Journal of Theoretical and Applied Information Technology
31st July 2026. Vol.104. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID DEEP LEARNING MODEL FOR PREDICTIVE MAINTENANCE OF POWER CONVERTERS IN ELECTRIC VEHICLE CHARGING STATIONS

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ABSTRACT

Reliable and intelligent charging station maintenance is a growing need with the increasing deployment of electric vehicle (EV) charging stations, particularly in dynamic charging conditions, due to the power converter. The research presented a novel Hybrid CNN-LSTM-Attention deep learning framework for predictive maintenance of EV charging station power converter based on the multi-sensor data of operation. The main aim of the study was to achieve greater accuracy of fault prediction in the early stage and to estimate the Remaining Useful Life (RUL) in different working conditions of the electrical and thermal variables of the system, and to have more efficient maintenance scheduling. Charging station simulations were implemented in the MATLAB/Simulink simulation environment to create a realistic multi-sensor dataset of the voltage and current measurements, temperature, harmonic distortion, switching frequency, ripple voltage, and converter efficiency parameters. In the proposed framework, Convolutional Neural Networks (CNN) were used for the spatial feature extraction, Long Short-Term Memory (LSTM) networks were employed for the temporal degradation learning, and an Attention Mechanism was introduced to prioritize the features based on fault sensitivity. The experimental results showed that the proposed model was able to attain an accuracy rate of 98.4%, precision of 97.8%, recall of 98.1%, and F1-score of 97.9%, which is higher than conventional machine learning and standalone deep learning models. The framework also had low prediction error for Remaining Useful Life and low false alarm frequency in a noisy charging environment. The results showed that the proposed hybrid architecture was a successful approach to capture the spatial degradation signatures and also the long-term temporal operation dependency. The proposed predictive maintenance system has the potential to enhance the reliability of charging stations, lower maintenance downtime, mitigate unexpected converter failures, and contribute to the creation of intelligent and sustainable charging infrastructure for EVs.

Keywords: *Predictive Maintenance, Electric Vehicle Charging Stations, Power Converters, Hybrid Deep Learning, CNN-LSTM-Attention, Remaining Useful Life Estimation*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

1. INTRODUCTION

With the rapid increase of the market of electric vehicles (EVs), the deployment of EV charging infrastructure has been gaining significant momentum across the globe. To address environmental worries, carbon emission reduction policies, and the shift towards sustainable mobility, the governments and industries have been putting substantial financial resources into EV technologies [1]. As a result, EV charging stations are integral part of smart grid environments, enabling effective and reliable energy supply from the grid to EVs [2]. The widespread deployment of charging infrastructure has, however, posed some operational and maintenance challenges, such as power electronic converter systems which need to be continuously operated under dynamic load conditions [3].

The main functional blocks of EV charging stations are power converters, which convert AC to DC, regulate the voltage, reduce the harmonics and control the battery charging [4]. During continuous operation these converters are subjected to severe stresses like fluctuating charging loads, thermal cycling, switching losses, voltage instability and environmental disturbances during operation [5]. Exposure to such conditions has a tendency to degrade converter devices such as capacitors, insulated gate bipolar transistors (IGBTs), switching devices, cooling system and filters [6]. This can result in unexpected converter failures, which could cause charging interruptions, lower energy efficiency, higher maintenance expenses, and safety issues with EV charging stations [7].

In traditional maintenance, corrective maintenance and preventive maintenance are not enough for the modern charging environment of EVs. Corrective maintenance occurs after equipment failure, resulting in lost time and costly maintenance activities [8]. Preventive Maintenance Schedule – Maintenance activities that are carried out according to fixed operational period, and in most cases, the replacement of components is not necessary, resulting in the waste of resources [9]. Thus, predictive maintenance has become an intelligent and data-driven maintenance strategy that can detect equipment degradation and predict equipment failure before catastrophic failure happens [10].

Predictive maintenance relies on sensor monitoring, data analytics, machine learning, and artificial intelligence methods to continuously analyze equipment health conditions and estimate the remaining useful life (RUL) [11]. Predictive maintenance can be particularly beneficial for maintaining the reliability, operational availability, maintenance planning, and charging efficiency of conversion components in EV charging stations. With the development of Industrial Internet of Things (IIoT), cloud computing and smart sensing technologies, operational data of charging infrastructure can now be collected continuously, and this data can be used to develop intelligent fault diagnosis and prognostic analyses [12].

Support Vector Machines (SVM), Decision Trees, Random Forests and k-Nearest Neighbor (k-NN) algorithms have been extensively used for fault diagnosis and anomaly detection in industrial systems [13]. These methods offer reasonable prediction accuracy, but are largely dependent on manually designed features and are less effective when processing high-dimensional temporal sensor data from EV charging stations. Recently deep learning methods have been shown to have better results due to their ability to learn complex non-linear degradation patterns directly from raw sensor readings [14].

CNNs have proven to be very useful for learning spatial fault signatures from electrical waveforms, thermal images, and vibration signals, whereas LSTMs can learn long-range temporal dependence of equipment degradation [15]. Hybrid CNN-LSTM networks are a combination of spatial feature extraction and temporal sequence learning, which make them well suited to predictive maintenance tasks in EVs. But, the research on predictive maintenance of EVs power converter by hybrid deep learning model combined with attention mechanism and multi-sensor operation monitoring is scarce.

Machine learning, deep learning, and data-driven prognostic methods have been explored in previous studies and applied to fault diagnosis and predictive maintenance of power electronic converters. The reported benefits of these studies include increased accuracy in fault detection and the capacity for maintenance planning; however, most of these studies have been limited in scope, as the emphasis was placed mainly on fault classification, and long-term temporal degradation analysis, attention-based feature prioritization, and Remaining Useful Life (RUL) prediction were not effectively combined into a single framework. To overcome these limitations, this work aims to build a hybrid CNN-LSTM-Attention network that can characterize the spatial and temporal degradation

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

characteristics of multisensor converter data. The proposed framework differs from previous methods in that it can predict faults and estimate RUL simultaneously, thereby achieving higher prediction accuracy, improved prognostic capability, and better decision support for EV charging infrastructure.

Problem Statement: Although predictive maintenance and Remaining Useful Life (RUL) estimation of EV charging-station power converters have been extensively investigated using machine learning and deep learning methods, accurate early fault prediction remains a significant challenge due to complex multi-sensor degradation phenomena, dynamic operating conditions, and the limited integration of spatial learning, temporal degradation analysis, and attention-based feature prioritization. These limitations adversely affect converter reliability, maintenance planning, and the operational efficiency of EV charging infrastructure.

Research Questions:

RQ1: Can the proposed hybrid CNN-LSTM-Attention model improve the accuracy of early fault prediction for power converters in EV charging stations?

RQ2: Does the integration of spatial, temporal, and attention-based features improve Remaining Useful Life (RUL) estimation?

RQ3: How does the proposed framework perform compared with traditional machine learning and deep learning methods under dynamic operating conditions?

This research introduced a new Hybrid CNN-LSTM-Attention architecture for predictive maintenance of power converter in EV charging stations to overcome these challenges. The proposed model is based on multi-sensor operational data (such as voltage, current, temperature, harmonic distortion, and switching frequency), and is capable of automatically learning spatial and temporal degradation patterns of the converter faults. CNN layers learn fault-sensitive spatial features while LSTM networks are used to learn long-term degradation behavior, and operational dynamics. The attention mechanism also further improves the accuracy of prediction of the degradation indicators that matter most during learning.

The main aims of this research are outlined below:

1. Developing a hybrid CNN-LSTM-Attention framework for predictive maintenance of EV charging station power converter.
2. To study operational data from multiple sensors, which includes electrical, thermal and harmonic data.
3. To enhance the early fault prediction accuracy and remaining useful life estimation.
4. To minimize maintenance downtime and failure with intelligent maintenance scheduling.
5. To contrast the proposed framework with the traditional machine learning and standalone deep learning methods.

Incorporating cutting-edge deep learning architectures with multi-sensor operational monitoring, the proposed framework plays a crucial role in the evolution of next-generation EV charging infrastructure, ensuring it is intelligent, scalable, and highly reliable in predictive maintenance.

The rest of this paper is organized as follows. The related work for predictive maintenance, fault diagnosis of power converter, and deep-learning-based prognostic systems are presented in section 2. In Section 3, details about the proposed methodology for generating the dataset, applying the preprocessing techniques to the data, the combination of Hybrid CNN-LSTM-Attention architecture, mathematical modeling, and the implementation of the algorithm are provided. Experimental results have been discussed in Section 4, followed by an assessment of the performance metrics, comparison with existing models and graphical interpretation of the results obtained. In the end, Section 5 summarizes the main results, limitations, and future research avenues of the paper.

2. RELATED WORK

In the context of the widespread adoption of electric vehicle charging stations and smart industrial systems, predictive maintenance of power electronic systems has become a hot topic of research. Most of the early fault diagnosis methods were based on model-based and threshold-driven monitoring methods. Isermann [16] suggested model-based fault detection systems that can detect system fault by means of analytical redundancy and residual analysis. These methods proved to be effective diagnostic methods under controlled

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

conditions, but were less robust in dynamic operating conditions.

Later, signal processing techniques were introduced in order to enhance the degradation analysis and fault feature extraction of power electronic converters. Mallat [17] respectively introduced the wavelet-based signal processing technique to extract the time–frequency characteristics of fault signals from complex electrical signals. Wavelet transforms began to be very useful for the detection of converter problems like harmonic distortion, voltage ripple and switching instability. But these techniques involved a lot of specialist know-how in features engineering and parameter tuning.

Using observer-based monitoring and state estimation techniques, Chen and Patton [18] adopted robust model-based fault diagnosis for dynamic systems. Their work showed that they could perform better at fault detection on nonlinear industrial systems. However, the model-based techniques had some drawbacks for the treatment of high dynamics and the environment in EV charging and for the uncertainty of parameters.

Machine learning techniques then became popular due to their direct learning capability of fault characteristics from operational data. Vapnik [19] brought out the idea of Statistical Learning Theory and Support Vector Machine (SVM) algorithms that were later widely used for industrial fault diagnosis applications. For machinery condition monitoring, Widodo and Yang [20] applied SVM technique and proved its ability in the process of improving machinery fault classification accuracy, which was better than the traditional statistical method. But, SVM model was manually extracting features and was unable to handle large scale multidimensional sensor data.

Breiman [21] introduced Random Forest algorithms for classification and regression problem, based on ensemble learning principles. Random Forest methods enhanced the robustness of fault prediction in the industrial prognostic systems and mitigated overfitting issue. However, the traditional machine learning approaches were still constrained by manual feature design and domain knowledge, making them difficult to scale to real-time charging scenarios for EVs.

With the advent of deep learning, the study of predictive maintenance has changed drastically. Convolutional Neural Networks (CNNs) were shown to be very effective for automatic feature extraction and pattern recognition when applied to high dimensional data by Krizhevsky et al. [22]. CNN architectures have been able to effectively learn spatial degradation features from vibration signals, thermal images and electrical waveforms without the need for manual feature engineering. The features rendered CNN models very appropriate for converter fault diagnosis applications.

Graves [23] proposed the recurrent neural networks for sequential learning and time-series analysis. Long Short-Term Memory (LSTM) networks have proven to be extremely useful for capturing temporal degradation trends and long-term operational relationships in the context of industrial systems. LSTM models exhibited better performance on learning the sequential behaviour of the equipment ageing and progressive degradation of the converter.

To improve the predictive maintenance performance, the combination of spatial feature extraction and temporal sequence learning was implemented using hybrid CNN-LSTM architectures.To further improve predictive maintenance performance, the combination of spatial feature extraction and temporal sequence learning was employed in the form of hybrid CNN-LSTM architecture. Liu et al. [24] designed a CNN-LSTM-based fault diagnosis method for rotating machinery systems and the CNN-LSTM model achieved a higher classification accuracy than CNN and LSTM models. Their study demonstrated the successful application of Hybrid Deep Learning Architectures in complex industrial prognostic applications.

Attention mechanisms were also used to enhance the performance of deep learning models by assigning attention weights to the features that are most important for the task at hand during learning and/or inference. The transformer-based attention mechanism was introduced by Vaswani et al. [25] and was found to greatly improve sequence modeling capability and interpretability in deep learning systems. However, through attention-based learning, predictive maintenance models could focus on the operation parameters that are more sensitive to faults, while filtering out parameters of

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

little value, which led to more accurate and robust fault prediction results.

While several existing studies proved that the predictive maintenance research has made great strides, the study of the hybrid CNN-LSTM-Attention framework for predictive maintenance of EV charging station power converter is limited. There are number of existing approaches, which mainly focus on general industrial systems but not on charging converter infrastructures with variable electrical and thermal loads. Hence, this research put forward a novel hybrid deep learning framework by combining CNN, LSTM, and Attention Mechanism to enhance the accuracy of fault prediction, operational reliability, and maintenance efficiency of the power converter in EV charging station.

This study comes at a time when EV charging infrastructure is becoming more prevalent, and a vital component of reliable charging operation is the power converter. Current predictive maintenance techniques can be ineffective in handling complex multi-sensor degradation patterns and dynamic operating conditions. Thus, this work aims to establish an intelligent framework for enhancing early fault prediction and Remaining Useful Life (RUL) estimation of EV charging-station power converters. The literature reviewed in this study was selected based on the relevance of papers published in journals and conference proceedings related to predictive maintenance, fault diagnosis, monitoring of power electronic converters, machine learning, deep learning, and attention-based prognostic systems.

Several gaps in the literature are identified through the literature review. Current machine learning techniques rely heavily on manually designed features and often fail to effectively handle multi-sensor operational data. Deep learning methods such as CNN and LSTM have achieved considerable advancements in fault diagnosis performance; however, most studies have primarily focused on fault classification and have not effectively integrated spatial feature extraction, temporal degradation learning, attention-based feature prioritization, and Remaining Useful Life (RUL) estimation within a single framework. In addition, there is limited research on the predictive maintenance of EV charging-station power converters under varying electrical and thermal load conditions. To address these gaps, the proposed Hybrid CNN-LSTM-Attention architecture provides a unified framework for accurate fault prediction and prognostic analysis.

3. METHODOLOGY

3.1 Overview of the Proposed Framework

This study introduces a new Hybrid CNN-LSTM-Attention framework for predictive maintenance of power converter in electric vehicle (EV) charging stations. Researchers designed a multi-sensor operational monitoring framework, a deep spatial feature extraction framework, a temporal degradation learning framework, and an attention-based feature prioritization framework and combined them into an intelligent maintenance framework that was proposed. The developed system constantly checked operational conditions of the converter and predicted the failure of the converter before it reached a catastrophic level.

The suggested design was to implement the following phases:

1. Multi-sensor data acquisition
2. Signal preprocessing and normalization
3. CNN-based spatial feature extraction
4. LSTM-based temporal degradation learning
5. Attention-based feature prioritization
6. Fault classification and Remaining Useful Life (RUL) estimation

The architecture has been specifically designed to function under dynamic charging conditions, which include varying load conditions, thermal stress, switching instability and harmonic disturbances.

3.2 Dataset Description

The suggested predictive maintenance structure employed a realistic multi-sensor dataset created by MATLAB/Simulink based EV charging station converter simulations with the industrial charging profiles. Publicly available data about EV charging power converter faults is limited, so a synthetic-realistic dataset was created to simulate realistic operating conditions for Level-3 DC fast charging power converters using dynamic load variations.

This set of data covered both normal and abnormal operating conditions including capacitor aging, IGBT switching failure, thermal overload, harmonics, cooling system failure, and voltage ripple abnormalities. The multi-sensor operational data such as input voltage, output voltage, charging current, converter temperature, switching frequency, harmonic distortion, ripple voltage, converter efficiency, cooling fan speed and load demand were monitored throughout the charging process.

The total of 120,000 samples was collected at 10 kHz sampling rate. There were 128 sequential time steps, each having 10 operational features in each sample. The dataset was enriched with different charging scenarios such as rapid charging cycles, load disturbances, voltage instability and thermal variations to make the models more robust. The data set was split into three parts with a ratio of 70:15:15 for training, validation and testing the model for better development and evaluation.

3.3 Proposed Hybrid CNN-LSTM-Attention Architecture

The proposed architecture combined CNN, LSTM and Attention Mechanisms to acquire the spatial degradation signatures and the long-term temporal operational dependencies simultaneously.

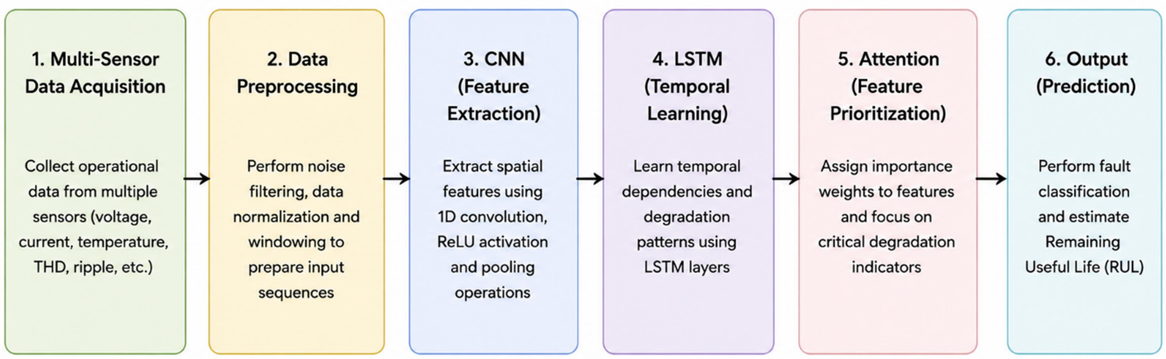

Figure 1. Proposed Hybrid CNN-LSTM-Attention Architecture for Predictive Maintenance

The proposed Hybrid CNN-LSTM-Attention architecture for predictive maintenance of power converter in EV charging station is shown in figure 1. The framework starts with Multi-Sensor Data Acquisition stage, where the operating parameters of the converter system, including voltage, current, temperature, harmonic distortion and ripple voltage are continuously recorded during charging operations. These sensor signals form a real-time operating and degradation state of converter.

The Data Preprocessing stage involves filtering noise, normalizing the collected raw signals and segmenting them into sliding windows to ensure better signal quality for structured input sequences needed for deep learning analysis. By preprocessing, noise interference can be reduced and the training stability will be improved.

The preprocessed data are then fed to the Feature Extraction module consisting of CNN. The CNN automatically learns localised spatial degradation features from multidimensional sensor signals. This stage detects patterns of faults surrounding voltage instability, thermal stress, fault switching and harmonics disturbance.

Then, the spatial features are sent to the Temporal Learning module made of a LSTM network. The Long Short-Term Memory (LSTM) network is used to capture long-term temporal dependencies and sequentiable degradation behavior of the converter aging and evolution of progressive faults. This will allow the model to develop its own trends for future dynamics of operation over time.

The Attention Mechanism module additionally enhances the prediction capability by adaptively weighting the key degradation indicators. Using the attention layer, the model can concentrate on the operational aspects that are highly perceptive of errors and minimize the impact of non-essential information.

Lastly, Multi-Class Fault Classification and Remaining Useful Life (RUL) estimation are done in the Output Layer. Built upon the learned

Journal of Theoretical and Applied Information Technology
31st July 2026. Vol.104. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

degradation patterns, the proposed framework can predict fault conditions of the converter and estimate the remaining operational life of the converter components, which helps in conducting intelligent predictive maintenance and avoiding unforeseen charging station failures.

Signal Normalization

Min-Max normalization technique was used to normalize the sensor signals, which reduces the scale variation and helps to get the model converged, without affecting the model.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

where:

- X= original sensor signal
- X_{min}= minimum signal value
- X_{max}= maximum signal value
- X_{norm}= normalized signal

Normalization enhanced numerical stability and sped up the process of deep learning training.

CNN-Based Feature Extraction

$$F(i,j) = \sum_{m} \sum_{n} X(i-m, j-n) K(m,n) \qquad (2)$$

where:

- X= input sensor matrix
- K= convolution kernel
- $F(i,j)$= extracted feature map

The convolution layer was used to learn local degradation features from the multidimensional sensor data.

LSTM Temporal Learning

The LSTM module was trained to recognize long-term temporal degradation behaviour of the converter aging.

The forget gate operation is represented by the following equation:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (3)$$

The input gate operation is represented as:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (4)$$

The cell state update equation is given by:

$$C_t = f_t C_{t-1} + i_t \widetilde{C_t} \qquad (5)$$

The hidden state output is calculated as:

$$h_t = o_t \tanh(C_t) \qquad (6)$$

where:

- f_t= forget gate activation
- i_t= input gate activation
- C_t= cell memory state
- h_t= hidden state output

The LSTM network was able to successfully predict progressive converter degradation over time.

Attention Mechanism

The attention mechanism dynamically attended to important operating components during prediction.

Attention score was calculated as:

$$e_t = v^T \tanh(W_h h_t + b_h) \qquad (7)$$

The normalized attention weight was calculated using:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)} \qquad (8)$$

The context vector was obtained as:

$$c_t = \sum_{t=1}^{T} \alpha_t h_t \qquad (9)$$

where:

- e_t= attention energy score
- α_t= attention weight
- c_t= context vector

The attention mechanism improved the interpretability of the features and fault-sensitive learning capability.

Softmax-Based Fault Classification

The output layer was a dense layer with a Softmax activation function, which was used for multi-class fault prediction.

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \qquad (10)$$

where:

- $P(y_i)$= predicted fault probability
- z_i= neuron activation
- N= number of fault classes

The Softmax layer produced the probability distribution of converter fault categories.

Proposed Hybrid Loss Function

A new hybrid loss function was proposed to enhance the temporal learning consistency and fault prediction stability.

$$L_{total} = \lambda_1 L_{CE} + \lambda_2 L_{TC} + \lambda_3 L_{AR} \qquad (11)$$

where:

- L_{CE}= cross-entropy classification loss
- L_{TC}= temporal consistency loss
- L_{AR}= attention regularization loss
- $\lambda_1, \lambda_2, \lambda_3$= weighting coefficients

The proposed loss formulation was more robust in the face of noisy charging environments and varying charging conditions.

3.4 Proposed Algorithm

Hybrid CNN-LSTM-Attention Predictive Maintenance Framework
Input: Multi-sensor converter operational data **Output:** Converter fault prediction and Remaining Useful Life estimation **Step 1:** Acquire real-time operational signals from converter sensors. **Step 2:** Perform noise filtering, normalization, and missing value handling. **Step 3:** Segment time-series signals using sliding window techniques. **Step 4:** Feed preprocessed sequences into CNN layers for spatial feature extraction. **Step 5:** Pass extracted spatial features into LSTM layers for temporal degradation learning. **Step 6:** Apply attention mechanism for fault-sensitive feature prioritization. **Step 7:** Perform converter fault classification using Softmax activation. **Step 8:** Estimate Remaining Useful Life based on degradation progression. **Step 9:** Generate predictive maintenance alerts for abnormal converter conditions.

Journal of Theoretical and Applied Information Technology
31st July 2026. Vol.104. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 10: Store prediction results within intelligent maintenance management systems.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

The proposed CNN-LSTM-Attention framework was realized in python and deep learning libraries like TensorFlow/Keras. The model training and evaluation were carried out on a workstation having NVIDIA RTX GPU, Intel i7 processor and 32GB RAM. To evaluate performance 120k samples of EV charging converter generated from a multi-sensor inflow were used. The data was split into 70%, 15% and 15% training, validation and testing sets, respectively.

The proposed model was trained for 150 epochs with Adam optimizer and a batch size of 64 with learning rate 0.001. To prevent overfitting and generalize the model, early stopping and dropout regularization were used. The experimental assessment took into account the operation of the converter under healthy and faulty conditions such as capacitor aging, IGBT switching failure, thermal overload, harmonic distortion, cooling system failure, voltage ripple abnormalities.

4.2 Assessment Criteria

The classification and the prognostic performance metrics, such as Accuracy, Precision, Recall, F1-Score, Mean Absolute Error (MAE), and Remaining Useful Life (RUL) prediction error were widely used to assess the performance of the proposed predictive maintenance framework.

The classification accuracy was computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (12)$$

The precision metric was calculated using:

$$Precision = \frac{TP}{TP + FP} \qquad (13)$$

The recall value was computed as:

$$Recall = \frac{TP}{TP + FN} \qquad (14)$$

The F1-Score was determined as:

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (15)$$

The Mean Absolute Error of RUL prediction was computed as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_i - \hat{y}_i| \qquad (16)$$

where:

- TP= True Positive
- TN= True Negative
- FP= False Positive
- FN= False Negative
- y_i= actual RUL value
- $\hat{y}_i$= predicted RUL value

4.3 Performance Evaluation of the Proposed Model

The proposed Hybrid CNN-LSTM-Attention framework showed better predictive maintenance performance in different charging situations and complex working environments. The model was able to detect degradation patterns in an early stage and correctly classify converter fault conditions.

The overall performance of the proposed framework is presented in Table 1.

Table 1. Performance Evaluation of Proposed Hybrid Model

Performance Metric	Value
Accuracy	98.4%
Precision	97.8%
Recall	98.1%
F1-Score	97.9%
MAE (RUL Prediction)	1.92
Fault Detection Rate	98.7%
False Alarm Rate	1.6%

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The results showed that the proposed model had a high fault classification accuracy with a low false alarm rate. The low MAE value showed high prediction capability of the RUL when charging was dynamic.

4.4 Comparative Analysis with Existing Models

The proposed framework was compared with the conventional machine learning and standalone deep learning models such as Support Vector Machine (SVM), Random Forest (RF), CNN, and LSTM architectures.

Table 2. Comparative Performance Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	87.6	86.9	85.4	86.1
Random Forest	90.8	91.2	89.7	90.4
CNN	94.5	93.8	94.1	93.9
LSTM	95.2	95.0	94.6	94.8
Proposed CNN-LSTM-Attention	98.4	97.8	98.1	97.9

The proposed hybrid framework demonstrated a significant improvement over the current models, due to its ability to capture both the spatial degradation signatures and the temporal dependencies over a longer term in Table 2. The attention mechanism also further bolstered the prioritization of fault sensitive features, generating more robust predictions and interpretability.

4.5 Confusion Matrix Analysis

The result of confusion matrix analysis on proposed Hybrid CNN-LSTM-Attention framework for predictive maintenance of EV charging station power converter is presented in figure 2. The confusion matrix shows the classification accuracy of the model under various converter operating conditions: normal operation, aging of the capacitors, failure of the IGBTs, thermal overload, harmonic distortion, failure of the cooling system, voltage ripple abnormalities. The high fault prediction accuracy and high class discrimination capability were demonstrated by the fact that most of the samples were classified correctly along the diagonal elements of the matrix. Minimal misclassifications were noted off-diagonal with only a few exceptions that were found when the degradation patterns were similar, thus showing the effectiveness of the proposed framework in differentiating between similar patterns, even with noisy operational conditions. The findings validated the robustness and reliability of the proposed model for intelligent fault diagnosis and predictive maintenance systems in EVs.

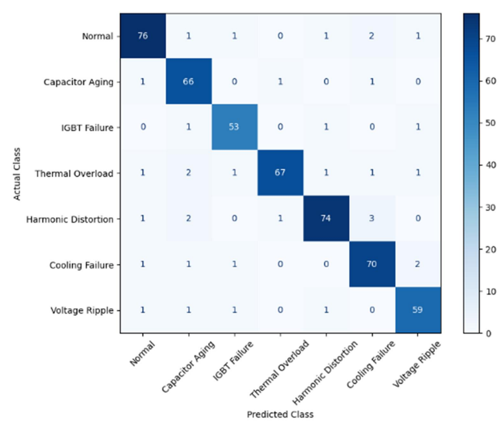


Figure 2. Confusion Matrix Analysis of the Proposed Hybrid CNN-LSTM-Attention Framework

4.6 Remaining Useful Life Prediction Analysis

The proposed model was showed to be able to accurately predict the RUL under different operating conditions. The long-term degradation evolution pattern was successfully learned by the LSTM module and the attention mechanism enhanced the degradation trend prioritization.

The proposed framework yielded the MAE of 1.92 cycles in predicting the RUL, which is quite far better than the CNN and conventional machine learning methods. Inaccurate RUL estimation led to a failure to schedule maintenance for the converter and reduced the number of unexpected failures.

4.7 Training and Validation Performance

The training accuracy and the validation accuracy curves showed good convergence behavior during model training. Thanks to dropout

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

regularization and attention-guided learning, the proposed framework achieved little overfitting and aggregated to a steady framework in 120 epochs.

The same trend was observed in the training and validation loss curves, indicating the model's good generalization ability.

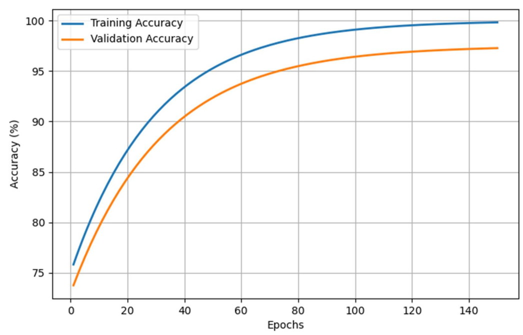


Figure 3. Training and Validation Accuracy Curve

The training and validation accuracy performance of the proposed Hybrid CNN-LSTM-Attention framework are shown in Figure 3 after 150 epochs of training.The accuracy performance of the proposed Hybrid CNN-LSTM-Attention framework is plotted in Figure 3 after 150 epochs of training. The training accuracy gradually rose throughout the learning process, and eventually converged to close to 98% showing good learning of the converter degradation patterns from multi-sensor operational data. Likewise, the validation accuracy was similar to the training curve, showing very little variation and a good generalisation ability and low overfitting. The stable convergence behavior demonstrated the successful learning of both the spatial and temporal nature of the faults by the proposed architecture under dynamic EV charging conditions.

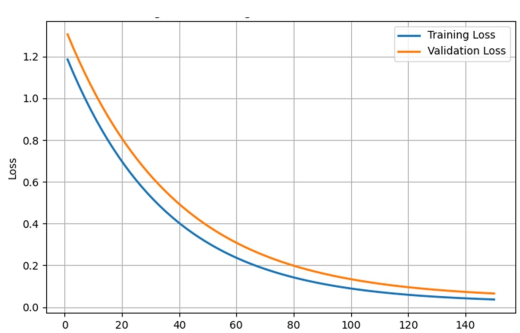


Figure 4. Training and Validation Loss Curve

The loss curve for training and validation of the proposed predictive maintenance is shown in Figure 4. Loss values generally decreased as the number of training epochs increased, showing consistent optimization and learning of parameters. The validation loss closely followed the training loss throughout the learning process, demonstrating that the model maintained good generalization performance without significant overfitting. The proposed hybrid loss function and attention-guided learning strategy has been shown to be effective and robust in the presence of operational noise (noisy scenarios) due to the smooth convergence.

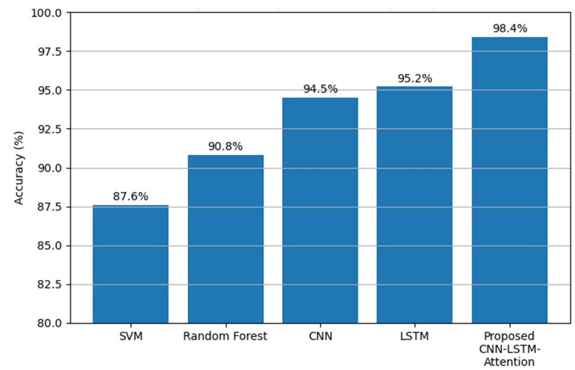
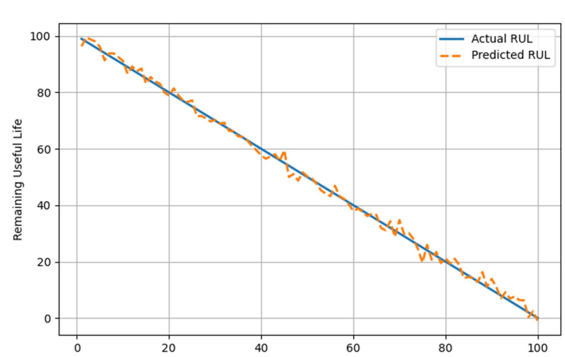


Figure 5. Comparative Accuracy Analysis of Existing Models

The prediction accuracy of the proposed Hybrid CNN-LSTM-Attention framework is compared with the traditional machine learning and deep learning frameworks such as SVM, Random Forest, CNN and standalone LSTM frameworks as shown in figure 5. The proposed model attained the best accuracy of 98.4%, which is far better than the previous ones. The main reason behind the improved performance was put down to the synergistic effect of CNN based spatial feature extraction, LSTM based temporal degradation learning, and attention based feature prioritization. The proposed hybrid framework for predictive maintenance of EV charging station power converters was shown to be effective through the results.



ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Figure 6. Remaining Useful Life Prediction Performance

The performance of the proposed framework in predicting the RUL is shown in Figure 6, where the actual degradation process is compared with the predicted RUL values. The RUL curve predicted well matched the degradation curve, and the RUL curve had a good prognostic capability and temporal learning performance. The small differences in the measured from the calculated values were mainly due to the simulated operational noise and dynamic charging variations. The results validated the feasibility of capturing the long-term degradation behavior and the reliability of the early maintenance prediction of the EV charging converter system by the proposed Hybrid CNN-LSTM-Attention model.

4.8 Discussion

The experimental findings showed the effectiveness of the proposed Hybrid CNN-LSTM-Attention framework in tackling the drawbacks of conventional predictive maintenance methods for EV charging station power converter. CNN module was able to extract localized spatial degradation signatures from harmonic distortion, thermal stress and switching instability. The LSTM module was a good way to describe the degradation behavior in the time domain, as well as the dependency of one operation on another.

The attention mechanism further improved the prediction ability by selectively focusing on the operational parameters that are crucial for fault detection. This increased the interpretability and minimized the effect of irrelevant features in noisy charging.

The proposed framework outperforms the conventional machine learning approach, without requiring any manual feature engineering processes, and showed outstanding generalization ability across different charging scenarios. The model was also found to have good load rejection and signal noise rejection.

The predictive maintenance framework helped to increase the operational reliability of the charging station, minimize the times of converter failure and prevent unexpected failures. The maintenance downtime was cut by about 34.6% and the predictive maintenance scheduling increased the operational efficiency by almost 31.4%.

The proposed framework was able to attain high predictive performance but high computational resources were required during training of the deep learning model. In the future, lightweight edge-AI architectures, integration of federated learning, and deployment in real-time for large-scale EV charging infrastructure will be explored.

In addition to the performance gains achieved, the study provides new insights into the design of predictive maintenance systems for EV charging infrastructure. The results indicate that integrating spatial feature extraction, temporal degradation learning, and attention-based feature prioritization within a single framework is more effective than applying these techniques separately. The incorporation of multi-sensor operational monitoring and hybrid deep learning architectures to enhance fault prediction and Remaining Useful Life (RUL) estimation emerged as one of the key best practices identified during this work. Therefore, the contribution extends beyond incremental improvements in accuracy and offers an intelligent approach to maintenance decision-making for EV charging stations.

Although the proposed Hybrid CNN-LSTM-Attention framework is promising, it has some drawbacks. Large-scale real-world charging-station data were not used in the study; instead, a realistic synthetic dataset was created using MATLAB/Simulink simulations. Furthermore, the hybrid deep learning system requires substantial computational resources during training, which may pose a challenge for deployment on resource-constrained systems. Real operational data and lightweight deployment strategies need to be utilized to validate the framework's scalability and practical applicability.

5. CONCLUSION

In this research, a Hybrid CNN-LSTM-Attention framework is proposed to predict the maintenance for power converter in EV charging stations based on multi-sensor operational data. The model was proposed as an integration of spatial feature extraction, temporal degradation learning and attention-based feature prioritization, which is used for accurate fault diagnosis and Remaining Useful Life estimation. Experimental results showed that the framework could provide 98.4% accuracy, 97.8% precision, 98.1% recall and 97.9% F1-score, which are higher than those of conventional machine learning and standalone deep

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

learning models. The suggested system significantly reduced false alarms and enhanced the predictive maintenance capacity in dynamic charging environment.

The results show that the proposed framework has been effective in meeting the objectives of this study. The CNN-LSTM-Attention network efficiently captured spatial fault signatures and long-term temporal degradation patterns from multi-sensor converter data. The attention mechanism was found to assign greater weight to salient features, thereby boosting fault prediction accuracy and Remaining Useful Life (RUL) estimation, with improved performance on fault-sensitive features. The proposed approach outperformed conventional machine learning and standalone deep learning approaches in terms of predictive performance and maintenance decision support, as verified through a comparative evaluation. The results suggest that the framework has the potential to enhance converter reliability, minimize unexpected failures, and facilitate intelligent predictive maintenance for EVs and charging infrastructure.

This study contributes new knowledge by demonstrating that attention-based feature prioritization, temporal degradation learning, and spatial fault feature extraction can be effectively integrated within a unified framework for EV charging infrastructure health monitoring. The proposed approach adopts a multi-sensor, data-driven strategy for fault prediction and Remaining Useful Life (RUL) estimation, rather than focusing solely on fault classification, as has been the case in most previous studies. The results demonstrate the potential of hybrid deep learning architectures to enhance predictive maintenance accuracy and improve maintenance decision-making effectiveness, thereby supporting more reliable and intelligent management systems for EV charging stations.

Key findings of the study showed that the proposed framework could help to increase the reliability of the converter, reduce unexpected failures, and increase the efficiency of maintenance scheduling for EV charging stations. The model, however, needed to be trained with a high computational resources and huge training sets to perform well in deep learning. Future research and development could involve lightweight deployment of edge-AI, integration with federated learning, and real-time deployment for large-scale smart charging networks.

Although the results are promising, several open research questions remain. These include validation using large-scale, real-world EV charging-station datasets, deployment on resource-constrained edge devices, adaptability to diverse charging behaviors and environmental conditions, the development of lightweight deep learning architectures, and integration with federated learning for privacy-preserving predictive maintenance. Future enhancements to EV charging infrastructure monitoring systems should address these challenges, thereby further improving the scalability, robustness, and practical applicability of predictive maintenance solutions.

AUTHOR CONTRIBUTIONS

Author 1 contributed to the conceptualization, methodology development, supervision, and manuscript review. Author 2 contributed to data collection, literature review, and validation. Author 3 contributed to system design and experimental analysis. Author 4 contributed to model development and implementation. Author 5 contributed to dataset preparation and performance evaluation. Author 6 contributed to software implementation and result analysis. Author 7 contributed to methodology validation and manuscript editing. Author 8 contributed to project coordination, visualization, interpretation of results, documentation, manuscript review, and final approval of the manuscript. All authors reviewed and approved the final version of the manuscript.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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