EARLY DETECTION OF LITHIUM DENDRITE RISK IN EV BATTERIES USING QUANTUM SUPPORT VECTOR MACHINES

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Vishak Senthilkumar **Aravindhan S** **Manesh Ram**

ABSTRACT

The overall number of electric vehicles (EVs) on the roads is increasing and the need for the safety and reliability of their batteries is becoming more important. Dendrite formation is one of the most critical issues facing an electric vehicle's battery and can cause not only safety hazards but also destruction of the battery itself. This project offers a unique procedure for spotting battery dendrite risk early, using a hybrid machine learning model that merges both classical and quantum computing methods. Quantum Support Vector Machines classify the health of the battery time-series data, which consists of voltage, current and temperature. The sensors that are placed on the battery gather continuous data for a certain period of time and this data is then divided into smaller segments using a sliding window technique of pre-processing. For each segment, various statistics including average, variance and rate of change are computed to identify potential features in the battery's behavior. Features that have been selected are subsequently provided to the hybrid model where the QSVM further pushes the feature transformation process making it easier to detect very slight abnormalities which are signs of dendrite growth. It is the objective of this model to generate real-time, very precise predictions of dendrite risk that will facilitate quick actions taken and thus better management of the overall battery. The fusion of quantum computing and traditional machine learning techniques is what marks a key milestone for the EVs battery health monitoring sector.

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LIST OF ABBREVIATIONS

QSVM Quantum Support Vector Machine

QML Quantum Machine Learning

SVM Support Vector Machine

EV Electric Vehicle

QAOA Quantum Approximate Optimization Algorithm

NISQ Noisy Intermediate-Scale Quantum

CHAPTER 1

INTRODUCTION

EVs can contribute to sustainable transportation and lithium-ion batteries are the key to their operation. The charging process subjects the EV batteries to different electrical and thermal conditions, which when allowed to get out of check may lead to abnormal behavior. Thermal runaway is one of the most important safety issues since the phenomenon, which is defined as an abrupt rise in temperature, may cause battery deterioration or system malfunction. Such abnormal conditions must therefore be identified early in order to be able to ensure that operations are safe and also to guarantee reliability of the system.

Due to the growing implementation of sensor-based battery management systems, nowadays it is possible to collect a considerable amount of time-stamped battery charging data in real time. This data is usually continuous measurements, including voltage, current, temperature and state of charge, measured during the charge, which are recorded during the charging cycle. This data is usually analyzed with machine learning methods and used to identify abnormal charging conduct. Nevertheless, most of the current methods are based on classical machine learning models only, and these might not be able to depict the complicated nonlinear relationships that can exist in multivariate time-series sensor data.

The new developments in quantum computing provided quantum-inspired machine learning (QML) methods that present alternative data representation and transformation techniques. Despite the fact that modern quantum devices have not offered any computational advantage of practical datasets, hybrid learning systems with classical and quantum-inspired components have been considered, because the feature representation can be improved. Here, it is assumed that QML will not replace the classical machine learning, but it represents another processing layer that can be added to the already existing learning pipeline.

This paper suggests a hybrid classical-quantum learning model to detect anomalies in EV battery charging systems with real time stamped sensor data. It is based on the suggested procedure that combines the classical time-series preprocessing and feature extraction with a quantum-inspired processing layer that is aimed at executing nonlinear feature transformation. The resulting hybrid feature representation is then studied with a classical classifier to determine abnormal charging patterns that relate to thermal runaway.

This project will have the main goal of designing and deploying an entire learning pipeline showing the extent to which advanced machine learning techniques can be integrated in a safety-critical and real world application. Instead of prioritizing the superior performance or computational acceleration, it focuses on the architectural design, feasibility, and the systematization of evaluation of hybrid feature representations of time-series anomaly detection. The efficiency of the suggested framework is assessed with the help of the data set of time-stamped sensor readings that were recorded in EV battery charge and thermal runaway events.

Table 1.1 Literature Review

Paper	**Methodology**	**Limitations**	**Ideas for Adoption**
Comparative Investigation of Quantum and Classical Kernel Functions Applied in Support Vector Machine Algorithms	Performs a comparative study of classical kernels and quantum kernels within the SVM framework. Different quantum feature maps are evaluated using QSVM on benchmark datasets.	Uses quantum simulators; high kernel computation cost; limited scalability; lacks real-world application focus.	Adopt the quantum kernel comparison framework to evaluate classical SVM versus QSVM for battery time-series features, justifying improved separability for early dendrite-risk patterns.
Assessment of Quantum Feature Map for Binary Forest Classification using QSVM	Evaluates multiple Pauli-based quantum feature maps for binary classification. Features are normalized, reduced, encoded, and classified using QSVM with Pareto-front analysis.	Relies on simulators; inconsistent QSVM superiority; scalability limitations in NISQ-era hardware.	Apply quantum feature map selection strategies to battery sensor data and use Pareto analysis to balance accuracy and computational cost.

Paper	**Methodology**	**Limitations**	**Ideas for Adoption**
Hybrid Quantum–Classical Framework for Urban Traffic State Classification	Implements a hybrid pipeline combining classical feature extraction with quantum encoding and QSVM-based classification.	Limited dataset; simulator-based execution; real-time scalability not addressed.	Use the hybrid classical–quantum architecture for battery monitoring by applying QSVM after classical preprocessing of voltage and temperature data.
AutoQML: A Framework for Automated Quantum Machine Learning	Introduces automated quantum model selection, feature encoding, and hyperparameter tuning in hybrid workflows.	High computational overhead; simulator dependence; not tailored for time-series data.	Adopt automated quantum kernel and hyperparameter tuning to reduce manual QSVM optimization for battery datasets.
Real-Time Quantum Machine Learning-Based Anomaly Detection for Lithium-Ion Battery Packs	Proposes quantum-enhanced K-Means clustering for real-time anomaly detection using battery sensor data.	Focuses on clustering; requires multiple qubits; real-time hardware feasibility unclear.	Extend the anomaly detection framework by replacing clustering with QSVM-based supervised dendrite-risk classification.

Paper	**Methodology**	**Limitations**	**Ideas for Adoption**
Quantum Kernel-Based Support Vector Machine with QAOA Embedding for Lung Cancer Prediction	Uses QAOA-based quantum feature embedding with QSVM, achieving better results for small datasets.	Simulator execution; high cost; evaluated only on static medical data.	Adopt QAOA-based quantum embedding for capturing nonlinear patterns in reduced battery feature sets.

CHAPTER 2

DESIGN

2.1 DESIGN OVERVIEW

The proposed system design aims at coming up with a workable and dependable hybrid Quantum Support Vector Machine (QSVM)-based system in detecting anomalies and assessing risks in electric vehicle (EV) battery charging systems. The architecture is inspired by currently available quantum machine learning-based battery anomaly detection solutions, especially those based on an unsupervised clustering algorithm like K-means. Although the clustering-based methods have proven to be useful in finding rough deviations, they fail to perceive fine or earlier deviations and lack a decisional margin. The proposed system, to overcome such shortcomings, substitutes the clustering process with an explicit risk-oriented decision layer and the margin-based hybrid QSVM classifier.

The system is designed based on modular pipeline architecture where every module has a particular role to play and the structured outputs are sent out to the next process. The approach is appropriate in the real world because this modular design enhances interpretability, scalability and easy integration with the currently available battery management systems.

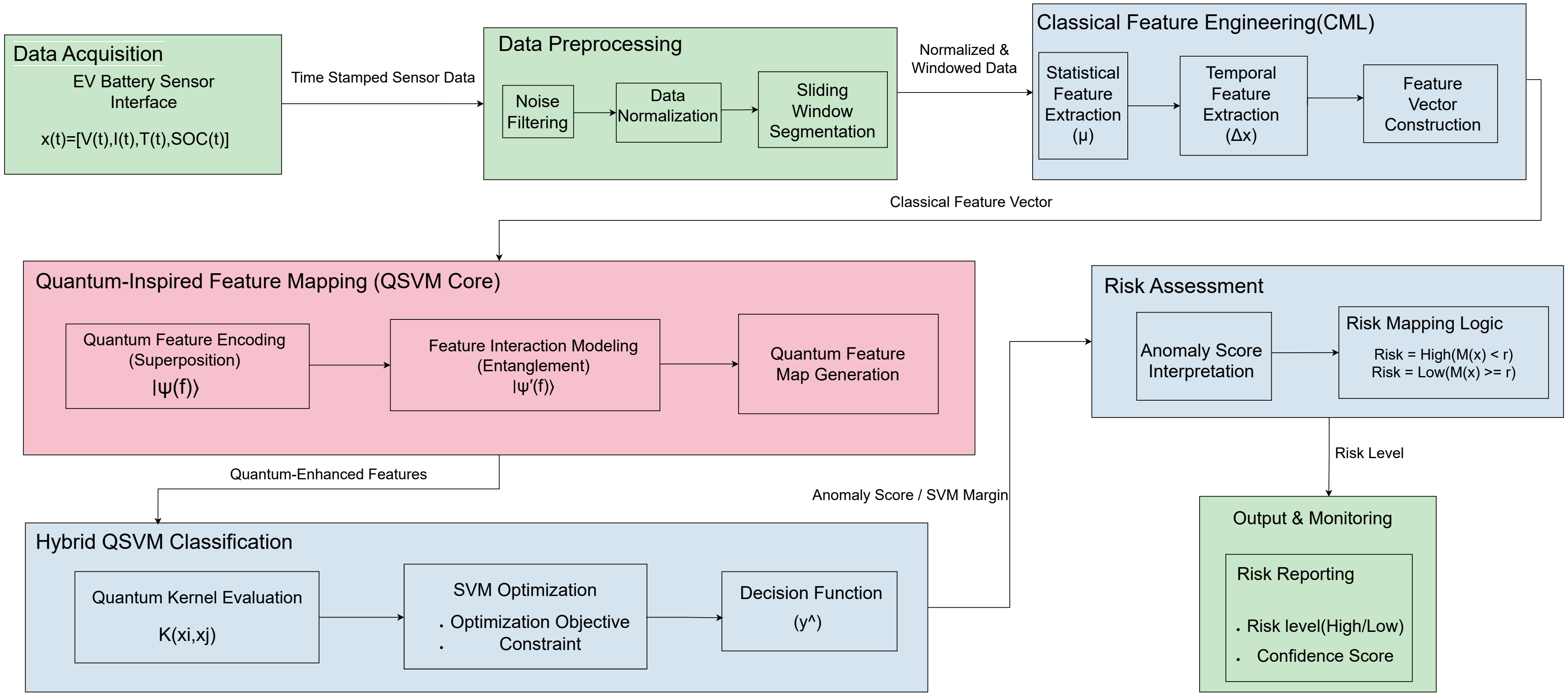


Figure 2.1 Architecture of the Proposed QSVM-Based EV Battery System

2.2 SYSTEM OVERVIEW

The time-stamped EV battery sensor data is processed in the following modules according to the proposed system: data acquisition, preprocessing, classical feature engineering, quantum-inspired feature mapping, hybrid QSVM classification, risk assessment, and output monitoring. Data preparation and baseline feature extraction is done using classical machine learning methods, whilst the representation of features is improved using quantum-inspired learning principles. A QSVM-based classifier is used to produce the final decision in a form of a risk-level in battery charging.

The proposed design uses a supervised or semi-supervised QSVM as opposed to the base reference work which has been using the unsupervised clustering method to detect anomaly. It allows clearly defined decision boundaries, better noise sensitivity, and more dependable detection of early warning features associated with unsafe charging behavior.

2.2.1 Design: Data Acquisition Module

The data acquisition module is the interface of the system and gathers time stamps of sensor data of EV battery packs through charging cycles. A set of synchronized readings of voltage, current, temperature, and state of charge (SOC) is stored in each record of the data.

This is a multivariate time series representation of battery behavior. Mitigation Multiple parameters interact with each other to form many of the battery anomalies and not single threshold violations. This module is as per the standard battery monitoring practices and comparable to the data collection methodology as employed by the base framework.

2.2.2 Design: Data Preprocessing Module

Raw sensor data can be noisy, have outliers, and dissimilar scales between parameters. In order to solve these problems, the preprocessing module is used to filter noise, normalize and segment the time.

Noise filtering cushions the effects of sudden upheavals and errors by the sensors. Normalization brings all sensor parameters in similar range such that, no single feature takes control of the learning process. Then a sliding window segmentation method is used to subdivide the continuous time-series data into fixed length windows. Each of the windows reflects short term charging dynamics and it is an independent learning sample.

This preprocessing methodology allows analysis of time behavior and adheres to common time-series processing procedures in battery monitoring systems.

2.2.3 Design: Classical Feature Engineering Module

After preprocessing, classical feature engineering is performed to obtain meaningful descriptors of every time window. Statistical characteristics like mean and variance are used to represent the general operating characteristics and temporal characteristics like change of rate and stability measure the dynamism of charging behavior.

A set of these features is represented as a classical structured feature vector of each window. The module is able to give an interpretable and computationally efficient baseline representation and is equivalent to the classical feature extraction step in the base paper. It also removes the dimensionality of unprocessed sensor measurements, which is convenient to process later with quantum-inspired algorithms.

2.2.4 Design: Quantum-Inspired Feature Mapping Module

The primary contribution of the given system is the quantum-inspired feature mapping module. This module converts the classical features instead of clustering or classifying them directly, into a higher-dimensional Hilbert space, via quantum-inspired encoding methods.

At the initial step, the superposition-based representation is used to encode classical feature vectors, where several components of features can be expressed at the same time. The second stage is an entanglement-inspired transformations that are used to model feature interactions. Such interactions are essential in EV battery systems, in which interacting temperature, voltage, and current are often the cause of unsafe charging behavior.

Even though many of these transformations are runnable on classical hardware, they are based on the mathematical form of quantum state representation, leading to the richer and more expressive feature space without needing physical quantum computation.

2.2.5 Design: Hybrid QSVM Classification Module

The proposed system uses a hybrid QSVM classifier to detect the existence of anomalous charging behavior. In contrast to the base paper that employed K-means clustering algorithm to learn the decision boundary, the QSVM learns the margin-based decision boundary, which divides normal and abnormal charging patterns in the quantum-enhanced feature space.

The QSVM is a quantum-inspired kernel with the classical SVM optimization. This hybrid architecture maintains the stability and scalability of traditional SVMs and enjoys the improved feature representation. The QSVM has a higher ability to resist noise, fewer rare anomalies, and more distinct separation between normal and abnormal behavior than any of the clustering-based algorithms.

2.2.6 Design: Risk Assessment and Outputs

The system does not simply label anomalies, instead having a risk assessment module. The QSVM margin or anomaly score is assessed with the help of predetermined thresholds in order to determine each charging window as a High Risk or Low Risk one. Such a distinction between the detection and interpretation is more informative and conforms to the real-world battery management needs.

The risk level and a confidence score are the ultimate output and allow anticipating the potential danger and preventive measures in the case of unsafe charging conditions.

2.2.7 Design Summary

Overall, the proposed construction can be seen as an extension of current quantum machine learning-based battery anomaly detection models by introducing quantum-inspired feature mapping in a classical learning framework and substituting the decision logic based on clustering with a hybrid QSVM classifier. The modular architecture supports a high level of detection of anomalies at the same time being interpretable, computationally efficient, and feasible in practice to the applications of EV battery safety.

CHAPTER 3

PERFORMANCE METRICS

3.1 ACCURACY

Accuracy measures the proportion of correctly classified samples among all test instances.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{3.1}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

3.2 RECALL

Recall refers to evaluating the model's skill to accurately classify real anomalous examples

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3.2}$$

High recall is critical when it comes to safety monitoring for EV battery packs, as a lack of recognition of an anomaly can cause serious problems.

3.3 FEATURE SPACE SEPARABILITY

Feature Space Separability(FSS) This refers to the separability in the feature space that results after the quantum-inspired processing step

$$\text{FSS} = \frac{||\mu_{\text{normal}} - \mu_{\text{anomaly}}||_2}{\sigma_{\text{normal}} + \sigma_{\text{anomaly}}} \tag{3.3}$$

A larger FSS value means better class separability achieved by the quantum support feature transformation process.

3.4 VARIANCE AMPLIFICATION RATIO

Variance Amplification Ratio(VAR) measures the amount of variance in features that is increased by the quantum-inspired transformation.

$$\mathrm{VAR} = \frac{\mathrm{Var}(Q(x))}{\mathrm{Var}(x)} \tag{3.4}$$

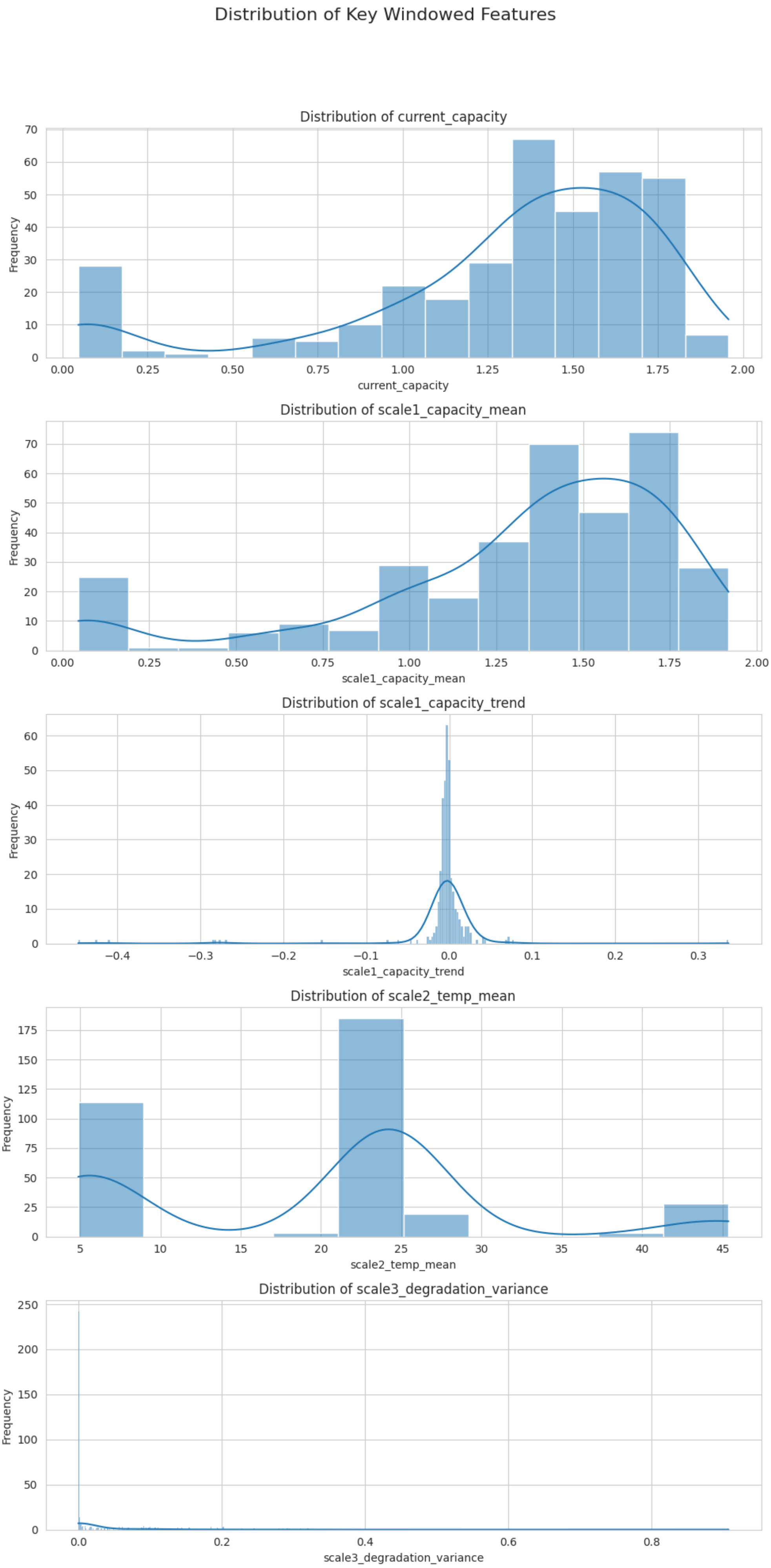
Q(x) means the quantum-transformed feature vector.

CHAPTER 4

TESTING

4.1 VISUALIZATION OF KEY FEATURE DISTRIBUTIONS

Let's visualize the distributions of some representative features from the windowed_features_df using histograms. This helps us understand their range, central tendency, and identify potential outliers or unexpected patterns.


Distribution of Key Windowed Features
Distribution of current_capacity
Frequency
current_capacity
Distribution of scale1_capacity_mean
Frequency
scale1_capacity_mean
Distribution of scale1_capacity_trend
Frequency
scale1_capacity_trend
Distribution of scale2_temp_mean
Frequency
scale2_temp_mean
Distribution of scale3_degradation_variance
Frequency
scale3_degradation_variance

CHAPTER 5

CONCLUSIONS

This powerful data processing pipeline established a cornerstone. We successfully converted raw, heterogeneous battery data into a standardized, clean, and feature-rich dataset. These multi-scale temporal features now prepare for the next phase of this project: the development and training of Quantum Machine Learning models for predictive analytics, with the main focus on early detection and understanding of battery dendrite formation to enhance battery safety, life, and performance. Feature vectors generated at this step are the required input for advanced machine learning algorithms and allow the study of subtle signatures of degradation that might indicate dendrite growth.