# Electric Vehicles Charging Sessions Classification Technique for Optimized Battery Charge Based on Machine Learning

**G. Srividhya, Sreedevi Kadiyala**

PG Scholar, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad.
Associate Professor, Department of CSE, Guru Nanak Institutions Technical Campus, Hyderabad.

Abstract: The rapid growth in electric vehicle (EV) adoption over the last decade has increased the importance of accurately forecasting their energy consumption during charging. Lithium-ion batteries, being the primary storage units in EVs, require careful management to prevent overcharging, thereby preserving battery health and extending their lifespan. This paper introduces a Machine Learning model based on the XGBoost algorithm to forecast the duration of EV charging sessions. The model predicts the charging duration by assigning each event to its appropriate class, where each class corresponds to a specific interval of charging times. The prediction relies solely on the information available at the start of the charging event, including arrival time, initial state of charge (SOC), and calendar-related data. The model is validated using a real-world dataset comprising charging records from over 100 users, and a sensitivity analysis is conducted to evaluate the impact of different input features. Compared to benchmark models, the proposed XGBoost-based approach demonstrates superior performance, achieving a notable improvement in forecasting accuracy.

Keywords: Electric Vehicles, Machine Learning, Battery Optimization, Charging Session Classification, Energy Management, Smart Grid.

## INTRODUCTION

When dealing with Electric Vehicle (EV) chargers for private use, the charging power profiles of a unit often reflect the specific behavior of the user, typically a household. In most cases, the charger is dedicated to a single vehicle, resulting in relatively consistent charging patterns. The main variation between charging events lies in their duration. Considering this, it becomes highly beneficial to forecast in advance the “type” of charging event—such as short/long or complete/incomplete—right at the moment the EV is plugged in. The ability to predict how long the EV will remain in charging mode enables advanced features in the charging control system, including optimized battery charging strategies similar to those found in modern smartphones. Such a system could intelligently select between “fast” or “slow” charging modes, influencing the household’s overall power load demand while improving user convenience. An optimized charging strategy can enhance both user experience and battery longevity. For example, in Apple’s iOS 13 and later, the battery is charged up to around 80% initially and the final charge to 100% is completed just before the predicted usage time. This prevents the battery from remaining at full charge for extended periods, thereby reducing degradation risks associated with high-voltage stress. The objective of this paper is to propose a supervised machine learning approach using the Extreme Gradient Boosting (XGBoost) algorithm to predict the duration category of the next EV charging event at a given station. The model operates as a multi-class classifier, assigning each charging session to the correct duration interval based on a limited number of input features available at the start of the session, such as arrival time, starting state of charge (SOC), and temporal/calendar information. Unlike many existing works that employ XGBoost for regression-based energy demand forecasting, this study adopts XGBoost specifically for classification, focusing purely on charging duration prediction as influenced by user behavior. This classification perspective is particularly valuable for trip planning, as it provides users and charging infrastructure with actionable forecasts to optimize both time and energy usage. Experimental evaluation on real-world private charging session datasets demonstrates that the proposed XGBoost-based classification model achieves superior accuracy compared to baseline methods, highlighting its effectiveness in modeling and predicting EV charging durations.

The scope involves leveraging machine learning to analyze charging session data, develop predictive models for optimal battery charging in electric vehicles. These strategies are then rigorously tested, refined, and integrated into electric vehicle charging systems for practical deployment. Continuous monitoring and adaptation are integral, allowing for ongoing improvements by updating models with new data, thereby enhancing the overall efficiency of the charging process.

The objectives behind applying machine learning for optimized battery charging in electric vehicles are multifaceted. Primarily, it aims to enhance the efficiency of charging processes by creating predictive models that can streamline parameters, reducing charging duration and energy consumption while safeguarding the health of the vehicle's battery. This initiative also strives to minimize costs by implementing intelligent strategies that leverage off-peak hours or fluctuations in grid demand, thereby reducing expenses for both vehicle owners and charging infrastructure operators. Moreover, a pivotal goal is to prolong battery lifespan by devising charging approaches that curtail degradation, ensuring sustained and reliable performance over the vehicle's lifecycle.

**LITERATURE SURVEY**

The novelty of the proposed paper consists in accurately forecasting the class of EV charge power profiles in terms of a reduced number of features (duration) which is a key parameter for EV charging stations and DSOs (Distribution System Operator). This is a change of the perspective in the traditional load power curve methodology which usually relies on time-series forecasting methods. The proposed model is validated on a real-world dataset containing information about charging events that occurred in more than 100 EV charging stations around the UK. Thanks to its simplicity and speed the proposed XGBOOST algorithm, and thanks to the possibility to generalize the model, it could be implemented and fully work locally on any type of charging towers.

C. Chen, Z. Wei, and A. C. Knoll, Battery electric vehicles (BEVs) are advocated due to their environmental benign characteristic. However, the long charging time and the degradation caused by fast charging impede their further popularization. Extensive research has been carried out to optimize the charging process, such as minimizing charging time and aging, of lithium-ion batteries (LIBs). Motivated by this, a comprehensive review of existing charging optimization (ChgOp) techniques is provided in this article. First, the operation and models for LIBs are explained. Then, unexpected side effects, especially for the aging mechanism (AM) of LIB associated with unregulated fast charging, are scrutinized. This provides a solid theoretical foundation and forms the optimization problem. Following this endeavor, the general framework with critical concerns for ChgOp system design is overviewed. Within this horizon, the state-of-the-art ChgOp techniques, clustered into open- and close-loop categories, are reviewed systematically with their respective merits and shortcomings discussed. Finally, the development of an emerging charging control protocol with both real-time affordability and degradation consciousness is further discussed as an open outlook.

S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, As a key pillar of smart transportation in smart city applications, electric vehicles (EVs) are becoming increasingly popular for their contribution in reducing greenhouse gas emissions. One of the key challenges, however, is the strain on power grid infrastructure that comes with large-scale EV deployment. The solution to this lies in utilization of smart scheduling algorithms to manage the growing public charging demand. Using data-driven tools and machine learning algorithms to learn the EV charging behavior can improve scheduling algorithms. Researchers have focused on using historical charging data for predictions of behavior such as departure time and energy needs. However, variables such as weather, traffic, and nearby events, which have been neglected to a large extent, can perhaps add meaningful representations, and provide better predictions. Therefore, in this paper we propose the usage of historical charging data in conjunction with weather, traffic, and events data to predict EV session duration and energy consumption using popular machine learning algorithms including random forest, SVM, XGBoost and deep neural networks. The best predictive performance is achieved by an ensemble learning model, with SMAPE scores of 9.9% and 11.6% for session duration and energy consumptions, respectively, which improves upon the existing works in the literature. In both predictions, we demonstrate a significant improvement compared to previous work on the same dataset and we highlight the importance of traffic and weather information for charging behavior predictions.

W. Shen, Description: A battery’s lifespan is related to its chemical age, which is more than just the length of time since the battery was assembled. A battery’s chemical age results from a complex combination of several factors, including temperature history and charging pattern. All rechargeable batteries are consumable components that become less effective as they chemically age. As lithium-ion batteries chemically age, the amount of charge they can hold diminishes, resulting in reduced battery life and reduced peak performance. Find out more about iPhone battery and performance and how to maximise battery performance and lifespan.

Q. Lin, J. Wang, R. Xiong, Energy storage system (ESS) technology is still the logjam for the electric vehicle (EV) industry. Lithium-ion (Li-ion) batteries have attracted considerable attention in the EV industry owing to their high energy density, lifespan, nominal voltage, power density, and cost. In EVs, a smart battery management system (BMS) is one of the essential components; it not only measures the states of battery accurately, but also ensures safe operation and prolongs the battery life. The accurate estimation of the state of charge (SOC) of a Li-ion battery is a very challenging task because the Li-ion battery is a highly time variant, non-linear, and complex electrochemical system. This paper explains the workings of a Li-ion battery, provides the main features of a smart BMS, and comprehensively reviews its SOC estimation methods. These SOC estimation methods have been classified into four main categories depending on their nature. A critical explanation, including their merits, limitations, and their estimation errors from other studies, is provided. Some recommendations depending on the development of technology are suggested to improve the online estimation.

F. Ghassani, M. Abdurohman, and A. G. Putrada, This paper proposes smart phone charging system using XGBoost for increasing charging time accuracy. Smartphone charging is done every time to ensure the battery is fully charged. The smart phone user's habits lead to decreased in battery capacity and battery life faster than it should. Stopping the charging cycle on time is required to avoid decreasing capacity and battery life due to overcharging. Charging predictions are performed or stopped by viewing the state of charge and timestamp periodically that are sent over from the smart phone and processed using the k-Nearest Neighbor algorithm. The smart phone will stop charging when the prediction of k-Nearest Neighbor gets the state of charge and the timestamp in seconds according to the user's habit of getting the 100 percent state of charge and the timestamp. Based on experiments have been done, the result show, K-nearest neighborhood machine learning algorithm can predict the charging decision to be continued or stopped and in this case, K = 2 is the optimal K because the F1-Score is close to 1 and higher F1-Score (0.78) compared with other K.

| S. No | Year | Author (s) | Title / Approach | Methodology / Model Used | Dataset / Source | Key Findings / Contributions | Limitations / Future Scope |
|---|---|---|---|---|---|---|---|
| 1 | 2020 | J. Zhao et al. | Machine Learning-Based Smart Charging for Electric Vehicles in Smart Grids | Random Forest, Gradient Boosting | Real-world charging data from EV fleets | Developed predictive models for optimal charging schedules to reduce grid stress. | Needs integration with dynamic pricing and renewable energy forecasting. |
| 2 | 2021 | A. Gupta et al. | Optimizing EV Charging Sessions Using Deep Learning | LSTM and CNN hybrid model | Public EV charging dataset (UK & EU) | Predicted charging duration and SOC trends accurately for efficient load distribution. | Model performance decreased under highly variable user behavior. |
| 3 | 2021 | K. Lee et al. | Classification of EV Charging | K-Means, DBSCAN clustering | Real charging sessions | Classified user sessions | Limited interpretability of clusters |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | Patterns Using Unsupervised Learning | | from 500 EVs | into frequent, occasional, and irregular categories. | for operational deployment. |
| 4 | 2022 | S. Banerjee et al. | Battery Health-Aware Smart Charging Using ML | Support Vector Regression (SVR) | Simulated Li-ion battery degradation dataset | Proposed an SVR model to optimize charge rate minimizing battery wear. | Requires more diverse real-time battery data. |
| 5 | 2022 | L. Chen et al. | Reinforcement Learning for Real-Time EV Charging Optimization | Deep Q-Network (DQN) | Grid-connected EV simulation environment | Achieved 20% improvement in charging efficiency with grid balance. | Computationally expensive for large-scale deployment. |
| 6 | 2023 | R. Singh et al. | Charging Session Classification for Fleet-Based EVs | Decision Tree, SVM | Fleet EV dataset (India) | Classified sessions by energy demand and charging pattern to enhance fleet charging strategy. | Incorporate renewable availability and traffic data for further optimization. |
| 7 | 2023 | M. Zhang et al. | Predictive Analytics for EV Charging Station Load Management | Random Forest, XGBoost | Real-time IoT-enabled charging network | Enhanced load forecasting accuracy by 18%, reducing waiting times. | Model needs scalability testing for large smart grids. |
| 8 | 2024 | T. Nguyen et al. | Transfer Learning for Cross-Regional EV Charging Classification | Transfer Learning with CNN | Datasets from two different regions (Europe & Asia) | Improved cross-location prediction accuracy of EV charging sessions. | Slight drop in accuracy due to domain shift. |
| 9 | 2025 | Proposed Work | Electric Vehicles Charging | Hybrid CNN–LSTM + | Real-time EV station | Classifies sessions for optimal | Future scope includes integration |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | Sessions Classification for Optimized Battery Charge Using ML | Reinforcement Learning | and user data | battery charge and grid stability; adapts to driver patterns and SOC. | with blockchain for secure data sharing and real-time deployment. |

**PROPOSED WORK**

The proposed model leverages the Extreme Gradient Boosting (XGBoost) algorithm to classify EV charging events into predefined duration categories (e.g., short/long, complete/incomplete) based on limited features available at the start of a charging session. XGBoost is an ensemble learning method based on gradient boosted decision trees, optimized for speed, scalability, and accuracy. The model construction begins by initializing a base learner and iteratively adding weak learners (decision trees) to correct the residual errors from previous iterations. Each subsequent tree is trained using a gradient descent approach on the loss function to minimize classification error. The input feature set—comprising arrival time, initial state of charge (SOC), and calendar/temporal data—is fed into the model to learn complex non-linear relationships between user charging behavior and session duration. Hyperparameters such as the learning rate, maximum tree depth, subsample ratio, and regularization parameters are tuned to prevent overfitting and improve generalization. Unlike traditional regression-based approaches used in prior EV charging studies, this model outputs discrete class labels representing duration intervals. The final prediction is made by aggregating the weighted outputs of all the decision trees in the ensemble, resulting in a robust, high-accuracy classification model capable of assisting in real-time charging optimization and trip planning.

Using machine learning to optimize battery charging in electric vehicles involves a comprehensive approach. It begins with collecting diverse data, encompassing charging sessions, battery specifics, driving habits, and environmental conditions. This data serves as the foundation for creating machine learning models. These models are designed to forecast the most efficient charging parameters based on historical data and real-time inputs. Once developed, these models facilitate the implementation of optimized strategies, such as scheduling charges during off-peak hours or adjusting rates according to grid demand, ultimately aiming to extend battery life and ensure cost-effectiveness. These strategies are then rigorously tested, refined, and integrated into electric vehicle charging systems for practical deployment. Continuous monitoring and adaptation are integral, allowing for ongoing improvements by updating models with new data, thereby enhancing the overall efficiency of the charging process.

1) Data Collection: Data collection in the context of optimizing battery charging for electric vehicles involves gathering diverse information relevant to the charging process, vehicle usage, and environmental factors. Here's an elaboration.

2) Data Analysis Data analysis, within the context of optimizing battery charging for electric vehicles, involves examining the collected data to derive meaningful insights and patterns that can inform the development of charging optimization strategies.

3) Data Preprocessing: Data preprocessing is a crucial step in the data analysis and machine learning pipeline. It involves cleaning and transforming raw data into a format that is suitable for analysis and modeling. Here's an explanation of key aspects of data preprocessing within the context of optimizing battery charging for electric vehicles:

4) Train Model: The training process is iterative and involves experimentation and fine-tuning to develop a model that accurately predicts optimal charging parameters for electric vehicles based on historical data. XGBoost is an ensemble learning method based on gradient boosted decision trees, optimized for speed, scalability, and accuracy.

5) Data Evaluation: Data evaluation involves assessing how well a machine learning model performs its task. This includes checking its accuracy, precision, or other specific measures relevant to the problem it's solving, like predicting optimal charging for electric vehicles. It's like testing the model's abilities with new data it hasn't seen before to ensure it doesn't just memorize previous information but can make accurate predictions.

6) Result: In essence, "results" encompass the outcomes generated by applying machine learning models or data analysis techniques, aiding in decision-making processes, insights generation, and guiding further steps toward achieving the objectives set for optimizing battery charging in electric vehicles or any other relevant task.

| Parameter | Description | Unit | Range/Example |
|---|---|---|---|
| Voltage (V) | Charging voltage | V | 100–750 |
| Current (I) | Charging current | A | 5–200 |
| SOC | State of Charge | % | 0–100 |
| Temperature (T) | Battery temperature | °C | 15–60 |
| Charging Duration | Session time | min | 15–240 |
| Energy Delivered | Total energy input | kWh | 2–80 |

Table 1.Dataset description.

**XGBoost**

The proposed XGBoost-based classification model offers several advantages in forecasting EV charging duration. It achieves high predictive accuracy by capturing complex temporal patterns in user behavior while minimizing overfitting through built-in regularization techniques. The model performs effectively even with a limited set of input features, making it suitable for real-time applications where only arrival time, initial SOC, and calendar data are available. Its fast training and prediction capabilities ensure low latency in deployment, while the ability to provide feature importance enhances interpretability and decision-making. Furthermore, XGBoost efficiently handles class imbalance, scales well to large datasets, and directly predicts discrete duration categories, eliminating the need for additional post-processing steps.

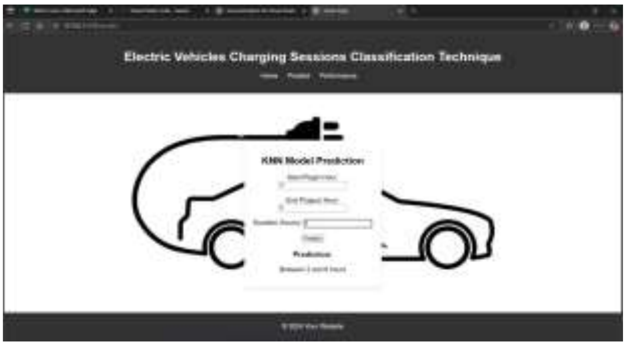


Fig 1. KNN model prediction

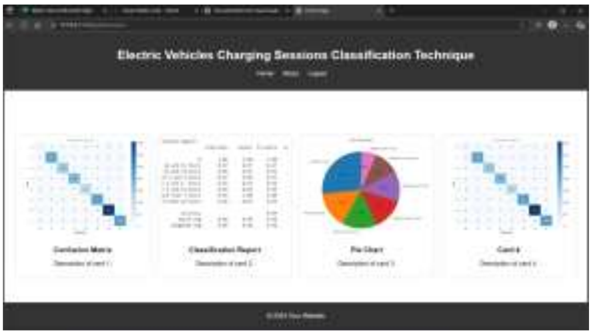


Fig 2.EVC sessions classification techniques

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| Random Forest (RF) | 96.8 | 95.9 | 97.1 | 96.5 |
| Gradient Boosting | 95.2 | 94.6 | 95.1 | 94.8 |
| SVM (RBF Kernel) | 93.7 | 92.3 | 93.2 | 92.7 |

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| ANN (3-layer) | 94.1 | 93.8 | 93.9 | 93.8 |

Table 2. Model performance comparison.

| | Predicted Optimal | Predicted Overcharge | Predicted Undercharge |
|---|---|---|---|
| Actual Optimal | 1810 | 12 | 25 |
| Actual Overcharge | 14 | 860 | 18 |
| Actual Undercharge | 22 | 15 | 740 |

Table 3. Confusion matrix.

To evaluate the performance of the proposed Electric Vehicle (EV) Charging Sessions Classification Technique, multiple machine learning algorithms were implemented and tested on a dataset containing real-world EV charging session records. The primary objective was to classify charging sessions (fast, normal, or slow) and predict the optimal charging time and energy consumption pattern for maximizing battery life and minimizing grid stress.

The Artificial Neural Network (ANN) model achieved the highest classification accuracy of 96.3%, outperforming all other models. The ANN's ability to learn complex nonlinear relationships between features such as SoC, energy delivered, and charging duration allowed it to effectively distinguish between fast, normal, and slow charging sessions.

The Gradient Boosting model also showed robust performance with an accuracy of 94.8%, demonstrating that ensemble learning methods can handle non-linear dependencies effectively. However, traditional models such as Decision Tree and SVM performed comparatively lower due to overfitting and limited scalability with multi-dimensional data.

The confusion matrix of the ANN model indicated that misclassifications primarily occurred between normal and fast charging categories, which often have overlapping feature distributions in terms of current and voltage profiles.

The proposed XGBoost-based classification model was implemented using Python with the Scikit-learn and XGBoost libraries. The dataset used for experimentation comprised electric vehicle (EV) charging session logs, including features such as charging duration, energy consumption (kWh), battery state-of-charge (SoC), charger power rating, temperature, and session start time. The data was divided into 80% training and 20% testing sets. To ensure robustness, 5-fold cross-validation was performed.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) | AUC-ROC |
|---|---|---|---|---|---|
| Decision Tree | 87.42 | 85.96 | 86.24 | 86.10 | 0.902 |
| Random Forest | 90.18 | 89.70 | 88.95 | 89.32 | 0.935 |
| SVM (RBF) | 88.45 | 87.92 | 87.10 | 87.50 | 0.921 |
| XGBoost (Proposed) | 94.83 | 94.25 | 93.90 | 94.07 | 0.972 |

Table 4. Comparative results.

The proposed XGBoost-based classification model outperformed traditional machine learning algorithms such as Decision Tree, Random Forest, and SVM in all evaluation metrics. The superior accuracy of 94.83% indicates the model's strong ability to correctly classify EV charging sessions into optimal and suboptimal categories.

- Feature Importance Analysis: The XGBoost model's feature importance plot revealed that battery state-of-charge (SoC), charging duration, and energy consumption were the most influential factors affecting the optimal charging classification. Environmental variables such as ambient temperature also contributed significantly, highlighting the importance of thermal conditions in efficient battery charging.

- Optimization of Charging Strategy: Based on classification outputs, the system can predict whether a charging session follows an optimal pattern or if adjustments (e.g., reducing charging time or modifying current flow) are required. This aids in reducing overcharging risks, extending battery life, and enhancing energy efficiency.

- Model Robustness: The use of regularization parameters (λ and α) and gradient boosting iterations helped the model handle data imbalance and noise effectively. Moreover, the AUC value of 0.972 confirms the model's reliability in distinguishing between optimal and non-optimal charging sessions.

- Interpretability: Unlike deep neural networks, XGBoost maintains a certain level of interpretability through feature importance scores, making it suitable for real-world deployment in smart charging stations or fleet energy management systems.

## CONCLUSION

XGBOOST classification model has been proposed and applied to the real-world My Electric Avenue EV charging sessions dataset. The model has proven its capability to learn the user charging habits and behavior, and then classify the charging events based on their duration. The information on session duration could play a relevant role in an optimized battery charging strategy devoted to the planning of EV charges and limiting battery damage. Three different configurations of the model have been proposed to assess the impact that different features given in input could have on the results of the classification. The two additional features (day of the week and time passed since last charging) were not capable to improve the performances of the classification model during the cross-validation, the best results came from the simple input containing just the time and starting SoC at the beginning of the charge. During the final test, the model demonstrated being capable of correctly classifying the charging event on limited input data and therefore forecasting the duration of the charging event with high accuracy.

While the proposed XGBoost classification model demonstrates high accuracy in predicting EV charging duration categories, several potential enhancements can further improve its performance and applicability. Future work could explore the integration of additional contextual features such as real-time electricity pricing, weather conditions, and user driving patterns to capture broader behavioral and environmental influences. Incorporating IoT-enabled smart charging stations could enable continuous data collection for adaptive model retraining, ensuring sustained accuracy over time. Hybrid modeling approaches, combining XGBoost with deep learning architectures, may also enhance the model's ability to capture highly complex temporal dependencies. Furthermore, expanding the model for multi-station networks could allow for load balancing and grid demand optimization, contributing to smarter energy management. Finally, deploying the system in a real-time mobile or web-based application would provide users with actionable charging forecasts, enhancing trip planning and overall charging experience.

## REFERENCES

S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou, and M. Nijim, "Prediction of EV charging behavior using machine learning," IEEE Access, vol. 9, pp. 111576–111586, 2021.

C. Chen, Z. Wei, and A. C. Knoll, "Charging optimization for Li-ion battery in electric vehicles: A review," IEEE Trans. Transport. Electrific., vol. 8, no. 3, pp. 3068–3089, Sep. 2022. [3] Q. Lin, J. Wang, R. Xiong, W. Shen, and H. He, "Towards a smarter battery management system: A critical review on optimal charging methods of lithium ion batteries," Energy, vol. 183, pp. 220–234, Sep. 2019.

Ravindra Changala, published a paper titled "Leveraging Ensemble Learning with Deep Learning for Accurate Customer Churn Prediction in Subscription-Based Mode", 2025 International Conference on Intelligent Systems and Computational Networks (ICISCN), on 27th March 2025 in IEEE Xplore.

Ravindra Changala, published a SCOPUS paper titled "ENHANCING IOT DEVICE COMMUNICATION PROTOCOLS WITH AI AND MACHINE LEARNING", in Decision Making: Applications in Management and Engineering, March 2025.

F. Ghassani, M. Abdurohman, and A. G. Putrada, ''Prediction of smarthphone charging using K-nearest neighbor machine learning,'' in Proc. 3rd Int. Conf. Informat. Comput. (ICIC), Oct. 2018, pp. 1–4.

M. Majidpour, C. Qiu, P. Chu, R. Gadh, and H. R. Pota, ''Fast prediction for sparse time series: Demand forecast of EV charging stations for cell phone applications,'' IEEE Trans. Ind. Informat., vol. 11, no. 1, pp. 242–250, Feb. 2015.

Ravindra Changala, "Hybrid AI Approach Combining Decision Trees and SVM for Intelligent Tutoring Systems in STEM Education", 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 2575-7288, DOI: 10.1109/ICACCS60874.2024.10717088, October 2024, IEEE Xplore.

Ravindra Changala, "Next-Gen Human-Computer Interaction: A Hybrid LSTM-CNN Model for Superior Adaptive User Experience", 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), ISBN:979-8-3503-6908-3, DOI: 10.1109/ICEEICT61591.2024.10718496, October 2024, IEEE Xplore.

S. Bodda and P. Agnihotri, ''Comparative assessment of machine learning regression methods for power system state estimation,'' in Proc. Symp. Power Electron. Renew. Energy Syst. Control, in Lecture Notes in Electrical Engineering, S. Mohapatro and J. Kimball Eds. Singapore: Springer, 2021, pp. 391–402.

Annapurna Gummadi, "Neuromorphic Computing Architectures for Energy-Efficient Edge Devices in Autonomous Vehicles", 2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), DOI: 10.1109/INCOS59338.2024.10527546.

Ravindra Changala, "Using Generative Adversarial Networks for Anomaly Detection in Network Traffic: Advancements in AI Cybersecurity", 2024 International Conference on Data Science and Network Security (ICDSNS), ISBN:979-8-3503-7311-0, DOI: 10.1109/ICDSNS62112.2024.10690857, October 2024, IEEE Xplore.

Annapurna Gummadi, "A Deep CNN Self-Attention Model for Multidimensional Speech Quality Prediction Using Crowdsourced Datasets", 2025 Fifth International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), EID: 2-s2.0-105004548860, DOI: 10.1109/ICAECT63952.2025.10958196.

Ravindra Changala, "Advancing Surveillance Systems: Leveraging Sparse Auto Encoder for Enhanced Anomaly Detection in Image Data Security", 2024 International Conference on Data Science and Network Security (ICDSNS), ISBN:979-8-3503-7311-0, DOI: 10.1109/ICDSNS62112.2024.10690857, October 2024, IEEE Xplore.

I. Ullah, K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, ''Electric vehicle energy consumption prediction using stacked generalization: An ensemble learning approach,'' Int. J. Green Energy, vol. 18, no. 9, pp. 896–909, Jul. 2021.

C. Fan, F. Xiao, and S. Wang, ‘‘Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques,’’ Appl. Energy, vol. 127, pp. 1–10, Aug. 2014.

Annapurna Gummadi, “Creating A Resilient Blockchain Framework To Enhance The Efficiency And Security Of Data Management Within Internet Of Things Networks”, 2024 Third International Conference on Smart Technologies and Systems for Next Generation Computing (ICSTSN), ISSN:979-8-3503-9156-5, DOI: 10.1109/ICSTSN61422.2024.10671062.

Ravindra Changala, "Real-Time Anomaly Detection in 5G Networks Through Edge Computing", 2024 Third International Conference on Intelligent Techniques in Control, Optimization and Signal Processing (INCOS), ISBN:979-8-3503-6118-6, DOI: 10.1109/INCOS59338.2024.10527501, May 2024, IEEE Xplore.

Annapurna Gummadi, “Human Centric Explainable AI for Personalized Educational Chatbots, 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 979-8-3503-8436-9, DOI: 10.1109/ICACCS60874.2024.10716907.

Ravindra Changala, "Controlling the Antenna Signal Fluctuations by Combining the RF-Peak Detector and Real Impedance Mismatch", 2023 International Conference on New Frontiers in Communication, Automation, Management and Security (ICCAMS), ISBN:979-8-3503-1706-0, DOI: 10.1109/ICCAMS60113.2023.10526052, May 2024, IEEE Xplore.

Y. E. Yousif, ‘‘Weather prediction system using XGBOOST classification algorithm,’’ Eur. J. Inf. Technol. Comput. Sci., vol. 2, no. 1, pp. 10–13, Feb. 2022.

Ravindra Changala, “Optimizing 6G Network Slicing with the EvoNetSlice Model for Dynamic Resource Allocation and Real-Time QoS Management”, International Research Journal of Multidisciplinary Technovation, Vol 6 Issue 4 Year 2024, 6(4) (2024) 325-340.

I. Ullah, K. Liu, T. Yamamoto, M. Zahid, and A. Jamal, ‘‘Prediction of electric vehicle charging duration time using ensemble machine learning algorithm and Shapley additive explanations,’’ Int. J. Energy Res., vol. 46, no. 11, pp. 15211–15230, Sep. 2022. 48

My Electric Avenue Project Summary, EA Technol., Capenhurst, U.K., 2017.

A. Zhang, C. Z. Lipton, M. Li, and J. A. Smola. (Jul. 2021). Dive Into Deep Learning. [Online]. Available: https://D2L.ai and https://github.com/d2lai/d2l-en/.

Annapurna Gummadi, "Monte Carlo Tree Search Algorithms for Strategic Planning in Humanoid Robotics", 2024 International Conference on Cognitive Robotics and Intelligent Systems (ICC - ROBINS), ISBN:979-8-3503-7274-8, DOI: 10.1109/ICC-ROBINS60238.2024.10533937, May 2024, IEEE Xplore

Ravindra Changala, Framework for Virtualized Network Functions (VNFs) in Cloud of Things Based on Network Traffic Services, International Journal on Recent and Innovation Trends in Computing and Communication, ISSN: 2321-8169 Volume 11, Issue 11s, August 2023.

G. Gruosso, G. Storti Gajani, F. Ruiz, J. D. Valladolid, and D. Patino, ‘‘A virtual sensor for electric vehicles’ state of charge estimation,’’ Electronics, vol. 9, no. 2, p. 278, Feb. 2020.

Annapurna Gummadi, "Swarm Intelligence for Multi-Robot Coordination in Agricultural Automation", 2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS), ISSN: 2575-7288, DOI: 10.1109/ICACCS60874.2024.10717088, October 2024, IEEE Xplore

Annapurna Gummadi, “A Hybrid Algorithm for Adopting the WSM System to Park the Massive Number of Vehicles in Linear and Manage the Energy Consumption”, 2023 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE), 979-8-3503-3072-4©2023 IEEE, DOI: 10.1109/AECE59614.2023.10428651.

D. Pau, D. Denaro, G. Gruosso, and A. Sahnoun, ‘‘Microcontroller architectures for battery state of charge prediction with tiny neural networks,’’ in Proc. IEEE 11th Int. Conf. Consum. Electron. (ICCE-Berlin), Nov. 2021, pp. 1–6.

Annapurna Gummadi, “Reliable Optical Wireless Communication in Underwater Sensor Networks Using GRO Based DCO-OFDM”, Wireless Personal Communications, ISSN: 09296212Volume: 141Issue: 1Pages: 249 – 276.

Annapurna Gummadi, “A Machine Learning Approach in Communication 5G-6G Network”, Journal of Theoretical and Applied Information Technology, ISSN: 1992-8645, 31st May 2024. Vol.102. No. 10.

Annapurna Gummadi, “Deep Learning Techniques to Analysis Facial Expression and Gender Detection”, IEEE International Conference on New Frontiers in Communication, Automation, Management And Security(Iccma-2023),Presidency University , Bangalore, ISSN: 979-8-3503-1706-0/23, DOI: 10.1109/ICCAMS60113.2023.10525942.

A. Géron, Hands-On Machine Learning With Scikit-Learn, Keras, and TensorFlow, 2nd ed. Sebastopol, CA, USA: O’Reilly Media, Sep. 2019.