

EV Society™

EV BATTERY SAFETY SYSTEM

AI POWERED EV BATTERY FIRE PREVENTION SYSTEM



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Intern, Guest Speaker

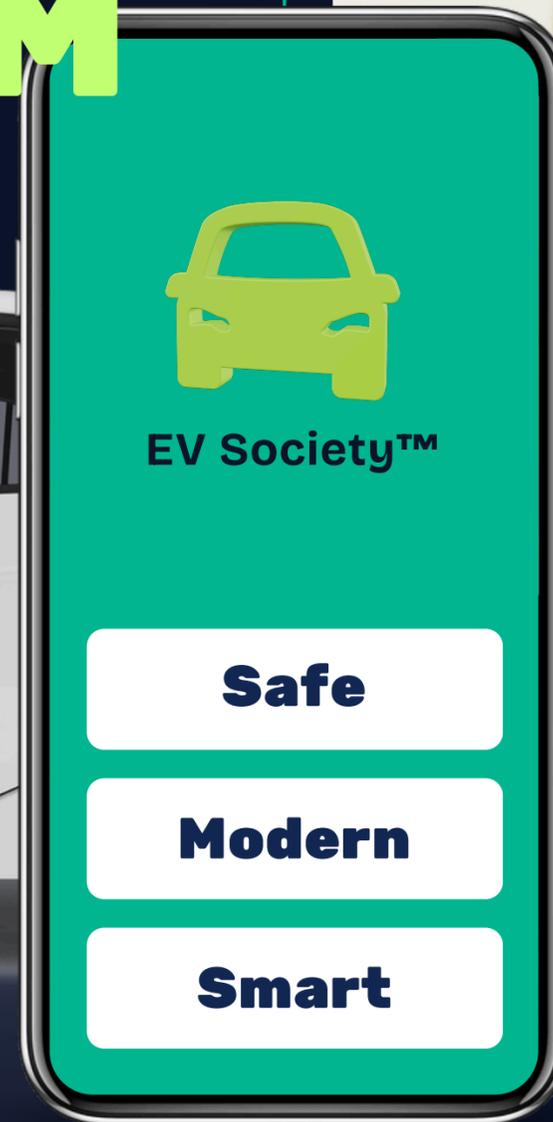
WWW.EVSOCIETY.ORG



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8:00 pm IST



INTRODUCTION

An EV battery pack is made up of many lithium-ion cells, either hundreds of large cells or a few thousand smaller ones, depending on the design.

Now, the problem usually begins with just one single cell. That first cell may fail due to reasons such as a battery management system (BMS) malfunction, an internal short circuit, improper or faulty charging, a manufacturing defect, or severe external damage to the battery pack. When that one cell fails, it starts generating excessive heat. If the heat is not controlled, it spreads to the neighbouring cells. This triggers a chain reaction known as thermal runaway, where one overheated cell causes the next one to overheat and ignite.

As this process continues from cell to cell, the fire grows stronger and spreads through the battery pack. That is why, although EV fires are uncommon, they can appear intense and are relatively more difficult to extinguish once the chain reaction begins.



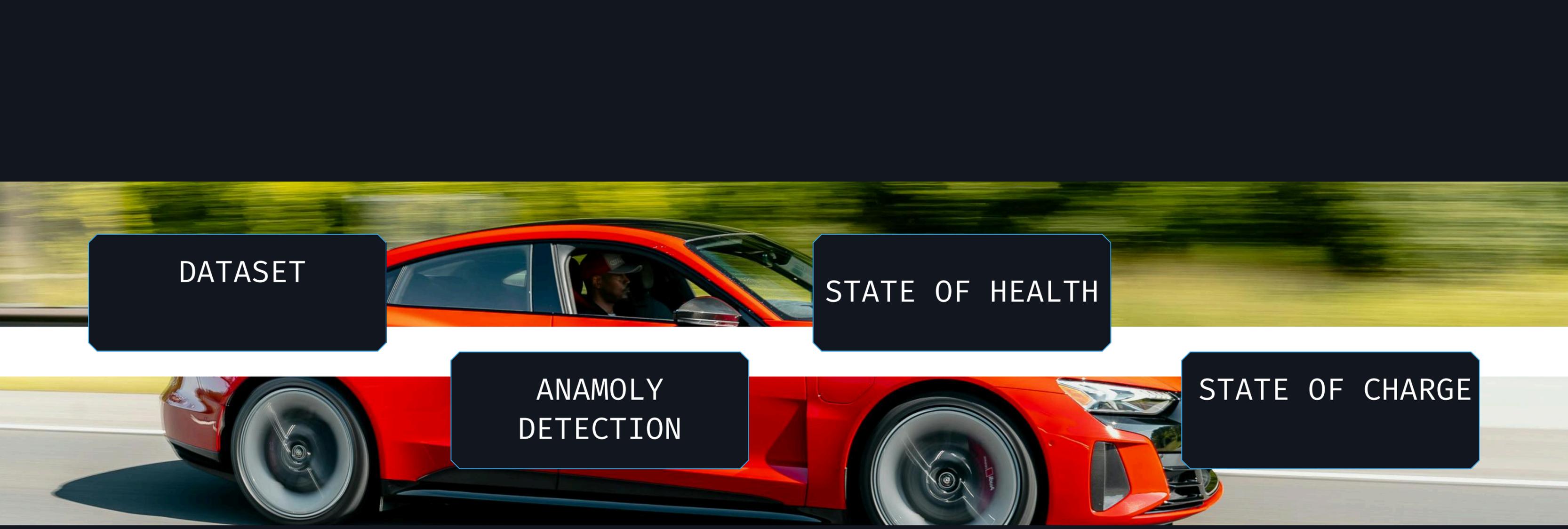


Mahindra BE.6 Electric SUV Catches Fire in UP! The Company Explains What Really Caused the Blaze.

The sensor data showed the BE.6 was driven over 10 minutes on a fully deflated rear tyre, causing heat buildup that ignited the rubber and all occupants escaped safely.

INSTANCES OF ELECTRIC VEHICLES CATCHING FIRE

- EV fires usually start from a single failing cell → heat spreads → thermal runaway
(Not every EV fire is battery-related; some are caused by crashes, tyres, wiring, or external heat)
- EVs can catch fire — but they're statistically less likely to than petrol/diesel vehicles
(~25 EV fires per 100,000 vehicles vs ~1,500+ per 100,000 gasoline vehicles)



DATASET

STATE OF HEALTH

ANAMOLY
DETECTION

STATE OF CHARGE

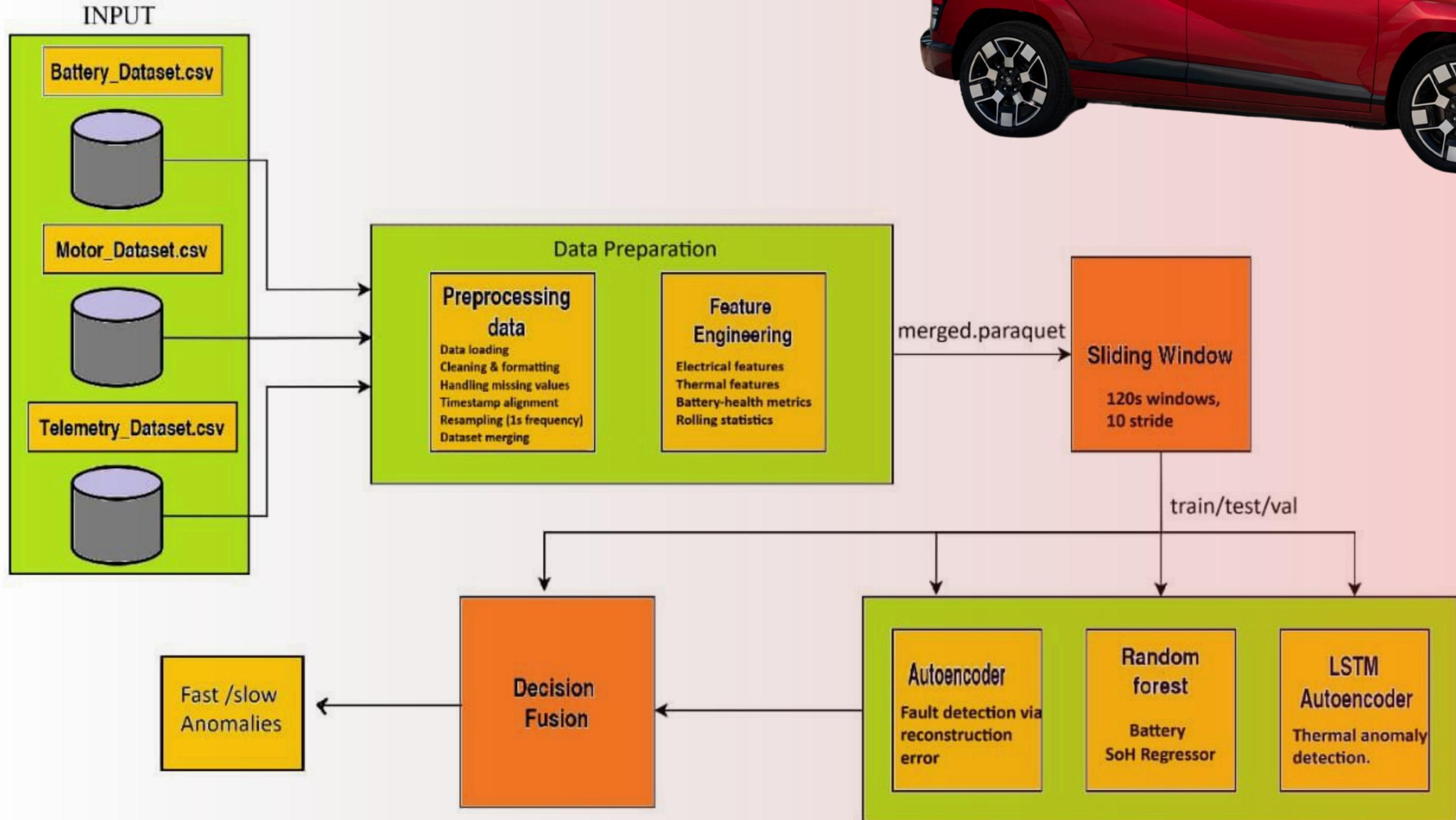
PROBLEM
STATEMENT:

...

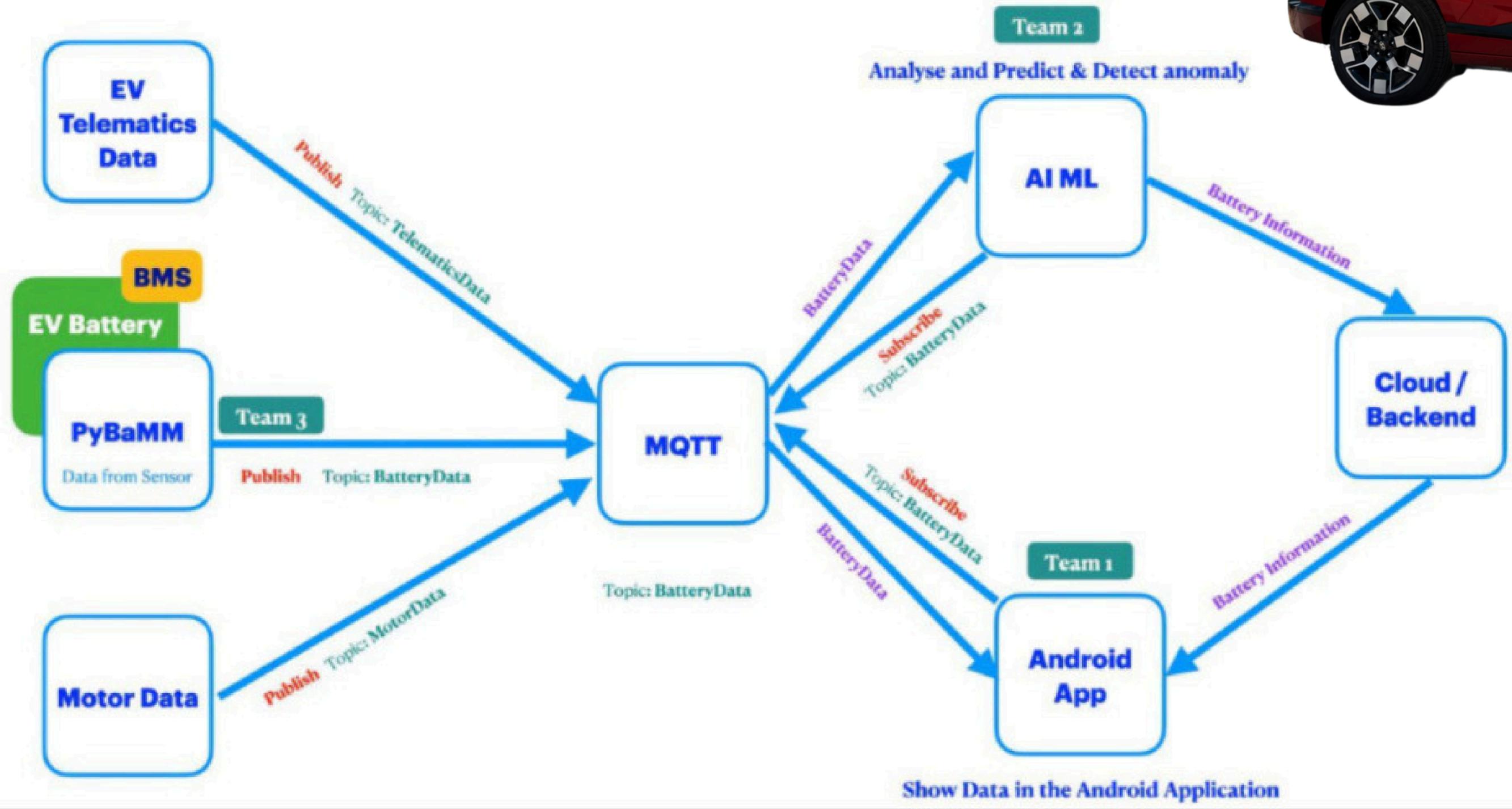
For a given dataset consisting of EV battery operational parameters such as voltage, current, temperature, state of charge (SOC), number of charge/discharge cycles, and other sensor readings, develop an AI-powered Battery Health Prediction and Failure Detection System using machine learning algorithms to:
Predict State of Charge (SOC), State of Health (SOH) and Perform real-time anomaly detection

HOW DO WE
FIND SOLUTION
USING AIML?

ARCHITECTURE



OVERALL ARCHITECTURE



DATASET USED

Dataset Sources Overview

Dataset Name	No. of Rows	Source System	Purpose
Battery BMS Dataset	6026 rows	Battery Management System	Battery electrical & thermal behavior
Motor Dataset	5000 rows	Electric Motor Controller	Motor performance & fault detection
Telemetry Dataset	5431 rows	Vehicle Sensors	Driving behavior & environment
Final Merged Dataset	6025 rows	Combined	ML training & prediction



DATASET AND PREPROCESSING

EXPLORER

- EV-AIML
 - .github
 - .venv
 - config
 - data
 - processed
 - windows
 - check.py
 - data_summary.csv
 - merged_enhanced.parquet
 - battery_bms_dataset.csv
 - motor_dataset.csv
 - tele_dataset.csv
 - data_scripts
 - __pycache__
 - data
 - 01_load_data.py
 - 02_make_windows.py
 - check_again.py
 - inference
 - models
 - training
 - dashboard_models.py
 - dashboard_preprocessed_data.py
 - inference_fault_autoencoder.py
 - inference_fault_visual.py
 - inference_thermal_autoencoder.py
 - inference_thermal_visual.py
 - README.md
 - requirements.txt
 - test.py

data > battery_bms_dataset.csv > data

You, 5 months ago | 1 author (You)

	Pack Voltage (V)	Pack Current (A)	Pack Power (W)	SoC (%)	SoH (%)	Battery Temp (°C)	Battery Status
1	344.94	-31.91	99	45.55			Non-Healthy
2	414.09	-7.97	-3299.97	46.63	92.4	26.46	Healthy
3	387.84	106.36	41252.22	34.09	86.88	32.13	Healthy
4	371.84	-48.0	-17847.78	68.58	72.5	43.21	Non-Healthy
5	318.72	110.89	35344.67	58.13	75.57	36.87	Non-Healthy
6	318.72	-123.56	-39380.86	89.26	76.58	45.85	Non-Healthy
7	306.97	83.04	25490.65	22.57	77.74	53.64	Non-Healthy
8	403.94	104.26	42116.64	71.51	86.96	24.08	Healthy
9	372.13	-95.45	-35521.92	81.04	85.12	44.83	Healthy
10	384.97	-20.9	-8044.32	80.76	76.09	28.06	Non-Healthy
11	302.47	-100.35	-30352.9	90.89	72.03	34.51	Non-Healthy
12	416.39	61.98	25808.32	78.32	75.14	21.15	Non-Healthy
13	399.89	10.6	4240.6	94.22	99.53	24.76	Healthy
14	325.48	40.6	13213.54	46.61	84.06	31.19	Non-Healthy
15	321.82	-91.05	-29302.88	60.26	96.02	31.97	Healthy
16	322.01	-86.48	-27846.09	21.13	95.46	51.49	Non-Healthy
17	336.51	-137.55	-46287.09	20.56	85.35	45.96	Healthy
18	362.97	-53.38	-19375.29	39.21	91.2	54.03	Non-Healthy
19	351.83	17.92	6306.05	28.06	75.78	40.97	Non-Healthy
20	334.95	107.38	35966.82	40.82	90.65	28.46	Healthy
21	373.42	50.08	18700.33	34.16	78.17	31.47	Non-Healthy
22	316.74	-19.38	-6138.76	22.28	94.96	31.19	Healthy
23	335.06	135.94	45546.37	92.74	72.51	31.43	Non-Healthy
24	343.96	65.77	22623.7	20.66	93.19	43.55	Healthy
25	354.73	129.05	45777.54	78.89	73.0	38.58	Non-Healthy
26	394.22	8.28	3262.73	32.17	96.44	33.49	Healthy
27	323.96	-72.33	-23431.67	92.98	79.13	25.22	Non-Healthy
28	361.71	-134.15	-48523.87	91.42	89.63	20.77	Healthy
29	371.09	67.83	25169.33	72.31	84.63	27.66	Non-Healthy
30	305.57	-113.61	-34715.99	73.78	80.99	23.76	Non-Healthy
31	372.91	-59.17	-22063.86	20.43	89.36	47.49	Healthy
32	320.46	9.74	3121.72	98.79	98.43	23.94	Healthy
33	307.81	19.32	5948.35	90.23	71.24	45.35	Non-Healthy
34	412.87	20.17	12488.4	91.61	97.57	22.5	Healthy

ML AND DL MODELS USED

- WHAT IS AUTOENCODER?
- WHAT IS RANDOM FOREST?
- HOW DOES THESE WORK?

LSTM
AUTOENCODER

RANDOM
FOREST

AUTOENCODER

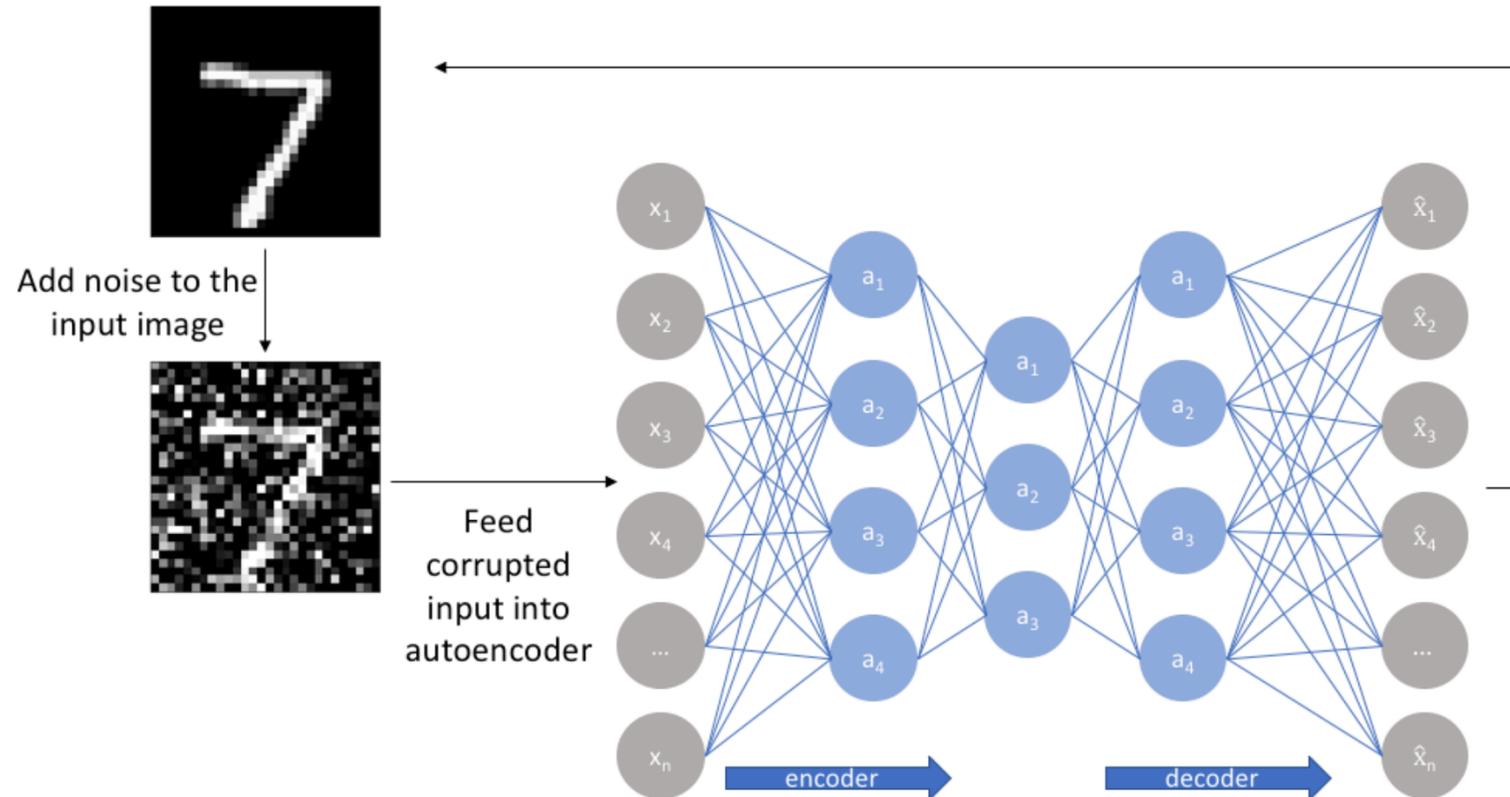
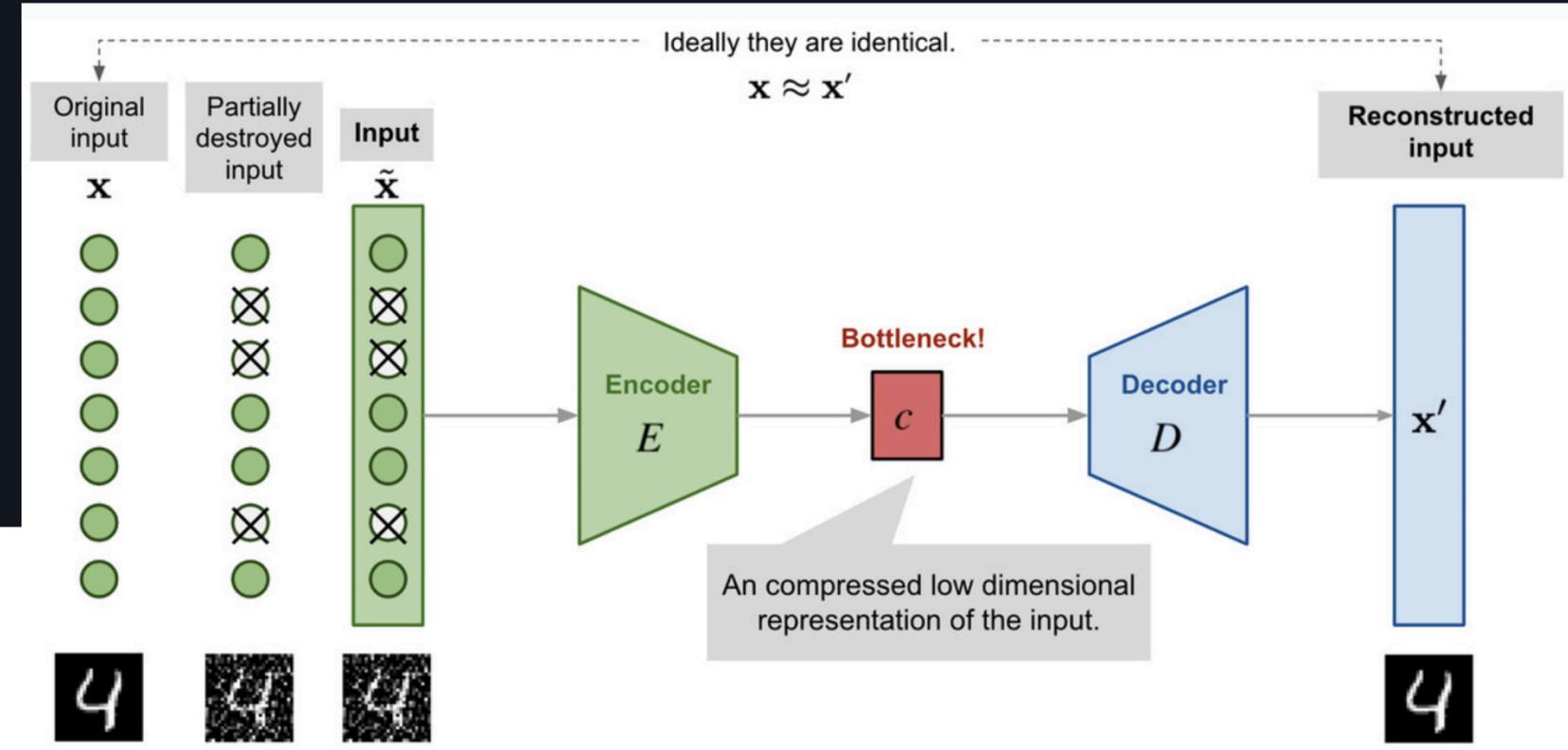


Task	Script	Model	Output
Fault Detection	<code>`train_fault_encoder.py`</code>	Autoencoder	Detects anomalies & metrics
SoH Regression	<code>`train_soh_regressor.py`</code>	Random Forest	Predicts battery SoH (%)
Thermal Anomaly Detection	<code>`train_thermal_autoencoder.py`</code>	LSTM Autoencoder	Detects thermal anomalies

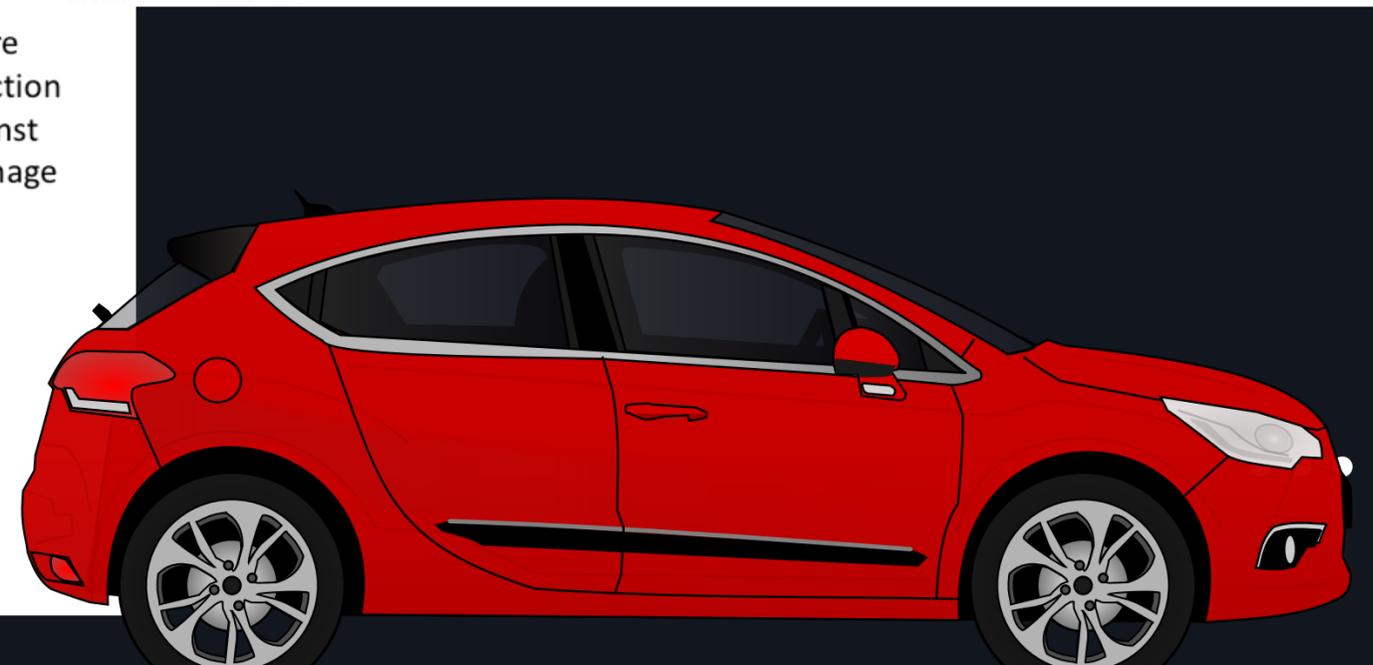
HOW DOES AUTOENCODERS WORK?

LSTM
AUTOENCODER

AUTOENCODER



Measure reconstruction loss against original image



IMPLEMENTATION

⚡ Fault Autoencoder

Goal: Detect anomalies in battery and motor data.

Method: Autoencoder reconstruction error; anomalies occur when error exceeds threshold.

Metrics

```
{  
  "THRESHOLD_95" : 1.7025846242904663  
  "NUM_ANOMALIES_DETECTED" : 5  
  "TOTAL_TEST_SAMPLES" : 89  
}
```

Goal: Detect operational faults in battery and motor data.

Method: Autoencoder detects anomalies using reconstruction error.

Results: Threshold = 1.70, Anomalies Detected = 5 / 89 samples

Performance: The model is balanced, shows no overfitting, and accurately identifies unusual behavior in test data.

Conclusion: Works reliably for detecting real-time motor or battery faults.

IMPLEMENTATION

Thermal Autoencoder

Goal: Detect thermal anomalies in battery data (fire risk).

Method: Sequence autoencoder; anomalies detected via reconstruction error.

Stats

```
{  
  "THRESHOLD_95" : "np.float32(2.2800226)"  
  "NUM_ANOMALIES_DETECTED" : 3  
}
```

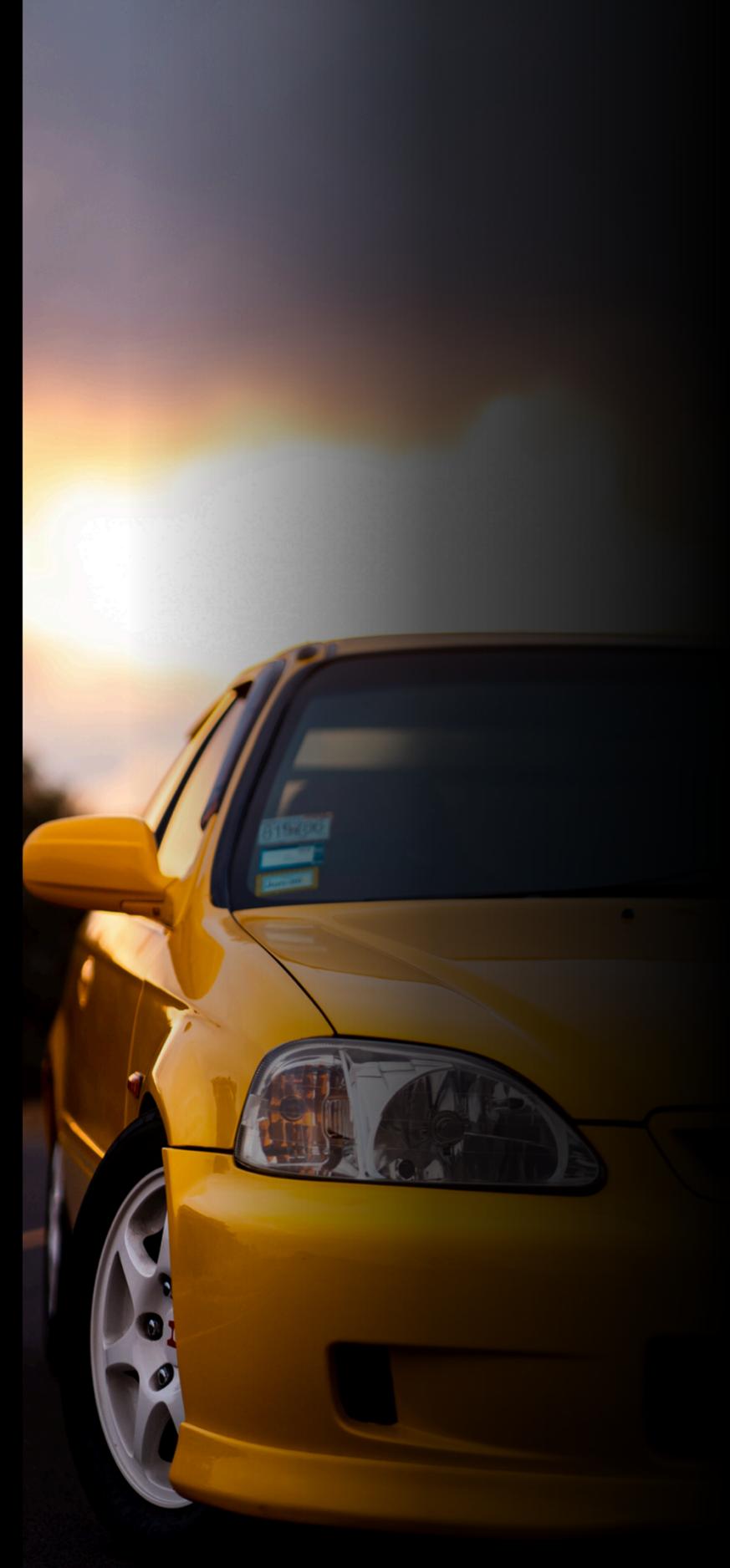
Goal: Detect temperature-related or fire-risk anomalies.

Method: Sequence autoencoder analyzes temperature patterns over time.

Results: Threshold = 2.28, Anomalies Detected=3

Performance: The model is stable, captures time-based variations effectively, and shows balanced generalization.

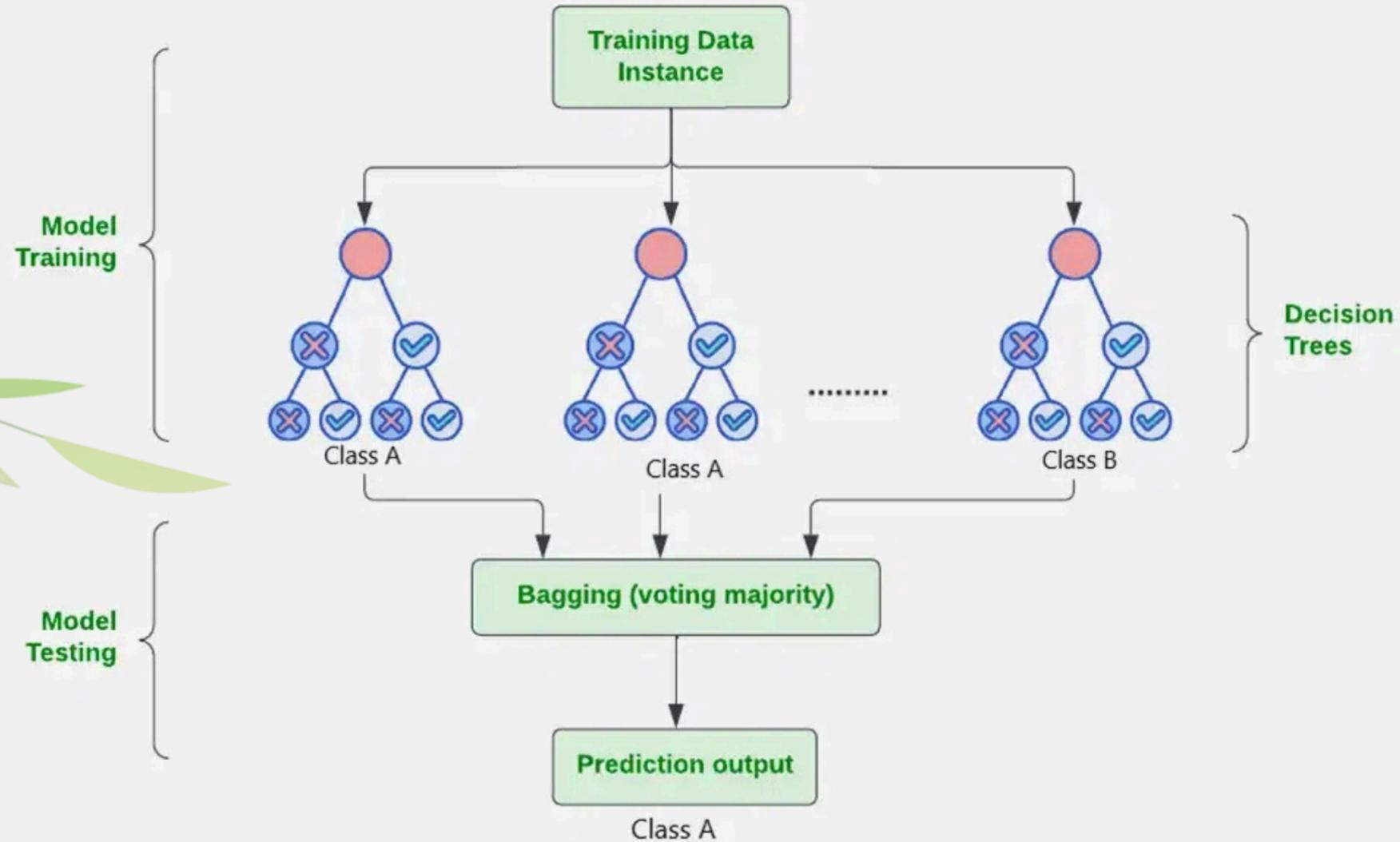
Conclusion: Provides accurate thermal anomaly detection and supports early fire-risk prediction



HOW DOES RANDOM FOREST WORK ?

RANDOM FOREST

Random Forest Algorithm in Machine Learning



IMPLEMENTATION

SoH Regressor

Goal: Predict battery State of Health (SoH).

Method: Random Forest regression; predict % battery health.

Model Metrics

```
{
  "train": {
    "MAE": 0.029477929953512373
    "RMSE": 0.04038418760992698
    "R2": 0.9999792260126628
  }
  "val": {
    "MAE": 0.056388826906011935
    "RMSE": 0.08121200795900019
    "R2": 0.9998965871650155
  }
  "test": {
    "MAE": 0.023065776396333414
    "RMSE": 0.025243188581174414
    "R2": 0
  }
}
```

The battery is middle aged
so soh and soc values are
around 75.16

Battery Health Status

Filter Predicted SoH Range (%)



Sample	True_SoH(%)	Predicted_SoH(%)	Status
0	1	75.17	85.01 Moderate ▲
1	2	75.17	84.25 Moderate ▲
2	3	75.17	84.96 Moderate ▲
3	4	75.17	85.48 Moderate ▲
4	5	75.17	84.96 Moderate ▲
5	6	75.17	84.88 Moderate ▲
6	7	75.17	84.98 Moderate ▲
7	8	75.17	84.87 Moderate ▲
8	9	75.17	84.97 Moderate ▲
9	10	75.17	85.23 Moderate ▲

Goal: Estimate State of Health (SoH) and State of Charge (SoC) of the battery.

Results: SoH \approx 75.16%

Performance: The model is overfitting because the dataset contains limited variation in SoH values (mostly mid-range).

Conclusion: Predicts mid-life battery condition well, but needs more diverse data to learn full degradation patterns



CLOUD DEPLOYEMNET

Cloud Deployment:
Dockerize and deploy on
AWS EC2 with FastAPI/
Flask APIs for live and
historical data.

UI Integration

Provide APIs for CS team
dashboard showing SOC,
SOH, charging state, real-
time charts, and AI
results.

Real-Time MQTT Data:

EC team sends live
motor, battery, and
telematics data; AI
system processes and
displays anomalies.

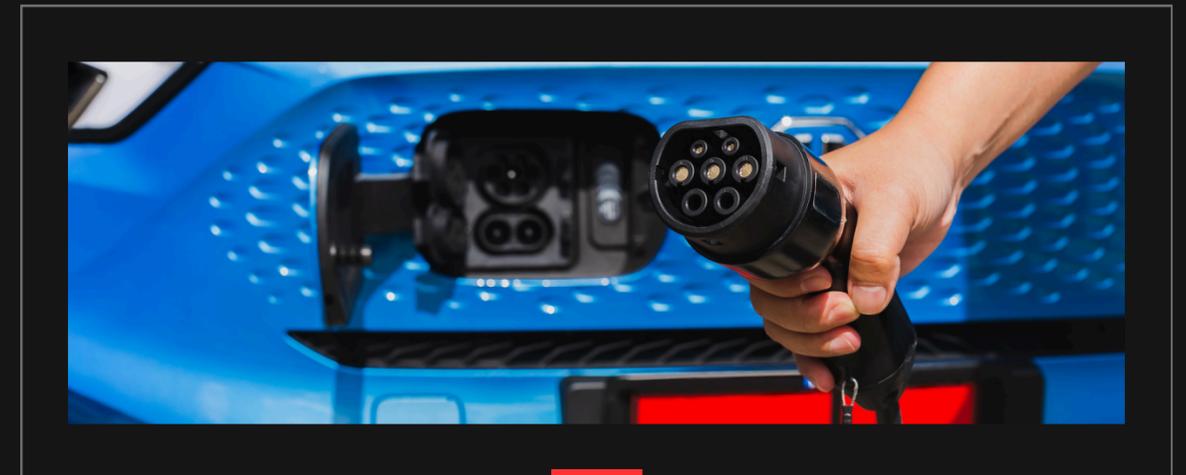
Fault Localization

Use Explainable AI
to pinpoint issues
like rotor fault or
battery module
overheating



FUTURE WORK

CONCLUSION



THIS PROJECT DEVELOPS AN AI-BASED EV BATTERY HEALTH AND FAULT DETECTION SYSTEM THAT INTEGRATES BATTERY, MOTOR, AND VEHICLE TELEMETRY DATA INTO A UNIFIED DATASET. USING RANDOM FOREST FOR STATE OF HEALTH (SOH) PREDICTION AND AUTOENCODER-BASED MODELS FOR ELECTRICAL AND THERMAL ANOMALY DETECTION,

THE SYSTEM IDENTIFIES POTENTIAL FAULTS AND FIRE-RISK CONDITIONS. BY COMBINING MULTI-SENSOR DATA WITH MACHINE LEARNING, THE FRAMEWORK ENABLES SAFER BATTERY MONITORING, SMARTER CHARGING DECISIONS, AND IMPROVED RELIABILITY IN ELECTRIC VEHICLES.

THANK YOU

