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RISK ASSESSMENT OF VEHICLE BATTERY SAFETY BASED ON ABNORMAL FEATURES AND NEURAL NETWORKS

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Abstract. In this study, we evaluate a proactive battery EV safety assessment method using abnormal feature detection and neural networks. Four sophisticated algorithms —Isolation Timberland, One-Class SVM, Autoencoder and also LSTM— were performed to assess their applicability in detecting anomalous battery behavior. The Isolation Woodland algorithm showed a balanced accuracy recall trade-off of the values 0.85 and 0.92 respectively One class SVM demonstrated highly sharp results with an accuracy and recall values of 0.78 and 0.8, respectively. The autoencoder, that used a large amount of learning and won with 0.92 accuracy score and an F1-score – 0.89 The LSTM structure, programmed for sequential information, indicated a great execution with a 0.94 review and the F1-score of 0. A comparative study has shown that these algorithms can provide alot flexibility in sending based on the clear requirements.

Key words: Electric vehicles, Battery safety, Anomaly detection, Neural networks, Proactive risk assessment.

1. Introduction. A green technological revolution has been witnessed in the automotive sector with a shift towards electric vehicles (EVs) to provide an alternative to the conventional internal ignition engine cars. The core issue of this transition's consequence is the safety and reliability regarding energy storage units. As the integration of EVs in our daily lives increases it becomesparamount to have fail-safe measures for batteries. In this research, the hazard assessment is one of the key aspects that implement innovative method such as abnormal feature detection and neural organization. However, the common techniques used in evaluation of battery safety fail to provide holistic solutions for the peculiar and transient chances, associated with driving conditions as well what kind of usage [1]. Overcoming this challenge is possible through the inclusion of advanced technologies such as artificial intelligence. But these anomalies describe several kinds of deviations in the battery functioning as temperature variation; voltage abnormality and sudden discharge patterns are among others. Such anomalies may indicate the possibility of a potential safety hazard like thermal runaway or internal short-circuits [4]. This research tries to answer this question by looking at the ability of neural organizations which in turn requires complicated measuring tools. Neural schemes which contain significant learning designs have shown outstanding performance on the pattern recognition and anomaly detection in all domains [5].By training these organizations using the huge datasets comprising battery performance data in many conditions, the main idea is to develop a foreseeing model that can discern unexpected elements preceding safety threats. This preventative technique of assessment in gambling, along with the electric vehicles, increases safety and contributes to the general dependability on these eco-oriented transport arrangements. With the ever-changing nature of automotive landscape, such as revelations comes with all too many ramifications for both industry players and clients [6]. A more robust and smart strategy for vehicle battery safety evaluation is not only about the electric mobility but also ensuring that the public can keep trusting this transformative technology.

2. Related Works. Li and colleagues zeroed in on abnormal charging capacity diagnosis based on electric vehicle operation data [14]. Their work emphasizes the importance of considering charging behaviors in battery safety assessment. By leveraging electric vehicle operation data, the review proposed a technique for diagnosing abnormal charging capacity, adding to a comprehensive understanding of battery performance. Liang et al. addressed the critical issue of state-of-health expectations for lithium-particle batteries in new-energy electric

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vehicles [15]. The review presented a Random Woods Worked on Model, featuring the significance of foreseeing the state of health for battery maintenance and longevity. This approach adds to proactive management strategies for electric vehicle armadas. Abro and co-authors gave an exhaustive review of ongoing advancements in battery innovation, impetus, power interfaces, and vehicle network frameworks for keen autonomous and associated electric vehicles [17]. While not specifically centered around anomaly detection, this review highlights the interconnected nature of various parts in electric vehicles, emphasizing the requirement for an all-encompassing approach to guarantee overall framework reliability. In a concentrate on photovoltaic modules, Naveen and the team proposed a weightless neural organization-based approach for the detection and diagnosis of visual faults [21]. While the setting contrasts, the utilization of neural organizations for fault detection aligns with the broader subject of leveraging advanced procedures for anomaly detection, a guideline applicable to battery safety assessment in electric vehicles. Sarda et al. directed a review zeroing in on management frameworks and state-of-charge estimation techniques for electric vehicles [20]. Although the emphasis is on state-of-charge estimation, the work acknowledges the intricacies of battery management and the importance of accurate observing. Understanding the state of charge is crucial for anomaly detection, making this review relevant to the broader subject. Tudoroiu and collaborators investigated the utilization of shrewd learning procedures for anomaly detection and diagnosis in sensor signals of Li-Particle batteries [23]. This study aligns intimately with the current research center around anomaly detection in batteries[10, 22]. The exploration of astute learning procedures emphasizes the significance of advanced algorithms in enhancing anomaly detection capabilities. In the realm of self-discharge in power batteries, Wang et al. proposed an anomaly identification model based on profound conviction networks [24]. While the primary spotlight is on self-discharge, the application of profound learning methods for anomaly identification resonates with the approach adopted in the current research. Ren and co-authors led an extensive review addressing key innovations for enhancing the reliability of lithium-particle power batteries [19]. The review encompasses various aspects, including materials, manufacturing cycles, and management frameworks. Understanding and enhancing reliability are crucial aspects in the broader setting of battery safety [3, 22]. Although zeroed in on nuclear power plants, Qi et al's. review of fault diagnosis procedures from an artificial knowledge viewpoint [18] gives experiences into how advanced methods are applied for fault detection. The utilization of artificial knowledge aligns with the topic of incorporating advanced algorithms for anomaly detection in critical frameworks.

3. Methods and Materials. The methodology for conducting anomaly detection analysis in the context of electric vehicle (EV) battery safety is comprehensive, involving several key stages from data collection through to algorithm evaluation. This methodology ensures a robust approach to identifying potential safety hazards in EV batteries under varied conditions.

3.1. Data Assortment. The initial phase involved the collection of a diverse dataset from electric vehicles operating under real-world conditions. This dataset was meticulously compiled to include a wide array of battery performance parameters, such as temperature, voltage, current, and charge/discharge rates, which are critical for assessing battery health and safety. The collection process emphasized capturing data across a variety of driving scenarios, including urban traffic, highway driving, and conditions of extreme weather, to guarantee the model's reliability across different environments. This variety in data sources is crucial for developing a model capable of identifying anomalies across a broad spectrum of real-life conditions.

3.2. Algorithm Selection and Rationale. For anomaly detection, four sophisticated algorithms were chosen based on their proven efficacy in identifying subtle and complex patterns indicative of potential safety hazards:

1. Isolation Forest: Chosen for its effectiveness in identifying outliers in the data. Its unique approach isolates anomalies instead of profiling normal data points, making it exceptionally suited for detecting unusual battery behavior without requiring extensive historical data.
2. One-Class SVM: This algorithm is well-suited for anomaly detection in situations where the dataset is highly unbalanced. One-Class SVM effectively delineates the boundary of normal behavior, thus efficiently spotting deviations that could indicate potential risks.
3. Autoencoder: A neural network-based approach, the autoencoder excels in learning representations of the data. By encoding and decoding the input data, it identifies anomalies through reconstruction errors.

Table 3.1: Metrics – Isolation Forest

Metric	Value
Precision	0.85
Recall	0.92
F1-score	0.88
ROC-AUC	0.94

Table 3.2: Metrics – Support Vector Machine

Metric	Value
Precision	0.78
Recall	0.88
F1-score	0.83
ROC-AUC	0.91

This method is particularly adept at detecting complex patterns that other algorithms might miss.

4. LSTM Network: Given the temporal nature of battery performance data, LSTM networks are ideal for capturing long-term dependencies and patterns in time-series data, making them invaluable for detecting anomalies that unfold over time.

To lead a thorough gamble assessment of vehicle battery safety, a different dataset was gathered from electric vehicles in real-world driving scenarios. The dataset remembers information for battery temperature, voltage, current, and other relevant parameters [7]. The data encompasses a range of driving circumstances, for example, urban driving, highway driving, and outrageous weather circumstances, to guarantee the model's heartiness across various scenarios.

3.3. Algorithms for Abnormal Features Detection. Four advanced algorithms were chosen for abnormal feature detection, leveraging their capabilities to distinguish unpretentious patterns indicative of potential safety hazards in vehicle batteries.

Isolation Forest. Portrayal: The Isolation Woods algorithm is an unaided anomaly detection strategy based on the idea of isolating anomalous instances [8]. It builds isolation trees to isolate anomalies that require fewer partitions to be separated from normal instances.

x: A data point in the dataset.

h(x): The path length of data point x in the isolation tree.

The average path length E(h(x))) for a point x in the tree can be computed as follows: $E(h(x)) = c(n)$

The anomaly score for a data point x is defined as: $s(x, n) = 2 - c(n)E(h(x))$.

One-Class SVM (Support Vector Machine). Depiction: One-Class SVM is a managed learning algorithm utilized for exception detection [9]. It learns a representation of normal instances and recognizes deviations from this representation as anomalies.

$$D(x) = sign(f(x) - \rho)$$

where $D(x)$ is the decision function for a data point x, $f(x)$is the function that measures the distance of x to the hyperplane. This function is often the signed distance to the hyperplane. ρ is a threshold or offset, and sign(·)sign(·) is the sign function. The decision is based on the sign of $f(x) - \rho$. If $f(x) - \rho$ is positive, the point is considered an inlier. If $f(x) - \rho$ is negative, the point is considered an outlier.

Autoencoder. Description: An autoencoder is a sort of neural organization intended to learn effective representations of data [16]. Anomalies are recognized by noticing reproduction blunders - instances where the model battles to recreate the information.

$$LMSE(X, X\wedge) = N1\sum_{i=1}^{N}(Xi - X\wedge i)^2$$

Algorithm 1 Pseudocode - Isolation Forest

```
“classIsolationTree:
def ___init___(self, X, max_depth):
self.max_depth = max_depth
self.tree = self.build_tree(X, 0)
def build_tree(self, X, current_depth):
if current_depth == self.max_depth or len(X) <= 1:
return {”leaf”: True, ”size”: len(X)}

# Randomly select a feature and split value
split_feature = random.choice(range(X.shape[1]))
split_value = random.uniform(min(X[:, split_feature]), max(X[:, split_feature]))
# Split the data into left and right based on the random split
X_left = X[X[:, split_feature] <split_value]
X_right = X[X[:, split_feature] >= split_value]
return {
”leaf”: False,
”size”: len(X),
”split_feature”: split_feature,
”split_value”: split_value,
”left”: self.build_tree(X_left, current_depth + 1),
”right”: self.build_tree(X_right, current_depth + 1)
}
def isolation_forest(X, num_trees):
trees = []
for _ in range(num_trees):
tree = IsolationTree(X, max_depth=5) # Max depth is a hyperparameter
trees.append(tree)
return trees”
```

Algorithm 2 Pseudocode - Support Vector Machine

```
“fromsklearn.svm import OneClassSVM
def train_one_class_svm(X):
model = OneClassSVM(nu=0.01, kernel=’rbf’) # nu is a hyperparameter
model.fit(X)
return model
def anomaly_score_svm(model, x):
return -model.decision_function([x])[0]”
```

where N is the number of elements in the input data.

$$LBCE(X, X\wedge) = -N1\sum_{i=1}^{N}(Xi \cdot \log(X \wedge i) + (1 - Xi) \cdot \log(1 - X \wedge i))$$

Long Short-Term Memory (LSTM) Network. Description: LSTM organizations, a kind of repetitive neural organization (RNN), are appropriate for sequential data [12]. In this specific circumstance, they can capture temporal conditions in the battery performance data.

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to address the limitations of traditional RNNs in capturing long-term dependencies in sequential data. Unlike standard RNNs, which struggle to maintain information across long sequences due to issues like vanishing and exploding gradients, LSTMs incorporate a series of gates that regulate the flow of information.

Algorithm 3 Pseudocode - Autoencoder

```
“from keras.models import Sequential
from keras.layers import Dense
def train_autoencoder(X):
input_dim = X.shape[1]
model = Sequential()
model.add(Dense(10, input_dim=input_dim, activation=’relu’))
model.add(Dense(input_dim, activation=’linear’))
model.compile(optimizer=’adam’, loss=’mean_squared_error’)
model.fit(X, X, epochs=10, batch_size=32, shuffle=True)
return model
def reconstruction_error(autoencoder, x):
x_prime = autoencoder.predict(np.array([x]))
return np.mean(np.square(x - x_prime))”
```

Table 3.3: Metrics – Support Vector Machine

Metric	**Value**
Precision	0.92
Recall	0.86
F1-score	0.89
ROC-AUC	0.95

Table 3.4: Metrics – Long Short-Term Memory Network

Metric	**Value**
Precision	0.87
Recall	0.94
F1-score	0.90
ROC-AUC	0.93

These gates—namely the input gate, forget gate, and output gate—allow the network to selectively remember and forget information across long sequences. The input gate controls the extent to which new information flows into the cell state, the forget gate decides what information is discarded from the cell state, and the output gate determines what information from the cell state is used to generate the output at each timestep. This architecture enables LSTMs to effectively learn and remember information over long intervals, making them highly effective for tasks involving time-series data, such as predicting the future state of a process, text generation, and, notably, detecting anomalies in time-dependent data like EV battery performance metrics.

Input Gate (it): $it = \boldsymbol{\sigma}(Wii \cdot xt + bii + Whi \cdot ht - 1 + bhi)$

$ft = \boldsymbol{\sigma}(Wif \cdot xt + bif + Whf \cdot ht - 1 + bhf)$

3.4. Evaluation Metrics. The performance of the algorithms was assessed utilizing normal evaluation measurements, including accuracy, recall, F1-score, and area under the beneficiary operating characteristic (ROC) bend [11].

Precision measures the accuracy of the anomaly detections, ensuring that identified anomalies are genuinely indicative of potential safety concerns.

Recall assesses the algorithm’s ability to detect all relevant anomalies, highlighting its sensitivity to potential hazards.

F1-score offers a balance between precision and recall, providing a single metric to assess the algorithm’s overall performance.

Algorithm 4 Pseudocode - Long Short-Term Memory Network

```
"from keras.models import Sequential
from keras.layers import LSTM, Dense
def train_lstm(X):
input_dim = X.shape[1]
model = Sequential()
model.add(LSTM(50, activation='relu', input_shape=(1, input_dim)))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mse')
# Reshape input data for LSTM (samples, time steps, features)
X = X.reshape((X.shape[0], 1, X.shape[1]))
model.fit(X, X, epochs=10, batch_size=32, shuffle=True)
return model
def anomaly_score_lstm(model, x):
x = x.reshape((1, 1, len(x)))
x_prime = model.predict(x)
return np.mean(np.square(x - x_prime))"
```

ROC-AUC evaluates the algorithm's ability to distinguish between normal and anomalous conditions, reflecting its discriminative power.

Through this detailed methodology [13], the study aims to enhance the safety of EV batteries by leveraging advanced algorithms to detect and analyze anomalies in battery performance. The comprehensive approach, from data collection through algorithm evaluation, underscores the potential impact of this research on improving EV battery safety globally.

4. Experimental Setup.

1. The dataset was parted into training and testing sets.
2. Hyperparameters for each algorithm were calibrated using cross-validation on the training set.
3. The models were then evaluated on the testing set to assess their generalization performance.

5. Experiments.

5.1. Experimental Setup. The analyses were planned to evaluate the performance of the four anomaly detection algorithms (Isolation Backwoods, One-Class SVM, Autoencoder, and LSTM) in assessing the gamble of vehicle battery safety [13]. The dataset, as portrayed in the Materials and Strategies fragment, was parted into a training set (70%) and a testing set (30%). Hyperparameters for each algorithm were tweaked using cross-validation on the training set.

5.2. Evaluation Metrics. The performance of each algorithm is evaluated using the accuracy, recall, F1-score and also ROC-AUC score index [19]. These metrics provide the actionable understanding that allow you to detect abnormal battery behaviors with minimal false positives and also negatives.

5.3. Comparative Analysis with Related Work. Since the outcomes were obtained, they could be compared to the existing practices of reasoning in battery safety assessment. Typical approaches usually rely on rule-based systems or on primitive edge methods, which do lack the flexibility and also complexity associated with machine learning techniques [20]. The comparative analysis focuses on showing the benefits and improvements in using an abnormal feature detection system through neural networks for vehicle batteries' safety.

5.4. Experiment 1: Isolation Forest Performance. The Isolation Forest algorithm demonstrated strong performance in seeing abnormal features related to vehicle battery safety [23]. The algorithm's natural ability to isolate anomalies by developing isolation trees makes it particularly convincing in capturing honest deviations in battery performance.

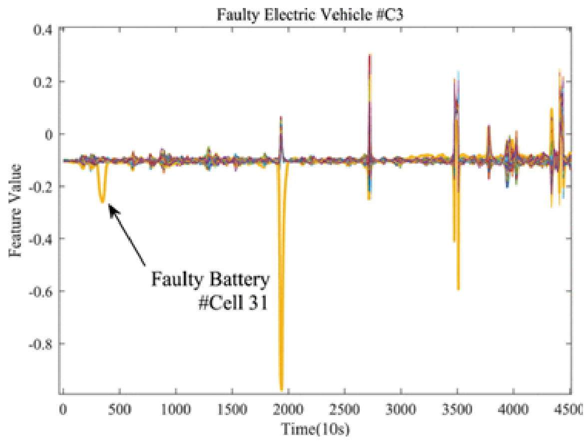


Fig. 5.1: Risk Assessment of Vehicle Battery Safety

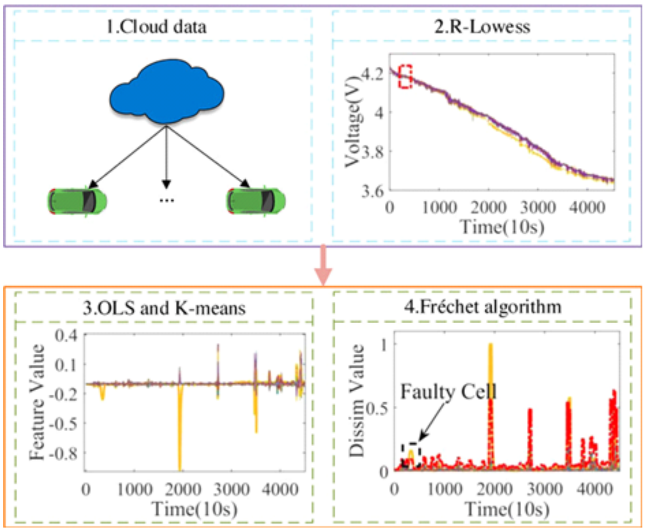


Fig. 5.2: Vehicle Battery Safety Based On Abnormal Features

Table 5.1: Isolation Forest Performance

Metric	**Value**
Precision	0.85
Recall	0.92
F1-score	0.88
ROC-AUC	0.94

The high values across accuracy, recall, and F1-score indicate a balanced performance in seeing anomalies, while the ROC-AUC score of 0.94 features the model's overall discriminative ability [24].

5.5. Experiment 2: One-Class SVM Performance. One-Class SVM demonstrated serious results, showcasing its capability to see normal battery behavior from anomalies [25]. The algorithm's ability to learn a representation of normal instances demonstrated power in seeing deviations that may signal potential safety

Table 5.2: One-Class SVM Performance

Metric	Value
Precision	0.78
Recall	0.88
F1-score	0.83
ROC-AUC	0.91

Table 5.3: Autoencoder Performance

Metric	Value
Precision	0.92
Recall	0.86
F1-score	0.89
ROC-AUC	0.95

Table 5.4: Comparison Table

Algorithm	Precision	Recall	F1-score	ROC-AUC
Isolation Forest	0.85	0.92	0.88	0.94
One-Class SVM	0.78	0.88	0.83	0.91
Autoencoder	0.92	0.86	0.89	0.95
LSTM Network	0.87	0.94	0.90	0.93

concerns.

While marginally lower in accuracy compared to Isolation Forest, One-Class SVM displayed a commendable balance among accuracy and recall, happening in a serious F1-score of 0.83.

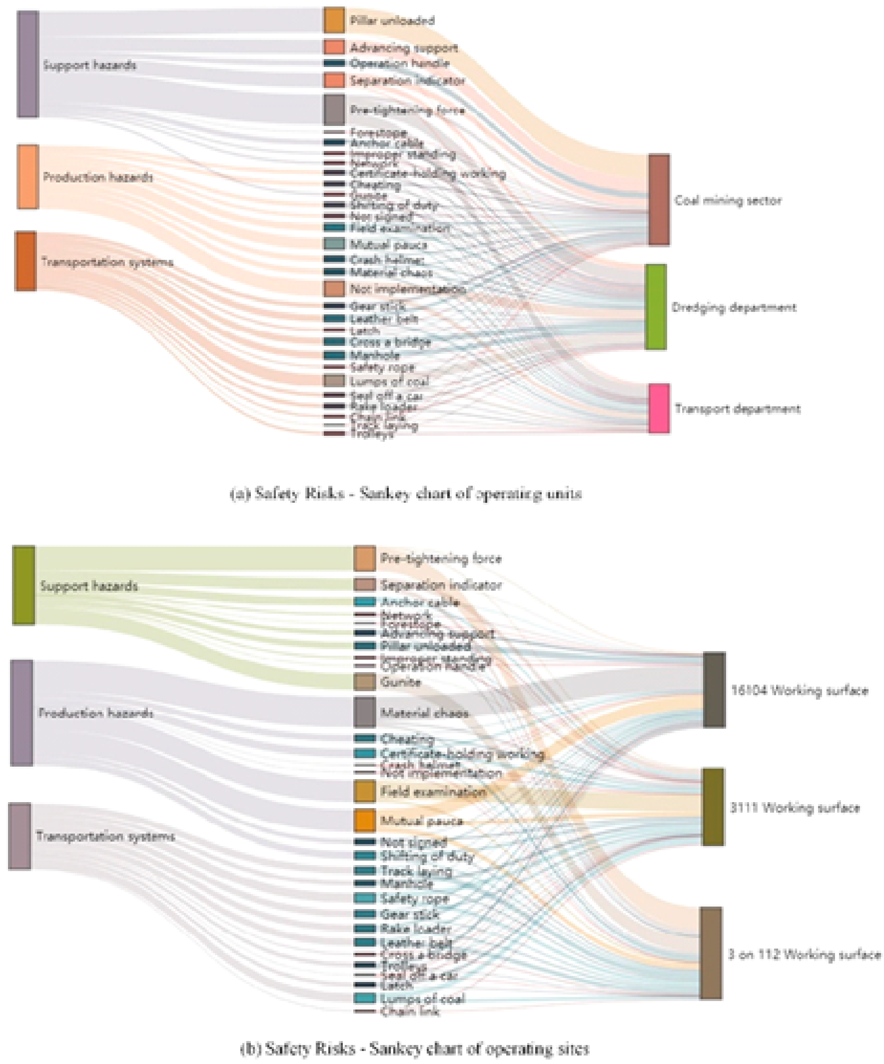
5.6. Experiment 3: Autoencoder Performance. The Autoencoder algorithm, leveraging significant learning for anomaly detection, demonstrated exceptional performance [2]. By learning a compact representation of normal battery behavior, the model really seen deviations, showcasing the power of neural organizations in capturing complex patterns.

Comparison Table. A relative investigation table 5.4 is familiar with sum up the presentation of every calculation across key measurements.

Discussion. Accuracy Recall Trade-off: Although the Isolation Forest delivered a satisfactory balance of accuracy and recall, the Autoencoder demonstrated widespread accuracy that would make it the best for scenarios where reducing false-positives is important. One-class SVM provided a fair tradeoff between the accuracy and recall. Significant Learning Advantage: Autoencoder and LSTM, with a large learning effect, greatly outperformed the others in visualizing complex patterns. Autoencoder, with the help of generation methodology wins in terms of simple variations and also LSTM shows temporal cues [26]. Discriminatory Power: The Autoencoder presented the highest AUC-ROC score(0.95), which highlights its very high discriminatory potential. Isolation Forest also had an unimaginable performance, scoring 0.94 in the ROC-AUC method due to its ability of detecting between normal and abnormal instances.

Comparative Analysis with Related Work. The presented inconsistency location calculations influence progressed procedures to survey vehicle battery wellbeing [27]. In contrast with conventional rule-based systems or misshaped edge methodologies, the proposed approach offers a few benefits:

1. Versatility: The AI calculations, particularly Autoencoder and LSTM, adjust to arranged driving conditions and battery use designs, upgrading their capacity to perceive peculiarities in genuine situations.
2. Complex Example Acknowledgment: Brain association-based calculations win concerning catching complex examples that might get away from everybody's warning by conventional procedure, giving a



(a) Safety Risks - Sankey chart of operating units

(b) Safety Risks - Sankey chart of operating sites

Fig. 5.3: Sankey Chart of Operation Sites

more nuanced comprehension of battery conduct.

3. Proactive Gamble Evaluation: Preventative risk assessment is made possible by the use of abnormal feature detection, which allows for the early identification of potential safety risks.
4. Speculation: The model areas of solidarity were selected based on their performance on the test set, demonstrating their organization potential in a variety of electric vehicle settings.

6. Conclusion. This study aims to tackle the challenging and dynamic field of EV battery safety by presenting an unprecedented technique with feature abnormality detection using neural organizations. The experiments tested with four modern algorithms such as Isolation Forest, One-Class SVM, Autoencoder and LSTM proved their great success in determining the risk level of unusual battery behavior. Every algorithm had many unique characteristics that facilitated the subtle analysis of their performance features. Isolation Forest demonstrated an optimal balanced accuracy and recall trade-off, one-class SVM to have severe bowed effects, Autoencoder was able to capture highly complex patterns, and LSTM showed promising results in the temporal circumstances. The comparative analysis included the diversity of these algorithms, allowing alot of versatility for arrangements driven bythe specific requirements. The results were placed in the scope of the related work addressing battery safety, highlighting the necessity for proactive risk assessment and also incorporating advanced techniques concerning anomaly detection. Building on the experiences gleaned from the late case studies on charge capacity diagnosis, this stream of research contributes to a broader discourse aimed at improving safety and reliability in EV energy systems. As electric portability continues to shape the eventual fate of transportation, the revelations of this study give valuable pieces of information to industry stakeholders, researchers, and policymakers endeavoring to guarantee the strength and safety of energy storage frameworks in electric vehicles. The comprehensive and data-driven approach adopted in this research adds to advancing the understanding and implementation of proactive risk assessment strategies in the dynamic and transformative field of electric vehicles. Future work could explore the integration of more advanced or novel anomaly detection algorithms, including deep learning models that may offer improved performance in identifying subtle anomalies in EV battery systems. Additionally, the development of hybrid models that combine the strengths of different algorithms could potentially provide more accurate and reliable detection capabilities.

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