SYNTHETIC-TO-SMART: ENHANCING EV BATTERY INSIGHTS USING TIMEGAN AND TEMPORAL FUSION TRANSFORMER

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Introduction:

1. Electric Vehicles (EVs) are transforming modern transportation systems, but their reliability heavily depends on efficient battery management systems. Lithium-ion batteries exhibit complex nonlinear degradation patterns influenced by temperature, load conditions, and repeated charge–discharge cycles.
2. Accurate prediction of key battery health indicators such as **State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL)** is essential for ensuring safety, optimizing performance, and enabling predictive maintenance.
3. However, real-world EV battery datasets are often **limited, noisy, and imbalanced**, making it difficult for traditional and deep learning models to generalize effectively.
4. To address these challenges, this project proposes a **hybrid framework combining TimeGAN for synthetic data generation and Temporal Fusion Transformer (TFT) for prediction**, enabling robust and interpretable battery analytics.

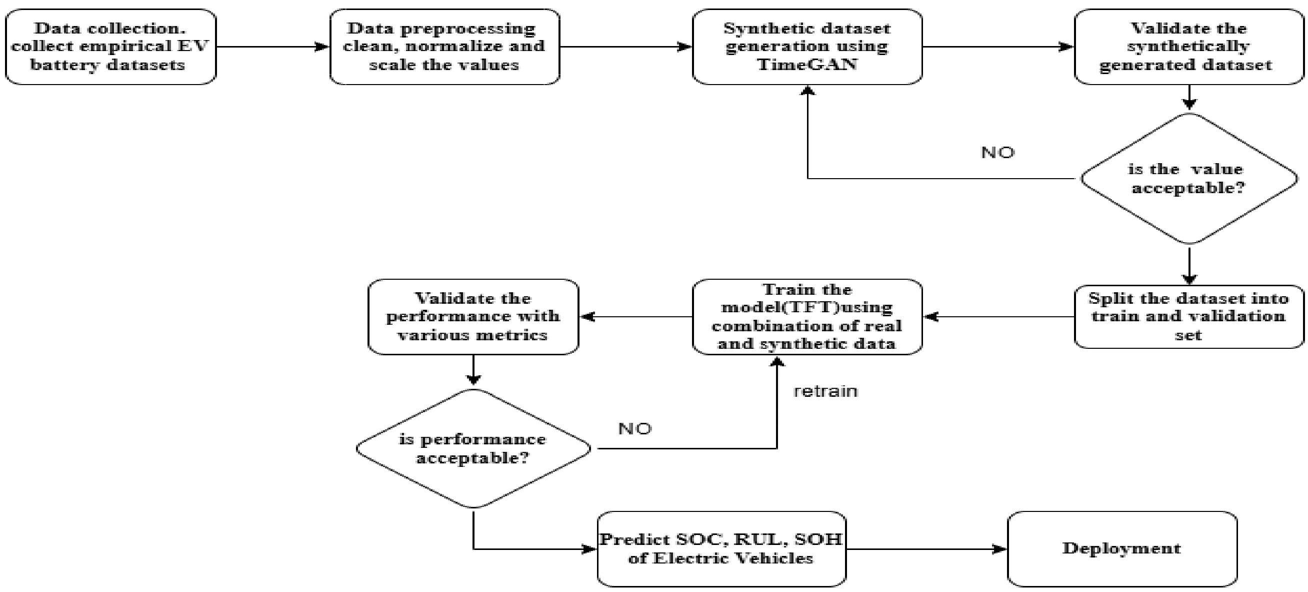

Figure 1: Overall workflow of the proposed TimeGAN–TFT framework (Synthetic data generation → Data augmentation → TFT-based prediction)

Objectives:

1. To develop a hybrid framework combining TimeGAN and TFT for battery prediction.
2. To generate high-quality synthetic battery data to overcome data scarcity.
3. To accurately predict SOC, SOH, and RUL using multivariate time-series data.
4. To improve model interpretability and robustness for real-world BMS applications.

Methodology:

The proposed system consists of the following stages:

- **Data Collection & Preprocessing:**
  Multivariate battery data (voltage, current, temperature, cycles) is normalized and structured into time-series sequences.
- **Synthetic Data Generation (TimeGAN):**
  TimeGAN generates realistic battery sequences while preserving temporal dependencies and feature correlations.
- **Data Validation:**
  Synthetic data is validated using statistical methods and visualization (e.g., t-SNE) to ensure similarity with real data.
- **Prediction Model (TFT):**
  Temporal Fusion Transformer is used to predict SOC, SOH, and RUL using attention mechanisms and variable selection networks.
- **Training & Optimization:**
  The model is trained using RMSE loss with optimization techniques like Adam optimizer and early stopping.

Result and Conclusion:

The proposed TimeGAN–Temporal Fusion Transformer (TFT) framework produced the following results:

- State of Charge (SOC) RMSE: 0.4756
- State of Health (SOH) RMSE: 0.3750
- Remaining Useful Life (RUL) RMSE: 0.0401

  The predicted values closely match the actual values, demonstrating accurate prediction of battery health parameters.

In conclusion, the proposed system effectively predicts SOC, SOH, and RUL with high accuracy and can be used for reliable battery health monitoring in electric vehicles.

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Future Scope:

The future scope of this project includes:

1. Extending the model to large-scale real-world EV fleet datasets.
2. Integrating physics-based constraints for improved interpretability.
3. Deploying the model in real-time embedded Battery Management Systems (BMS).