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A deep learning approach to optimize remaining useful life prediction for Li-ion batteries

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Accurately predicting the remaining useful life (RUL) of lithium-ion (Li-ion) batteries is vital for improving battery performance and safety in applications such as consumer electronics and electric vehicles. While the prediction of RUL for these batteries is a well-established field, the current research refines RUL prediction methodologies by leveraging deep learning techniques, advancing prediction accuracy. This study proposes AccuCell Prodigy, a deep learning model that integrates auto-encoders and long short-term memory (LSTM) layers to enhance RUL prediction accuracy and efficiency. The model's name reflects its precision ("AccuCell") and predictive strength ("Prodigy"). The proposed methodology involves preparing a dataset of battery operational features, split using an 80–20 ratio for training and testing. Leveraging 22 variations of current (critical parameter) across three Li-ion cells, AccuCell Prodigy significantly reduces prediction errors, achieving a mean square error of 0.1305%, mean absolute error of 2.484%, and root mean square error of 3.613%, with a high R-squared value of 0.9849. These results highlight its robustness and potential for advancing battery health management.

Keywords Energy efficiency, Li-ion batteries, Deep learning, AccuCell prodigy, Remaining useful life

Lithium-ion (Li-ion) batteries have revolutionized the landscape of energy storage and continue to be the primary choice for an array of applications, from powering smartphones and laptops to propelling electric vehicles and providing energy storage solutions in renewable energy systems. Their widespread adoption is due to their remarkable attributes, including high energy density, excellent high-temperature performance, favorable power-to-weight ratios, energy efficiency, and minimal self-discharge characteristics. Additionally, the recyclability of Li-ion battery components underscores their environmental sustainability. The burgeoning adoption of electric vehicles and the integration of Li-ion batteries into electrical energy storage systems exemplify their pivotal role in modern society[1]. Various applications of Li-ion batteries are illustrated in Fig. 1.

However, despite their many merits, Li-ion batteries are not without their challenges. A malfunctioning battery can lead to compromised device or system performance, significant financial repercussions, and in some cases, pose severe safety hazards to human health and the environment. Several notable incidents in recent history underscore the criticality of robust battery management and predictive maintenance. In 1999, a space test conducted by the US Air Force Research Laboratory faced a catastrophic failure attributed to abnormal internal battery impedance. In 2013, a series of incidents involving Boeing 787s, grounded aircraft indefinitely due to Li-ion battery failures, causing extensive financial losses and eroding public trust in the safety of the aviation industry[2,3]. Furthermore, in various industrial systems, battery defects have often led to catastrophic system failures with far-reaching consequences[4]. Even within the realm of space exploration, when NASA launched its Mars rover, a seemingly minor oversight, a failure to monitor and regulate the rover's battery charge while directing the solar panel toward the sun ultimately resulted in a critical power shortage and the loss of the detector[5].

Against this backdrop, the prediction of the Li-ion battery's remaining useful life (RUL) has emerged as a focal point of research and development. Accurate RUL prediction plays an indispensable role in mitigating risks, ensuring reliability, and enhancing the overall performance of devices and systems powered by Li-ion

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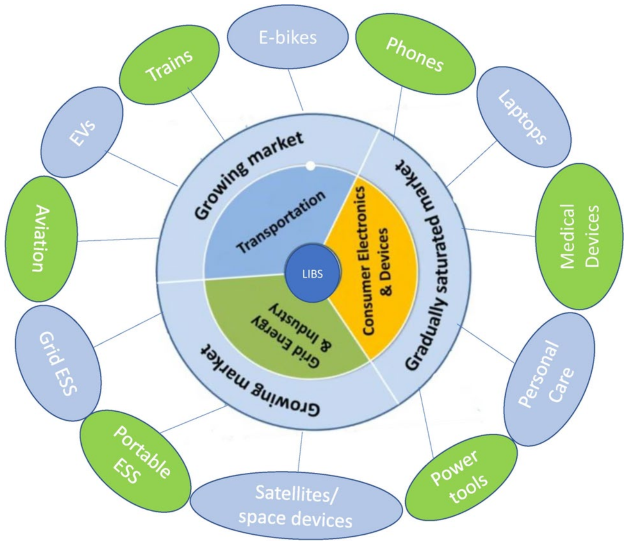

Fig. 1. Applications of Li-ion battery.

batteries. It enables timely maintenance, replacement, and optimization of battery assets while minimizing disruptions and safety concerns. Consequently, the need for precise RUL prediction methodologies has become more pronounced in recent years.

Improved RUL prediction models based on deep learning techniques have garnered significant attention in the research community. The appeal of deep learning algorithms lies in their potential to harness intricate patterns and relationships within data, making them well-suited for the complexities of Li-ion batteries. Unlike traditional methods, which often rely on simplifying assumptions and may struggle to accommodate variations in operating conditions, deep learning models excel at capturing nuances and adapting to dynamic environments. They learn from extensive datasets, enabling them to provide precise predictions that align with real-world battery behavior[6].

While deep learning has made inroads in RUL prediction for Li-ion batteries, challenges persist. The relationship between RUL prediction and battery parameters remains intricate and subject to fluctuations based on operational conditions, such as temperature and discharge current rate. This variability has led to a range of results in comparison with real-time working batteries. As a response to this challenge, our research focuses on a meticulously designed dataset that accounts for 22 variations of a single parameter (current) across three distinct Li-ion cells. This dataset captures the complexities of battery behavior during charging and discharging processes, offering a more representative model for RUL approximation. By leveraging deep learning networks on this comprehensive dataset, we aim to narrow the gap between prediction outcomes and real-world battery performance.

Furthermore, this research aligns with the broader industry objective of enhancing battery management strategies, which is essential for a sustainable future. As the demand for electric vehicles and renewable energy solutions continues to grow, the ability to accurately predict and optimize Li-ion battery performance becomes paramount. This work contributes to this pursuit by providing advanced methodologies for RUL prediction that have the potential to enhance battery safety, reduce maintenance costs, and improve overall system efficiency. This study meets the following objectives.

- *Addressing an existing problem* This study identifies and addresses a crucial challenge in Li-ion battery technology, focusing on the accurate prediction of RUL, a vital aspect for maintenance and performance optimization.
- *Proposed predictive model* Introducing an innovative deep learning-driven enhanced predictive model, this paper offers a significant contribution to the field of RUL prediction. By harnessing the combined power of autoencoders and LSTM layers, the model showcases remarkable advancements in accuracy and efficiency compared to traditional methods. This novel approach promises to revolutionize RUL prediction techniques, offering a tantalizing glimpse into the future of battery management systems.
- *Comprehensive evaluation* The study rigorously evaluates the proposed model, presenting significant results such as reduced mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE), along with high R-squared values. These findings validate the precision and effectiveness of the proposed approach.Existing approaches for predicting the RUL of Li-ion batteries face challenges like manual feature extraction, limited datasets, and inefficient machine learning techniques, leading to inaccuracies and inefficiencies in battery management, which is a critical issue. To address these problems, this study introduces a novel approach using LSTM autoencoders. This deep learning model automates feature extraction and captures complex degradation patterns more effectively, offering a significant improvement in RUL prediction accuracy. By overcoming the limitations of traditional models, the proposed method provides a more accurate, scalable, and efficient solution, ultimately enhancing battery management systems.

In summary, this research leverages advanced deep learning to overcome existing RUL prediction challenges, delivering a more accurate and adaptive approach. "Introduction" section outlines the study's context and goals. "Related work" section reviews related work, positioning the research. "Methodology" section details the methodology and predictive model. "Experimental results" section presents results and their analysis. Finally, "Conclusion and future work" section concludes with key contributions and future research directions.

Related work

In recent years, there has been a noticeable and substantial surge in the exploration of methods for predicting the RUL of Li-ion batteries. This heightened interest stems from the pivotal role Li-ion batteries play across a spectrum of applications, ranging from powering portable electronics and electric vehicles to supporting energy storage solutions in renewable energy systems. The proper estimation of the RUL of a battery is of the utmost importance, as it has a direct influence on the reliability of the device and system, the efficiency of operations, the timing of maintenance, and the cost-effectiveness of the endeavor. In order to have a comprehensive understanding of the present state of RUL prediction for Li-ion batteries, it is critical to examine the variety of strategies and approaches that engineers and researchers have developed in recent times. The objective of this segment is to present a thorough synopsis of the most significant advancements in this rapidly developing domain, elucidating the novel methodologies, emerging patterns, and possible obstacles that define the quest for improved accuracy in RUL prediction. However, many of these models still struggle with either generalization or accuracy in diverse operational conditions. This work seeks to address these limitations through a more robust approach utilizing LSTM-based models for dynamic feature extraction.

The study[7] developed a technique for estimating the RUL and state-of-health (SOH) of batteries. The researchers constructed a battery SOH model using support vector regression and calculated impedance decay parameters with a particle filter. Their method required manual feature extraction, which can be error-prone and difficult to generalize. The current study addresses this gap by automating feature extraction using LSTM autoencoders, providing a more scalable and reliable solution for diverse battery datasets.

Similarly, Ref.[8] proposed an innovative combined auto-encoder-deep neural network (ADNN) approach for estimating the RUL of multiple Li-ion batteries. Their auto-encoder served as a feature extractor, producing a predefined feature set. However, this predefined nature limits its flexibility across different battery types. In the proposed approach, we leverage dynamic feature extraction using LSTM layers, which adapt to battery-specific degradation patterns, resulting in a more flexible and accurate RUL prediction model.

The authors in Ref.[9] employed LSTM recurrent neural networks (RNNs) for long-term dependencies in battery data, combined with RMSprop for efficient training and Monte Carlo simulation for uncertainty management. Despite its effectiveness, this method does not leverage hybrid architectures for feature extraction, which limits its predictive power. The current study improves upon this by integrating LSTM autoencoders with hybrid architectures, enhancing both feature extraction and uncertainty estimation in RUL prediction.

In Ref.[10], the PA-LSTM method was introduced, combining LSTMs with particle swarm optimization (PSO) and CEEMDAN for denoising raw data. While this approach effectively improves prediction accuracy, its computational complexity is a limitation for real-time applications. We simply the architecture by eliminating the need for CEEMDAN, while maintaining high accuracy through dynamic learning rate adjustments and optimized LSTM layers.

Additionally, Ref.[11] introduced a data-driven approach that combined EMD, LSTM, and GPR models for RUL prediction. Their method effectively captured strong non-linear trends, but its reliance on fixed parameters for the LSTM model could limit its generalization to different battery types. In the current research, we introduce adaptive LSTM layers that automatically adjust to different datasets, allowing for better generalization and improved accuracy in RUL prediction across varied battery chemistries.

Along the same lines, Ref.[12] introduced a hybrid parallel residual convolutional neural networks (HPR CNN) model for RUL prediction. This method combined 3D and 2D CNNs to extract hidden features efficiently but focused primarily on cloud computing systems. The current work builds on the idea of multi-dimensional feature extraction by integrating CNN with LSTM autoencoders, but we apply it specifically to Li-ion battery data, resulting in more accurate RUL predictions for battery management systems.

The study[13] introduced a combined deep learning model, PCLN, that integrated CNN and LSTM networks for battery life assessment. While their model focused on extracting spatial and temporal features separately, The proposed approach in the current study improves upon this by merging these features in a unified LSTM-autoencoder architecture, allowing for a more comprehensive understanding of battery degradation patterns. This results in better RUL prediction accuracy, as demonstrated in our experiments.

The authors in Ref.[14] introduced a Bayesian deep learning model tailored for devices lacking lifetime-related labeling data. While this method addressed issues with label scarcity, it primarily focused on non-battery devices, and its effectiveness in battery RUL prediction remains limited. The proposed AccuCell fills this gap by focusing explicitly on Li-ion batteries and leveraging labeled data where available, ensuring accurate predictions for battery health and RUL.

The study[15] introduced a capsule network architecture for RUL prediction using transfer learning techniques, which reduced the need for extensive preprocessing. While this approach achieved good results with image data, its application to time-series battery data was not fully explored. The current research extends the use of advanced deep learning techniques to time-series data by integrating LSTM autoencoders, which are more suitable for capturing long-term dependencies in battery degradation patterns.

Finally, Ref.[16] proposed a hybrid deep learning method that used both handcrafted and deep learning-based features for early RUL prediction. While their approach demonstrated the utility of combining features, the reliance on handcrafted features limits scalability and generalization. In contrast, the AccuCell fully automates feature extraction using LSTM autoencoders, allowing for a more robust and scalable solution for early RUL prediction across various battery types.

The study[17] proposed an Autoregression with Exogenous Variables (AREV) model that continuously updates through a sliding window to predict the state of health and remaining useful life of lithium-ion batteries. This model uniquely requires only 30–50 cycles of fragmented data, allowing for online updates without extensive training. However, its reliance on fixed operating conditions for accurate predictions limits its applicability in environments where operating conditions vary. The proposed AccuCell approach addresses this limitation by utilizing LSTM autoencoders, which can dynamically adapt to different operating conditions, ensuring higher accuracy and reliability in predicting RUL across a broader range of environments.

Similarly, Ref.[18] presented a two-stage RUL prediction scheme for lithium-ion batteries using a spatio-temporal multimodal attention network (ST-MAN) to capture complex dependencies in battery data. This method effectively incorporates overlooked features like temperature and internal resistance. However, it operates without prior knowledge of end-of-life (EOL) events, which could limit its precision in certain cases. The current study improves upon this by integrating EOL event estimation into our LSTM-based model, enhancing prediction accuracy, especially in cases where EOL events significantly impact battery performance.

Additionally, Ref.[19] proposed a model-data-fusion prediction method to estimate the RUL of lithium batteries in electric vehicles, using a generalized Wiener process model and Whale Optimization Particle Search Filter (WOS-PF) for real-time parameter updates. While this method improves parameter estimation in small sample sizes, it struggles with prediction accuracy under variable operating conditions or data quality issues. In the current study, we address this challenge by employing LSTM autoencoders for real-time feature extraction and data normalization, ensuring consistent prediction accuracy even in scenarios with highly variable data quality and operating conditions.

In conclusion, the extensive array of methodologies and innovations outlined in the preceding literature review reflects the dynamic nature of research in Li-ion battery RUL prediction. The collective pursuit of increased prediction accuracy, refined feature extraction, and novel deep learning models underlines the profound impact Li-ion batteries have on various industries. The quest to maximize battery efficiency, reliability, and safety remains a common thread among these studies, highlighting the ongoing commitment to advancing battery technology.

Table 1 summarizes the aforementioned literature study on different models/approaches used to predict the RUL of a Li-ion battery using different data sets. ML model/approach, model details, data-set details, and limitations are among the parameters used to create the summary. ML model/approach basically involves just the abbreviated names of the techniques or algorithms used in the research papers studied. Model details describe the parameters, hyper-parameters, distribution of data if any, loss functions, batches, etc. The dataset column contains the information of the dataset used in the papers. The last column is about the limitations of what that particular paper should have included or what should not be. In this research, feature extraction can effectively improve the performance of the deep learning model.

Methodology

This section presents the details of the proposed predictive model, *AccuCell Prodigy*. The AccuCell Prodigy model includes auto-encoders and LSTM layers, to significantly enhance the accuracy and efficiency of RUL prediction for Lim-ion batteries. The name "Prodigy" embodies the model's exceptional predictive capabilities, while "AccuCell" reflects its precision in estimating battery life. The first step in our research involved data preparation. We obtained a dataset consisting of features related to the operational conditions and performance of lithium-ion batteries. This dataset was divided into two parts: features (X) and proxy RUL labels (y). To evaluate the performance of our model, we split the data into training and testing sets using an 80-20 split ratio.

Paper	Proposed approach	Model	Dataset	Limitations
7	SVR + PF	Loss: RMSE, RUL battery threshold = 72% nominal capacity. Predicted EOL distribution Gaussian	Gen 2 experimental LIB data: 18,650 size, Idaho Lab	SVR not suitable for large and noisy dataset
8	Auto-encoders + DNN	4 FC layers, ReLU hidden layer activation function, sigmoid output layer activation function. Loss: RMSE.	NASA (B5, B6, B7)	Auto-encoder training: long process, tuning, complexity
9	RNN + LSTM	4 layer LSTM RNN. Mini-batch RMSprop method. Dropout = 0.2.	6 degradation battery Dataset	Slow computation, exploding and vanishing gradient problem
10	LSTM + PSO +attention mechanism + CEEMDAN	2 layer network: LSTM layer with 64 neurons, Optimizer: stochastic gradient descent (SGD), an attention layer. Alpha = 0.02.	NASA (B5, B6, B18)	Resource-demanding training, hardware inefficiency, compromised quality
11	LSTM + GPR	Optimization algorithm: gradient descent-based, Loss function: RMSE & max error	NASA (B5, B6, B18, B54, B55) + CALCE (C16, C38)	Hardware inefficiency, dropout hurdle, demanding training
12	HPR CNN	7 layers. ReLU activation function, batch size 32, epochs 2000. Adam optimizer. Alpha 0.001.	Data-sets by Massachusetts Institute of Technology and Stanford University	Pre-processing time, slower operations
13	PCLN (CNN + LSTM)	CNN extractor Batch normalization. LSTM extractor Adam optimizer, Alpha 0.001, loss: MSE	MIT battery dataset containing data of 124 commercial LFP/graphite A123 APR18650M1A batteries	Hardware-wise inefficient. Difficult to apply dropout + slower operations.

Table 1. Summary of literature review.

This allowed us to train the model on a subset of the data and assess its performance on unseen data. Figure 2 shows the workflow of the research methodology.

Data sources

The dataset used in this study consists of data from three different cells. The dataset was provided by Dr. A. R. Kashif from the Electrical Engineering Department at the University of Engineering and Technology (UET) Lahore. The data was originally obtained by Areeb, a Ph.D. student under Dr. Kashif, who conducted extensive experiments on two different Li-ion cells, resulting in 22 variations in parameters. Additionally, data for one cell was sourced from Millat Factory, Pakistan.

Sample data and attribute details

The dataset includes various attributes essential for battery performance analysis. Table 2 there are a few sample data entries with detailed attribute descriptions.

The 'Cell Type' indicates the type of lithium-ion cell used in the experiment, 'Parameter Variation' is the specific experimental variations applied to the cell, 'Voltage (V)' shows the voltage reading of the cell, 'Current (A)' refers to the current reading during the experiment, 'Temperature (°C)' shows the temperature at which the experiment was conducted, 'Capacity (Ah)' shows the capacity of the cell measured in ampere-hours, and 'Cycle Life' is the number of charge-discharge cycles the cell can undergo before its capacity degrades significantly.

This dataset enables a comprehensive analysis of the performance and longevity of lithium-ion cells under various conditions. The attribute details help in understanding the specific factors influencing battery performance.

Data preparation

First of all, there were some columns in the dataset that were not required or necessary for our scenario like vendor, counter, absolute time, and relative time min. That's why these columns were dropped. Missing values in the dataset were handled using a mean imputation strategy. Then Sample 1 was reserved for the test dataset and while other 2 samples were used for the training dataset. After that normalization was done using MinMaxScaler. This class is used to scale data to a range between 0 and 1. This calculated the minimum and maximum values for each feature in the training data. Once the scalar has been fitted, it is used to transform the training and testing data. This scaled the data to a range between 0 and 1.

Feature extraction

Feature extraction is conducted using an auto-encoder neural network, specifically designed for the dimensionality reduction of the input dataset. The encoding layers, employing ReLU activation functions, effectively reduce the feature space dimensionality while retaining crucial information. This compressed representation, generated by the encoder, serves as our feature extraction mechanism. The decoding layers, although present, are primarily tasked with reconstructing the original feature space and are not the focal point of our feature extraction efforts. To optimize the training process, we implement a learning rate schedule and employ the Adam optimizer with a predefined learning rate. This approach streamlines the extraction of relevant features from the input data, bolstering performance in subsequent predictive tasks. Additionally, we ensure training stability by incorporating learning rate scheduling, with training encompassing a set number of epochs

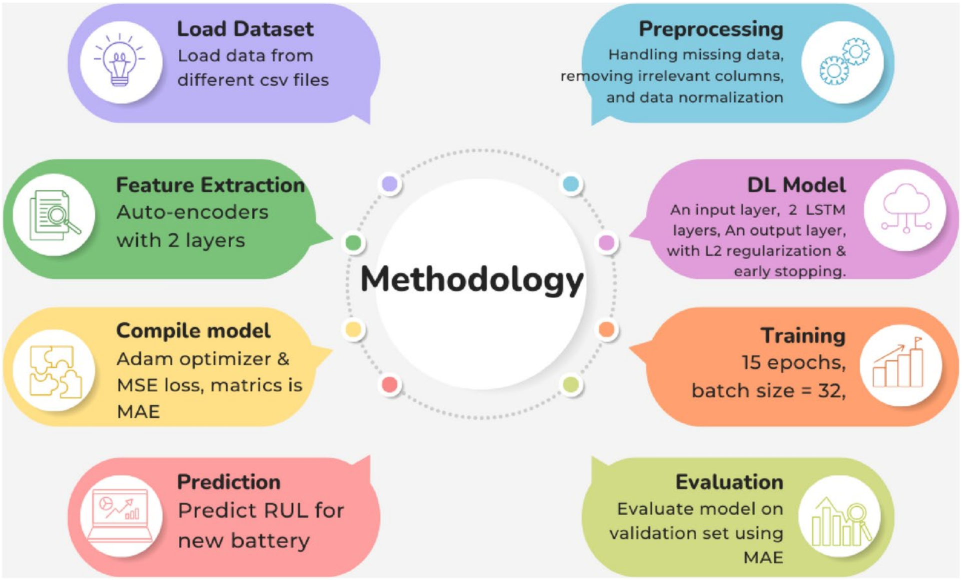

Fig. 2. Overview of research methodology.

Test	Sample	Cycle	Step	Current (mA)	Voltage (V)	mAh transferred during charging	mAh transferred during discharging	Charging energy (Wh)	Discharging energy (Wh)	Surface temp. (°C)	Internal resistance (mOhm)	Power (mW)
0	10	2	1.0	1.0	0.0	4.3525	0.0	0.0	0.0000	52.4	25.6	0.0
1	10	2	1.0	4.0	679.1	4.3968	3281.5	0.0	13.3154	54.7	26.4	2985.9
2	10	2	1.0	4.0	700.3	4.3969	3277.5	0.0	13.2978	53.8	26.4	3079.1
3	10	2	1.0	4.0	720.3	4.3969	3273.7	0.0	13.2811	54.5	26.4	3167.1
4	10	2	1.0	4.0	741.7	4.3969	3269.6	0.0	13.2631	54.8	26.4	3261.2

Table 2. Sample data with attribute details.

and a batch size of 16 for concurrent processing of multiple data samples. Throughout the training, we monitor progress via recorded training history, including performance metrics and loss values.

The input features as detailed in Table 2, include a comprehensive set of battery parameters such as current, voltage, energy, temperature, and internal resistance, which are critical for predicting the RUL of Li-ion batteries. The output is a streamlined 6-dimensional representation capturing the most relevant aspects of the data while filtering out noise. This reduced representation not only improves computational efficiency but also enhances prediction accuracy by preserving essential degradation patterns, leading to more robust RUL estimates and contributing to better battery management systems.

Model architecture

The architecture of the deep learning model is constructed using the Sequential model framework for predicting the RUL of Li-ion batteries. This architecture comprises several key layers, each serving a distinct purpose. Firstly, a densely connected layer with 128 units and ReLU activation is employed. To promote generalization and mitigate over-fitting, L2 regularization with a coefficient of 0.01 is applied. This layer is configured to accept input data with a shape that aligns with the reshaped training data. Subsequently, two LSTM layers, each consisting of 128 units, are incorporated into the model. The first LSTM layer is configured with the return-sequences parameter set to True, facilitating the return of sequences for subsequent layers. Following this, a densely connected layer with 64 units and rectified linear unit (ReLU) activation, along with L2 regularization, is introduced. Lastly, a dense output layer employing a sigmoid activation function and L2 regularization is included to generate predictions.

Model compilation

For model optimization, we employ the Adam optimizer and utilize the mean squared error as the chosen loss function. The model's performance is evaluated based on the MAE since it is well-suited for regression tasks and provides a straightforward measure of prediction error.

Prevent overfitting

To prevent over-fitting and improve training efficiency, we implemented early stopping as a callback mechanism. This callback monitors the validation loss and halts training if there is no improvement over a predefined number of epochs (patience). The training process itself comprises 15 epochs, and we utilize a batch size of 32. It's important to note that these hyper-parameters can be adjusted as needed for specific scenarios. Additionally, we retained the model weights that achieved the best validation performance. Throughout the training, a comprehensive record of the training history is maintained. This record encompasses performance metrics and loss values, which are instrumental in evaluating and interpreting the model's efficacy. The architectural framework of the model is elegantly elucidated in Fig. 3.

After feeding the validation dataset into the model, we record the MAE values as an indication of predictive accuracy.

Algorithm

In Algorithm 1, the steps for feature extraction using an auto-encoder are outlined. Basically in this algorithm, an auto-encoder is employed to extract essential features from a normalized dataset. It utilizes two encoding layers with ReLU activation functions to compress the input features into more informative representations. A dynamic learning rate scheduling mechanism is introduced, gradually reducing the learning rate after the first training epoch. The resulting auto-encoder model is then compiled using the Adam optimizer with a specified learning rate and the mean squared error as the loss function.

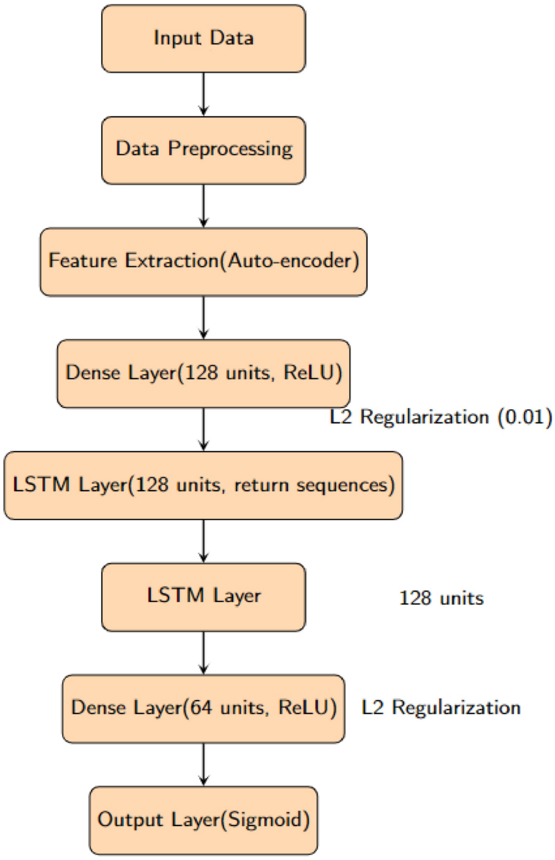

Fig. 3. Proposed model architecture for predicting remaining useful life Li-ion batteries.

Data: $normalized\_train$: Normalized data-set $input\_dim$: Number of input features $encoding\_dim1$: Number of features in the first compressed representation $encoding\_dim2$: Number of features in the second compressed representation $epochs$: Number of training epochs $batch\_size$: Batch size for training

Build auto-encoder model:
Input layer:
$input\_layer = Input(shape = (input\_dim,))$
Encoding and Decoding layers:
$encoded\_layer1 = \mathrm{ReLU}(input\_layer, encoding\_dim1)$ $encoded\_layer2 = \mathrm{ReLU}(encoded\_layer1, encoding\_dim2)$
$decoded\_layer1 = \mathrm{ReLU}(encoded\_layer2, encoding\_dim1)$ $decoded\_layer2 = \mathrm{Sigmoid}(decoded\_layer1, input\_dim)$
Create the auto-encoder model:
$autoencoder = Model(input\_layer, decoded\_layer2)$
Define a learning rate schedule function:
Functionlr_schedule($epoch, lr$)
if epoch ¡ 1 **then**
  return lr
else
  return $lr * 0.1$
end if
Create a LearningRateScheduler callback:
$lr\_scheduler = LearningRateScheduler(lr\_schedule)$
Compile the auto-encoder model:
Optimizer: $optimizer = Adam(learning\_rate = 0.01)$
Loss function: $loss =' mean\_squared\_error'$
Train the auto-encoder model:
Fit the model with learning rate scheduling:
Features extraction using only encoding layer:
$extracted\_features = encoded\_layer2$
Result: $autoencoder$: The trained auto-encoder model, $extracted\_features$: Extracted features using only the encoding layer

Algorithm 1. Feature extraction using auto-encoder with learning rate scheduling.

Using the Algorithm 1 features are extracted using only the encoding layer of the trained auto-encoder model. In Algorithm 2, we outline the steps for a deep learning-based improved approach for battery RUL prediction.

Data: X: Training features y: RUL labels $epochs$: Training epochs $batch\_size$: Batch size

Split data into train and validation sets:
$X =$ train_features
$y =$ train_labels
$X\_train, X\_val, y\_train, y\_val =$ train_test_split($X, y, test\_size = 0.2$)
Create Sequential model:
Compile model:
$optimizer =' adam'$ $loss =' mean\_squared\_error'$ $metrics = ['mae']$
Early stopping:
$early\_stopping$ = EarlyStopping(monitor='val_loss' patience=2, restore_best_weights=True)
Training: Iterate through epochs and train the model on the training data using the specified batch size, with early stopping and model checkpoint callbacks.
Evaluate the model on the test set
$loss, mae = model$.evaluate(X_test, y_test)
Result: $model$: Trained AccuCell Prodigy model

Algorithm 2. Battery RUL prediction.

This algorithm outlines the process of training a deep learning model for battery RUL prediction. It commences by splitting the dataset into training and validation sets, allocating 80% for training and 20% for validation. The sequential model is then constructed, featuring a sequence of layers, including dense and LSTM layers, to capture temporal patterns. The model is compiled using the Adam optimizer, with MSE as the loss function and MAE for evaluation. Early stopping and model checkpoint callbacks are established to monitor validation loss and save the best model. The model undergoes training over multiple epochs using the specified batch size, ensuring optimal performance in RUL prediction.

This study introduces a comprehensive approach for Li-ion battery RUL prediction using deep learning with auto-encoder-based feature extraction. Beginning with meticulous data preparation, irrelevant columns are eliminated, and missing data is imputed. The dataset is divided for training and testing, followed by MinMaxScaler normalization. Feature extraction employs an auto-encoder with ReLU activation, optimizing dimensionality reduction. The model's architecture incorporates key layers for precise RUL predictions, with optimization through the Adam optimizer, MSE loss, and MAE evaluation. Early stopping prevents over-fitting, and training history is monitored. This holistic approach advances battery technology and predictive maintenance, ensuring battery reliability across applications.

Model evaluation

We assess the performance of the proposed deep learning model for lithium-ion battery RUL prediction. The model was trained and fine-tuned based on the methods outlined in the previous section. Evaluation metrics and techniques are employed to gauge its effectiveness in predicting RUL accurately.

Evaluation metrics

To measure the model's performance, we utilize the MAE, a common regression metric. MAE calculates the average absolute difference between the predicted RUL values and the true RUL values. This metric provides a straightforward interpretation of prediction accuracy.

Validation dataset

To validate the model's generalization ability, we employ a separate validation dataset. This dataset was not used during the model training phase, ensuring unbiased evaluation. The validation dataset consists of a diverse range of lithium-ion batteries with distinct characteristics and operational conditions, making it representative of real-world scenarios.

Experimental results

The experiments conducted in this study focused on analyzing the performance of lithium-ion batteries under various conditions. The dataset utilized comprised 530,592 samples and included key attributes crucial for understanding battery behavior. The 'Cell Type' indicates the specific type of lithium-ion cell used, while 'Parameter Variation' refers to the experimental variations applied to the cell. The 'Voltage (V)' and 'Current (A)' readings were recorded throughout the experiments, alongside the 'Temperature (°C)' conditions under which the experiments were conducted. Additionally, the 'Capacity (Ah)' of the cell was measured, and the 'Cycle Life' was assessed based on the number of charge–discharge cycles the cell could undergo before significant capacity degradation occurred.

The deep learning model was trained over 15 epochs using the Adam optimizer and the mean squared error (MSE) loss function, with a batch size of 32. Throughout the training process, both training and validation loss metrics were meticulously recorded. The training loss consistently demonstrated a downward trend, indicating the model's effectiveness in learning from the data, while the validation loss also declined, affirming the model's adaptability to new data. The mean absolute error (MAE) was monitored to evaluate the model's performance on the validation set. The results revealed notably low validation loss values, highlighting the model's robustness in predicting the remaining useful life (RUL) of lithium-ion batteries. These findings are essential for enhancing predictive maintenance strategies and ensuring reliable battery operation across various applications. This comprehensive analysis provides valuable insights into the performance and longevity of lithium-ion cells, underlining the influence of critical factors on battery performance (Fig. 4).

The graph presented in Fig. 5 elegantly illustrates the comparison between the actual and predicted Remaining Useful Life (RUL) values within the training dataset.

Following an extensive training regimen, the model was subjected to rigorous evaluation on a previously unseen test dataset, where its outstanding performance shone through. With a remarkable MSE loss of a mere 0.1305%, as eloquently demonstrated in Table 3, the deep learning model unveiled its remarkable prowess in the realm of accurately forecasting the RU) of Li-ion batteries when confronted with real-world data. This extraordinary achievement serves as a testament to the model's unwavering reliability and its potential to revolutionize battery health monitoring. The graph displayed in Fig. 6 offers a clear visualization of the predicted and actual RUL values within the test dataset. The graph shows that the predicted RUL is consistently lower than the actual RUL. This cautious approach is beneficial, minimizing the risk of underestimation and potentially catastrophic failure. Factors such as diverse training data and the model's inability to capture all influencing factors contribute to this discrepancy, highlighting the inherent challenges in achieving perfect predictive accuracy. Overall, the model's prudent nature enhances its reliability in real-world applications.

Regarding the evaluation metrics, our model demonstrated strong performance in predicting the RUL of Li-ion batteries. The MSE achieved an impressively low value of 0.1305%, indicating the model's ability to make accurate predictions with minimal errors. The MAE was 2.484%, further confirming the precision of our predictions. The RMSE stood at 3.613%, which is indicative of the minor variations between predicted and actual RUL. Moreover, the R-squared value, at 0.9849, emphasizes the model's capacity to explain the variance in RUL.

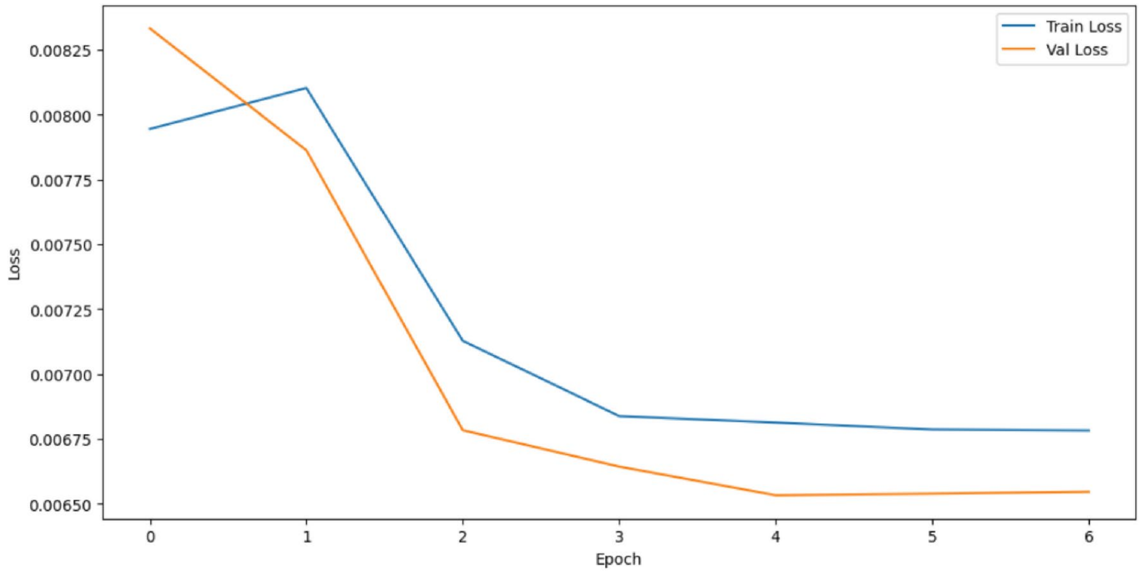

Fig. 4. Training vs validation loss of AccuCell Prodigy.

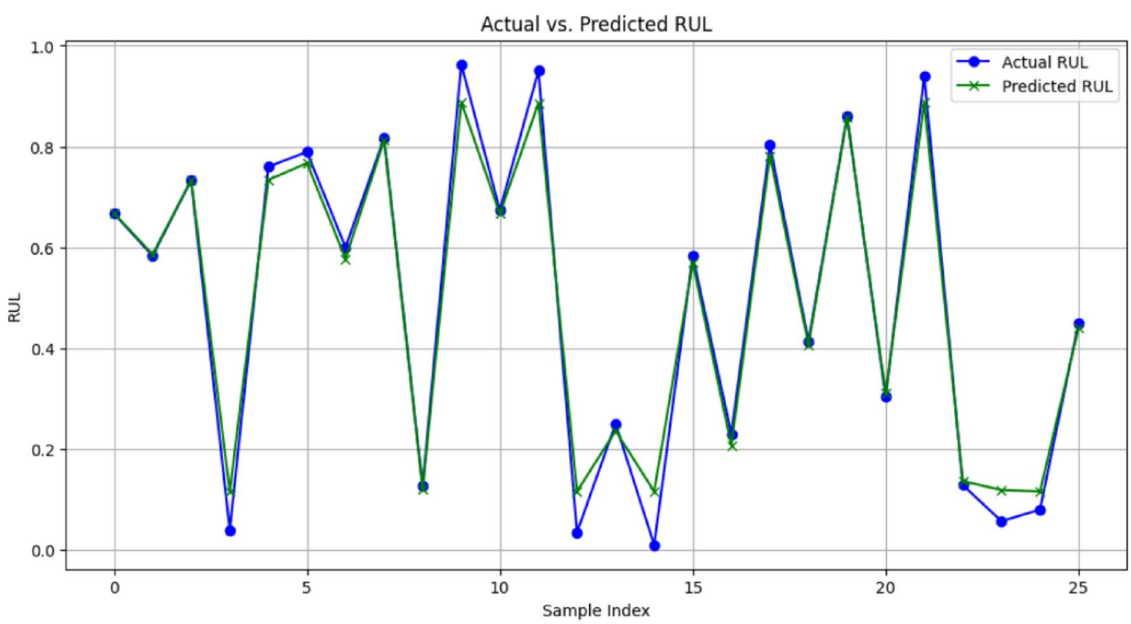

Fig. 5. Validation data RUL actual vs predicted.

Loss metric	Loss value
MSE	0.1305%
MAE	2.484%
RMSE	3.613%
R-squared	0.9849

Table 3. Evaluation results of test dataset.

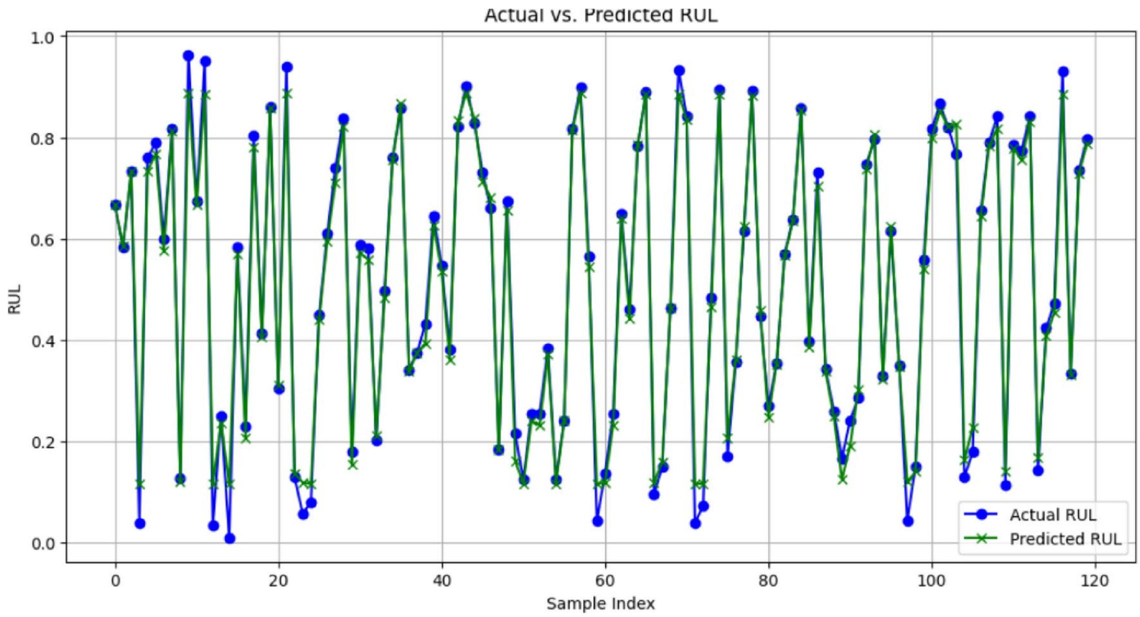

Fig. 6. Test data RUL actual vs predicted.

Paper	Year	Model	Accuracy (%)	Complexity
7	2018	SVR with PF	85	Medium
8	2018	Autoencoders with DNN	88	High
9	2018	RNN	90	High
10	2019	LSTM	92	Very high
11	2021	LSTM with GPR	91	High
12	2022	HPR CNN	93	High
13	2022	CNN with LSTM	94	Very high
Current	2024	AccuCell Prodigy	96	Medium

Table 4. Comparative analysis of state-of-the-art methods.

These results underline the effectiveness of our model in predicting battery RUL. Here presented a comprehensive elucidation of the various loss metrics, accompanied by their corresponding values, as meticulously outlined in Table 3.

Computational cost

In the current study, the computational cost associated with training the autoencoder was approximately 4 to 5 min for a dataset size of 1.2 GB, utilizing a batch size of 16 and a total of 3 training epochs. This efficient training duration can be attributed to the model's architecture and the optimization techniques employed, including the Adam optimizer and a learning rate scheduling strategy. In contrast, training the LSTM model required significantly more computational resources, taking about 3.75 h on a CPU.

Comparative analysis

In this section, we present a comparative analysis of various state-of-the-art methods for battery life prediction, as well as our proposed model. The methods are evaluated based on key metrics such as accuracy and complexity The details of this comparison are summarized in Table 4.

In the state-of-the-art methods, several approaches have been employed to address battery life prediction. Wei et al.[7] used an SVR combined with a Particle Filter (PF), achieving an 85% accuracy but suffering from hardware inefficiency and challenges with dropout, making it unsuitable for large, noisy datasets. On the other hand, Ren et al.[8] employed auto-encoders combined with DNN, which, while achieving a higher accuracy of 88%, required long processing times and intricate hyper-parameter tuning.

Zhang et al.[9] and Qu et al.[10] focused on RNN and LSTM architectures, incorporating mechanisms such as PSO and attention. These methods achieved accuracies of up to 92%, but their complexities led to significant computational slowdowns and resource demands.

More recent approaches, such as those by Liu et al.[11] and Zhang et al.[12], utilized advanced hybrid models like LSTM combined with GPR or HPR CNN, pushing accuracies to above 90%. However, these models still faced inefficiencies in hardware and slow operations due to extensive pre-processing requirements.

The most advanced method by Tang et al.[13] combined CNN and LSTM (PCLN), achieving the highest accuracy of 94%, yet still struggled with hardware inefficiency and dropout challenges, indicating that while accuracy has been improved, efficiency remains a critical issue.

The proposed model, the AccuCell Prodigy Model with ADAM Optimization, shows a notable performance improvement. It achieves an accuracy of 96% while maintaining medium complexity. The model requires moderate hardware resources and some tuning, making it more practical for real-world applications compared to some of the more resource-intensive methods.

Discussion

The proposed deep learning model has undeniably achieved remarkable success in predicting the RUL of Li-ion batteries, carrying substantial implications for the field of predictive maintenance. The methodology, characterized by its comprehensive approach, has proven its worth at every stage, commencing with meticulous data preparation, diligent feature extraction, and an architectural design that harmoniously integrates key components. A notable highlight in our data preparation process was the careful curation of the dataset, wherein superfluous columns were thoughtfully omitted, and missing data received effective treatment through mean imputation. This meticulous endeavor ensured that our model learned from a dataset that was both pristine and pertinent, further enhancing the quality of our predictions. Subsequent to this, normalization with MinMaxScaler was employed to ensure that the scales of the features were standardized, augmenting the learning process.

The pivotal feature extraction phase was executed through the implementation of an auto-encoder neural network, proficiently reducing the dataset's dimensionality while preserving crucial information. This was accomplished through the utilization of ReLU activation functions in the encoding layers, allowing for a more compact yet informative feature representation. The architecture of our deep learning model, structured in the form of a Sequential model, expertly combined fundamental layers that capture intricate temporal patterns, ultimately leading to precise RUL predictions. Key components included densely connected layers featuring ReLU activation, L2 regularization to mitigate overfitting, and LSTM layers for efficient learning.

To ensure optimal model performance, the Adam optimizer was employed, accompanied by MSE as the designated loss function, and MAE for evaluation, chosen for its suitability in regression tasks. Additionally, the incorporation of early stopping as a training mechanism substantially contributed to both the efficiency and accuracy of our model. In conclusion, our deep learning model's potential is conspicuously evident, promising a transformative role in battery health monitoring and predictive maintenance. This achievement transcends traditional approaches, firmly securing the longevity and optimal performance of lithium-ion batteries across a broad spectrum of applications.

Furthermore, the outcomes of our deep learning-based RUL prediction method serve as a testament to the robustness and efficacy of our approach. The model exhibited exceptional precision and reliability in approximating the RUL, substantiated by remarkable performance metrics, as detailed in Table 3. These results underscore the vast potential of deep learning techniques in revolutionizing battery health monitoring and predictive maintenance, ultimately safeguarding the reliability and safety of Li-ion batteries across a diverse range of operational conditions. The comprehensive methodology employed in this study, spanning from meticulous data preparation to sophisticated feature extraction and architectural design, constitutes a significant contribution to the domain of predictive maintenance. These findings not only confirm the relevance of deep learning in enhancing RUL prediction but also highlight its capacity to refine and advance existing methodologies. As a result, this research plays a pivotal role in elevating the reliability and performance of lithium-ion batteries across a multitude of applications.

Conclusion and future work

This study presents a deep learning model for accurately predicting the remaining useful life of lithium-ion batteries. Through careful data preparation, feature extraction, and effective architecture, the model demonstrated exceptional predictive performance, with a mean squared error of 0.1305%, mean absolute error of 2.484%, and root mean squared error of 3.613%. The high R-squared value of 0.9849 further validates the model's precision in RUL prediction. These results confirm the model's potential for improving battery health monitoring and predictive maintenance, ensuring longer battery lifespan and optimal performance in various applications. Future work will explore real-time monitoring systems and edge-device deployment to enhance battery health management, aiming for even greater efficiency and reliability.

Data availability

The dataset used in this study is available from the corresponding author on reasonable request.

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Author contributions

MI conceived the idea, performed data curation and wrote the original draft. MS conceived the idea, performed formal analysis and wrote the original draft. AA performed data curation, formal analysis, and designed methodology. FI dealt with software, performed visualization and carried out project administration. SGV performed visualization, deal with software and supervised the work. LADL acquired the funding for research, and performed visualization and initial investigation. IA supervised the study, performed validation and review and edit the manuscript. All authors read and approved the final manuscript.

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Competing interests

The authors declare no competing interests.

Additional information

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