Implementation Of AI-Based Intelligent Battery Energy Management Electric Vehicles

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***Abstract*—Electric Vehicles (EVs) are becoming increasingly important due to growing environmental concerns and the demand for sustainable transportation. Conventional Battery Management Systems (BMS) often struggle with nonlinear battery characteristics, temperature variations, and dynamic operating conditions. This paper presents an AI-based Battery Energy Management System (BEMS) using three machine learning algorithms—Linear Regression, Random Forest, and XGBoost—trained on a publicly available 5-year EV battery dataset covering voltage, current, temperature, State of Charge (SOC), and State of Health (SOH) parameters. After rigorous preprocessing (data cleaning, feature selection, normalization, 80/20 train-test split), all three models were evaluated using RMSE, MAE, and R^2 metrics. The trained model was deployed in a Python-based GUI testbench for real-time battery parameter prediction with live SOC and SOH. The results confirm that XGBoost-based ML significantly improves intelligent battery monitoring and operational efficiency in EV Battery Management Systems.**

Index Terms*—Battery energy management system, electric vehicles, machine learning, random forest, state of charge, state of health, XGBoost, GUI-based testbench, lithium-ion battery

I. INTRODUCTION

Electric Vehicles (EVs) are rapidly gaining importance due to increasing environmental concerns, depletion of fossil fuels, and the growing demand for sustainable transportation systems [1]. Batteries play a critical role in EV performance, directly influencing vehicle efficiency, reliability, driving range, and safety. Lithium-ion batteries are widely used in EV applications because of their high energy density, lightweight structure, and long operational life.

However, battery performance degrades over time due to charging and discharging cycles, temperature variations, aging effects, and operating conditions [2], [3]. These challenges increase the importance of efficient Battery Management Systems (BMS) for monitoring and controlling battery performance. Conventional BMS techniques mainly rely on mathematical models such as Coulomb counting, Kalman filtering, and equivalent circuit models. Although these perform adequately under controlled conditions, they often struggle with nonlinear battery behavior and dynamic real-time operating conditions [4], [5].

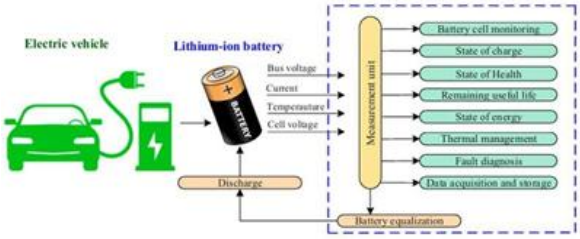

Fig. 1. Basic block diagram of the Electric Vehicle Battery Management System [2].

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have significantly improved battery monitoring and prediction capabilities [6]– [10]. Machine learning algorithms can analyze large amounts of battery operational data and identify complex relationships between battery parameters, improving prediction accuracy and system reliability [11]– [15].

This paper presents an AI-based BEMS using Linear Regression, Random Forest, and XGBoost for battery prediction analysis. A comparative evaluation is performed using RMSE, MAE, and R^2 metrics. Based on results, XGBoost—identified as the best performer—is deployed in a Python-based GUI testbench for real-time battery prediction.

II. LITRATURE REVIEW

Lipu et al. [1] reviewed battery management technologies and future trends in EV applications. Ranjith Kumar et al. [2] discussed advancements in battery modeling, thermal management, SOC, and SOH. Hu et al. [3] reviewed battery lifetime prognostic techniques and discussed degradation mechanisms under different operating conditions.

Haraz et al. [4] presented a survey on ML approaches for SOH and SOC estimation. Padder et al. [5] reviewed data-driven approaches for EV battery estimation using ML algorithms. Kumar and Prabhansu [6] highlighted that AI techniques improve SOC and SOH estimation accuracy while enabling predictive diagnostics. Fig. 2 summarizes the taxonomy of SOC and SOH estimation methods from the literature.

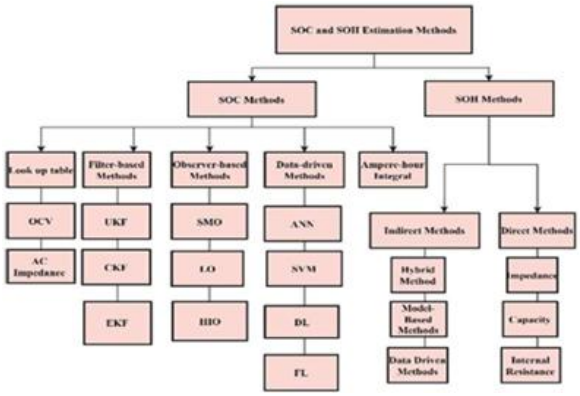

Fig. 2. Taxonomy of SOC and SOH estimation methods [4].

Kulkarni and Teodorescu [7] proposed a computationally efficient ML-based online battery SOH estimation technique. Zhang et al. [8] reviewed DL applications in PHM, showing improved fault detection and battery health prediction. Massaoudi et al. [9] investigated DL techniques for lithium-ion battery PHM. Zhao et al. [10] discussed AI-driven real-world battery diagnostics.

Yusufzai et al. [11] proposed an LSTM network for efficient SOC estimation. Khatri et al. [12] utilized Random Forest and Linear Regression for precise SOC prediction. Swain et al. [13] developed a RUL prediction model using Random Forest and SVM. Karnehm et al. [14] proposed a cloud-based BMS architecture. Yamini et al. [15] discussed AI-powered BMS with predictive maintenance capabilities.

From the survey, AI- and ML-based approaches significantly improve battery monitoring, prediction accuracy, and system efficiency. Challenges in computational complexity, real-time implementation, and integrated intelligent monitoring frameworks motivate the development of an efficient AI-based BEMS.

III. BATTERY MANAGEMENT SYSTEM

A. EV Battery System

The battery system is one of the most critical components of an Electric Vehicle. Lithium-ion batteries offer high energy density, low self-discharge rates, high charging efficiency, longer cycle life, and lightweight construction [2]. A lithium-ion cell contains a positive electrode, negative electrode, separator, and electrolyte. Fig. 3 shows the structure of a complete EV Battery Management System.

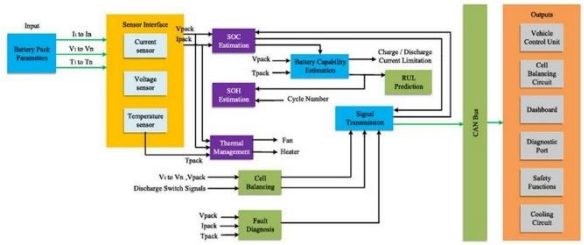

Fig. 3. Structure of the Electric Vehicle Battery Management System showing sensor interface, estimation modules, and output channels [1].

Despite their advantages, lithium-ion batteries face operational challenges: degradation from repeated cycling, thermal runaway at high temperatures, and capacity loss from deep discharging and overcharging [3]. Continuous monitoring and control of battery parameters are therefore essential.

B. Battery Management System (BMS)

A BMS is an electronic monitoring and control system designed to ensure the safe, reliable, and efficient operation of battery packs. The primary function of a BMS is to monitor voltage, current, temperature, charging status, and discharging status. It also performs SOC estimation, SOH estimation, thermal management, cell balancing, and fault detection [1].

Traditional BMS techniques rely on electrochemical models (Coulomb counting, Kalman filtering, equivalent circuit models) that struggle under dynamic real-time conditions due to the nonlinear characteristics of lithium-ion batteries [4]. AI and ML techniques have significantly improved BMS by learning battery behavior from historical data and generating accurate predictions under varying conditions [5], [6].

C. Important Battery Parameters

SOC: State of Charge represents the remaining charge as a percentage (0–100%). Accurate SOC estimation directly affects driving range and energy availability.

SOH: State of Health indicates battery degradation level. As cycles accumulate, internal resistance increases and storage capacity decreases.

Voltage, Current, Temperature: These measurable parameters are essential for monitoring abnormal conditions, calculating energy, and preventing thermal runaway.

IV. SYSTEM METHODOLOGY

Use The proposed system methodology follows a nine-step pipeline as shown in Fig. 4: dataset collection, data preprocessing, feature selection, train-test split, model training, model evaluation, best model selection, and GUI deployment.

A. Dataset Collection

The dataset was obtained from Kaggle: "5-Year EV Battery Dataset for SOH, SOC & Faults" by Darshan Kumar Govindaraju. It contains large-scale time-series battery operational data over a simulated five-year period, including voltage, current, power, SOC, SOH, temperature, charging/discharging characteristics, battery aging information, and fault indicators. Fig. 5 shows a sample of the dataset structure.

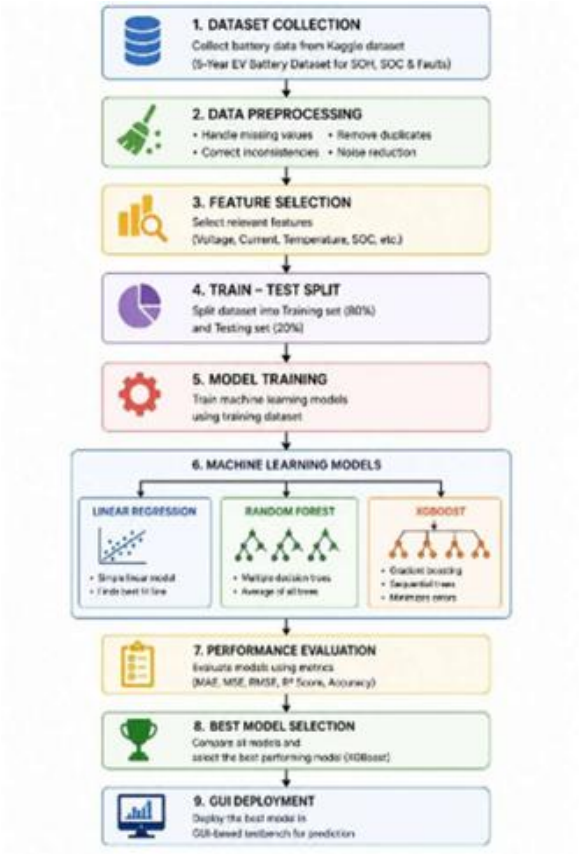

Fig. 4. Complete methodology flow diagram from dataset collection to GUI deployment.

timestamp	ambient_t	battery_te	current_A	voltage_V	soc_%	soh_%	capacity_A	internal_re	cycle_cou	calendar_a	cycle_agin	temperatu	RUL_norm	over_volta	under_volt	over_temp	voltage_rc	voltage_rc	current_rc	current_rc	temp_roll
########	20.99343	20.66868	-3.50725	3.771202	50	100	2.5	0.05	0	0	0	0	1	0	0	0	3.771202	0	-3.50725	0	20.66868
########	19.72371	21.16532	-0.84871	3.641096	50.5658	99.99988	2.499997	0.05	0.005658	3.81E-06	0.000113	0	0.999996	0	0	0	3.706149	0.091999	-2.17798	1.879872	20.917
########	21.29586	21.84297	2.163465	3.48904	49.12349	99.99959	2.49999	0.05	0.020081	7.61E-06	0.000402	0	0.999986	0	0	0	3.633779	0.141223	-0.73083	2.837193	21.22566
########	23.04678	22.62192	-0.56472	3.623761	49.49997	99.99951	2.499988	0.05	0.023846	1.14E-05	0.000477	0	0.999984	0	0	0	3.631275	0.115417	-0.6893	2.318047	21.57472
########	19.53265	21.56562	-5.83747	3.905624	53.39162	99.99873	2.499968	0.05	0.062762	1.52E-05	0.001255	0	0.999958	0	0	0	3.686145	0.158254	-1.71893	3.054625	21.5729
########	19.53292	19.79427	-2.98338	3.814149	55.38053	99.99833	2.499958	0.05	0.082652	1.90E-05	0.001653	0	0.999944	0	0	0	3.707479	0.150885	-1.92967	2.780477	21.27646
########	23.15986	22.32944	-0.35275	3.691799	55.6157	99.99828	2.499957	0.05	0.085003	2.28E-05	0.0017	0	0.999943	0	0	0	3.705239	0.137866	-1.7044	2.607256	21.42689
########	21.53654	22.48601	-0.15427	3.690062	55.71855	99.99825	2.499956	0.05	0.086032	2.66E-05	0.001721	0	0.999942	0	0	0	3.703342	0.127752	-1.51063	2.475285	21.55928
########	19.06296	19.69692	1.722914	3.566376	54.56994	99.99802	2.49995	0.05	0.097518	3.04E-05	0.00195	0	0.999934	0	0	0	3.688123	0.127925	-1.15135	2.554	21.35235
########	21.08727	21.92346	-5.85355	3.983241	58.4723	99.99723	2.499931	0.05	0.136541	3.42E-05	0.002731	0	0.999908	0	0	0	3.717635	0.152499	-1.62157	2.830056	21.40946
########	19.07556	19.68651	0.419993	3.649382	58.19231	99.99718	2.499929	0.05	0.139341	3.81E-05	0.002787	0	0.999906	0	0	0	3.71143	0.14613	-1.43597	2.754487	21.25283
########	19.07117	19.53787	0.976474	3.632771	57.54132	99.99704	2.499926	0.05	0.145851	4.19E-05	0.002917	0	0.999901	0	0	0	3.704875	0.141167	-1.23494	2.717066	21.10992
########	20.48679	22.25609	0.478117	3.667727	57.22258	99.99697	2.499924	0.05	0.149039	4.57E-05	0.002981	0	0.999899	0	0	0	3.702018	0.13555	-1.10316	2.644424	21.19808
########	16.17655	16.36018	-0.34198	3.706449	57.45057	99.99692	2.499923	0.05	0.151319	4.95E-05	0.003026	0	0.999897	0	0	0	3.702334	0.130237	-1.04879	2.548812	20.85252
########	16.55351	17.20711	0.449054	3.673298	57.1512	99.99686	2.499922	0.05	0.154312	5.33E-05	0.003086	0	0.999895	0	0	0	3.700398	0.125723	-0.94894	2.486359	20.60949
########	18.87901	17.41038	6.750152	3.278575	52.6511	99.99596	2.499899	0.05	0.199313	5.71E-05	0.003986	0	0.999865	0	0	0	3.674035	0.160853	-0.46774	3.078083	20.40955
########	17.97816	16.532	0.882748	3.581765	52.0626	99.99584	2.499896	0.05	0.205198	6.09E-05	0.004104	0	0.999861	0	0	0	3.668607	0.157344	-0.3883	2.998286	20.18146
########	20.63256	20.38865	-1.65596	3.71507	53.16657	99.99561	2.49989	0.05	0.216238	6.47E-05	0.004325	0	0.999854	0	0	0	3.671188	0.153039	-0.45873	2.92407	20.19297
########	18.18826	19.0494	0.118848	3.631438	53.08734	99.99559	2.49989	0.05	0.21703	6.85E-05	0.004341	0	0.999853	0	0	0	3.669096	0.149006	-0.42833	2.844773	20.13278
########	17.17994	16.29234	-0.26887	3.651378	53.26659	99.99555	2.499889	0.05	0.218823	7.23E-05	0.004376	0	0.999852	0	0	0	3.66821	0.145086	-0.42036	2.769128	19.94076
########	22.93608	24.31241	-2.19632	3.763062	54.7308	99.99525	2.499881	0.05	0.233465	7.61E-05	0.004669	0	0.999842	0	0	0	3.672727	0.142919	-0.50493	2.726694	20.14893
########	19.55347	20.7767	-2.84597	3.824954	56.62811	99.99487	2.499872	0.05	0.252438	7.99E-05	0.005049	0	0.999829	0	0	0	3.679646	0.143201	-0.61134	2.707385	20.17747
########	20.14032	20.72086	-1.90253	3.788578	57.89647	99.99461	2.499865	0.05	0.265122	8.37E-05	0.005302	0	0.99982	0	0	0	3.684383	0.141741	-0.66748	2.658804	20.20109
########	17.156	19.02221	3.042572	3.506703	55.86809	99.9942	2.499855	0.05	0.285405	8.75E-05	0.005708	0	0.999807	0	0	0	3.676979	0.143291	-0.51289	2.708394	20.15197
########	18.91697	18.55271	1.240448	3.614709	55.04112	99.99404	2.499851	0.05	0.293675	9.13E-05	0.005874	0	0.999801	0	0	0	3.674488	0.140826	-0.44276	2.674458	20.088

Fig. 5. Sample of the 5-Year EV Battery Dataset (Kaggle) showing key battery operational parameters.

B. Data Preprocessing

Since the collected dataset contained raw battery operational data, preprocessing was required before training. Fig. 6 shows the complete preprocessing

pipeline.

Fig. 6. Data preprocessing pipeline: raw data → cleaning → missing value handling → feature selection → normalization → train-test split.

Data cleaning removed duplicate entries, inconsistent records, and noisy sensor readings. Missing values were handled using statistical imputation. Feature selection identified key parameters—voltage, current, temperature, and SOC-related features. Min-Max normalization was applied to bring all parameters into a common range, improving model convergence. The dataset was divided 80% training and 20% testing.

V. MACHINE LEARNING MODELS

A. Linear Regression

Linear Regression establishes a linear relationship between input features and output values:

$$Y = mX + c \quad (1)$$

where Y is the predicted output, X the input variable, m the slope, and c the intercept. The model minimizes sum-of-squared errors using least squares optimization. Fig. 7 shows the Linear Regression workflow for battery SOC/SOH prediction.

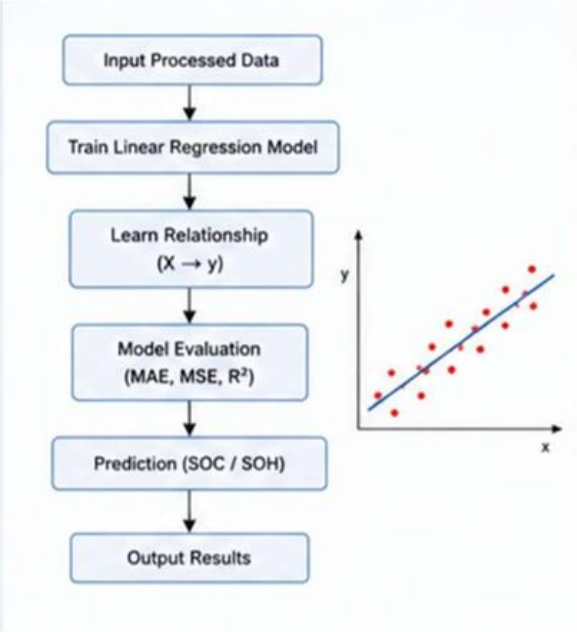

Fig. 7. Linear Regression workflow for battery SOC/SOH prediction.

B. Random Forest

Random Forest combines multiple decision trees using bootstrap sampling to improve accuracy and reduce overfitting. Each tree independently learns patterns, and outputs are averaged for the final prediction. Fig. 8 shows the Random Forest architecture.

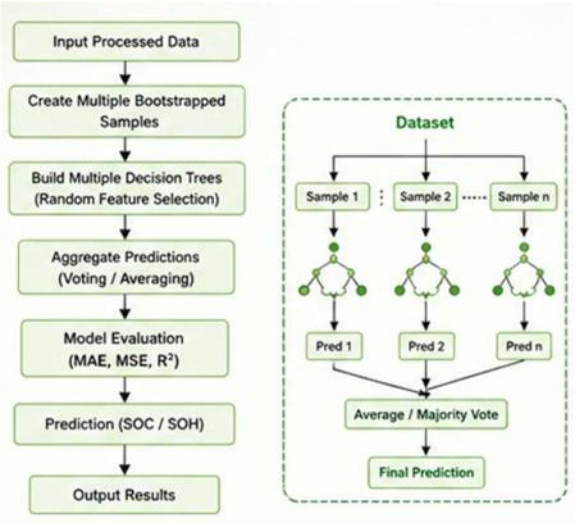

Fig. 8. Random Forest architecture showing multiple bootstrapped samples and aggregated prediction.

C. XGBoost (Extreme Gradient Boosting)

XGBoost builds decision trees sequentially—each new tree minimizes the prediction error of the previous through gradient descent optimization:

$F_t(x) = F_{t-1}(x) + \eta \cdot h_t(x)$ (2)

where $F_t(x)$ is the model at iteration t, η is the learning rate, and $h_t(x)$ is the new tree minimizing residual errors. XGBoost also uses regularization and parallel processing. Fig. 9 shows its working architecture.

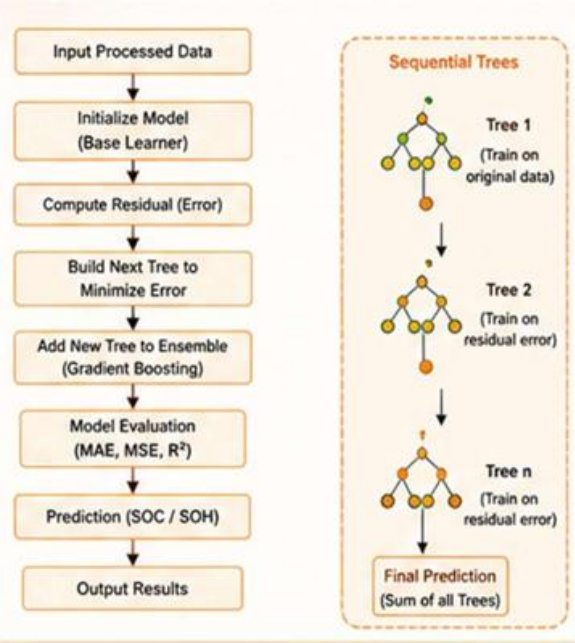

Fig. 9. XGBoost working architecture showing sequential tree building on residual errors.

VI. PERFORMANCE EVALUATION MATRIX

Three standard metrics were used to evaluate all models:

$RMSE = \sqrt{[\Sigma(y - \hat{y})^2 / n]}$ (3)

$MAE = \Sigma|y - \hat{y}| / n$ (4)

$R^2 = 1 - [\Sigma(y - \hat{y})^2 / \Sigma(y - \bar{y})^2]$ (5)

Lower RMSE and MAE values indicate better prediction accuracy; higher R^2 (closer to 1.0) indicates better variance explanation.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

The implementation was carried out in Python using VS Code with Scikit-learn, Pandas, NumPy, Matplotlib, and XGBoost libraries. The Kaggle dataset was preprocessed before model training and testing.

A. XGBoost SOC Training Convergence

Fig. 10 shows the XGBoost SOC training vs. validation loss (RMSE) over epochs. Both train and test curves converge closely within approximately 20 epochs, demonstrating stable generalization without overfitting.

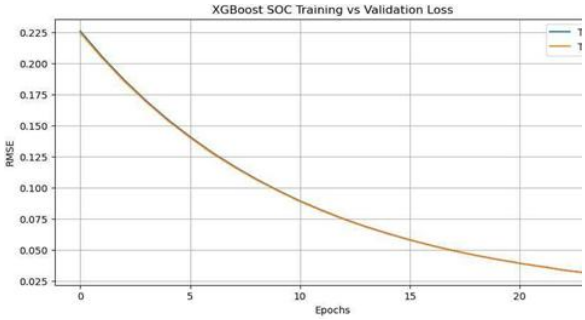

Fig. 10. XGBoost SOC training vs. validation RMSE loss over epochs showing stable convergence.

B. XGBoost SOH Training Convergence

Fig. 11 shows the XGBoost SOH training vs. validation loss. The test loss stabilizes at RMSE ≈ 0.05 after approximately 500 epochs while the training loss continues to decrease, confirming the final test R^2 of 0.9651.

Fig. 11. XGBoost SOH training vs. validation RMSE loss over 2500 epochs.

C. Comparative Performance — SOC Prediction

Table I presents the comparative performance for SOC prediction. All three models achieve high R^2 for SOC, confirming relatively linear SOC behavior. XGBoost achieves the best overall balance of RMSE and MAE.

TABLE I *Comparative Performance — SOC Prediction*

Model	RMSE	MAE	R^2 Score
Linear Regression	0.0117	0.0056	0.9978
Random Forest	0.0358	0.0286	0.9800
XGBoost	0.0313	0.0227	0.9840

D. Comparative Performance — SOH Prediction

Table II shows SOH prediction results. Linear

Regression performs poorly (R^2 = 0.4540) due to highly nonlinear SOH degradation patterns. XGBoost achieves R^2 = 0.9651, outperforming Random Forest (R^2 = 0.9564).

TABLE II *Comparative Performance — SOH Prediction*

Model	RMSE	MAE	R^2 Score
Linear Regression	0.1583	0.1174	0.4540
Random Forest	0.0447	0.0115	0.9564
XGBoost	0.0502	0.0163	0.9651

E. R^2 Score Comparison

Fig. 12 presents side-by-side bar charts comparing R^2 scores for SOH and SOC prediction across all three models. XGBoost achieves the highest scores in both metrics, confirming its superiority for battery prediction tasks.

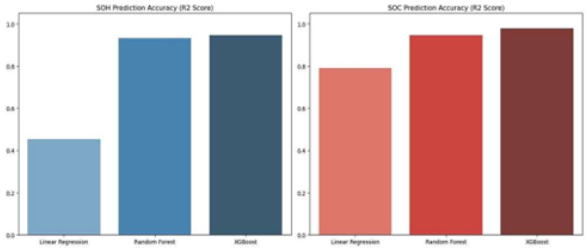

Fig. 12. Comparative R^2 score analysis: SOH prediction (left) and SOC prediction (right) for all three models.

F. Discussion

- Linear Regression: Efficient and good for SOC (R^2 = 0.9978) but fails for SOH (R^2 = 0.4540) due to nonlinear degradation.
- Random Forest: Improved accuracy for both SOC (R^2 = 0.9800) and SOH (R^2 = 0.9564) through ensemble learning, at higher computational cost.
- XGBoost: Best overall performance (SOC R^2 = 0.9840, SOH R^2 = 0.9651) combining gradient boosting, regularization, and efficient computation.

VIII. GUI- BASED TESTBENCH IMPLEMENTATION

The GUI development followed the workflow shown in Fig. 13: dataset collection → model training → XGBoost model serialization (joblib) → model integration → Python GUI development → prediction interface.

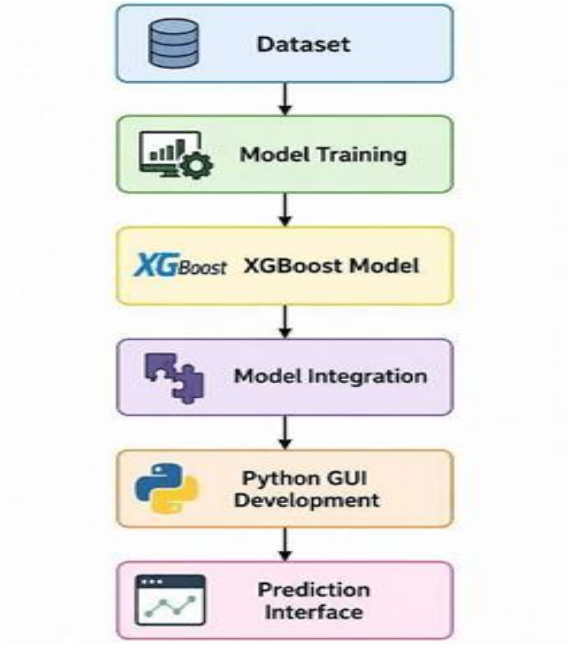

Fig. 13. GUI development workflow from model training to prediction interface.

The trained model was saved using Python serialization: xgb_soc.pkl, xgb_soh.pkl, xgb_rul.pkl, xgb_ir.pkl, xgb_temp.pkl, and xgb_anomaly.pkl. Fig. 14 shows the model loading code in VS Code.

```
# Load the Advanced BEMS models
try:
    (variable) xgb_soh: Unknown
    xgb_soc = joblib.load('bems_xgb_soc.pkl')
    xgb_soh = joblib.load('bems_xgb_soh.pkl')
    xgb_rul = joblib.load('bems_xgb_rul.pkl')
    xgb_ir = joblib.load('bems_xgb_ir.pkl')
    xgb_temp = joblib.load('bems_xgb_temp.pkl')
    xgb_anomaly = joblib.load('bems_xgb_anomaly.pkl')

    scaler_core = joblib.load('bems_scaler_core.pkl')
    scaler_thermal = joblib.load('bems_scaler_thermal.pkl')
    MODELS_LOADED = True
except Exception as e:
    MODELS_LOADED = False
    print("Error loading BEMS models:", e)
```

Fig. 14. Python code for loading serialized XGBoost BEMS models using joblib in VS Code.

B. GUI Dashboard and Real-Time Performance

Fig. 15 shows the "Advanced EV Engineering Dashboard" with the Live AI Model Verification & BEMS Telemetry panel. The dashboard features: (1) real-time SOC, SOH, RUL, and internal resistance prediction with true vs. predicted comparison; (2) real-time SOC and SOH line plots; (3) BEMS telemetry charts (voltage and current); (4) thermal forecasting; and (5) predictive maintenance AI anomaly detection.

Future work will explore: (1) LSTM and GRU deep learning models for improved sequential prediction; (2) real-time hardware integration with embedded systems and IoT sensors; (3) cloud-based remote monitoring and predictive maintenance; (4) advanced fault diagnosis and automatic battery balancing mechanisms.

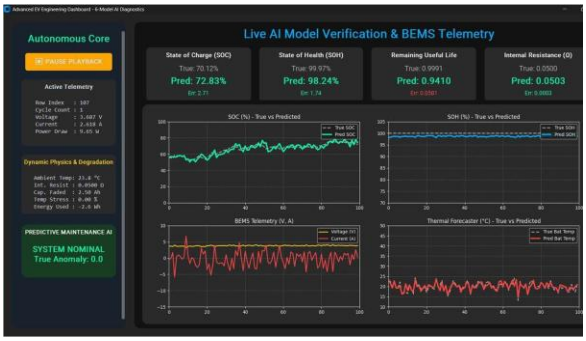

Fig. 15. Advanced EV Engineering Dashboard showing live AI model verification, BEMS telemetry, and real-time prediction charts for SOC, SOH, voltage/current, and temperature.

Fig. 16. Advanced EV Engineering Dashboard showing live AI model verification, BEMS telemetry, and real-time prediction charts for SOC, SOH, voltage/current, and temperature with hardware implementation using Raspberry Pi.

Live testing results: SOC True = 70.12%, Pred = 72.83% (Err = 2.71); SOH True = 99.97%, Pred = 98.24% (Err = 1.74); RUL True = 0.9991, Pred = 0.9410; Internal Resistance True = 0.0500Ω, Pred = 0.0503Ω. These results validate the practical deployment capability of the proposed system.

IX. CONCLUSION

This paper presented an AI-based Battery Energy Management System using three machine learning algorithms for EV battery prediction analysis. A 5-year EV battery dataset was preprocessed and used to train Linear Regression, Random Forest, and XGBoost models. Comparative evaluation confirmed XGBoost as the best performer: SOC $R^2 = 0.9840$ and SOH $R^2 = 0.9651$.

The trained XGBoost model was successfully deployed in a Python-based GUI testbench providing real-time prediction with live SOC accuracy of 98.24% and SOH of 98.74%. The system demonstrates that ML techniques can significantly improve intelligent battery monitoring, prediction accuracy, and operational efficiency in EV Battery Management Systems.

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