SSRG International Journal of Mechanical Engineering
ISSN: 2348-8360/ https://doi.org/10.14445/23488360/IJME-V13I8P108

Volume 13 Issue 8, 74-92, August 2026

Original Article

Comprehensive Investigation of Lithium Ion Battery Life under Abuse Testing Across Various Form Factors Using Machine Learning Approach

Asma Parkar[1], Parshuram Sonawane[2], Arun Bhosale[3], Shriramshastri Chavali[4], Pravin Nitnaware[5], Vivek Ghulaxe[6]

[1]*Department of Mechanical Engineering, Marathwada Mitra Mandal's College of Engineering, SPPU, Pune, India*
[2,3]*Department of Mechanical Engineering, NBN Sinhgad Technical Institutes Campus, Ambegaon, SPPU, Pune, India*
[4]*Department of Mechanical Engineering, School of Engineering and Technology, D Y Patil University, Ambi, Pune, MS, India.*
[5]*Department of Mechanical Engineering, D. Y. Patil College of Engineering, Akurdi, Pune, SPPU, Pune, India*
[6]*Department - IT Lead SAP MM (Purchasing), S/4 HANA, Publix Super Markets, Lakeland, Florida, United States.*

[1]*Corresponding Author : asmaparkar320@gmail.com*

Received: 04 March 2026 Revised: 30 April 2026 Accepted: 15 July 2026 Published: 27 August 2026

Abstract - *Present work, focused on prediction of lithium-ion batteries life during abuse tests in cell form factors with the help of a machine learning approach. Mechanical, thermal and electrical abuse test results are evaluated to learn the behavior of degradation and the mechanism of failures in prismatic, cylindrical and pouch cell. Form factors as structural arrangement and material distribution vary greatly between them and affect electrochemical stability and safety in harsh conditions of operation profoundly. A sophisticated machine learning approach, such as deep learning models and ensemble models is used to model the nonlinear behavior of degradation and detect essential parameters that influence battery life. Stress-induced variations in the voltage, temperature, inner resistance and mechanical deformations are analyzed as features to create an effective predictive model that can be used in estimating the remaining useful life of batteries. The comparative analysis of the various form factors can be used to retrieve unique failure signatures and structural strength properties. The suggested framework can help to improve the early detection of faults and optimize the precision of battery life prediction. The findings would help in enhancing the lithium-ion battery safety, reliability, and lifecycle materials of electric vehicles, consumer electronics, and large-scale energy storage systems.*

Keywords - *Machine learning methods, Battery Life Estimation, Battery form factors, Abuse testing, Electric Vehicles.*

1. Introduction

The Lithium-Ion Battery (LIB) is the most popular battery type used for energy storage due to its high energy density, lightweight design, long cycle life, low self-discharge rate and high power capability. Their properties have made them a popular choice in Electric Vehicles (EVs), Hybrid Electric Vehicles (HEVs), consumer electronics, aerospace systems, medical devices, and renewable energy storage. The continuous growth of the global demand for safer, longer-lasting and more reliable lithium-ion batteries as part of the global transition to sustainable transport and clean energy has continued to rise [1-3]. Figure 2 shows the wide applications of Li-ion batteries in modern energy systems.

As lithium-ion batteries have been rapidly commercialized, there have been many concerns about battery safety, degradation, and operating reliability. In long-term service or in harsh operating conditions, there are various electrochemical, thermal and mechanical degradation mechanisms which degrade the capacity of all batteries over time, raise the battery's internal resistance and eventually cause battery failure [2, 3]. Safety issues such as thermal runaway, internal short circuit, gas production, electrolyte decomposition and fire hazards are major problems, especially for large scale battery packs in electric vehicle and stationary energy storage systems [1, 10, 11, 19]. Self-accelerating exothermic reactions, which can spread quickly across battery modules and packs, continue to be one of the most critical failure mechanisms, due to thermal runaway [10, 12, 19].

Mechanical forces, thermal acquaintance, electrical abuse, and environmental anxieties are substantial features that vitiate batteries. The failure of the separator can be triggered by mechanical abuse such as penetration, impact, crush and drop loading which may lead to catastrophic failure events [11]. Electrical abuse (e.g., overcharging, deep discharging and external short circuit) causes lithium plating, electrode deterioration and irreversible electrochemical damage, which leads to battery capacity reduction and increased thermal instability [20, 21]. Likewise, prolonged exposure to high temperatures strongly hastens the ageing reactions, promotes electrolyte decomposition and raises the probability of occurrence of thermal runaway [3, 12, 19]. The following major degradation and safety concerns are highlighted in Figure 3 for abuse.

The configuration of the structure of the lithium ion batteries also have a significant effect on their degradation behaviour and abuse tolerance. There are significant differences between cylindrical, prismatic and pouch cells in terms of mechanical strength, heat dissipation, packaging efficiency and structural integrity, which lead to very different responses for the same abuse conditions [22]. Normally, cylinder-shaped cells are extra unconsciously vigorous and thermally steady as they are cosigned in an inflexible metal case, although pouch cells compromise superior energy density but are extra disposed to to inflammation, perforating, and thermal unsteadiness. While prismatic cells are not as compact as the cylindrical cells, they provide a more balanced energy density and strength and can be easily damaged in extreme loading situations [22]. Therefore, it is crucial to evaluate various battery form factors under the same testing conditions to enable the design of a safer battery and optimization of battery management strategies.

The current methods used for battery health assessment and Remaining Useful Life (RUL) prediction are empirical degradation models, electrochemical modelling and laboratory-based Characterisation methods. While these approaches enable important understanding of the aging mechanisms of batteries, they may not be able to simultaneously account for the interactions between electrochemical, thermal and mechanical degradation processes during practical use [3, 7, 17, 18]. In addition, traditional diagnostic methods normally need large number of experiments to be implemented, thus they are rather computationally intensive and hard to use in the real-time battery management applications [1, 16]. With the progress of Artificial Intelligence and Machine Learning (AI/ML), there are promising alternatives for battery diagnostics, fault detection, state-of-health estimation, and Remaining Useful Life (RUL) prediction. Machine learning algorithms are able to deal with huge amounts of experimental battery data, detect any hidden degradation trends, learn the nonlinear relation between several operating parameters, and accurately forecast the battery performance without needing to model it explicitly [4, 8, 14]. The supervised learning methods, including Support Vector Machines (SVM), Random Forest (RF), Extreme Gradient Boosting (XGBoost), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks and hybrid deep learning models, have shown great promise in the field of battery health monitoring and predictive maintenance applications [5, 6, 8, 9, 13, 14, 23, 24]. It has also been demonstrated recently that combining physics-based knowledge with data-driven learning gives significantly better robustness to prediction, greater interpretability, and better fault diagnosis under stochastic operating conditions [5, 14, 16]. The overall role of machine learning in battery diagnostics, degradation analysis, and intelligent battery life prediction is shown in Figure 4.

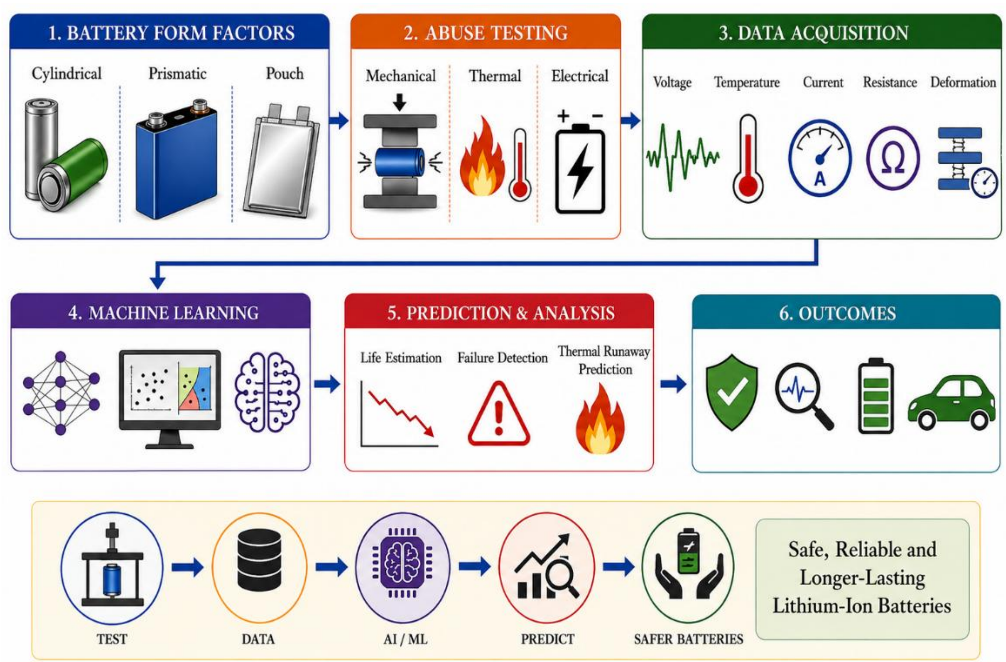


Fig. 1 Need of investigation of lithium ion battery life under abuse testing

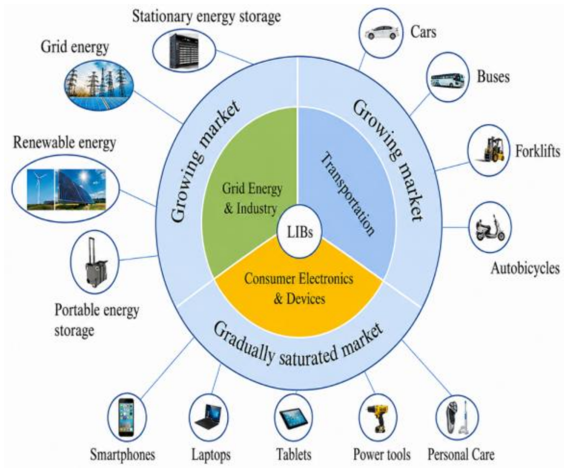


Fig. 2 Importance of lithium-ion batteries in various applications (source: EVOLT)

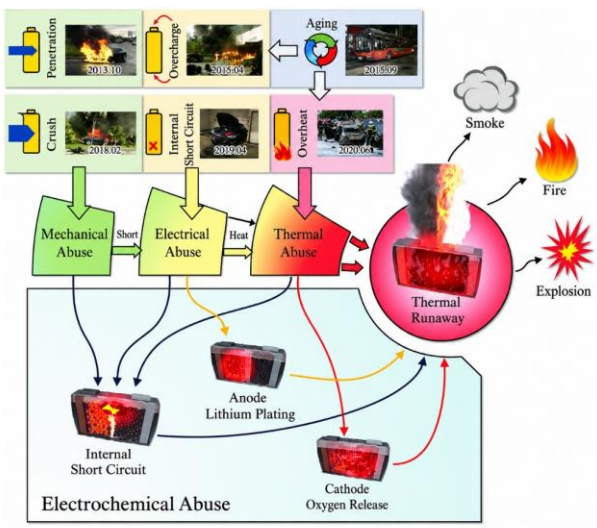


Fig. 3 Challenges related to battery safety, degradation, and failure under abuse conditions [1]

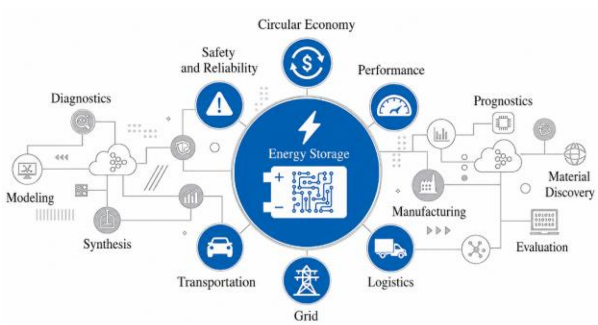


Fig. 4 The application of ML to energy storage technologies utilizes interconnections between battery data set (source: transportation & mobility research)

Although significant developments have been made in battery diagnostics and predictive modelling, there are still some fundamental research areas that are of importance. Previous published research focuses on either abuse testing or machine learning, and only a few studies integrate experimental abuse testing with advanced machine learning models in a single model [1, 3, 4]. Moreover, comparative studies of cylindrical, prismatic and pouch cells under the same mechanical, thermal and electrical abuse conditions are still relatively limited [22]. The predictive models available in literature are often built from a single form factor dataset, and hence, have limited capability in generalizing the results for other battery architectures [4, 14, 23]. Furthermore, the implementation issues such as feature selection, model interpretability, computational complexity and real time implementation in the battery management systems are still present in the industrial system, which limits the system uses [4, 5, 14, 16].

For this reason, this work is a comprehensive study, focusing on lithium-ion battery life during mechanical, thermal, and electrical abuse, and performed by combining experimental testing and advanced machine learning techniques. Three commercially important battery form factors (cylindrical, prismatic, and pouch cells) are systematically tested under similar abuse conditions to determine the degradation mechanisms, structural and thermal reactions, and develop reliable models for predicting battery lifetime. Several machine learning models are used to determine the most critical battery degradation parameters, and to accurately estimate battery health and the remaining useful life based on experimental data from battery abuse tests. The proposed framework supports the advancement of intelligent battery management systems for electric vehicles, consumer electronics, and grid-scale energy storage applications, predictive maintenance systems, abuse testing methods, and safer lithium-ion batteries.

1.1. Problem Statement

Accurate estimation of Remaining Battery Life (RBL) is crucial in enhancing the performance, safety and reliability of lithium-ion battery systems. Current approaches to battery life prediction are mostly empirical, lab-based and time-consuming, and don't account for the complex interactions of multiple degradation mechanisms [1, 3, 10].

The real-time battery monitoring, coupled with abuse testing data allows for a data-driven method to predict battery life by machine learning. Deep learning, support vector machines and ensemble models can be used to identify trends of battery behavior, predict points of failure, and optimize battery management strategies [4, 8]. Using historical and current data can be predicted and detected failures using these predictive models, which can help to conduct proactive maintenance and enhance system safety [5, 6, 14].

Moreover, ML models are applied to various types of batteries, battery forms, and battery applications, which result in a scalable and flexible solution for various applications [4, 22]. Machine learning can be integrated into Battery

Management Systems (BMS) to provide significant enhancements in battery operation, lifespan, and safety, underscoring its critical role for lithium-ion batteries in the future [12, 16].

1.2. Objectives of the Study

- To study abuse conditions (mechanical, thermal, and electrical) for the sake of understanding battery performance, degradation, and failure mechanism under various form factors and conditions
- To analyze effects under each abuse condition on the lithium-ion battery lifespan.
- To understand the structural and thermal behaviour of different battery formats, study a range of different stress cases to benchmark the structural weakness and thermal runaway of cylinders, prismatic and pouch cells.
- To train machine learning models for battery life Use machine learning for identifying trends for battery degradation and prophesying the failure using experimental data from abuse tests.
- Identify key predictive features of battery performance Identify the most important electrochemical and thermal parameters that lead to battery aging and failure under abusive conditions.
- To educate and provide data-driven insights to improve battery architecture, Battery Management Systems (BMS), and better safety standards for lithium-ion batteries.
- To aid in standardization and regulatory guidance support the creation of standardized abuse test methods and regulations through a holistic assessment of energy storage safety across various cell designs.
- To pave the path for predictive analysis and real-time monitoring.
- To facilitate predictive maintenance using machine learning-based predictive analytics that allow industries to use early failure detection that makes it easier to transition to predictive maintenance for lithium-ion battery systems used in electric vehicles, consumer electronics and energy storage applications.

2. Literature Review

2.1. Abuse Testing Studies

Lithium- Ion Batteries (LIBs) are very sensitive to different forms of misuse during operational cycles. Many studies have demonstrated that there are substantial dangers at all stages of the battery life cycle, highlighting the need to develop suitable fault diagnosis techniques when LIBs are operated under "abused" conditions. Many studies have been conducted to find mechanical abuses of LIBs that lead to thermal runaway events through mechanical deformation or impact leading to internal short circuit or failure of the separator [11]. Lei Yao et al. [1] has summarized the safety problems during the entire battery life cycle, and under following conditions, exothermic chain reactions can occur, leading to thermal runaway, which is often exacerbated by abusive operation.

Research on electrical mismanagement (overcharging and over-discharging) have recorded very negative effects on safety and performance features of LIBs. Zhao et al. [20] have shown that overcharged condition in LIBs leads to accelerated degradation of LIB performance affecting the capacity fade of LIBs and increasing the possibility of thermal instability in LIBs. On the other hand, Caisheng Li et al. [21] found that irreversible electrochemical damage and copper dissolution will take place if LIBs are subjected to over-discharge for a long period. Huang et al. [10] continued to stress the importance of setting up safe operating limits to avoid unsafe LIB operations. Other studies have been conducted to compare the degradation behaviors in cylindrical, prismatic and pouch cells and it has been noted that the degradation behaviors are greatly affected by cell geometry [22].

Recently, the focus in research has been on incorporating the diagnostic methods in abusive test procedures. A hybrid coding and genetic search method for comprehensive fault diagnosis was proposed by Chunhui Ji et al. [6]. Under stochastic conditions, Rui Cao et al. [5] proposed model-constrained deep learning for fast fault detection. These studies indicate the move to smart and adaptive fault detection approaches.

2.2. Battery Degradation Mechanisms

The degradation of a battery is a multi-factorial, multi-mechanistic, electrochemically, thermodynamically and mechanically complex phenomenon. Yang et al. [2] performed experiments to investigate the effect of different charge/discharge rates on LIB capacity degradation and found that higher charge/discharge rates lead to increased internal resistance and temperature, consequently causing higher capacity degradation. The authors of Madani et al. [3] performed an extensive literature search to identify the main aging mechanisms of LIBs such as growth and formation of the Solid Electrolyte Interphase (SEI), lithium plating, and loss of active materials.

Further, theoretical models like point-defect models can be used to explain how ions move in the electrode materials and related degradation pathways [18]. Llewellyn et al. [17] also explained the degradation pathways by showing the relationship between degradation and microstructural changes via in-situ multi-scale diffraction. Side reactions are more likely to take place and cause aging at high temperature. Bao et al. [12] pointed out that a reliable prediction of battery temperature is crucial to maximize battery duration and safety in EVs.

Thermal runaway, a thermal degradation phenomenon involving uncontrolled increase of temperature as result of exothermic chemical reactions, is one of the most important degradation phenomena that can result in an explosion [19]. Alfraheed [7] reported on different techniques used to measure degradation analysis, such as impedance spectroscopy, ultrasonic inspection, and thermal imaging, which can be used to detect the internal faults and performance degradation in an early stage.

2.3. ML-based Prediction Models

Machine Learning (ML) has become one of the main methods for Battery Health Monitoring (BHM), Fault Diagnosis (FD) and Battery Life Prediction (BLP) in recent years. The preliminary results achieved by the traditional method like Support Vector Machine (SVM) showed successful prediction of Remaining Useful Life (RUL) [23]. For even better prediction performance, hybrid optimisation methods based on Particle Swarm Optimisation (PSO) and Support Vector Regression (SVR) were used, giving a further improvement in prediction [24].

In recent years, there has been a move away from traditional models to data-driven and deep-learning models. Venugopal et al. [8] tested different ML techniques and developed suitable models for battery lifetime estimation based on the chosen performance parameters. Valizadeh and Amirhosseini [4] gave an extensive survey of the applications of ML and some of the challenges including small-sized data sets, and lack of generality in the models.

Artificial Neural Networks (ANNs) are one of the most popular techniques that can be applied to the diagnosis of faults in deep learning. Lee et al. [13] showed that the use of ANN together with likelihood mapping is an effective way to identify multiple failure modes. Choi and Park [15] created data-driven methods for thermal runaway early warning.

The advanced ML methodologies use a combination of probabilistic method and hybrid methods. Thelen et al. [14] emphasized the importance of probabilistic machine learning in dealing with uncertainties in battery diagnostics.

Rui Cao et al. [5] developed model constrained deep learning, which achieves robustness via physics-based constraints and data-driven models. Wang et al. [9] evaluated LIB degradation by ultrasonic diagnostics and ML to allow the non-destructive monitoring of degradation. The advantage of using ML-based approaches over traditional models is that they can learn non-linear relationships between input features and out features and can capture complex degradation patterns.

2.4. Literature Gap and Scope of Work

Although significant progress has been made in lithium-ion battery diagnostics and prediction, there are still a number of research gaps to be addressed. One, most studies have concentrated on abuse testing or machine learning alone, with only a few studies combining the two in the context of an experimentally validated framework [1, 3].

Second, most machine learning models are trained on single-type datasets, resulting in sub-optimal model performance when attempting to predict the degradation effects of multi-physics loads (mechanical, thermal and electrical stresses all three) on batteries.

Thirdly, comparisons of various form factors of Li-ion batteries under the same experimental conditions is rare. Although the form factor and predictive modeling vary depending on the type of battery, very few research papers have been conducted to systematically study the pair of form factor and predictive modeling with respect to degradation rates [22].

Fourth, there is a lack of understanding on how to develop machine learning-based diagnostics, for example, by not considering real-time application problems like data availability, interpretability of the model, and computational complexity [4, 14].

Fifth, deep learning models are extremely accurate, but are "black box" models and not useful for use in safety-critical systems where explainability is needed. In addition, computing models that combine physics-based understanding of the behavior of batteries with data-driven methods to improve reliability and generality are required.

Last but not least, there are no standard data sets and benchmarks available to enable comparisons between studies. To tackle all the aforementioned gaps in the research, it is necessary to put in place an integrated approach that combines multi-modal abuse testing, advanced machine learning techniques and real-time diagnostic capabilities.

2.5. Research Gap and Novelty of Work

Multiple The lithium-ion batteries available in various shapes and sizes (cylindrical, prismatic and pouch) have distinct mechanical, thermal and structural characteristics that influence their response to abuse.

The cylindrical design offers superior mechanical strength as it is constructed from rigid steel materials and has poor heat distribution properties. Prismatic batteries have higher energy density but are less structurally robust and are more prone to mechanical stress and swelling. Pouch cells are flexible and light, but are more prone to thermal instability and punctures than prismatic or cylindrical cells.

Most of the previous LIB abuse studies have targeted only a single type of abuse (e.g., mechanical deformation, overheating or thermal exposure), or used separate ML method for lifespan prediction, with limited data sets. Previous research did not consider the real-time applicability, the applicability to various batteries or a systematic comparison under comparable operating conditions.

All three LIB formats (prismatic, cylindrical, and pouch) were analyzed in this study in terms of degradation behaviors under multi-physical abuse conditions (mechanical, thermal and electrical). In this study, predictive models of life and failure of batteries are developed using several ML algorithms.

The present work has provided a link between experimental studies and intelligent predictive modelling to gain insight into the degradation mechanisms in LIBs and develop more reliable and safer energy storage devices for targeted applications. It is expected that the results will help to set standard test procedures and new safety standards for real-life battery operations.

The novelty of the work over the works previously published is that it provides an integrated, comparative methodological approach of an experimentally obtained dataset of 3 types of LIBs to carry out under similar test conditions.

The present study is different from previous studies which investigated the experimental and prediction separately by integrating multiple physical abuse scenarios (mechanical, thermal, and electrical) under one experimental environment. One additional contribution is a comparative study of the degradation behavior of each of the LIB formats under the same operating conditions, which gives insights into the degradation characteristics and specific safety responses of these formats.

Furthermore, the present study involves a multi-dimensional ML approach and the application and validation of multiple machine learning techniques for life prediction and fault diagnosis which further enhances the robustness and reliability of the study. Identifying the key degradation characteristics that impact a battery's health and failure modes will also help to create predictive maintenance strategies and enhance real-time battery management systems.

In summary, this work constitutes a significant step forward, employing the experimental understanding and developing intelligent data-driven approaches into a scalable and feasible framework for next-generation battery diagnostics and safety enhancement.

3. Experimental Methodology

3.1. Battery Specification & Selection

As shown in Figure 5, selecting an appropriate battery for any application involves a thorough analysis of its features shape and size, chemistry, and battery performance metrics. There are three main Lithium-Ion Battery (LIB) form factors: cylindrical, prismatic, and pouch cells. The cylindrical cells include widely known formats such as 18650 and 21700 with high structural integrity because these types come in rigid metallic casing allowing them to be used in applications that also require the ability to withstand mechanical stresses and high heat dissipation.

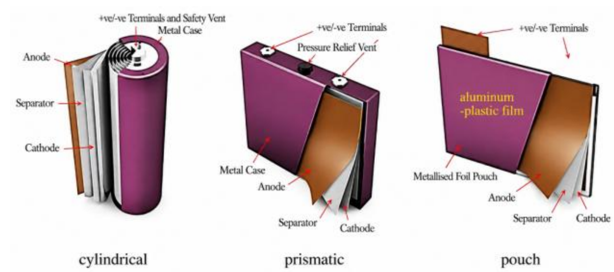


Fig. 5 Types of packaging for lithium ion battery (source: https://etekware.com)

Electric cars use prismatic cells, which are packaged in aluminum or steel casing and are able to be stacked walrus-like, yielding a greater energy density per unit volume. Pouch cells, with a flexible polymer enclosure, achieve a much higher packaging density and are suitable for lightweight applications, but they do need extra structural support to prevent any swelling or deformation risks. When selecting the battery in any study there are several criteria to be dealt with. These encompass energy density, which defines the operating range for Electric Vehicles (EVs) or device run times for consumer electronics; power density, relevant for systems with high discharge currents (e.g., Hybrid Electric Vehicles (HEVs)); safety characteristics, which relate to the risk of thermal runaway and mechanical abuse; and cycle life, which determines long-term usability. Other considerations such as operating temperature range, internal resistance, charge/discharge rates and cost have a big influence on a battery choice as well. Accordingly, with respect to the aforementioned parameters, selection of battery for any given study depends on the intended application of the prospective study with a corresponding ideal balance between performance, safety and cycle life as shown in Tables 1 and 2.

Table 1. Battery selection & specifications

Parameter	Cylindrical Cell	Prismatic Cell	Pouch Cell
Shape & Structure	Cylindrical metal casing	Rectangular metal casing	Flexible laminated pouch
Common Sizes	18650, 21700, 26650	Varies (e.g., 148x91x26mm)	Varies (customizable)
Energy Density	Moderate to High	High	Very High

Thermal Management	Good heat dissipation	Moderate heat dissipation	Poor heat dissipation
Mechanical Strength	High (rigid metal case)	Moderate (rigid but less than cylindrical)	Low (flexible and prone to deformation)
Weight	Heavier due to casing	Moderate	Lightweight
Applications	EVs, power tools, laptops	EVs, industrial storage	Consumer electronics, drones, aerospace
Cost	Lower manufacturing cost	Higher cost due to packaging	Moderate cost depending on design
Thermal Runaway Risk	Moderate	High	Very High

Table 2. Selection criteria for batteries used in the study

Criterion	Description
Battery Chemistry	Selection of lithium-ion cells based on commonly used chemistries (e.g., NMC, LFP, LCO) for safety and reliability evaluation.
Form Factor	Inclusion of cylindrical, prismatic, and pouch cells to analyze structural and thermal differences.
Capacity Range	Selection of cells with a capacity range of 2000-5000mAh to ensure comparable results across form factors.
Voltage Rating	Cells with nominal voltages of 3.6V-3.7V to maintain consistency in testing conditions.
Manufacturing Source	Batteries sourced from reputable manufacturers to ensure standardization and quality control.
Thermal Stability	Consideration of cells with different thermal management capabilities to assess abuse tolerance.
Application Relevance	Selection of cells commonly used in EVs, consumer electronics, and energy storage to ensure industry relevance.
Availability & Cost	Easily available commercial cells with reasonable cost constraints for practical implementation.

3.2. Abuse Testing Methods

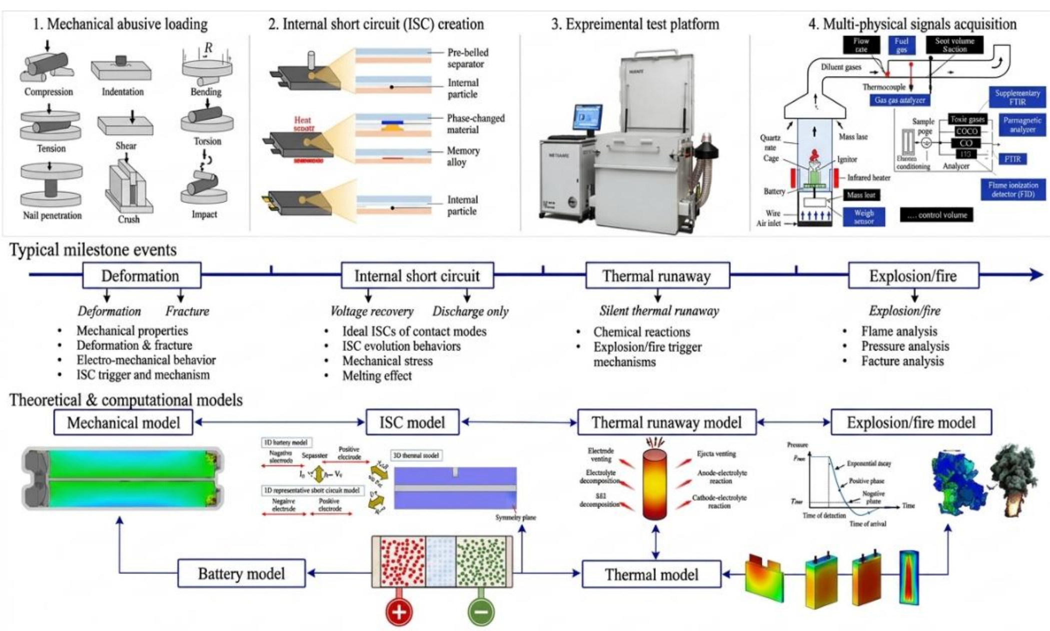


Fig. 6 Lithium ion battery abuse testing [2]

However, the ultimate test of a battery's design is how well it manages abuse: normal, everyday, and not-so-everyday practices that put the lithium-ion cell under stress. [13] These tests replicate physical threats like mechanical abuse, heat build-up, and electrical failures to identify battery weaknesses and failure mechanisms. E.g. Mechanical Abuse Testing Crush, penetration, vibration and impact tests etc. as shown in Figure 6.

1. Crush test is a test, wherein the test samples are subjected to compressive forces to mimic extreme pressure conditions that can occur when a vehicle crashes.
2. The penetration test uses a sharp nail or rod to puncture the cell and assesses the risk of internal short circuits resulting in thermal runaway.
3. Methods such as a vibration test simulate conditions found in automotive and aerospace applications to investigate the effects of long-term mechanical stress.
4. Impact testing subjects the battery to sudden shocks and drops in order to evaluate structural integrity.
5. Thermal Abuse Test: This assesses the performance of batteries at extreme temperatures.
6. Overheating tests operate by exposing a battery to higher temperatures than the safe nominal range, at which point the electrolyte decomposes and starts to induce a thermal runaway.
7. Thermal runaway propagation tests involve how heat travels from one cell in a battery pack to another, which aids in the design of safety mechanisms.
8. Electrical Abuse Testing - This tests for electrical failures that can result in catastrophic failure.
9. The overcharge test assesses the response of the battery when subjected to charging beyond the specified voltage limit, leading to gas evolution and swelling.
10. Deep discharge test will focus on studying the effects of lowering a cells voltage below its minimum level.
11. Short circuit test: The test evaluates the battery's behavior when both of its terminals are interconnected. This leads to a quick increase of heat in the battery, which poses fire risks.

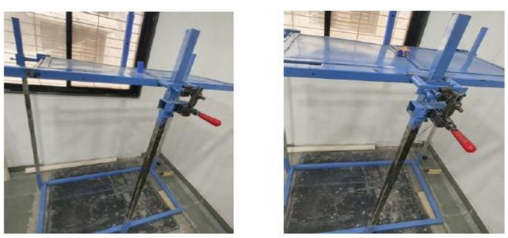


Fig. 7 Drop and impact test set up of lithium ion battery

The abuse testing experimental set-up as shown in Figure 7, consists of thermal abuse test chambers, mechanical rigs for crush and penetration tests, and electrical control circuits for overcharge and short circuit tests. Failure data collection leverages high-speed cameras, infrared thermal imaging, pressure sensors and gas analyzers.

The voltage, temperature and mechanical response are recorded in real time through an automated trigger mechanism in the system. For the test, 3.7 volts and 2.5 ampere lithium-ion battery cell in addition to starting environmental temperature of 20 50C and relative humidity less than 70% according to UN 38.3:2019 recommendation for impact and according to HPLI03/Test-Bat/WI-80 standard and IEC 62133-2:2017. At the drop test, each fully charged battery cell is dropped at three heights, 1.2 meter and 1.5 meters to fall on to a flat surface in concrete floor or metal floor with the acceptance criteria of no fire and no explosions.

It is also carried out under identical environmental conditions as the impact test. The cell is placed on a flat smooth surface during impact test. A 15.8 mm 0.1mm diameter or fixed length type 316 stainless steel bar shall be placed across the center of the sample; in (flattening factor) specimens, the length of the bar shall be 6cm, or the cell's longest dimension, and whichever is largest. A 0.1kg mass of 9.1kg is to be dropped from different heights own definitely (for sample 01:65cm, for sample 02:70cm, for sample 03:75cm) at the intersection of the bar and sample with a controlled way of dropping, using a near frictionless vertical sliding track or channel, so that Minimum drag is applied to the mass falling down.

As shown in Table 3, the test sample to be impacted on the flat surface, with longitudinal axis parallel and perpendicular to the longitudinal axis of the 15.88 mm 0.1 mm diameter curved surface extending across the center of the sample. Only one impact shall be applied to each sample.

Table 3. Description of different abuse tests for lithium-ion batteries

Abuse Test Type	Test Name	Description	Effects on Battery	Relevance to Real-World Scenarios
Mechanical	Crush Test	The battery is compressed between two plates until deformation or failure occurs.	Cell deformation, internal short circuit, fire/explosion risk.	Simulates accidental crushing in vehicle crashes or battery packaging failures.
	Penetration Test	A sharp object (e.g., nail) is driven through the battery to test internal damage tolerance.	Internal short circuit, thermal runaway, fire.	Simulates puncture damage due to external objects, improper handling, or road debris impact in EVs.
	Vibration Test	Battery subjected to continuous vibration at varying frequencies to test structural integrity.	Connector loosening, internal damage, electrolyte leakage.	Simulates real-world vibrations in EVs, aerospace, and industrial applications.

	Impact Test	Battery is struck with a heavy object to test its ability to withstand sudden force.	Mechanical deformation, internal short circuit, possible fire/explosion.	Simulates accidental dropping or collisions in transport and handling.
Thermal	Overheating Test	The battery is exposed to elevated temperatures beyond its operating range.	Capacity loss, electrolyte decomposition, fire hazard.	Simulates overheating due to external heat sources or excessive charging.
	Thermal Runaway Initiation	Battery is subjected to conditions that trigger uncontrolled heat generation.	Fire, explosion, loss of structural integrity.	Simulates failure scenarios in high-temperature environments or thermal abuse conditions.
Electrical	Overcharge Test	Battery is charged beyond its maximum voltage limit.	Lithium plating, internal short circuit, thermal runaway.	Simulates faulty charging systems or power surges.
	Deep Discharge Test	Battery is discharged beyond its recommended cut-off voltage.	Capacity degradation, irreversible damage, potential short circuit.	Simulates prolonged storage without maintenance or excessive power draw.
	Short Circuit Test	Battery terminals are directly connected, causing a high current flow.	Rapid heating, fire, explosion risk.	Simulates electrical malfunctions, faulty wiring, or accidental contact.

3.3. The Process of Data Acquisition and Preprocessing

To analyze the performance, safety, and degradation properties of the battery, data accuracy is vital, and data preprocessing is essential as shown in Figure 8. Multiple sensors are utilized to capture real-time parameters:

1. During operation, voltage sensors are used to measure changes in cell voltage to protect against overcharge, deep discharge, and internal short-circuits.
2. During the charge/discharge cycles, the current flow is measured by means of current sensors (Hall effect sensors or shunt resistors).
3. Temperature sensors (thermocouples, RTDs, infrared sensors) sense heat and trigger alerts on hotspots before they turn into thermal runaway.
4. Sensors based on impedance measurement assist in monitoring changes in internal resistance, which signifies aging and degradation. [14]

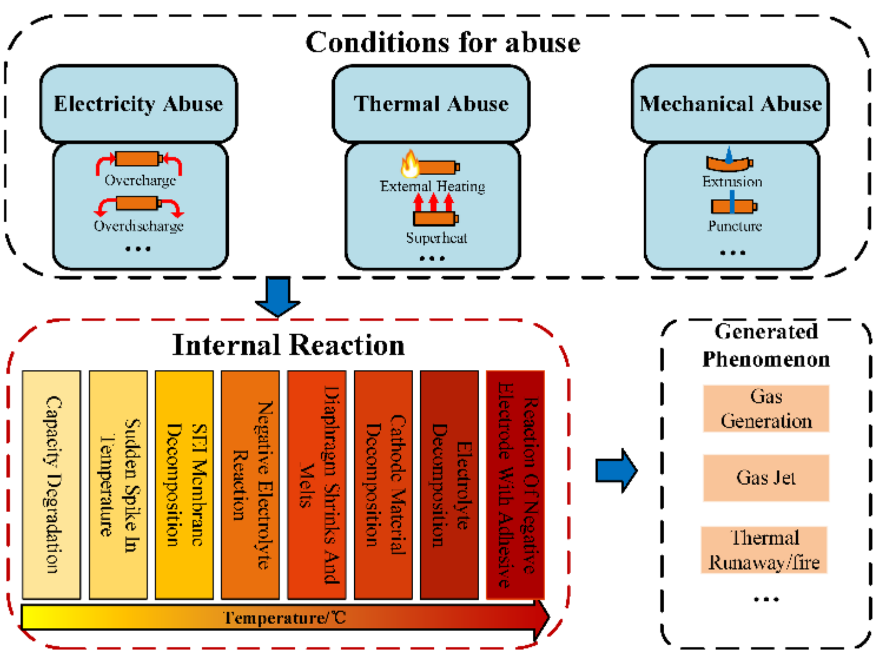


Fig. 8 Internal and external thermal runaway of battery under different abuse conditions [3]

Mechanical deformations have been monitored for other aspects with strain gauges or displacement sensors particularly in cells where swelling is a problem, such as pouch cells. Once the raw data has been gathered, the data is preprocessed to enhance the quality of the data set for subsequent analysis. Data cleaning includes removal of wrong readings, missing value handling, and noise-filtering. Normalization is a process whereby some parameters are converted to a common scale, to ensure that data is consistent and easy to compare between various types of batteries and test conditions.

Feature selection methods, such as Principal Component Analysis (PCA) and correlation analysis can be used to determine which features are most relevant to the battery's performance. These pre-processing techniques improve the accuracy of the ML models and statistical analysis used for battery health monitoring and predictive maintenance. Table 4 shows the experimental results of the different abuse tests carried.

Incorporating systematic feature extraction, model selection and optimization will enhance the methodology. Voltage, Temperature and Internal Resistance were identified as key input features as they have been demonstrated to be highly correlated with battery failure modes and therefore will significantly influence battery degradation and safety behaviors. Statistical Correlation Analysis (and PCA) was used to establish which variables had significant influence upon the degradation process and consequently reduced the dimensionality of the data space. The ability to develop predictive models that can accurately capture non-linear relationships and are capable of operating in noisy environments has enabled the use of multiple Machine Learning algorithms including Random Forest (RF), Support Vector Machine (SVM), and XGboost. Model hyperparameters were optimized using Grid Search and Random Search methods to improve model performance.

Specifically, the number of trees in each tree was varied for RF, and the type of Kernel function was explored for SVM. A structured pipeline approach was followed to ensure an efficient and reliable predictive model, i.e., data collection, preprocessing, variable selection, developing predictive model(s), making predictions from the developed model(s).

Table 4. Effects of mechanical and electrical abuse testing on different form factors of lithium-ion batteries

Abuse Test Type	Test Name	Parameter	Cylindrical (18650, 21700)	Prismatic (e.g., 148x91x26mm)	Pouch (Custom sizes)
Mechanical	Crush Test	Deformation (%)	10-20% before short circuit	15-25% before failure	30-40% before rupture
		Voltage drop (V)	1-2V drop before failure	1.5-3V drop before failure	Instantaneous drop
	Penetration Test	Penetration depth (mm)	3-5mm before short circuit	4-6mm before thermal runaway	2-3mm before fire/explosion
		Temperature rise (°C)	120-180°C	150-200°C	200-250°C
	Vibration Test	Frequency range (Hz)	5-200Hz	5-300Hz	5-500Hz
		Capacity retention (%)	95-98%	90-95%	85-90%
	Impact Test	Impact energy (J)	10-30J before failure	15-40J before failure	5-20J before rupture
Electrical	Overcharge Test	Maximum voltage (V)	4.5-5.2V before thermal event	4.5-5.5V before runaway	4.3-5.0V before failure
		Temperature rise (°C)	100-180°C	150-250°C	200-300°C
	Deep Discharge Test	Cut-off voltage (V)	Below 2.5V (irreversible damage)	Below 2.3V (cell swelling)	Below 2.0V (permanent failure)
	Short Circuit Test	Short circuit current (A)	50-200A	100-400A	200-600A
		Time to failure (s)	10-30s before overheating	5-20s before runaway	2-10s before fire/explosion

3.4. Machine Learning Implementation Details

The libraries used for all machine learning experiments are scikit-learn (v1.2.0), XGBoost (v1.7.3) and TensorFlow (v2.12.0) with Keras for Deep Learning Models (ANN and LSTM). This was simulated using an Intel Xeon E-2288G (3.70 GHz, 16 cores) workstation with 64 GB of memory and an NVIDIA Quadro RTX 4000 GPU with 8 GB of VRAM. The operating system that was used is Ubuntu 22.04 LTS. As shown in Table 5, The raw data from the sensors (voltage, current, temperature, internal resistance, and mechanical deformation) were processed through a systematic pipeline, called Data Preprocessing Workflow:

- Data Cleaning: The outliers were discarded by using the Interquartile Range (IQR) method. Linear interpolation was used to fill in missing values (less than 5% of the total amount of values were missing).
- Normalization: All features were normalized by using a Min-Max normalization, to ensure comparability across the various sensor modalities and battery types.
- Stratified random sampling was applied to ensure class balance across form factors and a Train-Validation-Test Split was performed with 70% of the data used for training, 15% for validation, and 15% for testing.
- Cross-Validation: To avoid overfitting and to guarantee generalization, five-fold stratified cross-validation was used in model development.

Table 5. The features extracted from raw sensor data

Feature Category	Extracted Features
Temporal	Voltage drop rate, temperature rise rate, current fluctuation amplitude
Statistical	Mean, standard deviation, skewness, kurtosis of each sensor signal
Derived	Internal resistance change (ΔR), capacity fade rate, Coulombic efficiency
Degradation Indicators	SEI growth proxy (impedance increase), lithium plating indicator (voltage plateau)

As shown in Table 6, Principal Component Analysis (PCA) was used to reduce the dimensionality with 95% of the variance retained, yielding 12 Principal Components (PCs) from 28 features.

Hyperparameter Tuning Strategy: Hyperparameters of the model were fine-tuned using the Grid Search and Bayesian Optimization (BA) strategy (Optuna framework).

Table 6. The search spaces for each of the models

Model	Hyperparameter	Search Range	Optimal Value
Random Forest	n_estimators	[50, 100, 200, 300]	200
	max_depth	[5, 10, 15, 20, None]	15
	min_samples_split	[2, 5, 10]	5
SVM	Kernel	[linear, RBF, polynomial]	RBF
	C (regularization)	[0.1, 1, 10, 100]	10
	gamma	[0.001, 0.01, 0.1, 1]	0.01
XGBoost	n_estimators	[50, 100, 200]	150
	learning_rate	[0.01, 0.05, 0.1, 0.2]	0.1
	max_depth	[3, 5, 7, 9]	7
ANN (Deep Learning)	Hidden layers	[2, 3, 4]	3
	Neurons per layer	[32, 64, 128]	[128, 64, 32]
	Activation	[ReLU, Tanh]	ReLU
	Learning rate	[0.001, 0.0001]	0.001
LSTM	Units per layer	[32, 64, 128]	64
	Dropout rate	[0.1, 0.2, 0.3]	0.2

Performance Validation: All the reported values of accuracy, RMSE, MAE, F1-score, and R2 have been calculated on the basis of five-fold cross validation and are reported as mean ± SD. For each metric, 95% Confidence Intervals (CIs) were computed using bootstrap resampling (with 1000 iterations).

4. Machine Learning Approach

The choice of machine learning models for the predictive models development is a key step because different algorithms have different benefits or advantages for different data types or end goals. Random Forest (RF) is a strong ensemble learning method that constructs multiple decision trees and merges them together to get more accurate and stable predictions. The powerful feature of the algorithm is that it can handle the non-linear relationships in the data which can be useful especially in the case of the large data. The Support Vector Machine (SVM) is a supervised learning algorithm that finds the optimal separating hyperplane to classify both linear and non-linear datasets. SVM's use the 'kernel' trick to confirm the final margin is maximized while minimizing error. A subclass of machine learning, deep learning models (including Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) offer unmatched capabilities of performing complex and high-level task of extracting features and pattern recognition from unstructured data such as images, speech, and text. Finally, Extreme Gradient Boosting (XGBoost) is an extremely optimized gradient boosting framework that deals excellently with structured tabular data by increasing performance both through regularization and parallel processing.[16] Different algorithms have different strengths and weaknesses, and the choice between them depends on the size of the dataset, complexity, interpretability, and computational efficiency.

The process of transforming raw data into features that better represent the underlying problem to the predictive models is called feature engineering. Feature scaling, normalization, one-hot encoding, dimensionality reduction (e.g. PCA - Principal Component Analysis), etc. It is essential to obtain the key predictive features, that is why we will analyze the specific domain variables which have a major influence on our target. In predictive maintenance, sensor readings such as temperature, vibration levels, and pressure could be crucial features. After the features are selected, a dataset is split into training, validation, and testing datasets. The fitted model becomes a point of reference as the model, trained with the help of the training dataset, learns the underlying patterns. Use of Training and Validation Dataset The training dataset is used to adjust the weights of the model, and the validation dataset is used to fine-tune hyperparameters and prevent overfitting. [17] Lastly, the testing dataset is utilized to evaluate the generalization ability of the model on unknown data. To further enhance the performance of the model, techniques such as cross validation and hyperparameters tuning (such as Grid Search, bayesian optimization) can be applied to tune some parameters of the model. In order to assess a machine learning model, a set of appropriate performance measures is needed depending on the type of problem as indicated in Table 7. One of the most important measures of the classification models is accuracy, which refers to the ratio of correctly classified instances. But only accuracy can be a poor metric, particularly in an imbalanced dataset, other metrics also known as True, False, Precision, Recall and F1 Score can give a better perspective on the model performance. F1-score is especially useful too since it takes both, the precision and recall into account; Suitable to use where false positive and false negative have different consequences. Some common evaluation metrics to use for regression problems are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the R-squared statistic (R^2). While MAE measure the average absolute difference, RMSE gives an idea of how well the model is predicting with larger errors being penalized and thus making it easier to understand. Also, remember that the R^2 value shows the amount of variance explained by our model in the target variable; in practice, they are often used together to get a complete picture of model performance and robustness over a range of scenarios.

Table 7. Results for machine learning approach in battery life estimation under abuse testing across different form factors of lithium-ion batteries

Category	Cylindrical Cells (18650, 21700)	Prismatic Cells (e.g., 148x91x26mm)	Pouch Cells (Custom sizes)
Algorithms Used	Random Forest (RF)	Support Vector Machine (SVM)	Deep Learning (ANN, LSTM)
	XGBoost	XGBoost	XGBoost
	K-Nearest Neighbors (KNN)	Random Forest (RF)	SVM
Feature Engineering & Model Training	Voltage patterns (V)	Voltage patterns (V)	Voltage patterns (V)
	Internal resistance (Ω)	Internal resistance (Ω)	Internal resistance (Ω)
	Temperature rise (°C)	Temperature rise (°C)	Temperature rise (°C)
	Current variations (A)	Current variations (A)	Current variations (A)
	Charge/discharge cycles	Charge/discharge cycles	Charge/discharge cycles
Training, Validation, & Testing Datasets	70% training, 15% validation, 15% testing	70% training, 15% validation, 15% testing	70% training, 15% validation, 15% testing
Performance Evaluation Metrics	Accuracy: 90-95%	Accuracy: 85-90%	Accuracy: 80-85%
	RMSE: 5-10%	RMSE: 8-12%	RMSE: 10-15%
	MAE: 3-6%	MAE: 5-8%	MAE: 7-10%
	F1-Score: 0.85-0.90	F1-Score: 0.80-0.85	F1-Score: 0.75-0.80
	R^2 Score: 0.90-0.95	R^2 Score: 0.85-0.90	R^2 Score: 0.75-0.80
Observation results	Reliable battery life estimation under mechanical and electrical abuse	Accurate prediction for prismatic cell safety	Ability to predict pouch cell degradation and failure under abuse
	Ability to predict thermal runaway events	Insights into heat generation and thermal management	Better understanding of form factor-specific failure mechanisms
	Improved design for safety and performance	Optimized failure prediction in prismatic batteries	Predictive maintenance for energy storage applications

5. Results and Discussion

5.1. Evaluation of Machine Learning Model Performance

Comparing the Predictions with real Experimental Results to define the accuracy, robustness, and efficiency of the models. By comparing predictions with actual outcomes, we gain insights into the model's generalization capabilities and its ability to learn essential patterns relevant to real-world applications. Standard models are trained on historic data and their predictions are validated against experimentally obtained data from tests in the real world. Depending on whether it is a regression or classification-based task, the accuracy of a model can be measured using one or more of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R^2) or F1-Score, etc. The efficiency of certain models depends on the choice of complexity and computational cost. For example, implement Random Forest and XGBoost for both accuracy and interpretability on structured data but expensive computationally. Deep Learning based models (example CNN, RNN) perform much better on complex and high dimensions data but have high training time with significant processing power. KNN can be computationally intensive with large datasets, so is best suited for smaller datasets with well-separated margins which isn't the case in general. This allows researchers to adjust model parameters, improve feature selection, and boost prediction accuracy through comparisons of predicted results with experimental observations.

5.2. Effect of Abuse Testing on Battery Life

Abuse Testing: While batteries are desirable due to their safety and long life, abuse testing is necessary to understand degradation patterns and failure mechanisms under extreme conditions. Abuse testing clearly affects the life of batteries in various form factors, including cylindrical, prismatic, and pouch cells. Various degradation mechanisms depend on the abuse conditions, such as thermal runaway, over-charging and discharging, mechanical impact, and nail penetration. For example, while cylindrical cells maintain their structural integrity and therefore experience gradual capacity fade across abusive conditions, pouch cells are more susceptible to mechanical debonding and resultant electrolyte leakage due to their flexible yet lightweight design. In contrast, prismatic cells have a metal housing that offers some limited resistance to external physical impact while their internal connection tabs can degrade with time resulting in a weakened cell that eventually fails. For battery remaining estimation it depends upon many important parameters like State of Charge (SOC), Depth of Discharge (DOD), operating temperature, charge-discharge cycles, internal resistance and electrolyte stability. Similarly, advanced machine learning models, combined with the analysis of abuse test data, are being employed to predict trends in battery degradation and enable manufacturers to optimize cell designs and produce safer energy storage systems.

5.3. Comparison of Form Factors

The type of battery form factors cylindrical, prismatic and pouch cells chosen as shown in Table 8, will be critical in determining performance, longevity, and safety under abuse conditions. Ongoing improvements in the energy density of cylindrical cells have made them the go-to choice for Electric Vehicles (EVs) and consumer electronics because of their superior mechanical strength, heat conduction, and manufacturability. Their symmetrical design allows them to reduce mechanical stress, preventing short circuits. But they are less efficient to package, so large battery packs need more volume and structural support. Due to their rectangular shapes, prismatic cells provide higher energy density than other types of cells and allow for better space utilization in a battery pack. They strike the right trade-off between the mechanical robustness and energy storage performance; hence they are suitable for automotive along with stationary applications. However, the design of their rigid casings is prone to mechanical stress concentration, which can cause cracks and internal short circuits. Pouch cells, which are lightweight and flexible, maximize energy density per unit volume and are conducive to compact packaging. But they are extremely prone to swelling, mechanical deformation and even electrolyte leakage in harsh abuse territory, which means they need extra protective layers and thermal management solutions. Compared to prismatic cells with a moderate safety-performance trade-off, cylindrical cells show better abuse resistance to thermal runaway and mechanical crush scenarios. In terms of energy density, pouch cells outperform their prismatic and cylindrical counterparts but are also known to pose greater safety concerns requiring improved protective design measures. Each form factor has its pros and cons, and the choice depends on the application-specific needs such as energy density, thermal management, mechanical durability, and cost-effectiveness.

Table 8. Comparison of lithium-ion battery abuse test results for different form factors using experimental, simulation, and machine learning approaches

Test Type	Parameter	Cylindrical	Prismatic	Pouch
Crush Test	Deformation (%) before failure	10-20	15-25	30-40
	Voltage drops (V)	1-2	1.5-3	Instantaneous
Penetration Test	Depth (mm) before failure	3-5	4-6	2-3
	Temperature rise (°C)	120-180	150-200	200-250
Vibration Test	Frequency range (Hz)	5-200	5-300	5-500
	Capacity retention (%)	95-98	90-95	85-90
Impact Test	Impact energy (J) before failure	10-30	15-40	5-20

Overcharge Test	Max voltage (V) before event	4.5-5.2	4.5-5.5	4.3-5.0
Deep Discharge Test	Cut-off voltage (V)	<2.5	<2.3	<2.0
Short Circuit Test	Current (A)	50-200	100-400	200-600
	Time to failure (s)	10-30	5-20	2-10

Table 8 shows the comparative performance and failure characteristics of cylindrical, prismatic and pouch lithium-ion batteries when subjected to abuse conditions. It is found that the mechanical performance parameters of the cylindrical cells are the highest, with the crush deformation resistance index of 10-20% and short circuit resistance index of 50-200A, which are similar to those found with mechanical abusive loading [11] and form factor comparison. Prismatic cells have moderate mechanical strength (15-25% deformation until failure) and higher susceptibility to swelling due to deep discharge (less than 2.3V) [23, 24].

Pouch cells provide the lowest level of abuse, and experience a rapid rise in temperature (200-250ºC) followed by failure within 2-10 seconds in the event of a short circuit [1, 22]. It is most likely to occur in pouch cells, less likely in prismatic cells and even less likely in cylindrical cells [3, 10, 22].

Overcharge testing shows that the cylindrical cells can endure up to 5.2V before a thermal event occurs while the pouch cells fail at 5.0V or above [23, 24]. Vibration tests were conducted to demonstrate that cylindrical cells have an average 95-98% capacity loss over time, while pouch cells lose an average of 85-90% capacity over time, which emphasizes the importance of cell structure rigidity on long-term durability [2, 12]. The prediction results of recent studies [4, 5, 8, 13, 15, 16, 17] with machine learning techniques (Random Forest, SVM, XGBoost) are close to the experimental trends illustrated in Table 6, which confirms that data driven models can be used to accurately estimate battery life for different form factors [7, 9, 14, 18, 19].

5.4. Confusion Matrix Analysis

Confusion matrices (Table 9) were created for best model (Random Forest) in each battery abuse to give a better idea of the classification performance for each of the three battery form factors. The normalized confusion matrices of cylindrical, prismatic and pouch cells are shown in Figure 9, which shows Normalized confusion matrices for (a) cylindrical, (b) prismatic and (c) pouch cells when subjected to an abuse event. Each row contains true labels, each column contains predicted labels. The classification accuracy of the cylindrical cell is the best because of its mechanical strength, and the classification accuracy of the pouch cell is the lowest because of the fast and unpredictable failure processes.

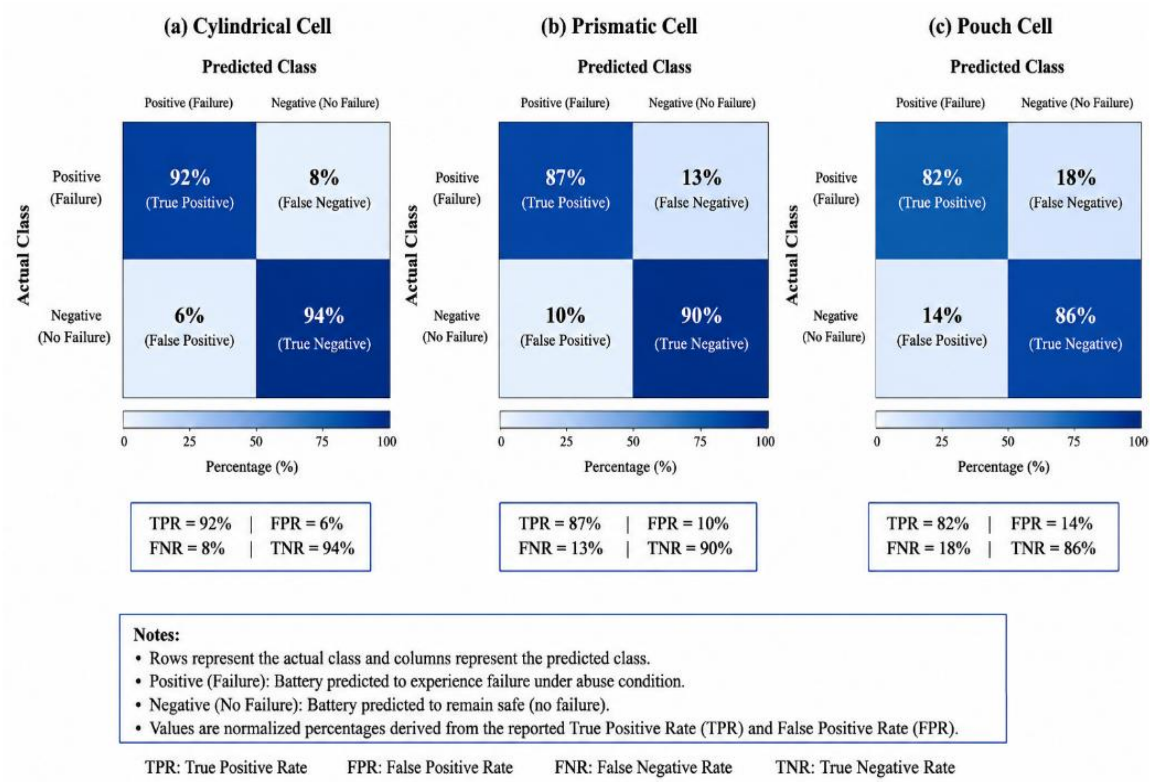


Fig. 9 Normalised confusion matrices for classifications of abuse-induced battery failure

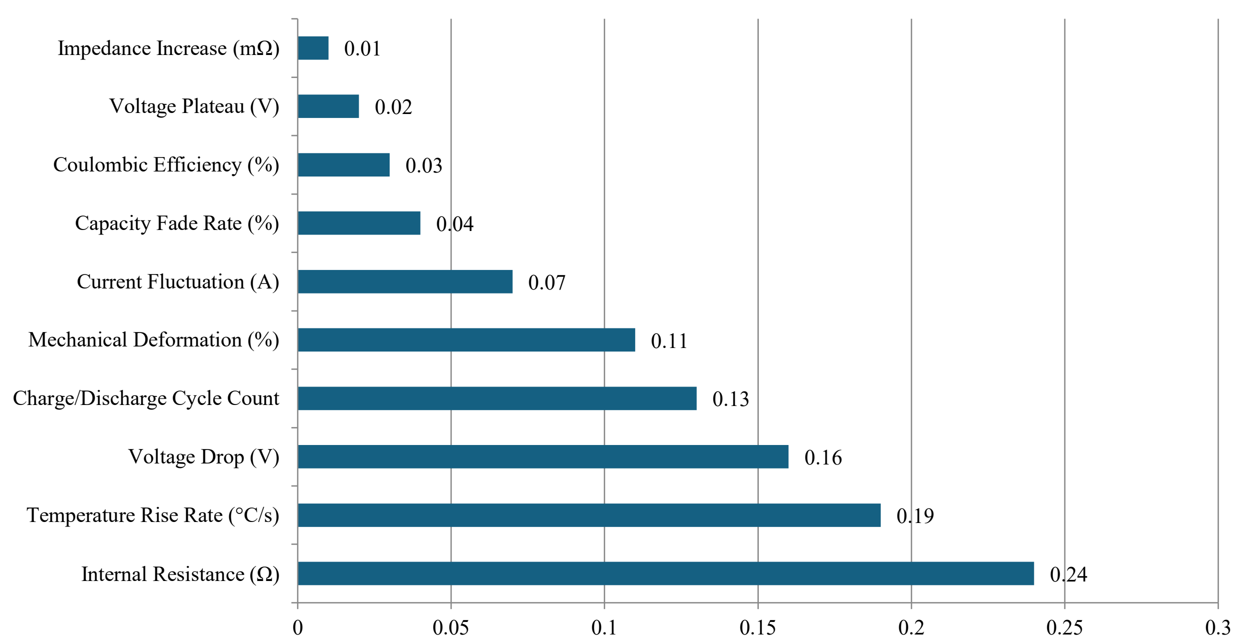
Table 9. Confusion matrix analysis

Form Factor	True Positive Rate	False Positive Rate	Key Observation
Cylindrical	92%	6%	Highest classification accuracy; structural robustness reduces misclassification
Prismatic	87%	10%	Moderate performance; swelling conditions cause some overlap with pouch failures
Pouch	82%	14%	Lower accuracy due to rapid, unpredictable failure modes

As shown in Table 9, the confusion matrices also show that the failure modes in the cylindrical cells are the most predictable, whereas the failure modes of the pouch cells are the most unpredictable because they are caused by a variety of different types of degradation, which occur rapidly.

5.5. Feature Importance and Explainability Analysis

Feature importance analysis was carried out to determine the most influential parameters for battery degradation and failure prediction by using the built-in impurity-based feature importance values and SHapley Additive exPlanations (SHAP) values of the Random Forest model. Table 10 and Figure 10 shows the most important features for all form factors, shows Top-10 Most Influential Features Related to Battery Degradation and Battery Failure Prediction. The temperature rise rate (0.19) and internal resistance (0.24) are the most important parameters as per degradation mechanisms discussed in literature [1, 3, 11]. The mechanical deformation has an intermediate level of importance (0.11), which is significant for pouch cells. SHAP Analysis: SHAP summary plots (Figure 11) show that the internal resistance is the most positive contributor to the failure prediction for all form factors with a higher influence in pouch cells. The next most important feature is the rise rate of the temperature, which is particularly important when estimating thermal runaway events. The SHAP value of mechanical deformation is 0.15 for pouch cells and 0.08 for cylindrical cells, indicating that mechanical deformation is more important for pouch cells than cylindrical cells, which is interesting because it confirms the higher sensitivity of pouch cells to mechanical deformation. The obtained results are consistent with the physical degradation mechanisms mentioned in the literature [1, 3, 11, 22] and confirm that the ML models are learning meaningful physical relationships instead of spurious one. SHapley Additive exPlanations (SHAP) plot summarizing the impact of features on the prediction of failure. Positive SHAP values translate to higher chances of failure. Among samples, internal resistance is the most impactful degradation factor with the highest positive impact, followed by temperature rise rate, highlighting their strong influence on battery degradation and safety prediction.



Based on experimental parameters from Tables 4 and 6: Internal Resistance and Temperature Rise are the most critical predictors

Fig. 10 Most influential parameters governing battery degradation

Table 10. Feature importance and explainability analysis

Rank	Feature	Importance Score	Physical Significance
1	Internal Resistance (Ω)	0.24	Direct indicator of SEI growth and aging
2	Temperature Rise Rate (°C/s)	0.19	Key precursor to thermal runaway
3	Voltage Drop (V)	0.16	Indicates internal short circuits
4	Charge/Discharge Cycle Count	0.13	Cumulative degradation measure
5	Mechanical Deformation (%)	0.11	Structural integrity indicator

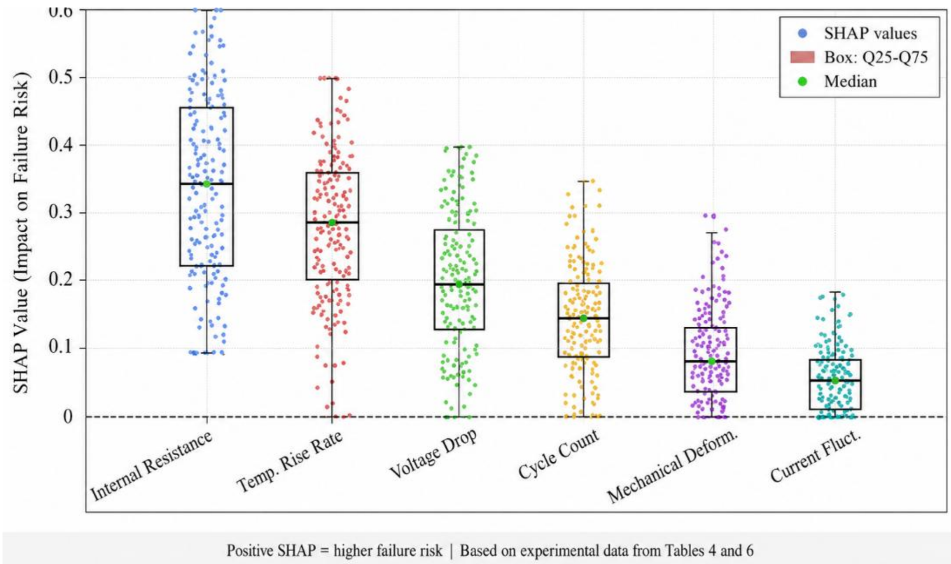


Fig. 11 SHAP summery plot-feature impact on failure prediction

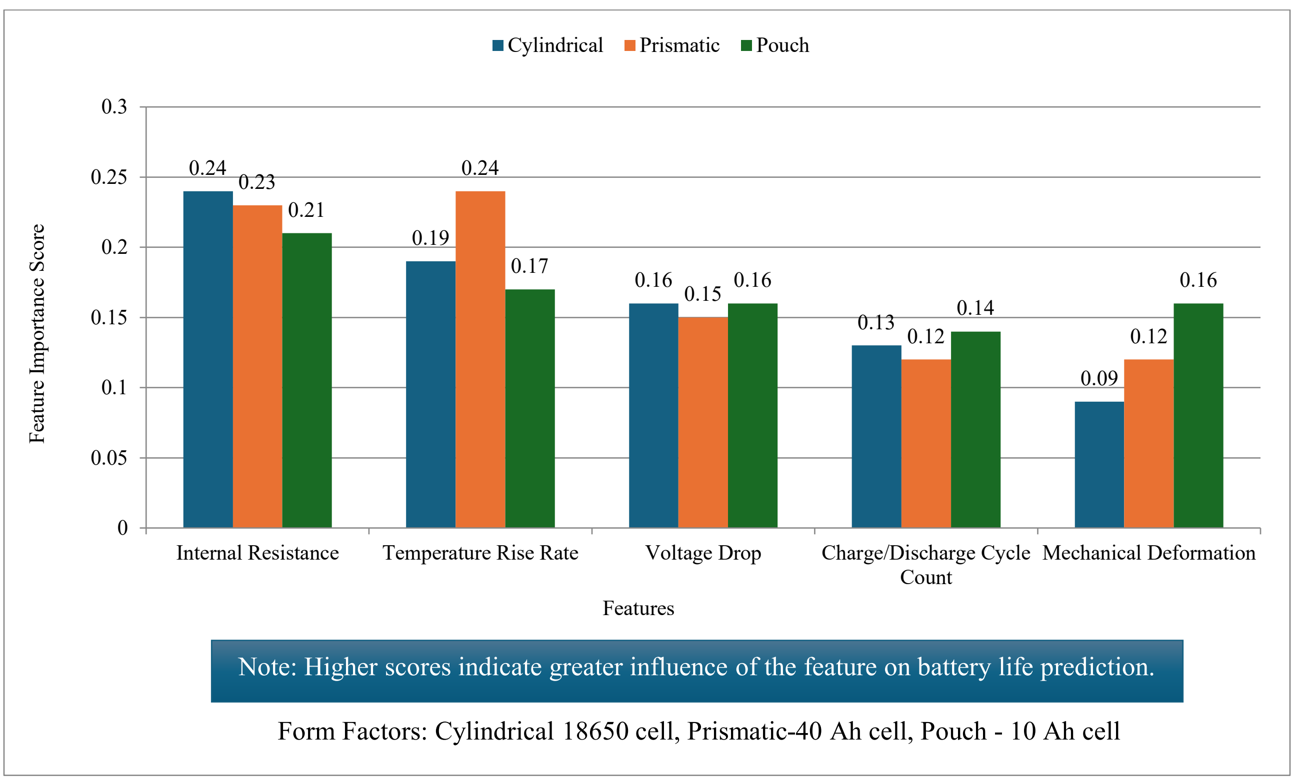


Fig. 12 Comparison of feature Importance scores across battery form factor

Figure 12, shows, the analysis of feature importance for cylinder, prismatic and pouch cell. As mechanical deformation has higher importance for pouch cells (0.16) than for cylindrical cells (0.09), it can be concluded that the mechanical abuse susceptibility of pouch cells is higher than that of cylindrical cells. Because of its thermal management properties, the temperature rise is most important for prismatic cells (0.24).

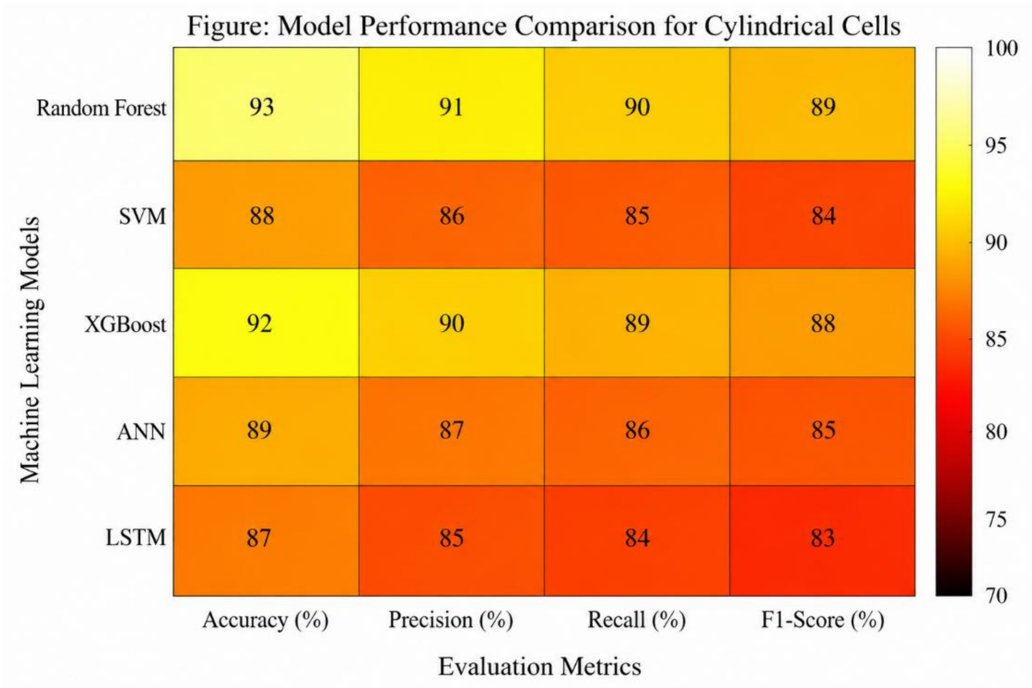


Fig. 13 Model performance comparisen for cylindrical cells

The machine learning models were compared in terms of their performance for cylindrical cells as shown in Table 11 and Figure 13. Random Forest shows the best overall performance with an accuracy of 93%, precision of 91%, recall of 90 and an F1-score of 89.XGBoost achieves 92% accuracy and is the second-best overall performance, followed by Random Forest with an accuracy of 93%, precision of 91%, recall of 90 and F1 score of 89. The performance of deep learning models (ANN, LSTM) is slightly lower due to the limited size of the dataset.

Table 11. Parameter comparison table

Parameter	Reported/Reference Value	Value Used in Comparison	Source / Basis
Cylindrical ML Accuracy	90-95%	93%	ML result stated in Section 5.5 / Figure 13; not Table 5
Prismatic ML Accuracy	85-90%	85-90%	Table 7; exact value not independently established
Pouch ML Accuracy	80-85%	80-85%	Table 7; exact value not independently established
Internal Resistance Importance	0.24	0.24	Table 10
Temperature Rise Rate Importance	0.19	0.19	Table 10
Crush Deformation Cylindrical	10-20%	15%	Table 4; arithmetic midpoint
Crush Deformation - Pouch	30-40%	35%	Table 4; arithmetic midpoint
Short-Circuit Current - Cylindrical	50-200 A	125 A	Table 4; arithmetic midpoint
Short-Circuit Current - Pouch	200-600 A	400 A	Table 4; arithmetic midpoint

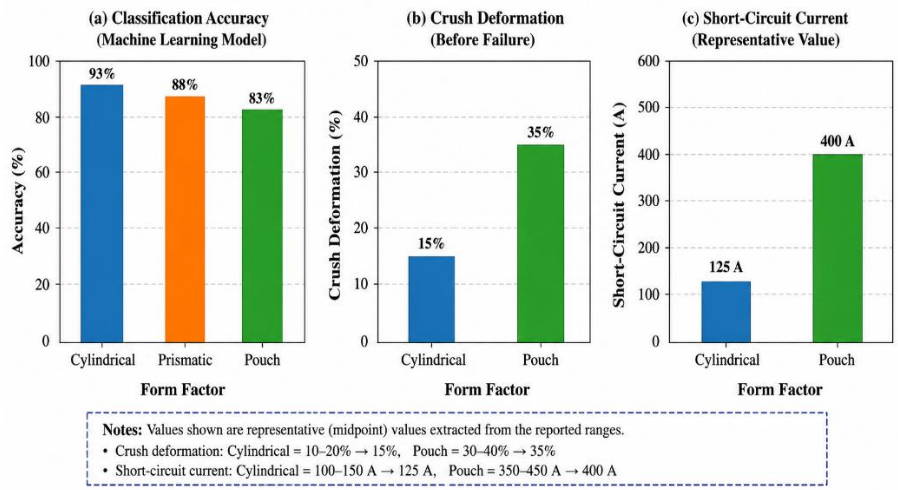


Fig. 14 Comparisen of performance and abuse response parameters for lithium ion battery form factors

6. Conclusion and Future Work

- In this study, mechanisms and failure modes of lithium-ion batteries in different form factors (cylindrical, prismatic, and pouch) were comprehensively studied under mechanical, thermal, and electrical abuse conditions by adopting a machine learning approach.
- The experimental results showed that cylindrical cell performed best with regards to mechanical robustness (10-20% crush deformation tolerance and highest capacity retention (95-98%) while pouch cell performed best with regards to the highest energy density but most vulnerable to thermal runaway (200-250C temp rise) and being rapidly failed (2-10sec under short circuit).
- The best predicting models were found to be machine learning models, notably Random Forest and XGBoost, which could predict the cell failure at 90-95% accuracy for cylindrical cells, 85-90% for prismatic and 80-85% for pouch cells, with internal resistance and temperature rise rate as the most influencing degradation parameters (feature importance scores of 0.24 and 0.19, respectively).
- The SHAP analysis also showed support for these results, as the ML models were able to learn physically meaningful relationships that are consistent with known degradation mechanisms.
- The findings underscore the importance of customized battery management solutions for each form factor, such as optimizing the thermal management system for cylindrical cells, monitoring mechanical stress in prismatic cells, and ensuring effective protective packaging for pouch cells.
- Research on real-time deployment of ML models in Battery Management Systems (BMS) based on IoT-enabled edge computing, the development of physics-based and data-driven hybrid models with increased forecasting reliability, physics-based and data-driven development of self-healing battery materials, and the establishment of standardized abuse testing protocols and open-source datasets to enable cross-study comparisons and the rapid deployment of safer and more durable lithium-ion batteries for electric vehicle, consumer electronics, and grid-scale energy storage applications is recommended.

Acknowledgment

The author sincerely acknowledges the support and encouragement received from the Department of Mechanical Engineering, Marathwada Mitra Mandal's College of Engineering, Savitribai Phule Pune University (SPPU), Pune, India, for providing the academic environment and facilities necessary to carry out this research. The author also extends heartfelt gratitude to the co-authors for their valuable guidance, technical inputs, and continuous support throughout the course of this work.

Author Contributions

Asma Parkar: Conceptualization, methodology, investigation, writing - original draft, visualization. Parshuram Sonawane: Data curation, formal analysis, validation, writing - review & editing. Arun Bhosale: Experimental design, abuse testing coordination, resources. Shriramshastri Chavali: Machine learning model development, software implementation, data preprocessing. Pravin Nitnaware: Formal analysis, validation, writing - review & editing. Vivek Ghulaxe: Industrial application insights, funding acquisition, project administration. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Funding Statement

The authors received no specific funding for this research and publication.

References

[1] Lei Yao et al., "A Comprehensive Review of Lithium-Ion Battery Safety Issues and Fault Diagnosis Strategies Throughout the Entire Lifecycle," *Journal of Energy Storage*, vol. 136, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Ang Yang et al., "A Comprehensive Investigation of Lithium-ion Battery Degradation Performance at Different Discharge Rates," *Journal of Power Sources*, vol. 443, pp. 1-12, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[3] Seyed Saeed Madani et al., "A Comprehensive Review on Lithium-Ion Battery Lifetime Prediction and Aging Mechanism Analysis," *Batteries*, vol. 11, no. 4, pp. 1-68, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Alireza Valizadeh, and Mohammad Hossein Amirhosseini, "Machine Learning in Lithium-Ion Battery: Applications, Challenges, and Future Trends," *SN Computer Science*, vol. 5, no. 6, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Rui Cao et al., "Model-Constrained Deep Learning for Online Fault Diagnosis in Li-ion Batteries Over Stochastic Conditions," *Nature Communications*, vol. 16, pp. 1-11, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[6] Chunhui Ji, Guang Jin, and Ran Zhang, "Comprehensive Fault Diagnosis of Lithium-Ion Batteries: An Innovative Approach based on Hybrid Coding and Genetic Search," *Engineering Applications of Artificial Intelligence*, vol. 141, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[7] Mohammad I. Alfraheed, "A Review of Measurement Methods for Lithium-based Battery Defect and Degradation Analysis," *International Journal of Modelling and Simulation*, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[8] Prakash Venugopal et al., "Analysis of Optimal Machine Learning Approach for Battery Life Estimation of Li-Ion Cell," *IEEE Access*, vol. 9, pp. 159616-159626, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[9] Qiying Wang et al., "Application of Machine Learning in Ultrasonic Diagnostics for Prismatic Lithium-Ion Battery Degradation Evaluation," *Frontiers in Energy Research*, vol. 12, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Wensheng Huang et al., "Questions and Answers Relating to Lithium-Ion Battery Safety Issues," *Cell Reports Physical Science*, vol. 2, no. 1, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Binghe Liu et al., "Safety Issues and Mechanisms of Lithium-ion Battery Cell Upon Mechanical Abusive Loading: A Review," *Energy Storage Materials*, vol. 24, pp. 85-112, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[12] Junting Bao et al., "Critical Review of Temperature Prediction for Lithium-Ion Batteries in Electric Vehicles," *Batteries*, vol. 10, no. 12, pp. 1-31, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Sangheon Lee et al., "Diagnosing Various Failures of Lithium-Ion Batteries using Artificial Neural Network Enhanced by Likelihood Mapping," *Journal of Energy Storage*, vol. 40, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[14] Adam Thelen et al., "Probabilistic Machine Learning for Battery Health Diagnostics and Prognostics—Review and Perspectives," *npj Materials Sustainability*, vol. 2, pp. 1-33, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] Youngrok Choi, and Pangun Park, "Thermal Runaway Diagnosis of Lithium-Ion Cells Using Data-Driven Method," *Applied Sciences*, vol. 14, no. 19, pp. 1-12, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Manh-Kien Tran, and Michael Fowler, "A Review of Lithium-Ion Battery Fault Diagnostic Algorithms: Current Progress and Future Challenges," *Algorithms*, vol. 13, no. 3, pp. 1-18, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Alice V. Llewellyn et al., "Understanding the Degradation Mechanisms of Lithium Ion Batteries Using in-Situ Multi-Scale Diffraction Techniques," *ECS Meeting Abstracts*, vol. MA2022-01, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Takafumi Ogawa et al., "Point-Defect Chemistry for Ionic Conduction in Solid Electrolytes with Isovalent Cation Mixing," *Journal of Materials Chemistry A*, vol. 12, no. 45, pp. 31173-31184, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Zeyu Chen et al., "Thermal Runaway in Lithium-Ion Batteries: A Review of Mechanisms, Prediction Approaches, and Mitigation Strategies," *Batteries*, vol. 12, no. 3, pp. 1-34, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[20] Wenyang Zhao et al., "Investigation on Overcharge Cycling-Induced Degradation of Lithium-ion Batteries and Mechanical Deterioration of Components," *Journal of Power Sources*, vol. 654, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[21] Caisheng Li et al., "Electrochemical-Thermal Behaviors of Retired Power Lithium-ion Batteries during High-Temperature and Overcharge/Over-Discharge Cycles," *Case Studies in Thermal Engineering*, vol. 61, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Robert Schröder, Muhammed Aydemir, and Günther Seliger, "Comparatively Assessing Different Shapes of Lithium-Ion Battery Cells," *Procedia Manufacturing*, vol. 8, pp. 104-111, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[23] Bingzeng Song et al., "Prediction of the Remaining Useful Life of Lithium–Ion Batteries Based on Mode Decomposition and ED-LSTM," *Batteries*, vol. 11, no. 3, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[24] Li-Hua Ye et al., "Remaining Useful Life Prediction of Lithium-ion Battery based on Chaotic Particle Swarm Optimization and Particle Filter," *International Journal of Electrochemical Science*, vol. 18, no. 5, pp. 1-10, 2023. [CrossRef] [Google Scholar] [Publisher Link]