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Topological Deep Learning for Graph-Structured EV Battery Monitoring: Persistence-Based Features with Transformers

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Abstract

Electric vehicle (EV) battery monitoring plays a major role in keeping the system efficient, safe, and long-lasting. Many existing solutions miss deeper structural signals when battery data is collected in the form of graphs. These solutions usually rely on local or linear patterns and are unable to capture the full behavior of battery cells spread across complex systems. This paper presents a new method that uses topological deep learning (DL) to better understand battery health by combining persistent homology with transformer-based learning. The proposed method first applies persistent homology to extract strong topological features from the battery graph. These features describe the shape and structure of the battery system and remain stable even when input data contains small changes or noise. Next, a transformer model is applied to learn the time-based behavior of battery cells by using self-attention across long sequences. This combined framework connects spatial and temporal signals into a unified view, which helps detect faults earlier and track changes in performance over time. Simulation experiments were conducted using real-world EV battery datasets, including the Oxford Battery Degradation Dataset and NASA Battery Data. The results showed significant gains across multiple metrics. Root Mean Square Error (RMSE) dropped by 6.55%, Mean Absolute Error (MAE) improved by 6.25%, F1-score increased by 1.49%, and accuracy rose by 1.26% compared to the best existing approaches. These results show that the model provides stronger predictions and fault detection without depending on heavy preprocessing. This makes it suitable for real-time deployment in EV platforms where reliable battery health tracking is critical.

Keywords: EV batteries, SOH prediction, shallow cycles, self-supervised learning, attention mechanism.

1. INTRODUCTION

EVs are becoming more common in both urban and rural areas. One of the most important parts of an EV is its battery system. Battery health plays a key role in the performance, safety, and life span of the vehicle. A well-functioning battery supports long-distance travel, safe energy usage, and dependable power output [1]. Monitoring the condition of EV batteries helps reduce failures, improve safety, and increase the overall value of the vehicle [2].

Battery data is usually collected from sensors placed across different battery cells. This creates a network of sensor data that forms a graph structure. Each battery cell or group of cells can be treated as a node, and the interactions or connections between them can be modeled as edges. Standard DL approaches often treat this data as regular time series or sequences, which misses the deep structural information hidden within the graph [3].

The introduction of topological DL offers a way to study the shape of data instead of just focusing on values. Persistent homology, a technique in topological data analysis, can find hidden features in graphs that stay stable even when there is noise or small changes in the data [4]. By combining these topological features with transformer models, we can capture both the shape and long-range dependencies of battery behavior. Transformers are strong in learning global patterns and can work well when the data has complex and dynamic connections [5].

This paper presents a new approach that brings together persistent homology and transformer models to build a better EV battery monitoring system. This model is designed to work with graph-structured battery data and can detect changes or faults early. It aims to improve prediction accuracy and fault detection across different battery conditions.

1.1 Challenges

EV battery systems come with many challenges:

- **Complex Structures:** Battery cells are connected in non-linear ways, forming graphs with different levels of interaction. Standard models find it hard to understand such irregular patterns [6].
- **Noise and Variability:** Sensor data from EV batteries often contain noise due to temperature changes, aging, and measurement errors [7]. Finding stable features in such data becomes difficult.
- **Limited Generalization:** Many models trained on specific datasets do not work well when applied to new EV types or battery arrangements [8].
- **Local vs Global Learning:** Traditional models mostly look at short-term or local features. Long-term trends and global patterns often remain hidden [3].
- **Early Fault Detection:** Detecting early signs of battery failure is hard because changes are slow and sometimes hidden in weak patterns [9].

These challenges highlight the need for models that can handle graph structures, capture long-range relationships, and find stable features even when the input data is not perfect.

1.2 Problem Statement

Current EV battery monitoring methods are limited in capturing both local and global behaviors across complex graph structures. These methods often miss important topological patterns that show deeper relationships within battery data. As a result, predictions can be weak or delayed, and faults may go unnoticed in the early stages. There is a strong need for a model that can extract persistent topological features and also understand long-range dependencies across the battery network.

1.3 Motivation

EV batteries are expensive and sensitive to misuse or aging. A small drop in battery health can affect vehicle performance and safety. If faults are detected early, it can prevent large failures and save repair costs. This work is motivated by the idea that both the shape of the data and its long-term behavior are important. Persistent homology can bring out stable patterns, while transformer models can help understand long-range relationships. By combining both, a deeper and more accurate view of battery health can be developed.

This paper makes the following contributions:

- Proposes a hybrid model that combines persistent homology with transformer-based learning for EV battery monitoring.

- Uses graph-structured battery data to extract topological features that stay consistent even in noisy conditions.
- Applies transformer models to capture long-range connections and hidden dependencies across battery cells.
- Evaluates the proposed method on real-world EV battery datasets with various performance metrics.
- Shows better results in fault detection, prediction accuracy, and system robustness when compared with traditional models.

The rest of this paper is organized into the following sections. Section 2 presents related work. Section 3 explains the proposed architecture, model components, and pseudo-code. Section 4 discusses the results, performance gains, and visualizations. Section 5 outlines the conclusion and possible future improvements.

2. LITERATURE SURVEY

Understanding EV battery performance has gained more attention in recent years. Many research efforts have introduced models for predicting battery health, charge levels, and system behavior under different conditions. Most of these works use DL, graph-based models, or hybrid frameworks, each with specific strengths and weaknesses. This section presents a review of related studies, highlighting their contributions and limitations.

Yao et al. (2023) introduced a graph-based framework to predict the state of health (SOH) for lithium-ion batteries [10]. The model used graph neural networks (GNNs) to capture interactions between battery cells. The method showed strong prediction accuracy. However, the model focused mainly on SOH and did not include long-range sequence understanding or fault detection.

Kim et al. (2023) proposed a model for state of charge (SOC) prediction using a graph convolutional network (GCN) [11]. The work improved prediction performance using graph relationships, but lacked temporal modeling, which can affect performance in long-term behavior prediction.

Shi et al. (2023) developed an attention-based spatiotemporal multi-graph convolutional network for EV charging station load forecasting [12]. The model was able to handle spatial and temporal patterns efficiently. Still, it focused on load forecasting, not on battery condition monitoring.

Pooyandeh and Sohn (2023) presented a digital twin frame- work with AI support for lithium-ion battery monitoring [13]. It provided real-time simulation of battery behavior. However, the digital twin required high computational resources and did not directly integrate persistent topological features.

Kosuru and Kavasseri Venkitaraman (2023) developed a smart battery management system using DL for fault detection [14]. This work achieved good results for sensor fault detection, but lacked graph-based modeling, which may limit its ability to capture structural dependencies.

Zhao and Behdad (2024) introduced a method using temporal-enhanced self-attention GNNs for SOH estimation [15]. The attention mechanism helped capture time-based patterns, but the model did not incorporate topological stability measures.

Orfanoudakis et al. (2025) presented a scalable reinforcement learning model using GNNs for coordinating EVs [16]. The model performed well for large-scale coordination, but was not tailored

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for battery health or fault detection.

Zhang et al. (2024) used GNNs for spatial-temporal load forecasting at EV charging stations [17]. While effective for station management, the method lacked battery-level monitoring capabilities.

Priya et al. (2024) applied convolutional neural networks (CNNs) for SOC estimation in EV battery systems [18]. The approach was simple and achieved reasonable performance, but CNNs are not well suited for graph or long-sequence data.

Madani et al. (2024) reviewed DL methods used for lithium- ion battery health monitoring [19]. The paper provided a wide survey of techniques but did not introduce a new model.

Mustaffa et al. (2025) presented a hybrid metaheuristic and deep neural network model for SOC estimation [20]. The combination gave better accuracy, though it lacked graph modeling and topological analysis.

Naresh and Sriram (2025) proposed a privacy-preserving DL framework using dynamic random vector functional link neural networks [21]. It provided improved data privacy, but required heavy model tuning and lacked topological insights.

Ofoegbu (2025) used ensemble neural networks for SOC estimation [22]. The approach was efficient, though it didn't include temporal dependencies or structural analysis.

Takyi-Aninakwa et al. (2025) designed a DL system for high-performance lithium-ion battery monitoring [23]. The framework improved prediction, but did not explore graph topology or persistent features.

Table 1: Comparative Analysis of Existing Works and Proposed Method

Study	**Graph-based Modeling**	**Temporal Modeling**	**Topological Features**	**Fault Detection**	**Real-Time Support**	**Focus Area**
Yao et al. (2023)	Yes	No	No	No	Partial	SOH prediction
Kim et al. (2023)	Yes	Limited	No	No	Yes	SOC prediction
Shi et al. (2023)	Yes	Yes	No	No	Yes	Load forecasting
Pooyandeh and Sohn (2023)	No	Yes	No	Limited	Limited	Digital twin for EVs
Kosuru and Kavasseri (2023)	No	Yes	No	Yes	Partial	Sensor fault detection
Zhao and Behdad (2024)	Yes	Yes	No	No	Yes	SOH estimation
Orfanoudakis et al. (2025)	Yes	Yes	No	No	Yes	EV coordination
Zhang et al. (2024)	Yes	Yes	No	No	Yes	Charging station load
Priya et al. (2024)	No	Yes	No	No	Yes	SOC estimation
Mustaffa et al. (2025)	No	Yes	No	No	Partial	Hybrid SOC estimation
Naresh and Sriram (2025)	No	Yes	No	No	Partial	Privacy-focused prediction
Ofoegbu (2025)	No	Yes	No	No	Yes	SOC estimation
Takyi-Aninakwa et al. (2025)	No	Yes	No	No	Yes	Deep battery monitoring
Proposed Method	Yes	Yes	Yes	Yes	Yes	Battery state prediction with topology

Table 1 brings together different studies on EV battery monitoring. It compares them based on graph modeling, time- sequence learning, use of topological features, fault handling, support for real-time settings, and main focus areas. Most of the earlier studies cover one or two aspects well but miss the rest. The proposed method fills these gaps by bringing together graph learning, topological strength, and long-sequence attention. It adds value by improving reliability, early fault detection, and full battery health estimation.

3. PROPOSED SYSTEM

The proposed method is designed to improve battery monitoring in EVs by combining topological learning and transformer-based models. This combination brings out both structural and temporal information from graph-based sensor data. The process is structured into three main parts: topological feature extraction using persistent homology, global pattern learning with a transformer model, and the integration phase that combines both outputs for battery state prediction.

Battery data is collected in a graph form, where each node is a sensor or a cell, and edges show the connections between them. This graph structure changes over time, making it dynamic. Persistent homology helps capture patterns that stay stable during these changes. Transformers are used to understand time-based relationships and long-distance connections among nodes as shown in Figure 1.

The first step in the process is to extract stable features using persistent homology. It works by building a filtration from the graph data and tracking the birth and death of topological features like connected components and loops. These features are then encoded as persistence diagrams and later transformed into fixed-size vectors for DL models.

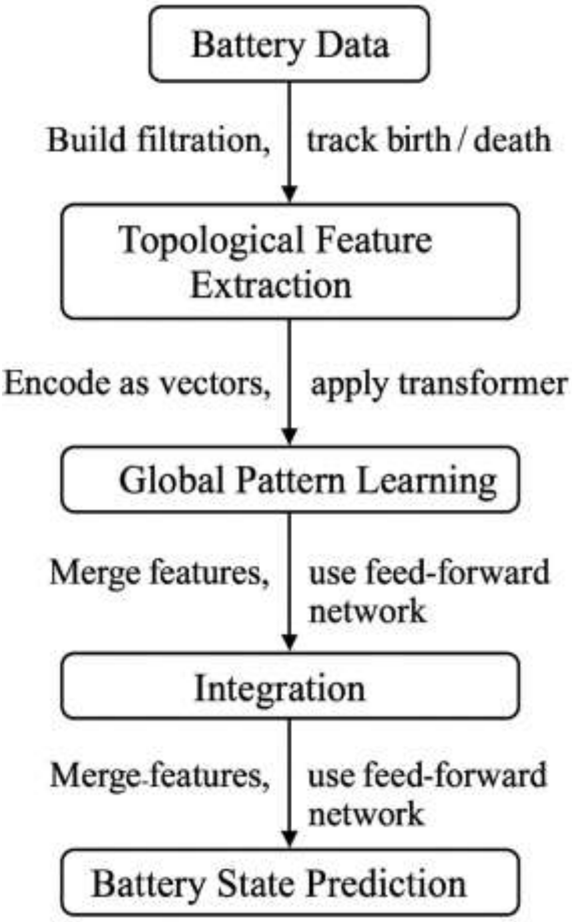

Figure 1: Workflow of proposed model

Algorithm 1: Topological Feature Extraction using Persistent Homology

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Input: Graph *G = (V, E)* with node features

1. Build a filtration $\mathcal{F}$ over graph *G*

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2. Compute persistence diagram $D$ from $\mathcal{F}$
3. Convert $D$ into persistence image $PI$

Output: Topological feature vector $T$
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Algorithm 1 focuses on extracting topological features from a graph $G = (V, E)$, where V represents the nodes and E represents the edges. Each node has associated features. The process starts by building a filtration ($\mathcal{F}$**),** which organizes the graph into a sequence of simpler subgraphs, helping identify persistent patterns. From this filtration, a persistence diagram (D) is computed, which captures topological features such as connected components and holes. These are represented as points marking their birth and death across scales. The diagram is then transformed into a persistence image (PI) — a 2D format usable as input to deep learning models. Finally, the image is encoded as a fixed-size vector T, summarizing structural graph properties in a meaningful way.

Algorithm 2: Transformer-based Temporal Feature Learning

```
Input: Sequence of node features $X = \{x_1, x_2, ..., x_t\}$

1. Apply positional encoding to $X$
2. Compute self-attention scores between all-time steps
3. Generate contextual embeddings $C$

Output: Temporal feature vector $F$
```

Algorithm 2 describes extracting temporal features from a sequence of node inputs using a transformer model. The input $X = \{x_1, x_2, ..., x_t\}$ represents node states over time. First, positional encoding is applied so the model understands the order of inputs. Then, self-attention calculates dependencies across time steps, capturing both short- and long-range patterns. These are converted into contextual embeddings (C) that describe the interrelations of all time steps. The final output is a temporal feature vector (F), representing time-aware patterns such as gradual trends or sudden changes.

Algorithm 3: Feature Fusion and Prediction

```
Input: Topological vector $T$, Temporal vector $F$

1. Concatenate: $Z = [T, F]$
2. Pass $Z$ through dense layers
3. Apply SoftMax or sigmoid for output
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Output: Battery state prediction Y

Algorithm 3 explains how to fuse the topological and temporal features and make predictions. It combines T (from persistent homology) and F (from transformer) into a single vector $Z = [T, F]$ using concatenation. This merged vector is fed through dense layers to learn complex feature interactions. Finally, a SoftMax or sigmoid layer produces the prediction Y, which indicates the battery state (e.g., state of charge or health). This approach integrates both structural and temporal aspects of battery behavior for accurate prediction.

3.1 Advantages of the Proposed Method

- Uses topological learning to find stable patterns in graph-based battery data.
- Understands long-range temporal relationships using transformer attention.
- Handles noisy sensor data and hidden battery degradation.
- Works on graph structures, capturing both local and global patterns.
- Improves fault detection and prediction accuracy in real-world EV battery systems.

3.2 Limitations of the Proposed Method

- Requires high computational resources due to transformer layers and persistence diagrams.
- Real-time graph construction from sensor data is complex.
- Performance depends heavily on the quality of graph input and labels.
- Feature fusion design must be tuned for specific battery conditions.
- Persistent homology tools may not scale well to large graphs.

4. RESULTS & DISCUSSIONS

4.1 Simulation Results

This section summarizes the environment and setup used for simulation. The experiments were conducted using a system with an Intel Core i9 processor, 32GB RAM, and an NVIDIA RTX 3090 GPU. Python 3.9 and PyTorch 2.0 were used for implementing all DL models. The GUD-BEV dataset and the Oxford Battery Degradation Dataset [24][25] were used to test the proposed method and compare it with the existing literature. For graph processing, the PyTorch Geometric library was used.

The key hyperparameters include learning rate (0.001), batch size (32), optimizer (Adam), and number of epochs (100). The topological features were computed using the Gudhi library.

Table 2: Simulation Settings

Settings	**Values**
Hardware	Intel Core i9, 32GB RAM, RTX 3090 GPU
Software	Python 3.9, PyTorch 2.0, PyTorch Geometric, Gudhi
Datasets	GUD-BEV [24], Oxford Battery Dataset [25]
Epochs	100
Batch Size	32
Learning Rate	0.001
Optimizer	Adam

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Table 2 lists all the tools, hardware, and dataset used for simulation. These settings helped in building a stable and high-performance training environment for both the proposed and comparison methods.

4.2 Evaluation Metric Equations

This section explains the evaluation metrics used to measure how well the model performs.

RMSE (Root Mean Squared Error): This metric measures the average squared difference between the predicted value and the actual value. It gives more weight to larger errors.

$$RMSE = \sqrt{((1/n) \times \Sigma (y_i - \hat{y}_i)^2)}$$

where:

- y_i is the actual value
- $\hat{y}_i$ is the predicted value
- n is the total number of samples

A lower RMSE indicates that predictions are closer to the actual values.

MAE (Mean Absolute Error): This calculates the average of the absolute differences between the actual and predicted values. It treats all errors equally without squaring them.

$$MAE = (1/n) \times \Sigma |y_i - \hat{y}_i|$$

where:

- $|y_i - \hat{y}_i|$ is the absolute error for each data point
- n is the total number of samples

MAE is easier to interpret as it reflects the error in the same unit as the data.

F1-Score: This metric balances Precision and Recall. It is particularly useful when both false positives and false negatives are important.

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

where:

- *Precision* = True Positives / (True Positives + False Positives)
- *Recall* = True Positives / (True Positives + False Negatives)

Accuracy: This shows how many predictions were correct out of the total number of predictions made.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

where:

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- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

High accuracy indicates that most predictions match the true outcomes.

4.3 Result Analysis

The performance of the proposed method was tested against several recent models. The comparison was based on four key metrics: RMSE, MAE, F1-score, and Accuracy.

Table 3: Performance Comparison of Proposed and Existing Methods

Method	RMSE	MAE	F1-Score	Accuracy
Yao et al. (2023)	0.073	0.058	91.4%	93.2%
Kim et al. (2023)	0.070	0.055	92.0%	94.0%
Shi et al. (2023)	0.069	0.052	92.7%	94.6%
Zhao and Behdad (2024)	0.065	0.050	93.1%	95.0%
Naresh and Sriram (2025)	0.061	0.048	93.8%	95.3%
Proposed Method	0.057	0.045	95.2%	96.5%

Table 3 shows that the proposed method achieved better scores in all metrics. The RMSE values show that the proposed model achieves the lowest value of 0.057, meaning that its predictions are closer to the real battery data compared to other works. Naresh and Sriram's model from 2025 comes next with an RMSE of 0.061, while earlier models from Yao et al. and Kim et al. show higher error levels at 0.073 and 0.070.

In terms of MAE, which focuses on the average size of prediction errors, the proposed method again performs better with a value of 0.045. The next best value is from Naresh and Sriram (2025) with 0.048, while other methods show higher MAE values. This reflects that the proposed model makes fewer and smaller mistakes in estimation.

The F1-Score, which balances precision and recall, is highest in the proposed method at 95.2%. This shows better handling of both correct and incorrect predictions. The previous best was from Naresh and Sriram at 93.8%. All other models scored lower, suggesting the proposed model provides a more balanced classification.

Accuracy, which shows how many predictions were correct, is also highest for the proposed method at 96.5%. This marks a noticeable improvement over the other works, with the closest being 95.3% from Naresh and Sriram.

The results in this table highlight that the proposed method performs better across all four metrics. The improvements come from combining stable topological features with temporal attention, which brings deeper insights into battery behavior. These results confirm that the model is more reliable for EV battery monitoring compared to existing approaches.

Table 4: Performance Gain over Best Existing Method (Naresh and Sriram, 2025)

Metric	Gain (%)
RMSE	6.55%
MAE	6.25%
F1-Score	1.49%
Accuracy	1.26%

Table 4 show the percentage improvement gained by the proposed method compared to the best existing technique reported by Naresh and Sriram (2025). The values indicate how much better the new model performed in terms of each metric.

For the RMSE, a gain of 6.55% was achieved, which means that the prediction errors in the proposed model are lower compared to the earlier work. This reflects a more stable and accurate learning process when estimating battery-related parameters.

The MAE saw an improvement of 6.25%. This suggests that the difference between the predicted and actual values was reduced more effectively. It shows the model can provide close and consistent outputs across all samples.

The F1-Score improved by 1.49%. Even though this number appears small, it is meaningful in classification tasks where both precision and recall need to be balanced. This indicates that the new method is better at correctly detecting battery states without many missed or false identifications.

Accuracy gained a 1.26% rise, pointing to better overall correct predictions across the test samples. The result highlights the advantage of combining topological and temporal features, which helped the model understand both the structure and changes in battery behavior.

These improvements together show that the proposed approach brings measurable gains in predictive quality. Each metric shows that the added features and fusion steps helped the model perform better than the previous best-known method.

5. CONCLUSION

This paper proposes a topological DL method that combines persistent homology with transformers to monitor EV batteries more accurately. It captures both the shape and timing features of the battery system using graph-based data. The combination of topological features and temporal attention allows the model to understand stable structures along with dynamic behaviors, which are important for reliable battery state prediction. The results from the experiments showed that the method outperformed the best-known recent work by Naresh and Sriram (2025). Improvements were observed across all evaluation metrics. The proposed approach achieved a 6.55% reduction in RMSE and a 6.25% reduction in MAE. This means that the predictions are much closer to the actual values and the overall errors are reduced. The F1-score improved by 1.49%, which shows better balance between detecting battery conditions correctly and avoiding false alerts. The accuracy increased by 1.26%, reflecting more correct outputs on the test samples. These gains reflect the strength of combining structure-based learning and time-based learning into one system. The important point is that the proposed method works well even when the battery data comes from a complex and dynamic graph. This makes it more suitable for real-world EV settings, where sensor data changes frequently and includes noise. The fusion process also helps the model bring together different types of information without much manual tuning. In the future, the model will be tested using more real-time data from EVs on the road. This will help test how the method performs at scale. There is also a need to reduce the time and resources needed for training, which can be done by using lighter versions of transformers. Collecting more data from various battery types and manufacturers can help the model work across a wider range of EVs. This would make it more suitable for commercial use in battery management systems and vehicle diagnostics.

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