Federated learning Framework for Vehicular Predictive Maintenance Battery SoH

(Model aggregation using knowledge distillation)

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Problem Statement

Now a days battery degradation is a critical challenge for electric vehicles, portable electronics.

Accurate prediction of the SoH can improve maintenance scheduling and increase efficiency, and extend battery lifespan.

However, collecting centralized data for training raises privacy concerns.

Objective

Our goal is to create a privacy preserving, collaborative predictive model for battery State of Health (SoH) utilizing Federated Learning and Knowledge Distillation, with LSTM networks for sequential data.

What is SoH?

State of health (SoH) is a measure of a battery's overall condition and remaining useful life

$$\text{SoH} = \left(\frac{\text{Current Capacity}}{\text{Initial Capacity}} \right) \times 100$$

When the SOH of the battery declines to 70 % or 75 % or less, the battery is usually considered to have reached its end of life

Motivation

- Privacy Concerns

  Avoid sharing raw battery data between clients and the central server.

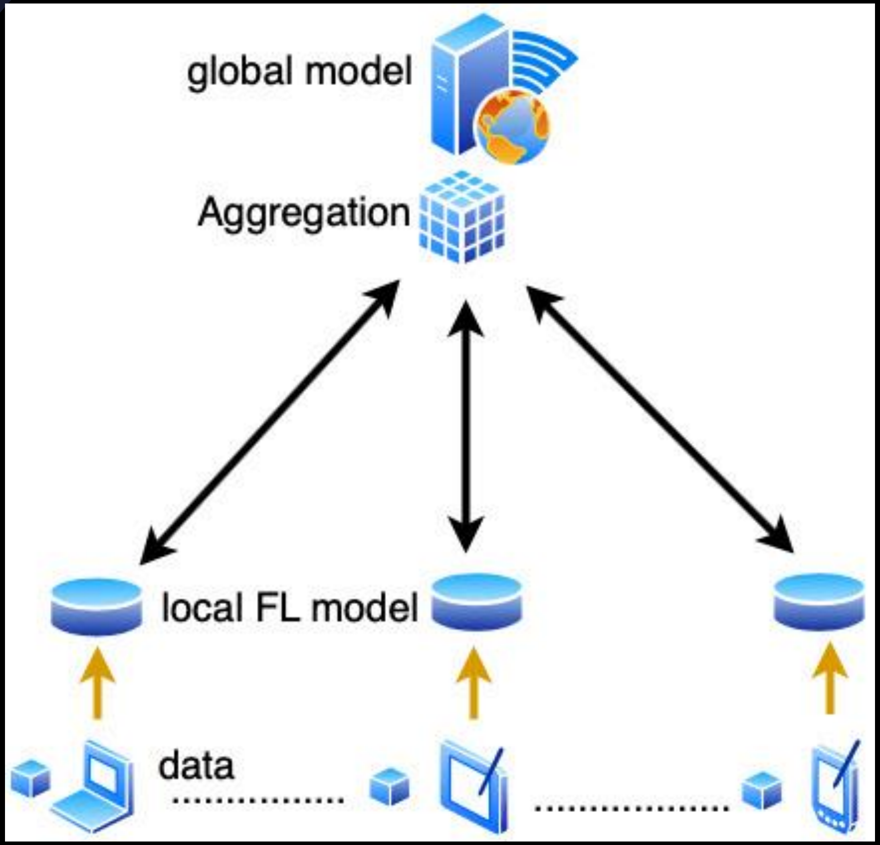
- Global Insights

  Combine localized training for better generalization.

Federated Learning with Knowledge Distillation offers a secure and effective solution for multi-client SoH prediction

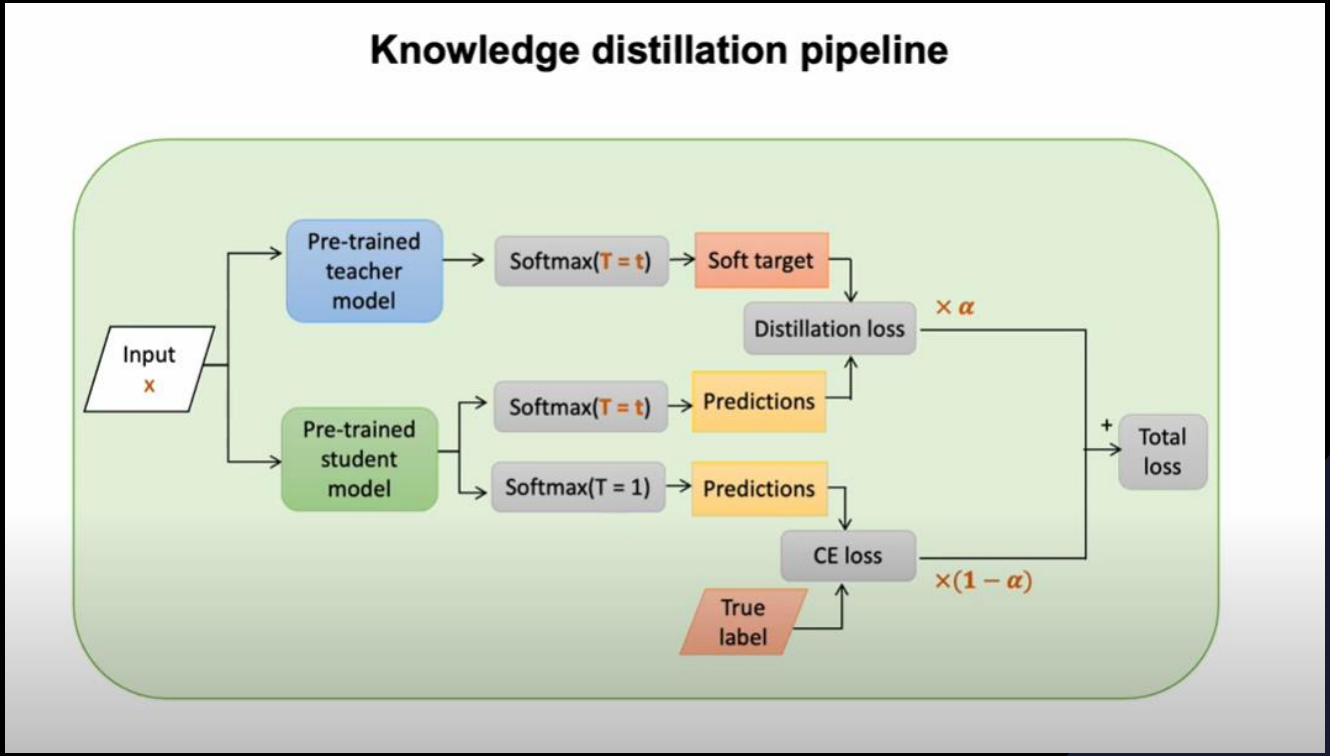
Federated Learning

- Federated learning (FL) is a machine learning technique that trains models on distributed datasets without exchanging local data samples.



Knowledge Distillation

- A technique that transfers knowledge from a large, pre-trained model to a smaller model.



Datasets

Battery1.csv: Collected from Client 1.

Battery2.csv: Collected from Client 2.

Battery3.csv: Collected from Client 3.

Battery4.csv: Global centralized dataset (used for model aggregation).

Features Extracted:

- cycle: Operational cycle of the battery.
- capacity: Remaining capacity of the battery.
- Voltage_measured: Voltage across the battery terminals.
- Current_measured: Measured current during operation.
- Current_load: Load current applied to the battery.

Model Architecture

- Four LSTM models, each trained on client-specific data.
- Architecture:

  4 LSTM layers (200 units each).

  Dropout layers for regularization.

  Dense layer for output (single unit).

Methodology

- **Data Preprocessing**

  Normalize data using MinMaxScaler.

  Create sliding window sequences for LSTM input.

- **Local Training**

  Train LSTM models for each client using their respective data.

- **Global Model Training**

  Use Knowledge Distillation to aggregate client models into a unified global model.

- **Evaluation**

  Test the global model and analyze the results.

Loss Functions

Mean Squared Error (MSE):

Used to minimize the difference between predicted and actual SoH values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Kullback-Leibler (KL) Divergence:

Applied in knowledge distillation to measure the similarity between the soft predictions of the global and client models.

$$KL(p\|q) = \sum_i p_i \log \frac{p_i}{q_i}$$

Distillation Loss:

Combination of student loss (MSE) and distillation loss (KL Divergence) with a temperature parameter:

$$Loss = \alpha \cdot MSE + (1 - \alpha) \cdot KL$$

Contributions

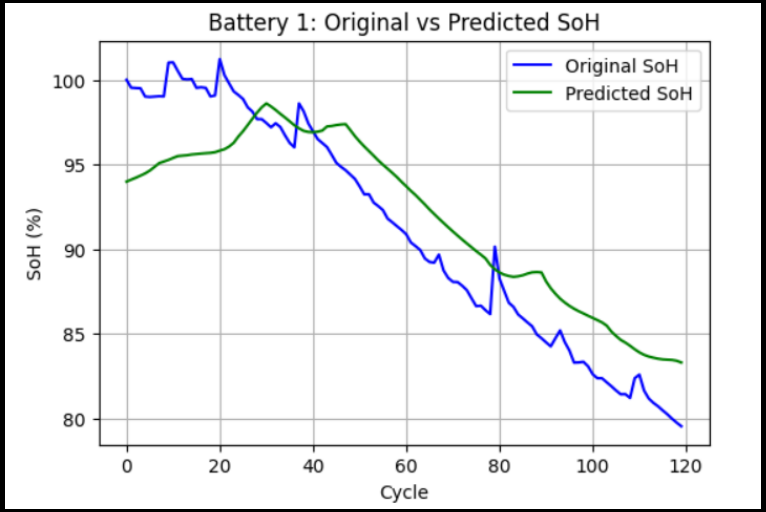
- Dhiraj and Sandeep and Vipin:

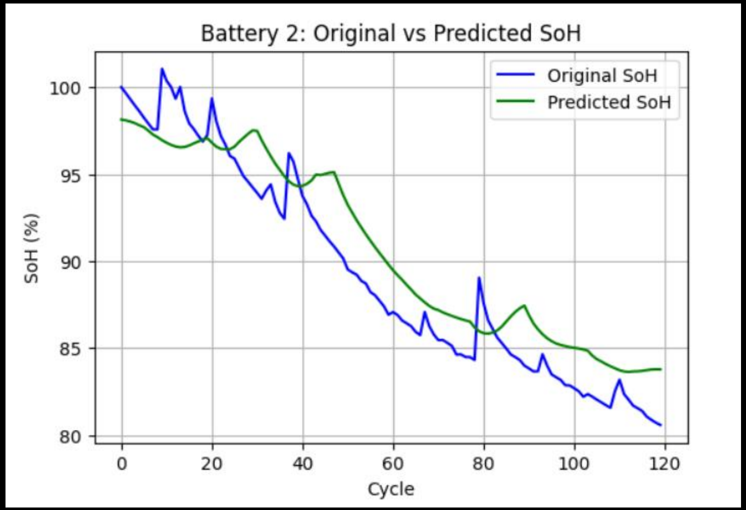
  Data preprocessing, feature engineering, Evaluation and testing.

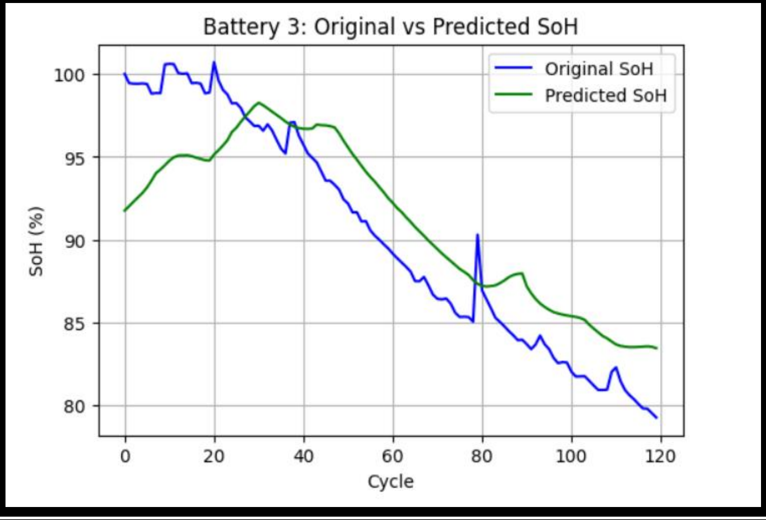
- Aditya and Princu:

  Local model training using LSTM, Implementation of knowledge distillation and global model training.

Results


Battery 1: Original vs Predicted SoH
Original SoH
Predicted SoH
SoH (%)
100
95
90
85
80
0
20
40
60
80
100
120
Cycle


Battery 2: Original vs Predicted SoH
Original SoH
Predicted SoH
SoH (%)
100
95
90
85
80
0
20
40
60
80
100
120
Cycle


Battery 3: Original vs Predicted SoH
Original SoH
Predicted SoH
SoH (%)
100
95
90
85
80
0
20
40
60
80
100
120
Cycle

Results

- Evaluating global model on test data of client 1

  Client 1 - MSE: 0.0196 , Accuracy: 96.90%

- Evaluating global model on test data of client 2

  Client 2 - MSE: 0.0106 , Accuracy: 97.66%

- Evaluating global model on test data of client 3

  Client 3 - MSE: 0.0252 , Accuracy: 96.55%

Average MSE across all clients: 0.0185