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Research Article

A Comparative Analysis Of Deep Learning For Remaining Useful Life Estimation

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ABSTRACT

Predicting Remaining Useful Life (RUL) accurately in when it comes to Lithium-ion (Li-ion) batteries is very important as the demand for it is ever increasing. The maintenance and accurate prediction of the RUL of the batteries is growing as the demand for it is increasing in an exponential order mainly due to the sudden growth in the EV industry. This paper performs a comparative analysis on four of the most widely implemented deep learning architectures for RUL prediction using a dataset developed by the Centre for Advanced Life Cycle Engineering (CALCE). Models that are implemented include Long Short-Term Memory (LSTM) networks, Convolution Neural Networks (CNNs), a hybrid Autoencoder + LSTM architecture, and Transformer based model. These models are evaluated for performance on basis of computed parameters such as MSE and MAE i.e. the Mean Squared Error and Mean Absolute Error. They are also evaluated on the R^2 score. This comparison of performance between the models aims to identify the model that predicts the RUL most accurately, contributing to the better battery health management system. The experimental results show us that hybrid models such as the Transformer based model and the LSTM + Autoencoder model have a superior prediction performance in comparison to traditional deep learning models such as LSTMs and CNNs.

Keywords: Remaining Useful Life (RUL); Performance; Comparative Analysis; Estimation; Long Short-Term Memory (LSTM) networks; Convolution Neural Networks (CNNs); Autoencoder; Transformer based model.

1. Introduction

A long lifespan and an efficient operation of a major equipment is of great importance in asset management, specifically in the field of engineering and industry. Traditionally, strategies for maintenance followed a fixed-interval simple approach. This simple approach has a lot of limitations. On one side, if the maintenance is unnecessary, it puts a strain on the available resources and possibly bring in needless cost on perfectly healthy resources, on the other side, if said maintenance is delayed, they can cause catastrophic breakdowns, putting in risk the productivity and the safety. The concept of Remaining Useful Life (RUL) came out as a game changing solution, as it introduced a data-driven approach to the management of assets. RUL in simple terms is the predicted amount of time an asset, such as a system, machinery or even a component can function properly without needing major repair or replacement.
This origin of this concept came because of the growing need to streamline and optimize the process of maintenance strategies. By considering many parameters of an asset and these parameters are particular to that asset, RUL algorithms can assess this data and come out with data-driven conclusions as to the amount of Remaining Useful Life that particular asset has before needing maintenance or change. Since these are data-driven conclusions, they are highly accurate. This data gives the power to make proactive decisions, allowing resources to be strategically allocated and maintenance to be planned smartly. The importance of RUL is much more than just preventing big losses. Firstly, the maintenance cost is optimized as they can avoid unnecessary servicing by intervening only when needed, this leads to the financial savings of the organization. Secondly,

operational safety is enhanced using RUL. The detection of potential risks early on allows for proactive decision making. This helps reduce the different casualties like risking human life or the equipment surrounding the asset. Furthermore, RUL is responsible for enhanced equipment reliability. RUL is a strategic asset management tool as it provides a window into the future.

Some challenges that we face in general while attempting to predict RUL are that there are often only a few sensors that are available to monitor component health, which can limit the information available, along with any data noise and inconsistency of these sensor readings due to environmental factors or sensor malfunctions, making it difficult to extract reliable degradation trends and reduce the quality of condition data collected. Another challenge faced is that not all degradation modes would be well-understood or monitored by sensors, which may lead to blind spots in the prediction process. Another challenge faced is that not all degradation modes would be well-understood or monitored by sensors, which may lead to blind spots in the prediction process. These degradation mechanisms can be highly non-linear and vary significantly across components, even if they are within the same type. This would make it difficult to capture accurate degradation patterns.

Predicting the Remaining Useful Life (RUL) across different industries can offer a plethora of advantages for them while also optimization would be done on their processes. When a component's RUL is calculated, it is possible to avoid breakdowns because of predictive maintenance. These approaches are helpful in decreasing the costs of failures. Predicting the remaining life span may thus permit improved strategies for scheduling maintenance activities and planning their funding especially in making predictions for RUL. Such prognostic methods can be highly efficient in reducing economic costs due to component breakdown. RUL predictions can also allow for better planning and resource allocation for maintenance activities, where resources can be focused on critical components with shorter RUL, which can significantly improve maintenance strategies, enhance the availability and reliability of the equipment, and reduce its life cycle cost and downtime.

Deep learning ascertains RUL (Remaining Useful Life) for Lithium-Ion Batteries through the capacity to understand complicated patterns from huge datasets. Deep learning entails designing machine learning systems depending on neural networks that mimic brain neurons generated synthetically to represent and process data. Contrary to traditional machine learning approaches where humans need to select relevant features from datasets for the solution of a problem, deep learning in its basic form enables the automatic learning of relevant features from raw data, making it suitable for noisy or highly complex data, which is similar to data collected by sensors in Lithium-Ion Batteries. Deep learning is done through something called a neural network which in form and function is quite similar to the human brain. In our biological brains, we have nerve cells that communicate via synapses. These nerve cells are interconnected in layers through a series of synapses with each layer transforming the input signals from the previous layer to output signals. The networks of deep learning generally have a lot of such layers and helps in grasping the data in a structured way.

1. LSTM: LSTM models have memory cells, which are capable of storing information for a long period. It also has gates, allowing it to control the flow of information, hence allowing it to predict how long a lithium-ion battery can continue to function well and detect any anomalies.

2. Convolutional Neural Networks: It has layers of connected neurons that process the data and make predictions. There is an input, hidden, and output layer; some apply the activation function to learn the patterns and hence estimate the battery life from previous data.

3. Transformer Neural Networks: The transformers apply an attention mechanism that has the data processed effectively. These have an encoder and a decoder layer; each consists of an attention and feedforward network to learn complex relationships and make accurate predictions of the battery life.

4. Autoencoders + LSTM: Autoencoders in combination with LSTM avoid learning high level features of the data. They first learn these essential data features at the beginning of their training phase. LSTM subsequently builds on preceding behaviour by predicting battery longevity in the way people act over time. Hence, predicting for how long lithium-ion batteries will serve well is done through deep learning.

Using brain-like networks to understand data better, deep learning helps make the systems of the battery more dependable and long-lasting in fields like electric cars and the storage of renewable energy.

The research objective of this study is to compare the performance of different deep learning models for the prediction of the residual useful life of lithium-ion batteries. The first one makes visible the performance and accuracy of several architectures being part of the state of the art, where efforts are systematically investigated including Long Short-Term Memory, Convolutional Neural Networks, Transformer Neural Networks, Autoencoders, among others. Such comparative research helps to indicate strengths and weaknesses of each model, et al. Furthermore, this comparative analysis synthesizes multiple study findings and presents important insights into state-of-the-art RUL prediction techniques and helps in developing knowledge and providing insights for further research direction. Secondly, by understanding the performance of various DL models, practitioners and researchers will be able to make informed choices when selecting the appropriate method for their specific operating conditions, thus enhancing the reliability and usefulness of the RUL prediction systems in real-world scenarios. Contributing to the development of predictive maintenance strategies in RUL forecasts of lithium-ion batteries using different DL models will contribute to enhancing the management of the asset and cost savings at increased operational safety in various industries.

2. Literature Survey

This section explores a variety of traditional machine learning models, deep learning models, and hybrid techniques widely used for predicting the RUL of components. The traditional approach involves techniques such as Genetic Algorithms, Support Vector Regression (SVR) and later develops into hybrid deep learning architectures such as CNN, Transformer-based networks, Long short term memory (LSTM) and Gate Recurrent Units (GRU) models.
Genetic Algorithms (GAs) are shown to be a relevant tool in optimizing RUL prediction models. They are able to improve deep learning architectures, as demonstrated by (Ellefsen et al., 2019) where they reported a GA-based hyperparameter tuning of a semi-supervised deep learning model to obtain improved performance and faster convergence on the C-MAPSS dataset. In addition, (Xue et al., 2020) applied a GA to optimize an SVR model to predict the RUL of lithium-ion battery. Their approach combined the AUKF with the GA-optimized SVR, illustrating the potential of GAs to enhance a variety of RUL prediction models. Although these papers also acknowledge that some further study on the unsupervised learning techniques and degradation model complexity is needed, these papers reveal the huge contribution of GAs toward attaining more accurate and efficient RUL prediction.
Support Vector Regression is also making great strides in the prediction of RUL. (Xue et al., 2019) combined an adaptive unscented Kalman filter with a GA-optimized SVR model for effective multi-step RUL prediction of lithium-ion batteries. This attests to the efficiency of GAs in optimizing SVR for RUL tasks. In addition, (Wu et al., 2021) implemented SVR within a multimodal RUL prediction system for industrial manufacturing—successfully integrated with other machine and deep learning algorithms for better prediction accuracy. This work has shown that in both single and multi-modal RUL prediction frameworks, SVR looks increasingly promising. Nonetheless, ongoing research is addressing challenges in terms of sudden degradation of equipment.
LSTM networks create a stir in RUL prediction due to learning capabilities from sequential data. They shine in various applications. (Sun et al., 2023) have achieved high-accuracy battery RUL prediction by fusing LSTMs with advanced signal processing for noise reduction. Qu et al. have proposed the PA-LSTM that combines LSTMs with an optimization algorithm for better RUL prediction in lithium-ion batteries. These models are also quite helpful, given that LSTMs are fundamental elements of semi-supervised deep learning architectures, as proved by the research done by (Ellefsen et al., 2019), where improved RUL prediction on the C-MAPSS dataset was realized through hyperparameter tuning using LSTMs. Finally, Wu et al. succeeded in integrating LSTMs into a multi-modal RUL prediction system applied in industrial settings. New developments along these lines will make LSTMs flexible and effective for RUL prediction tasks, going a long way toward developing accurate and robust RUL prediction models across diverse application domains.

Table 1: Survey of widely used deep learning techniques.

Reference	Methodology	Models used	Dataset used
Xie et al. 2020	AMConvFGRNET (Attention-Convolution Forget-Gate Convolutional Recurrent Network)	CNN, LSTM	CMAPSS, Ball Screw Experiment dataset
Hu et al. 2022	Wavelet Denoising and Transformer Neural Network	TNN	CX237 and AQ01 datasets
Wei et al. 2021	MC_dropout GRU (Gated Recurrent Unit)	GRU	NASA's PCoE dataset
Tkiouat et al. 2018	CAE (Stacked Convolutional Autoencoder) and LSTM (Long Short-Term Memory)	LSTM, AE	Publicly available Li-ion battery degradation datasets
Zhang et al. 2022	Attn-BiLSTM (Attention-Bidirectional Long Short-Term Memory)	LSTM	NASA's PCoE dataset, CALCE datasets
Yang et al. 2019	Double-deep CNN (Convolutional Neural Network)	CNN	PRONOSTIA platform dataset
Yang et al. 2022	LSTM with Quantitative Uncertainty Techniques	LSTM	PHM2012 dataset
She et al. 2021	BiGRU (Bidirectional Gated Recurrent Unit) with Bootstrap Method	GRU	ABLT1A bearing dataset
Wu et al. 2021	Multistage Memory Life Prediction System (CNN, SVR, LSTM, LR)	CNN, LSTM, SVR	Shaft production systems data, CMAPSS dataset
Wang et al. 2022	BIGRU (Bidirectional Gated Recurrent Unit) with Fault Characteristics and CNN	GRU	CMAPSS dataset (FD001 and FD003)

AMConvFGRNET (Xie et al., 2020), were proposed to predict RUL by extracting effective features from a large amount of sensor data. Some studies have proposed frameworks with a double-deep CNN architecture: one CNN for identifying the fault onset point and the other CNN for RUL prediction based on the degradation pattern (Yang et al., 2019). Additionally, CNNs can be incorporated with other machine learning algorithms, like SVR, LSTM, and LR, in order to form a multi-stage prediction system leveraging the strengths of different techniques toward higher accuracy. This can be done based on many different sources of sensor data, such as sound, current, and temperature (Wu et al., 2021). Overall, the abilities of CNNs in feature extraction demonstrate that this method should have promising prospects in RUL prediction, especially when it's integrated with other techniques into a robust RUL prediction system for industrial application.
The use of GRUs in RUL prediction, because of the ability to handle the nonlinearity of sensor data from different applications, is picking up. Researchers are working on different variants of GRUs: MC-dropout GRU for the RUL prediction of lithium-ion battery (Wei et al., 2021), BiGRU for bearing RUL (She et al., 2021), and

BIGRU integrated with CNN for fault-aware RUL prediction in aircraft engines (Wang et al., 2022). One of the most critical challenges to be confronted is how to quantify uncertainty in RUL predictions. Wei et al. and She et al. both dealt with this by putting uncertainty estimation techniques into their GRU models. Besides, Wang et al. investigated the combination of fault information with sensor data to improve the prediction accuracy. Despite these works, gaps still exist: domain-specific RUL modeling, robust uncertainty quantification methods, and model adaptability to varying operation conditions.
Hybrid models, combining a wide range of techniques, have thus been motivated by this quest for superior RUL prediction. For example, (Ma et al., 2020) proposed a feature analytics and data-driven approach coupled with deep learning for RUL prediction. Their model extracts discharge features of the batteries and then uses an RNN with Bayesian optimization to achieve better results. Generalizability to other battery types is still a challenge. The other one is the interpretable deep learning approach with variational inference that (Kraus et al., 2019) proposed for the turbofan engines RUL prediction. This approach deals with the problem of interpretability alongside accuracy, hence achieving better results compared to the classical models, while exposing the process of degradation. Some limitations, such as not having uncertainty estimates, do exist. These hybrid models demonstrate potential for more precise and more informative RUL prediction models.

3. Proposed work

1.1. Long Short-Term Memory (LSTM)
LSTM stands for long short-term memory networks, a special kind of recurrent neural network designed for modeling very long-range dependencies and sequences in data, hence being found very useful for tasks such as prediction of remaining useful life on machinery parts. LSTM can store the information captured over a long period with the help of their unique memory cell architecture, which comes with three gates. They are input gate, forget gate and output gate. These gates control the amount of information that actually flows through them and, accordingly, the network selectively retains and forgets information. These gates include the input gate, the one that encourages influx of new data into a cell's aptitude, the forget gate, the one that decides what to eject, and the output gate, which allows exit of information from the cell state.

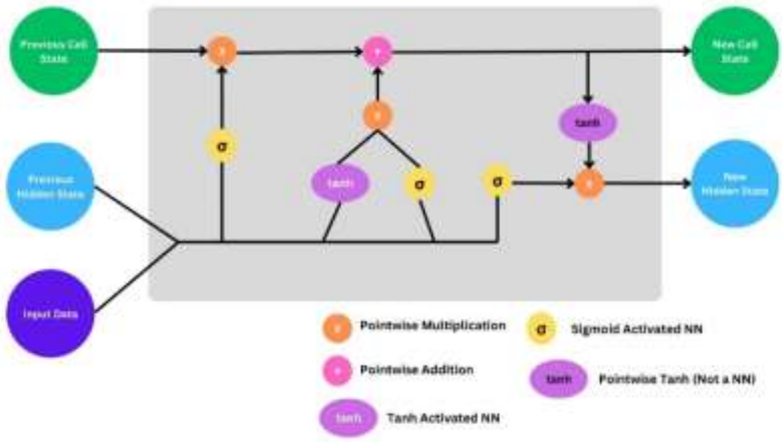


Fig. 1. Architecture of LSTM model. Previous cell states and input data determine the new output state

Helping LSTMs overcome vanishing and exploding gradient challenges in traditional RNNs is enabled by this architecture, leading to greater stability and performance when modelling long sequences. Even though their computational demands are high and they take longer training time because of their complexity, we need them because they are the only ones that can properly foresee time-dependent trends which are be used for RUL prediction. LSTMs are trained by historical sensor data and operational parameters to enable them learn complex patterns of degradation as well as operational conditions and make them capable of making precise predictions on how much longer such components will continue to serve their original purposes in various industries hence making it possible for people working in those sectors know what needs to be replaced before time catches up with them.

1.2. Convolutional Neural Network (CNN)
Convolutional Neural Networks (CNNs) are models for deep learning that are extremely famous for their capability to automatically extract features and identify patterns. It was initially created for image processing but nowadays it is also used in time series analysis as well as predictive maintenance. A CNN architecture involves the use of convolutions to scan through input data, creating features in the maps by using filters; pooling layers reduce these maps in size but ensure important information remains intact whereas fully connected transcripts help understand what they mean making a last prediction. CNNs analyse sensor data to learn wear and degradation patterns and transform time series data into overlapping segments to capture

temporal dependencies for predicting remaining useful life (RUL) of machinery parts. While they require significant computational resources and large datasets, CNNs are robust for feature extraction and accurate in prediction, ultimately aiding in predictive maintenance for improving operational efficiency in early failure detection.

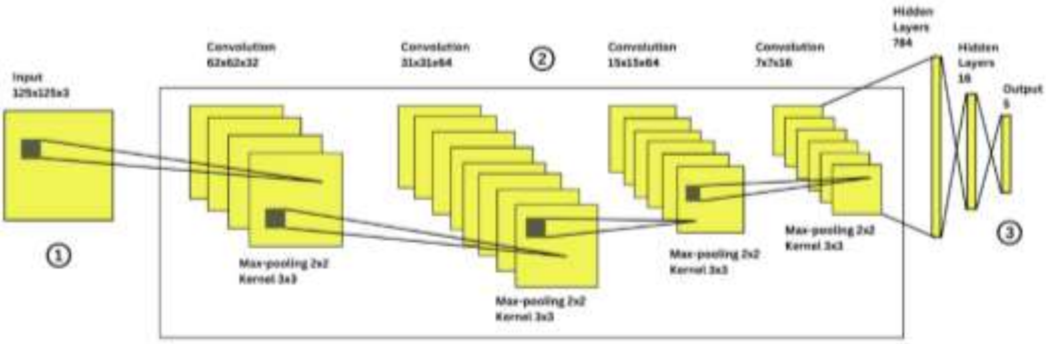


Fig. 2. The architecture of CNN model. (1) Input layer of CNN (2) Convolutional layers of CNN along with pooling layers (3) Output layer

1.3. Transformer based Neural Networks

Transformer Neural Networks (TNN) represent a new way of thinking in deep learning, and are especially appropriate for codes that need to predict useful life of components. Unlike their traditional counterparts, TNNs require an intermediary step in the form of data transformation which relates directly to the raw input data before sending it off to the network. This layer-wise transformation paradigm enables deep feed forward neural networks (TNNs) to comprehend intricate and correlated structures in data. Each of these networks possesses distinct strata that specialize in untangling the data representations, therefore boosting predictive capabilities.

The strong point about TNNs is that they are versatile and can be applied to different types of data hence producing better results. As the heterogeneous sensor data commonly encountered in RUL estimation tasks will be better handled in this key extraction features, it increases their prediction accuracy. Furthermore, TNNs exhibit robustness against noisy or incomplete data due to their ability to learn stability through data transformation. The inclusion of TNNs in the comparative analysis for RUL prediction methods provides a new approach which focuses on the effectiveness of variable-based methods for capturing temporal and spatial dependencies in data. Thus, TNNs represent a promising approach to enhance the predictive-maintenance industry to combine the principles of data transformation and deep learning to address the complexity of prediction and healthcare.

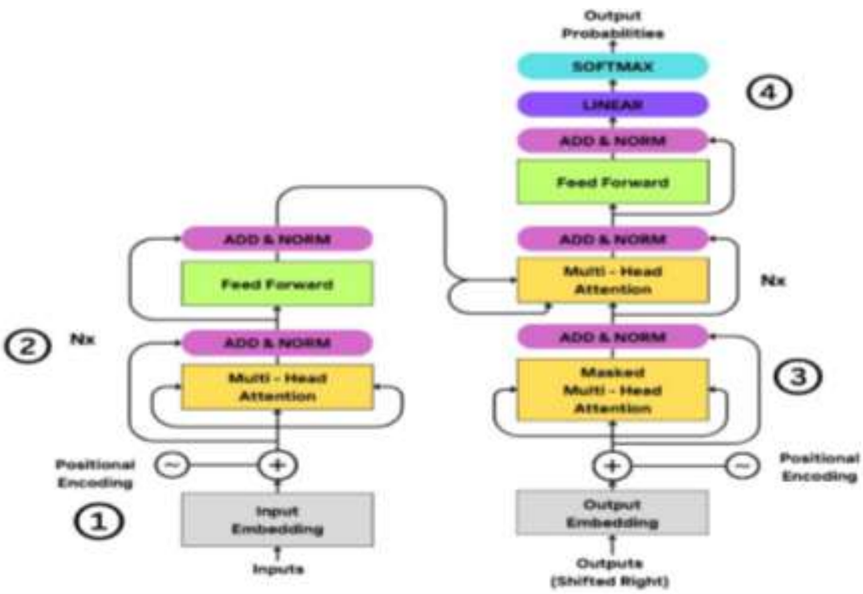


Fig. 3. Architecture of Transformer based networks: (1) Input Embedding and Positional Encoding (2) Multi-Head Attention, Add & Norm and normalizes the output (3) Output embedding with Multi-Head Attention, Add & Norm and Feed Forward (4) Linear Layer with Softmax Function extracts output probabilities.

1.4. LSTM Autoencoders

Integration with Long Short-Term Memory networks makes this combination an advanced marriage of two powerful neural network architectures, each contributing its particular strengths to the task of predicting the remaining useful life of parts in industrial systems. Autoencoders are known for their ability in unsupervised learning and are considered good techniques for mapping complex input data to concise representations. That is, they map noisy input data into important information and exclude unnecessary information. By compressing the input data into a lower-dimensional latent space and then reconstructing it, autoencoders facilitate the extraction of meaningful features that will be critical in estimating the RUL accurately.

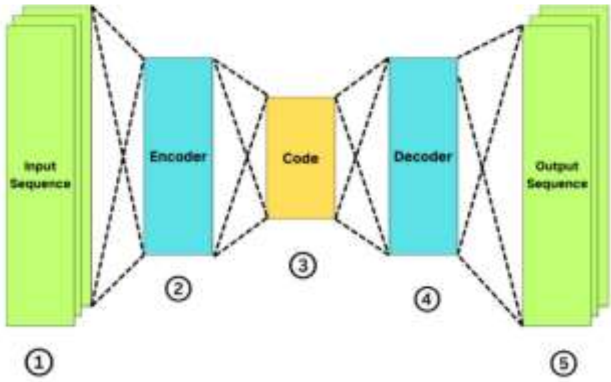


Fig. 4. LSTM + Autoencoders Architecture: 1. Input Sequence: It will consist of the input sequence that has to be fed through for processing. 2. Encoder: This layer compresses the input sequence into a latent representation—code. 3. Code / Latent Representation: Compressed version capturing the most important features of the input. 4. Decoder: The reconstruction of the input sequence based on the code. 5. Output Sequence: Reconstructed version of the input sequence, as returned by the decoder.

On the other hand, LSTMs are good at modeling sequential data and uncovering its temporal dependencies, making them widely applicable to the analysis of time-varying sensor readings prevalent in predictive maintenance tasks. Integrated, data models of autoencoder-LSTM architectures exhibit dual functionality: the autoencoder component learns compact representation of the input sensor data, while the LSTM layer processes sequential information encoded by the autoencoder, effectively capturing the temporal dynamics present within it. This enables the model to use both high-level features learned by the autoencoder and sequential patterns learned by the LSTM to make improved predictions. Moreover, training the model in an end-to-end fashion facilitates adaptive feature extraction and exploitation, further improving its ability to estimate RUL accurately. In the context of a comparative analysis for RUL prediction techniques, the inclusion of autoencoder-LSTM models offers a unique perspective, demonstrating the efficacy of combining unsupervised feature learning with sequence modelling to address the complexities of predictive maintenance in industrial systems. Thus, the fusion of autoencoders with LSTM networks stands as a promising approach for advancing the state-of-the-art in RUL estimation, offering a potent combination of feature extraction and temporal modelling to optimize maintenance strategies and prolong the lifespan of critical components.

2. Datasets and Experimental Results analysis

2.1. Dataset

This paper has made use of the CALCE (Centre for Advanced Life Cycle Engineering) battery dataset, where extensive cycling tests have been performed on an assortment of LCO/graphite cells. Cell specifications categorize a data set. All CS2 cells were charged by a methodology of constant current/ constant voltage. Until the voltage reached 4.2V, a constant current rate of 0.5°C was used, and the voltage (4.2V) was maintained until the charging current went below 0.05A. These batteries have a 2.7V discharge cutoff voltage, unless otherwise noted. CALCE 15 LCO is receiving data for prismatic CS2 cells categorized into six types based on experimental conditions and exposures. The 1st type is made up of 4 cells, each having a capacity of 0.9 Ah, while 2nd type has four cells, each having a capacity of 1.1 Ah, while there are 1–2 cells for 3rd and 6th types. The cells were incubated at 23 °C, cycled to varying depths, and then subjected to partial charging and discharging procedures before being tested under various C-rate specifications. The dataset is made up of cell cycling records including current, voltage, power during discharge/charge mode, inner resistance as well as impedance measurements. It contains data for various cycles. In order to use this dataset extensively, considerable preprocessing has been performed. The data was gathered for such batteries until they wear out at 80% state-of-health (SOH) level: up to 200 cycles for the 1st type and roughly 800 cycles for the rest of them.

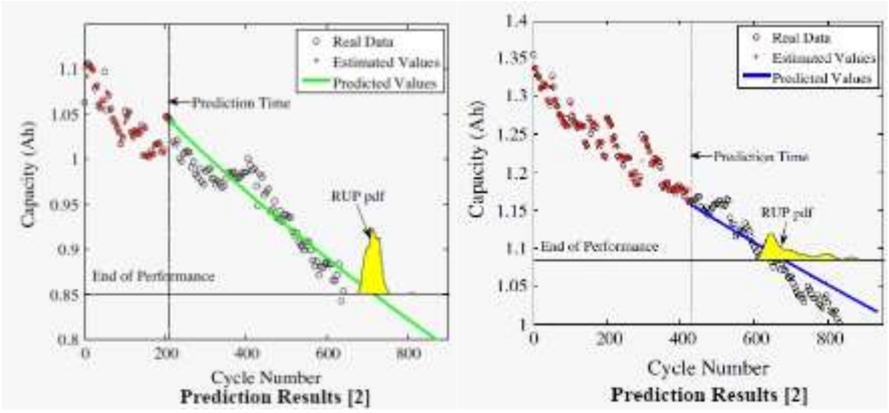


Fig. 5. (a) CS2 Cells Prediction Results; (b) CX2 Cells Prediction Results

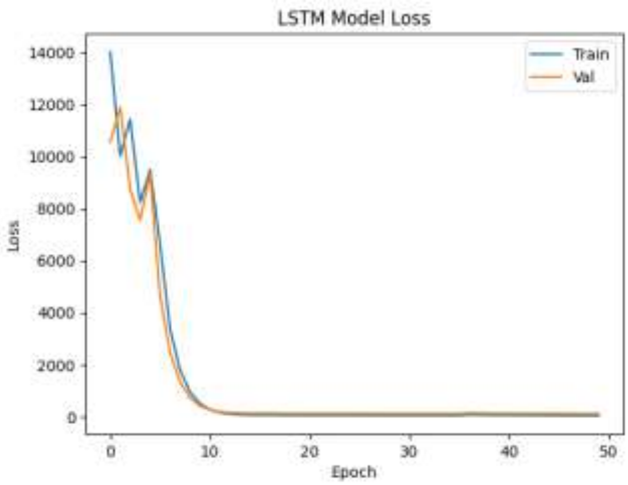
CALCE tested a second group of cells, which included 12 LCO prismatic CX2 cells, each having a capacity rating of 1.35 Ah, classified from 'Type-1' to 'Type-6'. The methodology of constant current / constant voltage has been used to charge all CX2 cells. Until the voltage reached 4.2V, a constant current rate of 0.5°C was used, and the voltage (4.2V) was maintained until the charging current went below 0.05A. These batteries have a 2.7V discharge cutoff voltage, unless otherwise noted. The 'Type-2' cells went through a cycling process that was comparable to the one seen in of the 1st type CS2 cells. Each of the remaining four groups include one cell that went through cycling with different charge and discharge protocols. Each cell went through cycling at varying temperatures i.e. 25 °C, 35 °C, 45 °C and 55 °C. Tests were performed in a semi-temperature regulated environment (25 ± 2 °C) on 16 LCO 1.5 Ah pouch cells and the effects were studied. The data has been structured based on DOD and discharge procedure and consists of cycler voltage, charge/discharge and current capacity details for 400 to 800 equivalent cycles.

2.2. Experimental Analysis

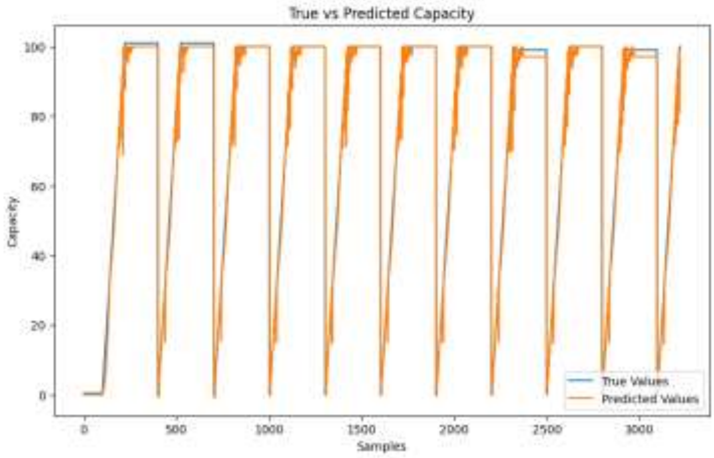
The following section explores in-depth the various deep learning models, their characteristics with relevant performance metrics.

2.2.1. LSTM

The effectiveness of the LSTM model was assessed based on various key metrics: Training Loss, Validation Loss, Mean Squared Error, Mean Absolute Error, and R^2 score. The graph displays that the implemented model is learning effectively, as both validation and training losses are decreasing, suggesting it is not overfitting. The MAE for the model is 2.2574, and that means, on average, the predictions are within 2.25 units of actual capacity.

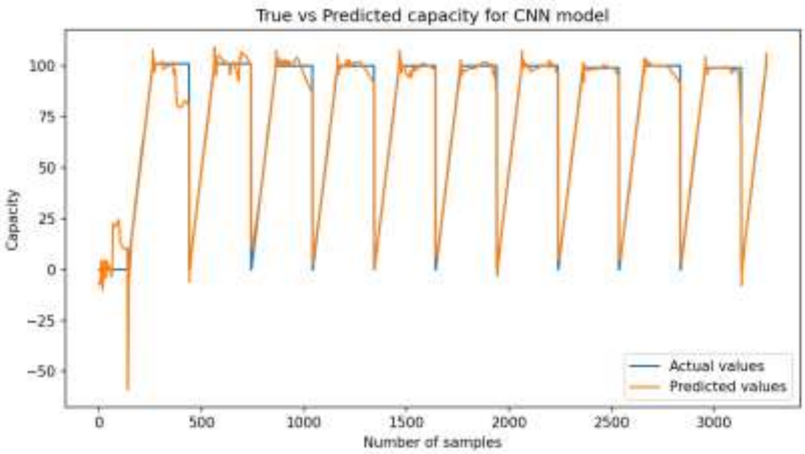


An MSE of 50.6359 then indicates that it captures the general trend well, even though there are bigger errors sometimes. With an R^2 score of 0.9561, it explains 95.6% of the variance in true capacity. It now is clear that an LSTM model has been very successful in learning capacity patterns and its predictions closely match real values. Additionally, the graph justifies the strong performance of the model, whereby the predicted values align well with the actual data trend.



2.2.2. CNN

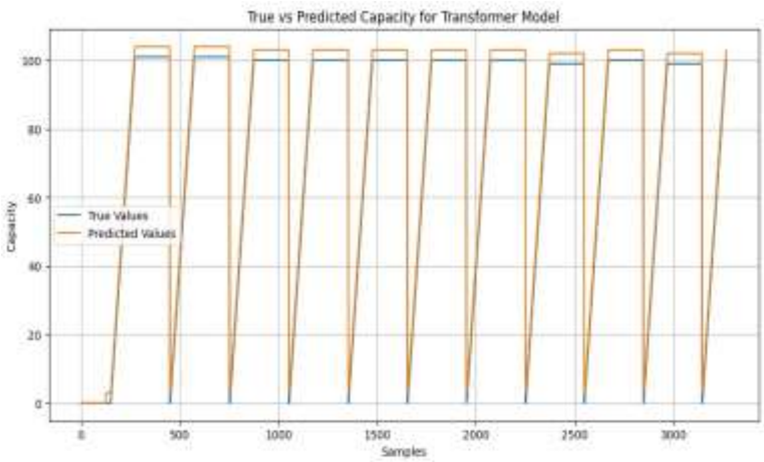
From what we can observe, the values generated from the CNN prediction deviate much from the test data at the initial stages. However, as we go into other subsequent stages, there is an increase in the accuracy of the capacity prediction.



Despite its poor prediction at the initial stage, the R2 score of this model is about 0.9583, which shows that CNN makes really accurate predictions. The Mean Squared Error and the Mean Absolute Error are about 50.38% and 2.79% accordingly. It may be due to the great dispersion of the predicted and actual values in the first stage.

2.2.3. Transformer based network

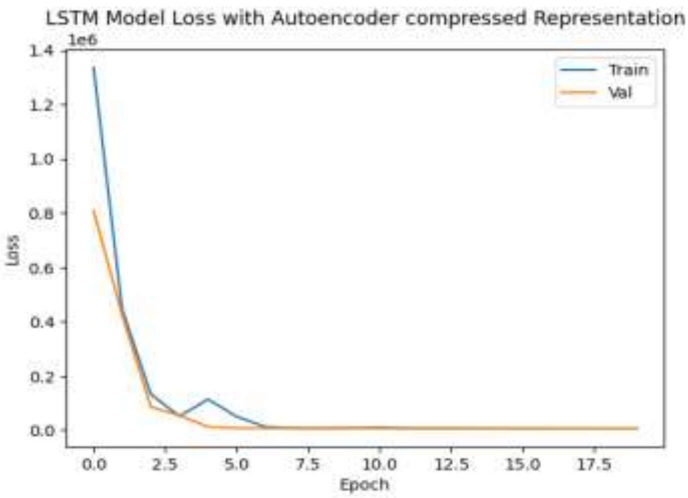
The Transformer Neural Networks look promising with respect to RUL predictions based on the performance metrics used. However, slight underprediction bias can still be seen in the model. The high R^2 score of 0.9699 tells of how good the fit of these models between the values that are actual and predicted. The implication here is that it really reflects the model's effectiveness in underpinning the patterns of underlying data.



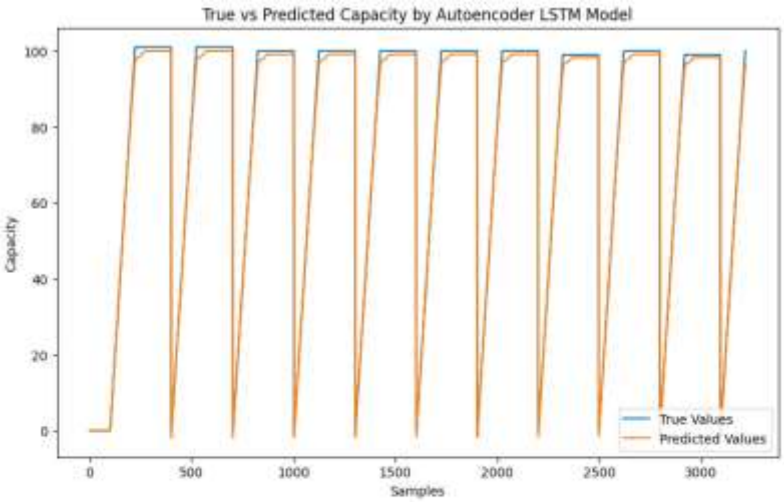
Further, a low mean absolute error of 1.8092 means consistent predictions with small average deviations between actual and predicted values. Overall, these metrics affirm that the Transformer's ability to estimate the RUL can be assessed with high accuracy.

2.2.4. LSTM with Autoencoders

We used several performance metrics for evaluating the effectiveness of the LSTM autoencoder model: Training Loss, Validation Loss, Mean Squared Error, Mean Absolute Error, and R^2 score. The line graph indicates that both the validation and the training losses are decreasing, pointing out the fact that the model is learning very well.



With an MAE of 1.2894, the model predicts fairly good accuracy; with an MSE of 32.1252, it can grasp general trends very well. With an R^2 score of 0.9722, the model explains 97.2% of the variance of actual capacity values, which means a high accuracy in estimating the capacity and thus a reliable model for that purpose.



2.3. Comparative Analysis

Table 2: Comparison between Deep Learning Models based on performance indicators.

Deep Learning Technique used	MAE (%)	MSE (%)	R^2 score
LSTM	2.2574302512733295	50.6358787953829	0.9561175848743891
Convolutional Neural Network	2.7163782037864235	50.388806997614786	0.9583243245928862
Transformer based Network	1.8091735610487512	39.871934721838109	0.9699158263917749
LSTM + Autoencoders	1.2894245896226801	32.12521550081203	0.9721594237891475

Among the four deep-learning models based on the R^2 score, their performance can be ranked in the following sequence with LSTM having the lowest R^2 score of 95.6 %, followed by Convolutional Neural Networks with an R^2 score of 95.8%. The Transformer based Network and the LSTM with Auto-encoders model have displayed the highest effectiveness with an R^2 score of 96.9% and 97.2% respectively.

The same trend can be observed in the case of mean-squared error, where the models have their performance ranked in the following order: LSTM, CNN, Transformer based Network and LSTM + Auto-encoders with their mean-squared errors being 50.63%, 50.38%, 39.87% and 32.12% respectively.

In the case of Mean Absolute Error (MAE). we can observe a slight deviation where the LSTM model has a better MAE than CNN model, being 2.25% and 2.71% respectively.

3. Conclusion

To effectively predict the RUL for Lithium-ion batteries four of the most widely used deep-learning models were explored due to their known efficiency. The models which were tested are as follows: LSTM, CNN, Transformer-based Network, and LSTM coupled with Auto-encoders. The MSE, MAE i.e. the Mean Squared Error and the Mean Absolute Error with the R^2 score were the key-performance indicators which were identified for evaluating the accuracy and precision of the models.
It can be seen that the LSTM + Autoencoders performed the most accurate prediction of RUL, with a minimum MAE of 1.29% and MSE of 32.12%. This was followed very closely by the performance of the Transformer-based Network, which recorded MAE of 1.81% and MSE of 39.87%. In the meantime, both models posted an R^2 score of more than 96.9% to indicate a strong relationship between the actual values and the predicted values of RUL. On the other hand, though LSTMs performed relatively well in MAE with a 2.26% error, they posted a higher MSE of 50.64% and a lower R^2 score of 0.956 than the top two models. CNNs posted a similar trend with a slightly higher MAE of 2.72% and MSE of 50.39% and a marginally better R^2 score of 0.958 than LSTMs.
Our comparative analysis comes to the conclusion that LSTM model that is augmented with Auto-encoders and the Transformer based model display the best performance compared to traditional deep learning architectures such as the CNN and LSTM when it comes to predicting the RUL in Lithium-ion batteries. These architectures that are advanced in nature have high accuracy, with minimal errors, and have established a strong correlation between the actual and the predicted values. The future scope in this field lies in optimizing the parameters by using methods such as hyperparameter tuning. In addition, using updated and live battery data will solidify their effectiveness in practical applications.

References

[1] Xie, Z., Du, S., Lv, J., Deng, Y. and Jia, S., 2020. A hybrid prognostics deep learning model for remaining useful life prediction. *Electronics*, *10*(1), p.39.
[2] Hu, W. and Zhao, S., 2022. Remaining useful life prediction of lithium-ion batteries based on wavelet denoising and transformer neural network. *Frontiers in Energy Research*, *10*, p.969168.
[3] Sun, C., Qu, A., Zhang, J., Shi, Q. and Jia, Z., 2022. Remaining useful life prediction for lithium-ion batteries based on improved variational mode decomposition and machine learning algorithm. *Energies*, *16*(1), p.313.
[4] Wei, M., Gu, H., Ye, M., Wang, Q., Xu, X. and Wu, C., 2021. Remaining useful life prediction of lithium-ion batteries based on Monte Carlo Dropout and gated recurrent unit. *Energy Reports*, *7*, pp.2862-2871.
[5] Hinchi, A.Z. and Tkiouat, M., 2018. Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network. *Procedia Computer Science*, *127*, pp.123-132.
[6] Song, K., Hu, D., Tong, Y. and Yue, X., 2023. Remaining life prediction of lithium-ion batteries based on health management: A review. *Journal of Energy Storage*, *57*, p.106193.
[7] Zhang, Z., Zhang, W., Yang, K. and Zhang, S., 2022. Remaining useful life prediction of lithium-ion batteries based on attention mechanism and bidirectional long short-term memory network. *Measurement*, *204*, p.112093.
[8] Qu, J., Liu, F., Ma, Y. and Fan, J., 2019. A neural-network-based method for RUL prediction and SOH monitoring of lithium-ion battery. *IEEE access*, *7*, pp.87178-87191.
[9] Ma, B., Yang, S., Zhang, L., Wang, W., Chen, S., Yang, X., Xie, H., Yu, H., Wang, H. and Liu, X., 2022. Remaining useful life and state of health prediction for lithium batteries based on differential thermal voltammetry and a deep-learning model. *Journal of Power Sources*, *548*, p.232030.
[10] Ellefsen, A.L., Bjørlykhaug, E., Æsøy, V., Ushakov, S. and Zhang, H., 2019. Remaining useful life predictions for turbofan engine degradation using semi-supervised deep architecture. *Reliability Engineering & System Safety*, *183*, pp.240-251.
[11] Xue, Z., Zhang, Y., Cheng, C. and Ma, G., 2020. Remaining useful life prediction of lithium-ion batteries with adaptive unscented kalman filter and optimized support vector regression. *Neurocomputing*, *376*, pp.95-102.
[12] Yang, B., Liu, R. and Zio, E., 2019. Remaining useful life prediction based on a double-convolutional neural network architecture. *IEEE Transactions on Industrial Electronics*, *66*(12), pp.9521-9530.
[13] Kraus, M. and Feuerriegel, S., 2019. Forecasting remaining useful life: Interpretable deep learning approach via variational Bayesian inferences. *Decision Support Systems*, *125*, p.113100.

[14] Yang, J., Peng, Y., Xie, J. and Wang, P., 2022. Remaining useful life prediction method for bearings based on LSTM with uncertainty quantification. *Sensors*, *22*(12), p.4549.
[15] She, D. and Jia, M., 2021. A BiGRU method for remaining useful life prediction of machinery. *Measurement*, *167*, p.108277.
[16] Wu, J.Y., Wu, M., Chen, Z., Li, X. and Yan, R., 2021. A joint classification-regression method for multi-stage remaining useful life prediction. *Journal of Manufacturing Systems*, *58*, pp.109-119.
[17] Wang, C., Peng, Z. and Liu, R., 2022. Prediction of Aero-Engine Remaining Useful Life Combined with Fault Information. *Machines*, *10*(10), p.927.
[18] Dolphin, R. (2018) LSTM Networks: A Detailed Explanation. Towards Data Science. Available at: https://towardsdatascience.com/lstm-networks-a-detailed-explanation-8fae6aefc7f9 (Accessed: 24 May 2024).
[19] Roy, R. (2020) LSTM-AutoEncoders. Medium. Available at: https://bobrupakroy.medium.com/lstm-autoencoders-a45a04667346 (Accessed: 24 May 2024).
[20] Ankit, U. (2020) Transformer Neural Networks: A Step-by-Step Breakdown. Built In. Available at: https://builtin.com/artificial-intelligence/transformer-neural-network (Accessed: 24 May 2024).
[21] Phung, S.L. and Rhee, E., (2019). The proposed CNN model architecture [Image]. In: A High-Accuracy Model Average Ensemble of Convolutional Neural Networks for Classification of Cloud Image Patches on Small Datasets. Applied Sciences, 9, p.4500. doi: 10.3390/app9214500. Available at: https://www.researchgate.net/figure/The-proposed-CNN-model-architecture_fig2_336805909 (Accessed: 24 May 2024).