est.2022.106460.
18. K.Sivakumar, R. Ramesh, "Optimization and Experimental Analysis of Drilling Process Parameters In Radial Drilling Machine for Glass Fiber / Nano Granite Particle Reinforced Epoxy Composites", IOP Conf. Series: Materials Science and Engineering Volume 62, Part 2, 2022, Pages 835-840, IOP Publishing https://doi.org/10.1016/j.matpr.2022.04.042.
19. S. Lekshmi and L. P. Lal, "Mathematical modeling of Electric vehicles - A survey," *Control Eng. Pract.*, vol. 92, no. February, p. 104138, 2019, doi: 10.1016/j.conengprac.2019.104138.
20. A. Abdollahi Arjanaki, A. Dehestani Kolagar, and M. R. Alizadeh Pahlavani, "A two-level power management strategy in a DC-coupled hybrid microgrid powered by fuel cell and energy storage systems with model predictive controlled interface converter," *J. Energy Storage*, vol. 52, no. PB, p. 104861, 2022, doi: 10.1016/j.est.2022.104861.
21. K.Sivakumar, D.Balamurali, R.Kalyankumar, P.V.M.Kathiresh, V.S. Sajith, B.Vignesh, "Mechanical characterization of glass fibre reinforced with natural fibre," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 50-56, 2019.
22. S. Sankarananth and P. Sivaraman, "Performance enhancement of multi-port bidirectional DC-DC converter using resilient backpropagation neural network method," *Sustain. Comput. Informatics Syst.*, vol. 36, no. January, p. 100783, 2022, doi: 10.1016/j.suscom.2022.100783.
23. K.Sivakumar, P.V.M.Kathiresh, David, V.S.Sajith, B.Vignesh, V.Vimalkumar, "Experimental investigation on aluminium metal matrix composite in EDM with various parameters (AL+SIC+MG)," in the Eleyon: Engineering Reports Vol.2, Issue No.1, PP: 17-23, 2019.
24. Preetha M & Sugitha S,2016, "A Survey on Misbehavior Report Authentication Scheme of Selfish node Detection Using Collaborative Approach in MANET", International Journal of Engineering Science and Computing, vol. 6, no. 5, pp. 5381-5384, ISSN 2321-3361.
25. K. Bhattacharjee and S. Das, "A search for good pseudo-random number generators: Survey and empirical studies," *Comput. Sci. Rev.*, vol. 45, p. 100471, 2022, doi: 10.1016/j.cosrev.2022.100471.