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FIRE RISK PREDICTION USING MACHINE LEARNING MODELS IN ELECTRIC VEHICLE LITHIUM-ION BATTERIES

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ABSTRACT

Many factors point to the growing popularity of Electric Vehicles (EVs) as an environmentally friendly and renewable substitute to traditional vehicles due to improvements in battery technology. Nevertheless, battery fault related fire incidents continue to be a challenge. This research paper discusses the prediction of Fire Risk in EVs using ML techniques. In this work, we consider a dataset involving crucial battery fault parameters like SoC, Temperature, current and Voltage and carry out evaluation of performance of different machine learning models such as Linear Regression, Random Forest Regressor, Gradient Boosting Regressor (GBR), and Extreme Gradient Boosting (XGBoost) to predict it. Results show that Gradient Boosting Regressor yields the lowest Root Mean Squared Error (RMSE), the highest R squared (R^2) value and the lowest Mean Absolute Error (MAE) compared to other models. Results show that machine learning (especially ensemble methods) is able to accurately predict the fire risk and improve the safety measure in EVs. The paper offers important results for development of safer and more reliable EV battery systems through the use of ML models for early fire detection and prevention.

Keywords -Electric Vehicles (EVs), Fire Risk Prediction, Lithium-ion batteries, Machine Learning, Gradient Boosting

1. INTRODUCTION:

The development of electric vehicles (EVs) has since experienced a fast adoption, with the introduction of which came a major advancement in the battery technology – lithium-ion batteries, which are the backbones of modern EVs. Although the challenges faced in battery safety, thermal management and fire protection become more pronounced as demand for EVs grows. These energy storage systems must be reliable and safe, since if the system failed, it could result in a severe outcome such as thermal runaway, fire, or even explosion. In a recent research trends, people leverage machine

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learning (ML) algorithms and advanced data driven techniques to predict and mitigate batteries risks such that battery safety and performance get better. In this literature review, we focus on the latest innovations in EV batteries related to thermal fault prediction, fire safety and protection, and safety assessment of EV batteries.

Thermal fault prediction in lithium ion batteries is one of the key areas of research in which machine learning is being used. In the work of Daniels et al. [1] they compared different ML algorithms for the predicting thermal faults on air cooled cylindrical Li-ion battery modules noting how location of temperature sensors is affected. Likewise, in [2] Kiasari and Aly examined like ways the thermal energy storage systems can be combined machine learning to strengthen EV battery's fire security. These studies show the potency of ML in better fault detection and prevention for risk of catastrophic failures. Moreover, Zhao et al. [3] have reviewed extensively on battery safety prognostics using machine learning, which underlines machine learning as the means of predicting potential hazards before the threats escalate. It is also very important to curb the thermal runaway in the case of EV battery safety.

In the work of Nejad et al. [4], they developed a visual foreign object detection system for wireless charging of EVs which employs the use of machine vision for improving vehicle charging safety. With over one hundred publications a year published, the field of EV battery safety and thermal management have grown up in such a way that the insights they are providing around the reliance on machine learning and data driven approaches in mitigating risks and increasing the reliability of energy storage systems are becoming increasingly important. These technologies not only contribute to the next generation of solutions for thermal fault prediction and fire protection, but also are employed to detect foreign objects, thermal runaway management and much more in the EV domain. With the continued development of the industry, it will be critical to continue to research and develop in these areas in order to enact safe and sustainable adoption of electric vehicles across the world.

2. LITERATURE REVIEW

As have Mao et. al [5], the current work has mainly investigated thermal runaway propagation (TRP) in open spaces; however, gaps in the knowledge of TRP in confined interval are missed as LIBs commonly used and transported in these environments. The results of recent experiments in which TRP is compared in enclosed and open clusters showed faster TRP and exponential heat release in

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closed space, while open space TRP is non self sustaining. The effectiveness of different mitigation strategies such as cell spacing, barriers, cover plates and aluminium tops varied, but lower ambient temperatures (<17.4°C) correspondingly appeared to severely limit TRP. This identifies the need for specific safety measures to lessen TRP risks in confined LIB applications.

As quoted by Mama et .al. [6], the rapid advancement of lithium ion battery technology has been instrumental in the need for state of the art innovative multiscale approaches to achieve best in class in performance, longevity, and safety in applications such as electric vehicle and energy storage. In this review, state-of-the-art models are presented from particle scale to pack level thermal management systems that integrate electrochemical to thermal coupled models for addressing challenge at multiscale and mitigating safety risks such as thermal runaway.It also explores the trade-offs between computational efficiency and model complexity, emphasizing the integration of battery management systems and cooling strategies for enhanced safety and performance. Zhao et al. [7] Battery Management Systems (BMSs) play a critical role in ensuring the safe and efficient operation of lithium-ion batteries (LIBs) in electric vehicles (EVs) by relying on accurate sensor data for state estimation, balance control, and fault diagnosis. However, sensor failures and inaccurate measurements due to external interference and complex operating conditions pose significant challenges. This study explores sensor fault modes, diagnostic methods—including model-based, signal processing, and data-driven approaches—and fault-tolerant control (FTC) techniques to maintain BMS stability. The analysis highlights the need for advanced fault diagnosis methods and proposes future research directions to enhance sensor reliability and BMS performance.

Yadav et al. [8] Accurate State of Charge (SoC) estimation is vital for the safety and efficiency of lithium-ion batteries in electric vehicles (EVs). The Augmented Adaptive Extended Kalman Filter (AAEKF) has been proposed as an advanced method for precise SoC estimation, combining Kalman filtering with adaptive robust control to handle system nonlinearities and parameter uncertainties. Simulation and experimental results using LiFePO4 batteries demonstrate that AAEKF achieves estimation errors below 3%, with improved convergence, real-time responsiveness, and robustness to disturbances and temperature variations. Compared to traditional Adaptive Extended Kalman Filter (AEKF), AAEKF shows superior performance, maintaining estimation errors under 5% across diverse operating conditions, making it a promising approach for enhancing Battery Management Systems (BMS) in EVs. Lee et. al. [9] discussed the transportation of electric vehicles (EVs) presents significant fire risks linked to lithium-ion battery thermal runaway, particularly influenced

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by the state of charge (SOC). This study examines the effects of SOC (70%, 50%, and 30%) on fire behaviour and efficiency of suppression SHOW more This soaking in combination with fire blankets was found to be an effective means of latency cooling and containment, and important points of SOC management and integrated suppression strategies for improving EV fire safety during maritime transport. With such demands for higher speeds and faster charging, increasing heat generation in electric vehicle batteries has become the need for sophisticated thermal management systems, as pointed out by Gasmelseed et. al. [10]. Nan fluids, with superior thermal conductivity as compared to the conventional fluids, are now gaining acceptance as promising coolants due to their thermal performance improvements of 2.9–30.5 %, with enhanced pumping power from higher viscosity. Nanoparticles such as Al2O3, CuO and AgO, at concentrations between 0.1 and 5% are widely studied, however they have not been extensively studied with respect to long term stability, hybrid nanofluid systems, and the economic and environmental impacts of thermal management based on nanofluid.

Problems regarding thermal runaway (TR) risks in the rapid expansion of lithium ion battery (lib) applications, including nickel cobalt manganese (Ncm) and lithium iron phosphate (lfp) batteries, has raised concern about the need for the reliable and sufficient means of internal short circuit (ISC) detection, and the TR warning. For validation, this study develops a simple yet effective approach for monitoring short circuit resistance evolution during TR development based on battery relaxation voltage, using ISC substitute experiments and mechanical abuse tests including four battery brands with different materials and shapes. The method is suitable for ambient temperature and current rate, resulting in the ability to detect ISC and TR warning with 4 min of relaxation data at a high degree of applicability to electric vehicles and energy storage systems. The computationally efficient solution for improving battery safety in commercial applications provided by this innovation is low cost. At the time, Muram et. al [12] noticed that while Lithium-ion batteries are essential to electric vehicle performance, they carry with them safety risks such as thermal runaway which can start fires or explosion if it is not halted properly. The main object of this study is to provide means of ensuring safety of battery management systems (BMS) aligned with the ISO 26262 standard, such as hazard identification, definition of safety goals, derivation of functional and technical safety requirements. The BMS strategy is validated by simulations and critical parameters in the electric vehicles are monitored and safety cases updated to prevent thermal runaway and maintain system safety.

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An overview of various thermal management systems (TMSs) used for lithium ion battery (LIB) in electric vehicles is given and also focuses on battery thermal management system (BTMS) based on phase change material (PCM) by Alghamdi et al. [13]. However, PCM alone decreased the battery's average temperature to 85°C, while integrating a thermoelectric cooling system further brought down the temperature to 76°C, but still in a hazardous range. With the addition of aluminium circular fins, the temperature was decreased to 65°C, and switching to axial fins showed optimal average temperature of 48°C. The rapid adoption of lithium ion batteries in electric vehicles (EVs) makes it critical to accurately estimate State of Health (SOH) to ensure battery safety and performance as stated in Wang et cetera [14]. Model-based and data driven methods have been reviewed often, but their complexity and high cost makes their application practical quite difficult. Resolving this is the main focus of this paper as it provides a comprehensive review of rapid SOH estimation techniques developed over the past decade and updated classifications and insights into the working principles, advantages, and disadvantages of current techniques. The review draws on experimental studies and practical challenges to provide guidance that is useful for advancing the research in academia and applications in engineering for EV battery management. Recently Lithium ion (Li-ion) batteries are widely accepted to be used in electric vehicles (EVs) with high energy density, long lifespan and low self discharge rates, providing us with a sustainable energy and environment replacement. Nevertheless, their performance and safety are greatly hindered by extreme temperature conditions, where high temperatures can suffer from thermal runaways, and low temperatures prone to lithium dendrite formation, which can cause failures. Phase change materials (PCM), which provide high storage and release of thermal energy, have been under study for the purpose of mitigating these issues by maintaining battery temperatures as stable as possible. Various thermal management strategies for Li-ion batteries are explored and the advantages as well as the limitations and cost effectiveness are compared relative to one another, as well as heating and cooling mechanisms are summarised. Future PCM based thermal management system advancements that improve safety, efficiency and lifetime of Li-ion batteries in EV are discussed.

Lithium-ion batteries (LIBs) [16] have been a leading rechargeable energy storage technology, possessing high energy density, power density, long lifetime and non memory effects and are best suited for various applications. The adoption of LIBs for range extending electric vehicles (EVs) is limited by both a reduction in driving range and size of the battery pack that can be realised, and these problems can be ameliorated by increasing the energy density of cells. However, with increased

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energy density driving range is also increased and the minimum number of cells required is also decreased, consequently reducing battery pack size. First, this review presents a critical analysis of LIB cell design strategies and discusses material-oriented and cell parameter-focused approaches to increase energy density for EVs with the distinct potential for improvements in LIB technology to bridge the gap between the requirements of the EV industry Demand for alternative fuel vehicles, such as battery electric vehicles (BEVs), is affecting the way that tunnel safety risks are shaped, particularly as these involve fire hazards and toxic emissions, and require reassessment of emergency response strategies; Strum et al. [17]. Present research has mainly been to investigate how battery cells and packs can meet fire safety requirements, however, there remains very limited full scale fire tests on actual vehicles in real tunnel conditions. In 2018 the Austrian Government launched a pioneering research project: it carried out, to the best of my knowledge, the first ever full scale fire tests performed on BEVs in a road tunnel to evaluate heat release, toxic emissions and fire fighting procedures. These tests address critical aspects related to the fire behaviour of BEVs relative to conventional vehicles and highlight the important need for specific fire intervention strategies. Results from these groundbreaking tests are presented in this paper and the data provides useful information to improve local tunnel safety protocols for the changing vehicle fleet.

US is the third largest EV market, lacking end of life recycling policy, but recycling of lithium-ion battery is critical to minimise the environmental footprint of electric vehicles (EVs) and strengthen the domestic supply chain. This study draws inspiration from the recycled content standards (RCSs) set by the European Union, whose standards the author explores for feasibility and projects that recycled closed-loop recycling of retired batteries can provide 11–18 percent of cobalt, 11–13 percent of lithium, and 17–24 percent of nickel demand by 2035. While domestic recycling of batteries is carbon beneficial, and may scale to be a profitable as well, the economics of recycling at home is still more than recycling away at home — which is where China no doubt has a competitive advantage — highlighting the need for policy intervention in order to promote recycling of critical materials both domestically and in support of a circular battery economy. Battery thermal runaway due to the overcharge is a critical trigger for safety in electric vehicles (EVs) in real operation [19]. In this study, electro-chemical-thermal coupling analysis is developed for multi-factor failure mechanisms of overcharge induced thermal runaway considering environmental variations and driver behaviours. By analyzing a real-world EV accident caused by overcharge, the research dissects pre-accident battery characteristics and proposes a multi-stage characterization framework, dividing

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overcharge into charge, fully-charged instant, and overcharge stages. A probability model for overcharge-induced thermal runaway is introduced, integrating environmental and behavioural factors, marking the first application of real accident data to such research. The findings aim to enhance overcharge protection strategies, improving safety for EV drivers and passengers.

Separator's role in the safety of lithium ion batteries, which are ubiquitously used in portable electronics and electric vehicles, is critical with separators serving as physical barriers and electrolyte reservoirs, and thus major concern with respect to safety and performance of the batteries [20]. Key performance indicators of all battery separator models, summarising recent advancements in the physical properties of battery separators and simulation studies, and the future designs and materials of battery separators are reviewed. In applications such as electric vehicles, delivering power and energy are pushed to extremes in lithium-ion batteries, and preventing thermal runaway (TR) is critical as described by McKerracher et. al.[21]. This review explores unique TR mechanism mitigating techniques like internal battery modifications with thermal shutdown mechanisms, advanced thermal management systems and technologies such as PTC material, self healing polymer electrolytes, and mist cooling. Furthermore, the need for the development of battery management systems (BMS) with temperature monitoring and suppression of critical thresholds is demonstrated for improving battery safety.

3. Machine Learning in EV Safety

The safety of electric vehicles (EVs) is enhanced through sophisticated monitoring and prediction as well control of unknown parameters using machine learning (ML). Battery management systems (BMS) is one of the main uses of ML in EV safety to predict and prevent potential problems such as thermal runaway which can cause fires and explosions. ML algorithms can detect early signs of degradation, e.g., from temperature sensors, as well as faults, such as opening circuit, by analysing data from temperature sensors, voltage and current measurements and can make time to intervene decisions. For instance, supervised learning models can provide SoH, SoC of prediction for batteries, whereas unsupervised learning analogies can be represented in battery behavior. In addition, techniques in reinforcement learning are under investigation for the purpose of optimizing charging protocols and thermal management, to produce safer, more efficient operation of batteries.

In addition to battery safety, ML is applied to predict vehicle safety by using predictive maintenance and driver assistance systems. Analysis of data coming from vehicle components such as brakes, tyres or motors in predictive maintenance models can help it to find opportunities for failures and

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mitigate the possibility of accidents. ML algorithms provide power to features in driver assistance systems such as collision detection, lane keeping assistance, and adaptive cruise control with the data from cameras, LiDAR or radar sensors. Real time object detection and scene understanding are supported by deep learning models in particular the convolutional neural networks (CNN), which gives autonomous or semi autonomous drive capabilities. ML is helping the creation of safer, more reliable EVs by using a large amounts of data from sensors and historical driving patterns to address very critical issues like battery safety, component reliability and accident prevention.

3.1 Machine Learning Models:

Linear Regression

Linear Regression functions as the base statistical technique which explains the connexion between dependent and independent variables. The model applies a linear relationship according to the following mathematical form [23]

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n + \varepsilon$$

Where:

- y is the target variable.
- β_0 is the intercept.
- β_i are the coefficients for independent variables x_i.
- ε is the error term.

Residual Sum of Squares enters as the main objective to reach minimal values which represent the difference between actual and forecasted values. The technique operates commonly because it delivers straightforward logic combined with high interpretability together with efficient computations.

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Random Forest Regressor

An ensemble learning method based on decision trees exists in the form of Random Forest Regressor. The training procedure generates various decision trees after which the model aggregates their output results through averaging for regression purposes to achieve better prediction quality. Key features include: [24]

Decision trees become more resistant to overfitting when numerous trees are built through this approach which helps handle complex interactions in large volumes of data.

XGBoost Regressor

XGBoost serves as a fast and productive implementation of gradient boosting which offers high scalability benefits [25]. The custom loss function optimization through gradient descent contains regularization terms which stop the model from overfitting.

XGBoost has gained fame through its successful competitions at Kaggle such as its ability to work with different dataset structures.

Gradient Boosting Regressor

Gradient Boosting Regressor builds multiple models one after another through loss function minimization. A weak learner such as a shallow decision tree gets fitted to the negative gradient of the loss function during each step of the algorithm. Loss Function Optimization Focuses on areas with high prediction error. A strong model emerges by combining weak learners through the process of Additive Modelling. The learning rate adjusts the weight of weak learner additions so the model avoids overfitting. Gradient Boosting works excellently with complex data relationships but demands precise optimization of its hyper parameters according to literature [26].

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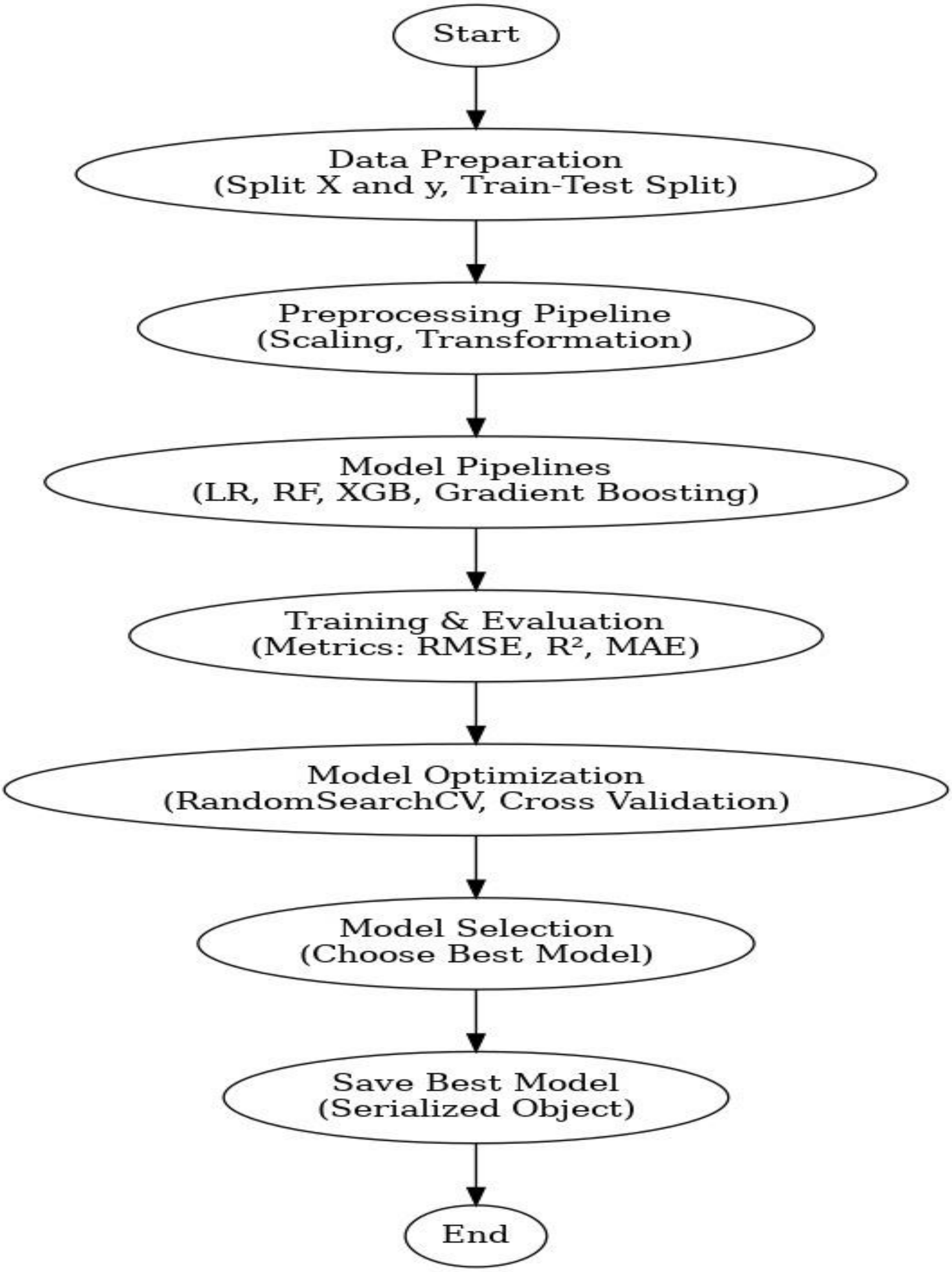

Fig. 1 Flowchart of the proposed methodology

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4. Results and Discussion:

The results section of the research paper conducts an extensive evaluation between several machine learning models designed to predict fire risks within electric vehicles (EVs). Performance assessment focused on Gradient Boosting Regressor (GBR), Random Forest (RF), Extreme Gradient Boosting (XGBoost) as well as Linear Regression (LR). The analysis utilises RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) with R2 (R-squared) and Explained Variance as the performance measurement metrics. A dataset consisting of 50000 observations features the measurements of State of charge (SoC) alongside Temperature, Current along with voltage. Gradient Boosting Regressor demonstrates superior performance compared to Linear Regression and other methods for determining fire risks in electric vehicles because of its ensemble approach

Table 1: Different parameters based on machine learning models

Sr. No.	**Machine learning model / parameters**	**RMSE**	**MAE**	**R^2**	**Explained Variance**
1.	Gradient Boosting Regressor (gbr)	0.0021	0.0004	0.9998	0.9998
2.	Random Forest (rf)	0.0042	0.0010	0.9990	0.9990
3.	Extreme Gradient Boosting(xgb)	0.0089	0.0024	0.9957	0.9957
4.	Linear Regression (lr)	0.1165	0.0806	0.2545	0.2547

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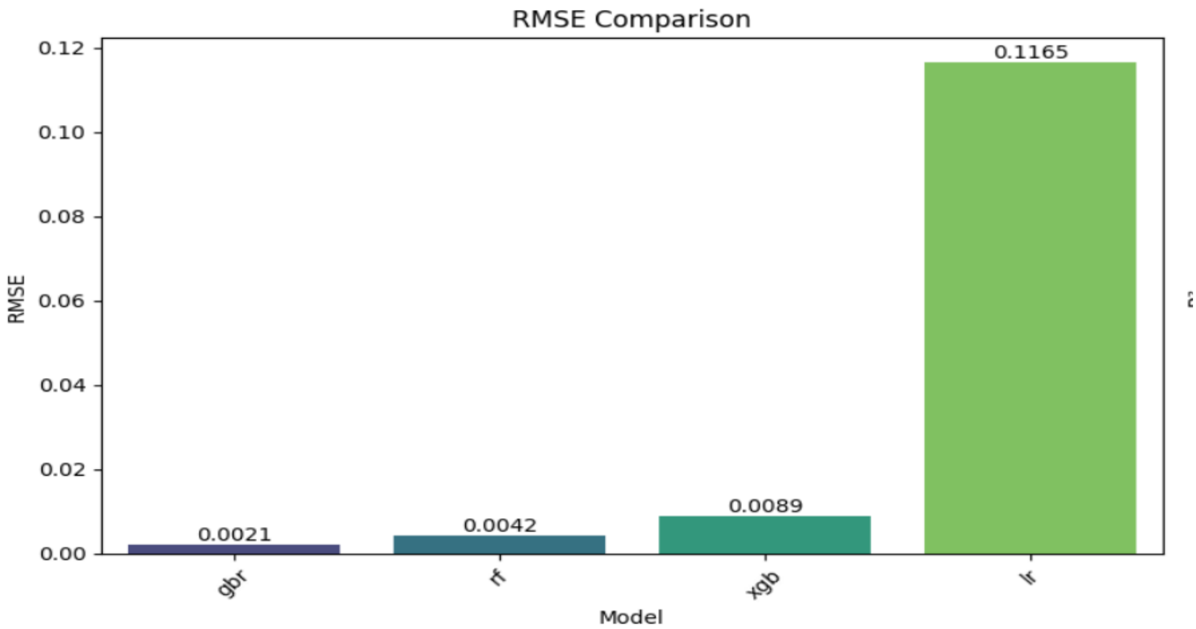

Figure 2 -Comparison of Root Mean Squared Error (RMSE) for Different Machine Learning Models

Visual data shows the comparison of RMSE values between four machine learning models. GBR achieves the best accuracy with the smallest RMSE value while RF follows then comes XGBoost and LR. Data from the graph establishes that GBR provides the most effective approach for lowering prediction error amounts

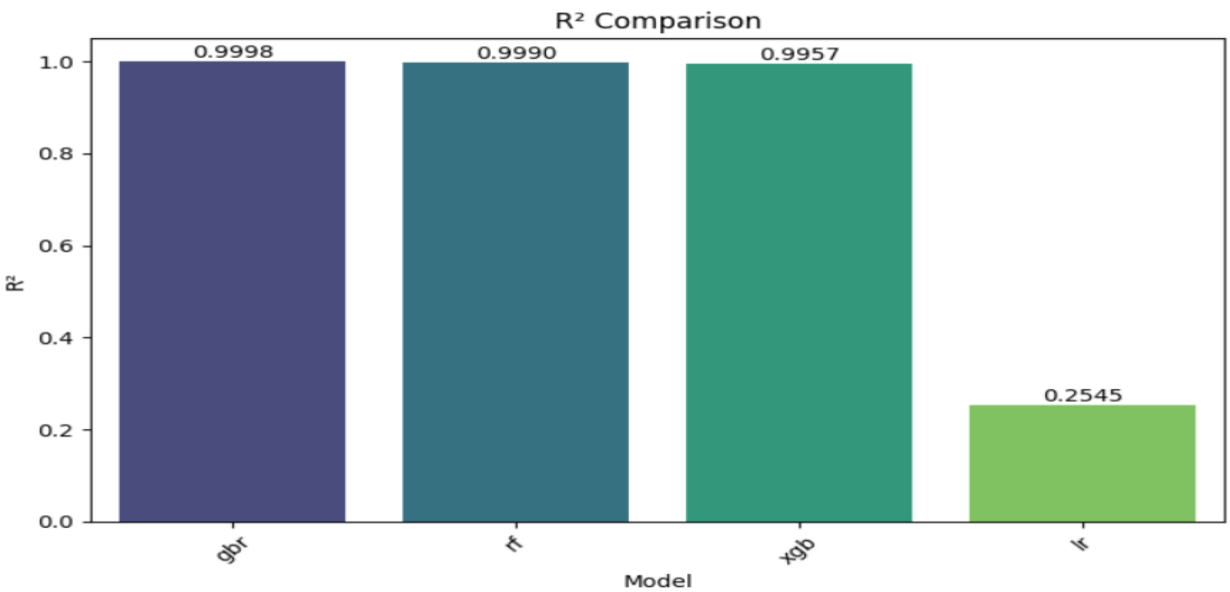

Figure 3 - Comparison of R squared (R^2) for Different Machine Learning Models.

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The R^2 values in this display show GBR at the top due to its superior fit against the data points. RF stands closest in line to the top spot but XGBoost and LR display lower performance. GBR demonstrates an excellent predictive power since its R^2 value indicates it explains almost the entire dataset variability.

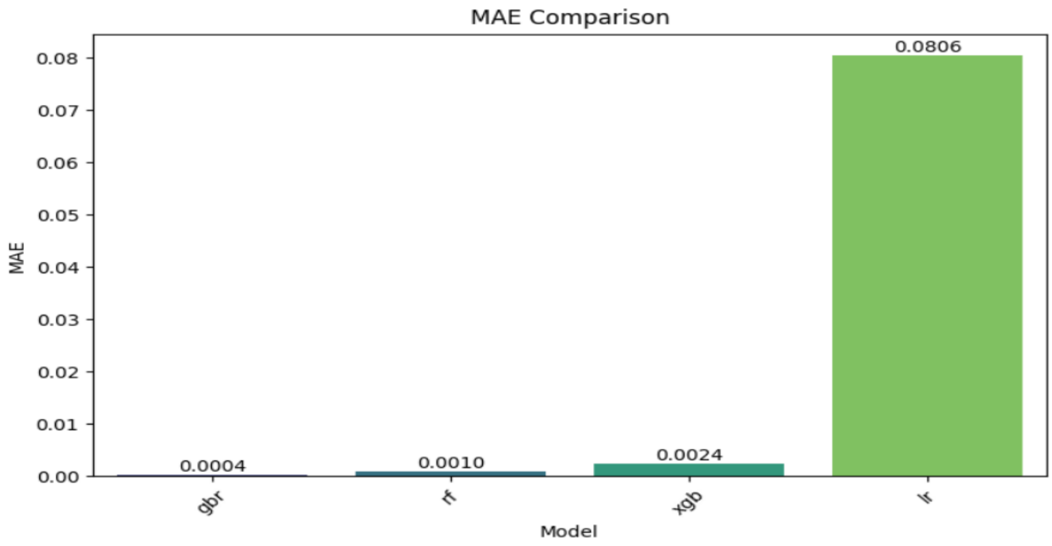

Figure 4- Comparison of Mean Absolute Error for Different Machine Learning Models

GBR stands out from other models because its MAE value remains the most minimal indicating it produces predictions with minimal average errors. The values for MAE indicate that RF and XGBoost yield higher deviations than LR which maintains the highest value indicating linear models have restricted applicability.

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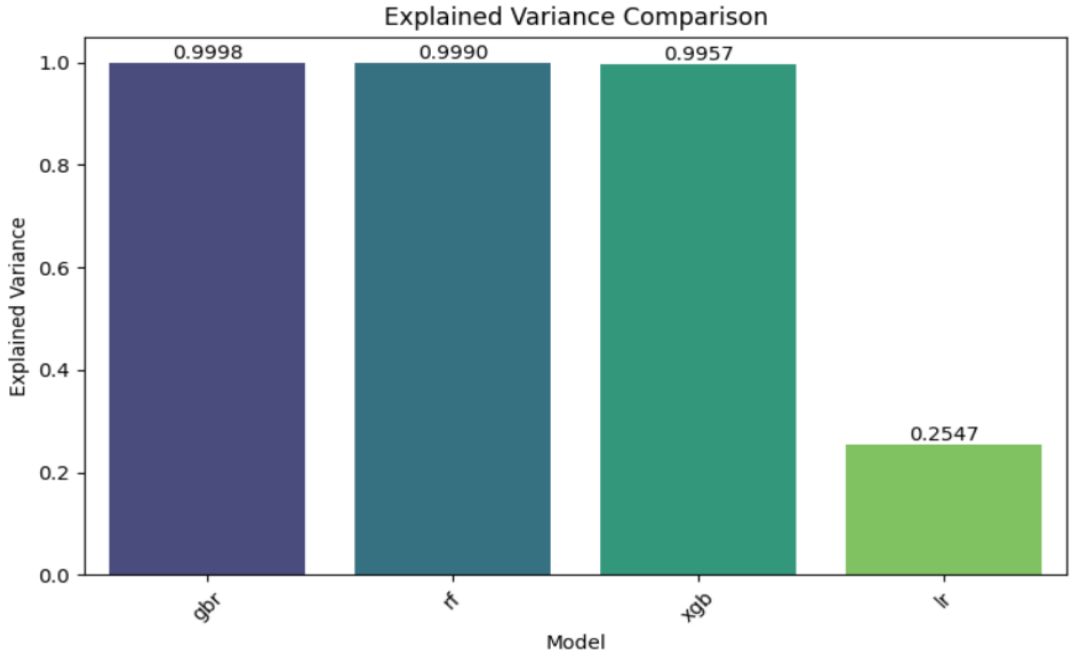

Figure 5 - Comparison of Explained Variance across Different Machine Learning Models

The Plot represents explained variance where GBR establishes itself as the leader. GBR demonstrates the highest Explained Variance because it absorbs almost all data variability which confirms its status as the most trustworthy model for fire risk assessment.

The cross-validation analysis demonstrates Root Mean Squared Error (RMSE) evaluation between Gradient Boosting Regressor (GBR), Random Forest (RF), Extreme Gradient Boosting (XGBoost) and Linear Regression (LR). The essential technique in testing machine learning algorithms requires cross-validation because it helps determine the reliability and generality of models through separate data sample evaluations.

Table 2: Cross Validation of RMSE

Sr. No.	Models Used	RMSE Values
1	Gradient Boosting Regressor (gbr)	0.0021
2	Random Forest (rf)	0.0042
3	Extreme Gradient Boosting(xgb)	0.0089
4	Linear Regression (lr)	0.1165

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The findings from Table 2 proved identical to the preceding model evaluation assessment. The prediction of EV fire risks shows Gradient Boosting Regressor (GBR) to be the most reliable and precise model through its attained minimal RMSE values throughout all cross-validation folds. Random Forest (RF) demonstrates an effective performance despite its lower capability when compared to GBR. The prediction results from Extreme Gradient Boosting (XGBoost) fall between moderate and the Linear Regression (LR) performs exceptionally poorly because of its high RMSE values along with poor generalisation abilities.

Advanced ensemble techniques such as GBR and RF must be utilised for predictive modelling of EV fire risks because they prove critical in complex assessment scenarios. These models demonstrate reliable performance through cross-validation procedures so they qualify as strong choices for integration into battery management systems (BMS) and other critical applications within the EV industry.

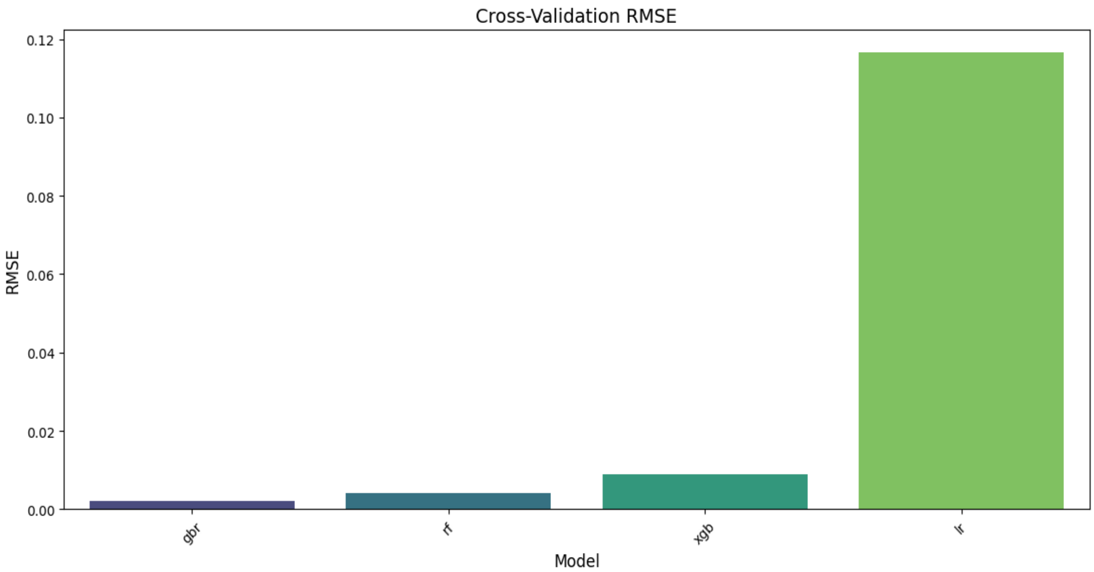

Figure 6- Cross Validation (RMSE) for Different Machine Learning Models

The RMSE ratings appear throughout different dataset segments on the cross-validation graph. GBR maintains the lowest RMSE value in all folds of experimentation which indicates its strong ability to apply the model effectively on fresh datasets. The empirical evidence obtained from this analysis adds substantial support to its practical deployment success.

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The discussion explores both the significance of the obtained results and assesses the performance of machine learning models regarding EV fire risk prediction. The main findings can be summarised into the following list:

GBR achieves top results because it effectively analyzes complex non-linear patterns existing within the data. The sequential model-building process of GBR enables it to extract complex patterns within the dataset because it corrects previous model errors. The complex interactions between State of Charge (SoC), Temperature and Voltage factors justify using this predictive method for detecting EV fire risks.

Surprisingly Random Forest delivered similar results as Grouped Boosting Randomization although its higher RMSE and MAE indicate that it does not detect the same subtle data patterns with the same level of accuracy. RF proves remarkably useful as a substitute for GBR because its solid mathematical foundation allows processing large datasets efficiently along with its robust behaviour.

The performance results of XGBoost demonstrated good results yet it scored lower than Random Forest and Gradient Boosting Regressor. The particulars of the dataset probably combined with the selected hyper parameters caused this reduction in performance. The recognised high efficiency of XGBoost did not lead to better results than other ensemble techniques in this situation.

Linear Regression demonstrated poor results as it shows that linear models struggle to process complex non-linear datasets. The linear assumption in LR does not match the non-linear relationships between features and target found in EV fire risk prediction thus making its use improper.

Cross-Validation Results:

Cross-validation procedures demonstrated the strong steadfastness of GBR by producing consistently low values of RMSE throughout all validation parts. GBR demonstrates strong abilities to predict unseen data effectively which makes it appropriate for real-world implementation.

The discussion highlights ensemble methods specifically GBR as powerful tools to predict EV fire risks which leads to a major improvement in EV battery system safety and reliability.

A research paper demonstrates that Gradient Boosting Regressor (GBR) from machine learning achieves suitable fire threat predictions in electric vehicle (EV) lithium-ion batteries by analysing their State of Charge (SoC) and Temperature and Current and Voltage properties. The GBR model

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achieved optimal prediction results through minimum RMSE and maximum R^2 values as well as minimum MAE after evaluating SoC and Temperature and Current and Voltage parameters. Gradient Boosting Regressor yielded superior outcomes than Random Forest and XGBoost and Linear Regression models. The validation tests confirmed that Gradient Boosting Regressor keeps its robust features while it maintains impressive generalization potential. Ensemble ML techniques demonstrate capability to improve EV battery safety by creating fire risk detection systems which lead to more reliable EV systems.

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