International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802405

Methods for Predicting Residual Energy in Batteries using Machine Learning

Hariprasad V[1], Balaji R[2]

Associate Professor, Department of Industrial Safety Engineering, K.S.Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India[1]

PG Student, Department of Industrial Safety Engineering, K.S.Rangasamy College of Technology, Tiruchengode, Tamil Nadu, India [2]

Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: Intended for the best possible use of the energy that is available, it is essential to be capable to anticipate battery residual life (RL). Battery management system- dependable, long lasting (SOC) so as to accurately forecast affirms of charge of batteries. It is very challenging to estimate SOC inference with significantly fewer ruin than now attainable because to the non-linear personality of battery drop. In this study, we use a group random forest replica to try and minimize data degradation for RL prediction. For the purpose of RL prediction, the model provides data collection, pre-processing, and classification utilizing haphazard forests and group haphazard forests. In terms of R2 and root mean square error (RMSE), the simulation is run. According to the simulation, the ensemble random forest model has a greater level of prediction accuracy.

KEYWORDS: Machine Learning, Random Forest, Data Pre-processing, Prediction Accuracy, Root Mean Square Error (RMSE), Battery Degradation.

I. INTRODUCTION

Machine learning (ML) is a computational art and a split of artificial intelligence (AI) that permits computers to discover not including explicit programming [1]. Artificial intelligence (AI) is frequently used when a large quantity of data is gathered from numerous bases and it is desired to dig up an unidentified aspect from the data set [2]. It is possible to forecast how a system will act under diverse equipped sites and constraints using the knowledge obtained from this sort of data scrutiny [3].

Due to several factors, it can be difficult to comprehend their behaviour. These parameters include operating temperatures, charging and discharging current rates, and others [4]. Consequently, the interaction of the aforesaid features, the systems are difficult to rationally characterize [5]. The conversion of electrochemical progression into reasoned equations can be challenging as a consequence of intrinsic and brutal nonlinearities of batteries, particularly Li-Ion batteries [6].The building of the reasoned forms also necessitates familiarity with a wide range of temperament in count to real operating conditions. These data are contested when they are difficult to get or cannot be measured. Therefore, inaccurate data could affect the analytical models [7]. Since the advent of data-driven methods like machine learning, the precision of state of charge (SoC) extents has significantly increased. The generalization performance, erudition skills for high precision and junction, and generalization performance have all increased [8]. The SOH and battery's usable life are inured to reckon the battery's performance (RUL). To forecast the SOH and RUL of a battery, artificial intelligence modus operandi like machine erudition and cavernous erudition can be applied. These methods are clever and flexible. Before drawing any judgments about the accuracy of estimation and prediction, training data must first be gathered [9]. The rapport amid the input and output parameters are shown to not be linear by creating a nonlinear map between them using the ANN technique. This can be used to show how complex the nonlinear model is perhaps issues with over-or under decent of data when using this tactic as the efficacy of this data-driven modus operandi depends largely on the eminence and extent of the data [10]. An intricate non-linear model can be represented by a non-linear map created using the ANN approach. A dual artificial neural network (ANN) based open circuit voltage (OCV) based SoC calculation routine can be built. The initial and jiffy tidy parameters of the electrochemical sculpt are, defined by the linear ANN battery model. The immense statistics and artificial intelligence businesses are anticipated to benefit from the expansion of SOH and RUL batteries using machine erudition technology. The vibrant

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802405

interior electrochemical mechanism was unknowable exterior state are both taken into account in an original approach to estimate SOH. The method is combined with a Markov chain and a probabilistic acquaintance based neural network. Predictive diagnostics are produced during partial load matching. A method that can handle the complexity of complex model is Gaussians process regression (GPR), which is comparable to a Bayesian non-parametric modus operandi.
By Ann sculpt that incorporates post- processing and boost over fitting, it is practicable to predict the SoC. Along with the previously mentioned, it is practicable to predict the SoC. Along with the previously studied approach of using BPNN to forecast SoC, the LSTM-RNN for scheming the battery charge. For forecast, the battery SoC estimate, deep feed forward neural networks are employed. It is easily converged; the coincident SoCs that were anticipated were inaccurate, as noted in the solution. Machine learning algorithms draw their prompts from tentative data when working with sculpts that have a lot of parameters and pragmatic amendments. The most current research shows that ML algorithms can accurately estimate Li-ion battery aging with an inaccuracy rate between 0.5% and 2.5% [11-14]. The correctness of the algorithm's complexity, the length of the sculpt development process, and the dependability of the results are all contained by this sort. We use a group random forest model to forecast RL to regulate minimize data deterioration in this work. The sculpt gathers data, pre processes it, and categorizes it using haphazard forest and group haphazard forest approaches in order to forecast RL.

II. COMPARABALE WORKS

To track the vigour of a lethal voltage and current hint using terminal voltage and current signals (SoH), Remmlinger et al. [15] developed an equivalent circuit model (ECM). To predict the battery's maximum power, Burgos et.al. [16] used an equivalent circuit fuzzy model in conjunction with a particle filter. To compute SOH and RUL and to evaluate battery health, Yu [17] constructed state-space models based on logistic regression and probability distribution function (PF) as well as Bayesian probabilistic methods. After considering how temperature affects battery performance, Le et al. [20] created a temperature salaried sculpts. Next, a twofold practice filter estimator was utilized in juxtaposition with the prior phase to estimate the SoH of LIBs. The application of neural associations in battery grade prophetic to foretell battery vigour has increased due to machine learning's explosive expansion. A fresh clarity of RUL was created, according to Wu et al. [21], and it was then used to guesstimate RUL using a feed-forward neural network (FFNN).

The RUL of the battery can be accurately estimated using this straightforward procedure. The fading incline crisis that an afflictions effortless intermittent neural network prevents long- short-term memory (LSTM) networks from being effective for forecasting time-series data. According to the novelists [22], an adaptive cubature Kaman sculpt should be used to predict the health affirm of a battery. The statistics indicate that this hybrid method has good generalize ability and a high degree of accuracy when it arrives to determining battery state of charge. According to a technique created by Zhang et al. [23], the RUL of LIB's may be predicted using LSTM and Monte Carlo simulations under a mixture of temperature and discharge rate circumstances. Liuy et al. [24] proposed a technique for estimating battery RUL that combines LSTM, empirical mode decomposition (EMD), and Gaussian process regression. The results of this investigation show that LSTM has a strong relationship with LIB deterioration data. It's probable that this model won't hold up in practice given the high level of prophecy ambiguity that grows with each forecast step. A more precise and effective battery management system is anticipated to emerge from the advance of appropriate data-driven methodologies.

III. RESEARCH METHODOLOGY

To facilitate create an precise system on chip (SoC), ML technologies are used. Below is a detailed list of the flow chart's most significant sections. The anticipated SoC guesstimate approach has been evaluated across a series of battery operating facts. Take eradicate the ML yield data and only extract the SoC attributes from it. A investigativesculpt for all algorithms, including haphazard Forest and group haphazard Forest, may be developed and used to diagnose SoC purposes due to the non-linear mapping amid input and SoC purposes. The lesson in this training module covers how to optimize important parameters. It is feasible to use a machine learning technique to estimate the SoC by using the four main lithium-ion battery metrics of voltage, current, capctiy, and temperature as inputs to an ML algorithm.

Lithium ion battery production uncertainty and the numerous capacity fading processes are thought to be the causes of the lofty-aspect of the parameter gap for lithium ion batteries. It was indispensable to phase viable LFP/graphite cells in a temperature proscribed environment extent under various fast charging conditions but with the same discharging conditions to scrutinize this area. Other lithium-ion batteries that use graphite as an electrode is largely to blame for cell

International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802405

degeneration. The firm urged hasty charging rate 3.6C was used as the preliminary point for the study's assessment of the routine of current cohort clout cells beneath tremendous hasty charging circumstances. During the experiment, the charging parameters were purposely modified, and are able to gather statistics straddling from 150 to 2300 charging sets. Cell temperatures can vary by up to 10°Cduring a sets of charging and discharging due to the enormous amount of heat produced during those processes. This temperature change is caused due to the interaction of internal impedance and charging strategy.

Consequently, each tree in the haphazard forest will expand to its full altitude and girth without needing to be processes further. The random forest's outputs will be more accurate and less likely to over fit the data the more tress it contains. This strategy is also helpful to for a number of basis, such as involuntary feature assortment and others. The top problems that need to be resolved are listed below. Then, build a bootstrap case tactic with a trade loom for the trivial set samples are in the k adjoining key course group neighbours'.

For each sample batch, build a random forest classifier employ the forecast taxing data set using barely information from the guidance dataset, which is supplied to the identical lump as the guidance dataset, a spark driver is then used to gather the results of the forecasts. To tackle the aforesaid unease the prerequisite to store all statistic stuff with the identical key in the matching detachment and on the matching lump, a global partition method is necessary. Because creating random forecasts requires numerous rounds, we decided to employ apache spark's potent comparable processing to speed up our method's calculations. The bootstrap procedure signify the precision of the sculpt cataloguing in accordance with the sampling procedure and evaluation procedure. The trivial course group samples are kept on a broadcast erratic and cached by spark in apiece lump using the bootstrap case methods, which is based on the k contiguous neighbour algorithm. This shows that in addition to a sampling ratio brink of 1, we also use a brink of 1 for case ratio and a hunt radius of 0 for the k adjoining neighbour algorithm.

IV. RESULTS AND DISCUSSION

The impedance dimensions were separated into two equal sets, each of which was acquired in a different random order from the other, for a total of 80% and 20% respectively. In order to conduct preliminary testing for machine learning algorithms, it was important to employ this partitioning to reduce the potential possibilities. In order to understand more about the sickie learn machine erudition package, which includes a suggested group random forest method, researches are putting it to the test.

To guarantee that the prior segmentation had no impact on the analysis's absolute results, cross validation was performed. The unique data deposit was divided into five sub deposit (crinkles) at this phase, with the enduring five crinkles being used for testing. There were five testing rounds in all. We evaluated the MAE and R2 for the regresses at the conclusion of each iteration to evaluate the model's performance. On the basis of the five rounds of confirmation, the middling values of the aforesaid metrics were determined and used to compare the two models. Impedance assessments specified in glacial synchronizes were used to tutor each classifier on the unique and pre-processed statistics. Depending on the classification algorithm, it is expected that employing polar version increases exactness for all classifiers by 20% to 30%.

When employing the polar representation, the random forest performs best in terms of accuracy, middling exactness of 0.915. Remarkably, no optimization was done once the parameters were skilled using sickie's-learn evasion locales. Additionally the ability of the repressors haphazard forest and group haphazard forest to replicate the SoC was examined. The investigation's findings showed as R2 and RMSE, the group random forest was a good number 5). The simulations still employ the capacity loss even if they are poles apart. By R2 and MAE, the random forest turns out to be the best repressors for the SoC. Standard deviation and correlation coefficient are typically 0.93 and 0.01, respectively as seen in Fig 5-7. The link between the actual data and the anticipated values of the random forest repressor for SoC and competence loss models.

V. CONCLUSION

We use an group random forest sculpt to forecast RL to minimize data deterioration in this work. The sculpt gathers data, pre-processors it, and categorizes it using haphazard forest and group haphazard forest approaches in order to forecast RL. The R2 and the RMSE are both used in the simulation. Prediction accuracy is increased when an group random forest model is used. Once the hyper parameters have been changed, real-time SoC estimations made using the provided method. With an MAE of 85%, the suggested ensemble RF technique data from intricate secular constitutions, this could account for the efficacy of the algorithm. According to the researches, a 10% reduction in MAE can be attained when group RF technique is applied rather than the entity RF Strategy. Consequently, we deduce that the suggested group radio occurrence based technique fosters better SoC ballpark figures by calculating a prospect allotment rather than improving point estimation accuracy. The machine erudition sculpt forecasts the state of charge view and then locate the best battery has to have enhanced characteristics included to choose the best battery for a particular purpose. SoC predictions and ensemble can be used to improve battery management systems for electric vehicles.

REFERENCES

1. Z. Tong, J. Miao, S. Tong, Y. Lu, Early prediction of remaining useful life for lithium-ion batteries based on a hybrid machine learning method, J Clean Prod 317 (2021) 128265.
2. K. Liu, Z. Wei, Z. Yang, K. Li, Mass load prediction for lithium-ion battery electrode clean production: a machine learning approach, J Clean Prod 289 (2021) 125159.
3. Y. Yang, A machine-learning prediction method of lithium-ion battery life based on charge process for different applications, Appl Energy 292 (2021) 116897.
4. C.Nagarajan and M.Madheswaran - 'Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques'- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
5. C.Nagarajan and M.Madheswaran - 'Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter' - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
6. C.Nagarajan and M.Madheswaran - 'Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis'- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
7. S.Tamilselvi, R.Prakash, C.Nagarajan,"Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller" Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025
8. S.Tamilselvi, R.Prakash, C.Nagarajan," Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance" Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
9. S.Thirunavukkarasu, C. Nagarajan, 2024, "Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
10. C. Nagarajan, M.Madheswaran and D.Ramasubramanian- 'Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model'- *Acta Electrotechnica et Informatica Journal* , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
11. C.Nagarajan and M.Madheswaran - 'DSP Based Fuzzy Controller for Series Parallel Resonant converter'- *Springer, Frontiers of Electrical and Electronic Engineering*, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
12. C.Nagarajan and M.Madheswaran - 'Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis'- *Iranian Journal of Electrical & Electronic Engineering*, Vol.8 (3), pp.259-267, September 2012.
13. C.Nagarajan and M.Madheswaran, "Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation" has been presented in ICTES'08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
14. Suganthi Mullainathan, Ramesh Natarajan, "An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques", Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721

15. M Suganthi, N Ramesh, "Treatment of water using natural zeolite as membrane filter", Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022
16. P. Venugopal, S.S. Shankar, C.P. Jebakumar, R. Agarwal, H.H. Alhelou, S.S. Reka, M.E.H. Golshan, Analysis of optimal machine learning approach for battery life estimation of
17. li-ion cell, IEEE Access 9 (2021) 159616-159626.
18. Z. Fei, F. Yang, K.L. Tsui, L. Li, Z. Zhang, Early prediction of battery lifetime via a machine learning based framework, Energy 225 (2021) 120205.
19. Anand, L., Maurya, M., Seetha, J., Nagaraju, D., Ravuri, A., & Vidhya, R. G. (2023, July). An intelligent approach to segment the liver cancer using Machine Learning Method. In 2023 4th international conference on electronics and sustainable communication systems (ICESC) (pp. 1488-1493). IEEE.
20. Rajendran, S., Sundarapandi, A. M. S., Krishnamurthy, A., & Thanarajan, T. (2022). An intelligent face recognition technology for iot-based smart city application using condition-cnn with foraging learning pso model. International Journal of Pattern Recognition and Artificial Intelligence, 36(14), 2256018.
21. Murugeshwari, B., & Sujatha, R. (2014). Preservation of Privacy for Multiparty Computation System with Homomorphic Encryption. International Journal of Emerging Technology and Advanced Engineering, 4(3), 530-535.
22. Sugumar, R. (2025). Unified AI Framework for Predictive Data Engineering and Real Time Prescription and Billing Systems. International Journal of Advanced Engineering Science and Information Technology (IJAESIT), 8(5), 17261.
23. Samrat, B., Thomas, P. K., Kumar, S., Benila, A., Bhardwaj, R., & Vigenesh, M. (2024, December). Industrial informatics in optimizing software-defined vehicles for logistics. In 2024 IEEE 2nd International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP) (pp. 1-9). IEEE.
24. Soundappan, S. J. (2024). AI-driven customer intelligence in enterprise lakehouse systems Sentiment Mining Governance-Aware Analytics and Real-Time Data Synchronization. International Journal of Advanced Engineering Science and Information Technology.
25. Rajasekar, M. (2024). AI-Powered Cyber-Secure Federated Learning on AWS for Next-Generation Digital Banking Analytics. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 7(3).
26. Deivendran, P., Babu, P. S., Malathi, G., Anbazhagan, K., & Kumar, R. S. (2023). Emotion Recognition for Challenged People Facial Appearance in Social using Neural Network. arXiv preprint arXiv:2305.06842.
27. Sugumar, R., & Murugeshwari, B. (2016). An Efficient MChord based Authentication for Vehicular Ad-Hoc Networks.
28. Pandey, V. K., Mishra, S., Rengarajan, A., Savita, & Roomi, M. M. (2024, March). Enhancing Weather Forecasting with Machine Learning Techniques. In International Conference on Renewable Power (pp. 147-156). Singapore: Springer Nature Singapore.
29. Mathew, A., & Alex, H. (2025). Federated Learning for Secure Genomic Research: Privacy-Preserving AI Solutions for Precision Medicine. Science and Technology: Developments and Applications Vol. 9, 36-43.
30. Selvi, G. V., Anbarasan, A. B., Murthy, B. A., & Prabavathy, S. (2023). An Application Oriented Integrated Unequal Clustering Algorithm for Wireless Sensor Network. In Underwater Vehicle Control and Communication Systems Based on Machine Learning Techniques (pp. 140-154). CRC Press.
31. Soundappan, S. J. (2025). Next Generation AI Enabled Holistic Cognitive Platform for Secure Cloud Network Intelligence Enterprise Systems and Digital Trust Optimization. International Journal of Computer Technology and Electronics Communication, 8(5), 11534-11542.
32. Rajasekar, M. (2024). Real-Time Predictive DevOps Intelligence for Risk-Aware Digital Business Processes in Cloud and SAP Ecosystems. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 7(4), 10713-10718.
33. Jagadeesh, S., & Sugumar, R. (2017). A comparative study on artificial bee colony with modified ABC algorithm. European Journal of Applied Sciences, 9(5), 243–248.
34. Murugeshwari, B., Sarukesi, K., & Jayakumar, C. (2010, March). An efficient method for knowledge hiding through database extension. In 2010 International Conference on Recent Trends in Information, Telecommunication and Computing (pp. 342-344). IEEE.
35. Reddy, K. V. V. K., & Vimal, V. R. (2024, July). A novel approach on improved segmentation and classification of remote sensing images using AlexNet compared over linear discriminant analysis with improved accuracy. In 2024 Second International Conference on Advances in Information Technology (ICAIT) (Vol. 1, pp. 1-6). IEEE.
36. Gowthami, D., & Vigenesh, M. (2024). Distributed and Lightweight Intrusion Detection for IoT: A Lightweight Pyramidal U-Net With Tri-Level Dual Inception-Based Framework. In The Convergence of Self-Sustaining Systems With AI and IoT (pp. 154-173). IGI Global Scientific Publishing.

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802405

37. Anand, P. V., & Anand, L. (2023, December). An Enhanced Breast Cancer Diagnosis using RESNET50. In 2023 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES) (pp. 1-5). IEEE.
38. Mathew, A. (2022). Leveraging Big Data Analytics to Power AI and ML (Machine Learning) Automation. Educational Research (IJMCER), 4(5), 131-134.
39. Dhinakaran, D. (2022). Joe Prathap P. M, Selvaraj D, Arul Kumar D and Murugeshwari B," Mining Privacy-Preserving Association Rules based on Parallel Processing in Cloud Computing,". International Journal of Engineering Trends and Technology, 70(3), 284-294.
40. Poornima, G., & Anand, L. (2024, April). Effective Machine Learning Methods for the Detection of Pulmonary Carcinoma. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 1-7). IEEE.
41. Rengarajan, A., Jayakumar, C., & Sugumar, R. (2012). Optimization Of Recent Attacks Using Internet Protocol. National Journal of System and Information Technology, 5(1), 8.
42. Mathew, A., & Romasco, L. (2024). Forensic Investigation of Artificial Intelligence Systems. Research Updates in Mathematics and Computer Science Vol. 4, 154-164.
43. Vekariya, V., Kumar, S., & Rengarajan, A. (2024). A distinctive and smart agricultural knowledge-based framework using ontology. In Sustainability in Digital Transformation Era: Driving Innovative & Growth (pp. 207-213). CRC Press.
44. Soundappan, S. J. (2020). Big data analytics in healthcare: Applications for pandemic forecasting. International Journal of Advanced Research in Computer Science & Technology, 3.
45. Sugumar, R. (2024). AI-Augmented Quality Engineering for Performance Optimization and Test Orchestration in Distributed Systems. International Journal of Science, Research and Technology, 7(5), 12835-12846.
46. Soundappan, S. J., & Sugumar, R. (2016). Optimal knowledge extraction technique based on hybridisation of improved artificial bee colony algorithm and cuckoo search algorithm. International Journal of Business Intelligence and Data Mining, 11(4), 338–356.
47. Mathew, A. (2025). Ahead of the breach: Predictive threat intelligence in aviation inspired by Scattered Spider attacks. Multidisciplinary International Journal of Research and Development (MIJRD), 4(6), 54–58.
48. Soundappan, S. J. (2021). DataOps: Orchestrating Reliable ML Data Pipelines. International Journal of Research and Applied Innovations, 4(4), 5533-5537.
49. Garg, V. K., Soundappan, S. J., & Kaur, E. M. (2020). Enhancement in intrusion detection system for WLAN using genetic algorithms. South Asian Research Journal of Engineering and Technology, 2(6), 62–64.
50. Anand, L., Tyagi, R., & Mehta, V. (2024, January). Food recognition using deep learning for recipe and restaurant recommendation. In Proceedings of Eighth International Conference on Information System Design and Intelligent Applications (pp. 269-279). Singapore: Springer Nature Singapore.
51. Kumar, A., & Anand, L. (2025). A Novel EEG-Based Deep Learning Framework for Enhancing Communication in Locked-In Syndrome Using P300 Speller and Attention Mechanisms. KSII Transactions on Internet and Information Systems (TIIS), 19(11), 3841-3855.
52. Soundappan, S. J. (2022). AI-Based Fault Detection and Isolation for Reliability in Modern Power Systems. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 5(4), 7106-7110.
53. Chandra, S., Rengarajan, A., Sahoo, G. S., & Sharma[4], S. (2024, October). Identifying Neuronal Damage and Plasticity by Analyzing Changes in Diffusion Tensor. In Proceedings of the 5th International Conference on Data Science, Machine Learning and Applications; Volume 2: ICDSMLA 2023, 15–16 December, Hyderabad, India (Vol. 2, p. 433). Springer Nature.